Hashtagability

A study of the potential of hashtags to do things on Twitter

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Declaration

I hereby declare that all of the work presented in this thesis is original material and analysis conducted by myself during the duration of this PhD.

None of the material has been published in another thesis, a peer reviewed journal or book.
Doctoral Training Undertaken

- Computer Programming for Social Scientists, Leeds University – Sept 2015
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Abstract

This interdisciplinary thesis explores hashtagability - the structural possibility of Twitter hashtags to do things or carry out functions - a new concept that helps to understand the 'becoming' of hashtags and provides the framework to study them. It is guided by the question of how hashtagability, realised as the potential of hashtags to become trends, can be analysed and explains why it should be. More specifically it develops new methods to analyse the realisation of hashtagability as the performance of gatekeeping and agenda-setting by users and the platform on the Twitter platform. It also develops a concept of *algorithmic ownership* which introduces a new dimension to the study of hashtags, which historically have never had an owner.

Conceptually the thesis is positioned in the context of the digital age and the digital economy. Twitter is explored as a platform that organises its members in a network society which is increasingly informed by algorithms. The thesis argues that the algorithmic ability to set the agenda of the platform by acting as the gatekeepers of Twitter Trends is exploited by some users who have developed techniques to manipulate algorithms by a form of orchestrated coordination which they exercise through the use of hashtags. The empirical exploration features two case studies: on Polish trending hashtags, which examines a decade of Polish trending hashtags by developing a strategy for historical data collection, and the UK 2017 General Election which looks at how Twitter's Trend Box could be explored as an algorithmic gatekeeper that sets the agenda of the platform.

Informed by literature review and methodological limitations of the first two case studies, the final empirical chapter introduces Hashtag Cloud Analysis – a method to investigate trending hashtags and to see the effect of Twitter Trend Box as an algorithmic gatekeeper in relation to changes in discussion dynamics by comparing pre- and post- Trend hashtag co-occurrences.
Chapter 1: Introduction to Hashtagability

Hashtag - a word or phrase, on social media websites and applications, preceded by a hash (#)

Oxford English Dictionary¹ (Online)

-ability - a suffix that stamps the noun with the irreducible quality of possibility.

Weber (2007:140)

Hashtagability

In just over a decade since their first use, hashtags have emerged as relevant objects of study for the social and computer sciences, the humanities and media studies. Since I started my initial research project (MA dissertation about hashtags on Instagram) in 2012, a range of books, journal articles and publications have come to address the various functions of hashtags as objects of empirical investigation. They received significant interest in academia from researchers from a range of disciplines such as sociology, political science, communication, media studies, branding, marketing and linguistics, amongst others. These studies show how hashtags are now fully integrated into the dynamics of contemporary culture and society and how they routinely become part of a wide range of objects or phenomena both online (i.e. Twitter Trends) or offline i.e. in advertising. There is no doubt that hashtags are important and worth studying. However, before I introduce my research questions and aims, I would like to explain the title of this thesis.

I have now been using and studying hashtags for almost a decade. They were born as a simple tool to categorise content on Twitter but since then have evolved so

¹ OED: http://www.oed.com/view/Entry/389023
much, that their initial function of categorising is sometimes not even worth mentioning. This thesis shows that almost everything that is interesting about hashtags happens either behind the closed door of the Twitter algorithm or behind the closed doors of Twitter users’ houses where hashtagging is being practiced increasingly not to talk to other Twitter users or to categorise content but to talk to Twitter algorithms and manipulate them in order to make hashtags trending. They are also used to make jokes, e.g. #toomuchfaketan, to comment, e.g. #yesiknow, play games (#GiveAMovieAName), watch television (#BBCQT), convey emotions (#Grrr) or build communities (#PhDChat). In just over a decade all these new functions were developed by Twitter users and there seems to be no end of this progress. As a result none of the definitions of hashtags that I came across in the last 8 years of my studies fully describe what hashtags do and most importantly their potential to do even more in the future, which is being continuously realised by Twitter users and Twitter as a platform.

In this thesis I would like to reframe the discussion about Twitter hashtags from describing what they do to focusing more on what possibilities or potential they have. In order to capture and study this potential I developed the concept of hashtagability, which is a combination of the word ‘hashtag’, understood as a word or phrase, on social media websites and applications, preceded by a hash (#) (Oxford English Dictionary) and the Weber’s (2007:140) notion of -ability, which he defines as a suffix that ‘stamps the noun with the irreducible quality of possibility’. In combination hashtag and -ability form Hashtagability - the (structural/platform) enabling of hashtags to potentially do things/carry out functions. This potential leaves room for users to do things in ways that are enabled (made easy) by the platform and in other ways. In short, the main argument is that hashtagability can be either realized by the users or the platform, most of the time in a combination of the two. In plain English, hashtagability means ‘the potential of the hashtag to do things’. This possibility as argued by Weber (2007:140) ‘is never fully realized or realizable: its reality depends on the future, but on the future in which the reader is inevitably implicated.’ This adds another dimension to this study - a creative tension that new functions of hashtags could emerge anytime or in fact they are possibly already emerging while this thesis is being printed. Millions of Twitter users scattered around the world are not practicing hashtagging, but hashtagability – the process of realising hashtag potential to create new functions or simply do things.
Although I define hashtagability in a rather sociological way, the readers from the field of media studies or computer sciences, should simply understand it as ‘the potential of the hashtag to do things’ compressed into a single word so that the sentence: ‘The study of the structural possibility of hashtags to act as a tool for content categorisation’ becomes ‘The study of hashtagability realised through content categorisation.’ As a result of this new optic of looking at hashtags and their abilities, this thesis become a study of hashtagability – the potential of hashtags to do things.

This project, by investigating how and why hashtags emerge on Twitter as trends, contributes to the emerging field of study that sits at the junction between media studies, data science and digital methods studies. It is guided by the following questions: how can hashtagability, realised as the potential of hashtags to become trends, be analysed and why should it be? More specifically, I aim to develop new methods to analyse the realisation of hashtagability as the performance of gatekeeping and agenda-setting by users and the platform on the Twitter platform. As part of this research, I develop two new concepts: hashtagability and algorithmic ownership and a tool called Trend Catcher which is used to perform Hashtag Cloud Analysis - the method of investigating trending hashtags through their co-occurrence. Hashtagability is a concept that helps to understand the ‘happening’ of hashtags and provides the framework to study them. Algorithmic ownership introduces a new dimension to the study of hashtags, which historically never had an owner. Trend Catcher is a practical tool that helps to identify how the Twitter algorithm acts as a gatekeeper and creates a heavily contested space. It brings together social and digital research methods to form Hashtag Cloud Analysis - a new way to study Twitter as a conversational tool.

The word Hashtag is relatively new. It was first used in 2007 by Chris Messina (2007: Online). Since then it has enjoyed a rapid spread on Twitter, across other social media and far beyond. Very quickly (by 2009) hashtags became integrated into the Twitter architecture and became internal clickable hyperlinks linking to platform’s search results for a given hashtag. In 2009 Twitter introduced ‘Trending topics’ based partially on popular hashtags. In 2012 ‘Hashtag’ was selected as the Word of the Year (Zimmer, 2013: Online) by The American Dialect Society (Zimmer and Carson, 2013: 81) and two years later received a separate category in the competition with #blacklivesmatter being the first winner in the category and also
the overall winner of the Word of the Year 2014 (Zimmer et al. 2015:84). In 2012 a couple called their baby Hashtag (Barkham: Online). About the same time hashtags were introduced on Instagram, Facebook, Google +, Flickr, YouTube and other social platforms. It all happened very rapidly just in five years since its creation in 2007 (Piatek, 2014).

Today hashtags are used both online and offline. Their initial function of categorising content and making it easier for future retrieval has been expanded to a number of other functions. They have become an integral part of conversations online (and offline) and are used as tools for building communities, adding context to discussions and commenting. There is no consensus as to how many tweets actually contain hashtags. Most likely this varies over time. Industry sources claim that in 2011 10% of the tweets contained them (Hashtags.org: Online). Gerlitz and Rieder (2013) found that in their sample from 1 day of Twitter activity 13.18% of tweets contained hashtags. There are also reports that estimate this figure is actually 24% (Cooper 2016: Online), or even 29% (Caleffi, 2015) which would suggest that there is an increasing trend. On the other hand, there are also voices (Rahimi, 2015: Online) to say that recently people started using fewer hashtags than before. Even if one accepts the figure of 10% it means that they are included in a staggering 50 million tweets a day, which makes them a truly global phenomenon that reaches out far beyond social media (Heyd and Puschmann, 2016; Scott, 2017).

Their use outside social media (both online and offline) is often strongly linked to social media. They either start somewhere else and then move back to social media or they start on social media and then become social phenomena that live their own life in the offline world. Very rarely hashtags used outside the online world are completely independent. For example, hashtags on television are used to encourage viewers to participate in a backchannel of discussion on Twitter or other social media (Atkinson, 2009; Harrington et al. 2012). There was a TV programme (@midnight with Chris Hardwick on Comedy Central in the US) that featured a daily game called ‘Hashtag Wars’. Participants were required to come up with phrases based on a daily changing hashtag theme. Other hashtags became world famous and social movements were created around them. #IranElection became the first long-trending international hashtag and the 2009 protests in Iran are today considered the first revolt to be catapulted onto the global stage by social media (Mottahedeh, 2015). #IranElection hashtag actually originated outside social media as a real
life/off-line historical event and only became trending on Twitter afterwards. This was followed by the Occupy Wall Street movement which became a protest that circled the entire world from a single #OccupyWallStreet hashtag (Berkovitz, 2011: Online; Papacharissi, 2015). In 2014 #YesAllWomen became popular globally as a grassroots campaign in which women shared their personal stories about harassment and discrimination (Grinberg, 2014: Online). The "Je suis Charlie" slogan was first used on Twitter as the hashtag #jesuischarlie as a solidarity gesture with the Charlie Hebdo offices attacked in Paris. Two years later in 2017 the #MeToo campaign against sexual harassment in the workplace spread virally as a hashtag (Khomami, 2017: Online) in response to the public revelations of sexual misconduct allegations against Harvey Weinstein.

Hashtag use has also expanded outside of Twitter and the social media. In the music industry Kanye West coined the term ‘Hashtag Rap’ to describe a style ‘where the lyric is followed by a pause, then an unconnected phrase intended to be compared to the preceding lyric, like a hashtag on Twitter’ (Mercer, 2013: Online). In the food industry Bird's Eye released in 2014 'frozen potato shapes for the social media generation' (Bamford, 2014: Online) called Mashtags and one of the shapes was a hashtag (Figure 1).

![Figure 1: Birds Eye launches Mashtags potato shapes (Bamford, 2014: Online)](image-url)
There was also a short trend (Meltzer, 2012: Online; Kamer, 2013: Online) when people would use a hand gesture called the "finger hashtag". In order to produce it one would use both hands to form a peace sign, and then the fingers had to be crossed to form the symbol of a hashtag (see Figure 2).

Finally, hashtags not only migrated from Twitter to the off-line world but also inspired the creation of new online formats. In 2010, during the World Cup in South Africa Twitter introduced hashflags - a combination of the # symbol and emoticons representing flags. These were later used again in the 2014 World Cup in Brazil (Woods, 2014: Online), in 2015 during General Elections in the UK (Unknown, 2015) and the Eurovision Song Contest in Vienna (Eurovision TV, 2015: Online). Another example of a new format inspired by a hashtag is a cashtag - a company ticker symbol preceded by the dollar sign i.e. $ABC, which allows users to search posts discussing companies and their stocks. This feature was originally invented in 2009 by StockTwits - a social media platform for investors, and only copied by Twitter in 2012 (Kim, 2012: Online; Taylor, 2012: 2012).
Hashtags have clearly migrated from Twitter to other media but also to the offline world. In her study of spoken, face-to-face communication using hashtags Scott (2017) presents the following example of the conversation that took place in the Guardian Online comments section from the 6th of January 2013:

@roolby: Where are the hover boards I was promised for the millennium in the decades before #stillwaiting#stillwaiting #nonsensepredictions

@LePendu: You’re not on Twitter – hashtags don’t work here

@roolby: @LePerdu – hashtags work everywhere

If the above exchange actually happened on Twitter, all the hashtags would have been active links. Because it happened somewhere else (still online), the hashtags do not link to any search results. Guardian Online simply does not support this feature and does not make hashtags clickable.

The first comment that ‘hashtags don’t work here’ seems to be referring to this lack of clickability. This user seems to be surprised that whoever posted the comment containing hashtags is not aware that not all websites support them. The reply shows that they do not need to be clickable and searchable ‘to work’ as they ‘work everywhere’. The decrease of the importance of the clickability of a hashtag is visible with the rise of the commenting and expressing emotions functions as described above. Heyd and Puschmann (2016) describe this as a functional shift linked to hashtags having recently become an instrument for creative self-expression and language play, that is, they are now more often used as a commentary tool to express a user’s attitude towards text. When people comment with hashtags, they do not use it to categorise their post under the right ‘emotion’ but to visually differentiate the text of the comment from the body of the post they are commenting on. The same rules seem to apply to hashtags used offline. Caleffi (2015: 66) argues that the main reason people use hashtags offline is to emphasise the message and hashtags help to highlight it.

Before describing this thesis and its structure in more detail, I will take a brief etymological detour. Etymologically the word hashtag is a combination of two words: ‘hash’ and ‘tag’. Hashtags can only exist if they start with the # symbol. This symbol provides the key visual characteristic both online and offline and makes it searchable on social media. Without the # symbol in front of them hashtags do not
become clickable links and in fact it is technically impossible to create a hashtag without the # symbol.

Houston (2011: Online) describes the long and fascinating history of the # sign and traces its roots to ancient Roman term *libra pondo*, used to describe a pound in weight. The *libra* part of the term means ‘scales’ and *pondo* originates from the verb *pondere* - ‘to weigh’. Interestingly in Latin both *libra* and *pondo* were also used independently to describe the same thing — a pound in weight. This duality in meaning created the # sign. Firstly, in the 14th century the abbreviation ‘lb’ for *libra* entered English language and ‘according to common scribal practice it was accessorised with a line drawn across the letters to highlight the use of a contraction. Jotted down in haste, as can be seen in Isaac Newton’s elegant scrawl below (see Figure X), ‘ทะเล’ was transformed into ‘#’ by the carelessly rushing pens of successive scribes. (Houston 2011: Online)

![Figure 3: Historical 'hashtags'. (Houston 2011: Online)](http://www.shadycharacters.co.uk/2011/05/the-octothorpe-part-1-of-2/#attachment_82)

Figure: ‘ทะเล’ as an abbreviation for *libra*, or ‘pound in weight’. On the left, a handwritten ‘ทะเล’ by Isaac Newton, and on the right, a printed ‘ทะเล’ crossed by a bar denoting its status as an abbreviation. Source:

At the same time *pondo* was changing as well. First it became the Old English *pund* and later re-emerged as the modern word ‘pound’. Then the # and the ‘pound’ were finally ‘reunited’ creating the ‘pound sign which in modern English evolved into many different names. Apart from ‘pound’ and ‘number’ it is also known as: ‘hash’, ‘crunch’, ‘hex’, ‘flash’, ‘grid’, ‘tic-tac-toe’, ‘pig-pen’, ‘square’ or ‘octothorpe’ depending what it is used for. The original meaning of the pound sign (the pound in weight) was later extended to numerous different meanings depending on the context. When # is

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2 http://www.shadycharacters.co.uk/2011/05/the-octothorpe-part-1-of-2/#attachment_82
accompanied by a number i.e. #5 it is read as ‘number five’, in chess it signifies checkmate and in press releases the three hash symbols in a row (‘###’) indicate the end of the press release. In programming language, it indicates that what follows is a comment rather than part of the programming. It is treated as a tool to highlight a special meaning of what follows it.

The ‘tag’ component of the word hashtag originates in Information Technology where it is defined as a keyword or term assigned to a piece of information that helps to describe it and allows it to be found again by browsing or searching. In other words, it is metadata - data that provides information about other data and is used to aid classification. The most basic definition of a tag could be simply ‘data about data’. On 23rd August 2007 Chris Messina combined the hash symbol with the tag for the first time on Twitter and two days later the word hashtag was used for the first time by Stowe Boyd to describe Twitter Groupings that ‘define shared experience (...) involving all those using the tag’. The widespread success of hashtags since their first use in 2007 resulted in the addition of the word hashtag to many English language dictionaries. Oxford English Dictionary⁴ (OED) defines it today as ‘a word or phrase, on social media websites and applications, preceded by a hash (#) and used to identify messages relating to a specific topic’ (OED: Online).

When a hashtag suddenly becomes very popular, it can be potentially included in Twitter Trending Topics, which Twitter founder Biz Stone (2009: Online) described as:

\[
\text{trending phrases (that) are surfaced in the Twitter home page just under the new search box and they're updated throughout the day. Built on our search technology, trends are a compelling if rudimentary way to explore a collective global consciousness.} \quad \text{(Stone, 2009: Online)}
\]

In short Twitter trends are simply words, phrases or hashtags that suddenly became popular on Twitter. The number of trending phrases or hashtags depends on many

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³ This is perhaps one of the reasons why hashtags containing only numbers are not allowed on Twitter as they would be confused with the meaning of the # symbol as a number.

⁴ OED: http://www.oed.com/view/Entry/389023
factors such as time of the day, geography but also a language. It also depends on the practices of users in different locations.

The significance of Twitter Trends

Why is it relevant to think about hashtagability in relation to Twitter Trends? First of all, it is important to recognise that the functions of hashtags are not pre-given or fixed, but emerge from a combination of platform affordances and use. There is a big difference between trending phrases or words and trending hashtags. All non-hashtag trends are most likely included in Twitter’s trend list because they naturally occurred in Twitter user’s conversations. Hashtags are different as their creator had an intention for them to stand out by adding the hash sign in front of the word or phrase. Most of the time the intention is either to categorise content or simply make it more searchable, but it is possible that the intention was to make the hashtag trending. The inclusion of the hashtag in Twitter Trend box offers significantly increased visibility of the topic. Because of this visibility, which according to Carrascosa et al. (2013) is comparable to traditional advertising, Trending Topics contribute to the collective awareness of what is trending and potentially could have an impact on the public agenda of the Twitter community and beyond. Postill (2014: 57) described how demonstrators and protesters strategically plan their street campaigns so that they occur on Twitter’s ‘trending topics’. Often trends originate outside Twitter as a piece of news (Kwak et al. 2010; Asur et al. 2011; Naaman et al. 2011; Zubiaga et al. 2015) and then get ‘transferred’ into Twitter Trends.

Thinking about hashtagability in relation to Trends is important because it is possible that they originate entirely on Twitter without any ‘outside’ event ‘causing/motivating’ them. When the latter happens, it is often difficult or impossible to establish the original source and as a result to say who sets the agenda for the entire Trending Topics box. Such a situation raises serious questions and some researchers have already addressed it. For example, Ratkiewicz et al. (2010) studied the spread of political astroturf memes on Twitter. Astroturf is a term for campaigns disguised as spontaneous, popular “grassroots” behaviour that are in reality carried out by a single person or organisation. This kind of campaigns are illegal in the UK, the US and the European Union (Foresman, 2010; Roberts, 2012; Malbon, 2013). Ratkiewicz et al. (2010) argue that an attacker equipped with the right choice of
words could influence the public well beyond his own social network by orchestrating and initiating spreading behaviour.

**Chapter Summaries**

Following this Introduction which defines hashtagability and introduces hashtags and trends, chapter Two provides the conceptual framework of the thesis. It positions the thesis in the context of the Digital Age (Dewar 1998), Digital Economy and Cognitive Capitalism (Boutang 2011; Thrift 2006) in which social media platforms such as Twitter play a significant role by providing technical infrastructure for networked interactions (Levy and Kerckhove, 1998 as cited in Flew (2007: 21) and extracting value from these interactions. The chapter shows that these interactions are increasingly managed by algorithms to the extent that algorithmically generated spaces such as Twitter Trend Box are enabled to perform gatekeeping and set the agenda of the platform. As a consequence, the new techniques, known as Coordinated Inauthentic Behaviour that allow groups of users to manipulate these algorithms, were developed and became a worthy object of studying.

Chapter Three starts with the exploration of different definitions of hashtags, followed by a short discussion and a suggested new definition. It then provides a review of how hashtags have been studied in politics, marketing, linguistics and communication, which is followed by the pre-history of tags and tagging, and the history of hashtags on Twitter tracing their roots in the Information Technology, Digital Media and Social Science traditions. Early hashtags are theorised as an example of social categorisation which happens through consumption of content. In the final sections chapter shows how hashtags were adopted on Twitter and by Twitter as a result of orchestration.

Chapter Four is the beginning of the study of hashtagability. The chapter explores the potential of what could be done with hashtags by users and how this potential is realised by hashtagging etiquette and the technical infrastructure developed by the platform. The numerous functions of hashtags are explored including the original function of categorisation, followed by conversational function. The chapter also looks at the use of hashtags as comments and how hashtagability is realised by the community building function. The other two explored functions are defined as emotive and providing context. Finally, chapter starts the discussion about
hashtagability understood as a performative vehicle that enables hashtags to become trends and to be used to create trends.

Chapters Five and Six set out a range of methodological and epistemological challenges faced by this thesis. The specific methods used for data collection and analysis are presented at the beginning of each empirical chapter (Seven, Eight and Nine).

Chapter Five introduces Twitter Trending Topics Box as an algorithmic gatekeeping device enabled by hashtagability and realised through the trend generating function. It theorises Trend Box as a delineation device which could be used as a starting point of the analysis of how algorithms work and what knowledge they produce. The chapter then introduces the concept of algorithmic ownership – the first original contribution this study is making to the fields of digital media and social science. The final section of this chapter explores Coordinated Inauthentic Behaviour on Twitter by showing how groups of users are able to exploit the hashtagability for their benefit by manipulating Trending Topics algorithm and making their hashtag trending.

Chapter Six offers the exploration of trends as algorithms from a quantitative data perspective and discusses the methodological challenges relating to Twitter research. It positions the thesis methodologically in the field of data science and explores the strengths and weaknesses of research methods derived from Big Data by systematically analysing tools that are available to study Twitter. It signals the possible problems with data representativeness and validity and explores know issues related to the study of algorithms, such as lack of access or expertise. Finally, it describes the methodological challenges behind the research design and the organisation of case studies based on methodological limitations.

Chapter Seven is the first empirical chapter and explores the history and the developments of hashtagability - the potential of hashtags and their users to develop new functions on the platform. It traces the history of the emergence of new functions of hashtags using Polish trending hashtags as a case study. It describes an innovative method of data collection that allowed to surface almost a decade of historical hashtags by operationalising the available trend archives and Twitter's native search in a way that they allowed to create an extended list of historical trends arranged by their first use. The limitations of data collection strategy used in this
chapter show the significance of time in this type of research and inform data collection strategy in the following two chapters.

Chapter Eight is the second empirical chapter. It aims to establish what types of hashtag trends get selected by the algorithm to be featured in the Trend Box and measure the ‘agenda setting power’ of traditional media and Twitter. The chapter does it by analysing hashtag trends identified during General Election 2017 in the UK and trying to quantify the impact of orchestration on Trend Box in order to study how gatekeeping is performed on Twitter. This chapter uses Twitter REST API to collect data and then analyses it using metrics generated by Twitter and network metrics generated by Netlytic 5 application. Based on the findings, this chapter informs the design and creation of Trend Catcher - a tool described in chapter eight which was developed in order to understand how Twitter trends are formed and what their formation can tell us about their origin.

Chapter Nine is the final empirical chapter. It continues the exploration of the form of hashtagability that creates hashtag trends, by introducing Hashtag Cloud Analysis (HCA) - the method of investigating trending hashtags through their co-occurrence. It describes the process of the development of Trend Catcher - a custom made tool used for capturing the ‘becoming’ of trends which uses the ‘Becoming Trend’ and ‘Being Trend’ phases to delineate the two life stages of trending hashtags.

Overall, this interdisciplinary thesis carefully responds to the two research questions (i.e. how can hashtagability, realised as the potential of hashtags to become trends, be analysed? And why should it be analysed?). More specifically, it offers a fresh, new way of looking at hashtags (in comparison to other studies that focus on their typology or where they originate) and how they emerge on Twitter as Trends. As a result, it builds on and extends the understanding of digital media by applying digital methods, exploring and developing innovative research methods. It also hopes to contribute to the development of a new interdisciplinary methodologies by introducing two new theoretical concepts: hashtagability and algorithmic ownership, and a new methodological concept of a Hashtag Cloud which is used to develop Hashtag Cloud Analysis - the innovative method of investigating trending hashtags through their co-occurrence. Hashtag Cloud Analysis and Trend Catcher

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5 Available at https://netlytic.org/
Application are very practical contributions that offer a real-life solution to very practical issues such as spread of disinformation or identification of Coordinated Inauthentic Behaviour, especially during elections or other major world events. In that sense this thesis reaches out beyond academia and has the potential to be developed further not only academically but also commercially.
Chapter 2: Conceptual framework

Introduction

We live in a Digital Age. At the turn of the century, the revolution started and as a result, we now live in the new economy primarily based on Information Technology (Castells 1996). Since 2002 we are able to store more information in digital than analogue media. Digital information can then be transmitted over the Internet or computer networks and it was this combination of digital information, media and networks that started a new era in industrial history, called the Digital Age (Dewar 1998).

This new, digital economy has more recently been theorised as Cognitive Capitalism (Boutang 2011; Thrift 2006) that is centred around the accumulation of immaterial assets which are protected through Intellectual Property Rights. The giant corporations of the Industrial Era such as Exxon Mobil, BP or Gazprom were replaced by the likes of Facebook, Google or Amazon. The new platforms do not produce anything - they almost solely rely on the work of their members organised in a Network Society (Castells, 1996:34). Value is extracted from the collective intelligence of their members who create social knowledge by simultaneously expanding the extent of their networked interactions (Levy and Kerckhove, 1998 as cited in Flew (2007: 21). These interactions are increasingly managed through algorithms, that act as gatekeepers (Lewin 1947) and gatewatchers (Bruns 2005). There is an increased body of evidence that these algorithms have the ability to set the agenda (McCombs and Shaw 1976, Aruguete 2017: 51) of these platforms and beyond. It has now been proved beyond doubt (Weedon et al, 2017: 4) that there are organised actors (private organisations or states) who conduct Information Operations that aim to distort ‘domestic or foreign political sentiment or (…) to achieve a strategic and/or geopolitical outcome. These operations can use a combination of methods, such as false news, disinformation, or networks of fake accounts aimed at manipulating public opinion (“false amplifiers”). One of the key techniques to manipulate public opinion and set the agenda is described as a Coordinated Inauthentic Behaviour which might come in a form of coordinated
sharing of comments, coordinated likes, repeated posting across multiple accounts or even the creation of Astroturf groups - an organised activity that purports to reflect authentic individuals but is actually manufactured, as in “fake grass-roots.” (Weedon et al, 2017: 9).

There is a growing body of research (Huang et al 2010; Recuero and Araújo 2012a) that suggests that Twitter Platform and especially the algorithm that determines Twitter Trending Topics could be affected by Coordinated Inauthentic Behaviour. There are numerous examples of Trends being ‘created’ by groups of fans or political activists in a coordinated manner. There is also a growing number of state actors that are attempting to exploit social media (Howard and Bradshaw, 2018: Online). This thesis investigates how hashtag trends can be analysed and why they should be. It presents, explores and develops methods, tools and techniques that can be used to understand trending hashtags and how they could be used to manipulate public opinion by creating Trends. Methodologically it follows the tradition of Digital Methods (Burrows, 2009), that seek to learn from the methods built into the dominant devices online and repurpose them for social and cultural research. I start with the analysis of natively digital objects (hashtags and Trends) and explore how Twitter as a platform makes use of them. Once my findings are made with the online data, I attempt to ground them in both online and offline worlds.

For example, when studying algorithms, I take Seaver’s (2014: 1-2) advice to look at their applications, effects and circulation, rather than focusing purely on the ‘mathematical proof’ of how they operate. Seaver (2014: 2) argues that the ‘mathematical approach’ is very limiting, closed to outsiders and does not allow the researcher to ask questions about the impact of algorithms on culture, society, the public sphere, interpretation or politics. This is similar to Burrows (2009: 8) who argues that ‘the Internet (should be) employed as a site of research for far more than just online culture. The issue no longer is how much of society and culture is online, but rather how to diagnose cultural change and societal conditions using the Internet.’ Following on, this thesis treats Digital Methods as a methodological framework for social and cultural research on the Web that seeks to move Internet research beyond the study of online culture. I do not aim to develop a toolkit for Internet research (only), or operating instructions for a software package. I use Digital Methods, as recommended by Burrows (2013), to answer a broader question of how can one study Twitter Trending Hashtags to learn something about society.
rather than Twitter use. The ethical outline for this thesis was developed by following the Social Media Research Guide to Ethics (Townsend & Wallace, 2016). I also consulted the British Sociological Association's 2006 Statement of Ethical Practice (BSA, 2006).

The previous chapter opened up a discussion on contemporary usage of hashtags and how potentially hashtags could be used to manipulate Twitter's algorithms and create trends. In this chapter, after outlining the conceptual framework, I look at Twitter as a platform. The aim of the chapter is to position both Twitter and hashtags in a wider context of the Cognitive Capitalism and the Digital Age.

**Cognitive Capitalism of the Digital Media**

Hilbert and López (2011) estimate that in 1986 less than 1% of the world's media storage capacity was digital. 20 years later, in 2007, it was already 94%. Since the year 2002 humans were able to store more information in digital than in analogue media, and it is considered the beginning of the digital age. The term digital media is used to describe any media that are encoded in machine-readable formats that can be transmitted over the internet or computer networks. This can include text, audio, video or graphics. Digital Media combined with the Internet and personal computing has had a significant impact on society and culture and caused disruption in several industries such as journalism, publishing, education, commerce and politics. It also created new challenges for copyright and intellectual property laws. Dewar (1998) argues that it was the development of digital media, that started a new era in industrial history, called the Digital Age.

The Digital Age, also known as the Computer Age or the Information Age can be characterised by the rapid shift from traditional industry that the Industrial Revolution brought through industrialisation to the new economy, primarily based on Information Technology (Castells 1996). This new, digital economy is also known as Cognitive Capitalism. Boutang (2011) argues that Cognitive Capitalism is centred around the accumulation of immaterial assets which are protected through Intellectual Property Rights. These patents are then used by their owners for the creation of a surplus value resulting from monopolistic practices. The weight of the
immaterial is an outcome of the new computer technologies (such as the Internet) and digitised data which created the network society ("a society where the key social structures and activities are organised around electronically processed information networks." Castells, 1996: 34) and a collective intelligence ("It is a form of universally distributed intelligence, constantly enhanced, coordinated in real time, and resulting in the effective mobilisation of skills." Levy: 1994). Levy and Kerckhove (1998) as cited in Flew (2007: 21) argue that collective intelligence 'refers to capacity of networked ICTs (Information communication technologies) to enhance the collective pool of social knowledge by simultaneously expanding the extent of human interactions.'

A quick look at a list of the largest companies in the world by market value (2019⁶) shows that companies such as Google, Apple, Facebook and Amazon (known as Big Tech or GAFA) that rely on the accumulation of immaterial assets have replaced the energy giants such as Exxon Mobil, BP, Gazprom, PetroChina and Royal Dutch Shell known as "Big Oil". Big Tech The growth of these companies also outpaced that of the traditional Big Media companies such as Disney or 21st Century Fox.

The origin of Google’s power is based on an invisible algorithm, called Page Rank. Pasquinelli (2009) argues that thanks to the Page Rank algorithm, Google established its own proprietary hierarchy of value and became the first systematic global rentier of the common intellect or what Levy would describe as a collective intelligence ‘Google produces and accumulates value through the PageRank algorithm by rendering the collective knowledge into a proprietary scale of values’ (Pasquinelli; 2009: 4). By doing that, Google became the Internet’s gatekeeper and gained the ability to influence the importance placed on topics of the public agenda.

**Algorithms**

Algorithms are almost everywhere. The music industry uses Auto-Tune, a device run by algorithms which bends pitches sung by an artist or performed by an instrument

to the nearest true semitone, so that a song sounds better. OKCupid, an online dating site, makes use of an algorithm which on top of matching people by common interests, also weights their answers by how important the question is to them and their prospective partner. It is one of the more effective online dating sites and apparently couples who meet through the site tend to have better marriages (Cacioppo et al. 2013). IBM’s CRUSH (Criminal Reduction Utilizing Statistical History) also known as predictive analysis is used by police departments around the world to reduce crime by forecasting criminal ‘hot spots’ (Dvorsky, 2012: Online). The National Security Agency (NSA) has numerous surveillance programs run by algorithms that they use to monitor our phone calls, emails, webcam images, and geographical locations. The financial sector has a long history of using algorithms to predict market movements but recently they went one step further and developed a practice of high-frequency stock trading - a rapid trading which is conducted automatically by the bots run by algorithms, which make buy/sell decisions in milliseconds. As a result, humans are being gradually removed from this trading loop. Amazon and Netflix monitor what we buy online and suggest related items based on our past purchases using algorithms. Google AdWords tracks users’ behaviour online, words they use, and search queries to deliver contextual advertising. Facebook’s EdgeRank does the same but with the News Feed users are getting a predetermined selection of items that Facebook’s algorithms ‘think’ are of interest to the user based on factors such as the number of comments, creator of the story or type of post/media. Lastly, Google’s PageRank works in conjunction with web crawlers to evaluate the importance of a website based on the number and quality of links to a page and numerous other known and unknown factors, in order to provide a search results page - a list of links to ten pages that PageRank decides are the most relevant to the search term.

The most striking thing about the most powerful algorithms in the world is that we do not know too much about them. For example, Google Search Engine is a starting point for most online browsing but no one outside (and possibly inside) really knows how it works, which causes a lot of speculation. We know that algorithms are designed by individuals, teams of individuals and some of them change their design independently of human decision based on the result of ongoing A/B testing. They are increasingly difficult to study because of the proprietary nature of commercial systems in the Cognitive Economy (Seaver 2014: 2; Kitchin 2014: 17). In other
words, the companies that own them do not want to share information about their design. The other problem is the lack of the technical know-how required to make sense of them. It is possible that even if one was given access to the entire infrastructure of Google, it wouldn’t be possible to fully understand how Pagerank works purely because the algorithm is too complex. Lewis (2015: Online) argues that it is updated between 500 and 600 times a year and although most of the changes are relatively small, there have also been numerous major updates since it was originally created. Examples of past updates include:

- Boston Update in 2002 with a focus on prioritising local results, combating link spam, dodgy SEO practices and emphasising fresh content;
- Panda Update in 2011 focused on rewarding websites with the quality content over link farms, which helped to eliminate spam websites from the results;
- Penguin Update in 2012 dealt with over-optimised websites with dodgy linking practices and those linking to gambling or adult websites. Also, websites using paid links were penalised;
- Hummingbird Update in 2013 was the most significant change by far - it focused on providing results which predicted user’s intent in their search. Instead of leaving users to refine their search, Google’s algorithm is trying to work out the intent of the user and apply it to the results automatically.
- Pigeon Update in 2014 focused on providing more relevant search results based on a local perspective. Geographical locations and distances were added to the algorithm so that the results gave greater relevance to local businesses and websites.

More recently Google announced that it was to start using a machine-learning artificial intelligence system called “RankBrain” to generate its search results:

*RankBrain uses artificial intelligence to embed vast amounts of written language into mathematical entities - called vectors - that the computer can understand. If RankBrain sees a word or phrase it isn’t familiar with, the machine can make a guess as to what words or phrases might have a similar meaning and filter the result accordingly, making it more effective at handling never-before-seen search queries.* Clark (2015: Online)
All these updates make it even more complicated to understand how Google Search Algorithm works. Sullivan (2016: Online) claims that Google uses ‘more than 200 major ranking signals (things Google uses to help determine how to rank Web pages) that are evaluated that, in turn, might have up to 10,000 variations or sub-signals’. When Google CEO Eric Schmidt was asked about the list of these signals, he refused to supply it and said: ‘Why don’t we publish these things? (...) the fundamental answer is we’re always changing [and] (...) it’s a business secret of Google.’ (Sullivan, 2010: Online)

Millions of people use Google Search every day and the order in which search results are displayed is extremely important, both for the producers and the consumers of the content. For businesses being ‘high’ on Google search result for a good keyword can translate into millions of pounds of profit. For consumers it can be a matter of life and death if for example they choose which doctor to go to based on Google Search results. For many researchers (Madsen, 2012) Google search engine is the starting point for their research on the digital economy. It is clear that Google’s algorithms are extremely important but still so little is known about them. The same can be said about Facebook EdgeRank or Twitter Trending Topics - they are significant as millions of people rely on them in their daily search for information. They help to determine what news is important and what does not get made visible - they act as digital gatekeepers. Wallace (2018) argues that with the rise of algorithms and users co-existing as decision-makers and items reaching high visibility through decentralised gatekeeping mechanisms that the classic gatekeeping theory is no longer adequate in describing contemporary news selection processes online and the new approaches are needed.

**Gatekeeping and Gatewatching in the Digital Age**

The term ‘gatekeeping’ was first used by Lewin (1943) in a paper describing the decision making process behind the journey of food between the various sources such as a shop or a garden and the table in the time of war. Lewin argued that the process requires a series of decisions (i.e. discovery of food, the purchase or
transportation) and as a result becomes a channel. In order to enter and then move from one end to the other the food had to go through a 'gatekeeper' or several gatekeepers. In the case of food, it was a housewife or a maid and not all household members had equal weight in decision making. When the term is used in journalism, the food item is replaced by a news item and the decision whether it enters the channel or moves from one section to the other is made by a media gatekeeper(s). (Bass 1969). The entrance to the channel and its sections are called gates and the process of a news item passing through these gates, guarded by gatekeepers is gatekeeping. In his later work Lewin (1947) introduced the idea of feedback in group decision making process and argued that each gatekeeper has a set of considerations he/she uses in making decisions and these may vary depending on the considerations of the group.

The first studies of gatekeeping, although without explicitly using the term, were conducted almost a century ago and were associated with media and journalism. Park (1922) analysed how editors were choosing certain items for publication and how they were making decisions about the importance of certain news or reports. Similar studies (White 1950: 386; Snider 1967: 402) attempted to establish how mass communication gatekeepers regulate their gates. They found out that only 10% of the suggested content got published and the process was highly subjective, based on the editor's personal experiences and expectations.

The modern definition of gatekeeping is still based on the original idea of a gatekeeper as the controlling point between the channel and its external environment (Lewin, 1951: 186). Gatekeepers 'facilitate or constrain the diffusion of information as they decide which messages to allow past the gates' (Shoemaker and Vos 2009: 21). Shoemaker (1991: 1) described it as the process of choosing hundreds from the billions of available messages. The selected messages then reach a given person on a given day. A gate is treated here as an in or out decision point (Shoemaker 1991:2) in a channel - very much as it was in the original research (Lewin: 1943). The selection of information is important but media gatekeeping is more complex than this. Donohue et al. (1972: 43) argue that gatekeepers also make decisions about 'message encoding, such as selection, shaping, display, timing, withholding, or repetition of entire messages'. Bass (1969) identified two distinct roles in media gatekeeping: the news gatherers and the news processors. Gatherers find and consolidate information and processors turn them into the news product. It
is possible that the process could be performed by the same person but it clearly has several stages.

More recently, the new Digital Age and development of search engines such as Google or social networks such as Twitter significantly changed the process of media gatekeeping. Bruns (2005) argues that there is a shift from gatekeeping to gatewatching. Traditional gatekeepers increasingly rely on material from citizen journalists found on social networks rather than spending time and money on their own, independent research. ‘Gatewatchers fundamentally publicise news (by pointing to sources) rather than publish it (by compiling an apparently complete report from the available sources)’ (Bruns 2005: Online).

The role of a gatekeeper is also being increasingly carried out by non-journalistic actors and platforms. The Arab Spring or the Occupy movement showed that traditional media are no longer exclusive gatekeepers. In Egypt (2011) and Turkey (2013) traditional media controlled by the state were replaced by Twitter, which was used as the source of and a tool to spread alternative information (Demirhan 2014; Meraz and Papacharissi 2013). In the West alternative news portals or even individuals on social media suddenly became competitors of traditional media for the power over the public agenda (Fletcher and Park 2017). These individuals often apply different news selection criteria than traditional media outlets (Jürgens et al 2011; Meraz and Papacharissi 2013). Finally, an increasing amount of news is generated and made visible by non-human actors but algorithms, that base their selection process on the behaviour of humans. Algorithms are designed, based on human behaviour, to make certain news items visible. Such gatekeeping algorithms not only influence what we read, but also the attitudes we form about what we read (Thorson 2008: 486).

**Networked Gatekeeping**

In the field of mass media research, the concept of gatekeeping was associated with highly centred networks that prevented the spread of information by actors other than those sitting in the centre of these networks. Until the recent development of digital media, the news infrastructure was organized around sender (editor) -
receiver (audience) roles and source-destination directions. The audience was there to receive and was unable to share any information as the cost of production and distribution (of, for example, print communication or TV broadcasting) was too high.

This model changed dramatically with the emergence of digital media. Centralised wired networks were replaced by digital networks and suddenly everyone with access to digital media could communicate with millions of other users at minimal cost. The information filtered by gatekeepers of traditional media outlets could be easily redistributed and changed by the audience as it moved through gateways on digital channels. The ‘gated’ acquired the possibility of becoming a source of information. Bastos et al. (2013: 260) notice that ‘the traditional notion of source-destination was no longer a meaningful way to describe information control in information networks.’ As a result, editors and audiences of broadcasting media were replaced by hubs and nodes in digital networks. The internal process in which editors were responsible for the decision whether the information was filtered for publication or not, was replaced by a process of multiple users passing information forward. It is impossible to say who is gatekeeping the ‘final product’ because the product is constantly changing as readers constantly add new elements to the story. They can act as editors, reporters, and witnesses. The role of the traditional media gatekeeper (editor in the newspaper or broadcast media) was reduced from the decision maker of whether the story would be surfaced, to the follower of the story reported by multiple ‘reporters’ in a truly decentralised process.

As the process of gatekeeping became more decentralised and the role of the audience changed from being just a passive receiver of information to playing an active role in pushing the story forward, or even being the source of the story, new gatekeepers emerged on digital networks to help to organise and filter the multitude of stories. These were not human beings but algorithms.

Google’s Page Rank algorithm is the very heart of the company. Carr (2008: 219) explains it:

"At the heart of [Google] is the PageRank algorithm that Brin and Page wrote while they were graduate students at Stanford in the 1990. They saw that every time a person with a Web site links to another site, he is expressing a judgment. He is declaring that he considers the other site important. They further realized that while every link on the Web contains a little bit of human intelligence, all"
the links combined contain a great deal of intelligence – far more, in fact, that any individual mind could possibly possess. Google’s search engine mines that intelligence, link by link, and uses it to determine the importance of all the pages on the Web. The greater the number of links that lead to a site, the greater its value. As John Markoff puts it, Google’s software “systematically exploits human knowledge and decisions about what is significant”. Every time we write a link, or even click on one, we are feeding our intelligence into Google’s system. We are making the machine a little smarter – and Brin, Page, and all of Google’s shareholders a little richer. Carr (2008: 219)

The above description shows how Google, a relatively new digital platform that does not produce anything physical has become the very heart of the new (cognitive) economy, which employs us all to create value. In return, we receive the list of ranked search results arranged by the algorithm but based on our behaviour. The list of ranked links can take Google users to other digital assets such as websites, social media, digital databases, digital audio, digital video, digital images, software or electronic books (in short digital media) distributed throughout the entire Internet but most importantly it acquires an agenda-setting ability. The search results that are ranked higher are presented as more prominent and the audience might regard them as more important.

Agenda-setting theory

Agenda-setting theory (McCombs and Shaw, 2002), describes how the media can influence viewers by establishing a hierarchy of news prevalence. It suggests that the media are able to influence the audience by instilling/promoting some content over other content: that is, if a news item is covered frequently and prominently, the audience will regard the issue as more important. Agenda-setting is understood as the creation of public awareness and concern of salient issues by the media. It assumes that the media do not reflect but filter and shape reality, and that the concentration on selected topics/issues can lead the public to see these topics as more important than others.
Since the publication of the original research of McCombs and Shaw (1976) the media landscape has changed dramatically. (Shaw, Hamm and Knott, 2000) The emergence of new media platforms has taken place and traditional media have suffered significant financial difficulties since the beginning of the XXI century. As argued previously, the public gained access to the variety of new, digital media sources without having to rely on journalists or other media professionals. Conway et al. (2015: 374) looks into the impact of the new media (Twitter) on the agenda-setting capabilities of the traditional media and concludes that they have a ‘symbiotic relationship that varies in intensity and duration depending on the issues being analysed’. Aruguete (2017: 51) explores the extent to which the dynamics of the information created in new media –particularly in blogs and Twitter– is distorting the boundaries of the traditional postulates of the agenda-setting theoretical perspective. She concludes that ‘It is a fact that new media have gained ground in the dispute for setting the agenda.’ However, she fails to answer some of the key questions that she started her research with: ‘Do social networks set conversation topics or do they repeat the agenda of topics proposed by elite media? Does the agenda setting power claimed by official information sources persist in the new media environment? Do the new media constitute a real challenge for traditional journalism standards or do they serve as a normalizing tool? Finally, are trending topics an adequate measurement of the expression of public opinion?’

These are the questions that will guide my empirical research, especially chapter eight, as they are very relevant in relation to Twitter Trends. I will look at social media from the perspective of a Coordinated Inauthentic Behaviour that could be used to manipulate Twitter’s Trending Topics algorithms in order to set the agenda on the platform.

**Coordinated Inauthentic Behaviour**

Weedon et al (2017) who are part of Facebook’s Security team introduced the term Coordinated Inauthentic Behaviour in response to the criticism the platform received after the 2016 elections in the US (Office of the Director of National Intelligence: 2017: Online), Britain (Cadwalladr. 2017) and the Philippines (Corpus
Ong and Cabanes, 2018) which showed how the new media ecosystems are vulnerable to disinformation. Starbird (2019: Online) defines Coordinated Inauthentic Behaviour as disinformation campaigns that purposely entangle orchestrated action with organic activity. ‘Audiences become willing but unwitting collaborators, helping to achieve campaigners’ goals.’

Historically this technique of manipulating unwitting collaborators has been used for more than a century. Early in the XX century Lenin argued that Western freedoms (e.g. of speech or the press) could be exploited for the purposes of subversion and the spread of propaganda (Rees 1984). Soviets targeted western journalists as “unwitting agents” (Bittman, 1985). They would give them anonymous tips that offered a “scoop” or aligned with their existing beliefs. The journalists would then unwittingly introduce the disinformation into the press without realizing the true intentions. (Starbird et al, 2019:4)

In the XX century journalists or editors acted as gatekeepers, so targeting them was the most efficient technique. In the new Digital Age, where platforms and their audiences act as algorithmic gatekeepers, there was a shift in how these bad actors operate. Disinformation is not only spread by ‘paid trolls’ or ‘bots’. In reality, ‘effective disinformation campaigns involve diverse participants; they might even include a majority of ‘unwitting agents’ who are unaware of their role, but who amplify and embellish messages that polarize communities and sow doubt about science, mainstream journalism and Western governments.’ (Satarbird 2019: Online). The term ‘Coordinated Inauthentic Behaviour’ is not about false information or fake news. Accurate or true information can be used to spread false news via setting a false context; for example, a photograph can be purposely mislabelled so that unknowing users unwittingly spread misinformation. Alternatively, misleading information can be packaged as real news – known as ‘junk news’ (Bradshaw et al. 2019). As a result, we not only need to focus on the techniques used by those who try to spread disinformation but also analyse the behaviour of social media users (the audience), who in case of Twitter Trends act alongside algorithmic gatekeepers and can be used by the attacker.

Finally, we need to acknowledge that the technology (platforms and the algorithms that run them) are not neutral. They have values embedded in their very design and are directed by internal policies that might not always be aligned with the interest of
the public or researchers. Acker and Donovan (2019) illustrate this with their case study of how platforms’ data archives of Coordinated Inauthentic Behaviour prevent researchers from examining the contexts of manipulation. Obviously, one also needs to acknowledge that technology on its own (social media platforms or their algorithms) cannot be held solely responsible for the spread of online, networked propaganda. Benkler et al. (2018:22-23) argue that it is specific technologies, under specific political, cultural and institutional conditions that can ‘tip societies into instability’ and that technology on its own is unable to cause destabilisation on a national scale.

Before I introduce hashtags, their history and how they have been studied academically, the final section of this chapter will look at Twitter as the platform and its main features.

**Twitter as a platform**

Twitter is an American owned company that runs a microblogging and social network service. It was founded in 2006 and in October 2018 its membership was approximately 330 million monthly active users (Omnico, 2020: Online)⁷ which makes Twitter one of the leading social media platforms alongside platforms such as Facebook, Instagram, Pinterest, LinkedIn or Snapchat. The company went public in 2013 and its market value increased from an estimated $4.4bn in 2018 (Dennison, 2018: Online) to $28.7b in 2020⁸. Twitter revenue increased from $2.4 billion in 2017 to $3 billion in 2018, a 24.5% increase⁹. In 2019 Twitter was employing 4600 employees in 35 office locations¹⁰ across 20 countries. Twitter is headquartered in San Francisco, California.

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⁷ There is a total of 1.3 billion accounts, but only 330 million are active: https://www.socialpilot.co/blog/social-media-statistics

⁸ Available at Craft.co – Twitter Competitors: https://craft.co/twitter/competitors

⁹ Available at Craft.co – Twitter Revenue: https://craft.co/twitter/revenue

¹⁰ Available at Craft.co – Twitter Locations: https://craft.co/twitter/locations
Twitter is an example of a Web 2.0 website (DiNucci, 1999: 221), also known as the Participatory Social Web (Blank: 2012). The term describes websites that rely on user-generated content, are easy to use and are compatible with other products, systems or devices. This is in contrast with the first generation of websites, known as Web 1.0 where people were limited to viewing the content in a passive manner. Cormode and Krishnamurthy (2008: Online) argue that 'the essential difference between Web 1.0 and Web 2.0 is that content creators were few in Web 1.0 with the vast majority of users simply acting as consumers of content, while any participant can be a content creator in Web 2.0 and numerous technological aids have been created to maximize the potential for content creation.' As a classic example of a Web 2.0 social networking service, Twitter also allows its users to create personal profiles for the site and facilitates the development of online social networks by connecting users profiles with those of other individuals or groups (Obar and Wildman, 2015).

As a platform, Twitter allows its users to post (tweet) messages, known as Tweets, which, in default setting, are publicly visible. Users can change their settings to make these private in which case they will be only visible to their followers. Tweets can be posted via the Twitter website, or compatible external applications (such as those for mobile phone apps), or by text messages in some countries. Originally there was a limit of 140 characters for each tweet; in 2017, Twitter doubled the limit to 280. Tweets can also contain images, gifs or links.

The platform allows users to subscribe to other users' tweets; this is known as "following". The subscribers then become "followers" (Stone 2009: Online). All publicly available tweets can be liked or forwarded by other users to their own feed, in a process known as a "retweet", often abbreviated to "RT" (Newton, 2015: Online). The first tweet was posted by Jack Dorsey\(^\text{11}\) (the creator of Twitter) on March 21, 2006 and read "just setting up my twttr". It then took 3 years, 2 months and 1 day to reach the billionth Tweet (Twitter, 2011\(^\text{12}\)). It is estimated that in January 2020, on average, around 6,000 tweets are tweeted on Twitter every second, which

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\(^{11}\) https://twitter.com/jack/status/20

corresponds to over 350,000 tweets sent per minute, 500 million tweets per day and around 200 billion tweets per year (Internet Live Stats\textsuperscript{13}).

**Conclusion**

This chapter elaborated a conceptual framework for the thesis by positioning it in the wider context of the digital age, the digital economy and cognitive capitalism - an economic system centred around the accumulation of immaterial assets. It presented Twitter as one of the leading companies that organises their members in what could be described as a network society. Such companies extract value from the activity or ‘labour’ of their users by continuously expanding the extent and intensity of their users' networked interactions (Levy and Kerckhove, 1998 as cited in Flew (2007: 21). The chapter showed that these networked interactions are increasingly managed by algorithms which have acquired the potential to set the agenda of digital platforms by acting as gatekeepers. As a result, social media users developed techniques to manipulate these algorithms, known as Coordinated Inauthentic Behaviour, in order to set the agenda of platforms.

As it will be shown in Chapters Three and Four, hashtagability, realised as the potential of hashtags to become trends can happen through Coordinated Inauthentic Behaviour. The exploration of potentially orchestrated Twitter trends helps to understand a very current and pressing social issue, which makes this study significant from the social, political and digital media perspectives. From the perspective of the aims of the thesis, the chapter explained why trends are worth studying. The next chapter will investigate the lineage of hashtags and track their roots in order to lay out the groundwork for the concept of hashtagability.

\textsuperscript{13} \url{https://www.internetlivestats.com/twitter-statistics/}
Chapter 3: The history of hashtags

Introduction

This chapter lays out the groundwork for the concept of hashtagability by looking at the lineage of hashtags and tracing their roots. Particular attention is paid to the changing role of metadata and the practice of tagging, which later contributed to the emergence of hashtags. The chapter uses Kehoe and Gee’s (2011) historical perspective to illustrate the changes in the ways tagging was performed online and how the power of categorising has gradually shifted from authors to readers, who eventually have come to be known as users. More specifically, the aim of this chapter is to define hashtags, review how they have been studied in politics, marketing, linguistics and communication, and trace their history. I start with the analysis of five different dictionary definitions of hashtags, which is then followed by a short discussion and a suggested new definition. The chapter then looks at the history of tags and tagging and traces its roots in the Information Technology, Digital Media and Social Science traditions.

My Introduction chapter traced the history of the # symbol back to the ancient Roman times. In this chapter I start in 1970, with the first uses of # in Information Technology. I then provide a detailed account of how # was used on IRC to form channels. In the second part of the chapter the discussion focuses on the history of tagging and how it has changed over the years with the development of the World Wide Web and Web 2.0. I analyse three historical perspectives: author’s, peer’s and user’s (Kehoe and Gee, 2011) which show how this development has led to the new phenomenon that is today known as Folksonomy (Vander Wal 2004, Peters 2009), ‘people’s taxonomy’ (Pink, 2005: Online) or ‘collaborative tagging’ (Baca and Shubitowski, 2009). I then argue that because of the development of Web 2.0 and social media we are observing a strong shift from hierarchical (scientific) to non-hierarchical classifications based on tags added by users. I then position folksonomies in relation to the scientific taxonomy and identify key differences and
possible problems they might create. These include issues with lack of synonym control or semantic ambiguity.

The final part is the description of how hashtags appeared on Twitter as a user-led innovation and a natural consequence of developments in social tagging. It argues that the emergence of hashtags was a natural process rather than a revolutionary invention.

**Hashtags - definitions**

In order to keep track of their conversations Twitter users developed a number of other conventions such as the use of prefix '@', known as @reply, to direct a message at someone or the use of '#', known as hashtag, to categorise their posts and make them searchable. Twitter makes it extremely easy to use hashtags in these ways. From the user perspective, it is enough just to type some text preceded by the # symbol. Searching for a hashtag on the Twitter platform produces each message that has been tagged with it in the form of feed that can be ordered using different filters. For example, Twitter operates on the hashtag #PhDlife to generate the list of all posts that have been tagged using that hashtag. Twitter's generic feed means that all users see the same content i.e. Twitter 'Latest' search filter for a hashtag generates exactly the same list of posts to all users searching for it at the same time. Twitter’s personalised feed is when users get personalised search results i.e. Twitter 'Top' search filter. According to Twitter Help Centre\(^\text{14}\) selecting 'Top Tweets' option shows Tweets people ‘are likely to care about most first.’ The order of the Tweets is the outcome of a complex set of constantly changing algorithms, co-ordinated through the platform. Before I explore how Twitter’s algorithms work, it is worth looking deeper into hashtags and their history.

As described in the Introduction Chapter, hashtag is a relatively new word. It was first used in 2007 by Chris Messina on Twitter. The widespread success of hashtags since their first use resulted in the addition of the word hashtag to many English

\(^{14}\) Twitter Help Centre available at: https://help.twitter.com/en/using-twitter/top-search-results-faqs

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language dictionaries. Oxford English Dictionary (OED), Merriam Webster Dictionary (MWD) and the Official Scrabble Players Dictionary (OSD) included it in 2014. This was followed by numerous other dictionaries such as Cambridge Dictionary (CD), dictionary.com (DC), Webopedia and multiple Internet slang dictionaries.

As a relatively new word, hashtag’s meaning has not yet been set in stone. The following five definitions are similar but they also show some differences especially when it comes to defining the functions of hashtags. Firstly, Oxford English Dictionary\(^\text{15}\) (OED) defines hashtag as ‘a word or phrase, on social media websites and applications, preceded by a hash (#) and used to identify messages relating to a specific topic’ (OED: Online). Merriam Webster Dictionary\(^\text{16}\) (MWD) provides two definitions of hashtag. In a simple one it is defined as ‘a word or phrase that starts with the symbol # and that briefly indicates what a message (such as a tweet) is about’. In a full definition hashtag is ‘a word or phrase preceded by the symbol # that classifies or categorizes the accompanying text (such as a tweet)’. It then extends this definition in the editor’s note:

*Social media has made the hashtag a ubiquitous part of Internet culture (...). Originally designed for categorizing posts, the hashtag can now be a tool for a supplementary coy or witty comment (e.g., #awkward). The word tag can mean "a word or phrase used for description or identification."* (MWD: Online)

According to the Official Scrabble Players Dictionary\(^\text{17}\) (OSPD) hashtag is ‘a word or phrase, preceded by the symbol # that categorises the accompanying text' (OSPD: Online). Lastly, dictionary.com\(^\text{18}\) (DC) defines hashtag as ‘a word or phrase (on social-media websites) preceded by a hash mark (#), used within a message to identify a keyword or topic of interest and facilitate a search for it’ (DC: Online).

Table 1 (below) decomposes the five definitions above in order to find similarities and differences between them. The column on the left (DICT) indicates which

\(^{15}\) OED: http://www.oed.com/view/Entry/389023

\(^{16}\) MWD: http://www.merriam-webster.com/dictionary/hashtag

\(^{17}\) OSPD: http://scrabble.hasbro.com/en-us/tools#dictionary

\(^{18}\) DC: http://www.dictionary.com/browse/hashtag
dictionary the definition comes from. The three columns (blue, green and yellow) show how different dictionaries define hashtags, their visual characteristics and functions.

<table>
<thead>
<tr>
<th>DICT</th>
<th>What is hashtag?</th>
<th>What is the characteristic?</th>
<th>What is it used for (function)?</th>
</tr>
</thead>
<tbody>
<tr>
<td>OED</td>
<td>a word or phrase</td>
<td>preceded by a hash (#)</td>
<td>used to identify messages relating to a specific topic</td>
</tr>
<tr>
<td>MWD1</td>
<td>a word or phrase</td>
<td>starts with the symbol #</td>
<td>briefly indicates what a message is about</td>
</tr>
<tr>
<td>MWD2</td>
<td>a word or phrase</td>
<td>preceded by the symbol #</td>
<td>classifies or categorizes the accompanying text</td>
</tr>
<tr>
<td>OSPD</td>
<td>a word or phrase</td>
<td>preceded by the symbol #</td>
<td>categorises the accompanying text</td>
</tr>
<tr>
<td>DC</td>
<td>a word or phrase</td>
<td>preceded by a hash mark (#)</td>
<td>used within a message to identify a keyword or topic of interest and facilitate a search for it</td>
</tr>
</tbody>
</table>

Table 1: Decomposed Hashtag definitions

A quick look at the Table above shows that the five definitions have two things in common - they all describe hashtags as a word or phrase (see the blue column) that is preceded by or starts with the symbol # (see the green column). The fourth (yellow) column which describes what hashtags are used for (their functions) is different in all five definitions but a few recurring themes can be observed. According to these definitions hashtags are used for:

- identification (or indication) of topics (OED and MWD1) or keywords (DC),
- classification or categorisation of accompanying text (MWD1 and OSPD), or
• as a tool for a supplementary coy or witty comment (MWD2)

Problems and the new definition

The above definitions are quite basic and immediately some problems become apparent. First of all, some hashtags are neither words or phrases. The examples of such hashtags are, for instance, abbreviations. MWD\textsuperscript{19} (Online) defines abbreviation as a shortened form of a word or phrase. Technically they mean the same (as words) and it might seem unnecessary to make that distinction as abbreviation is in fact a short version of ‘a word or phrase’. In practice it is important to do that when defining hashtags as not all abbreviations used in hashtags are immediately obvious for everyone. There are for example widely recognised abbreviations such as #IMF which most people know stands for International Monetary Fund or #tbh which means ‘to be honest’ in online language. On the other hand, as will be shown in the following chapters, there are many ‘private’ or ‘community abbreviation’ hashtags on Twitter which are only clear for small groups of people often specifically interested in a niche topic, for example #MM93 or #AE41. To make it even more complicated, some of these abbreviations contain numbers. Finally, there is also a group of hashtags that are not abbreviations and do not have a meaning. These hashtags consist of random letters sometimes used in combination with numbers. A lot of times they are simply spelling mistakes. Such hashtags never really get too much attention either in social science or amongst Twitter users but it needs to be noted that they exist.

Based on these observations I suggest the following (more technical and precise) definition:

Hashtag is a string of alphanumeric characters usually in the form of words, phrases or abbreviations that starts with the symbol # indicating a special meaning. It is used for the identification of topics, classification and categorisation of the accompanying text on social media in order to facilitate a search for it or as a tool for commenting.

\textsuperscript{19}MWD: http://www.merriam-webster.com/dictionary/abbreviation
Hashtags in academia

Twitter (and later hashtags) has received significant interest in academia from researchers from many different fields such as politics (Tumasjan et al. 2011; Conover et al. 2011; Yardi and boyd, 2010 or Suh et al. 2010), civil unrest/society/social movements (Vis, 2012; Lotan et al. 2011) and brand related communication (Stieglitz and Krüger, 2011; Park et al. 2011). When analysing Twitter, those early researchers mostly studied metrics such as @replies, retweets, lists but gradually also hashtags started appearing in studies.

Hashtags in political studies

In political studies Small (2011) analysed #cdnpoli (the most popular hashtag about politics in Canada) over a period of 4 months in order to show how Canadians use it as an aggregator of news. Bruns and Burgess (2011) studied several hashtags (e.g. #spill) on Australian politics and noticed that these hashtag-organised parts of the Twittersphere could be divided into topical hashtag communities and ad hoc publics. Papacharissi and Oliveira (2012) traced the rhythms of news storytelling on Twitter via the #Egypt hashtag to study how it creates a collective narrative. Glasgow and Fink (2013) studied 65 unique hashtags relevant to the 2011 London riots cleanup including #riotcleanup, #riotwombles and #londoncleanup and analysed emergent social networks directly relating to responses to the crisis in relation to hashtag lifespan. Vicari (2013) explored the most prominent hashtag on the Italian demonstrations on October 15: #15Ott in order to understand public reasoning around social contention. Finally the emergence of political hashtags was described by Bonilla and Rosa (2015) who studied #Ferguson hashtag and showed ‘how engaging in “hashtag activism” can forge a shared political temporality.’ More recently Pancer and Poole (2016) studied political hashtags in the US and found out that posts containing hashtags decrease likes and retweets which as a result decreases users’ engagement.
Hashtags in marketing and brand communication

The popularity of hashtags makes them a good tool for marketing, brand communication and PR. Page (2012) studied how different groups (celebrities, ordinary users and corporations) use hashtags for self-branding. They noticed that hashtags are used more often by all analysed groups in regular updates rather than in addressed messages (messages including @mentions). In other words, they are one-to-many rather than one-to-one broadcasts. This pattern was the strongest (10 times more likely in updates than in addressed messages) amongst corporate accounts. Ordinary users were most likely to use hashtags in addressed messages but they were still more likely (2.5 times) to use them in regular updates.

Page (2012) also studied different functions of hashtags and divided these into two categories: “topic-based” and “evaluative”. She established that “hashtags are primarily used to make the topic of a tweet visible, rather than to emphasize stance” and that examples of expressive uses of hashtags are in the minority. In other words, she established that users were more likely to use hashtags in the manner of folksonomic tagging than as an internet meme or as an idiosyncratic creation (i.e. #epicfail). Expressive uses of hashtags were most likely to be found in updates posted by ordinary users, and least often in corporate account posts.

Page (2012) also studied how different groups use hashtags. She found that ordinary users mostly use them to contribute to commentaries linked to national events either to do with politics (i.e. #ge2010, #ukelection, #leadersdebate), TV shows (i.e. #eurovision) or sport (i.e. #cricket, #rugby). Interestingly the same applies to celebrities but there is a significant difference - these were the national events (sports, tv shows etc.) that celebrities were performing or participating in themselves. By doing that celebrities were projecting their own identity in relation to their own performances or products rather than being just the viewers as was the case with ordinary users.

Page (2012) also observed significant differences between ordinary and corporate users in the way they use hashtags when talking about professional expertise. First of all, ordinary users used hashtags less frequently and secondly their hashtags were always more general (i.e. a priest using #synod, and lawyer using #law or #business)
than the more specific and individual tags used by corporations. Page thinks this is linked to the differences in economic power:

_The difference in the individuated company names used as hashtags by corporate accounts compared with the superordinate terms used to identify ‘ordinary’ Tweeters within professional communities is clearly shaped by economic power: those with greater power (corporations) can individuate their identity, whereas those with less economic capital (‘ordinary’ Twitter members) must affiliate themselves within a wider generic category._ (Page, 2012: 193)

Page (2012) analysed these different behaviours as different self-branding techniques. Corporations use hashtags to promote their brand or field of expertise, celebrities use them to promote their performances and product and ordinary users remain commentators on events or products created by others. Overall Page argues that hashtags are mostly used by corporations and celebrities in one-to-many broadcast with the aim of engaging the audience with the promoted commodity.

Another area that is interesting from the marketing point of view is how hashtags spread on Twitter. There are numerous studies that deal with this issue and they are described in detail in the section about trends and how hashtags become popular. At this point I will mention just a few which are more to do with the actual strategies that can be applied by marketers, rather than the studies of social networks created by hashtags. One of these studies was conducted by Cunha et al. (2011) who established that shorter hashtags usually become more popular than long ones. Romero at al. (2011: 695) studied hashtags in relation to their ‘persistence’ understood as ‘the relative extent to which repeated exposures to a piece of information continue to have significant marginal effects on its adoption’. They discovered that politically controversial hashtags are particularly persistent and that repeated exposure to these hashtags has an unusually large effect on a tag’s adoption. On the other hand, hashtag idioms (Huang et al. 2010 defines these as micro-memes e.g. #cantlivewithout, #dontyouhate, #iloveitwhen) are particularly non-persistent and multiple exposures have the opposite effect. In other words, multiple repeated exposure has a significant effect on the adoption of politically controversial messages (hashtags) and less effect on the adoption of idiom hashtags. Posch et al. (2013) divided hashtags into eight categories: Celebrity, Games, Idiom, Movies/TV, Music,
Political, Sports and Technology and confirmed that the hashtags in the category ‘idioms’ showed a significantly lower informational coverage than hashtags from all other categories. This was shown by analysing the number of links included in posts belonging to all eight categories. The results showed that hashtag idioms contained almost no links. Another interesting observation was that the social structure of idioms changes much faster than of other hashtags. For example, the hashtag category technology had a very stable social structure indicating that users who are interested in this field contribute to the hashtag on regular basis.

Hashtags in linguistics

The study of hashtags has also become popular in the field of linguistics. Kovaz et al. (2013) studied automatic sarcasm detection on Twitter by examining Tweets that included #sarcasm. Kunneman et al. (2015) studied the same hashtag and concluded that the use of hashtags reduces the further use of linguistic markers for signalling sarcasm i.e. exclamations or intensifiers. They argue that hashtags have become the online equivalent of non-verbal expressions used by people in offline interactions when conveying sarcasm. Finally, there is also an ongoing interest in the study of hashtags recommendations. Godin et al. (2013) designed a topic model for hashtag recommendation which was trained to cluster English language tweets for a number of topics from which keywords were suggested for new tweets. She and Chen (2014) treated hashtags as labels of topics and developed a supervised topic model to discover relationship among words, hashtags and topics of tweets. Li and Xu (2016) proposed a novel recommendation model based on Twitter users’ dynamic interests. Mahajan et al. (2016) developed a recommendation system that was able to recommend hashtags while the user is inserting hashtags as part of typing the message. Additionally, they studied a scenario where hashtags were recommended for the full message.
Hashtags in crisis communication

Twitter as a communication device to study natural disasters and crisis communication has received a lot of interest from researchers. Palen et al. (2010) studied the use of Twitter during the 2009 seasonal flood threat period to the Red River Valley on the U.S.-Canadian border, Mendoza et al. (2010) analysed the spread of rumours during natural disasters, Cheng et al. (2011) looked at Twitter during the early outbreak of H1N1 Flu.

The first major study that focused on a single hashtag in relation to a natural disaster (#qldfloods - used in crisis communication on Twitter in the 2011 South East Queensland Floods) was conducted by Bruns et al. (2012). They established that #qldfloods became the central coordinating mechanism for floods-related user activity on Twitter and tweets largely stayed on topic. Emergency services and media organisations were amongst the most visible participants and tweets focused mostly on sharing relevant information, advice, news media and multimedia reports. Wukich and Steinberg (2013) examined Twitter communication networks, specifically the roles played by non-profit and government agencies, that were engaged during disasters using four hashtags: #bostonstrong, #westexplosion, #peoria and #prayforok. They established that there were ‘relatively limited levels of non-profit and government involvement’ in these hashtags.

The pre-history of hashtags

In order to fully understand how hashtags work it is necessary to trace hashtags’ history in more detail with a focus on categorisation. One of first uses of # in Information Technology was very technical and took place in 1970 in the assembly language of the PDP-11 (minicomputers sold between 1970 and 1990s) as #N to indicate ‘immediate mode’, where N could be ‘a number, user defined symbol or expression’ (Unknown, 2011: Online). Almost a decade later # was used again for special keywords in the C programming language (Kernighan and Ritchie, 1978: 86). Then in 1993 it reappeared on IRC as one of the four special characters: '&' , '#', '+' or '!' known as IRC ‘channel prefixes’. These prefixes had to be followed by characters
(letters or numbers) which as a result formed IRC channels, defined as ‘named groups of one or more clients which all receive messages addressed to that channel’ (Kalt 2000: Online).

The creation and administration of channels on IRC was very simple. A channel was created immediately when the first user joined it and ceased to exist when the last user left it. During their existence any user (or client as they were called on IRC) was allowed to ‘reference the channel’ using the name of the channel. Interestingly, the user who created the channel automatically became a channel operator (also known as a "chop" or "chanop") and was considered to ‘own’ that channel. Chanops were also identified by the ‘@’ symbol next to their nickname whenever it was associated with a channel (Kalt, 2000: Online, Oikarinen and Reed, 1993: Online). It was possible for a channel to have multiple chanops (see Figure 4 which shows the #phpdebutant channel owned by multiple chanops).

![Figure 4: The #phpdebutant channel on IRC owned by multiple chanops](http://www.wdmedia.org/WFIC/index-en.php)

What is most significant in all these examples is the fact that throughout the years since 1970s, the # symbol always had to be followed by something i.e. ‘number, user defined symbol or expression’ in the assembly language of the PDP-11 or ‘letters or numbers’ which as a result formed IRC channels, defined as ‘named groups of one or more clients which all receive messages addressed to that channel’ (Kalt 2000: Online).

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numbers’ on IRC channels. As a result, # conveyed ‘a special meaning’ of what followed it; it conveyed the sense that what followed was different. The first uses were technical and that special meaning was mostly ‘special’ for computers or other coders. On Twitter the # symbol is special as it visually separates the hashtag from the body of the Tweet by making it a visible hyperlink. Secondly this hyperlink automatically links the Tweet to Twitter search results which are in the form of a list of all tweets containing the given hashtag. In other words, this list includes already existing Tweets with the same hashtag. Most of the time search result consists of posts already written by other users but it is possible that by using a hashtag for the first time one is also creating search results as the given post will be the only one included in the search results. This first post will start defining the meaning of a given hashtag.

Finally, hashtags can only be created if they start with the # symbol followed by an alphanumeric character or characters. The hash symbol on its own has no meaning other than the meaning of #. In order to gain meaning and create a hashtag, the # symbol needs to be followed by something - a tag. The next section looks into the history of classification and tagging to illustrate how these two (# and tags) ‘joined forces’ to eventually create hashtags.

Tags as metadata

Broadly speaking a tag, in Information Technology, is defined as a keyword or term assigned to a piece of information that helps to describe it and allows it to be found again by browsing or searching. In other words, it is metadata - data that provides information about other data and is used to aid classification. The most basic definition could be simply ‘data about data’. The term itself was coined by Bagley in 1968:

_Metadata. As important as being able to combine data elements to make composite data elements is the ability to associate explicitly with a data element a second data element which represents data "about" the first data element. This second data & element we might term a "metadata element"_ (Bagley, 1968:26).
More recently Guenther and Radebaugh (2004: 1) defined metadata as ‘structured information that describes, explains, locates, or otherwise makes it easier to retrieve, use, or manage an information resource’. Based on their definition, they suggest that there are three types of metadata: Descriptive (used for discovery and identification, as information to search and locate an object i.e. title, author, subject, keyword or publisher), Structural (used to describe how the components of an object are organised i.e. the order of pages in the chapter of a book) and Administrative (used for managing the resource i.e. the file type, or file timestamp). The first type is very useful to study the history of tagging as it helps to determine the ‘aboutness’ of a document and how related a text/website/post is to a ‘search query’ typed by a user into a search engine. Kehoe and Gee (2011) suggest three historical perspectives that show how tagging has changed over the years with the development of the World Wide Web and Web 2.0 specifically.

The first one is the author’s perspective and is linked to the early days of the web search. A good example of this perspective is where authors include meta tags (also known as keywords) in the header section of their websites. These meta tags were invisible to readers and were only read by early search engines. The pre-Google search engines were more like static online catalogues rather than the dynamic and always changing search engines we know today. These simple catalogues ranked pages based on how often a keyword or a meta-tag occurred in the page. The frequency of the keyword was the indication of the strength of the association the searched term had with the page. In other words, it was the measure of aboutness. These early search engines thus produced results based only on keywords frequency on the given page. This gave birth to the new web phenomenon defined by Convey (1996: Online) as spamdexing - the process of early search engine spamming (spam + indexing). Various techniques were used to manipulate search engines e.g. keyword stuffing (the placement of tags on a page) or placing hidden text containing meta-tags somewhere on the page (Gyoongyi and Garcia-Molina, 2005). The aim of these techniques was to achieve a high position in search engines for a popular search term, which in reality might have nothing to do with the content of the website. It was all happening behind the closed doors in the code of the website. Spamdexing was only possible while search engines relied solely on the information included in a given website, provided by the author of the text. The development of Google and its Page Rank algorithm has put an end to this spamming technique.
The next milestone in the development of tagging could be defined as the peer's perspective and is linked with the emergence of Google's PageRank algorithm. It is based on the links (written and created by other authors) that connect separate web pages. In this case the topic of the website is defined by external authors in the process of creating links. In other words, authors lost the power of determining what a given text/website was about and it was more significant what other people thought a given text was about. Control over the ‘aboutness’ of a given text was shifted from the author/webmaster to other webmasters who were able to place links on their websites. In HTML, links are defined in the following way:

\[ <a href="url">link text</a> \]

The ‘link text’ was treated by Google as a tag (label) that described what a linking text/website was about. In the example:

\[ <a href="www.bbc.co.uk">News</a> \]

the BBC website was ‘linked’ or ‘tagged’ as ‘News’ which tells Google that people think that the BBC is about ‘News’.

The emergence of Google Search Engine was a game changer. Millions of people started using it every day and the order in which search results were displayed became extremely significant, both for the producers and the consumers of online content. For businesses being 'high' on a Google search result for a 'good keyword' could translate into millions of pounds of profit. For consumers it could be a matter of life and death if for example they choose which doctor to go to based on Google Search results. An entire new business niche emerged in which people would build link farms or ‘exchange’ links on their respective websites. Back in the early Google days every webmaster was keen to accept as many links as possible to his or her own website and tried to limit the number of outgoing links. The history of major updates to PageRank algorithm shows how Google tried to deal with this: Boston Update in 2002 focused on combating link spam, Panda Update in 2011 focused on rewarding websites with quality content over link farms and finally Penguin Update in 2012 dealt with over-optimised websites with aggressive linking practices and those linking to gambling or adult websites. Also, websites using paid links were penalised.
More recently industry experts (2017) suggest that Google uses more than 200 so-called ‘major ranking signals’ so it has become extremely difficult to manipulate the algorithm by focusing purely on the strength of the links. Nevertheless, this history shows that the aboutness of a website/text or any online object could be determined externally by people other than the author of the actual text. This has led to the creation of a new social tagging economy, where it is the consumers rather than publishers, who are in charge.

The final third perspective could be described as the reader/user’s perspective where aboutness is defined in the process of social tagging on websites such as Flickr or del.icio.us. It is the readers who add and share tags to describe the text and decide what it is about. This tag then becomes a link to other texts or resources tagged with it by others on the same platform. This is the key difference between peer and reader’s perspectives: in the first one links (tags) are placed on external websites and in the latter it all happens on the same platform creating a tagging system. Another crucial difference is that in the reader’s perspective tags finally gain full visibility. In the author’s perspective it was hidden in the HTML code of the website accessible only to webmasters, while in the peer’s perspective links were often placed in the least visible part of the website as they were treated as more important for search engines rather than website’s users. One also needed to know HTML to use them. With the development of Web 2.0 tags gained prominence and became crucial components of these services.

**Folksonomy**

Marlow et al. (2006: 31) argues that ‘because of tags’ lack of predefined taxonomic structure, social tagging systems rely on shared and emergent social structures and behaviours, as well as related conceptual and linguistic structures of the user community’. Because of this the third perspective of social tagging is often described as a ‘people’s taxonomy’ or ‘grass-roots categorisation’ (Pink, 2005: Online).

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21 SEO Engine Land available at: https://searchengineland.com/8-major-google-ranking-signals-2017-278450
researchers (Baca and Shubitowski, 2009: Online) call it ‘collaborative tagging’, ‘social classification’, ‘social indexing’, ‘mob indexing’ or ‘folk categorisation’. Because the classification is being performed socially it becomes decentralised and non-hierarchical in comparison to traditional taxonomies. This kind of classification is also so significantly different from traditional, scientific classifications that the separate term - folksonomy is used to describe it. It was defined originally in 2004 as ‘the social classification happening at Furl, Flickr and Del.icio.us.’ (Smith 2004: Online). Peters (2009: 1-2) sees folksonomies as a phenomenon linked to the development of Web 2.0:

Folksonomies are part of a new generation of tools for the retrieval, deployment, representation and production of information, commonly termed ‘Web 2.0: In Web 2.0 it is no longer just journalists, authors, web designers or companies that generate content - every user can do so via numerous online services (...). The heavy growth of user-generated content increases the demand for suitable methods and facilities for the storage and retrieval of said content. In order to meet those demands, companies and computer scientists have developed collaborative information services like social bookmarking, photo sharing and video sharing, which enable users to store and publish their own information resources as well as to index these with their own customised tags. Thus the indirect cooperation of users creates a folksonomy for each collaborative information service comprised of each individual user’s tags. (Peters 2009: 1-2)

The term folksonomy was coined by Vander Wal in 2004 during a discussion at the IA Institute:22:

- Gene Smith: "Some of you might have noticed services like Furl, Flickr and Del.icio.us using user-defined labels or tags to organize and share information.... Is there a name for this kind of informal social classification?".

- Eric Scheid: "folk classification".

22 then called the Asylomar Institute for Information Architecture (AIFIA)
- *Thomas Vander Wal*: "So the user-created bottom-up categorical structure development with an emergent thesaurus would become a Folksonomy?".

(Smith, 2007: 1)

Later Vander Wal (2007) suggests the following definition:

*(Folksonomy is) the result of personal free tagging of information and objects (anything with a URL) for one’s own retrieval. The tagging is done in a social environment (usually shared and open to others). Folksonomy is created from the act of tagging by the person consuming the information.*  (Vander Wal, 2007: Online)

Vander Wal (2007: Online) traces the roots of folksonomy to the 1990s, when users of Compuserve forum libraries started adding keywords to the documents and objects they submitted to the database. The system administrators would keep these user generated keywords (open system) and add relevant keywords from a controlled vocabulary (closed system) making it the first mixed system of tagging. Later in the 1990s and early 2000s other services that used tagging appeared on the market. Bitzi.com was possibly one of the first volunteer tagging systems. Bitzi described itself as ‘a website where people cooperate to identify, describe, and discover files of all types.’ It is possibly the first service in the Internet history that described social tagging or folksonomy, most likely without even realising that it would be one of the key concepts of the Web 2.0. In this one short sentence they managed to squeeze: people and cooperation (the social), identification (classification), description (tagging) and discovery (searchability) - the key characteristics of the Web 2.0. Bitzi.com clearly was the next step of the evolution of social classification. Compuserve kept user generated keywords but system administrators would still add their own keywords from a controlled vocabulary list (or pre-existing classification if one compares it to the scientific taxonomy). Bitzi relied solely on user cooperation (truly open system) and no 'higher power' in the

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23 In 2018 it is already closed and can only be accessed via web.archive.org. No interaction with the service is possible anymore as it was saved by the archive in read-only mode. A quick look at Bitzi search option (not active) provides some more information about the scale of the Bitzi project: when the service was closed in 2013, its database contained 3,893,957 tagged files. Source: Bitzi search http://web.archive.org/web/20131216215420/http://bitzi.com/search/

person of system admins was necessary. It was a decentralised practice performed by many users.

The next step in tagging history was made in early 2000 with the creation of del.icio.us – another non-hierarchical classification tool which allowed users to tag each of their bookmarks with freely chosen tags. Interestingly, Del.icio.us was possibly the first time that the tag was linked not only to an object it describes (or is about) but also to the person who used it. It is quite similar to what happened on IRC when the # symbol was introduced in order to help to identify IRC channels. As described in section previously channels on IRC had their owners and operators known as a "chop" or "chanop". The big difference was that IRC channels were owned by people and Del.icio.us tags were only 'used' by people.

Very soon tags made their way to the Flickr photo sharing website. They made an incredible journey: firstly, they were keywords used to describe and discover 'files' hidden deep in the depths of the Internet on Bitzi and created by somebody else than the author. Later they were used to tag one's own bookmarks (bookmarks belonged to the creator of the tag, but they were links to the objects (e.g. articles or photos) created by other users) on Delicio.us. Finally, they are used to describe the user's own content on Flickr. This rapid development however did not happen without problems.

**Problems with folksonomies**

In social and information science, the process of ordering things into groups based on their differences and similarities is called classification. The study and practice of this process, including its principles, procedures and rules is called taxonomy. Bowker and Star (1999:10) define classification as a spatial, temporal or spatio-temporal segmentation of the world and describe it as a set of boxes (metaphorical or literal) into which things can be put. In an abstract, ideal sense, a classification system should exhibit the following properties according to Bowker and Star (1999:10):
1. There are consistent, unique classificatory principles in operation e.g. genetic principles of ordering – classifying things by their origin and descent (e.g. a genealogical map of a family’s history of marriage, birth and death). Another example of classification principles is sorting things by date received (temporal order) or sorting recipes by most frequently used (functional order).

2. Categories are mutually exclusive. In an ideal world, categories are clearly demarcated bins, into which any object addressed by the system will neatly and uniquely fit e.g. in the family genealogy one mother and one father give birth to a child, forever attributed to them as parents – there are no surrogate mothers, or issues of shared custody. A rose is a rose, not a rose sometimes and a daisy other times.

3. The system is complete – the ideal system of classification provides total coverage of the world it describes. Ignoring a new flower is impossible – it needs to be named. No empty categories are allowed. (Bowker and Star, 1999:10)

The history of scientific taxonomy has its roots in folk taxonomy - the naming systems that are used by people to describe and organise the world around them. Folk taxonomies are closest to people’s everyday language – they are based on social knowledge and are used in everyday language. They are very strongly embedded in local cultures and are applied to all areas of human activity. For example, different parts of the world have different systems of naming local plants and animals. According to Raven et al. (1971:1210) historically taxonomy can be defined as a codification of the folk taxonomic principles based on the assumption that there are roughly 25,000 to 50,000 organisms that need to be described. The principles they identify are the following:

1) In all languages, recognition is given to naturally occurring groupings of organisms. These groupings (taxa) appear to be treated as psychologically discontinuous units in nature and are easily recognisable.

2) These taxa are further grouped into a small number of classes known as taxonomic ethnobiological categories. These categories, definable in terms of linguistic and taxonomic criteria, seem to number five: unique beginner, life form, generic, specific, varietal.
3) *The five taxonomic ethnobiological categories are arranged hierarchically, and taxa assigned to each rank are mutually exclusive.*

4) *The taxon found as a member of the category unique beginner is often not labelled linguistically by a single expression; that is, the most inclusive taxon, for example, plant, animal, is rarely named.*

5) *Taxa that are members of the category life form are invariably few in number, ranging from five to ten, and these include a majority of all named taxa of lesser rank.*

6) *In most folk taxonomies, taxa that are members of the category generic are more numerous than life form taxa, but are nonetheless finite in number, usually about 500. Some particularly aberrant generic taxa—for example, cacti, pineapple, cassowary, pangolin, platypus—or those that are of great economic importance and interest may be unaffiliated; that is, they are not included in one of the life form taxa.*

7) *Specific and varietal taxa are, in general, less numerous than generics. Characteristically, they exist in sets of few members within a single generic. Sets of more than two members tend to refer to organisms of major cultural importance, and sets of 20 or more members inevitably do. Specific and varietal taxa can be recognized linguistically in that they are commonly labeled in a binomial or trinomial format that includes the name of the generic or specific to which they belong. Raven et al. (1971:1210)*

In the last 300 years humans have developed numerous scientific taxonomies (e.g. Linnaeus taxonomy), which try to deal with the imperfections (from a scientific point of view) of folk taxonomies. For example, scientific taxonomy will always try to use the same name for the same object, which is not the case in folk taxonomies. Also, in recent decades with the development of computer science, classifications as such have rapidly changed. There is a strong shift from hierarchical (scientific) to non-hierarchical classifications which usually rely on tags (labels) added by users of the data collections. In other words, there is a shift towards collaborative (social) tagging systems in which tags, as non-hierarchical units of description, play a crucial part. Folksonomy is a good example. In comparison to scientific taxonomy, folksonomy ‘sacrifices taxonomic perfection but lowers the barrier to entry (because) nobody
needs a degree in library science to participate (in it)’ (Pink, 2005: Online). Folksonomy is a trade-off between the systematic, scientific approach and a democratic social classification based on personal understanding of meanings. Vander Wal (2007: Online) argues that:

*The value in this external tagging is derived from people using their own vocabulary and adding explicit meaning, which may come from inferred understanding of the information/object. People are not so much categorising, as providing a means to connect items (placing hooks) to provide their meaning in their own understanding.* Vander Wal (2007: Online)

This kind of approach created numerous practical problems if one insists on comparing folksonomies with the scientific classifications (Smith, 2004: Online and Kehoe and Gee, 2011). First of all, there is no synonym control ("mac" and "macintosh" would be two separate tags). Folksonomy does not offer one definitive tag that should be used to describe a computer built by Mac. The two tags would have the same value. The only way one could find out which one is more 'proper' would be the suggestions systems based on the popularity of tags developed by many websites and many websites provide tags suggestions in the moment users starts typing the tag. The second problem of folksonomies is the lack of precision in using tags (i.e. Sophia could be a capital of Bulgaria or a female name). Kehoe and Gee (2011) define it as semantic ambiguity which has two possible types: homonymy - when words that have the same written or spoken form but different meanings (i.e. #bank) or polysemy - when a word has more than one meaning (i.e. #plain). The final two problems could be defined as syntactic variance (e.g. inflectionsblogs, blogging, blog) and semantic specificity (terms are selected at different levels on the semantic hierarchy, e.g.: Siamese cat, animal).

To describe these as problems follows from the assumptions that, as in scientific taxonomies, only one category should describe one object, that classification should be hierarchical and that there should not be any ambiguity in definitions. In other words, these ‘problems’ are based on the assumption that established rules of classification should apply to tagging. In reality tagging is very different to scientific classification and the development of social media and especially Twitter has made it even more distinctive. For example on Twitter (hash)tagging is often used not so much as a tool for categorising, (even though every single hashtag creates a
classification) but as a conversational tool and therefore is incorporated into the actual content it describes - it becomes part of that content (sentence or a post). That has very important linguistic implications. For example, in languages that have many cases (i.e. German has four and Hungarian 18) it is often difficult to decide which case should be used for tags that are part of the sentence. Should they all be in nominative case? If so, this makes reading sentences that include these hashtags in languages such as German or Hungarian very awkward. Some users choose to include all their hashtags in the correct (rather than nominative) case which reduces searchability as the same subject/topic can be described using numerous different tags depending on their function in the sentence. This shows that hashtags need to be looked at not just as tools for categorisation but also as an important part of content. The next section will explore the emergence of hashtags on Twitter and how they became part of the content.

The history of hashtag on Twitter

As described previously, the early development of social tagging is linked with the emergence of Del.icio.us and Flickr. The next milestone took place with the creation of the first social media platforms, especially with the development of Twitter. Initially tags (on Twitter called hashtags) were understood similarly to their counterparts on Web 2.0 services - as tools for social categorisation of content and to make the Web more searchable. In other words, they were treated as (visible) metadata used to describe content. The difference is that suddenly metadata on social media became extremely important. Kennedy and Moss (2015:1) argue that ‘the metadata that sits behind social media content is (...) considered by some to be more valuable than the content itself’.

When Twitter was launched in 2006 it was very basic and different to what it is today. Its first users were asked to simply share updates with their friends and colleagues in response to a simple question: ‘What are you doing?’ (Burgess, 2015). The platform had no extended functionalities as we know them today and these were

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only developed over the years mostly via user-led innovations, that were only later integrated into the architecture of the system (Bruns and Burgess, 2015:16). Interestingly a lot of these functionalities were more or less based or inspired by features developed earlier on IRC or C programming language. The examples of these user led innovations include @replies, used as cross-referencing functionality for addressing or mentioning other users (note similarities with IRC '@' symbol used to identify Channel Operators); the integration of multimedia uploads into the platform and lastly - hashtags - used as a simple tool to organise content on Twitter. In comparison to IRC channels, Twitter hashtags never had owners.

The # symbol was first used on Twitter by San Francisco based Technologist Chris Messina (known on Twitter then as @factoryjoe26) on 23rd August 2007 in a short post which read: ‘how do you feel about using # (pound) for groups. As in #barcamp [msg]?’ (see Figure 5 below).

![Image](https://example.com/image.png)

**Figure 5:** The historical Tweet in which the # symbol was first used by Chris Messina (@factoryjoe)

Two days later Messina (2007) explained that hashtags were a ‘rather messy proposal’ but also noted that they provide ‘some merit to improving contextualization, content filtering and exploratory serendipity within Twitter. (by using them)’. In these early days hashtags were not called hashtags yet and Messina referred to them as *channel tags*, #replys or simply *channels*. His original suggestion

\[26\] Chris Messina currently (2018) uses @chrismessina handle on Twitter
was to use these channel tags in the way they were originally used on IRC - as tools allowing users to follow and contribute to conversations:

*Every time someone uses a channel tag to mark a status, not only do we know something specific about that status, but others can eavesdrop on the context of it and then join in the channel and contribute as well. Rather than trying to ping-pong discussion between one or more individuals with daisy-chained @replies, using a simple #reply means that people not in the @reply queue will be able to follow along, as people do with Flickr or Delicious tags. Furthermore, topics that enter into existing channels will become visible to those who have previously joined in the discussion. And, perhaps best of all, anyone can choose to leave or remove topics that don’t interest them.* (Messina 2007: Online)

The above lengthy explanation shows the initial idea behind hashtags - it was a skilful combination of the special meaning of IRC channels and tagging techniques used previously on Flickr or Delicious. Bruns and Burgess, (2015:16) summarised it well by defining hashtags as ad hoc channels to which groupings of users could pay selective attention. The actual term ‘Hashtag’ was used for the first time two days after Messina’s original proposal. In his Twitter post Boyd wrote: ‘I support the hashtag convention: http://tinyurl.com/2qttlb #hashtag #factoryjoe #twitter’.

On 26 August 2007 Boyd used it again in his blog post "Hash Tags = Twitter Groupings" (Boyd, 2007: Online) where he described them as tools that ‘define shared experience (...) involving all those using the tag’. He then went on to complain that people are used to treating tags as ‘metadata for bookmarks tags (...) or blogs’ but in his opinion they ‘imply communities’ (Boyd 2007: Online). It was a truly visionary statement as time has proved that hashtags indeed form communities around them and not only act as tools for annotating content. The community forming functions of hashtags will be discussed in the next part of this chapter.

The early theoretical discussions about hashtags were taking place amongst interested parties in California but had there not been a disaster there is a very high chance that the history of hashtags would have been over after just these 3 days. ‘Luckily’ for hashtags, Messina never gave up the idea and it was his online activism during the San Diego bushfires in October 2007 and promotion of #sandiegofire hashtag to coordinate information about this disaster, that introduced the idea to the wider audience of Twitter.
Hashtags are going mainstream with #sandiegofire

The #sandiegofire hashtag is today considered as a major breakthrough for hashtags as such. Prior to these events hashtags were non-existent and only started gaining momentum afterwards. Some researchers claim that it is often during catastrophic events or major disaster that people adapt technologies. For example, Shklovski et al. (2008) studied New Orleans musicians in the aftermath of Hurricane Katrina (2005) and found out that ‘faced with a lack of information, people often take action and creatively adapt technologies not only to find information but also to disseminate it to others in the same circumstances’. Sutton et al. (2008) confirms that amongst those who used Twitter to either find or share information during fires in San Diego area, the majority discovered this technology during the wildfires. The adoption of technology during disasters is also indicated in other studies: Hughes and Palen (2009) established that Twitter users who join the platform ‘during and in apparent relation to a non-routine event’ tend to become long-term adopters of the technology. No one will ever be able to say with certainty if hashtags ‘benefited’ from the disaster but one of the first studies (Sutton et al. 2008) of natural disasters that included Twitter was about the practices by members of the public during the October 2007 wildfires in California. These were the fires that helped to catapult hashtags into the Twitter’s mainstream with the use of #sandiegofire hashtag.

Sutton et al’s (2008) study provides useful background information about the position of Twitter in relation to other websites/technologies back in 2007. They found that during the events just less than 10% of their respondents used Twitter to get information, which compares to 76% of people who used portals and websites advertised in traditional media, 54% who used mobile phones to contact friends and family, 38% who used alternative news sources or blogs, 15% who used various web forums and 10% who used Flickr or Picassa. When asked about the technology used to exchange information (share and post online) only 4% indicated that they broadcast via Twitter which was 5 times less than text messaging (20%) or two times less than Flickr or Picassa (8%). This clearly shows that Twitter was not the mainstream technology back in 2007 when Messina and his colleagues started promoting hashtags.
The beginning of this chapter described what led up to the creation of hashtags on 23 August 2007. After the initial hype there was the period of ‘lukewarm interest’ in them. Hashtags creator Chris Messina even admitted that in one of his blog posts:

*I know I’ve been beating the drum about hashtags for a while. People are either lukewarm to them or are annoyed and hate them. I get it. I do. But for some stupid reason I just can’t leave them alone.* (Messina 2007: Online)

Then two months later came 20 October 2007 and sudden bushfires started in the San Diego region of California. Today it is obvious to any Twitter user that most major events get their hashtags. If they are planned it is the marketing departments or organisers who suggest their own hashtag and make sure that all parties involved use it in their Twitter posts. In case of unplanned events hashtags appear organically - they are created by Twitter users. The complication of the organic hashtag is that very often many hashtags describing the same event are competing at the same time as different communities start using them independently - the issue which was described previously. Bowker and Star (2009) describe similar phenomena of numerous names competing for their position in classification. In comparison with scientific classification, in the case of hashtags as we know them today, the winner appears to be decided socially based on popularity and many other factors, that will be covered in the Twitter Trends section. This section will look into the historical stream of #sandiegofire in order to illustrate how the very phrase ‘SanDiego fire’ became a hashtag and how it was gradually adopted by the Twitter community supported by the active posting of one user and a great deal of luck.

When the San Diego bushfires started on 20 October 2007 Nate Ritter (@nateritter), one of the early Twitter users, started monitoring news media sources for information about it. He would then rapidly (even every two-to-three minutes) post information about the fire, road closures and neighbourhood evacuations on Twitter. Ritter later described it as an exercise in citizen journalism (Bigelow, 2014: Online). His first Tweet27 (Figure 6 below) read: ‘Ok, I’ll be twittering the San Diego fires now’ and was posted at 10:32am local time28 in California. The first Tweet was

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27 Available from Twitter: https://twitter.com/nateritter/status/355174462

28 All screenshots are showing London time hence there is 8hrs difference.
followed by another29 (Figure 7 below) that read: ‘San Diego fires: State is pushing 1000 fire engines to Southern California... They'll have to head down I-5 since I-15 is now closed’

![Figure 6: Screenshot of the first Tweet about San Diego fire posted by Nate Ritter](image)

The two above Tweets were posted within less than 15 minutes of each other. What is significant about them is that they both contained the phrase ‘San Diego Fires’. In the first tweet the phrase was included in the body of the tweet and in the second one it acted as a prefix followed by a colon. Then Ritter posts were noticed by the founder of hashtags and Ritter's friend - Chris Messina. On his blog Messina noted:

29 Available from Twitter: https://twitter.com/nateritter/status/355197652
Earlier today, my friend Nate Ritter started twittering about the San Diego fires, starting slowly and without any kind of uniformity to his posts. He eventually began prefixing his posts with “San Diego Fires”. Concerned that it would be challenging for folks to track “san diego fires” on Twitter because of inconsistency in using those words together, I wanted to apply hashtags as a mechanism for bringing people together around a common term (Messina 2007: Online)

When Messina was thinking about a hashtag for San Diego fires, he wanted to come up with a phrase that would become widely adopted - in other words the most hashtagable phrase. In order to do that, he followed an interesting process which illustrates how the initial use of hashtags was deeply rooted in Web 2.0 websites. As noted earlier at that time hashtags were hardly used on Twitter at all, so Messina was unable to check what hashtags other Twitter users were using to describe this event. In fact, they were not using any hashtags at all. Instead of checking on Twitter Messina went to Flickr’s Hot Tags to see what tags people were already using to describe the fires on that website. Figure 8 shows how he managed to identify the best phrase – ‘sandiegofire’ using Flickr.

![Explore / Tags / Hot tags](https://flic.kr/p/3AC2Sq)

**Figure 8: Screenshot of the Flickr’s Hot Tags posted by Chris Messina**

Available from Chris Messina on Flickr: https://flic.kr/p/3AC2Sq

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30 Available from Chris Messina on Flickr: https://flic.kr/p/3AC2Sq
‘Sandiegofire’ was neither the most popular nor the most obvious word to become a hashtag. Flickr’s Hot Tags contained at least another 9 words or phrases (santaanawinds, harrisfire, witchfire, witchcreekfire, brushfire, wildfire, fires, wildfires or malibufire) that could have become hashtags. The decision to use sandiegofire was most likely caused by the fact that Ritter was already using ‘San Diego Fires’ to identify his content and although it was not the most popular hashtag on Flickr, Messina thought it ‘had the best chance to be widely adopted, and that would also be recognizable in a stream of updates’ (Messina, 2007: Online). In other words he thought it was the most hashtagable phrase, that it had the potential to become a popular and widely adopted hashtag. Messina then contacted Ritter with his suggestion and after a few hours Ritter started using the hashtag #sandiegofire (Figure 9) in his posts.

It took 1 hour 23 minutes and about 50 Tweets (1 Tweet in less than 2 minutes on average) of almost continuous posting by Nate Ritter before the #sandiegofire hashtag got some engagement from other users. The first person to join by posting their own Tweet with #sandiegofire hashtag was @biz_line (Figure 10). The Tweet read: ‘I’m incompetent with a camera trying to photo my latest info product. I’m incompetent with camera! #sandiegofire All classes at SDSU.’ One can only guess what this Tweet meant. Most likely @biz_line user was trying to photograph San Diego fire and had some problems with the camera? SDSU was possibly a reference

_{Available from Twitter: https://twitter.com/nateritter/status/355818202_}
to San Diego State University in California. It was more to do with @biz_line’s personal experience with his/her camera than the actual San Diego fire. It did not provide any information apart from problems with a camera. Even the last sentence ‘All classes at SDSU’ is incomplete and cannot be treated as a piece of news. This was a very different kind of Tweet, in comparison to Ritter’s Tweets. It was not really informative. It acted more like a comment or the sharing of an experience. Nevertheless, it was the first example of someone completely unrelated to the creators of hashtags joining in the hashtag stream. From this moment on if anyone searched for #sandiegofire on Twitter, they would be able to see tweets from more than one person talking about the same topic.

![Screenshot of the first Tweet about San Diego fire posted with #sandiegofire hashtag from @biz_line account](https://twitter.com/biz_line/status/355962252)

Figure 10: Screenshot of the first Tweet about San Diego fire posted with #sandiegofire hashtag from @biz_line account

After another almost 3hrs and 44 Tweets from Nate Ritter, another person joined the conversation. Duncan Rawlinson (@lastminute) was looking for very specific information: ‘#sandiegofire if anyone in the twitterverse has specific info on fallbrook rice canyon fire msg me plz thanks.’ (Figure 11). At that time #sandiegofire had 3 users in total and other people started slowly to join in.

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32 Available from Twitter: https://twitter.com/biz_line/status/355962252
After another 25 Tweets from Ritter and 5hrs after the first use of #sandiegofire, user @dabloguiman provided information about #sandiegofire hashtag in Spanish (Figure 12).

Then, 7hrs after the start of the broadcast Lisa Brewster (@Adora) joined in #sandiegofire with a Tweet (Figure 13) about her personal experience of the fires. What is interesting is that up to this point #sandiegofire was always used either at

33 Available from Twitter: https://twitter.com/thelastminute/status/356281352
34 Available from Twitter: https://twitter.com/dabloguiman/status/356374082
the beginning or the end of the sentence as an annotating tag (also see Figure 17) or in the middle of the text but never as part of the sentence. There was always the main text and #sandiegofire was used to annotate it.

![Figure 13: Screenshot of one of the first Tweets about San Diego fire posted with #sandiegofire hashtag from @Adora account](image)

This started changing as more people joined in the broadcast. A couple of minutes after @Adora's Tweet, Messina commented about the usage of #sandiegofire hashtag and for the first time in the broadcast he included #sandiegofire in two functions - as an organising tag which annotates content and as part of the sentence/part of the content. This was the confirmation of Berendt and Hanser's (2006) claim, that 'Tags are not Metadata, but “Just More Content” – to Some People’. Messina's Tweet read: '@nateritter thanks for keeping us posted! Your #sandiegofire updates are really helpfull'. (Figure 14)

![Figure 14: Screenshot of one of the first Tweets about San Diego fire posted with #sandiegofire hashtag from @chrismessina account](image)
If he followed Nate Ritter’s style of hashtagging this post should have read: ‘[#sandiegofire --> TAG] [@nateritter thanks for keeping us posted! Your updates are really helpful! → CONTENT ANNOTATED BY TAG]’. Alternatively, he could have used Lisa Brewster’s style and include #sandiegofire at the end but it would still mean that the hashtag was being used to annotate content alone. The way Nate Ritter or Lisa Brewster used it was similar to how people use it on Instagram, where it is used to annotate photos or videos which are the main content. The way Messina used it was more ‘Twitter’ or conversational style as will be discussed in the hashtag functions section of this chapter.

The more conversational use of hashtags as shown by Messina (Figure 13) was soon followed by other users. User Michael (@bodyvisual) followed Messina and broke the convention of using #sandiegofire at the beginning of the Tweet. In his Tweet (Figure 15): ‘Looks like some elderly have died in #sandiegofire... really sad’ he also used #sandiegofire as a hashtag but also as part of the sentence.

Figure 15: Screenshot of one of the first Tweets about San Diego fire posted with #sandiegofire hashtag from @bodyvisual account

The differences in the usage of hashtags as described above continued in #sandiegofire and they continue today for the vast majority of hashtags on Twitter. The #sandiegofire event was a big breakthrough in the history of hashtags. Very soon others started joining in in large numbers. Suddenly hashtags were no longer a tool used by Messina's friends only but were adopted by numerous other users (Figure 16). In terms of the way #sandiegofire was used, other differences started emerging. Most people used it to talk about the actual event - some of them copied what Ritter
did (@hannabanana) and focused on providing ‘news-style’ Tweets. Others used #sandiegofire to promote their blog posts (@waderockett).

Regardless of their intentions, they all contributed to what was the first hashtag widely adopted by Twitter users. The channel was opened by Nate Ritter, who was inspired and instructed by Chris Messina and it was Messina's friends who became the first contributors. Eventually Ritter and Messina lost control over #sandiegofire and it became a truly independent stream shaped by other users’ engagement. Jerry Sheehan (in Bigelow, 2014) then chief of staff at the California Institute for Telecommunications and Information Technology (Calit2) commented:

Figure 16: Screenshot of #sandiegofire hashtag showing multiple users posting Tweets with it
The use of the # in the public safety event allowed the media to essentially turn citizens into news gatherers. If you remember the ’07 fires, there was a fair amount of crowdsourced content that was facilitated by Twitter. This crowdsourcing impulse for data gathering would lead to lots of great tools (…)”

Jerry Sheehan (Sheehan in Bigelow, 2014)

The San Diego fires stopped after few days and the #sandiegofire hashtag became less active for a while although it is continuously reactivated during anniversaries of the 2007 events and every time when fire happens again in San Diego. There is also an ongoing discussion on the #sandiegofire hashtag about it being the first successful use of hashtags. Most importantly, #sandiegofire has become the first hashtag that gained prominence through orchestration and is widely regarded as the hashtag that enabled the adoption of hashtags by Twitter users and the platform.

Conclusion

This chapter defined hashtags and provided their detailed history dating back to 1970, when they were first used in Information Technology. It described how they appeared on Twitter as a user-led innovation and how their adoption and the first successful use was in fact an orchestrated effort from a group of users. In this historical analysis I not only presented the key dates and actors but also look at the historical discussions around hashtags and how hashtag creators imagined they would work. It shows how hashtags were only adopted by Twitter users and then by Twitter only because their creators orchestrated their use. As a result, both Twitter users and Twitter as the platform created hashtagability - the structural potential of hashtags to carry out functions not present at the time of their introduction. The key takeaway from the chapter is that hashtags from their early days, even before being formally incorporated into Twitter’s architecture, were considered as a collaborative tool.

The next chapter will continue the exploration of hashtag’s history by studying how hashtagability was realised through the activities of users. In other words, it will look at functions of hashtags that were developed over the years following the incorporation of hashtags into the Twitter architecture.
Chapter 4: The History of Hashtagability

Tag spaces could be interesting and rich shared experiences, but no one seems to be really exploring that side of their existence. Del.icio.us has trained us to think of tags as metadata for bookmarks, and blogs have trained us to view them as metadata for posts. But tags imply communities, and no one is doing much to let those communities find themselves. Twitter hash tags could help.

Stowe Boyd, Online, 2007

Introduction

The previous chapter described the history of hashtags. The focus of this chapter is to define the numerous functions of hashtags on Twitter. All these functions, just as hashtags themselves, were creatively developed by Twitter users, which indicates that they (hashtags) have a great potential, the ability to do things or carry out different functions than originally intended. This chapter will look at the history of how hashtagability was realised through users and how they developed new uses of Twitter and hashtags (i.e. categorisation, conversation, or contextualisation) and how Twitter made this possible by developing the platform.

More specifically, this chapter is the beginning of the study of hashtagability - the potential of what could be done with hashtags by users and the platform. It starts

35 http://stoweboyd.com/post/39877198249/hash-tags-twitter-groupings
with the study of hashtagability realised through a practice of social classification (organisation of content) performed by Twitter users and how the technical development of Twitter 'confirmed' that this function is crucial, by making all hashtags clickable and linked to Twitter search results.

The key point is that even when hashtags are used as comments or to convey emotions and their clickability and searchability are not important, they still have classificatory effects. Emotive hashtags such as #grrr or conversational #GiveAMovieAName might not be the best labels to annotate and organise content, but they remain active links to Twitter search results and therefore even if this is not the intention of their users, they form a 'social classification'. In that sense the organisational function of hashtags, used to categorise content and facilitate search for it, remains the 'mother of all functions'. All other functions (e.g. conversational, emotive or performative) described in this chapter were developed independently by hashtag users but they do not remove or reduce the organisational function. Hashtags providing the means to search might not provide the best search terms, but this does not change the fact that they are a means to search. With that in mind, this chapter describes seven different functions of hashtags, six of which were developed by users.

The chapter links the conversational function of hashtags to practices of live tweeting while watching television (Johns, 2012) also known as 'second screens' (Lochrie and Coulton, 2012 and Zappavigna, 2017). When hashtags are used as comments, their clickability and searchability become irrelevant as hashtags are not there for other users to click on (Wikström, 2014: 136). The reason they are included in the post is to make them visually stand out as comment. The emotive function is very similar to hashtags acting as comments but instead of commenting, users explicitly write about their emotions i.e. #angry, #Worry, #Grrr, #ouch. The community building function of hashtags is linked to the research of Zappavigna (2015) who argues that they signal that there is a potential presence of other users who potentially use this hashtag. Hashtags can also be used to provide context for interpretation of the post by becoming a highlighting device or stylistic effect and finally have a performative function, which is linked with Twitter trends and orchestrated attempts to create them. This function is included in this chapter to signal this possibility and the entire following chapter will discuss Twitter Trends in detail.
The final section of this chapter focuses on the anatomy of hashtags. It analyses the set of rules that were developed by Twitter users and how Twitter as a platform made hashtags possible by developing technical infrastructure.

**Functions of hashtags**

**Hashtags as a tool for categorisation of content**

The definitions of hashtags introduced in the previous chapter define the function of a hashtag in the following ways:

1. It identifies messages relating to a specific topic (OED: Online)
2. It briefly indicates what a message (such as a tweet) is about (MWD: Online)
3. It classifies or categorizes the accompanying text (MWD: Online)
4. It is used as a tool for a supplementary coy or witty comment
5. It categorises the accompanying text (OSPD: Online)
6. It is used to identify a keyword or topic of interest and facilitate a search for it (DC: Online)

Apart from the fourth point which focuses on their function as a comment, the other five definitions focus on the organisational functions of hashtags. Hashtags are either described as tools that organise (classify or categorise) content and facilitate search for it or tools that identify specific topics or the accompanying text by acting as keywords. Scott (2015) argues that the main functionality of the hashtag is to help to retrieve related content. By creating a hashtag, a user considers it a topic that is related to and representative of tweet’s content. These hashtags might be in different forms: describing a TV programme i.e. #RipperStreet, micro-memes linking to the series of jokes on the same themes i.e. #Failed90sRappers or used to coordinate content over a longer time frame i.e. #hellomynameis which is used to promote an offline and online campaign in healthcare. All they have in common is that they
describe the content of tweets and after clicking them users are taken to search results relating to these tweets. It is because of this searchability that they help to organise content on Twitter and this organisational function of hashtags is the most obvious. It was used in most of the dictionary definitions and it is the ‘mother’ of all other functions. Even if one is using hashtags intentionally as a conversational or commentary tool, as will be shown in this chapter, an unintentional categorisation takes place as well. It might not be the best categorisation for future retrieval, but it does not change the fact that it happens. This is linked to the infrastructure of Twitter, which treats every hashtag (even if it’s purely conversational) as a link to search results.

From a linguistic perspective this organisational role of hashtags and their searchability could be analysed as a topic marking function. Kahlert et al. (2017) studied hashtags in relation to topic identification and argue that some hashtags only cover one topic (i.e. #ohNoHarry is purely about singer Harry Styles falling off a stage), other cover multi-topics (i.e. #volkswagen was about the 2015 emission scandal and new car models) but there are also hashtags that do not form a coherent topic at all (i.e. #love) due to the large amount of unrelated tweets). Such hashtags often act as comments or provide context to an individual tweet and their organisational function is nominal. Bonilla and Rosa (2015: 11) argue that the topic marking function works ‘on top of’ content organisation:

‘hashtags allow users to not simply “file” their comments but to performatively frame what these comments are “really about,” thereby enabling users to indicate a meaning that might not be otherwise apparent. (...) They locate texts within a specific conversation, allowing for their quick retrieval, while also marking texts as being “about” a specific topic’ (Bonilla and Rosa, 2015: 11)

While hashtags may help to indicate the aboutness of the tweet, on some occasions it is difficult to understand what some hashtags are about, for example #BaBB or #h3Ind. This difficulty created a demand to classify hashtags so that they have clear definitions that aid the classification process. As a result, a hashtag dictionary was created by Hashtags.org. Unfortunately, very quickly it turned into farms of commercial links rather than a helpful resource. Some of the definitions are very useful and informative. For example, #abandoned is defined as ‘referring to an
increasingly popular hobby of exploring neglected or abandoned spaces, usually involving photography. A quest to find the beauty in decay.’ However the fact that there is no one central authority that controls the dictionary and all definitions are user generated, means that most of the defined hashtags are either commercial (i.e. #m4mhelp\(^{36}\) is defined as: ‘Math For Middles Homework Help. Submit a question for help from a real math tutor’) or not informative at all (i.e. #BabyDonald\(^{37}\) is defined as ‘self-explanatory’). The other problem is that even if one finds a good definition such as #abandoned, there are already hundreds of other hashtags that could be used to describe similar content for example: #abandoned_world, #LeftBehind, #Decay or #abandonedplaces. Not only might these hashtags confuse users, they also compete with each other for their position in the search results and their visibility to users. The more users get to see them, the more often they will be used, which will increase their position even more.

All these are examples of social tagging, where the aim was not necessarily to categorise one’s content ‘correctly’ but to make a point or show one’s attitude to the object they describe. They all remain searchable and therefore fulfil the most important function that all hashtags have - they help to organise content on Twitter but as it will be shown in the next section, they also play many other functions.

**Conversational function**

The conversational function of hashtags was originally linked to practices of live-tweeting while watching television also known as ‘two screen viewing’ (Johns, 2012) or simply ‘second screens’ (Lochrie and Coulton, 2012 and Zappavigna, 2017). When this happens ‘Twitter does not necessarily replace existing media channels (...) but often complements them, providing its users with alternative opportunities to contribute more actively to the wider media sphere. This is true especially where Twitter is used alongside television, as a simple backchannel to live programming’ (Harrington et al, 2012). This phenomenon of Twitter acting as a conversational

\(^{36}\)https://www.hashtags.org/definition/m4mhelp/

\(^{37}\)https://www.hashtags.org/definition/BabyDonald/
backchannel was well described in the area of sport events (Harrington, 2014, Highfield, 2014, Kroon, 2017) programmes such as cooking game shows (Zappavigna, 2017), reality television (Lochrie and Coulton, 2012) or news (Deller, 2011). Very often hashtags used for these backchannel discussions become trending during the broadcast of the programme or transmission of a sport event as many people start using the hashtag at the same time, which creates the ‘burst of popularity’, which is necessary to make hashtag trending. Once a hashtag becomes trending it becomes even more visible. People who are not watching TV live but only observing the hashtag on Twitter can then join the conversation.

Another example of the conversational use of hashtags was described by Huang et al. (2010) in his study of micro-meme hashtags on Twitter. They defined micro-memes as the emergent topic for which the hashtag is created and which is used widely for a short time before it disappears. Other researchers call Twitter micro-memes ‘hashtag games’. (Wikström, 2014). Huang et al. (2010) noticed that in comparison with tagging systems on De.li.cious and other Web 2.0 applications tagging practices on Twitter with the use of micro-memes can be described as a new type of tagging because of its conversational, rather than organisational nature. The aim of conversational tagging is to filter and direct content so that it appears in the ‘right’ stream rather than simply to categorise it for future retrieval. The participation in micro-memes is a posteriori - users use the hashtag after seeing it being used by other users. The goal is not to facilitate retrieval but to join the conversation as it happens. This is very similar to discussion about live television on Twitter, where users are joining the conversation promoted with a hashtag on their TV screens.

Micro-meme hashtags are not used to describe content that already exists. Neither are live TV hashtags. In fact, it is the opposite - users create content to describe these hashtags, to react to them or to reply to what the hashtag says. Conversational hashtags (i.e. #itvdebate or #GiveAMovieAName) appear before the content and encourage users to create new content either in the form of a comment or a reply. As a result, it is the content that describes/responds to the hashtag rather than the hashtag describing the content. It is very likely that a user would have never used the hashtag or written the post if they were not inspired by the hashtag seen in Twitter Trending Topics or on live television. By replying to the hashtag, they participate in a multi-person conversation. Huang et al. (2010) defined such practice
where the tag itself becomes an important part of the message as conversational tagging.

Obviously, these conversational hashtags serve as a label for future retrieval of content (because all hashtags are labels and are searchable) but the key function is to serve as a prompt for user comment especially in Twitter Trending Topics. As will be shown in the chapter about Trends, the aim of Trending Topics is not to retrieve old content, but to indicate the most interesting topics, discussions or conversations that are happening at the moment. In the same way micro-memes and TV hashtags are not used to retrieve old tweets - they are used to create a common stream, which become multi-party conversations. Users can click on a given hashtag and scroll through the conversation in which every single post is a reply to the hashtag rather than unrelated posts with the same label. The following examples illustrate the difference between hashtags used for categorising and conversational hashtags. The first three posts are micro-memes that were posted in reply to the #GiveAMovieAName hashtag:

_The Shape Of Walter #GiveAMovieAName_

_Wanda woman #GiveAMovieAName_

_Look Hugh’s Talking #GiveAMovieAName_

These messages were only posted because their creators responded to #GiveAMovieAName hashtag, which most likely they saw in Twitter Trending Topics. The next chapter describes how micro-memes become Trends through the organised practices of their creators, who even use special software and mobile apps to coordinate the promotion of the hashtag and make it trending.

The next example is the post tweeted in response to trending #Giro101 hashtag, which was also promoted on live TV during the broadcast of Giro d’Italia bicycle race.

_Just coming back from training and turning on my television. WTF!! What happened!? #Giro101_

The final example is the post tweeted while a user was watching the BBC Question Time programme. Again, the comment was inspired by the programme and guests in the studio and it only appeared on Twitter as a response to that.
A white middle class panel are now answering a question about whether the country is a bastion of white middle class privilege #bbcqt

The use of #bbcqt means that this post belongs to the conversation about this programme rather than that it is categorised under this hashtag. If one wanted to categorise this post #SocialClass would possibly make a better hashtag. The last Tweet is a good example of a comment posted in reply to a conversational hashtag #bbcqt used as backchannel for the discussion about a TV programme. It is also possible that hashtags themselves become comments.

**Hashtags as comments**

The first two functions of hashtags are very different but they have one thing in common. They rely on hashtags being searchable. In the case of hashtags used for categorising content they act as labels that annotate content. In the case of conversational hashtags, the actual content is created in reaction to the hashtag. In both cases it is crucial that they are clickable and searchable as this is the only way that a hashtag can be consumed/used. We can either read all posts such as for example all those categorised as #nhs and we expect to find the archive about this topic. The same applies to hashtag games. It is fun to take part in them, but it is also fun to read the posts of others who contributed to them. The only way to do it happens through Twitter search.

In the case of hashtags used as comments, the clickability and searchability of hashtags are not important (Wikström, 2014: 136) as hashtags are not there for other users to click on. The reason they are included in the post as hashtags is to make them visually stand out as comment. They divide the post into two parts: the actual post and then the hashtag which acts as a comment. In the following example:

*Sarah Palin for President?? #Iwouldratherhaveamoosoe

hashtag #Iwouldratherhaveamoosoe is a user’s comment to the possibility that Sarah Palin could be selected to run for President. It is not a hashtag game nor an organisational hashtag. If it was an organisational hashtag it would look like this (Orlean: 2010: Online):
I would rather have a moose for President! #SarahPalin

The 'I would rather have a moose for President!' part of the post would be the comment and #SarahPalin would be a categorising tag. It is unlikely anyone would ever categorise or search for a tweet about Sarah Palin using #Iwouldratherhaveamoose hashtag. It is included in the post only to show the opinion of the user.

More examples of hashtags used as comments include #toomuchfaketan or #yesiknow. Again, all these hashtags are used not to help with categorisation or take part in a game. They are there to comment on the content of the tweet. Generally, such hashtags are not very popular and their search results consist of a list of completely unrelated posts. The two posts below with #yesiknow hashtag illustrate this 'unrelateness' of posts in the search results.

I was thinking the same. Maybe grow older gracefully rather than trying to look 20 again. #nomoresurgery #toomuchfaketan

And some lady just stared at me for ten minutes before finally telling me I look like that "one actress." #yesiknow #everyoneknows

Homework on a Saturday night? #nerd #yesiknow

Occasionally such commentary hashtags become internet memes, for example #EpicFail, enjoys enormous popularity online and offline:

#EpicFail: When you’re so excited about a press release, only to find out the intern sent the WRONG ONE to all your media outlets.

Dear @Microsoft, I’ve been awake for 24hrs straight because I spent the last 12 trying to get your screw up fixed. #furious #epicfail #lostacustomer

The real problem with this tweet is not the standard racism, it’s the stupidity. Migrants are net contributors. Not to mention the huge number of migrants who are NHS staff. #EpicFail

So your politically bigoted view selectively quotes part of a report but not all of it. Claiming some of the evidence but not accepting the conclusions. #epicfail

@bigbasket_com You guys are not delivering the order n giving stupid excuses even after escalating thrice. #delivery #CustomerService #useless #EpicFail
The popularity of the #EpicFail hashtag comment changed it into a kind of internet meme that people use to post funny photos and gifs. The only difference in comparison to hashtag games as described above is that #EpicFail is an ongoing meme. It does not have a spike of activity and then sudden death, which is the case with hashtags used in discussions about TV programmes or hashtag games. The classic hashtag games have a very short lifespan - they quickly achieve Trending Topics, enjoy some global/national popularity and then rapidly disappear. #EpicFail is different because it has constant popularity that does not have these 'bursts' which would make it trending. For these reasons it is categorised under comment hashtag rather than micro-meme, even though it has some characteristics of a micro-meme.

**Emotive function**

The emotive function of hashtags is very similar to hashtags acting as comments. Their role is to present how a user feels about what s/he wrote about the tweet. Instead of using a comment as in the previous category, some users choose to explicitly write about their emotions. The examples of such hashtags include: #angry, #Worry, #Grrr, #ouch. Similarly to commenting hashtags, emotive ones are also not included in tweets to make them searchable.

*Wish there was a severe fine for those people who think that playing music at extreme volume starting at 10:15pm and going till 2am is acceptable. Every single weekend. I'm bloody exhausted and just want to sleep. #angry*

*I forgot how bad shopping for a car sucks. The ones that are perfect for it should have what we're looking for always just out of our price range #grrrr*

Wikström (2014) observed yet another way of expressing emotion by means of representation of sound, for example the use of hashtags such as: #maaaan or #Jeeeesus as well as #grrrr.

*Nothing worse than a moaner on a Monday morning, just get on with it! #jeeeesus*

*Struggled with balancing equations last night to come in and listen to my professor talk about car pollution today... #maaaan*
In both cases the intention of the authors was not to categorise their posts (if they wanted to do it #jeeeesus would be spelt as #Jesus) but to ‘express an emotional state’. Hashtags are used because they visually stand out from the body of Tweet.

**Community building function**

Zappavigna (2015) sees hashtags as fulfilling an additional function - they signal that there is a potential presence of other users who potentially use this hashtag. All one needs to do is click on the hashtag and therefore join the ‘searchable talk’. If there are other users who used the same hashtag the search result will allow a user to ambiently connect with them and potentially join the process of generating more content (i.e. via creating more memes with a given hashtag). The term ‘Searchable talk’ suggested by Zappavigna (2012) is what connects the first two functions of hashtags: categorisation (and searchability) of content and the facilitation of conversations. As a result, it creates ambient communities, that is, it ‘amplifies the potential for users to connect with each other and establish interpersonal bonds.’ The hashtags role is to help to create co-presence and create communities around topics of interest.

Zappavigna’s Searchable talk is associated with Morville’s (2009) concept of ‘ambient findability’ (information can be found in any location). Zappavigna (2012) argues that with Twitter hashtags information can be found anywhere as long as one has access to online talk. The fact that the tweet is searchable (because it contains a hashtag linking to the search results) means that Twitter’s users can engage in ambient affiliation in which users do not interact directly and most likely do not even know each other. This kind of ambient affiliation would not be possible without search functionality.

Zappavigna (2012) uses the example of #Obama to illustrate how Twitter Search creates an ambient affiliative network in which a single tweet containing hashtag #Obama (and potentially other text) co-exists with other tweets containing #Obama (Figure 17). There are also other bonds i.e. #McCain or #hockey that are temporarily related to #Obama and which represent competing or alternative values.
Zappavigna (2012) acknowledges that ambient communities are dynamic and they change over time as hashtags change depending on what Twitter users are discussing at a given time. She argues that it is possible to divide these into two groups/kinds of communities: (i) fairly constant communities (i.e. complaining about something using hashtag #fail) and transient communities that depend on political or social factors (i.e. hashtag #election08 which was active only during the election). These are both associative communities that are not formed through reciprocal interaction but through searchable talk. They are purely semiotic and not reciprocally interactional.

The emergence of such virtual communities was predicted by Licklider and Taylor (1968: 37-38). They foresaw entities consisting of ‘geographically separated members’ creating communities ‘not of common location, but of common interest’. The actual term ‘virtual community’ was coined by Rheingold (2000). In his 2008 paper he defined a virtual community as:

Figure 17: Search creating an ambient affiliative network for hashtag #Obama from Zappavigna (2012: 97)
a group of people who may or may not meet one another face to face, and who exchange words and ideas through the mediation of computer bulletin boards and networks. Like any other community, it is also a collection of people who adhere to a certain (loose) social contract, and who share certain (eclectic) interests. (Rheingold, 2008: 3)

The way virtual communities are understood today means that membership usually requires you to become a member through a process of registration or at least subscription. In that sense becoming a Twitter user could be understood as joining a community of fellow Twitter users. When one thinks about hashtags, there is no formal process of ‘joining a hashtag community’ involved. There is no membership. The use of hashtags is completely open to everyone and there are no barriers at all to either use them in posts or to search for them. In that sense the community building function of hashtags is possibly the least obvious one as there is absolutely no formal or technical infrastructure on Twitter that would allow any extra steps (i.e. registration) involved in joining a hashtag community.

Also, because hashtags have no ownership as such, using them has no limits and anyone can do it anytime. With all that in mind, it might be surprising that the community building function of hashtags was discussed amongst the early adopters of hashtags as early as 2007. In fact, Steve Boyd talked about hashtags as tools for creating communities as early as 2 days after the actual idea of hashtags was born:

Del.icio.us has trained us to think of tags as metadata for bookmarks, and blogs have trained us to view them as metadata for posts. But tags imply communities, and no one is doing much to let those communities find themselves. Twitter hash tags could help. (Boyd, 2007 Online)

His idea that ‘hashtags could help’ with the creation of Twitter communities is based on his slightly different understanding of the term community. He actually defines it as a ‘grouping’ to differentiate it from the term ‘group' understood as a community one usually chooses to join and which allow its members to do things such as messaging other members of the group or sharing an album (Booth 2007: Online).

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38 As argued in Chapter Three, hashtags on IRC had their owners/creators, and they were publicly visible to all people using these hashtags. It is not the case on Twitter. Twitter’s infrastructure allows only to make an indirect connection between a hashtag and a user, which I theorise in the following chapter as an algorithmic ownership.
None of these are possible with hashtags. Groupings are different as they are ‘ad hoc assemblages of people with similar interests’ (Boyd, 2007:23 Online) or as Booth (2007: Online) clarifies they ‘are things that “happen” rather than things that people elect to join or build. Groupings emerge within a social network because of the way people are using it, they are things that occur naturally and all the time inside networks.’

This definition describes how hashtags can be understood as tools for creating communities. The act of creation takes place not through the process of joining but through the use of the hashtag. Usage and differences in usage are crucial as one or two letters difference in a hashtag means we are looking at a completely different community. Very often similar or almost identical communities (in terms of interest) use different hashtags. For example, Ford et al. (2014) studied the community around #PhDChat hashtag and found that numerous other unique tags were co-present in their dataset. These included hashtags such as: #phdforum, #highered, #ercchat, #socphd, #socchat, #acwri, #ercchat, #Gradhacker or #phdadvice. They all formed their own communities. For example #phdforum was used by a group connecting people in higher education, #socphd and #socchat were associated with #phdforum but their focus was on social research whereas #ercchat was similar to #PhDchat but with the emphasis on the issues of early career researchers. They were all separate communities but in the dataset downloaded by Ford et al. (2014) they showed up as hashtags co-occurring with #PhDchat. They clearly share topical proximity but each of them is a separate community and is ‘organised’ differently. For example, #Gradhacker community as well as using the hashtag on Twitter also had their own blog where they posted resources for graduate students. On the other hand, #phdadvice community was used by individuals without their own website.

Communities organised around hashtags do not rely on formal membership. The very design of hashtags makes it impossible. Hashtags are not owned by anyone so there is no possibility of controlling who joins a hashtag community. They do not rely on personal connections but on shared interest. They can be compared to what Booth (2007: Online) described as musical neighbourhoods - one of the features of Last.fm, which helped to connect people not only using their email addresses or according to actual confirmed ‘friendships’ by manually adding someone as a friend, but by their similar musical tastes. On one hand users had their elected community of people who they selectively choose to be connected with and with whom they
might not have musical tastes in common. On the other hand, the musical neighbours community were strangers to each other but connected via similar musical tastes. Similarly, on Twitter users can connect with others via formal following of another user or participate in informal communities around hashtags that are based on shared interests.

Interestingly Starbird and Palen (2011) described how the conditions of membership in a hashtag community can allow users to reverse this process to identify community users. In their study of “digital volunteers” in the aftermath of the 2010 Haiti earthquake they described online self-organising mechanisms used globally by collaborators. They noticed that hashtags were used to identify users participating in relevant conversations and then to organise activities. In other words, community hashtags were employed as a mechanism for identifying useful social connections.

Because no formal joining is required, membership in hashtag communities starts when one starts using a given hashtag. The ease of it is one of the key characteristics. Ebner and Muhlburger (2010) used the example of scientific conferences and described how easy it is to join and follow a conference community’s discussion on Twitter by simply tagging one’s message with the hashtag or following the tag. No setup is required and it is possible without even knowing a single person taking part in a discussion. A hashtag becomes a symbol of the community and acts as a filtered channel on which all materials, comments etc are available. Noon and Ulmer (2009) see conference hashtags as tools which make it easier to connect with others during the conference and share the experience of a given conference. The only ‘act’ that is required from a member is to start using the hashtag.

This usage can then become the object of a study. For example, Yang at al. (2012) used the number of retweets, replies, and mentions between hashtag community members to calculate the average level of interactions between them and found it to be significantly higher than among random users. They also compared Twitter hashtag communities with users using the same tag in other Web 2.0 websites such as Flickr, LiveJournal, or YouTube and established that the network density of hashtag communities on Twitter was around a thousand times larger. Based on that they concluded that ‘adopting a hashtag can be interpreted as the adoption of a community membership’ (Yang at al. 2012: 4).
Hashtags providing context

As early as 2007 the father of hashtags Messina argued that they might provide 'some merit to improving contextualization (…) within Twitter'. Scott (2015) argues that hashtags can perform the function of 'highlighting topics irrespective of their potential for retrieving related content' and provides the following example:

*I think all drs should be made to lie in a hospital bed wearing PJs & be stood over. See what it feels like. #vulnerability #powerbalance*

She argues that hashtags #vulnerability and #powerbalance are very unlikely candidates to be used for search in the topic of patient-doctor relationship in hospitals. Even if someone decided to use them, they would find a lot of content that is unrelated to the topic of patient-doctor relationship in hospitals. In other words, these two hashtags do not describe the content of the tweet well and are not useful for topical search retrieval. Scott thinks they are instead an example of a hashtag that is used to highlight a topic or theme for the tweet without fulfilling the role of categorising tweets for future retrieval. She argues that the hash symbol in this case has become a highlighting device or stylistic effect. Hashtags of this type are mostly added after the main content of the tweet rather than being integrated into the main sentence: they are not part of the main message and their role is to provide context for interpretation. In their usage they are very similar to hashtags used as comments or emotive hashtags. Their clickability is not important and if actually clicked, they produce very random search results. The following three tweets posted in #vulnerability hashtag illustrate this:

*The best person to be #REAL with, is God. #surrender #vulnerability #pray #faith #trust*

*Rise of the machines: how AI can help #cybersecurity. https://goo.gl/a6A2JF #vulnerability @wired*

*Always keen to support any initiative raising awareness to help understanding and acceptance of mental health issues. Look after each other peeps! #CrazySocks4Docs #vulnerability #metoo*
Each of these posts is ‘about’ something completely different. The first one is about god, the second about cyber security and the third about mental health. All of them used the same hashtag #vulnerability but in a very different context.

Bonilla and Rosa (2015: 5) argue that such hashtags ‘have the intertextual potential to link a broad range of tweets on a given topic or disparate topics as part of an intertextual chain, regardless of whether, from a given perspective, these tweets have anything to do with one another’. In other words when a hashtag is used in this way it does not generate relevant search results. Its only function is to provide context but on the level of the individual tweet. The search results it generates are just a list of disconnected posts that do not have anything meaningful in common. The context can be understood only when analysed with the actual post. The aim of such a hashtag is not to be clicked on but to signal the very broad context in which a given post was written. In other words, it acts not as categorisation but as contextualisation of the content it refers to. The other examples of such context hashtags could be #Uncertainty or #Success, which are so general that they could be added to any post in any category and work really well on the level of the individual post but at the same time create completely irrelevant and random search results. Kahlert et al (2017) who studied hashtags in relation to topic identification, argue that such hashtags do not form a coherent topic at all (i.e. #love) due to the large number of unrelated tweets.

**Performative function of a hashtag**

The next chapter describes how groups of fans ‘produce’ trending hashtags using various strategies. For example, hashtag #4YearsWithBTS created by fans of the South Korean boy band BTS to celebrate the 4th anniversary after the creation of the band or hashtag #WeLoveYouMinYoongi - a message from the fans to Min Yoon-gi - South Korean rapper, songwriter, and record producer - were both produced by fans. These fans form communities (fandoms) but these are based not only on shared interest as was described in the case of classic hashtag communities. Fans tend to form strong social, also known as bonding, ties between them which creates a sense
of intimacy and shared trust (Newman and Dale, 2005). These are interpersonal links, rather than just ties based on following the same hashtag.

Such communities have developed a variety of practices to create tight bonding ties within their fandoms. For example, there is a ‘nomination process’, which is a way of promoting fans with a low followership by a popular fan, so that other fans follow such users and there are even more ties within a group (Recuero et al 2012). This means that the fans form communities that, on top of shared interests, are also based on the bonds between members, who promote each other. When such communities use hashtags, these become trending for a short while and the fandom (and obviously their idol) get visibility by being included in Twitter Trending Topics. These practices situate such hashtags closer to micro-memes with the difference that not many people outside of the fandom actually take part in the ‘game’.

Huang et al (2010) described how micro-memes become conversational hashtags as many users react to them and post Tweets in response to these hashtags. Fandom hashtags are less conversational in that sense as they do not really start conversations on Twitter apart from increasing the number of posts from the members of the fandom. This is an ‘orchestrated conversation’ with the aim of making a hashtag trending so that they can make a statement with the hashtag itself. The conversations that took place to make it trending are irrelevant. In case of micro-memes as described by Huang et al (2010) the purpose of making such micro-meme hashtag trending was not only that more people post in reply to them but also so that people click on the hashtag and read Tweets that were posted in reply to it. These posts are funny, entertaining and simply interesting to read. In case of fandom trending hashtags, Tweets that were used to make them trending are not so important.

In fact, Recuero et al (2012) argue that they could be treated as spam because of the techniques applied by fans. For example, fans may include fan hashtags in every single tweet they post, even if it has nothing to do with the hashtag that is the topic of conversation. The only purpose is to make the fan hashtag trending as the entire message the fan is trying to get across is actually included in the hashtag. In this sense these hashtags are not conversational at all. They form a hybrid type of hashtag that places them somewhere in between being a community hashtag (as there clearly is an organised community behind it) and a micro-meme (as they use techniques that
are meant to convince the Twitter algorithm that they are actual conversations). These are communities with a purpose, and that purpose is not to have a conversation or share experiences as was the case with the community hashtags described above. Their purpose is to get their message across, so that as many people as possible can see it as a trending hashtag.

The performative function is linked with hashtag trends, which will be covered in the next chapter. This chapter will continue looking at hashtags (not necessarily trending hashtags) with the focus on how they were technically developed by the platform and what standards for using them were developed by Twitter users.

**The Anatomy of a Hashtag**

As described in the previous chapter, hashtags were introduced to Twitter as a user invention and there were no official details about valid characters, maximum length, or any other technical details about them. During the decade after their creation both its users and the platform developed hashtag etiquette. The key issues that had to be dealt with were related to the acceptable number of hashtags per tweet and the best length of a hashtag. The other issues were whether hashtags should be inserted at the beginning, in the middle or at the end of a tweet and what is considered to be hashtag spamming.

**Technical Standards of Hashtags**

In 2010 it was possible that the same hashtags were searchable on the desktop version of Twitter and not searchable on the mobile version (Eden 2010: Online). For example, hashtag #Français (Figure 18) was searchable on the desktop version but not on the mobile version with only the #Fran (figure 19) part able to be a hashtag as Twitter would treat the ‘ç’ as a special character and end the hashtag before this letter.
Another example of initial problems with hashtags were different language versions. The major complication was for the Japanese language, which is not a language separated by spaces, and therefore it was impossible to say which part of the sentence was a hashtag or not. This was dealt with by the Twitter technical team in 2011 alongside improvements in other languages. Since 2011 Twitter supports Chinese, Korean, and Russian hashtags as well.

The initial problems with hashtags, as signalled by Eden (2010: Online) were gradually dealt with by the Twitter technical team. Today Twitter Help Pages provide more information about ‘hashtag standards’. There are also numerous other resources that provide help with it. The key points are the following:
• Spaces and punctuation marks are not allowed\(^{39}\) in the body of a hashtag. If used, punctuation marks (, . ; ' ? ! etc.) will end a hashtag wherever punctuation occurs. For example, if one writes \#it'smagic, the message will be categorised under \#it.

• All characters need to be unspaced. Using space character within the body of a hashtag will automatically end it i.e. \#Donald Trump will be categorised under \#Donald

• In order for a hashtag to be included in search results the \# sign needs to be preceded by a space. If one writes Donald#Trump or 123#Trump, these tweets will not be shown in searches for the hashtag #Trump. The \# symbol must have a space directly in front of it.

• Although Twitter Help Page does not specifically discuss it, if a hashtag is preceded by a special character - for example $#abc or %#abc, it will be included in search results as #abc

• Only letters, numbers and underscores are allowed in the body of a hashtag.

• Hashtags made up entirely of numbers are not allowed. If one writes #1 or #123 these hashtags will not be hyperlinked and will therefore not be searchable.

• Hashtags can start with numbers but these need to be followed by a minimum of one letter or underscore and letter(s). For example, hashtag #123_ is not allowed as it does not contain any letters but hashtags #123_abc or #123abc are acceptable.

• There are no limitations of this type if hashtags start with letters. In this case they can end with underscore i.e. #abc_ or with numbers i.e. #abc123

• Hashtags are not case sensitive.

Alongside the development of the technical infrastructure, there were some developments in the way people used hashtags.

Hashtag Etiquette

Some marketing experts (Doctor, 2012: Online) advise that the best hashtags are short, composed of a single word or a few letters and recommend keeping hashtags under 6 characters long. Cunha et al. (2011) investigated whether the length of a hashtag influences its success or failure and established that shorter hashtags become more popular than long ones. They argue that this is most likely caused by the following factors: (i) long hashtags containing numerous words can potentially have a lot of variations (i.e. #thankyoumichael, #thanksmj, #michaeljacksonthanks), which makes them (ii) more difficult to remember as they might have different word order and finally (iii) longer hashtags are more prone to spelling mistakes. Especially the third point is important as in hashtags all words are written together and it is much easier to notice a mistake in ‘thankt you michael’ rather than in #thanktyoumichael. Lastly it is advisable to use embedded capitals (CamelCase) in order to increase readability of hashtags that are two or three words long. For example, #CamelCase is easier to read than #camelcase. Their findings are important in relation to hashtags that become trends. I will describe the impact of the hashtag’s length on the likelihood of becoming a trend in my first empirical chapter.

Although there are no formal limits, Twitter recommends the use of no more than two hashtags per tweet as best practice. Social media specialists suggest that the best results (21% higher engagement comparing to Tweets without a hashtag) can be achieved by using 1-2 hashtags and that using more than two hashtags actually reduces engagement by 17% (Lee, No date: Online). The situation is slightly different with posts that include an external link (i.e. a link to an Internet shop). If the goal is for the user to click on the link, it is best not to include any hashtags in such posts, as they (hashtags and links) will be competing with each other for clicks within one post. Hashtags increase engagement internally on the platform (Twitter) but decrease it for external links. The same applies to retweets and likes. Pancer and

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40 Until the end of 2017 all Tweets were limited to under 140 characters. Today the limit is 280 characters, so it is likely that this recommendation does not apply any more.

41 Twitter Help Center. Available at: https://help.twitter.com/en/using-twitter/how-to-use-hashtags
Poole (2016) established that messages containing hashtags decrease likes and retweets.

On the other hand, there are situations where the heavy usage of hashtags is recommended. In their research Starbird and Stamberger (2010) proposed a method of multi-tagging in emergency situations which they defined as the practice of 'tweaking' Tweets for crisis-reporting efficiency. They argued that users should use multiple hashtags in one Tweet in order to enhance their ability to rapidly produce parsable, crisis-relevant information in mass emergencies. They also provided actual scenarios illustrating the use of the proposed syntax:

The reporter on the ground @Joe_32 tweets the following two Tweets:

2:05pm @Joe_32: The fire is moving quickly, it's across the street now, but we're okay #lakewoodfire

2:06pm @Joe_32: Fire's blocking the street up ahead, my wife and I heading south instead #lakewoodfire

The emergency services react with the following Tweets:

2:06pm @RedCrossLW: #lakewoodfire #lwfire use this format: #fire #city [city] #addy [address or cross streets] #floor [floor]

2:08pm @RedCrossLW: #lakewoodfire #lwfire use this format: #imok [name] #city [city] #location [place] #addy [address or cross streets]

@Joe_32 begins to use the prescriptive syntax

2:52pm @Joe_32: #lakewoodfire #imok Joe Smith #city North Lakewood #location Quik Stop #addy 58th & Spruce

Other users (@Amy_Brine) start to use the proposed syntax:

8:20pm @Amy_Brine: #lakewoodfire #shelter Price Middle School #city Lakewood #addy 506 Lincoln Ave #num 200 #contact 555-555-5555

Starbird and Stamberger (2010: 4)

In the above example, some posts contain 6 hashtags but their role is not to be clicked on but to form a clear structure. In this kind of scenario using more than three hashtags would not be considered as spam or a nuisance. Starbird and Stamberger
(2010) proposed hashtag syntax was also put into practice in Italy in 2014. A syntax for codified hashtags consisted of 20 hashtags generated by combining #allertameteo (weather warning) + XXX, where final letters code the regional identification i.e. #allertameteoTOS (Tuscany). Grasso et al. (2017) established that only six out of the twenty proposed hashtags showed a significant adoption and concluded that most of them only formed “ephemeral” communities.

In theory, hashtags can be inserted anywhere in the body of the post. Most often they are inserted at the beginning or the end but it is also possible to insert them in the middle of the message i.e. ‘It’s a #beautiful day.’ The position of a hashtag is linked to the function of the hashtag in the Tweet. If one uses a hashtag in order to categorise a tweet and make sure it appears in the right search results, it will most likely appear at the end of the post as metadata added to describe the post. A good example of this type of hashtag is provided by two posts by @Joe_32 posted at 2:05pm and 2:06 in the syntax proposed by Starbird and Stamberger (2010) above. In both posts hashtag #lakewoodfire is positioned at the end of the tweet and is clearly not part of the sentence. It is used as a tag to categorise the sentence. Hashtags also appear at the end of the post when they are used to provide a context for the tweet. Scott (2015) gives an example of the following tweet:

*I think all drs should be made to lie in a hospital bed wearing PJs & be stood over. See what it feels like. #vulnerability #powerbalance*

Both hashtags #vulnerability and #powerbalance are not added to help with the searchability of the post as they are very unlikely candidates to be used for search in the topic of patient-doctor relationship in hospitals. They provide context and would make no sense if they were at the beginning or in the middle of the message. Finally, if one uses hashtags as a conversational tool, they could appear anywhere in the post. Rocheleau and Millette (2015) call this behaviour of tagging during rather than after the process of writing - ‘tagging while broadcasting’ and argue that based on this, a new form of user behaviour - multi-tagging, emerged on Twitter. The syntax proposed by Starbird and Stamberger (2010) could serve as an example of multi-tagging ‘with a purpose’.
The position of a hashtag in a Tweet usually depends on the function of the hashtag but what is even more important is whether the hashtag needs to be related to either the content it describes or be a logical part of this content. Adding hashtags to unrelated tweets or repeating the same hashtag without adding anything to the conversation, which are techniques used for hashtag spamming and were described by Piatek (2014) using examples from Instagram, are also considered hashtag spamming on Twitter and could lead to the account being filtered out from search results or even suspended. As Twitter algorithms are getting better and better in filtering out spam messages that add no value to conversations, new techniques and processes are developed over time to 'play the game' with the algorithm.

Conclusion

This chapter explored the concept of hashtagability - the (structural/platform) enabling of hashtags to potentially do things/carry out functions which gives users a room to do things in ways that are enabled (made easy) by the platform. It then described seven different functions of hashtags, that were developed by Twitter users and made possible by the platform. It briefly summarised what changes had to be made on the platform, and how these technical improvements were happening alongside the development of standards and etiquette. Most importantly, this chapter described hashtagability as a performative vehicle that enables hashtags to become trends and to be used to create trends.

The next chapter focuses on Twitter trends. It attempts to connect hashtags with trends and argue that the design of the Twitter platform allowed hashtags to become best agents to convey messages through Twitter Trends Box. Most importantly, the next chapter shows that the design of the platform allows hashtags to be used by numerous actors to orchestrate trends and in fact hashtags are currently the best tool on Twitter to perform Coordinated Inauthentic Behaviour and set the agenda of Twitter Trending Box.
Chapter 5: Qualitative approaches to studying Trends

Introduction

This chapter is a continuation of the previous one, which studied hashtagability realized through different functions of hashtags. The function of hashtags having the potential to create trends is central to this thesis and I explore it in this chapter from the perspective of the platform and then of a user. This chapter is the direct response to my research question of how hashtagability, realised as the potential of hashtags to become trends, can be analysed and why. I specifically look at Twitter as a platform and then Twitter users and how their behaviour changed with the introduction of trends.

Following the argument of Seaver (2014:2) that the study of algorithms should not focus predominantly on the mathematical/computational procedure but also look into ‘culture, society, the public sphere, interpretation, politics, and so on’ (Seaver 2014:2), this chapter looks at Trends from the perspective of a user of the platform. I analyse Trends as a space that can be seen as having the potential to set the agenda of the platform.

The chapter starts with a short review of approaches available to study algorithms with the focus on non-mathematical ones such as didactic or ethnographic. It then introduces trends and their social and cultural significance, followed by an introduction to Trend Box and possible ways of analysing trends. The three different types of Trend Boxes are then theorised as ‘Delineation Devices’ (Madsen, 2012) - entry points to the Twitter platform that organise content and actors in order to create spaces where information can be arranged according to their relevance. The following section builds on that and drawing on Lury and Day's (2019) analysis of algorithmic personalisation and Seaver’s (2012) description of a collaborative
filtering system/algorithm, introduces the concept of algorithmic ownership, which connects content (in the form of a hashtag) with a person. As argued in Chapter 1, Twitter’s architecture does not support any kind of explicit ownership of hashtags, so this conceptualization of ownership as algorithmic association is one of the innovative contributions of this thesis.

The chapter then presents the types of trends that have been identified by researchers and how they are generated from the user perspective. It focuses on Trends that are created by the orchestrated efforts of Twitter users e.g. fans, hashtag games or spammers. I describe techniques and practices that are used to manipulate Twitter algorithms known as Coordinated Inauthentic Behaviour. This section provides the user’s perspective on coordination, which the next chapter will analyse from the platform’s perspective.

Qualitative approaches to studying algorithms

A computer science definition of an algorithm comes from the Introduction to Algorithms (Cormen, et al. 2009:5, 13):

(...) an algorithm is any well-defined computational procedure that takes some value, or set of values, as input and produces some value, or set of values, as output. An algorithm is thus a sequence of computational steps that transform the input into the output. (Cormen, et al. 2009:5, 13)

In other words, an algorithm starts with data (input) and then by following a certain mathematical procedure produces more data. This definition focuses predominantly on the mathematical/computational procedure which in the case of Twitter trends is covered in the next chapter. This chapter focuses on qualitative approaches to studying algorithms as suggested by Seaver (2014) and Kitchin (2014). These can be defined as didactic and ethnographic.
Didactic model for studying algorithms - Anagnorisis

Seaver (2010) uses anagnorisis, Aristotle’s term from The Poetics, to describe an approach to the study of algorithms. It can be defined as the dramatic realisation of a pre-existing fact. Seaver’s examples from literature include Oedipus discovering his true parentage or King Lear discovering the treachery of his daughters. These ‘dramatic discoveries’ are only for the characters as the audience has known them right from the beginning. In a way anagnorisis means stating the obvious. What is important is the dramatic moment of realisation. Seaver provides an example of Eli Pariser, who in his book talks about the moment of recognition - ‘the realisation that his (Pariser’s) experience online was being quietly mediated by algorithmic filters’ (Seaver 2014: 3) and argues that this kind of model is too simplistic as it assumes that ‘knowing about algorithms is a matter of revealing them’ and that once they are in the open, they can be seen, they can be critiqued. Also, as an approach to the study of algorithms, anagnorisis is too reliant on revelation and does not tell much (or anything at all) about the journey or in other words about how algorithmic knowledge was achieved and produced. The anagnorisis model does not reveal any information about the process through which the knowledge was produced (apart from dramatic revelation) and once recognised, the knowledge is no longer in question. The fact of the discovery is important, rather than the journey that leads to that or important questions about the knowledge itself.

In order to illustrate the significance of Trending topics, this chapter uses anagnorisis as a didactic model to show how deeply Trending topics algorithms are embedded in the online culture and how people assume they understand them and even expect them to behave in a certain way. When this does not happen, users criticise Twitter for manipulating the algorithm.

Ethnographic approaches to studying algorithms

Ethnographic approaches to studying algorithm (Kitchin 2014) are based on studying the creators of algorithms, users and the broader social context surrounding them. Seaver (2012) defines them as the study of how they work “in the wild”, outside the rigid, quantitative logic of computation:
When we realize that we are not talking about algorithms in the technical sense, but rather algorithmic systems of which code stricto sensu is only a part, their defining features reverse: instead of formality, rigidity, and consistency, we find flux, revisability, and negotiation. The use of phrases like “the Google algorithm” or “the Facebook algorithm” should not fool us into thinking that our objects are simple, deterministic black boxes that need only to be opened. These algorithmic systems are not stand alone little boxes, but massive, networked ones with hundreds of hands reaching into them, tweaking and tuning, swapping out parts and experimenting with new arrangements. (...) We need to examine the logic that guides the hands, picking certain algorithms rather than others, choosing particular representations of data, and translating ideas into code (Seaver 2012: 10)

Kitchin (2014) suggests three approaches to achieve these goals. The first approach involves interviewing designers or conducting an ethnography of a coding team. It is an ethnographic approach which provides the story behind the production of algorithms, their purpose and assumptions. It can be done via interviews or participant observation. The second approach is much broader in its scope and involves unpacking the full socio-technical assemblage of algorithms. It is an approach that builds on interviews and ethnographies as discussed in the previous one but adds more methods such as discourse analysis of company documents or promotional/industry material, attending trade fairs and even documenting the biographies of key actors and the histories of projects (see Napoli 2013). The final ethnographic approach focuses on users of algorithms. It involves examining how algorithms work in the world based on the assumption that even though algorithms are designed theoretically, they always perform in context, in collaboration with people, data and under constantly changing conditions and therefore they produce 'localised and situated outcomes' (Kitchin 2014). They could produce outcomes that are not what the theoretical design of them predicted and their behaviour is often reshaped through the user's engagement. Based on that, Seaver (2012) argues that one can only learn about algorithms by observing their 'behaviour' 'in the world under different conditions'. This approach includes observation of the users of the algorithm, interviews about software usage, intentions, tactics of engagement and concerns.
This chapter will define trends and their significance. It will then illustrate the didactic approach and provide a description of trends that draws on the available literature, both by Twitter the company and other commentators.

**Twitter trends - definition and significance**

Twitter Trending Topics, also known as ‘Twitter Trends’ or simply Trends, was introduced to the Twitter platform in April 2009 by the Twitter company as a ‘way to explore a collective global consciousness’. (Stone 2009: Online). Visually, Trends are generated by Twitter’s algorithm based on user’s conversations on the platform and then presented in the form of a ranked, personalised list of clickable links that lead to Twitter's search results for that trend i.e. after clicking the #MeToo trend one would see the list of all Twitter posts that were posted with this hashtag.

Trends do not need to be hashtags, although the latest research (Annamoradnejad et al. 2019) suggests that almost 70% of them are. The remaining 30% of trends are simply words or phrases that suddenly became popular on Twitter. The fact that 70% of trends are hashtags is significant and this section will attempt to understand what makes hashtags so special that they dominate the Trends Box.

Trends appear on both mobile and web versions of Twitter (see Figures 20, 21, 22) in the form of Trend Box which occupies a highly visible space. Given the widespread use of Twitter, Carrascosa et al. (2013) argue it provides visibility that is comparable to traditional advertising.
Figure 20: Desktop version of Twitter.com. Trending Topics box visible on the left (30 Jan 2018)

United Kingdom trends - Change

#NationalCroissantDay
6,040 Tweets

#TuesdayThoughts
54.6K Tweets

Mahrez
13.1K Tweets

#AntManandtheWasp
Paul Rudd and Evangeline Lilly suit up for the Ant-Man and the Wasp trailer

#songsinbread

Steve Baker
3,370 Tweets

Aymeric Laporte
Aymeric Laporte signs for Manchester City

Brendan Cole
Brendan Cole is leaving Strictly Come Dancing

#CriticsCircleAwards

Michelle Mone

Figure 21: Trending Topics box for the desktop version of Twitter.com displaying trends for the UK using the website’s default settings. (30 Jan 2018)
The number of trending hashtags as opposed to other trends depends on many factors such as time of the day, geography but also the language used. It also depends on the practices of users in different locations. There is a convention that all football matches get their own hashtags and these usually become trending in relevant locations during the matches. Sometimes these even become trending globally for example during competition finals. It also depends on the language of users - for some languages it simply makes more sense to use a hashtag to categorise content around the same topic because these languages have more than one case e.g. German
(4 cases), Hungarian (18 cases) or Polish (7 cases). In these languages, it makes sense to replace one word describing the conversation with a hashtag and always use it in a nominative case so that the conversation is easier to be found by others. The alternative is that the same word would be written in many different versions depending on the case and as a result, the conversation would be less searchable. Assuming that users know about it and there is a consensus that some words should become a hashtag and be used in nominative case regardless of the linguistic correctness, this might have the effect of more hashtags in these languages becoming trends in comparison to languages that only have a single case (i.e. English).

In this thesis I take the position that there is one big difference between trending phrases or words and trending hashtags. All non-hashtag trends are most likely included in Twitter's trend list because they naturally occurred (without intent to make them trending) in Twitter user's conversations i.e. users started chatting about the natural disaster or an event. Hashtags are different as they need to be created. Someone had to take extra effort to add the # symbol in front of the word. In other words someone had an intention for them to stand out by adding the hash sign in front of a word or phrase. Most of the time the intention is either to categorise content, make it more searchable or use it as a comment (see previous chapter for all different functions of hashtags) but it is possible that the intention is to make the hashtag trending. The next section looks at the situation when a hashtag that is widely expected to trend does not do that.

**The significance of trends**

Freddie Gray was a young African American man who was arrested in Baltimore, US and while being transported in a police van went into a coma and subsequently died. As a direct consequence of Gray’s death numerous demonstrations were held nationwide in the US and the #FreddyGray hashtag was used online to discuss the events. The general feeling amongst the Twitter audience at the time was that this was a major media event and many users found it surprising that #FreddyGray never became a trend. Shawn Carrie, a freelance journalist was one of them. In his tweet (see Figure 22 below) he called for an explanation as to why #FreddyGray never
became a trend and indicated that it ‘doesn’t make sense’ implying that according to his understanding of algorithms, this should have become a trend. Another user replied that this is possibly ‘internet censorship’ and implied that the algorithmic Trending Topics were possibly censored by a human operator.

Figure 23: Shawn Carrié, a freelance journalist calling for an explanation as to why #FreddyGray never became a trend42

These individuals do not attempt to understand how algorithms decide what becomes a trend (they assume they know it) but focus on ascribing motives to their creators/operators. What is interesting about such cases is that users do not

42 Available from: https://twitter.com/shawncarrie/status/591426211533946881
‘discover’ that Twitter Trends are generated by the algorithm - that is absolutely obvious to them. What they discover is that the algorithm did not work in the way they assumed it would.

People are so familiar with the knowledge that Twitter Trending box is run by algorithms, that they do not question it anymore. More importantly, from this example it seems that some people assume they should be able to tell what will be included in Trends as if they knew and fully understood the algorithm. The dramatic realisation only takes place when the opposite happens, when something which according to this ‘common knowledge’ of an algorithm ‘should be trending’ but for some reason does not. This is an example of how the anagnorisis model is not only useful to reveal that news are mediated through algorithms but also about the surprising effects of this mediation.

Using an example from the theatre this process can be compared to someone watching the same play over and over again and then suddenly the ending changes, a kind of reversed anagnorisis model - a dramatic realisation of a pre-existing fact but with a surprising outcome for the audience. In a classic anagnorisis model as described by Seaver (2012), the audience knows about the fact right from the beginning, and it is just the actors that make the dramatic discovery. In a reversed anagnorisis model the audience think they know what is going to happen, but then it does not happen and the audience blame the actors who do not play according to the script. The audience think they know the script (the algorithm) and automatically assumes that the change is caused by a human factor (censorship? Or a mistake?). This could be compared to the practice of gate keeping in the traditional media. Whenever there is a significant event and it is not covered by the media, conspiracy theories proliferate.

The next section will attempt to deconstruct the algorithm using the ethnographic approach with the focus on unpacking the full socio-technical assemblage of algorithms by the analysis of company documents and industry material.
Deconstructing Trends

Twitter’s own documents and promotional material give some clues about how Trending Topics algorithms work. For example, the definition of Trending Topics offered by Twitter Help Centre 43 describes trends as ‘topics that are popular now, rather than topics that have been popular for a while or on a daily basis, to help you discover the hottest emerging topics of discussion on Twitter.’ The key words from the above definition are: ‘now’ and ‘emerging’ which means that the algorithm prioritises sudden spikes of popularity of a topic over continuously popular ones. This view seems to be supported by many studies that describe trends in terms of burstiness (as it will be shown in the final empirical chapter) but also by the actual users of Trending Topics. For example, Lotan, as cited in Garber (2011: Online), established that the reason #OccupyWallStreet never became trending in New York was the fact that it ‘grew over time, steadily and consistently’, and that this ‘actually impaired its ability to trend’. He explained that ‘If we see a systematic rise in volume, but no clear spike, it is possible that the topic will never trend, as the algorithm takes into account historical appearances of a trend.’ In other words, Trends are not determined by the volume of the tweets alone but also by the velocity of the usage. The Twitter Help Center 44 seems to confirm this: ‘the number of Tweets that are related to the trends is just one of the factors the algorithm looks at when ranking and determining trends’, implying that there are other factors.

Twitter also tells us that ‘the algorithm’ (or algorithmic system as Seaver would prefer) also groups together trends that belong to the same topic; for example it is possible for #MondayMotivation and #MotivationMonday to be represented as #MondayMotivation only. Some content might be prevented from trending by Twitter because it is against Twitter rules i.e. it contains profanity, incites hate on the basis of race or ethnicity etc. Finally, Twitter also takes the ‘newsworthiness of the content’ and ‘public interest’ into consideration when determining trends. The grouping of content belonging to similar topics or promotion of emerging content

seems to be logical and understandable but other factors such as ‘profanity’, ‘newsworthiness’ or ‘public interest’ are very vague. The lack of clear explanation of how the algorithm determines ‘public interest’ or ‘newsworthiness’ leads to regular accusations of censorship.

The earlier mentioned hashtag #OccupyWallStreet competed (and evidently lost) in New York with #ThankYouSteve created to commemorate the life of Steve Jobs and #KimKWedding used for discussion about Kim Kardashian’s wedding. There is no doubt that #ThankYouSteve was newsworthy but there could be questions asked about the public interest behind the trending #KimKWedding in comparison with non-trending #OccupyWallStreet. It is clear that the Twitter Trending Box has become a space that is closely watched by Twitter users and the media. The next section provides a detailed analysis of Twitter’s Trend box and how it can be used as a starting point for the analysis. It is the study of how Twitter makes trending possible as a platform. The following section will focus on different types of trends that can be generated on Twitter and the involvement of users in trend generation.

**Twitter Trending Box**

This section explores the significance of Twitter Trend box, not just for Twitter as a platform, but also far beyond. If we assume, as argued by Bruns (2005), that traditional media gatekeepers increasingly rely on material from citizen journalists found on social networks rather than spending time and money on their own independent research and as a result are becoming gatewatchers, then clearly Twitter Trending Box is the space for them to watch. The latest ‘State of Journalism’ report (Rack, 2019: Online) shows that Twitter is the leading social network used by journalists at 83%, a 13 per cent increase from 2018, with 38% saying they plan to use it more in 2020. Not only are journalists affected by what they see on Twitter Trend Box - all Twitter users see it every day, so it clearly helps to set the agenda of the platform but also far beyond i.e. #MeToo movement.

The examples described in the previous section (#OccupyWallStreet or #FreddyGrey) show that Twitter users have developed a set of assumptions as to how the algorithm operates and what should be included in the trends box – a kind
of expected result of the platform’s algorithmic gatekeeping. When, for whatever reason, a hashtag that is widely expected to be trending, does not do that, it raises some questions amongst the Twitter community - described earlier as a reversed anagnorisis. In this section I attempt to analyse what happens on the platform and how such issues are possible.

The first point to note is that Twitter’s Trend Box is generated not just by Trends algorithms, but also by recommendation algorithms. As a result, a hashtag could be trending, but still not be visible as a trend for some users. It is possible that two different users in the same location will see two different trending topics on their devices. This is linked to the personalisation of content that is also decided by the algorithmic system. In other words, firstly there is an algorithm that ‘decides’ what topics become trending in a specific location. I define this process as ‘entering the trends pool’. What enters the pool is being determined by the first (Trend) algorithm. Secondly, there is another algorithm that decides which trends (from the ‘pool of trends’ for a specific location) are displayed for an individual user.

These kinds of algorithms, that personalise content for the user are theorised as recommendation algorithms. Lury and Day (2019:5-6) distinguish two main types - collaborative filtering algorithms and content sharing algorithms, pointing out that they might be sometimes combined. The first type is ‘based on large amounts of digital data on users’ behaviour, activities or preferences and leads to predictions of what users will like based on their similarity to others. (...) The calculative process involved in this group of algorithms is sometimes described as ‘leveraging’ the behaviour of users since it requires the participation of many users to produce personalised recommendations for one person.’ The second type of recommendation algorithms works differently. Lury and Day (2019:5-6) argue they are ‘based on a description of an item in terms of discrete characteristics; the algorithm is then designed to produce recommendations for individual users of items that have similar properties to those that the individual liked in the past (or is examining in the present).’

Twitter does not provide any information as to what type of recommendation algorithm it uses, but the analysis of its help material indicates the platform combines the two types of recommendation algorithms. According to Twitter Help Centre when it comes to displaying Twitter Trends, they are individually tailored for
each user and by default they are based on three factors: who a user follows (1), the user's interest (2), and the user's location (3). Twitter explains that when using default settings, 'there will be many world and local news events and conversations that will appear in your trends regardless of your personalization.' It means that in default settings users may experience trends from many locations for example when they are based in London, they might get trends from London, the UK and global (world) trends as well. Every user can change these default settings and select specific trends location to be displayed for example, the UK or London which makes it even more complex and gives even more possibilities for Trends to look different for two users in the same location.

With or without manual selection, it is possible and very likely that they will see different Trending Topics on their screens because they follow different people and have different interests. It is also possible to see trends for a selected location regardless of where one is physically located. Even if one changes the preferred location of trends manually, the Twitter algorithm will still determine which trends from the new (not default) location will be displayed. Twitter does not explain if in such case the new Trending Topics would be based on the new location only or also on who one follows and their interest. On top of that, there are also differences in how trends are visible on different devices or third-party applications.

The easiest way to access Twitter Trends Box is through the Twitter web interface (see Figures 20, 21 and 22 in the previous section) which gives access to 10 personalised trends. Most likely, for the majority of users, this is their only experience of accessing trends. These could be for a specified location as described above or a default location decided by Twitter. The same applies to mobile applications but there is a difference in the visibility of trends or in other words in the number of trends that can be accessed. For example, the iPhone application displays by default 5 trends (see Figure 21 in the previous section) but gives an option to click on ‘show more’ which displays 20 trends. All these trends, either displayed on a computer or a mobile screen, have been double filtered - firstly by the algorithms that distinguish between trends and non-trends, and secondly by personalisation algorithms, which decide which trends out of the 'pool of trends' actually make it to the 5, 10 or 20 trends displayed to a particular end user. In the field of Digital Media, such a situation could be theorised as an algorithmic doublelegating performed by the platform on its users and realised through multiple
algorithmic systems. The Trend Box as an agenda setting space is doublegated to ensure that there is a connection between the content (Trends) and the audience (Users).

An alternative way of accessing Trends Box is via third party applications such as Trends24.in or Trendinalia.com, which are publicly available for everyone to use. For example, Trends24.in (See Figure 24 below) displays the top 10 trends for 24 hours in hourly intervals. There are also numerous other applications that offer slightly ‘shorter’ or ‘longer’ archives. The one thing all these applications have in common is that they offer trends without the personalisation filter as is the case with any of the Twitter’s own interfaces. The third-party applications get trends directly from Twitter using API (Application Programming Interface) and display them in the order provided by the API. In that way, they offer access to trends for a specific location unfiltered by a personalised list of trends. They act as advertising banners that display all available content (Trends) and allow users to see almost the entire Trend box that is only limited by the design of the platform.

![Figure 24: Trends24.in displays the top 10 trends for 24 hours in hourly intervals](image)

Finally, a further way of accessing trends is directly via Twitter API, which is a set of defined methods of communication between various software components. It works as a ‘data push’ device, which means that data is constantly flowing from Twitter via a specially created channel and it is the researcher’s job to develop tools to collect and process it, for example in the form of a dashboard (e.g. Chapter Nine). The key difference between using third party apps as described above and Twitter’s API is that the latter gives access to the entire list of trends at a given time. The entire list (which I describe as a ‘pool of trends’) as produced and ordered by Twitter’s
algorithm can be downloaded in intervals, giving access to every single trend in a given location, even if it was trending for just 5 minutes.

The external application or APIs as ways of accessing Trend Box are less significant from the user perspective as the vast majority of users access trends natively via the Twitter website or mobile app. The two other methods (the third-party apps and APIs) are more significant from the methodological perspective of this thesis and are discussed in the following chapters (Chapter Six - External applications and chapters Five and Seven - APIs). This chapter studies hashtagability with the focus on the users and how their actions and experiences determine Trends, so the focus will remain solely on Twitter's Trend Box accessed via Twitter (web or mobile). The next section attempts to theorise Twitter's Trending Topics box as a ‘calculative space’ that can be used as a ‘delineation device’ (Madsen, 2012), or a starting point for the analysis and see what knowledge it produces.

## Trending Box as a calculative space

The concept of ‘calculative space’ (Madsen 2012) is linked to the study of filters that organise information and knowledge on the web. This approach treats web-based information filters (such as Google search results) as starting points for data analysis and visualisations. ‘Calculative spaces’ are defined in terms taken from economic sociology as spaces that ‘allow actors to make distinctions between goods, decide on common operating principles for establishing relations between them and ultimately assign value to them’ (Callon and Muniesa 2005 in Madsen 2012: 60). They also include a mechanism that synthesises acts of valuation into ‘orders of worth’, which takes place during the organisation and ranking of their importance (Stark 2011 in Madsen 2012: 60). Madsen sees a strong parallel between the devices that constitute markets and the filters used as starting points for the analysis. He compares market devices that assign prices to goods with Google Search Engine, which assigns visibility and relevance to search term results, which as a result create ‘market of relevance’ dependent on a calculative space. This is similar to the market of goods studied by economic sociologists.
This ‘market of relevance’ needs information to be organised in a way that is clearly divided into ‘clearly demarcated pieces of information’ (Madsen 2012: 60). The process of ‘singularisation’ of the web pages/links is similar to the process of making distinctions between goods in economic markets. It generates search results pages which locate ‘some information in the centre of visibility while leaving other sources in the dark’. Web users have to decide, based on these lists of ratings or rankings, which links have value and which have not. Lastly, this calculative space is constructed by human (i.e. webmasters and web-users) and non-human (i.e. PageRank algorithm) actors, which both play a role in organising the ‘market of relevance’. When the calculative space is used as an entry point for the analysis, it becomes a ‘delineation device’:

‘an entry-point to the web that organizes digital traces left by a distributed set of actors in order to establish a space where information can be divided into detached digital objects to which values of relevance can be assigned.’ (Madsen: 2012: 60)

Different delineation devices (Madsen uses examples of Technorati and Google Blog Search) produce alternative calculative spaces (search results) and as a result they provide different outcomes, what Madsen defines as Web-Visions - lists of the specific actors, themes and documents that become visible to a user when entering the web through a specific delineation device at a specific time.

The concept of Web-vision is based on the concept of ‘screened visions’ used in economic sociology to describe the situation in which a trader looking for information about stocks on a computer has some information revealed to him and some is screened away from his view. Madsen (2012) suggests two distinct types of screened visions: myopic and hyperopic. Myopic vision can be defined, using an example of Google, as a search results list of URLs that are ranked according to specific criteria of relevance. This list is the immediate vision of the topic that the user receives from Google Search Engine and is the starting point for further exploration via clickable hyperlinks. Once one clicks on a hyperlink, you will ‘encounter a specific range of actors, themes and documents that form a specific narrative’ (Madsen 2012: 61). This extended visibility through clicking on hyperlinks is the ‘hyperopic vision’ of the device. The myopic vision is largely an effect of the delineation device (e.g. Google Search Engine) and ‘hyperopic vision’ is more
dependent on the researcher - it is an effect of the way the researcher operationalises the device, what software (crawler) is used for it and how.

It is obvious that Twitter Trending Topic box (web or mobile app) can be analysed using the same model and treated as a delineation device that creates calculative spaces as defined by Madsen (2012). It is a space generated by algorithmic personalisation filters that help to surface what Twitter Trending algorithm, based on users interactions, decides to make visible as a trending. The difference with the calculative spaces defined by Madsen is that Twitter Trends is not there in response to a search query: it is pre-generated by Twitter. Madsen's approach relies on prior knowledge of what one is looking for. There is no search on Twitter Trend box - the issues and their importance has already been defined by the algorithm. It not only suggests what is important at this very moment but also the order of importance by ranking trends. This has significant implications of how Twitter Trends can be used as a starting point for analysis.

The most significant implication for the purposes of this thesis is that when researching a specific topic on Search engines, one can always search for it and it will generate results, that can be used for analysis. With Twitter trends it is different because if the topic of the search is not trending, it will not be included in the Trending Topics list. The only solution is to search the historical trends data and try to see if there were any trends related to the research topics in the past. This approach has one significant limitation - access to data. If a hashtag related to the researched topic was trending years ago and then people lost interest in it, it is impossible to collect any data about it using API, as there are limits as to how far back one can go in data collection. As a result, Twitter Trending Box is not a useful site from which to analyse historical topics. The design of the algorithm and API limitations make this kind of research almost impossible to conduct. The methodology developed in Chapter 6 helps to solve this problem, but it uses external applications rather than Twitter Trending Topics Box on Twitter as the entry point for the analysis. The other option is to manually monitor live Trends via an external tool (to remove the recommendation algorithm of the Twitter's native Trend Box) for the event that is happening, for example General Election. This approach will be described in Chapter Eight.
Apart from the above limitations, Twitter’s native Trending Box can be seen as a delineation device if one assumes it is a topic for analysis on its own. In this case it offers a Myopic vision in a form of clickable links that are ranked according to specific criteria of relevance (by recommendation and trends algorithms). This list is the immediate vision of topics that are relevant on Twitter (and also locally and globally - depending on the settings of the recommendation algorithm) and is the starting point to further exploration via clickable hyperlinks. Once the user clicks on one of the links (hashtags or not) they are taken to Twitter search results which are by default filtered by Twitter (so called ‘Top results’) which include the list of tweets, their authors and sometimes a suggested range or users who are related to this trend. Madsen defines this as the ‘extended visibility’ or ‘hyperopic vision’ of the device. The myopic vision on Twitter (Trending Box) is largely an effect of the delineation device (e.g. Twitter trend and recommendation algorithms). 'Hyperopic vision' is more dependent on the person doing the search as search results are by default generated by recommendation algorithms dependent on the user and her/his previous actions, interests and so on.

The hyperopic vision of Trending Topics is interesting for another reason. It not only connects the trending hashtag with content that was tagged with it. It also connects Trending hashtags with users as each post in the search results for a given hashtag has a user associated with it. This creates the possibility of developing a concept of a kind of algorithmically generated association between a trend and a user, which I call algorithmic ownership.

**Algorithmic Ownership**

Chapter Two describes how the # symbol was used on IRC to create channels (Kalt, C. 2000: Online, Oikarinen and Reed 1993: Online) and only later migrated to Twitter via user-led innovation (Bruns and Burgess, 2015:16). IRC channels created by hashtags had operators (known as a "chops" or "chanops") who were considered to ‘own’ the channel they created. However, the architecture of Twitter has never included any reference to the ownership or made possible signs of ownership of hashtags. They are not registered to a user or a group of users. In theory they are not controlled by anyone as any user of Twitter can use any hashtag any time they wish.
On the other hand, one of the fathers of hashtags foresaw that in the future they will ‘imply communities’ (Boyd 2007) which in fact happened: the community building function of hashtags was described by Zappavigna (2015), who argues such communities are purely semiotic and not interactional (Chapter Four). There is no formal membership as Twitter does not provide any tools for this such as, for example, providing a way to have administrators or owners of these communities. Boyd (2007:23 Online) and Booth (2007) call such communities ‘Groupings’ and defined them as ‘ad hoc assemblages of people with similar interests’. They argue that they ‘are things that “happen” rather than things that people elect to join or build.

Because of lack of ownership and control over hashtags, there is a risk that the original or first user intended meaning of the hashtag can be changed by other Twitter users. This phenomenon is known as hashtag hijacking⁴⁵ - a form of cyber content attack, which takes place when a hashtag is hijacked by messages with undesirable content (Xanthopoulos et al. 2016). Jackson and Foucault Welles (2015) studied how #myNYPD hashtag promoted by the New York City Police Department and intended for the public to share photographs of officers was hijacked and turned into an online protest as thousands of citizens appropriated the hashtag to highlight instances of police brutality, abuse, and racial profiling. Sanderson et al. (2016) conducted a similar study analysing the hijacked #AskJameis campaign, originally employed by Florida State University (FSU). In other words, the creator of the hashtag might be the first person to use it on Twitter but then it is often someone else who makes it popular or ‘creates a grouping’ around it. In all cases, the meaning of a hashtag shifts in use. Assigning ownership to creators makes no sense.

Hollow Crown Fans group claim that they founded #ShakespeareSunday hashtag (see Figure 24 below) and every Sunday they animate the discussion within this hashtag.

⁴⁵ A classic industry example of hashtag hijacking is the history of #McDStories. It was launched as a Twitter campaign with the aim of inspiring positive stories about Happy Meals. Instead, it attracted a large number of negative Tweets and turned into a so called #bashtag - a hashtag used for criticising something, especially promotional content. Users repurposed the hashtag in order to criticise what it was originally intended to be promoted.
The fact that Hollow Crown Fans say on their profile that they founded #ShakespeareSunday does not mean that they have any rights to it. This kind of statement is a declaration and in reality, anyone could make the same claim on their profile. I established that Hollow Crown Fans were not the first people who started using this hashtag. It was first used by user @kellybet on 25 April 2010 (see Figure 25 below).

Figure 25: Hollow Crown Fans group claim that they founded #ShakespeareSunday hashtag

Figure 26: #ShakespeareSunday hashtag was first used by user @kellybet on 25 April 2010
What this suggests is that the ownership of hashtags needs to be defined in terms of association, rather than origination or formal administration. What follows from this is that the ownership of #ShakespeareSunday can be established by performing a Twitter search for it and checking who Twitter search algorithm associates with this hashtag. In the case of #ShakespeareSunday it is Hollow Crown Fans (last checked in February 2019). One could argue that Hollow Crown Fans hijacked the #ShakespeareSunday hashtag from the creator by posting numerous posts with it on a regular basis, but that they now maintain a kind of 'ownership' based on the consensus of the community of users who contribute to this hashtag every Sunday.

This kind of ownership can be identified with a process of extraction from the Twitter search results or Twitter’s Hyperopic vision (Madsen, 2012). Just like the Page Rank algorithm, which assigns weights to links between pages and then calculates their relative importance, Twitter’s search algorithm assigns weight to relations between hashtags and users. This concept was well described by Gerlitz and Helmond (2013) and their ‘likes economy’ created by Facebook and which is built on relational value, mediated by users’ participation. The weight of these relations helps to identify the ‘relational value’ in such search algorithms. Lury and Day (2019) used the same approach to study personalisation and argue that it ‘makes relations between people available for computational calculation’.

The development of Web 2.0 helped to make this ‘relational value’ more ‘social’ than previously, when the value was derived from the relationships between web pages (PageRank). On Twitter, this relational value can be understood in terms of ownership through an analysis of the social connections between content (hashtag) and a user. On Twitter this value is also constantly calculated by algorithms to generate the most relevant search results. Lury and Day (2019: 5) described how this works in relation to recommendation algorithms, which they say ‘penetrate all corners of the Internet, making personalised recommendations - directly and indirectly - to individuals with interests in a variety of fields, including movies, music, news, books, research publications, restaurants, jokes, financial services, products of all sorts and persons (for example, in online dating)’ (Lury and Day, 2019: 5).

To learn how these recommendation algorithms ascribe relational value, we can turn to Seaver (2012: Online), who describes one stage of the process as a matrix:
The archetypal form of a collaborative filtering system is a matrix: a grid, with items along one side, users along the other, and ratings at their intersections. This matrix is mostly empty (or “sparse”), since most users will have not rated most items. The work of the collaborative filtering algorithm, as it typically stated, is to predict what values will show up in the empty spaces of the matrix. These predictions are then provided in some form to the user as recommendations. Thus, at any given time, the matrix is in an anticipatory flux: new ratings from users arrive constantly, displacing their predicted values and shifting the others. (...) blank values are replaced by predictions, which are then replaced by actual ratings. Progress from emptiness, through prediction, to actualization makes the matrix a proleptic social representation, holding simultaneously a record of past correspondences between persons and things and the anticipation of future ones. (Seaver, 2012: Online)

Figure 27: A sample collaborative filtering grid with some cells empty (Seaver, 2012: Online)

46 Available at: https://limn.it/articles/algorithmic-recommendations-and-synaptic-functions/
Drawing on Lury and Day (2019) analysis of algorithmic personalisation and Seaver's (2012) description of a collaborative filtering system/algorithm, I develop the concept of the algorithmic ownership in terms of relational value. This is a form of distributed ownership in which content (i.e. a hashtag) is assigned to an owner (a person or persons) based on an algorithmic association of usernames (Twitter Handle) with the hashtag in the search results, as described in Seaver’s matrix above (see Figure 26 above). This form of ownership has the following features.

- It is performative. It can only be discovered by performing Twitter search. It is impossible to discover algorithmic owners without performing the search because it is only in the search results that Twitter shows the profiles associated with the search query/hashtag. This is a platform design limitation.
- It is distributed across users, attached to multiple, shifting usernames.
- It is fluid. It can change anytime depending on variables that the algorithm associates with the hashtag at a given time and the usage of a hashtag by Twitter users. It will be more stable for less popular hashtags, but its fluidity will be much greater for trending hashtags, which generate thousands of new tweets per minute.
- It is personalized; that is, not simply dependent on usage, but dependent on who is searching. Twitter algorithms personalise search results for users based on their behaviour, so it is possible that highly contested hashtags i.e. #MAGA might have different algorithmic owners depending on the profile of the user who is searching for it e.g. Donald Trump supporters might get distribution of algorithmic ownership, while those who oppose the president and their social networks using #MAGA in a different context, might see a different distribution ‘owning it’. Multiple people/organisations can be algorithmic owners of a hashtag in different locations and for different users who are searching for it.

The use of the term ‘ownership’ might not be ideal, as it is often associated with exclusive rights and control over property, which may be an object, land or an intangible. In case of algorithmic ownership there are no exclusive rights and no control over the use of the hashtag. However, algorithmic ownership does resonate with legal understandings of intellectual property, which define property in terms of relations between people in relation to something. This might be use (e.g. rent of land...
or a building), or exclusion (e.g. private property) and so on. In this case, ownership refers to the association made by the algorithm between users and a hashtag, rather than the actual hashtag, even though this ownership is not recognized in the formal terms of intellectual property law. What is owned is an association between users in relation to a hashtag. This is a form of ownership that needs to be constantly confirmed by other users.

The actions required to ‘confirm’ the ownership might be in the form of posting a hashtag several times with a different message or even the same message (spamming). The fandom trending hashtags or Hashtag Games described in the previous chapter, could be also seen as algorithmic ownership games if the creators of these hashtags not only intend to make them trending but also associate their names (handles) with it. Other ways of associating users with the hashtag are by replying to other users using the hashtag or simply performing a search, which might be acknowledged by the Twitter algorithm as an indicator that a user has an interest in this hashtag. As argued before, no one knows what actions Twitter algorithm uses to associate a hashtag search with a user and how actions are weighted. Most likely these ‘signals’ are always changing, but that does not change the fact, that the ownership of that association between a hashtag and a user, needs to be constantly confirmed in order to be continued, and that the conditions of that ownership, while in part a consequence of user actions are also provided by Twitter.

This form of ownership explains why trending is of such significance. For example, TV broadcasters usually display their hashtags (for example #itvdebate, #bbcpm or #bbcqt) on screen during a programme to encourage viewers to participate in a backchannel of discussion via social media. There are two reasons for this. First, they want to make sure that the discussion is taking place under their own hashtag, which they then can measure and quantify in their reports. They can also analyse it using sentiment analysis etc. Secondly by doing this they are providing a channel for discussion on social media. Promoting an official hashtag enables them to aggregate more posts under one hashtag, increasing their chances of being able to assert some kind of algorithmic ownership (Schneider, 2011: Online). And getting such tags recognized as trends enables them to assert ownership in relation to more users. Chapter Eight discusses this in detail.
All these efforts to channel a hashtag do not change the fact that broadcasters or fan groups do not own hashtags they are using in the conventional sense. It is distributed and constantly changing and does not have formal terms and conditions. In fact, ephemerality is one of the main features of this kind of ownership as it fluctuates across accounts based on their relative strengths in relation to a given hashtag.

The next section will look at different types of Trends that appear in Twitter Trending Box and how users are able to make a hashtag trend through orchestration, enabling users to create value from this algorithmic ownership.

**Types of Trends**

There are many ways to classify Twitter trends. This chapter will introduce four: the first two are useful because they help to position Trends in the wider context of the general interests of Twitter users (topical classification) and how people use hashtags as conversational tools (classification based on the type of discussion hashtags initiate). The third and fourth classifications are important because they help to connect Trends with the offline world and show that they could be generated by Coordinated Inauthentic Behaviour.

A basic classification of Twitter Trends is based on topical differences and relies on general knowledge of the world (Lee et al. 2011). It is performed by grouping hashtags (trends) into simple categories such as sport, technology or news. It is helpful to answer the question of what categories are the most popular and generally give an idea of what is popular on Twitter. To generate it, Lee et al. (2011) created a dataset consisting of 23000+ trends using Twitter API, from which they randomly selected 768 topics. These were then labelled using two annotators, with a third annotator being added when there was disagreement. As a result, Lee et al identified 18 classes: art & design, books, charity & deals, fashion, food & drink, health, humour, music, politics, religion, holidays & dates, science, sports, technology, business, tv & movies, other news, and other. Figure 28 shows the distribution of topics across the 18 classes with the ‘sports’ category being the most popular one, followed by ‘other’ and ‘other news’. The least popular categories were ‘Art & Design’ and ‘Health’.
Another simple classification was suggested by Benhardus and Kalita (2013), who following Gruhl et al’s (2004) advice, proposed the classification of trending topics into three groups depending on the temporality of the discussion they initiated. The first group included trends consisting of spikes (‘short-term, high intensity discussion that is often in response to a recent event’ for example #worldcup, ‘Oil spill’ or ‘Vuvuzela’). The second group included chatter trends (‘persistent discussion at a constant level that are largely user-initiated’ for example #iconfess or #dontcountonit). The third group was a mix of both: for example, #theview.

Another classification of trends is based on their source. Kwak et al. (2010) argue that the majority (over 85%) of trending topics are news in nature. Asur et al. (2011) suggested a division of trends into two simple categories: news and not news. One of the ways of looking at news is that it is information/discussion concerning events that happen outside Twitter. It describes planned or unplanned events that happen either globally or locally but always outside the Twitter ecosystem. On the other hand, trends that are not news in nature, using this simple binary distinction and following the same logic, must be the opposite - they must originate from within the Twitter ecosystem. They are generated by internal Twitter discussions and do not have triggers in the outside world. As a result the key two types of trends can be
defined as these that originate outside and those that originate inside Twitter ecosystem.

Naaman et al. (2011) develop a complex classification of trends with the two main categories (the top level of taxonomy) being: exogenous and endogenous trends which they defined in the following way:

\[
\text{Trends in exogenous categories capture an activity, interest, or event that originated outside of the Twitter system (e.g., an earthquake). Trends in endogenous categories are Twitter-only activities that do not correspond to external events (e.g., a popular post by a celebrity)}\ (\text{Naaman et al. 2011: 908})
\]

These two main categories are then divided into the following subcategories:

**Exogenous Trends:**

- Broadcast-media events:
  - Broadcast of local media events i.e. football game
  - Broadcast of global/national media events i.e. MusicAwards
- Global news events:
  - Breaking news events i.e. earthquake
  - Nonbreaking news events i.e. health care reform
- National holidays and memorial days i.e. Halloween
- Local participatory and physical events:
  - Planned events i.e. marathon
  - Unplanned events i.e. snow

**Endogenous Trends:**

- Memes: i.e. #in2010 (in December 2009, users imagine their near future)
- Retweets i.e. users “forwarding” en masse a single tweet from a popular user
- Fan community activities: i.e. 2pac (the anniversary of the death of Tupac Shakur).

The final classification is the most interesting for this thesis as it distinguishes between trends that are naturally occurring and those that are only occurring because of coordination. Recuero and Araújo (2012a) define Naturally occurring
trends as organic topics and Coordinated Trends as artificial. In this thesis I am using the ‘Naturally occurring vs. Coordinated (or Orchestrated) Trends’ distinction as it is in line with the most recent literature (Weedon et al 2017; Cadwalladr. 2017; Corpus Ong and Cabanes, 2018; Starbird 2019: Online) and allows me to consider how hashtagability has been developed. This distinction puts Coordinated Inauthentic Behaviour at the centre of the debate.

The simple definition of a Naturally occurring trend is a trend that emerges without effortful/purposeful coordination by a group of Twitter users. A Coordinated Trend is created by Twitter users acting with the intention of getting their message/hashtag into the Trending Topics list. Drawing on their analysis sampling 460 Trending Topics from Brazil, collected during a three-month period in 2011/2012, Recuero and Araújo (2012a) argue that 60% of the trends were created by Coordinated Inauthentic Behaviour. They were mostly about personalities (88%) with only a fraction about protests (4%) or marketing promotions (4%). The Naturally Occurring topics were mostly memes (38%), related to events (38%) or about personalities or celebrities (24%) which led the authors to the conclusion that fandoms around celebrities create most trending topics.

These findings are rather disturbing if one assumes the reach of Trending Topics. If 60% of trends are generated 'artificially' by a form of coordinated behaviour, it is clear that unknown actors have a significant impact on the agenda of Twitter. The next section looks at how this coordinated behaviour is organised.

Ways of orchestrating trends

Coordinated Fandom trends

The most common strategy of coordination is simply activating the fan groups by using Twitter or other communicators to call fans to action. Another strategy involves fans including the hashtag they are trying to make trending in every single tweet they post. This is potentially dangerous as it can activate Twitter spam detection algorithms. In order to deal with this problem fans teach each other how to avoid spam detection by reminding each other that tweeting the same thing has
this effect. The final strategy involves using the first three points but in cooperation with other fan groups.

Recuero and Araujo (2012b) provide detailed description of the strategies that fans use to artificially promote a topic: the process usually starts with a single user or a group of users (seeds) requesting other users to use a specific hashtag. Usually there is no discussion about the tag and the aim of making a hashtag Trending Topic is made explicitly clear right at the beginning. There is no further explanation apart from when to start the operation. This gives users time to prepare so that all efforts can be concentrated in a short period of specified time. Users start using the tag in all their Tweets but make sure they do not post the tag on its own or in the same post twice because this could activate Twitter’s spam detection algorithm. Users might also start using what Recuero and Araujo (2012b) call Tag Hitchhiking, which means that they use the specified tag in all their tweets, even in the posts that have nothing to do with it. Finally, users start encouraging other users who are part of the community/group/fandom to tweet the tag if they have not done so yet.

Recuero et al. (2012) define five types of hashtags created by the fans based on their goals. These can all be positioned in the ‘Endogenous Trends’ category and ‘Fan community activities’ subcategory using Naaman’s et al. (2011) categorisation:

- Tribute Hashtags - the aim is to show their love for the idol
- Promotion Hashtags - to promote the band’s activity or something fans find important
- Response Hashtags - to reply to a hashtag, media story or celebrity who may have said something negative about the band
- Requests Hashtags - to make a request for the band or for other fans
- War Hashtags - Topics that are created within fan wars to answer other - usually negative hashtags. They have two subcategories:
  - one group of fans against other group of fans, where the dispute was about ‘who is the best’
  - war between fans and anti-fans. Mostly, these wars seem to start when a group of fans is making too much ‘noise’ on Twitter and other users (non-fans) start a hashtag against the idols to annoy the fans.
Hashtag games can be defined as mini word games played on Twitter with the use of a hashtag which usually contains a question that users are trying to answer or the beginning of a sentence that users are trying to finish in a humorous way. There are no barriers of entry. In fact, what is needed is creativity and a sense of humour. Hashtag games are what Huang et al. (2010) call micro-memes; they are prompted by seeing examples. The goal of such hashtags is not to facilitate retrieval but to join the conversation as it happens.

Raza (2016: Online) sees hashtag games as tools for fun. One of the examples he gives is the American comedy TV show (@midnight) that used hashtag games and asked its viewers to take part by tweeting using selected hashtags during the show. As a result, these hashtags usually become trends during or shortly after the programme. Alexander (2011: Online) described the actual process of playing hashtag games as ‘a high speed, competitive yet collaborative comedy writing drill’. One does not need a large followership in order to play. Hashtag games are not based on user’s profiles but on the content one publishes. People join games by looking at a hashtag search stream rather than by looking at people’s individual profiles.

Sheridan (2011: Online) sees hashtag games as ‘a topic or theme with a “#” in front of it (...) written by the whole world. Someone tags a tweet (e.g. #JewishHorrorMovies), others join in and Twitter magically sorts all those tweets onto one page.’ This is a rather simplistic way of looking at hashtag games as it assumes that these topics appear out of the blue and become popular by sheer luck, which is not the case. Hashtag games are usually well-planned events with the aim of gaming Twitter’s Trending topics algorithm. From the perspective of the player, who is not involved in preparation of the game but only takes part in the final stage - posting in response to a hashtag, the following definition could be used:

‘(...) a hashtag game is a sort of Twitter prompt that comes in the form of a hashtag inviting Twitter users to contribute simple statements that adhere to that prompt. It is a form of word game that has no real winners, just a way to

interact with a community of people to do something fun and positive. It challenges users to be creative in their tweeting and think outside of the box. The ultimate goal of a hashtag game is to make it to a trending topic on Twitter. (Raza 2016: Online)

Another useful definition comes from Hashtag Roundup page (Dwoskin, 2015: Online) - the key place for hashtag games on the Internet. The main difference is that they are treated here as planned events that have creators rather than just topics that magically appear on Twitter and somehow become popular:

*Hashtag games are live events that take place on Twitter, created by individuals who want to share their hashtag with the world. (...) Think of the hashtag as the premise/topic. It is a call to action, and a challenge to add your creative idea to that hashtag. Hashtag games generate 1,000s of tweets (sometimes 10's of thousands) focused on that topic.* (Hashtag Roundup Page, Dwoskin, 2015: Online)

One might argue that there are no real winners or there is no physical prize but in fact this is not entirely true. There might be no individual winners but there are definitely collective winners. The goal of the game, apart from having fun and being creative, is to make the hashtag trending so that the trend makes the hashtag even more popular and more people join. The technical infrastructure including websites, specialised Twitter accounts and mobile applications has been created in recent years to help the players of hashtag games to get better organised in terms of timing and promotion to ensure that a game becomes a trend. In other words, these games do not just happen. There are authors behind them who know how to create engaging hashtags and then how to run the game. As argued by Haskell (2015: Online) they are ‘very carefully authored and orchestrated’. The role of the author or host(s) behind every game is to operate a set of rules in order to land a hashtag in the Trending Topics box. That is also the ultimate prize of the game. Other important achievements include the number of hours or days that the game is trending for, if it becomes global or not and finally if any celebrities join in or talk about it. These games might not have winners amongst thousands of users that contribute to them but the real winners are their authors and hosts, who have clear goals.
The vast majority of the games that become trending topics on Twitter originate from well established ‘games publishers’. The key account is @TheHashtagGame which developed its own mobile application called Hashtag Roundup. The key feature of the website and application is the list of scheduled games and their hosts. This tells players when the game will start but does not provide the actual hashtag until the very beginning of the game. Figure 29 shows how hashtag games are being promoted on @TheHashtagGame account on Twitter. The post right at the bottom is a reminder about the time when the game will start. It also provides the general theme of the game by providing the name of the account responsible for the game - in this case @MusicalHashtags. Finally, it provides information about the hosts of the game.

The actual hashtag – for example, #ExplosiveSongs- is only revealed the minute the game becomes active. This is not surprising - the creators of the game understand how Trending Topics algorithm works and want to avoid situations that the number of tweets containing game’s hashtags grows steadily, which could potentially compromise the chances of the hashtag to become trending. To be successful, the game needs an immediate burst of activity in a very short time, rather than a steady increase over a long time. Once the hashtag is published every effort is made by players to post as much content with it as possible so that the Twitter algorithm records it as an emerging event, a sudden burst of popularity. During this crucial time the hosts of the game and other accounts involved in the game post as much content as possible with the games hashtag, retweet their respective posts and try to encourage as many other users, who were originally not involved in the creation of the game, to post their tweets as well. The period between the start of the game and the moment of a hashtag becomes a trend is described as adaptation (Yardi et al. 2009) or formation (Asur et al. 2011) and in Naturally Occurring trends is characterised by the burst of activity around a hashtag. The activity around the Orchestrated hashtag needs to resemble organic behaviour as much as possible because otherwise Twitter might classify it as spam.
Once a hashtag becomes a trend it immediately gets more visibility and many users who initially did not know about the game start contributing. By that time there are usually hundreds of messages posted in response to the hashtag, so it would take a lot of time to scroll down in Twitter search to the first messages that explain that it started as a game. Most users never do that, which leaves them with the impression that the hashtag started naturally, that it simply appeared out of nowhere and became trending. The role of creators once the hashtag becomes a trend is to select the top 10 posts that were posted in response to it and enjoy the popularity of their creation. This is the ‘value’ they acquire from the distributed algorithmic ownership of the trend. Their ability to make their role visible is supported by the platform since
their posts tend to appear at the top of search results for the hashtag for other users. This is because Twitter algorithms acknowledge a high association between their actions and the hashtag in the trend formation stage.

The vast majority of hashtag games are created for fun and can be treated as light entertainment. There are also games that have different aims. For example, Urbic (2017: Online) describes games that are designed to be used as inspirational and motivational tools for writers. These are not so well organised as the fun games described above and their audience is very different. They are not designed to target the general public but focus on people who are interested in writing. For example, #1lineWed encourages people to share a line from their work in progress every Wednesday and #Friday5th is about sharing the fifth line of any chapter in a manuscript. There is no official website that lists all these games in one place and most of the lists are compiled by authors/writers and published on their personal websites/blogs.

Another difference between hashtag games played by writers and the general public is that those created by the former do not usually become trends. Their pace is much slower and there is no emphasis on popularity at all. In that sense they are more a community game played for inspiration rather than a high-speed hashtag game. The same can be said about scientific hashtag games, which are also slower than the ones used purely for entertainment but at the same time are more open than the ones used by writers. Shiffman (2017: Online) argues they can be a tool for public education and outreach resulting in high level of interaction and engagement. From the perspective of a scientist they are an exercise that makes one a better communicator in science (Thaler 2015: Online). They contribute to experimentation with language and turn complex scientific terms into engaging and entertaining content. Similarly to entertainment games, scientific hashtag games have a dedicated Twitter account (@ScicommGames) where all games are published on a daily basis. There is also a scientific hashtag games calendar\textsuperscript{48} which features games such as #AreYouSIO2 or #TrickyBirdID. The key thing about hashtag games played by writers and scientists is that they do not usually become trends in an organised and orchestrated way. If it happens it is occasional and always by chance.

\textsuperscript{48}Scientific Hashtag Games Calendar: https://natbat.github.io/scicomm-calendar/
Hashtag games are different than trends generated by fandom communities because they are carefully planned events. Fandom communities tend to create their games reactively and although one can expect their hashtags to appear trending (sooner or later), it is impossible to say when this would happen or who will suggest a hashtag. Hashtag games on the other hand are much better organised. They run according to a strict schedule and have people/accounts responsible for running them. The way the schedule is organised reflects both the requirement of time that is needed to make a hashtag trending and the time of the day. The organisers always set a minimum of 1 hour and 30 minutes between the release of two games, which they argue is an optimal window to make one hashtag trending without cannibalising the next one. Only when the time has passed is the new hashtag revealed so that all effort can be put into its promotion. In addition, the themes of games often reflect the time of the day or day of the week. There is a daily #HashNight theme at 11pm and #SneakyFridays theme every Friday. On Sundays, there is Sundays with Doc and on Mondays there is Monday Mayhem. These themes remain consistent and the only thing that changes daily is the actual hashtag.

In this regard hashtag games are similar to TV programmes or series. They all have titles (themes) but each episode has an individual title as well (hashtag). For example, Musical Hashtags is a weekly theme and #ExplosiveSongs was the title of an episode. Another similarity with television is that hashtag games, because of their popularity and the extremely high speed at which new posts are published, could be seen as a kind of a live broadcast. The audience search for a given hashtag and then simply do nothing but observe as hundreds of posts are posted in a matter of minutes. This ‘broadcast’ includes tweets from game creators, other users, brands that are trying to sell their products using the hashtag’s popularity to promote their own products and spammers who are piggybacking on the trend. After a while, a broadcast (hashtag) is over and the audience moves on to the next broadcast (trending hashtag).

As most of the games rely on users’ sense of humour, there is always a risk that some users might find a game offensive. For example, the controversial #ReplaceMovieTitleWithEbola became trending as a reaction to the first confirmed case of Ebola in America. It became a trend, so clearly there was a group of users that found the game funny and entertaining but at the same time there were people who found it offensive (Campbell, 2014: Online). There are also numerous examples of
users confusing a serious trending hashtag with a hashtag game. For example, DiGiorno Pizza brand joined #WhyIStayed hashtag with the following reply "#whyistayed You had pizza." They thought it was a trending hashtag game and wanted to join and use it for promotion of their brand with a funny comment. As it turned out this hashtag was used by women to discuss their experiences in abusive relationships and to fight the victim-blaming attitude (Griner, 2014; Keller 2014). A similar thing happened to Entenmann's brand when they assumed that #notguilty hashtag was a game and joined it with the following tweet:

Who's #notguilty about eating all the tasty treats they want?!

They later learnt that it was not a game but a response hashtag to the ‘Not Guilty’ verdict of a murder case, which some Twitter users perceived as injustice (Tsotsis 2011: Online). As a result, both DiGiorno Pizza and Entenmanns had to apologise and suffered a serious brand crisis. The two above examples illustrate how things can go unintentionally wrong with trends. The next section will focus on the practices that intentionally abuse trends.

Spam in Twitter Trends

The first attempts to spam Trending Topics appeared almost immediately after they were introduced to Twitter in 2009. One of the early examples was the UK furniture maker Habitat, who used trending hashtag #Mousavi during political unrest in Iran to promote their products and encourage users to join their mailing list. The actual tweet has already been deleted but numerous articles (Keane, 2009: Online) recorded its content. It read:

#MOUSAVI Join the database for free to win a £1,000 gift card.

This tweet clearly has nothing to do with Iran or Mousavi and the only reason for using #MOUSAVI hashtag was because it was trending at the time and Habitat wanted to piggyback on its popularity. Similarly, Kenneth Cole (clothes designer) used trending hashtag #Cairo during the unrest in Egypt in 2011 to promote his new collection (Tsotsis 2011: Online). He tweeted the following message:
Millions are in uproar in #Cairo. Rumor is they heard our new spring collection is now available online at http://bit.ly/KCairo - KC.

Just as was the case with Habitat, Cole’s tweet had nothing to do with the events in Egypt at that time. There is also no way that these brands made a mistake that these hashtags were hashtag games as was the case with #notguilty and Entenmanns or #WhyIStayed and DiGiorno Pizza. #MOUSAVI and #Cairo were clearly not games and the intentions of Habitat and Cole could not have been clearer - they intended to promote their products using popular trends. The only difference is that Cole tried to somehow link his products to #Cairo hashtag in what seems to be an attempt at a joke. Habitat’s post was completely unrelated to the content of #MOUSAVI stream. In both cases users found these practices unacceptable and both brands apologised and deleted their messages.

The two above examples illustrate how tempting it is for brands to use Twitter Trends to promote their products and how easily this can be done. However, one cannot say that these two tweets can be treated as an organised spamming techniques. They caused some angry reactions from other users and most likely created some bad PR but in comparison to organised spamming techniques they could be considered as examples of temporary bad taste rather than a systematic nuisance. The real spammers are far more organised and aggressive.

The Twitter Help Centre provides an extensive list of behaviours that are considered spam (i.e. aggressive following behaviour or creating multiple accounts) but in this section I will focus purely on one spamming technique described by Twitter\(^49\) as ‘posting repeatedly to trending topics to try to grab attention’. Examples of such posts can be found in the vast majority of Trending hashtags today. Figures 30 and 31 show how an online shop selling accessories for mobile phones uses Trends to promote its products. There is a complete lack of connection between the actual message:

Something to brighten your day! http://lsooq.com/products/hd-optical-telescope-8x ... . Get 10% off use code "2Day10"! and the list of hashtags that follow it: ‘#rt  مشاهير تجيه #CanadaDayWeekend  #aidsawareness

None of these hashtags are categorising the message and the message itself was not posted in response to for example weekly micro meme #FridayFeeling, which is included in the post. The only reason why these hashtags are included in the message is because they are all trending and offer high visibility.

*Figure 30: An example of spamming Twitter Trends*
In terms of the actual practice of tweeting, just in one hour between 11:57 and 12:57 UK time on 30/06/2018 this account posted 84 tweets. All of them are very similar to each other *see Figures... and ...) and contain a short description of the product they are selling, a photograph of it and about 10 hashtags, all of which were trending at the time or not long before the message was posted.

It is clear that spammers are not targeting a single country as a quick look at the list of hashtags shows that their intended reach is truly global: on that day #CanadaDayWeekend was trending in Canada, #aidsawareness in India, #karaparaask in Argentina and #IntrustSuperPremiership in Australia. There seem to be no geographical boundaries and the list of targeted countries most likely was generated by analysing in which location a given trend was trending at the time. It is difficult to imagine that such accounts are run by human beings; most likely these posts are automatically generated by spamming algorithms that use global trending topics to produce the list of hashtags that are then included in these posts.

Figure 31: An example of spamming Twitter Trends
Another example of spam in Twitter Trends is linked to fan culture. Figure\textsuperscript{50} ... shows a tweet that was posted with a trending #FRAARG hashtag used to discuss a football match between France and Argentina. The post has nothing to do with the match and it is hard to imagine that football fans discussing the match would be interested in the concert of a teenage idol. This is an example of fans, rather than companies, using trending hashtags to get their message across.

**Conclusion**

Twitter Trends engage hundreds of thousands, or if they become global, millions of users. Hashtags that become trending almost immediately get large audiences and can be used to get a message across in a co-ordinated manner.

This chapter introduces Twitter Trending Topics Box as a significant algorithmic gatekeeping device enabled by hashtagability and realized through the trend generating function. When used natively on Twitter, it can be described as a doublegated agenda setting space, because on top of being algorithmically generated (gate one) it is also personalised through another set of recommendation algorithms (gate two). The chapter then theorises Trend Box methodologically as a delineation device - a starting point of the analysis of how algorithms work and what knowledge they produce. As a result, it defines the two different visions (myopic and hyperopic) it creates following Madsen’s (2012) theory of screened visions. The hyperopic vision, which on Twitter exists in the form of search results for a given hashtag, generated by recommendation algorithm, was then studied from the perspective of the association of users with the search term. The chapter then introduces the concept of algorithmic ownership, which will be further redeveloped and tested in Chapter Seven which will investigate whether being a hashtag creator has any impact on the algorithmic association with the hashtag.

The chapter also shows how groups of users learnt to manipulate Trending Topics algorithm and to make their hashtag trending and to exploit the hashtagability for their benefit - even if it is just for fun. The examples of hashtag games or fandom

\textsuperscript{50}https://twitter.com/ArkayDale/status/1013067469148131329
hashtags seem to be innocent and one might think that there is no harm in the group of teenagers having some fun while talking about their idols. The same could be said about hashtag games, which are innocent jokes designed to provide light entertainment to adults.

On the other hand, if a group of teenagers can make a hashtag trending by following a set of simple techniques, it is also possible that similar techniques can be used by politicians to get their message across or to mock their political opponents. It could also be used by marketing teams to market goods or services and create the false impression that the discussions about these appear naturally, implying that they are popular and used/desired by many. It can be used by anyone to influence the agenda of the platform on a local and global scale.

This chapter shows how such coordination takes place from the perspective of the user and in this way helps to answer my research question of *How can hashtag trends be analysed?* It also introduces the significance of Trends and provides a critical review of qualitative methods to study hashtag trends on Twitter. Finally, it lays down the groundwork for the chapter that immediately follows, which tries to answer the same question but using quantitative methods and from the perspective of the platform only.
Chapter 6: Methodological challenges

*The era of Big Data has begun. Computer scientists, physicists, economists, mathematicians, political scientists, bio-informaticists, sociologists, and many others are clamoring for access to the massive quantities of information produced by and about people, things, and their interactions.*

Boyd and Crawford (2011)

**Introduction**

Big Data and Data Mining techniques make it possible to examine large amounts of data and identify hidden patterns or unknown correlations. Those who possess that knowledge can make better (business/social policy) decisions, increase their profits or increase/model customer engagement on social media. John Law *et al.* (2011) noticed that social media platforms such as Twitter, Instagram or Facebook not only enable new ways of organising social life for its users but have also become sources of data for scientific analysis. Beer and Burrows (2007) see them as sites where production, collection and analysis of social data takes place. At the same time they have also become a source of methodological headaches for researchers. Their rapid development has serious methodological implications for social research (Savage, 2009; Rogers, 2013) and especially quantitative research is affected (Uprichard, Burrows and Byrne, 2008).

The two chapters (Five and Six) of the thesis focus on the methodological challenges of studying Twitter Trends as the function that was enabled by hashtagability - the potential of hashtags that gave Twitter users room to create trends in ways that were then enabled and preformatted by the platform through its algorithm. Chapter Five used qualitative approaches to look at the platform and the user by analysing what is available/visible on the surface of user behaviours and Trend Box as a device. This chapter focuses entirely on the platform and the data it generates,
or in other words on what is hidden from the regular user and what can only be surfaced through the use of data tools. It does not discuss specific methodology used for data collection and analysis, as these are considered at the beginning of each empirical chapter. Instead, this chapter positions the thesis methodologically in the field of data science, with all the benefits and limitations of research methods derived from Big Data and the study of Twitter Trend algorithms. It summarises what and how data is available from Twitter, what methodological issues this research is facing and critically analyses the available studies of Twitter trends algorithm which then provides the groundwork for the research design of the empirical chapters.

The aim of this chapter is to continue to outline the groundwork for the study of hashtagability realised through data and Twitter algorithms that is the principal focus of this thesis. More practically, it describes the methodology (techniques, tools and procedures) that will be used in the three case studies developed in the following empirical chapters. It also positions this methodology in the field of Big Data. After a brief historical contextualization, it discusses the main characteristics of Big Data and introduces different data mining techniques. It then looks specifically at Twitter and tries to answer the following questions:

- How is data technically made available by Twitter?
- What (in what format) data is available from Twitter?
- What are the limitations of Twitter data?
- How can algorithms be studied using Twitter data?

The answer to the first question is presented in terms of a discussion about the different types of APIs that Twitter offers and their advantages and disadvantages. This discussion informs the selection of two different APIs for the methodology employed in the empirical chapters. The second question is answered by reviewing different types of Twitter metrics from the most basic ones such as hashtags or URLs to the most complex, custom made metrics such as user diversity. This review uses the examples of the research described in the previous chapter (especially the typology of Trends) but this time describes how it was operationalised using Twitter metrics. Most importantly it lays the groundwork for the creation of the new metrics deployed in the final empirical chapter.

The answer to the third question focuses on issues with the complexity and the size of platforms, which causes problems with sampling. It follows the argument of
Gerlitz and Rieder (2013) that there are significant differences between the practices of sampling in traditional quantitative sociology and social media research. Firstly, social media data is not produced through surveys but pre-exists their collection, which means that data is already there - ready to be analysed providing one has access to it. Secondly datasets pulled out of social media are not raw data but ‘come in formats specific to their platforms with analytical features, such as counts, already built into them’ that favour highly particular modes of analysis (Marres and Weltevrede, 2012). This is significant as it raises serious questions whether the decision about the use of the method was made by the researcher or was it in a way forced by the format of the data and its metrics. Lastly, sample selections on social media are rarely related to full datasets but mostly follow a case study design (Rieder, 2012). The chapter also discusses starting points for the analysis in relation to data and knowledge they produce.

The final question is studied by analysing different quantitative approaches to study algorithms. It covers problems with access to the knowledge on how social media platforms work (Seaver, 2014) and the relative lack of expertise currently available to analyse algorithms that run these platforms (Kitchin, 2014 and Seaver, 2014). This question is significant from the research design perspective and informs the design of the following empirical chapters.

**Methodological framework: Big Data**

In recent debates Big Data is recognised as a loosely defined term used to describe data sets so large and complex that they become awkward to work with using standard statistical software; often supercomputers are required to analyse it (Snijders et al. 2012). This view has recently changed (Manovich, 2011) as more and more Big Data can now be analysed using standard software on desktop computers or even mobile phones. These everyday machines now have enough storage capacity to store data and enough processing power to process Big Data. The inter-connectivity of computer technology and software has made it possible to transfer and analyse data on different devices using different pieces of software. Boyd and Crawford (2011: 2) argue that:
Big Data is no longer just the domain of actuaries and scientists. New technologies have made it possible for a wide range of people – including humanities and social science academics, marketers, governmental organisations, educational institutions, and motivated individuals – to produce, share, interact with, and organise data. Massive data sets that were once obscure and distinct are being aggregated and made easily accessible. Data is increasingly digital air - the oxygen we breathe and the carbon dioxide that we exhale. It can be a source of both sustenance and pollution. (Crawford 2011: 2)

De Mauro et al. (2014: Online) conducted a survey of existing definitions of Big Data and suggested the following formal definition:

*Big Data represents the Information assets characterized by such a High Volume, Velocity and Variety to require specific Technology and Analytical Methods for its transformation into Value.* (De Mauro et al. 2014: Online)

Volume, Velocity and Variety (known as the 3 Vs) were suggested by Laney (2001) as characteristics of data and were later associated to the concept of Big Data and used as its definition by other researchers (Beyer & Laney 2012; Eaton et al. 2012; Zaslavsky et al. 2013). The 3Vs model was later extended by other researchers with other features such as Value (Dijcks 2012), Veracity (Schroeck et al. 2012), Variability or Complexity and Unstructuredness (Suthaharan 2013).

Volume refers to the quantity of generated and stored data. According to Marr (2018: Online), 90% of the data in the world today has been created in the last two years alone. This phenomenal growth is linked to the development of the Internet of Things (IoT), the network of devices that connect to the Internet and share data with each other. IoT devices include devices such as computers or smartphones, but also objects that have been designed to gather and communicate data over a network such as smart speakers or home thermostats. Most of these devices are installed in factories, businesses or healthcare to manage machines, increase efficiency and save costs. In 2016, there were around 5 billion things connected to the Internet and it is predicted that in 2021 the market will more than double and increase to nearly 11.6 billion (Symanowich, No date: Online).
All these devices generate data. Social media also play their part. As of April 2019, Facebook had 2.3 billion active users (Clement, 2020) - almost 30% of the world’s 7.7 billion population. Other social media are smaller in size, but their active user base is also significant - Instagram has 1 billion active users, Twitter – 330 million (just over 4% of the world’s population), followed by LinkedIn with 303 million. China has its own version of Twitter - Sina Weibo, which in April 2019 had 462 billion active users - 6% of the world population and almost a third of the population of China.

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51 Available from: [https://whatis.techtarget.com/definition/3Vs](https://whatis.techtarget.com/definition/3Vs)

52 Live world population data available from: [https://www.worldometers.info/world-population/](https://www.worldometers.info/world-population/)
Velocity refers to the speed at which the data is generated and processed. The most obvious examples are high-frequency stock trading algorithms which reflect market changes within microseconds or machine to machine processes that exchange data between billions of devices or online gaming systems that support millions of concurrent users, each producing multiple inputs per second. On social media, Instagram users post around 50,000 images every minute. In 2017 there were 456,000 tweets sent every minute globally. There are 4.3 billion Facebook messages, 5.75 billion Facebook likes posted daily on Facebook. All these leave a digital trace, that can be analysed. Every minute, social media users contribute to billions of images, posts, videos, tweets etc. The data is generated in what is called real time.

Variety refers to the type and nature of the data, which can be generated from text, images, audio, video, web, GPS data, sensor data, relational databases, documents, SMS, pdf, flash, etc. As new applications are introduced new data formats come to life. Data is also generated by multiple users such as people, machines (planes),

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applications (Facebook), sensors, devices (mobile phones), readers, scanners, microphones, cameras etc. The structure can no longer be imposed to keep control over the analysis. In principle Big Data encompasses structured, semi-structured and unstructured data\(^{54}\), however the main focus of analysis is on unstructured data.

Veracity (confidence or trust in the data) is an indication of data integrity and the ability for an organisation/individual to trust the data and be able to confidently use it to make crucial decisions. Firican (2017: Online) argues that ‘it refers to the provenance or reliability of the data source, its context, and how meaningful it is to the analysis based on it’. As researchers, we often do not know who created the source of data, what methodology was used to collect it, who was included and who was not. We do not know if data comes raw or it was modified by someone else. Without knowing the answers to these questions, it is impossible to determine the veracity of information.

Finally, Variability refers to the inconsistency of the data set which can hamper processes to handle and manage it. Normally, these inconsistencies need to be found by anomaly and outlier detection methods in order for any meaningful analytics to occur. It can also be linked to the Variety of data dimensions resulting from multiple data types and sources as described above or issues with inconsistent data upload speed or Velocity.

The ‘New Face’ of quantitative research

The recent developments in processing power and interconnectivity of computer technology as described above have created unprecedented quantities of digital data. This ‘deluge’ was followed by the emergence of an interdisciplinary field in science called Data Mining - the science of extracting useful knowledge from huge data repositories (Chakrabarti, 2006). Data mining techniques are currently being widely used by industry, science, engineering and government and there is a growing consensus that data mining can bring value to all these fields. The developments

\(^{54}\) Data that either does not have a pre-defined data model or is not organized in a pre-defined manner
have also changed the face of quantitative research. Uprichard, Burrows and Byrne (2008) argue that, with the development of the Big Data research techniques, a ‘New Face’ of quantitative research has emerged and that it is very different to the old, traditional one. They observe a shift in the way the ‘New Face’ (Big Data research) deals (amongst other things) with **causality**, **sampling** and **interpretation**.

Firstly, they argue, new quantitative research does not rely on linear causal models or put too much faith in finding causes. Instead, it makes it possible to analyse the non-linear relationships within big data and as a result a more complex analysis is possible. A good example of this lack of interest in causality is the Amazon recommendation system, which is not concerned with why people who like book A also like book B. All that matters is the fact that two items usually sell together; Amazon can monetise this correlation by suggesting book B to the customer who purchased book A. The reasons for the correlation are insignificant. It is a shift from the interest in finding underlying causes towards being able to explore and describe correlation (Mayer-Schonberger and Cukier 2013: 52).

Big Data has also changed the way we think about **sampling**. Uprichard, Burrows and Byrne (2008) argue that the new approach is not interested in probability sampling and that sampling in Big Data research is only used to confirm descriptions of populations rather than inferring to them and as a result statistical inference is seen as unnecessary or irrelevant.

Lastly, the ‘New Face’ has a completely different approach to the **interpretation** of data. Traditional qualitative research was focused on explanation and confirmation, while the ‘New Face’ focuses on ‘description, exploration, classification, case profiling and visualisation’. It is a shift from focusing on the variable to a ‘focus on the case and describing the types of cases’ (Uprichard, Burrows and Byrne, 2008). This chapter will look in detail how all these changes affect Twitter research. Before it covers the limitations, it will try to answer the first two questions of how and what data is available from Twitter.
How to get data from Twitter?

There are many tools that allow for the capture of Tweets directly from the Twitter website, for example, NCapture. It is also possible to scrape or collect Twitter data directly from the platform - this technique will be described in detail in the chapter about Polish hashtags. The most commonly used method of gathering data is directly mining the Twitter API (Application Programming Interface), which is a set of clearly defined methods of communication between various software components. Twitter API not only provides a database of Tweets, but also the metadata that is associated with the Tweets. There are three different types of Twitter API: The Streaming API, the Rest API and the Search API.

The Streaming API

The Streaming API is the most popular data source for Twitter-based large-scale research (Gaffney and Puschmann, 2014). It is a ‘push’ based API, which means that data is constantly flowing from the requested URL (endpoint) and it is the researcher's job to develop tools to collect and process it. The API provides access to live data ('live polling'), therefore it is not good for historical analysis. It also has several bandwidth limitations which can have a considerable impact on the representativeness of sampling. The most common 'spritzer' bandwidth, which is available to all regular users on Twitter, delivers up to 1% of all Tweets posted on the system. The 'garden hose' bandwidth, which delivers up to 10% of all Tweets is only granted by Twitter occasionally to users who have 'defensible and compelling reasons' for increased access. Lastly, the 'firehose' bandwidth, which delivers all Tweets, is only available for business users for a price or through authorised resellers. (Singletary, 2012)

Most of the researchers who use Streaming API settle for the 'spritzer' access, as a 1% sample in most cases is more than enough for small-scale research (Gerlitz and Rieder, 2013). However, one needs to be aware of risks. Most importantly Twitter has usage spikes and 'quiet periods' depending on the subject, geographical location, language, time of the day, day of the week etc. All these factors need to be taken into
consideration to make sure that the sample is representative. Collecting data for long periods of time can help to deal with this issue. Another problem is the randomness of the sample. Most of the researchers agree that a 1% sample is random (Gerlitz and Rieder, 2013) or has an ‘acceptable degree of randomness’ (Gaffney and Puschmann, 2014). Lastly, Streaming API allows two different points of access to data: sample and filter. Sample provides access to 1% of all Tweets posted on the system, selected at random. Gerlitz and Rieder (2013) analysed 1% sample for 24hrs and found that the results reflected the daily spikes and lows of Twitter usage. The Filter access point allows for three different parameters (Track, Follow and Locations) to select specific results from the live stream. The Track parameter allows researchers to search for specific keywords or hashtags. The Follow parameter allows researchers to search for specific user accounts, and the Locations parameter allows researchers to search for geotagged Tweets. The Filter point of access allows researchers to receive anywhere from 1% of the tweets to over 40% of tweets in near real-time depending on the criteria users request and the current traffic.

The Trend Catcher tool developed for this thesis and described in chapter 8 uses Streaming Twitter API to access data from Twitter.

The REST API

The REST API (Representational State Transfer) API is a ‘pull’ based API which means it provides data that is already ‘there’ on Twitter. It does not provide a ‘live’ connection to the Twitter data stream (as was the case with the Streaming API), but ‘pulls’ data that has already been stored. One might say that it gives access to historical data. It is possible to set it in a way so that it performs the ‘pull’ at regular intervals, and as such can be seen as an ongoing, almost live data collection technique. However, it has one serious limitation - it is rate-limited. For example, Twitter REST API v1.1 search/tweets endpoint, used by Netlytic application (used for data collection in the chapter about GE2017), which returns a collection of relevant Tweets matching a specified query has a requests frequency of every 15

minutes and returns a maximum of 1000 records per request. In order to minimize this restriction, many applications are set automatically to repeat their requests every 15 minutes and build datasets much larger than the 1000 records that is allowed by Twitter. For example, Lee et al. (2011) describe how they used it to download trending topics every 30 minutes and created a dataset consisting of 23000+ trends.

This technique of constantly repeating requests every 15 minutes and updating a database is very useful but has another limitation - it cannot be used for search terms that produce more than 1000 records in a given 15 minute interval (see GE2017 Chapter for details). If that is the case (for example for the most popular hashtags on Twitter) Streaming API with the Track parameter should be used.

**The Search API**

The Search API is a ‘pull’ API as well; it simply replicates the Twitter search function. Twitter actively discourages the use of this API and plans to discontinue it in the future.

**What data is available from Twitter?**

As was described in the previous section, the most common and efficient way of exploring Twitter happens via an API, which not only provides a database of Tweets, but also the metadata that is associated with them. The exploration of Tweets and their metadata helps to establish basic metrics for the analysis of communication on Twitter and makes the result of Twitter based research comparable. Basic metrics on Twitter include: the name of the sender (Twitter username and numerical ID), the recipient of the message (@mentioned if any), timestamps accurate to the second, hashtags (#hashtag if any) or URLs (link to other websites if any).

In comparison with the data traditionally used in quantitative sociology, Twitter data is preformatted by the platform or in other words is already ‘there’. This has significant implications because there is no way of designing a ‘raw data’ collection
process (Gerlitz and Rieder 2013). When analysing the data, one needs to recognize reliance on what is already available from the platform; the collection process can only build on the predefined dataset. In other words, researchers are free to get the data as long as they ask for data that is already included in the dataset in the format that was decided by the platform. As a result, data is not raw - it comes in formats (metrics) specific to platforms (Marres and Weltevrede, 2012).

The Table 2 below presents an example of data collected from Twitter via Netlytic application using Twitter API. The first three columns and the last column are metrics that emerge from Twitter metadata. These are Link, publication date, author and source (application used to post the Tweet). The Tweet column has metrics that refer to information that is included in the actual Tweet. It includes the information that the Tweet is a retweet from @SportExtraHD and that four hashtags were added to it: #Ronaldo #messi #lewandowski #suarez.

<table>
<thead>
<tr>
<th>Link</th>
<th>pubdate</th>
<th>Author</th>
<th>Tweet</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td><a href="http://twitter.com/calcio_totale/statuses/682938331295027201">http://twitter.com/calcio_totale/statuses/682938331295027201</a></td>
<td>01/01/2016 10:56:01</td>
<td>calcio_totale</td>
<td>RT @SportExtraHD: Europe’s top highest scorers of 2015 #Ronaldo #messi #lewandowski #suarez <a href="https://t.co/3BPkJLAUTs">https://t.co/3BPkJLAUTs</a></td>
<td>Twitter for Android</td>
</tr>
<tr>
<td><a href="http://twitter.com/footballgrace1/statuses/682954849865076736">http://twitter.com/footballgrace1/statuses/682954849865076736</a></td>
<td>01/01/2016 12:01:39</td>
<td>footballgrace1</td>
<td>really best...#Ronaldo. #Messi . #lewandowski . #Suarez <a href="https://t.co/sQCgd168ci">https://t.co/sQCgd168ci</a></td>
<td>Twitter Web Client</td>
</tr>
</tbody>
</table>

Table 2: An example of data collected from Twitter via Netlytic application using Twitter API

Bruns and Steglitz (2015) distinguish four different types of Twitter metrics: basic, temporal, user and group metrics. There are also network metrics - based on the characteristics of the social network generated from the dataset.
Basic Twitter metrics

Basic metrics on Twitter include the name of the sender (Twitter username and numerical ID), recipient of the message (@mentioned if any), timestamp accurate to the second, tweet type (RT - Retweet or @reply), hashtag (#hashtag if any) and URL (link to other websites if any). These metrics can also be divided into two other groups: intended or unintended by the user. The first group includes metrics that the user intentionally adds to the Tweet such as a hashtag or @reply. The second group includes metrics that most users are unlikely to be aware that Twitter is collecting. These include the name of the device used to post the Tweet or the timestamp of the post accurate to the second.

Basic metrics are very powerful tools to analyse users’ behaviour on Twitter. For example, the previous chapter discusses different types of trends e.g. Exogenous and Endogenous or Naturally occurring and Coordinated. These typologies were methodologically operationalised using basic Twitter metrics. Naaman et al. (2011) developed a complex classification of trends with the two main categories: exogenous (originating outside of Twitter) and endogenous (Twitter only, not corresponding to external events). They establish that exogenous trends have a higher proportion of messages with URLs (basic metric) than endogenous trends.

56 The typology has many subcategories, all described in the previous chapter

57 Naaman et al (2011) also looked at differences between subcategories and the main category and differences between subcategories. They found that breaking exogenous trends have a larger proportion of retweet messages and a smaller proportion of reply messages than other exogenous events. This could be an indication of the informational nature of breaking events. They spread via retweets but there is less discussion. Naaman et al also observed significant differences between Memes and Retweet Endogenous Trends. For example, Retweet trends had more messages with URLs and a higher proportion of unique URLs than meme trends. Interestingly more meme trends than retweet trends had a single hashtag that appears in more than 10% of the trend’s messages. They also had more hashtags per message than retweet trends, but were not different when the trending term was removed from consideration. The reason for this could be that memes are often identified by a hashtag. The final difference between meme and retweet trends (later confirmed by findings of Recuero and Araújo, 2012a) was that meme trends had more messages per author on average and a higher proportion of messages from the single top author than retweet trends. This means that for meme trends there is a limited number of users who are responsible for a fairly significant part of the content, whereas retweet trends seem to be more “democratic” and participatory.
This finding shows that trends generated by external events tend to have more links to the outside world and endogenous trends tend to be more platform related and their aim is not to drive traffic to external assets (e.g. websites) but to keep the user on the platform.

The authors also find that the average term length for exogenous trends was shorter than the length of terms used in endogenous trends. This finding is interesting in light of my own findings in Chapter 6 about the increasing average length of Polish trending hashtags, which could indicate that Twitter is increasingly becoming a conversational platform on its own and hashtags help to facilitate that. A further finding of Naaman et al. (2011) shows that fewer exogenous trends have a unique hashtag appearing in at least 10% of the messages compared to endogenous trends. This might indicate less agreement between authors of exogenous trends, which could be caused by the fact that exogenous trends start from many users acting independently and choosing different hashtags for their posts in the trend. In contrast, endogenous trends usually focus on a single hashtag right from the beginning. This is significant and suggests that when creating an algorithm to classify trends one should look at the number of co-occurring hashtags as an indicator of the source of the trend.

Naaman et al. (2011) also establish that exogenous trends have a smaller proportion of retweets in the trend's tweets compared to endogenous trends. This suggests that more original content was being created based on exogenous sources. Endogenous trends were often a retransmission of the content that was already in the system. Finally, the proportion of replies in exogenous trends was higher than endogenous ones meaning that there was more discussion in exogenous trends.

Similar metrics are used by Recuero and Araújo (2012b and 2012a) in their study of Orchestrated trends (see Chapter Five for details). Using basic metrics, they establish that the majority of coordinated trends were hashtags rather than popular phrases or words and that orchestrated trending topics were also usually longer (on average 13.1 characters long, the longest was 32 characters long) than Naturally Occurring ones which on average contained 9.9 characters (the longest was 15 characters long). Based on these findings, they theorise that Naturally Occurring Topics only hint at what they are about e.g. #Fire, whereas Orchestrated ones usually contain a full statement - hence the extra length #FireIsDangerous.
Temporal Twitter metrics

Temporal metrics describe patterns captured in a dataset over time. They can be as simple as the number of users talking between two dates about a given hashtag or as advanced as spikes in activity of some users during certain times, allowing for the identification of heated discussions or arising controversy. For example, Yardi et al. (2009) examine the entire life cycle of the endogenous (native to Twitter) trending micro-meme #robotpickuplines and argue that most activity occurred during the first 24 hours after the creation of the hashtag with the first few hours being the most significant.

User Twitter metrics

User metrics can be used to help to identify types of users and the approaches they take to their communication on Twitter. Bruns and Steglitz (2015) illustrate this kind of use of metric with the example of a categorization of individual users who take one of the three approaches to tweeting:

- an enunciative approach - these users can be identified by posting mainly original Tweets;
- a conversational approach – these users can be identified by the large number of @replies they make;
- a disseminative approach – these users can be identified by the large number of retweets they make.

This kind of metric can also be used to establish the importance of the user in relation to his/her followers by comparing the number of @replies to Retweets.

All these user metrics can be monitored over time and therefore when analysed in search of temporal user behaviour patterns, they become temporal metrics as described in the previous section. For example, Recuero and Araújo (2012a) use a mix of user and temporal metrics and notice that orchestrated trends are usually created by fewer users tweeting a lot (average 446 users with average 12 tweets per user). In comparison, Naturally Occurring trends usually result from many users
tweeting about them but with many fewer Tweets (on average 647 users with average 4 tweets per user).

**Group metrics**

Group metrics can be used to put users into groups. These groups can be based on pre-existing criteria (determined by a specific research agenda) or on criteria emergent from the dataset. One of the most common criteria is rate of user activity, which most of the time on Twitter or any other social media platform will be distributed following the power law - a small number of highly active users will dominate the dataset with a large number of published Tweets, while the much larger number of inactive or less active users will publish many fewer Tweets and form what is known as a 'long tail'. The classification of users using the 1/9/90 (alternatively 10/90) percent rules (Tedjamulia, Dean, Olsen and Albrecht, 2005) can be applied in order to distinguish between Lead (1%) Highly active (9%) and Inactive (90%) groups of users.

**Network metrics**

Network metrics (also known as network properties) are generated using advanced tools such as Gephi\(^{58}\) on Netlytic\(^{59}\), that use special algorithms to analyse networks obtained from the platform. They are generated in the process of investigating social network structures through the use of networks and graph theory, known as Social Network Analysis (SNA). This type of analysis (used in Chapter 7 to study the UK 2017 general election) describes networked structures in terms of nodes (for example individual actors, people, or items within the network) and the ties, edges, or links (relationships or interactions) that connect them. Netlytic Application (used to get data for the general election case study) performs SNA and measures five network properties: Diameter, Density, Reciprocity, Centralisation and Modularity.

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\(^{58}\) Available at: https://gephi.org/

\(^{59}\) Available at: https://netlytic.org/
The **Diameter** of a network measures the longest of all the calculated shortest paths between two network participants. In other words, it measures the longest distance between two participants. It indicates a network's size by calculating the number of nodes between the two sides of the network (graph). To find the diameter of a graph, one needs to first find the shortest path between each pair of nodes. Once the shortest path length from every node to all other nodes is calculated, the diameter is the longest of all the calculated path lengths. It is a useful measure of the reach of the network - it indicates how long it will take to reach any node in the network (Cheliotis 2010).

The **Density** of a network is a proportion of existing ties (edges) to the total number of possible ties in a network. It is calculated by dividing the number of existing ties (connections) by the number of possible ties. Density helps to determine how close participants are within the network. The closer it gets to 1, the more participants are talking with many others, which suggests a close-knit community. A perfectly connected network is called a clique (Cheliotis 2010). On the other hand, if the value is closer to 0, this suggests that participants are not connected to each other in the network. Density and diameter help to assess the speed of information flow.

**Reciprocity** is defined as the ratio of the number of links between nodes pointing in both directions (also called reciprocal ties) to the total number of links (not all possible ties) (Cheliotis 2010). A high reciprocity indicates that many participants have two-way conversations, whereas a low value suggests many one-sided conversations.

**Centralisation** measures the average degree centrality of all nodes within a network. A degree of centrality for a single node is the measure of a node's degree of connectedness, which could be interpreted as popularity or influence. Centralisation helps to assess which nodes are central with respect to spreading information and influencing others (Cheliotis 2010). Networks with a high centralisation (value close to 1) have a few central participants who dominate the flow of information. In decentralised networks (with a low centralisation - value close to 0) information flows more freely between many participants.

**Modularity** measures the strength of division of a network into clusters (modules) and helps to determine whether the clusters found represent distinct communities in the network (Chen et al, 2013). A cluster is a group of densely connected nodes.
that are more likely to communicate with each other than to nodes outside of the cluster. High modularity suggests dense connections between the nodes within clusters but sparse connections between nodes in different clusters and indicates clear divisions between communities. Low modularity (in Netlytic usually less than 0.5), suggests that clusters overlap more and the network is more likely to consist of a core group of nodes.

Gerlitz and Rieder (2013) used Social Network metrics to categorise their hashtags based on ‘emergent topic clusters, co-appearance and proximity measures’. In the obtained hashtag network, by using a Gephi modularity algorithm they managed to identify **topic clusters**. For example, they identified clusters dedicated to following which included hashtags such as #teamfollowback, #rt, #followback and #sougofollow (Figure 34) and clusters about Arab countries and pornography. They also identified a diffuse ‘everyday life on Twitter’ zone (Figure 35) where hashtags relating to food, birthdays, funny images, or rants coexist.

![Image: Everyday life on Twitter zone on Co-occurrence map of hashtags (spatialisation: Force Atlas 2; size: frequency of occurrence; colour: communities detected by modularity) by Gerlitz and Rieder (2013: Online)](image)

*Figure 34: Everyday life on Twitter zone on Co-occurrence map of hashtags (spatialisation: Force Atlas 2; size: frequency of occurrence; colour: communities detected by modularity) by Gerlitz and Rieder (2013: Online)*
Gerlitz and Rieder (2013) also found that network metrics such as the number of connections (node's degree) can be used to classify hashtags into two different groups: "combination" hashtags that are not topic-bound (for example #love, #me, #lol, #instagram or the various “follow” hashtags) and specific topic markers (for example #arianarikkumacontest, #thingsidowhendisbored, #calloutsomeonebeautiful, #sosargentinosi). Figure 36 shows these differences on a graph. The two extreme cases of #love and #arianarikkumacontest illustrate differences between these hashtags very well. #love has about 5 times lower word frequency than #arianarikkumacontest but about a 10 times higher number of connections (node's degree). It is clearly visible that most of the hashtags in the dataset tend to cluster in one area of the graph which means that they have similar characteristics.
Figure 36: Hashtag node's degree in relation to frequency by Gerlitz and Rieder (2013: Online)

Social Network metrics were also used by Recuero and Araújo (2012a) in their study of Coordinated Trends. They established that orchestrated topics had more dense and clustered networks than Naturally Occurring. The in-degree of networks behind coordinated trending topics was also on average higher than in the Naturally occurring. These differences suggest that Orchestrated trending topics have tight communities behind them.

A new custom-made metric: User diversity

Twitter data also gives the possibility of creating brand new metrics building on the basic ones. Gerlitz and Rieder (2013) created a “user diversity” metric (derived by dividing the number of unique users of a hashtag by the number of tweets the user appears in, normalised to a percentage value). By doing this they managed to distinguish hashtags that have a “shoutout” character (for example #thingsidowhenigetbored, #calloutsomeonebeautiful, #love - which are located on

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A score of 100 means that no user has used the hashtag twice, while a score of 1 indicates that the hashtag in question has been used by a single account. Gerlitz and Rieder (2013)
the right side of the graph - see Figure 37) from ‘terms that become more “insisting”, moving closer to becoming spam’, which tend to be located on the left side of the graph) as their user diversity decreases.

![Figure 37: Hashtag user diversity in relation to frequency by Gerlitz and Rieder (2013: Online)](image)

**Problems with Twitter data**

Using an API is the most efficient way of exploring Twitter but it does not come without problems - the most serious ones are to do with representativeness and validity. The majority of APIs do not give access to all Twitter data but are limited to the most recent 1000 tweets or to a sample of anything from 1 to 40%.

**Sampling on Twitter**

Sampling techniques in the context of social science have been discussed in depth by many researchers (Bryman, 2012; Gilbert, 2008; Gorard, 2003; Noy, 2008; Uprichard, 2011). There are two main approaches: probability techniques which
emphasise the representative relationship between the entire population and selected sample, and non-probability approaches which determine the sample via a priori knowledge of the population (i.e. predefined groups) or the purpose of the research (i.e. some predefined criteria e.g. age group or topic) rather than strict representational relations. Gerlitz and Rieder (2013) argue that most of the approaches to sampling data on Twitter take the second, ‘non-probabilistic, non-representative route of delineating their samples which are based on features specific to the platform’. They also describe the three main sampling techniques that are used on Twitter following this non-representative approach:

*Topic-based sampling*

Topic-based sampling relies on data collected via Twitter REST - API with the use of hashtags or keywords. It assumes that the content of Twitter will group around the shared use of these hashtags or keywords and is used to identify emerging patterns or describe medium-specific practices. It considers keywords or hashtags to be sufficient identifiers for issues. The examples of research using this technique include studies of emerging patterns in brand communication (Stieglitz and Krüger, 2011); public unrest and events (Vis, 2012); and hashtag practices (Bruns and Stieglitz, 2012). This thesis uses topic-based sampling in the case-study of the UK General Election in Chapter Eight.

*The snowball sampling technique*

The snowball sampling technique is based on topic-based sampling and presupposes the existence of coherent network topologies. It starts with already existing or predefined (by experts or manual collection) lists of users (e.g. Rieder, 2012) that are then extended in a process of ‘snowballing’, which is often based on platform specific relations such as user followings. Examples of research using this technique include studies of: topic- or activity-based user groups (Paßmann, Boeschoten, and Schäfer, 2014); cultural specificity (Garcia-Gavilanes, Quercia, and Jaimes, 2006); the dissemination of content (Krishnamurthy, Gill and Arlitt, 2008).
Marker based sampling

Marker based sampling uses metadata provided by a platform such as geographical location, language, nationality or any other elements provided in user profiles or provided by the platform such as software used to post a message. Critics argue that this technique places too much faith in Twitter’s capacity to identify language or location especially in light of Rieder’s (2012) argument that less than two percent of Tweets are geotagged and language detection is less than satisfactory.

All three of the above techniques have a starting point - they either start with a keyword, predefined lists of users or geography etc. They are all linked to Twitter’s REST API or Streaming API with a filter access point with one of the three parameters (Track, Follow and Locations). There is also another sampling technique that is linked to Twitter’s Streaming API - Twitter API Random Sampling.

Twitter API Random sampling

Random sampling became possible on Twitter with the development of Streaming API, which provides a constant connection with Twitter’s server and allows for the collection of a one percent, random sample of the full Twitter stream.

Problems with sampling on Twitter

All three non-probability approaches have serious limitations. Gerlitz and Rieder (2013) identified these as problems with: representativeness (can the results be generalisable?), exhaustiveness (are all relevant units included in the sample?), cleanliness (how many irrelevant units are there in the sample?) and scoping (how does the sample compare to samples collected by others?). There are also other possible issues including randomness and validity.

The very nature of a non-probability approach to sampling is that they determine the sample via a priori knowledge of the population rather than strict representational relations. This raises two questions:
There seems to be a consensus that Twitter studies are likely to have problems of representativeness. Some researchers (Blank, 2016) even suggest that Twitter data is not suitable for any research where representativeness is important, such as forecasting elections or gaining insight into attitudes, sentiments, or activities of large populations. In general, he argues that Twitter data is more suitable for corporate use than for social science research. When interviewed by Sutcliffe (2017: Online) Blank argued that in the commercial world ‘if a product is disproportionately bought by the same population groups that use Twitter then it may be possible to forecast sales using Twitter data.’
Interestingly Mellon and Proser (2017) argue that all these differences between Twitter users and general population, caused by the demographic composition of social media users, can be eliminated by controlling for age, gender, and education.

One of the ways of dealing with the issues with the external representativeness of Twitter data, is to shift the focus from trying to represent offline in the online world, to trying to make sense of what is happening online based on online data or filters. This shifts the focus from external to internal (Twitter only) representativeness.

**Starting point and generalisability**

As argued above, all non-probability sampling approaches require some *a priori* knowledge of the population - a starting point. Madsen (2012) suggests a typology of starting points for visualisations organised according to the data they use as a starting point, the ontology they ascribe to them and their proposed function. The typology of approaches could be illustrated with a two-dimensional graph (Figure 38) on which approaches are positioned in relation to each other. The horizontal axis represents the type of data that is used.

*Figure 38: Typology filled with visualizations according to their starting points, their ontology and their function (Madsen, 2012: 59)*
On the far-left side there are ‘relevance-driven’ approaches. These are built using ‘relevant and reliable’ data. The starting point is based on the knowledge obtained prior to the creation of the visualisation. The visualisations on the far right are created based on specific information-filter (filter-driven approaches) and focus on that filter rather than on its ‘capability to provide reliable data’. In other words, the starting point is based on the knowledge of the filter and not the problem/issue itself.

The vertical axis presents differences in relation to the ontological status of the visualisation. The approaches aiming to be an ‘objective representation of something external’ are located at the top of the axis. They are designed to be unbiased and ‘correspond to the phenomenon represented’. Madsen compares this approach to ‘a photographer who chooses her angle and lightning with an ambition of interfering as little as possible with the object photographed. In order to explain why a photograph looks a certain way she would refer to the nature of the object photographed (Carusi et al. 2010).’

Staying in the artistic world, Madsen (2012: 53) describes the approaches at the bottom of the vertical axis as ‘abstract and surrealist paintings’. When we are looking at these paintings ‘the purpose is not to draw inferences about the nature of the object portrayed but rather to get an idea of how it was seen by the painter’. These approaches are seen as ‘socio-technical modes of seeing’ - they are the result of the mix of technological, human and social ‘ingredients' and as such depend heavily on ‘human choices and technological systems’ in the process of creating them.

The first three approaches on the graph are strongly relevance driven and use offline sources as starting points. Webometric Analysis aims to be an objective representation of the ‘real’ world and recommends that starting points be ‘identified through a triangulation of trusted sources that are subsequently validated by field experts’ and that these sources be ‘only used to the extent that they can contribute to a relevant and reliable sample’. (Madsen, 2012: 54). Social Network Analysis recommends a similar approach to Webometric Analysis but without using external experts. The Controversy Mapping approach starts with a ‘trusted corpus of publicly available documents from official organisations, media sources, image galleries and videos portals [which] are validated as being relevant to the controversy by a set of human coders.’ (Madsen, 2012: 56). All these approaches aim for external representativeness and try to mirror online with the offline.
At the lower end of the vertical axis there are more socio-technical (subjective) approaches. For example Web-Sphere Analysis and Cross-Sphere Analysis do not attempt to be valid representations of offline social networks but try to ‘follow the web’ (start with web search) or ‘follow the filter’ (start with the search on a specific website) instead (Rogers, 2009). These approaches are not driven by relevance - it does not matter if the returned results (links to websites, articles) are relevant or reliable. Finally, there is The Web Vision Analysis approach which treats web-based information filters as a starting point. This approach was described in detail in Chapter Four as Twitter Trending Topics Box is simply an algorithmically generated information filter.

In none of my case studies do I approach the analysis with a predefined list of keywords or search terms. All the searches that I perform either using Twitter Platform or APIs are based on the information that appears in the Trend Box, namely trending hashtags. I do not find my search terms or keywords offline. I do not even find them anywhere else online. They come exclusively from Twitter Trend Box. In this regard, this thesis offers an extreme version of a filter driven analysis. In three of the case studies I then apply different techniques to analyse the data, but the starting point is always the same - Twitter Trend Box. As a result, the knowledge that is produced is not an objective representation of the offline world but should be seen as constructed from Twitter data.

By following the above approach, this study acknowledges that the results of the three empirical studies are not externally representative, but because the analysis starts online anyway, they are not intended to be so. Instead, the focus is on the internal representativeness, which is empirically tested in Chapter Eight.

*Is a Twitter data sample representative of Twitter?*

The second question about representativeness focuses on Twitter only and the relationship between a sample and the entire Twitter population. This case is even more complex. REST API allows you to collect 1000 Tweets at a time. Netlytic application (which uses REST API to collect data) allows researchers to repeat the query for the same search term every 15 minutes. In case of Twitter Trends, if they were identified early enough, so that the search request was made before 1000
Tweets were posted with a given keyword/hashtag, and then no more than 1000 messages were posted in every 15 minute interval, then all posts with the related keyword/hashtag can be collected. The dataset will include all messages for the given issue (search term).

Unfortunately, there are some issues with representativeness of REST API method for data collection when it comes to very popular search terms - those with more than 1000 messages per a given time interval. Depending on the geography, there are often more than 1000 messages posted with a given hashtag before it becomes trending, so it is impossible to collect all Tweets containing this hashtag. Also, if the term (hashtag) is extremely popular (e.g. during a football match) then there are usually more than 1000 tweets posted every 15 minutes, which again makes it impossible to collect all data. There could also be usage spikes, for example after a goal, and quiet periods, where less than 1000 Tweets would be posted. As a result, the sample for very popular Tweets is rarely truly representative of all Tweets about an issue. Not surprisingly, there will always be questions about the generality of any claims derived based on samples obtained via these techniques and REST API from Twitter. Gerlitz and Rieder (2013: Online) argue that all these issues ‘do not invalidate results (...) however [they] raise questions about the generality of derived claims, as case-based approaches only allow for sense-making from inside the sample and not in relation to the entire population of tweets.’

The situation with the representativeness of a Twitter sample looks better with random sampling, which became possible with the development of the Streaming API. It provides a constant connection with Twitter’s server and allows for the collection of a one percent, random sample of the full Twitter stream or between 1 and 40% sample for selected specific keywords, hashtags, users or locations. Some researchers (boyd and Crawford, 2012) raise questions about the validity of the sample taken from the Twitter stream based on the fact that it is not known how Tweets are distributed throughout the time interval (is it a random sample from 1 hour or are Tweets from the beginning of the hour over-represented?). Others (González-Bailón, Wang, and Rivero, 2013) argue that it is impossible to assess the selection bias of any API without access to a complete stream. Gerlitz and Rieder (2013) answered some of these questions by comparing the volume of Tweets published by high volume bot accounts from their sample (collected via STREAMING API) with the number of Tweets Twitter normally published in a complete stream.
They found out there was a pattern of consistency with a random selection procedure\textsuperscript{61}, which indicates that the Twitter sample was representative of all public Tweets.

The final question that remains unanswered in a consideration of the questions raised in the chapter in relation to the aims of the thesis is the comparison between the two data collection methods (Streaming and REST APIs).

\textit{Streaming API vs REST API}

The two data collection methods - Streaming and REST APIs - have their advantages and disadvantages. REST API allows the researcher to collect all data for a given keyword or a hashtag, provided it is not extremely popular and does not exceed 1000 posts in a given time interval. Streaming API helps to deal with this issue by only returning a sample of the posts from a given time interval. In theory it is possible to obtain a larger sample by using REST API, but it would be still less representative than the smaller one obtained using Streaming API. The below hypothetical situation illustrates this (Table 3 below). In the first hour of data collection there were 5600 Tweets posted with the given hashtag. In the second hour the hashtag became even more popular and there were 7200 Tweets posted. It was followed by 4300 in the third hour, 2100 in the fourth and 900 in the fifth. Assuming that REST API was collecting data every 15 minutes it would collect 4000 Tweets each hour in the first three hours and all 2100 Tweets in the fourth hour and all 900 Tweets in the fifth hour. From the total of 20100 Tweets, REST API would collect 15000 (75%). Streaming API would collect anything between 201 and 8040 Tweets during this time depending on the criteria users' request and the current traffic.

\footnote{Rieder (2012) started with a manually selected “core” of 496 accounts selected by a group of researchers. It consisted mainly of politicians from all major parties, as well as activists, bloggers, and media professionals that had achieved a certain visibility on Twitter. In the next step, Rieder ‘snowballed’ from the initial list by acquiring all users’ friends and followers through the API}
It is possible that the sample collected by REST API, even though much larger, could be less representative than the one collected by Streaming API, especially if one wants to see the distribution of Tweets over time. The two tables (Table 4 and 5) below illustrate the limitations of REST API approach. In the first scenario all 7200 Tweets that were posted in the second hour were evenly distributed. The first problem with REST API approach is that all 1000 tweets collected at each 15-minute intervals were from the second half of this 15 minute interval. The missing 800 Tweets at each interval, are always those that were posted in the first half of the interval. Assuming that all Tweets collected by Streaming API were randomly selected throughout the entire interval, it makes them more representative as they also cover the first half of the interval.

<table>
<thead>
<tr>
<th>hr</th>
<th># of Tweets</th>
<th>REST API</th>
<th>STREAMING API (1%)</th>
<th>Streaming API (40%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>5600</td>
<td>4000</td>
<td>56</td>
<td>2240</td>
</tr>
<tr>
<td>2</td>
<td>7200</td>
<td>4000</td>
<td>72</td>
<td>2880</td>
</tr>
<tr>
<td>3</td>
<td>4300</td>
<td>4000</td>
<td>43</td>
<td>1720</td>
</tr>
<tr>
<td>4</td>
<td>2100</td>
<td>2100</td>
<td>21</td>
<td>840</td>
</tr>
<tr>
<td>5</td>
<td>900</td>
<td>900</td>
<td>9</td>
<td>360</td>
</tr>
<tr>
<td>TOT ALS:</td>
<td>20100</td>
<td>15000</td>
<td>201</td>
<td>8040</td>
</tr>
</tbody>
</table>

Table 3: Comparison of representativeness of data collection strategy between Streaming and REST APIs

The second example deals with a scenario of uneven distribution of Tweets throughout the hour. In the first, third and fourth quarters of the hour Tweets were...
coming at the same rate of 1000 per every 15 minutes, but in the second quarter, there was a sudden hike (e.g. someone scored a goal at a football match) and four times more Tweets were posted. Data collected via REST API, won’t show this hike at all. Exactly 1000 Tweets will be collected for each quarter of an hour. Streaming API will in this case show the hike, assuming that the data collection was randomly distributed throughout the hour.

<table>
<thead>
<tr>
<th></th>
<th># of Tweets</th>
<th>REST API</th>
<th>STREAMING API (1%)</th>
<th>Streaming API (40%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>7200</td>
<td>4000</td>
<td>72</td>
<td>2880</td>
</tr>
<tr>
<td>Q1</td>
<td>1000</td>
<td>1000</td>
<td>10</td>
<td>400</td>
</tr>
<tr>
<td>Q2</td>
<td>4200</td>
<td>1000</td>
<td>42</td>
<td>1680</td>
</tr>
<tr>
<td>Q3</td>
<td>1000</td>
<td>1000</td>
<td>10</td>
<td>400</td>
</tr>
<tr>
<td>Q4</td>
<td>1000</td>
<td>1000</td>
<td>10</td>
<td>400</td>
</tr>
</tbody>
</table>

Table 5: Comparison of representativeness of data collection strategy between Streaming and REST APIs

These examples illustrate problems with REST API - it works well for less popular hashtags, in which case virtually all data can be collected as long as it does not exceed 1000 Tweets per time interval. Unfortunately, it becomes unrepresentative when analysing much more popular hashtags/trends. In these cases, Streaming API data is more representative even though the sample is significantly smaller.

Gerlitz and Rieder (2013) attempted to compare data collected via two approaches. They captured the sample of 24hrs Twitter activity using Streaming API, starting on 23 Jan 2013 at 7 p.m. (GMT). Their sample included 4,376,230 tweets, sent from 3,370,796 accounts. They compared it with data collected by boyd et al. (2010), who captured a random sample of 720,000 Tweets at 5-minute intervals from the Twitter public timeline over the period of time between 26 January 2009 and 13 June 2009 (a total of 139 days) using the REST API. Their sample included Tweets from 437,708 unique users, but similarly to Gerlitz and Rieder (2013) did not include tweets from those with protected accounts.

boyd et al. (2010) collected their sample over the period of 139 days (between 26 January 2009 and 13 June 2009) at 5-minute intervals. In total they collected
720,000 Tweets, which means that on average they collected 5180 Tweets per day (720,000 Tweets/139 days). In comparison, Gerlitz and Rieder (2013) sample included 4,376,230 Tweets from one day (24hrs). There is a clear difference in sample sizes (overall and comparing 24hrs collected by Gerlitz and Rieder to average daily number of Tweets collected by boyd et al.) Also, there is a 3 year difference in time of collection, which could have a significant impact on the results. Lastly, the methodology of sampling is also very different - boyd et al established their own sampling filter which was getting data in 5 minute intervals and Gerlitz and Rieder relied on the Twitter Streaming API filter. The Table 6 below shows a comparison of the results.

<table>
<thead>
<tr>
<th>Research by</th>
<th>boyd et al. 2010</th>
<th>Gerlitz and Rieder 2013</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sample size</td>
<td>720,000 Tweets</td>
<td>4,376,230 Tweets</td>
</tr>
<tr>
<td>Collection time</td>
<td>139 days</td>
<td>24hrs</td>
</tr>
<tr>
<td>Tweets containing</td>
<td></td>
<td></td>
</tr>
<tr>
<td>a hashtag</td>
<td>5%</td>
<td>13.18%</td>
</tr>
<tr>
<td>a URL</td>
<td>22%</td>
<td>11.7%</td>
</tr>
<tr>
<td>an @user mention</td>
<td>36%</td>
<td>57.2%</td>
</tr>
<tr>
<td>tweets beginning with @user</td>
<td>86%</td>
<td>46.8%</td>
</tr>
</tbody>
</table>

Table 6: Results of comparison of data collected by boyd et al. (2010: Online) and Gerlitz and Rieder (2013: Online)

The differences between the results are enormous. In the Gerlitz and Rieder sample there are almost three times more Tweets containing a hashtag and significantly more Tweets containing an @user mention. On the other hand, the boyd et al. sample had twice as many Tweets containing a URL and almost twice as many Tweets beginning with @user. One of the explanations could be the different methodologies. Another could be the three-year difference between data collections. Yet another could be that user practices have changed enormously during this time. The chapter about Polish hashtags will show that hashtags usage has indeed changed over time, which might explain some of such differences.
Validity of data

Gerlitz and Rieder (2014) also argue that the validity of the data collection in small sample research is grounded in medium specificity and this medium specificity (what you can actually do or get from a medium such as Twitter in terms of data?) may result in skewed findings. They argue that sampling techniques should not only be used to analyse internal relations between points in the data that has already been collected but ‘also to analyse the relation between the collection and a baseline’. As a solution they propose using random sample provided through the Streaming API, generated via a long-term data collection, as a baseline for case approaches. This is an interesting concept, but extremely time and resources consuming. One would need to establish an ongoing connection to the Streaming API and then use REST API for specific case studies and always validate all data collected via the latter by comparing it to data generated by the STEAMING API. If conducted at the same time, theoretically the results should be comparable and one should not be seeing such differences as in Table 6 above.

Another possible solution, especially for studies of not very popular hashtags/topics, could be getting data ‘natively’ (directly) from Twitter by scraping it from the web version of the platform instead of using an API. There are many tools that allow for the capture of Tweets directly from the Twitter website, for example NCapture. Doing this has some disadvantages and does not scale up. A variation of this method was used in the chapter about Polish hashtags and was the most time-consuming part of data collection. It may be of value when analysing a few hashtags, but when collecting data for thousands, as was the case in my research, the time it takes becomes an issue. In fact, I had to eliminate certain hashtags from the collection process entirely because I was unable to collect data for all of them. As a result I was forced to redefine my sample - originally it was supposed to contain all trends in Poland but because of the time limitation of the thesis I had to reduce it to all hashtags in Poland that originated in Poland and were in the Polish language’. This obviously raised problems with the validity - was I actually measuring what I intended to measure? Chapter Seven (About Polish Trends) provides more details about this specific issue.

Up to this point this chapter has shown how data from Twitter does not come raw but pre - formatted in relation to metrics. It has described possible issues with data
collection and the impact this has on the representativeness and validity of research findings. The final section will focus on algorithms rather than data, since the study of algorithms seems to have obvious relevance for the concerns of this thesis. The previous chapter described qualitative approaches to studying algorithms and this section will discuss possible issues one might face when trying to study them quantitatively.

**Problems with quantitative approaches to studying algorithms**

As discussed in the last chapter, Seaver (2014: 2) argues that researchers analysing the logic behind algorithms face two main problems: the proprietary nature of commercial systems (access), and the technical know-how required to make sense of them (expertise). Mathematical approaches provide some of this know-how. However, they assume that the researcher has access to the actual algorithm and the knowledge of coding/understanding of how algorithms work, which is almost never the case and definitely not the case when it comes to Twitter.

**Examining pseudo-code/source code or producing one's own code**

Examining pseudo-code/source code is a basic way of examining algorithms. It involves the deconstruction of the code by analysing documentation or programmers’ comments, in order to establish how an algorithm works and how it generates its outcomes. It assumes that a researcher has access both to the algorithm and to knowledge of how to analyse it. Unfortunately, this approach has several limitations when it comes to analysing today’s algorithmic assemblages. For example, code is most of the times created by many people and even those who produce it find it hard to fully understand it or do not want to share this knowledge.

Seaver (2012) argues that researchers will never be able to get access to what is happening ‘behind the scenes’ of online giants as this is limited to high-level engineers who know about changes that have been made to the architecture of the algorithm. It seems that he sees all calls for transparency aimed at gaining access to
the knowledge about the architecture of algorithms as naive and does not believe that full transparency is possible:

As we know from anthropological research on governments, regulation, and “audit culture,” transparency in practice is complicated and by no means a guarantee that the information provided will be complete, accurate, or understandable (Strathern 2000; Hetherington 2011; Hull 2012). Transparency has its limits (Ziewitz 2013). For the developers of algorithmic filtering systems themselves, there is a concern that revealing the details would render their algorithms useless, enabling bad-faith actors to game the system (not to mention aiding corporate competitors), thus negating transparency’s benefits (Granka 2010). (Seaver 2012: 7)

Seaver then defines two issues that are problematic for transparency. The first is the complexity of today’s algorithms. They are simple and logical only in theory. In practice, they are very sophisticated pieces of software. It is easy to assume that there is one person in a company, that knows the algorithm and fully understands the system but as noted above algorithms have collective authorship and are maintained and rewritten constantly by different teams of people, with different goals, different skills and different approaches. As a result, the assumption that there is a clearly understandable way that can be found by interviewing the individuals involved in the creation of algorithms operate is not sound. Based on this complexity another problem arises - one needs to be able to ask the right questions. It is not enough to ask only about what variables are included in the algorithm. In fact, most of the variables that are in the main global social media algorithms are known to the public. The key question is now not about what but how they operate and what weight these variables are getting as without that the true effects are impossible to establish.

One way to deal with the problem with the lack of transparency could be what Kitchin (2014:7) defines as ‘Reflexively producing one’s own code’. This practice involves reflecting and interrogating the researcher’s own experiences of translating and formulating an algorithm. This might involve an analysis of how an idea developed, how the code was written, how it fits in the legal system, institutional arrangements, targeted user database or market and so on. It seems to be a good idea for studies focusing on basic algorithms used for example by small companies. The
lack of access to the algorithm could be compensated by actually writing a similar or almost identical algorithm and reflexively studying the process of doing so. This might be a useful technique to study simple algorithms but it has no practical application when studying Twitter Trending Topics algorithm. No-one could realistically be expected to recreate it, not least because it is constantly changing. Because of these limitations, a lot of researchers turn to experimentation as a method to understand algorithms.

Before I introduce the second approach it is worth positioning this thesis in relation to the first one. I agree with Seaver that access is a major issue when studying algorithms. It is also the case with Twitter Trends, which are generated by algorithms. The available official information from Twitter is rather scarce (see the previous chapter and the next section of this chapter) hence for this study I followed Kitchen’s (2014:7) recommendation and closely studied the work of others, who recreated Twitter’s Trends algorithm. I then produced my own code (Trend Catcher tool) but not to replicate what Twitter does but to capture and repurpose it to generate additional knowledge of how trending hashtags are generated by the platform.

While I was working on the development of Trend Catcher, I followed the experimentation approach as described below.

**Experimentation**

For Seaver (2012) and Kitchin (2014), experimentation is a mode for analysing algorithms which try to deal with problems of access. It is operationalised via examination and observation of the output of the algorithm in order to establish how the system underpinning it works. It is based on the fact that each algorithm has two openings that enable lines of enquiry: input and output. By analysing what data goes into the algorithm and what data comes out it is possible to see something of how the algorithm is composed and how it works.

One example of experimentation is reverse engineering. It is based on the assumption that researchers know the input variables and by analysing the output variables, they can say how these two changed. One example of this approach
examined the results the Google search engine produced for the same term on different computers in different locations (Mahnke and Uprichard 2013); another example examined how Facebook’s EdgeRank prioritises posts in user timeline by posting and interacting with it on Facebook (Bucher 2012). Other examples follow debates on how users perceive an algorithm or interview people such as marketers and media strategists who make money from 'gaming an algorithm' (Bucher 2012). Seaver (2012) acknowledges that such experiments can provide some evidence but similarly to the method of anagnorisis they are very limited ‘when it comes to determining what algorithms are like with any specificity’.

Another kind of experiment described by Seaver is A/B Testing or ‘Online Controlled Experiments’. These are permanent experiments that are conducted on users of online services. Seaver argues that ‘A/B testing is now standard for large web companies, and there are even services that algorithmically assess the tests’ results, automatically implementing successful modifications on the fly.’ (Seaver 2014: 6). The same can be said about Google Ad Words or Facebook Audiences, which have A/B tests built into their infrastructure and encourage advertising managers to use them to experiment with their campaigns.

A/B Testing involves sorting users into experimental groups and serving them with different versions of the site/service. As a result, there is no single website/service that all users receive. In simple words: ‘You can’t log into the same Facebook twice.’ (Seaver 2012: 6). In fact, there are millions of different kinds of variation to the service ‘varying from interface design to all sorts of algorithmic detail’. This creates a paradoxical situation - as one tries to experiment on algorithms, they are experimenting on us at the same time. It is impossible to know one’s status relative to the other test groups, hence any kind of generalisation is virtually impossible.

In this study, I encountered a similar problem when studying Twitter Trend Box as a whole, but my problem was caused by the recommendation algorithm rather than A/B testing. The initial tests conducted on different devices using different Twitter accounts showed that Twitter personalises its Trend Box, so one could possibly paraphrase Seaver’s comment about Facebook and say that it is impossible to see the same Trend Box twice. This was a serious methodological issue and I dealt with it by finding different ways of accessing Twitter trends, for example, external applications (described in Chapter Seven) or Twitter API (described in Chapters Eight and Nine).
By doing that I was able to isolate the trends algorithm from the recommendation algorithm. I discuss this in detail in the next section about Twitter Trend Box as the starting point for the analysis.

To sum up: researchers using experiments to study algorithms face two major limitations: personalisation of content and A/B Testing. Indeed, Seaver argues, following Amatriain and Basilico’s notion that “everything is a recommendation” (2012: Online) that it is almost impossible (if not impossible) to abandon the position of a ‘user’ and get an unfiltered perspective. Every move one makes online sends a signal for example to Twitter and potentially could be used by their algorithms for the personalisation of content they are displaying. However, rather than abandoning the position of a user, I went in the opposite direction and spent significant time studying the literature of how users create trends (See Chapter Five) and immersed myself in the platform where I observed the development of trends over the period of almost a decade (see Chapter Seven). The concept of algorithmic ownership is also an attempt to capture this impossibility of having unfiltered perspective - it precisely discusses this fluidity and the ongoing dynamics created by recommendation algorithms.

**Conclusion**

There are two key takeaways from this chapter, which positioned Twitter data in the field of Big Data and laid the groundwork for the study of hashtagability realised through data and Twitter algorithms.

The first one is that due to serious problems with external representativeness of Twitter data, this thesis, apart from the Polish Historical Hashtags Case Study, which will be covered separately in Chapter Seven, will not make any claims about the general population based on its findings. It will focus on ensuring that data is representative from the internal/platform perspective, to be able to study the significance of hashtagability from the user and platform perspective.

The second takeaway concerns the techniques, tools and procedures that are used for data collection and analysis of Twitter data, in particular those that will be used
in the three case studies developed in the following empirical chapters. The chapter specifically:

- Informs the development of data collection methodology for the Historical Polish Trending Hashtags case study (Chapter Seven) by exploring all limitations of Twitter APIs. By discussing methodological problems with sampling and different starting points for the analysis, this chapter helps to develop the discussion about the external representativeness of the collected data. Finally, by exploring other studies that used hashtag length, it establishes that such a metric can be used to determine the typology of trending hashtags and generalise about the behaviour of users.

- Helps to set the stage for the data collection and analysis of General Election 2017 in the UK Case Study (Chapter Eight). It starts a discussion about problems with internal representativeness of data for trending hashtags obtained via REST API, which is an issue that will be empirically tested in Chapter Eight. It also introduces Social Network Analysis and five network properties, which will be used in Chapter Eight, and tested for their capacity to categorise and search for Coordinated Inauthentic Behaviour.

- Introduces Streaming API as a way of accessing Twitter data and discusses its benefit as an increased confidence in internal representativeness. By doing this it informs the design of data collection via Trend Catcher, a tool I developed for live capturing of Trending hashtags. It shows how custom made metrics can be assembled using basic or network metrics, which informs the design of Trend-Catcher data analysis algorithm. Finally, by discussing quantitative approaches to studying algorithms it helps to deconstruct Twitter’s Trending algorithm and redesign the data collection mechanism, so that it captures more relevant data.

This chapter did not cover any specific details of the research design of the case studies that will follow. These will be introduced at the beginning of each of the empirical chapters.

The following two case studies will empirically test concepts and methods described or developed in the first two parts of the thesis. The final Chapter will propose a new data collection and analysis application – Trend Catcher.
Chapter 7: Case Study 1 - Polish Historical Hashtags

Introduction

This chapter investigates changes in how people use hashtags on Twitter to perform different functions as described in Chapter Four. It also explores the connection between new functions and the users who introduce them to Twitter. Finally, it looks at hashtags and their creators to see if their creations can be linked to them in any other way than algorithmic ownership, as described in chapter Four, with a specific focus on the creators of micro-memes trends.

Chapters Three and Four looked at the history and the developments of hashtagability - the potential of hashtags and their users to develop new functions on the platform. The new functions are always introduced by users - Twitter does not even provide any guidance on how to use hashtags, so it is important to establish if these new functions are introduced/performed by a large number of accounts or by relatively small groups of individuals. This is significant because if the latter is the case, it means that a small group of users could have a large impact on Trending Topics and as a result on the agenda of the platform. The chapter then attempts to see if there is a link with between algorithmic ownership of hashtags - the concept developed in Chapter Five, which associates Twitter hashtags with users through an associative, fluid connection generated by Twitter’s recommendation algorithm, and authorship of hashtags.

The chapter develops a strategy for historical data collection using the concept of ‘screened visions’ (Madsen, 2012) and then uses the collected data to analyse the changing functions of hashtags in Poland over the period of ten years using three metrics:

1. The number of trending hashtags per year - this metric aims to indicate the changing functions of hashtags. It shows that the growing number of hashtag functions created a demand for new hashtags rather than reusing the already existing ones, which was the case in the first few years of the analysed period.
It helps to illustrate how the trend creation function significantly increased the number of hashtags that became trends.

2. The length of a trending hashtag is an indicator of the source and type of the trend. Naaman et al (2011) argues that the average length of endogenous (originating on Twitter) hashtags is longer than exogenous (originating outside Twitter) ones. Recuero and Araújo (2012a and 2012b) argue that the majority of coordinated trends are longer than Naturally Occurring ones. By analysing the changing length of hashtags over the period of ten years this study is able to see the impact of endogenous hashtag trends on the Trend box as an agenda setting tool.

3. Author's diversity, which is calculated by dividing the number of trending hashtags created in a given year by the number of unique authors of hashtags in this year, is helpful to understand the connection between the number of trends creators and functions of hashtags and specifically test if micro-memes or other hashtags that can be classified as orchestrated, have relatively fewer authors on average, than hashtags that were created without intent to use them for orchestration.

The analysis of the number of hashtags per year reveals that the use of hashtags in Poland can be divided into three distinctive periods: 2008 (1), 2009 - 2011 (2) and 2012 onwards (3). The first period could be defined as the adoption phase and all hashtags were used exclusively to categorise content. The second period is also characterised by the use of hashtags for categorising, but towards the end of the period users started using hashtags as a comment. The third period shows the radical increase of the use of hashtags as comments or jokes and from 2015 onwards as political micro-memes.

The analysis of hashtag length reveals that the average length of a hashtag in Poland increased twofold between 2008 and 2017 both as the number of letters (from 7.57 to 15.24) and as number of words (from just over 1 to almost 2.5). This is the key finding and indicates that the new functions, especially commenting and political micro-memes which tend to use longer hashtags, are on the rise. This has significant impact on the Twitter Trend box as these hashtags are surfaced by the algorithm based on coordinated effort of unknown authors.
The analysis of hashtag authors diversity revealed that between 2008 and 2014 it was increasing, meaning that more and more users were responsible for creating new trending hashtags. This trend was reversed in 2015 and since then there is a steady decrease in user's diversity, meaning that less and less users were responsible for creating new trending hashtags. This could be linked with the emergence of conversational hashtags and especially orchestrated political memes.

Finally, the comparison of Twitter hashtag authors with their algorithmic owners reveals that hashtag authorship (being the first to use it on the platform) has no connection with the algorithmic ownership of hashtags as defined in Chapter Five.

Although the analysis of types of trending hashtags or their functions in not new as it was shown in Chapters Four and Five, this chapter offers a novel method to conduct such analysis. It helps to explore these changing functions and types from a perspective of time, which adds to the understanding of how typology and functionality of hashtags was shaped by changes in user behaviours (and diversity) over time.

**Functions of hashtags**

This first section outlines how previous studies of hashtags identify characteristics that can be used as metrics for my investigation of changing trends in hashtag use.

As discussed in previous chapters, the most basic function of hashtags is categorisation of content. They help to organise it and make it searchable. Scott (2015) argues that they have also been used to perform other roles (for example highlighting and stylistic) in the communicative process. Huang et al. (2010) describes ‘conversational tagging’ - a practice of using hashtags (mostly micro-memes) with the aim of filtering and directing content so that it appears as the ‘right’ stream rather than simply categorising it for future retrieval. Wikström (2014) describes how hashtags are used as comments or tools for conveying emotions. Hashtags have also been described as tools for creating communities based on shared interests (Boyd, 2007, Booth, 2007, Yang at al. 2012), for example communities created around scientific conferences hashtags (Noon and Ulmer, 2009,
Ebner and Muhlburger, 2010). Finally, Hashtags have also been used as tools for providing context (Scott, 2015).

It is almost impossible to say when these different functions of hashtags started appearing on Twitter. No-one has ever created a timeline and it is likely that any such timeline would differ between countries and languages. It is difficult to say if the additional functions of conversation were a gradual or sudden process. However, their appearance might be gauged by considering word length. For example, the role of conversational hashtags (micro-memes) is to encourage users to engage with them and because of that they are likely to be longer than hashtags used to categorise content as they need to contain more information. When one is categorising, usually one word is enough i.e. #scandal or #blame but when one is encouraging someone to do something or respond, usually more words are necessary i.e. #AVeryEnglishScandal #IBlameItOn.

Greater length is also typical of hashtags used by fan communities. Fans generally try to include an entire message in the body of the hashtag, so there is no need to go anywhere else to understand the meaning i.e. #WELOVEYOUVLADI or #HappyAnniversaryLarry. This practice of including the entire sentence in one hashtag automatically makes these hashtags longer. Similarly, people using hashtags as comments or tools for providing context, do not need to worry about the length of their hashtag as it only works in the context of a single tweet and the clickability and searchability are not important. As a result, it does not matter if someone can remember the entire comment (i.e. #Iwouldratherhaveamoose or #toomuchfaketan) or the exact spelling (i.e. #jeeesus or #maaaan) and these hashtags can be longer. All the usual rules, as described in the etiquette of hashtags (Chapter Four), do not apply for most functions other than categorising as their users are not categorising for future retrieval, making sure the post appears in the right search stream; they are commenting and contextualising so that the hashtag is written to make sense in a single post rather than in search results. As a result, these hashtags can be more fun, more witty and most importantly - they tend to be longer. Not only the words used as hashtags can be longer but also there can be more words included in a single hashtag.

Finally, the new functions of hashtags increase the number of hashtags that originate on Twitter (endogenous hashtags), for example hashtag memes or comments in
comparison to these that are created in a direct response to external events (exogenous hashtags) for example news or TV debates. This is worth studying as Twitter native hashtags do not usually encourage debate as is the case with trending hashtags that are backchannels for TV news programmes e.g. #BBCQT or #Leaders Debate, but already offer the answer, for example #MakeJuneTheEndofMay, #WinForCorbyn or #CurseDominicRaab. By offering the answer in the hashtag, they use the Trend Box as a promotional space for political or marketing gains and by doing that they set the agenda on the platform.

Method and sampling

Historical research is a necessary method of exploring changing trends in hashtags use over the years. In order to collect representative, historical data about hashtags use one needs to go back to the second half of 2007, when the first hashtags were used on Twitter. This is problematic as there are no available archives that go back that far in time. Another problem is data representativeness. Since their creation in 2007 hashtags have become a global phenomenon, which means that millions of them are in use. This chapter develops a novel method of collecting historical hashtags data by using the third-party trends archive (Trendinalia) to identify trending hashtags and then searching for their first use directly on the platform. This two-stage process (identification of trends using available trend archives) and then finding their first use allowed me to ‘go back in time’ as far as 2008.

The sample analysed in this chapter consists of 2124 hashtags that were trending on Twitter in Poland between 18 October 2014 and 14 August 2017. After performing Twitter search for their first use, I extended this period by six additional years. As a result, the sample covers the period between 22 January 2008 and 14 August 2017. Almost half (1052) of these hashtags were created (used for the first time) between 22 January 2008 and 18 October 2014 and the remaining 1072 between 18 October 2014 and 14 August 2017.

The distribution of hashtags over the years shows some significant variations. The year with the fewest collected hashtags was 2008 (35 hashtags) and the highest number of collected hashtags was in 2016 (381). The average number of unique hashtags per year in the entire dataset is 212. Finally, it is important to note that the dataset covers only eight and a half months of 2017.
The next section describes methodological issues faced by this data collection approach and sampling strategy.

**Polish language trending hashtags**

Chapter Three described how hashtags are used differently by people who speak different languages or live in different countries. For example, in languages that have many cases (i.e. German has four) users often use these different cases to describe the same concept which from the technical point of view creates many different hashtags. This problem does not exist in English language, which only has one case. However because of its global reach English is not ideal for this type of the study, as it is very likely that people in South Africa adopted different functions of hashtags at different times than people in the UK or the US, hence the results collected for English language, without specifying the country, would be incomparable. Ideally the selected country and language have to be isolated from English hashtags but at the same time Twitter as a platform has to be popular enough to make the results representative (for that country).

After looking at three options: German, Russian and Polish, the decision was made to analyse Polish hashtags. The problem with German and Russian, methodologically speaking, was that both these languages are also used outside of their countries. German is used in Austria and parts of Switzerland and Russian is widely used in former soviet republics from Kazakhstan in Central Asia to Estonia and Latvia in the Baltics. The language might be the same but the way people use hashtags in different countries might be very different and I was unable to isolate countries from the language. The Polish language is ideal because of its isolation. It is used predominantly in Poland and if used in other countries with significant Polish minorities such as Germany, UK or US its user base is not strong enough to generate Twitter trends in these countries. Finally, Twitter is relatively popular in Poland and was adopted by Polish users as early as in 2007. Data about current Twitter penetration varies between 16 to 28%62,63 of the population.

Trend archives

Twitter does not have its own archive of historical trends. It only shows Trends that are trending at the moment. Also, as was argued in Chapter Four, all Twitter Trending Topics, when accessed via Twitter are personalised for each user making this list dependent on a specific user’s location or interests. No-one can get the full visibility of all Twitter trends for even a day using Twitter. It is only possible via third party services (e.g. Trends24.in, Trending-UK.com, Trendinalia.com or Trendogate.com) that connect to Twitter via API, collect data about trends on a daily basis and create Trend archives. They capture both hashtags and non-hashtags trends which are surfaced by the Twitter trend algorithms and then present them without any personalisation as lists or maps (e.g. Trendsmap.com). They usually do it for the entire world, that is then divided into countries (i.e. the UK or the US) and most countries are divided into regions (i.e. London, Coventry or Glasgow) making it possible to track trends for either a country or a city.

This chapter uses the Trendinalia.com Twitter Trends archive as the main source for archival trends and Trendogate as a backup list for days that Trendinalia data was not available. Trendinalia’s archive for Polish trends starts from 18 October 2014. Its list of available trends is the most comprehensive and it not only includes national trends but also local ones for all Polish cities. It also has the most accessible format. A simple click on the trend takes the user directly to Twitter search results for that hashtag on Twitter, which helps to save time.

The Trendinalia archive of daily Twitter trends is presented as a list of trends ordered by the total time they were detected as trending on a specific day. For example, the table 7 below presents the list of top 10 of trending topics in Poland on 18 October 2014 - the first date for which trends for Poland are available on the service64.

64 http://www.trendinalia.com/twitter-trending-topics/poland/poland-141018.html
**Table 7: Top 10 of trending topics in Poland on 18 October 2014 as generated by Trendinalia**

<table>
<thead>
<tr>
<th>Trend</th>
<th>Time (HH:MM)</th>
</tr>
</thead>
<tbody>
<tr>
<td>#TwitterowiczeNa6Obcy</td>
<td>22:20</td>
</tr>
<tr>
<td>Warszawie</td>
<td>20:15</td>
</tr>
<tr>
<td>#Kryptonite</td>
<td>19:10</td>
</tr>
<tr>
<td>#WeWantZaynsSongsInFOUR</td>
<td>12:20</td>
</tr>
<tr>
<td>Rosji</td>
<td>12:05</td>
</tr>
<tr>
<td>XDXD</td>
<td>11:55</td>
</tr>
<tr>
<td>Poland</td>
<td>11:15</td>
</tr>
<tr>
<td>#szkoła</td>
<td>11:05</td>
</tr>
<tr>
<td>Zayna</td>
<td>10:40</td>
</tr>
<tr>
<td>Dzień Dobry</td>
<td>09:40</td>
</tr>
</tbody>
</table>

On this day Trendinalia detected 45 trends in total, out of which 14 were hashtags. The top trend was ‘#TwitterowiczeNa6Obcy’ which was trending for 22hrs and 20 minutes. This was followed by a trend 'Warszawie’ which trended for 20hrs and 15 minutes. The interesting observation about non-hashtag trends for Poland is that in languages that have many cases (Polish has 7 cases), hashtags are much more likely to trend than none-hashtags because the latter ones could be cannibalising each other by having many versions of the same word. This problem of languages that have many cases was discussed in Chapters Two and Three. The following example shows how this problem presents itself in practice.

On 18 October 2014 in Poland the name of the Polish capital Warsaw (Warszawa in Polish) showed as a trend three times as: 'Warszawie' (20:15), 'Warszawy' (03:05) and 'Wawie' (02:15) and none of these is nominative case. ‘Warszawie’ which was trending for more than 20 hours is in locative case, ‘Warszawy’ is in genitive case and ‘Wawie’ is an abbreviation in locative case. There are also examples of two different spellings of the teenage singer Zayn Malik’s name. The first one is ‘Zayna’ and the second is ‘Zayn’a’. They are both in genitive cases but the second one is with the apostrophe. There were also two separate trends for ‘Tottenham’ (nominative case) and ‘Tottenhamu’ (genitive case) and for ‘Wrocławiu’ (locative case) and ‘Wrocławia’ (genitive case) used in discussions about the Polish city of Wroclaw. In comparison,
hashtags are much more likely to trend as they only come in one case, most of the time Nominative. The table 8 below presents the list of trending topics generated by Trendinalia for the same day in Poland but includes hashtags only. Similarly, to the previous table #TwitterowiczeNa6Obcy was the most popular trend but it was followed by #Kryptonite, which was trending for 19 hours and 10 minutes.

<table>
<thead>
<tr>
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<tbody>
<tr>
<td>#TwitterowiczeNa6Obcy</td>
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</tr>
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<td>#WeWantZaynsSongsInFOUR</td>
<td>12:20</td>
</tr>
<tr>
<td>#szkoła</td>
<td>11:05</td>
</tr>
<tr>
<td>#EMABiggestFansJustinBieber</td>
<td>06:15</td>
</tr>
<tr>
<td>#EMABiggestFansJustinBieber</td>
<td>05:45</td>
</tr>
<tr>
<td>#MarsComeToPoland</td>
<td>05:35</td>
</tr>
<tr>
<td>#MCITOT</td>
<td>03:50</td>
</tr>
<tr>
<td>#thevoiceofpoland</td>
<td>03:30</td>
</tr>
<tr>
<td>#epokalodowcowa</td>
<td>03:25</td>
</tr>
<tr>
<td>#wywiadztwitterowiczami</td>
<td>02:00</td>
</tr>
<tr>
<td>#21JumpStreet</td>
<td>01:45</td>
</tr>
<tr>
<td>#rozmowywtoku</td>
<td>00:10</td>
</tr>
<tr>
<td>#twojatwarzbrzmiznajomo</td>
<td>00:05</td>
</tr>
</tbody>
</table>

Table 8: the list of trending topics generated by Trendinalia for 18 October 2014 in Poland

**Sampling strategy**

Trendinalia’s archive contained Twitter Trends for 1032 days between 18 October 2014 and 14 August 2017. On average, there were about 125 trends each day of which 50 (40%) were trending hashtags, giving a total of almost 50,000 hashtags in the analysed period. From that number, all hashtags not originating in Poland (the majority of these were in English) were removed as the aim was to focus on changes in hashtag use by Polish users. These were mostly global fan hashtags or international sport hashtags. No data about the percentage of sport hashtags was recorded but Lee at al. (2011) claims that sport hashtags are responsible for almost
20% of the trends. Some hashtags in English were kept as they originated in Poland. For example, #EUROWAW2017 was first used by the Polish Parliament and #CEEInnovatorssummit was used by the Polish NGO to promote an international meeting taking place in Warsaw. Finally, there were some hashtags that were in English but which were paraphrases of international trends. For example, the hashtag #MakePolandPiSlessAgain is a paraphrase of Donald Trump’s ‘Make America Great Again’. In the Polish version ‘Great’ was replaced with ‘PiSless’, where PiS is an abbreviation for the Polish ruling party Prawo i Sprawiedliwość (Law and Justice). All such hashtags were kept and analysed.

Table 9 shows the distribution of Polish, English and International sports hashtags for all trending hashtags in Poland on 18 October 2014 as generated by Trendinalia. Hashtags highlighted in green were included in the dataset as Polish hashtags for example #szkoła or #epokalodowcowa. Hashtag #thevoiceofpoland was included as well as an example of a hashtag that is in English but originates in Poland as a name of a Polish TV show. All hashtags highlighted in red were not included in the dataset as they were either in English i.e. #MarsComeToPoland or were international sport hashtags i.e. #MCITOT (Manchester City vs. Tottenham).

<table>
<thead>
<tr>
<th>Trend</th>
<th>Time (HH:MM)</th>
<th>Language</th>
</tr>
</thead>
<tbody>
<tr>
<td>#TwitterowiczeNa6Obcy</td>
<td>22:20</td>
<td>PL</td>
</tr>
<tr>
<td>#Kryptonite</td>
<td>19:10</td>
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</tr>
<tr>
<td>#WeWantZaynsSongsInFOUR</td>
<td>12:20</td>
<td>ENG</td>
</tr>
<tr>
<td>#szkoła</td>
<td>11:05</td>
<td>PL</td>
</tr>
<tr>
<td>#EMABiggestFansJustinBieber</td>
<td>06:15</td>
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</tr>
<tr>
<td>#EMABiggestFansJustinBieber</td>
<td>05:45</td>
<td>ENG</td>
</tr>
<tr>
<td>#MarsComeToPoland</td>
<td>05:35</td>
<td>ENG</td>
</tr>
<tr>
<td>#MCITOT</td>
<td>03:50</td>
<td>INT</td>
</tr>
<tr>
<td>#thevoiceofpoland</td>
<td>03:30</td>
<td>ENG (PL)</td>
</tr>
<tr>
<td>#epokalodowcowa</td>
<td>03:25</td>
<td>PL</td>
</tr>
<tr>
<td>#wywiadztwitterowiczami</td>
<td>02:00</td>
<td>PL</td>
</tr>
<tr>
<td>#21JumpStreet</td>
<td>01:45</td>
<td>ENG</td>
</tr>
<tr>
<td>#rozmowywtoku</td>
<td>00:10</td>
<td>PL</td>
</tr>
<tr>
<td>#twojatwarzbrzmiznajomo</td>
<td>00:05</td>
<td>PL</td>
</tr>
</tbody>
</table>

Table 9: the distribution of Polish, English and International sports hashtags for all trending hashtags in Poland on 18 October 2014 as generated by Trendinalia
The archive also revealed that Trending Topics have a large number of recurring hashtag trends. For example, #piątunio, the Polish equivalent of #FridayFeeling hashtag in the English-speaking world, was a trend almost every single Friday throughout the entire 1032 day period. In total that was more than 100 weekly occurrences. This was counted only once because the aim was to identify changing uses. Another example is #miesięcznica (monthly meetings) hashtag used to commemorate the death of the Polish president in a plane crash in Smolensk in 2010. There is a group of people who meet every month to commemorate this event and a group of people who oppose it. As a result, #miesięcznica becomes trending every single month, sometimes even for a few days in a row (before and after the event). If that happens every month for almost 3 years, it appears as a trending hashtag on 100-200 days but only makes one appearance in the dataset.

Finally, there were numerous TV trending hashtags that were used as backchannels for an online discussion about news i.e. #wtylewizji, #wartorozmawiac or #minela20. Some of these are daily TV programmes and create short trends on a daily basis. This seems to confirm the findings of Asur et al (2011) and Kwak et al. (2010) who argue that the majority (in their sample it was over 85%) of trending topics are news. In the Polish trends archive the most popular TV hashtags were trends on more than 400 days during the 1032 days of collection period. There are also many examples of hashtags that are simply titles of popular TV series or shows which trend regularly on weekly or daily basis i.e. #nadobreinazle. In the dataset I created all the trends that occur daily or weekly are reduced to just a single record - their first use and the person who used them for the first time.

**Data collection strategy**

As a result of the above sampling strategy, the 50,000 original hashtags were reduced to 2124, giving an average of just over two new and original trends per day between 18 October 2014 and 14 August 2017.

After developing this data sampling strategy, a data collection method was developed to identify the first use of all 2124 trending hashtags and their authors. Applying Madsen’s (2012) theory of ‘screened visions’ (discussed in Chapter Five)
the Trendinalia archive became my Myopic vision - a list of clickable links ranked according to specific criteria of relevance (by the total time they were trending in a given day). Once I followed the link it opened my hyperopic vision in a form of Twitter search results. As Madsen (2012) observes, myopic vision is largely an effect of the delineation device (in this case Trendinalia platform) and 'hyperopic vision' is more dependent on the researcher - it is an effect of the way the researcher operationalises the device. In this case, hyperopic vision involved finding the very first instance (the actual first tweet containing a given hashtag) a hashtag was used on Twitter and the author. It was an extremely time-consuming process as it involved searching for a hashtag using Twitter's interface, using 'latest tweets' filter, and scrolling down until I got to the latest tweet in the entire list and the author.

The process took seven months between mid-January and mid-August 2017, which gives an average rate of 300 hashtags per month. For each of these hashtags Twitter search results were analysed using Twitter web interface (hyperopic vision) in order to find the first post that includes the hashtag. For some hashtags, especially those that were extremely popular or those that were first used back in 2008 or 2009, this process sometimes took more than 20 minutes. On average, it was possible to find the first use of a hashtag and make a note of the date and the author in about 10 minutes. In total it took almost 350 hours, just below 50 hours per month.

The Dataset

The data collection strategy described above allowed me to expand the period from just under three years between 18 October 2014 and 14 August 2017 of the myopic vision to just under a decade in hyperopic vision. The oldest identified hashtag #szkola (#school) was first used on 22 January 2008 and the most recent one #Rytel (name of the town in Poland) was used on 14 August 2017. This expansion of the period under study was possible because almost half (1052) of hashtags that were trending between 2014 and 2017 were in fact created between 2008 and 18 October 2014, which was the first day of available trends in the Trendinalia's archive.

Once all 2124 hashtags with their authors and the dates when they were created were entered into a Google Spreadsheet, all hashtags were ordered by the creation
date from the oldest to the most recent one. The dataset was divided into ten separate years and the number of unique hashtags was calculated for each year. In the next stage =LEN formula was used to automatically calculate the number of letters for each hashtag in the dataset. The # sign was included in the letter count for each hashtag for example #Eurowizja was counted as 10 letters and #dom as 4. Then the average number of letters per hashtag was calculated for each year using the =AVERAGE formula. The minimum (4), maximum (31), the average (13.397) and the median (13) number of letters for the entire dataset were then calculated (see Table 10 below) and the column chart (See Figure 39 below) was generated to check the distribution of the lengths of hashtags.

<table>
<thead>
<tr>
<th>Number of letters</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Min</td>
<td>4</td>
</tr>
<tr>
<td>Max</td>
<td>31</td>
</tr>
<tr>
<td>Average</td>
<td>13.397</td>
</tr>
<tr>
<td>Median</td>
<td>13</td>
</tr>
</tbody>
</table>

*Table 10: The minimum, maximum, the average and the median number of letters for the Polish Hashtags dataset*

*Figure 39: The distribution of lengths of hashtags in the Polish hashtags dataset*
The chart above shows a normal, bell shaped distribution of the number of letters per hashtag with a positive skew, which indicates that the tail on the right side is longer than the left side. The shortest hashtags in the dataset contain 4 letters and these were #dom (#home) #Żyd (#Jew) and #ŚDM (abbreviation for WorldYouthDay). The longest hashtag in the dataset contains 31 letters: #ObywatelskieWarmińskoMazurskie (the name of a political meeting taking place in one of the regions in Poland).

In the next stage of analysis, the number of words per hashtag were counted manually by following the specially developed procedure:

- All abbreviations were treated as one word. For example, hashtags #pzpn, which is the abbreviation for Polski Związek Piłki Nożnej (The Polish Football Association) or #JPII (abbreviation for John Paul II) were both treated as one word.
- If the abbreviation contained a number i.e. #TVN24 it was treated as one word as well.
- If a hashtag contained a full word and a number e.g. example #4czerwca (#4thJune) or #Oscary2010 (#Oscars2010), these were treated as two separate words.
- All particles such as ‘i’ (‘and’) or ‘w’ (‘in’) were treated as separate words. For example #PrawoiSprawiedliwość (#LawAndJustice) was counted as 3 separate words: Prawo(1) i(2) Sprawiedliwość(3).

The counting was performed independently by four Polish language speakers. The results were compared in order to find and correct any differences in counting. Once the final number was agreed, the average number of words for each year was calculated automatically using the =AVERAGE formula. Finally, the minimum (1), maximum (6), the average (2.05) and the median (2) number of words per hashtag for the entire dataset were calculated (see table 11 below) and the column chart (See Figure 40) was generated to check the distribution of the number of words per hashtags.

<table>
<thead>
<tr>
<th>Number of words</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Min</td>
<td>1</td>
</tr>
<tr>
<td>Max</td>
<td>6</td>
</tr>
</tbody>
</table>
Table 11: the minimum, maximum, the average and the median number of words per hashtag for the Polish Hashtags Dataset

<table>
<thead>
<tr>
<th>Year</th>
<th>Number of unique hashtags</th>
<th>Average number of letters</th>
<th>Average number of words</th>
<th># of unique authors</th>
<th>hashtags per author</th>
</tr>
</thead>
<tbody>
<tr>
<td>2008</td>
<td>35</td>
<td>7.57</td>
<td>1.06</td>
<td>12</td>
<td>2.92</td>
</tr>
<tr>
<td>2009</td>
<td>241</td>
<td>9.18</td>
<td>1.2</td>
<td>144</td>
<td>1.67</td>
</tr>
<tr>
<td>2010</td>
<td>193</td>
<td>11.52</td>
<td>1.55</td>
<td>132</td>
<td>1.46</td>
</tr>
<tr>
<td>2011</td>
<td>123</td>
<td>12.68</td>
<td>1.91</td>
<td>96</td>
<td>1.28</td>
</tr>
<tr>
<td>2012</td>
<td>166</td>
<td>13.69</td>
<td>2.14</td>
<td>144</td>
<td>1.15</td>
</tr>
<tr>
<td>2013</td>
<td>180</td>
<td>13.48</td>
<td>2.03</td>
<td>165</td>
<td>1.09</td>
</tr>
</tbody>
</table>

Figure 40: the distribution of the number of words per hashtags in the Polish Hashtags dataset

The chart above shows a normal, bell shaped distribution of the number of words per hashtag with a positive skew, which indicates that the tail on the right side is longer than the left side.

Finally, the unique number of hashtag authors was calculated for each year using =COUNTUNIQUE formula. Once all the calculations were performed the results were transferred to a single table (see Table 12 below) and the final column (hashtags per author) was added to show the diversity of authors. It was generated by dividing the number of unique hashtags (the second column) by the number of unique authors (the fourth column) for each year.
<table>
<thead>
<tr>
<th>Year</th>
<th>Hashtags</th>
<th>Average Letters</th>
<th>Average Words</th>
<th>Users</th>
<th>Average Hashtags</th>
</tr>
</thead>
<tbody>
<tr>
<td>2014</td>
<td>141</td>
<td>13.91</td>
<td>2.16</td>
<td>136</td>
<td>1.04</td>
</tr>
<tr>
<td>2015</td>
<td>293</td>
<td>14.52</td>
<td>2.28</td>
<td>269</td>
<td>1.09</td>
</tr>
<tr>
<td>2016</td>
<td>381</td>
<td>14.82</td>
<td>2.36</td>
<td>302</td>
<td>1.26</td>
</tr>
<tr>
<td>2017</td>
<td>371</td>
<td>15.24</td>
<td>2.44</td>
<td>282</td>
<td>1.32</td>
</tr>
<tr>
<td>TOTAL</td>
<td>2124</td>
<td>13.397</td>
<td>2.05</td>
<td>1682</td>
<td>1.26</td>
</tr>
</tbody>
</table>

*Table 12: The data summary table for the Polish Hashtags Dataset*

The last row in the table above shows that the dataset contains 2124 unique hashtags created by the 1682 unique users, meaning that on average a single user created 1.26 hashtags. The average number of letters in a single hashtag in the dataset is 13.397 and the average number of words is 2.05.

## Findings and Analysis

### The number of unique hashtags per year

Table 13 and Figure 41 illustrate the distribution of the number of hashtags collected for each year. No hashtags were detected for 2007 - the year when hashtags were first introduced on Twitter (in August 2007) by Chris Messina. It is very likely that hardly any (if any at all) hashtags were used in Polish language this year. Most of the hashtags used in 2008, were created by a very small number of users; in fact, 14 out of 17 Polish hashtags that were created in the first half of 2008, were generated by a single user. The oldest Polish hashtag #szkola (#school) identified in the dataset was used 3 months after #sandiegofire on 22 January 2008.

The distribution of hashtags over the years shows some significant variations. The year with the fewest collected hashtags was 2008 (35 hashtags) and the highest number of collected hashtags was in 2016 (381). It needs to be noted that the difference between 2016 and 2017 is very low - 381 in 2016 and 371 hashtags in 2017 but the dataset covers full 12 months of 2016 and only 8 and a half months of 2017. The average number of unique hashtags per year is 212. After a major increase
in the number of hashtags from 2008 to 2009, the number of unique, newly created hashtags started dropping in 2010 and 2011. Then in 2012 the trend changed and with the exception of 2014, the number of newly created hashtags started growing again.

<table>
<thead>
<tr>
<th>Year</th>
<th># of unique hashtags</th>
</tr>
</thead>
<tbody>
<tr>
<td>2008</td>
<td>35</td>
</tr>
<tr>
<td>2009</td>
<td>241</td>
</tr>
<tr>
<td>2010</td>
<td>193</td>
</tr>
<tr>
<td>2011</td>
<td>123</td>
</tr>
<tr>
<td>2012</td>
<td>166</td>
</tr>
<tr>
<td>2013</td>
<td>180</td>
</tr>
<tr>
<td>2014</td>
<td>141</td>
</tr>
<tr>
<td>2015</td>
<td>293</td>
</tr>
<tr>
<td>2016</td>
<td>381</td>
</tr>
<tr>
<td>2017</td>
<td>371</td>
</tr>
</tbody>
</table>

*Table 13: the distribution of the number of hashtags collected for each year in Poland*

*Figure 41: the distribution of the number of hashtags collected for each year in Poland (graph)*
The distribution of hashtags over the years can be divided into 3 periods: 2008, 2009-2011 and 2012 - 2017, which are described below with the qualitative analysis of the most prominent functions hashtags perform.

**2008: The adoption - categorising phase**

Only 35 new hashtags were detected in 2008. During this year hashtags were not an official feature of Twitter and were most likely used by early adopters of both hashtags and Twitter as a platform.

Table 14 below presents all 35 hashtags collected for 2008. They are divided into simple categories based on what they describe. 37% of these hashtags are very general categories that describe things that people use or experience everyday i.e. (#szkola) #school, (#pogoda) #weather or (#kawa) #coffee. 5 out of 35 are linked to TV or news i.e. (#Milionerzy) #Millionaires. There is one hashtag describing a well-known Polish celebrity - #Kubawojewódzki. The most interesting hashtags describe locations. There is #Polska (#Poland), Polish capital #Warszawa (#Warsaw), all major Polish cities such as #Wrocław, #Kraków or #Poznan and finally the main Polish river #Wisła (#Vistula). It looks as if the early users were putting these Polish places on the Twitter map.

<table>
<thead>
<tr>
<th>Hashtag</th>
<th>Translation</th>
<th>First use</th>
<th>Category</th>
</tr>
</thead>
<tbody>
<tr>
<td>#Szkola</td>
<td>#School</td>
<td>22/01/2008</td>
<td>General</td>
</tr>
<tr>
<td>#Autobus</td>
<td>#Bus</td>
<td>22/01/2008</td>
<td>General</td>
</tr>
<tr>
<td>#Pogoda</td>
<td>#Weather</td>
<td>22/01/2008</td>
<td>General</td>
</tr>
<tr>
<td>#Kawa</td>
<td>#Coffee</td>
<td>23/01/2008</td>
<td>General</td>
</tr>
<tr>
<td>#Dobranoc</td>
<td>#GoodNight</td>
<td>23/01/2008</td>
<td>General</td>
</tr>
<tr>
<td>#Dom</td>
<td>#House</td>
<td>23/01/2008</td>
<td>General</td>
</tr>
<tr>
<td>#Milionerzy</td>
<td>#Millionaires</td>
<td>02/02/2008</td>
<td>TV</td>
</tr>
<tr>
<td>#Wrocław</td>
<td>#Wroclaw</td>
<td>02/03/2008</td>
<td>City</td>
</tr>
<tr>
<td>#Kolacja</td>
<td>#Supper</td>
<td>26/03/2008</td>
<td>General</td>
</tr>
<tr>
<td>#Snieg</td>
<td>#Snow</td>
<td>28/03/2008</td>
<td>General</td>
</tr>
<tr>
<td>#Ranczo</td>
<td>#Ranch</td>
<td>14/04/2008</td>
<td>TV</td>
</tr>
</tbody>
</table>
Another interesting fact about these 35 hashtags is that only two of them are built of 2 words #KubaWojewódzki and #DzieńDziecka (#ChildrensDay). The remaining 33 are single words or abbreviations. None of these are conversational, comments or contextualising hashtags. They all describe places, people, TV programmes or entities that exist in the real world. There are no abstract hashtags. They are all very strongly linked to the real world.

Another interesting observation is how users negotiate the fact that the Polish language was not supported by Twitter in 2008 (some letters were not recognized). It is also interesting to see how these early users dealt with the fact that the Polish

<p>| | | | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>12</td>
<td>#Obiad</td>
<td>#Dinner</td>
<td>26/04/2008</td>
<td>General</td>
</tr>
<tr>
<td>13</td>
<td>#Eurowizja</td>
<td>#Eurovision</td>
<td>24/05/2008</td>
<td>TV</td>
</tr>
<tr>
<td>14</td>
<td>#KubaWojewódzki</td>
<td>#KubaWojewódzki</td>
<td>27/05/2008</td>
<td>Celebrity</td>
</tr>
<tr>
<td>15</td>
<td>#DzieńDziecka</td>
<td>#ChildrensDay</td>
<td>01/06/2008</td>
<td>Date</td>
</tr>
<tr>
<td>16</td>
<td>#Poznań</td>
<td>#Poznań</td>
<td>18/06/2008</td>
<td>City</td>
</tr>
<tr>
<td>17</td>
<td>#Warszawa</td>
<td>#Warsaw</td>
<td>20/06/2008</td>
<td>City</td>
</tr>
<tr>
<td>18</td>
<td>#Nauka</td>
<td>#Science</td>
<td>06/07/2008</td>
<td>General</td>
</tr>
<tr>
<td>19</td>
<td>#TVN24</td>
<td>#TVN24</td>
<td>24/07/2008</td>
<td>News</td>
</tr>
<tr>
<td>20</td>
<td>#Kraków</td>
<td>#Kraków</td>
<td>28/07/2008</td>
<td>City</td>
</tr>
<tr>
<td>21</td>
<td>#Wisła</td>
<td>#Wisła</td>
<td>30/07/2008</td>
<td>River</td>
</tr>
<tr>
<td>22</td>
<td>#Legia</td>
<td>#Legia</td>
<td>31/07/2008</td>
<td>Sport</td>
</tr>
<tr>
<td>23</td>
<td>#Burza</td>
<td>#Thunderstorm</td>
<td>04/08/2008</td>
<td>General</td>
</tr>
<tr>
<td>24</td>
<td>#Poniedziałek</td>
<td>#Monday</td>
<td>07/08/2008</td>
<td>General</td>
</tr>
<tr>
<td>25</td>
<td>#Praca</td>
<td>#Work</td>
<td>11/08/2008</td>
<td>General</td>
</tr>
<tr>
<td>26</td>
<td>#Gdańsk</td>
<td>#Gdańsk</td>
<td>31/08/2008</td>
<td>City</td>
</tr>
<tr>
<td>27</td>
<td>#Mecz</td>
<td>#Match</td>
<td>06/09/2008</td>
<td>Sport</td>
</tr>
<tr>
<td>28</td>
<td>#Kubica</td>
<td>#Kubica</td>
<td>28/09/2008</td>
<td>Sport</td>
</tr>
<tr>
<td>29</td>
<td>#GazetaPl</td>
<td>#GazetaPl</td>
<td>29/09/2008</td>
<td>News</td>
</tr>
<tr>
<td>30</td>
<td>#PZPN</td>
<td>#PZPN</td>
<td>31/10/2008</td>
<td>Sport</td>
</tr>
<tr>
<td>31</td>
<td>#Polska</td>
<td>#Poland</td>
<td>25/11/2008</td>
<td>Country</td>
</tr>
<tr>
<td>32</td>
<td>#Japonia</td>
<td>#Japan</td>
<td>04/12/2008</td>
<td>Country</td>
</tr>
<tr>
<td>33</td>
<td>#Wigilia</td>
<td>#Wigilia</td>
<td>22/12/2008</td>
<td>Date</td>
</tr>
<tr>
<td>34</td>
<td>#Łódź</td>
<td>#Łódź</td>
<td>23/12/2008</td>
<td>City</td>
</tr>
<tr>
<td>35</td>
<td>#Gdynia</td>
<td>#Gdynia</td>
<td>30/12/2008</td>
<td>City</td>
</tr>
</tbody>
</table>

Table 14: The categorisation of 35 hashtags collected for 2008 in the Polish Hashtags dataset.
language has 7 cases and while categorising, ideally the nominative case should be used. The figure 42 below shows how the first 6 instances of the oldest Polish hashtag recorded in the dataset - #szkoła (#school) - was used. The first thing that is noticeable is that the Polish letter 'ł' was not recognised by Twitter back in 2008. This is a known problem described by Eden (2010) and discussed in Chapter Three. Because of that #szkoła became #szko and the last two letters 'la' were not treated as a part of the hashtag and did not become a clickable hyperlink when Twitter made hashtags clickable in 2009. Obviously when these posts were written in 2008 that would not make any difference because at that time hashtags were not active links. Interestingly on one occasion (19 May 2008) hashtag #szkola was written without the polish letter 'ł' but with letter 'l' instead and this became the only instance that the entire hashtag was clickable.

Figure 42: Screenshot of tweets illustrating the problem of multiple cases in the Polish language when using hashtags
The above six tweets (Figure 42 above) show how early users dealt with the problem of multiple cases in the Polish language. In the three instances (26 May and twice on 4 June) hashtag #szkoła is not part of the sentence and is clearly used as a label to categorise the preceding text. For example, in ‘wykonuje plakat na plastyke :| #szkoła’ (I am working on a poster for my arts class :| #school) it is used at the end of the tweet and is in the nominative case. The same applies to the other two instances from 4 June. The practice is slightly different with the first two posts (22 January and 19 May) where hashtag #szkola is part of the sentence. It is still used in the nominative case but it could be argued that this is not the best choice for these sentences. The first sentence (22 January) ‘Zaraz trzeba zawijać na #autobus, i #szkoła’ could be translated as: ‘Time to go for a #bus and #school’. The more natural way of saying that would be ‘Time to go for a #bus and get to #school’ which in Polish would be: ‘Zaraz trzeba zawijać na #autobus, i jechać do #szkoły’. If a more conversational and natural language were to be used, a nominative case hashtag #szkoła would change into the genitive case #szkoly. The same applies to the second instance from 19 May. The Polish sentence: ‘ #szkola, znowu pada #pogoda’ (#school, it’s raining again, #weather) would sound much more natural as ‘W #szkole, znowu pada, #pogoda’ (at #school, it’s raining again, #weather). This would change the nominative #szkola into the dative case #szkole.

The problem with multiple cases is most visible in the tweet from 18 June 2008: ‘po ostatnim dniu #szkoła.y :] Jutro tylko po świadectwa’ (The final day of #school :) Tomorrow only diplomas (collection)’. Hashtag #szkola.y is written with several grammatical mistakes and in fact such a word does not exist in the Polish language. The correct word would be #szkoly in the genitive case but the user tried very hard to include the full word in the nominative case #szkoła and then to make it more readable and searchable (and to convert it into the dative case) by adding ‘.y’. As a result the word #szkola.y, which does not exist in the Polish language was created.

All these three examples of either using unnaturally sounding sentences or creating new words to ensure that the word is in the nominative case show that the user was trying to ensure that the hashtag could be used for categorisation. Also, all these first hashtags are very short, usually containing just a single word as shown in table... above. This indicates that this early usage was linked more or less exclusively to the function of categorising content and even when hashtags were used as part of the sentence, rather than a label at the end, the desire to categorise was stronger than...
the need for stylistic correctness. This is confirmed by numerous examples from other users in 2008. Figure 43 below shows how another user used hashtags #kawa (#coffee) in the nominative case even though it should be spelt #kawę in the accusative case (18 August) and hashtag #dom (#home) is followed by .u in order to keep the #dom part in the nominative case and only change it to the dative case by the usage of the dot. All these practices show how early users saw hashtags as tools for categorising content and how they attempted to do everything, even compromising their style of writing, to ensure their hashtags were in the right case for this use.

Figure 43: Screenshot of tweets illustrating the problem of multiple cases in the Polish language when using hashtags

2009-2011: Slow Phase

The second period covers years 2009 - 2011, where after an initial increase in 2009, the number of original hashtags decreases in 2010 and 2011. The possible explanation of the significant increase in the number of original hashtags in 2009 in comparison to 2008 is most likely the fact that in 2009 hashtags became an officially supported feature of Twitter and became clickable links, which gave them more visibility. Also, in 2009 Twitter introduced Trending Topics which apart from promoting popular words or phrases, also featured the most popular hashtags. As a result, hashtags gained more visibility on the platform. The decreasing trend of 2010-2011 could be potentially explained by the reduction of the novelty effect of 2009 but also by the fact that people were simply reusing hashtags already created in 2008 and 2009, so there was no need to create so many new hashtags.
The qualitative analysis of the dataset reveals that almost throughout the entire 2008-2011 period hashtags were used almost entirely for categorising content. The Table 15 below shows the list of hashtags created by @NewsweekPolska - one of the most active users of hashtags during this period. The vast majority of these are proper nouns, surnames of important politicians and journalists or historical dates (anniversaries). The use of hashtags to talk about people shows that these journalists and politicians were not using Twitter during this period, as otherwise they would be referred to using the @ convention, rather than through a hashtag.

<table>
<thead>
<tr>
<th>Hashtag</th>
<th>translation</th>
<th>Date</th>
</tr>
</thead>
<tbody>
<tr>
<td>#morawiecki</td>
<td>#morawiecki</td>
<td>07/05/2009</td>
</tr>
<tr>
<td>#IVRP</td>
<td>#IVRP</td>
<td>15/01/2010</td>
</tr>
<tr>
<td>#OdNowa</td>
<td>#FromTheBeginning</td>
<td>18/01/2010</td>
</tr>
<tr>
<td>#reprivatyzacja</td>
<td>#reprivatisation</td>
<td>19/01/2010</td>
</tr>
<tr>
<td>#schetyna</td>
<td>#schetyna</td>
<td>03/02/2010</td>
</tr>
<tr>
<td>#macierewicz</td>
<td>#macierewicz</td>
<td>23/02/2010</td>
</tr>
<tr>
<td>#uchodzię</td>
<td>#refugees</td>
<td>26/03/2010</td>
</tr>
<tr>
<td>#Waszczykowski</td>
<td>#Waszczykowski</td>
<td>08/04/2010</td>
</tr>
<tr>
<td>#PierwszaDama</td>
<td>#FirstLady</td>
<td>15/04/2010</td>
</tr>
<tr>
<td>#Wasiak</td>
<td>#Wasiak</td>
<td>26/04/2010</td>
</tr>
<tr>
<td>#DzieńFlagi</td>
<td>#FlagsDay</td>
<td>02/05/2010</td>
</tr>
<tr>
<td>#2maja</td>
<td>#2ndMay</td>
<td>02/05/2010</td>
</tr>
<tr>
<td>#Cenckiewicz</td>
<td>#Cenckiewicz</td>
<td>06/07/2010</td>
</tr>
<tr>
<td>#Wenderlich</td>
<td>#Wenderlich</td>
<td>07/07/2010</td>
</tr>
<tr>
<td>#PałacPrezydencki</td>
<td>#PresidentsPalace</td>
<td>20/07/2010</td>
</tr>
<tr>
<td>#NoweHoryzonty</td>
<td>#NewHorizons</td>
<td>23/07/2010</td>
</tr>
<tr>
<td>#śmigłowce</td>
<td>#helicopters</td>
<td>30/07/2010</td>
</tr>
<tr>
<td>#Kszczot</td>
<td>#Kszczot</td>
<td>31/07/2010</td>
</tr>
<tr>
<td>#imigranci</td>
<td>#migrants</td>
<td>11/08/2010</td>
</tr>
<tr>
<td>#Rzepliński</td>
<td>#Rzepliński</td>
<td>13/08/2010</td>
</tr>
<tr>
<td>#Giertych</td>
<td>#Giertych</td>
<td>17/08/2010</td>
</tr>
</tbody>
</table>
The first attempts to use hashtags as a comment or as a joke in the dataset took place in 2011 with #WinaPiS (#BlamePiS - PiS is a Polish political party) used on 04 January 2011 and #PrawicowyRisercz (#RightwingResearch) used on 21 June 2011.
2012-2017: Creative Phase

With each year from 2012, with the exception of 2014, more and more new hashtags were created every year. This change can be explained with the radical increase of the use of hashtags as comments or jokes from 2012. Just a few examples from the first quarter of 2012 include: #BrutalnaPrawda (#BrutalTruth) used on 09 January 2012, #PolskieAbsurdy (#PolishAbsurds) used on 17 January 2012 #NieDaSięUkryć (#ImpossibleToHide) used on 08 March 2012, #arogancjawładzy (#ArrogantGovernment) used on 17 March 2012 or #PRLbis (#PolishPeoplesRepublic2) first used on 30 March 2012. None of these are being used to categorise content. In other words, in 2012 Poles discovered that hashtags could be used as political or non-political comments. Then in 2015 the first political micro-memes start appearing in the dataset: #AndrzejMusisz (19 March 2015), #sekretyKuźniara (20 March 2015) and #ConatoBronek (03 April 2015). The first one in the dataset - #AndrzejMusisz (Andrzej - is the first name of Andrzej Duda - then a candidate to become the President of Poland, and ‘musisz’ means ‘you have to’ or ‘it’s a must’). This was one of the first political micro-memes created two months before the presidential election. It eventually became a trending, conversational hashtag, although it was initially created as a community hashtag used by Duda’s supporters to encourage each other and discuss what needed to be done to help Duda win the election. It became trending on 07 May 2015, three days before the first round of the presidential election and only then became truly conversational, meaning that people would tweet in response to it. It is very likely that it only became trending because of the real-life event (presidential election), a factor exogenous to Twitter. Figure 44 below shows how people created memes in response to it.

---

Please note that the data for 2017 only covers the first 7.5 months of the year.
Figure 44: An example of a political meme created in response to a political hashtag in Poland

#sekretyKuźniara (#KuźniarsSecrets - Kuźniar is the last name of a popular journalist in Poland) created on 20 March 2015 is the first truly conversational micro-meme hashtag detected in the dataset. It started trending just a few hours after it was created. Almost the entire content posted under this hashtag was created in response to it making it what Huang et al. (2010) define as a conversational hashtag.

The fact that the first conversational hashtags start appearing in the dataset only in 2015 illustrates some sampling and methodological issues. As was argued by Huang et al. (2010) and shown with #sekretyKuźniara (#KuźniarsSecrets) conversational hashtags usually start trending on the day they are created, very quickly become popular and then quickly disappear. People simply stop using them and move onto another micro-meme which becomes popular. As a result of this rapid but very short popularity, conversational hashtags usually gain visibility just once for a short time when they become trending. It is different to hashtags used for categorising, commenting or for discussions about TV programmes as these are being constantly reused.

Half of the collected hashtags in the dataset was first used between 22 January 2008 and 17 October 2014. They simply became trending (again) after 18 October 2014 and left that trace in the Trendinalia’s archive. This trace was used to find their first use date. It is different with conversational micro-memes as they usually trend only once. It is possible that some micro-memes became trending before 18 October 2014 and then never trended again afterwards. As a result, they never made it to the Trendimalia archive and it was impossible to retrieve them. It is very likely that the
first conversational micro-memes started appearing some time in 2014 or even 2013 and my data collection strategy did not bring these to the surface. That could be the explanation why there is a decrease in the number of new hashtags in 2014 which goes against the general trend of the annual increasing number of new hashtags that started in 2012. Most likely micro-meme hashtags started appearing in 2014 but the method of data collection used in this study did not include these early examples as they trended only once and it was before 18 October 2014, hence they were never listed in Trendinalia’s archive.

The average number of letters and words

The literature and previous studies as described in Chapter Three and Introduction section, suggest that the average length of hashtags should be increasing with the increasing numbers of endogenous micro-meme trends in recent years. The qualitative analysis of hashtags in the previous section, suggests that around 2014/2015 political micro-memes, originating entirely on Twitter started appearing on Twitter. This section looks at changes in the length of hashtags over the years operationalised as the average number of letters and the average number of words in a hashtag.

The average length of a hashtag in Poland (Figure 45 and Table 16 below) increased twofold between 2008 and 2017 from 7.57 to 15.24 letters on average. The same happened to the average number of words per hashtag (Figure 46 and Table 16 below) which increased from just over 1 to almost 2.5 in the studied decade. This is a key finding; it indicates that hashtagability is a process in which change can be measured using the length of hashtags.

<table>
<thead>
<tr>
<th>Year</th>
<th>Average length (letters)</th>
<th>Rate</th>
<th>Average number of words</th>
<th>Rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>2008</td>
<td>7.57</td>
<td>0.00%</td>
<td>1.06</td>
<td>0.00%</td>
</tr>
<tr>
<td>2009</td>
<td>9.18</td>
<td>21.00%</td>
<td>1.2</td>
<td>13.00%</td>
</tr>
<tr>
<td>2010</td>
<td>11.52</td>
<td>25.00%</td>
<td>1.55</td>
<td>29.00%</td>
</tr>
<tr>
<td>2011</td>
<td>12.68</td>
<td>10.00%</td>
<td>1.91</td>
<td>23.00%</td>
</tr>
<tr>
<td>2012</td>
<td>13.69</td>
<td>8.00%</td>
<td>2.14</td>
<td>12.00%</td>
</tr>
<tr>
<td>Year</td>
<td>Average Letters</td>
<td>Increase (%)</td>
<td>Average Words</td>
<td>Increase (%)</td>
</tr>
<tr>
<td>------</td>
<td>-----------------</td>
<td>--------------</td>
<td>---------------</td>
<td>--------------</td>
</tr>
<tr>
<td>2013</td>
<td>13.48</td>
<td>-2.00%</td>
<td>2.03</td>
<td>-5.00%</td>
</tr>
<tr>
<td>2014</td>
<td>13.91</td>
<td>3.00%</td>
<td>2.16</td>
<td>6.00%</td>
</tr>
<tr>
<td>2015</td>
<td>14.52</td>
<td>4.00%</td>
<td>2.28</td>
<td>5.00%</td>
</tr>
<tr>
<td>2016</td>
<td>14.82</td>
<td>2.00%</td>
<td>2.36</td>
<td>4.00%</td>
</tr>
<tr>
<td>2017</td>
<td>15.24</td>
<td>3.00%</td>
<td>2.44</td>
<td>3.00%</td>
</tr>
</tbody>
</table>

Table 16: The average number of letters and words in Poland per year

The most dramatic increases in the number of letters and words took place between 2008 and 2012 when the average number of letters per hashtags almost doubled from 7.57 to 13.69 and the number of words per hashtag doubled from 1.06 to 2.14. Interestingly between 2009 and 2011, as shown in Figure 40 the average number of newly created hashtags kept decreasing and at the same time the length of hashtags and number of words in a hashtag kept rapidly increasing.

Figure 45: The average length of hashtags (letters) per year in Poland between 2008 and 2017
As the analysis above suggests, until 2011 almost all hashtags were used for categorising content and only after this time did the first commenting hashtags start to appear. This finding, together with the changes in word length just described means that between 2008 and 2011 categorising hashtags were evolving from the general one word labels (on average 1.06 words in 2008) to more specific and longer labels (on average 1.91 words in 2011). It does not mean that users stopped using the short hashtags. It means that the short ones were created earlier and with time people had to create longer hashtags to categorise more and more objects from the real life i.e. #StadionNarodowy (#NationalStadium) or #ArmiaKrajowa (#HomeArmy). This is illustrated well by the comparison of Table 14 presenting hashtags created in 2008 and Table 15 showing hashtags created by Newsweek Poland mostly between 2009 and 2012. In both these tables all hashtags are used for categorising but their length (number of letters and number or words) are significantly different. In 2008 the average number of letters in a hashtag was 7.57 and it contained on average 1.06 words. The categorising hashtags created by Newsweek Poland between 2009 and 2012 had on average 13.05 letters and just over 2 words (2.04).
The small dip in 2013 in the increasing trend could be explained by the possible problem with sampling described in the previous section. It is quite likely that the first conversational hashtags (political memes) started appearing in 2013 and 2014 but because of their nature (they are being used only once rather than reused as is the case with categorising hashtags) they never made it to the dataset. Nevertheless 2013 is just a small dip (2% decrease in the average number of letters and 5% decrease in the average number of words as per Table 16 above) and the general trend over the 10-year period is clearly increasing.

The period from 2015 onwards is dominated by political memes. The comparison of two tables: hashtags created by Newsweek Poland between 2009 and 2012 (Table 15) and table of hashtags created by @AlonZoMourning1 between May 2015 and May 2017 (Table 17 below) shows this qualitative difference.

<table>
<thead>
<tr>
<th>Hashtag</th>
<th>English</th>
<th>Date</th>
</tr>
</thead>
<tbody>
<tr>
<td>#sekretyBronka</td>
<td>#BroneksSecret</td>
<td>22/05/2015</td>
</tr>
<tr>
<td>#apeleTuska</td>
<td>#TusksAppeal</td>
<td>03/03/2016</td>
</tr>
<tr>
<td>#miastaPetru</td>
<td>#PetrusCities</td>
<td>17/03/2016</td>
</tr>
<tr>
<td>#TrybunałyPetru</td>
<td>#PetrusTribunals</td>
<td>25/03/2016</td>
</tr>
<tr>
<td>#niespotkaObamy</td>
<td>#WontMeetObama</td>
<td>29/03/2016</td>
</tr>
<tr>
<td>#końskeeprzysłowia</td>
<td>#HorsesSayings</td>
<td>07/04/2016</td>
</tr>
<tr>
<td>#OdliczaniePetru</td>
<td>#PetrusCountdown</td>
<td>11/04/2016</td>
</tr>
<tr>
<td>#GościeHGW</td>
<td>#HGWsGuests</td>
<td>20/04/2016</td>
</tr>
<tr>
<td>#sznajfeldzizm</td>
<td>#sznajfeldzizm</td>
<td>28/04/2016</td>
</tr>
<tr>
<td>#BufetowaGate</td>
<td>#BuffetLadysGate</td>
<td>29/04/2016</td>
</tr>
<tr>
<td>#StoLatDlaPAD</td>
<td>#HappyBirthdayPAD</td>
<td>16/05/2016</td>
</tr>
<tr>
<td>#polszczyznaPetru</td>
<td>#PetrusPolish</td>
<td>20/05/2016</td>
</tr>
<tr>
<td>#inwektywyAgresorki</td>
<td>#AggressorsInvectives</td>
<td>02/06/2016</td>
</tr>
<tr>
<td>#wspomnieniaAgresorki</td>
<td>#AggressorsMemories</td>
<td>08/06/2016</td>
</tr>
<tr>
<td>#przez500plus</td>
<td>#BecauseOf500Plus</td>
<td>09/06/2016</td>
</tr>
<tr>
<td>#pawdzyBronka</td>
<td>#BroneksTruth</td>
<td>14/06/2016</td>
</tr>
<tr>
<td>#PiSprzésladuje</td>
<td>#PiShouts</td>
<td>17/06/2016</td>
</tr>
<tr>
<td>#PaLament</td>
<td>#PaLament</td>
<td>21/06/2016</td>
</tr>
</tbody>
</table>
Table 17: Hashtag trends created by a single user in Poland between 2015 and 2017

Newsweek Poland appear to be trying to categorise their tweets using hashtags. The average number of letters in their hashtags was 13.05 and the average number of words was 2.04. @AlonzoMourning1 used hashtags to mock his political opponents and support his own party and his hashtags were even longer - on average they had 14.96 letters and 2.37 words. This comparison is especially significant in the light of the findings of Recuero and Araujo (2012b) who studied the differences between Orchestrated and Naturally Appearing Trends. They established that Orchestrated trending hashtags usually contain a full statement or even a phrase and are also usually longer (in his study in Brazil on average they contained 13.1 characters) than
naturally appearing ones (on average 9.9 characters long). It could indicate that hashtag trends created by @AlonzoMourning1 were orchestrated.

**The diversity of hashtag authorship**

The average number of hashtags created by the same author in a year is a measure of diversity of hashtag creators. The higher the number the less diverse the community of hashtag creators is in a given year meaning, that is, a small number of users are responsible for the creation of a large number of hashtags. If the figure is closer to 1 there is greater diversity. If it is exactly 1, every hashtag in the dataset in a given year is created by a different user. This measure can be used to assess how hashtagability is realised through hashtag creators and how creator diversity can be linked to changes in the use of hashtag functions.

Out of the first 35 hashtags identified in 2008, 16 were first created by a single user, and 6 by another user; that is, 22 out of 35 hashtags created in 2008 were first used by just two users. This is striking in comparison with the following years. Figure 47 and Table 18 below show the diversity of hashtag authors over the years. In 2008 on average a single user created almost 3 unique hashtags. This dropped almost by half in the following two years to respectively 1.67 (in 2009) and 1.46 (in 2010) and kept decreasing until 2014 when on average one user created one hashtag meaning, reaching a high point in diversity. In 2015 the trend changed and the number of hashtags per user started growing. In 2017 it reached 1.32 hashtags per user.

The explanation of the decreasing trend between 2008 and 2014 is straightforward. As Twitter was becoming more and more popular, more users were joining and using hashtags. The sharp drop between 2008 and 2009 can be explained by the fact that in 2009 Twitter started hyperlinking all hashtags internally and they became one of the official features of the service. Simply put, more people learnt about them and started using them.

<table>
<thead>
<tr>
<th>Year</th>
<th># of unique hashtags</th>
<th># of unique authors</th>
<th>hashtags per author</th>
</tr>
</thead>
<tbody>
<tr>
<td>2008</td>
<td>35</td>
<td>12</td>
<td>2.92</td>
</tr>
<tr>
<td>2009</td>
<td>241</td>
<td>144</td>
<td>1.67</td>
</tr>
</tbody>
</table>
Table 18: the diversity of hashtag authors in Poland between 2008 and 2017

<table>
<thead>
<tr>
<th>Year</th>
<th>Hashtags</th>
<th>Mentions</th>
<th>Mentions/Hashtags</th>
</tr>
</thead>
<tbody>
<tr>
<td>2010</td>
<td>193</td>
<td>132</td>
<td>1.46</td>
</tr>
<tr>
<td>2011</td>
<td>123</td>
<td>96</td>
<td>1.28</td>
</tr>
<tr>
<td>2012</td>
<td>166</td>
<td>144</td>
<td>1.15</td>
</tr>
<tr>
<td>2013</td>
<td>180</td>
<td>165</td>
<td>1.09</td>
</tr>
<tr>
<td>2014</td>
<td>141</td>
<td>136</td>
<td>1.04</td>
</tr>
<tr>
<td>2015</td>
<td>293</td>
<td>269</td>
<td>1.09</td>
</tr>
<tr>
<td>2016</td>
<td>381</td>
<td>302</td>
<td>1.26</td>
</tr>
<tr>
<td>2017</td>
<td>371</td>
<td>282</td>
<td>1.32</td>
</tr>
</tbody>
</table>

The change of trend in 2014/2015 and the steady annual increase in the number of created hashtags per author since then may be linked to the emergence of conversational hashtags and especially political memes. Another factor could be the emergence of hashtag creators who specialise in political memes. These users usually have a large followership and are very successful in creating memes that very quickly become popular and become trending through orchestration. For example, the previous section discussed the example of a user @AlonzoMourning1 who in less than 2 years between 22 May 2015 and 09 May 2017 created 39 trending hashtags, all of them political memes supporting the ruling right wing party and mocking liberal and left wing opposition. A very high proportion of them focus on a single politician - Ryszard Petru, who was the leader of the liberal party at that time.
The emergence of accounts such as @AlonzoMourning1, that create political hashtag memes and help to make them popular, is – on the basis of the analysis above - the most likely possible explanation of the increase of the number of hashtags per author (decreased diversity) in the years between 2014 and 2017. In terms of strategy they act in similar ways to the fandom communities or hashtag games described in the previous chapter. Instead of focusing on their idol or coming up with a generally funny topic, they focus on mocking their political opponents or supporting policies suggested by their own party or the party they support. It is also possible that, similarly to fandom communities, they use special techniques to make their hashtags trending and get their message across.

The fact that certain accounts specialise in creating political hashtags and are very successful in making them trending raises an important question: do these trends occur naturally or they are also orchestrated by groups of users by manipulating Twitter’s algorithm? If the latter is true, it is possible that such groups have a disproportionately high impact on the Polish Trending Topics on Twitter and therefore can set the agenda on the platform. Looking at all trends that were possibly orchestrated by the same account as discussed above, it is clear they are very one-sided and are targeting specific political parties or even specific people and one must also ask the question about the impact of these on the targeted people/organisations. Is this a form of orchestrated cyber bullying that uses orchestration to manipulate Twitter algorithm and surface offensive, rude, and insulting messages via Trend Box, which might change the perception of the person/organisation amongst users and beyond? Secondly, what is the impact of such political memes on other Twitter users? It is possible that such trends disturb democratic processes by promoting values that support only one side on the political spectrum and create an impression that values of their political opponents are less popular or less worthy?

The next chapters will deal specifically with this issue, looking at trending hashtags during the 2017 General Election in the UK. The key takeaway from this section is that the steady annual increase in the number of created hashtags per author since 2014 is associated with the emergence of conversational hashtags and especially orchestrated political memes.
Hashtag authorship vs algorithmic ownership

The strategy of data collection for this chapter allowed the surfacing of the authors (creators) of hashtags, who are defined as users who were the first to use a hashtag on the Platform. The authorship was identified by operationalising an hyperopic vision that enabled the identification of the very first post with a given hashtag, namely by using ‘Latest’ filter and then searching back to the first use. ‘Latest’ filter is not a default option in Twitter’s search results. By default, Twitter always filters search results using ‘Top’ filter and then gives the option to change it to ‘Latest’, ‘People’, ‘Photos’ or ‘Videos’.

The ‘Top’ filter is applied by Twitter based on the personalisation algorithm as discussed in Chapter Four when describing the limitations of Twitter search results as a starting point of an analysis. The ‘People’ filter shows accounts associated with the search term but again the order of these is determined by Twitter’s recommendation algorithm. Videos and Photos filters are not relevant for this study. It would make no sense to use any of these four filters, apart from ‘Latest’ to identify hashtag authors. However, they are useful to study the difference between hashtag authorship (as defined in this chapter) and algorithmic ownership - the algorithmically generated association between a trending hashtag and a user (as defined in Chapter Four). This can be done by comparing the two Twitter search filters ‘Latest’ (arranged by time) and ‘Top’ (arranged by recommendation algorithm) to see if any of the authors of hashtags identified in the first filters are also showing as algorithmic owners of their creations in the second filter.

The result of this comparison exercise is striking - not a single author of trending hashtags identified through ‘Latest’ filter was featured by Twitter algorithm under ‘Top’ filter. This clearly suggests that hashtag authorship (being the first to use a hashtag on the platform) has no connection with the algorithmic ownership of hashtags as defined in Chapter Five. This result suggests being the first person to use the hashtag is not significantly weighted in the recommendation algorithm and that algorithmic ownership is likely based on interactions with the hashtag, and most likely, the most recent interaction. It is however possible that this result was only obtained because of the gap between the time when the hashtag was created or was trending and time of data collection and analysis. It is possible that if ‘Top’ filter was
used for search on the day when a given hashtag was trending, there may be an algorithmic association between the creator and the algorithmic owner.

**Conclusion**

This chapter analysed changes in how people use hashtags on Twitter to perform different functions. It also explored the connection between new functions and the users who introduce them. In short, it explored the history and the developments of hashtagability - the potential of hashtags and their users to develop new functions on the platform. In doing so, it developed a novel methodology that showed how hashtag trends can be analysed and why they should be, which is the question this thesis is guided by.

Following Madsen's (2012) notion of 'screened visions' this chapter used third party archives of Twitter trending hashtags to generate myopic vision of all trending hashtags in Poland for almost three years between 2014 and 2017. It then generated hyperopic visions for individual hashtags that were operationalised through Twitter's own search function. This data collection strategy helped to surface the history of Polish hashtags for almost a decade between 2008 and 2017. The collected data allowed to discover three distinctive phases of hashtags development:

- **The adoption phase (2008)**, characterised by a relatively low number of users and heavy use of very short hashtags for content categorisation.
- **The slow phase (2009 - 2011)**, characterised by the slow introduction of other than categorisation functions e.g. hashtags as comments and the radical increase in the average length of hashtags.
- **The creative phase (2012 - 2017)** characterised by the radical increase of the use of hashtags as comments or jokes and from 2015 onwards as political micro-memes, which is reflected by the increase of hashtags length and decrease of their creator's diversity.

There were however two serious limitations of this method. Firstly, the nature of trending micro-memes means that they disappear as quickly as they emerge. The data collection method allowed to collect data for trending micro-memes since 18 October 2014. If there were any micro-memes trends that had emerged before this
date, they were never surfaced using this method, unless they are emerged after 18 October 2014. Looking into the future, this should not be a problem with future applications of this method, as all data is now being collected on a daily basis by many archives. There is also an issue with time - historical analysis of trend authors showed that they never appear as their algorithmic owners. Most likely this is linked with the fact that both the first use and the date when the hashtag was trending were in the past. For example, if the hashtag was created on 15 Nov 2016, and was trending the same day, 2 hours after creation, and assuming that the creator was involved in the orchestration, the chances of the creator being also an algorithmic owner would have been much higher if the analysis was conducted on the day. For this study, I only conducted the search months or sometimes years after the day of trending, so it is very likely that the search results using 'Top' filter were very different than they would have been on the day. This limitation helped me to develop data collection strategy for the following two chapters, which addresses this problem by collecting data almost immediately (Chapter Eight) and immediately (Chapter Nine) after the emergence of the trend.

Analytically, the use of three metrics: date of the first use, the length of hashtag and hashtag’s author’s diversity, accompanied by qualitative analysis of content related to some of the identified hashtags, helped to surface trends in the changing functions of hashtags. It showed that with the growing number of functions that hashtags play on Twitter, their average length has been increasing over time in the analysed period. It also showed that mico-memes or other hashtags that can be classified as orchestrated in order to make them trending, have relatively fewer authors on average in comparison to hashtags that were created without intent to use them for orchestration e.g. hashtags used for categorisation. It is clear that hashtags have come a long way from just categorising content to becoming central part of content (when used as a comment) to finally becoming the content themselves, when they become trending and are visible in Twitter’s Trending Box. Hashtag’s continuous growing length is indicative of their changing functions and especially indicative of which function is becoming the most significant - the function of creating trends.

From the digital media perspective, the decreasing hashtag’s creator’s diversity and their increasing length suggest that their role of conveying a short message that is visible to millions as part of the Trend Box should be treated seriously. This chapter showed that there are anonymous users who are able to orchestrate political trends.
targeted at a person or organisation and they use hashtags to achieve their goals. It is possible that groups that use orchestration have disproportionately high impact on the Polish Trending Topics on Twitter and therefore can set the agenda on the platform, which might change the perception of the person/organisation that is targeted, amongst users and beyond. This finding helped to inform the selection of the topic for the analysis developed in the next chapter which is General Election 2017 in the UK, which is treated as a single political event and all trending hashtags related to it are collected using semi-automated method in search of orchestrated hashtags.

In sum, the historical analysis conducted in this chapter identified changes in hashtagability over time, including the identification of three distinct periods. It suggested that hashtagability – for the potential of hashtags to acquire new functions - is not initially realised by all Twitter users but by smaller groups, or even individual users, who in certain circumstances are able to introduce the new function or the new use to the platform. It showed that similarly to hashtags themselves, which were introduced to the platform by a small number of users (in the US e.g. #SanDiegoFire and Poland as well), hashtag's potential is possibly best realised by small groups of users. Trend orchestration with the use of hashtags is possibly the most significant realisation of hashtagability since this use of hashtags has the potential to reach millions of users. Hashtags were introduced to the platform by orchestration (i.e. #SanDiegoFire) and it seems that orchestration of hashtags to make them trending is currently responsible for the large proportion of the new trending hashtags.
Chapter 8: Case Study 2 - the 2017 UK General Election

Out of all of the events that happen and are recorded every day by correspondents, reporters, and the news agencies, the editor chooses certain items for publication which he regards as more important or more interesting than others. The remainder he condemns to oblivion and the wastebasket. There is an enormous amount of news 'killed' every day.

Robert Park (1922: 328)

Introduction

Agenda-setting theory (McCombs and Shaw 2002), describes how the media can influence viewers by establishing a hierarchy of news prevalence. The concentration of news on selected topics/issues can lead the public to perceive these topics as more important than others: the media do not only reflect the reality but also filter and shape it. Since the publication of the original research of McCombs and Shaw (1976), the media landscape has changed dramatically. New social media platforms changed the way traditional media operate and the public gained access to a variety of new media sources. Conway et al (2015) argue that Twitter and the traditional media have a ‘symbiotic relationship that varies in intensity and duration depending on the issues being analysed’. Aruguete (2017: 51) claims that ‘the new media have gained
ground in the dispute for setting the agenda.’ She poses two important questions, that have not been answered so far:

1. *Do social networks set conversation topics or do they repeat the agenda of topics proposed by elite media?*

2. *Does the agenda setting power claimed by official information sources persist in the new media environment?’*

This is where this chapter starts. It attempts to answer the above two questions in terms of hashtagability by looking at Twitter Trend Box. The specific question it asks is: how can Twitter’s Trend Box be studied as an algorithmic gatekeeper? It aims to establish what types of hashtag trends get selected by the algorithm to be featured in the Trend Box with the focus on the two main categories: exogenous (originating outside of Twitter, possibly from the traditional media) and endogenous (originating on Twitter). Based on the findings of this stage, it attempts to measure the ‘agenda setting power’ of traditional media and Twitter. This is done by shifting the focus from hashtags per se, to Twitter Trend box and how it ‘behaved’ during the 2017 UK General Election.

Methodologically, this chapter introduces a data collection strategy that uses a third-party Twitter Trends monitoring tool to identify hashtag trends related to the Election and then collects data using the Netlytic Application by connection to Twitter REST API. All collected hashtag trends are then manually categorised as exogenous and endogenous categories. This categorization is then analysed using Twitter’s own metrics and Social Network properties. The metrics are used to analyse the impact of each category of hashtag trends on the Trend Box to measure their ‘agenda setting power’.

The analysis reveals that Endogenous hashtag trends have a significant impact on Twitter Trend Box and are responsible for more than a quarter of the trends that were surfaced by the algorithm during the analysed period. 20% of all analysed trends belong to the Single Peak, Endogenous sub-category which has basic metrics and network properties similar to orchestrated fandom trends. The possibility that the majority of the trends in this sub-category are orchestrated is then addressed. Data shows that they never received as much engagement as Exogenous trends in terms of the number of messages or posters, but without a doubt, received a large
share of visibility in the Trend box. The conclusion drawn is that their ‘agenda setting power’ is larger than metrics such as number of messages or posters indicate.

Algorithmic Gatekeeping

The term ‘gatekeeping’ originates from Lewin’s (1943) research into the decision-making processes. In media and journalism gatekeeping is a process of news going through the channel where the entrance to the channel and its sections are called gates (Bass 1969). Gatekeepers are seen as ‘guards’ who monitor the process of a news item passing through these gates. They may act as news gatherers, news processors or both at the same time (Bass 1969).

The process of gatekeeping was analysed well before it was named. Parker (1922) studied how editors were choosing items for publication and how they were determining the importance of news or reports. Similar studies (White 1950: 386, Snider 1967: 402) attempted to establish how mass communication gatekeepers regulate news. The modern definition of a gatekeeping is still based on the original principle and gatekeepers are seen as facilitating or constraining ‘the diffusion of information as they decide which messages to allow past the gates’ (Shoemaker and Vos 2009: 21). In the late XX century, with the development of mass media, gatekeeping was seen as a process of choosing hundreds from the billions of available messages (Shoemaker 1991:1). Methodologically it was associated with highly centred networks in which only those sitting in the centre could spread the information. The infrastructure was organised around sender (editor) - receiver (audience) roles. There were clear source-destination directions: the audience’s role was to receive and the editor’s role was to send the information.

At the beginning of the XXI century with the development of digital media, the process of gatekeeping has undergone enormous changes. Centralised networks were rapidly replaced by digital networks and suddenly everyone could communicate with millions of other users providing they had access to digital/social media. More importantly, the information provided by gatekeepers of traditional media could be easily redistributed and changed by the audience as it moved through gateways on digital channels, completely transforming the sender-receiver model.
that had developed in the second half of XX century. The ‘gated’ could become a source of information themselves.

The rise of digital media also changed the role of traditional media gatekeepers. Bruns (2005) argues they became gate watchers, who now only act as news processors and rely – more and more - on the news gathering skills of citizen journalists. Gate watchers find their news on social networks rather than spending time and money on their own, independent research. Bastos et al. (2013: 260) goes one step further and argues that it has become impossible to say who is performing gatekeeping as the ‘final product’ is being constantly changed and repurposed by the audience, who can act as editors, reporters, and witnesses in a truly decentralised process. The role of the traditional media gatekeeper is reduced in this process to a follower of a story reported by multiple ‘reporters’ on different platforms.

This analysis highlights the increasing role of digital media platforms in what gets to count as news and the non-journalistic actors who use the platforms to generate news. For example, in Egypt in 2011 and Turkey in 2013 traditional media controlled by the state were replaced as a source of public information by Twitter, which became the source of and a tool to spread alternative information (Demirhan 2014; Meraz and Papacharissi 2013). Similar situations can be observed in the West, where alternative news portals or even individuals on social media are becoming competitors of traditional media (Fletcher and Park 2017). These actors have their own news selection criteria, which are often different to those of the traditional media outlets (Jürgens et al. 2011; Meraz and Papacharissi 2013).

Finally, there are also non-human, algorithmic gatekeepers that base their selection process on the behaviour of humans. This kind of gatekeeping is not based on a few citizen journalists breaking news on the platform, but on the analysis of thousands or millions of users and their behaviour to determine what news is worth surfacing. Users do not even need to actively publish any news - it is enough that they engage with content that is already on the platform. This is sufficient for algorithms to determine the newsworthiness of stories. Algorithms and users co-exist as ‘decision-makers’ and news reaches high visibility through decentralized gatekeeping mechanisms (Wallace, 2017).

Apart from a few studies (Bui 2010; Diakopoulos 2014; Lerman and Ghosh 2010; Lewis and Westlund 2014; Tandoc 2014; Welbers and Opgenhaffen 2018),
algorithmic gatekeeping has not received much attention in academia. Thurman (2015: 9) notes that there is ‘an almost exclusive concern with human gatekeepers’. This is despite a recognition of the significance of the changes described above. For example, Napoli (2014) argues that algorithmic gatekeepers now shape what is considered to be of public interest. Gillespie (2014) thinks they, or their proprietary companies, have now become governors of information flow on digital platforms. Their role in digital gatekeeping is rising, and they play a key role in the construction of social reality (Just and Latzer 2016), which links them with the original Agenda Setting Theory (McCombs and Shaw 1976, 2002) in which the media do not only reflect the reality but also filter and shape it. The 2017 UK General Election offers a great opportunity to study algorithmic gatekeeping in the UK.

**General Election 2017**

The decision to hold a General Election was announced by Theresa May on 18 April 2017 around 11am. On 25 April 2017, the election date was confirmed as 8 June meaning that there were 52 days between the initial announcement and the election date. The Prime Minister’s announcement was almost immediately reflected in the Twitter Trending box in the UK. Firstly, the number of trends per hour was almost immediately reduced from 80 (at 11:00) to 26 (at 12:00). It remained reduced for the next 5 hours. This was most likely caused by the dominance of the General Election topic - Twitter users almost stopped talking about anything else and the discussion was almost entirely about May’s announcement (Figure 48 below).
The first hashtags linked to General Election that became trending were: #GeneralElection, #GeneralElection2017, #GE17 and #GE2017. Clearly there was no agreement between users as to which hashtag should be used to discuss the election. Cram et al. (2017: Online) provides more details about popular hashtags throughout almost the entire election campaign. One of their main findings was that the traffic on Twitter during the Election campaign was increasingly event driven and there are visible spikes in Twitter data closely related to major media events such as TV debates (e.g. #BBCDebate, #BattleForNumber10 and #BBCQT). These spikes were strongly influenced by the official hashtags used by media outlets with the most popular hashtags being either related to TV and radio shows (e.g. #Peston or #Marr) or TV debates – see Figure 49 below.

Interestingly although these hashtags generated data spikes, Cram at al. (2017) argue that overall, they were ephemeral, especially when contrasted with issues such as Brexit or the NHS which remained popular throughout the campaign. Cram at al. (2017) claim that the key hashtags associated with TV debates die off almost immediately and that they do not play a significant role in setting a political agenda.

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66 https://www.trendinalia.com/twitter-trending-topics/unitedkingdom/unitedkingdom-170418.html
or in shaping debates. Cram et al. (2007: Online) see them as ‘a means of tracking who was watching and engaging with the particular media generated events’.

![Figure 49: Hashtags that peaked on a given day on Twitter during the study period. Source: Cram et al. (2017: Online)](image)

**Coordinated Inauthentic Behaviour**

The announcement of the new election presented an opportunity to develop the methodology to study the ‘agenda setting power‘ of the Twitter trend box for a single event of national and global importance. The election happened less than a year after the Brexit referendum (Cadwalladr. 2017), Donald Trump being elected the president of the US (Online, 2017) and Rodrigo Duerte the president of the Philippines (Corpus Ong and Cabanes, 2018) - all of which raised some serious questions about the spread of disinformation. Criticism was mostly focused on Facebook, which has led the platform to investigate the events and how the site was used by ‘bad’ actors to manipulate public perception.

One result of this investigation was the emergence of the term Coordinated Inauthentic Behavior (Weedon et al. 2017), understood as disinformation campaigns that purposely entangle orchestrated action with organic activity. Starbird (2019: Online) argues that as a result of such campaigns, ‘audiences become willing but unwitting collaborators, helping to achieve campaigners’ goals.’ A similar technique was used in the past by Soviets (Rees 1984) to influence Western journalists, who were given anonymous tips that offered a “scoop” and were aligned with their
beliefs. The journalists would then unwittingly introduce the disinformation into the press without realizing the true intentions of their informants (Starbird et al. 2019:4), essentially become “unwitting agents” (Bittman, 1985).

The digital age changed the process of gatekeeping and as described in the previous section, in the XXI century, platforms and their audiences became the new, algorithmic gatekeepers. The spread of disinformation happens on the platform/audience level, rather than through the co—option of individual journalists. The new, digital disinformation campaigns can only be effective if they target ‘a majority of ‘unwitting agents’ who are unaware of their role, but who amplify and embellish messages that polarize communities’ (Satarbird 2019: Online).

‘Coordinated Inauthentic Behaviour’ is an umbrella term for a set of advanced techniques developed by attackers to spread disinformation. The term does not necessarily imply that the spread involves creating fake news or disseminating false information. The techniques often use true information to spread false news by setting a false context; for example, an out of context photograph of a politician could be used to illustrate a political event in a way that can create an impression of lack of understanding of the cultural codes required in certain situations. If the audience has no way to verify the context, they may spread the image and as a result spread misinformation.

Twitter Trending Box has the potential to be a powerful tool with which to spread misinformation as it offers highly increased visibility of the message. In the latest (2019) Election in the UK Twitter banned all political advertising on the platform, making Trend Box an even more valuable space for potential attackers to target large audiences: a trending hashtag can operate as a ‘sponsored’ link. The techniques of orchestrating trends are known and well described in the context of fans (Recuero and Araujo, 2012b and Recuero et al. 2012), hashtag games (Huang et al. 2010) or spammers. It is possible that they were also used during the 2017 Election in the UK, to set/change the agenda of the platform. It is important to understand their impact as under specific political, cultural and institutional conditions they could ‘tip societies into instability’ (Benkler et al. 2018:22-23).
This is the focus of this chapter. The aim is to establish what types of hashtag trends get selected by the algorithm to be featured in the Trend Box and how hashtagability is realised by the Trend Box.

**Method and sampling**

The technology (platforms and the algorithms that run them) are not neutral. They have values embedded in their design and are directed by internal policies that might not always be aligned with the interest of the public or researchers. Acker and Donovan (2019) argue that platforms’ data archives of ‘coordinated inauthentic behavior’ prevent researchers from examining the contexts of manipulation. API limitations (discussed in Chapter Six) are one of the examples. The data collection strategy in this chapter tries to overcome some of these issues by downloading large amounts of data for each trending hashtag with almost no delay after it had been surfaced by the platform, by using Twitter REST API.

**Data collection strategy**

Most of the researchers who studied the 2017 General Election on Twitter used Streaming API to collect data. Cram et al (2017: Online) used it for 37 days between April 29th and June 4th, 2017. In total, they collected 34 million posts by searching for 56 keywords related to the event e.g. #GE2017, general elections, Theresa May, Corbyn, #jc4pm, Brexit or NHS. Gallacher at al. (2017: 1) also used STREAMING API to collect 1,363,000 tweets between the 1st and the 7th of May 2017. They searched for hashtags associated with the primary political parties in the UK, the major candidates, and the election itself. The problem with the above approaches is that, although they generate large numbers of Tweets, they do not cover the entire event.

The data collection approach for this study involved monitoring all trending hashtags in the UK during the period of the campaign and identifying trending hashtags that are related to the General Election. Similarly to the data collection method used in Chapter Six, I wanted to avoid Twitter Trend Box recommendation algorithm and monitored the election via the third party Twitter Trends Application for the UK (Trends24.in) which publishes a list of top 10 trends from Twitter every
hour (See Figure 50 below). I monitored Trends24 every 2 hours between 8am and 11pm every day for 53 days between the announcement of the election and the election day.

Figure 50: Trends24.in (Screenshot) publishes a list of top 10 trends from Twitter every hour and can be used for trend monitoring

Trend24 list became my myopic vision (Madsen, 2012) of the event. Once a hashtag related to the event was identified, I almost immediately set up a search query for it in Netlytic Application, which uses REST API to download a maximum of the 1000 latest posts for the hashtag. I also requested the continuous download of all new posts for the hashtag in intervals of 15 minutes for the remaining length of the campaign. By doing this I wanted to ensure that all posts for the hashtag were captured, even when it eventually stopped trending. This approach also allowed me to capture the creation of the trend for hashtags that I was already collecting data for, in case they became trends again. The data shows (Results and analysis section below) that about 45% of hashtags trended multiple times.

The aim of this technique was to start collecting data for the trending hashtags as early as possible - ideally in the very hour they were published as a trend. Twitter REST API limitation only allows for the collection of the 1000 posts posted prior to the start of the collection, so the earlier after the emergence of the trend the collection process started, the more data from the early stage of the trend could be collected.

Data collection for trending hashtags linked to the General Election started almost immediately after the announcement on 18 April 2017. A small group of hashtags collected prior to the General Election announcement is also included in the dataset for (#thepledge, #childpoverty, #farron, #wato and #NastyParty). The data
collection for these started between 10 and 17 April 2017. These were all included in my trial dataset, which I started collecting early in April 2017. After the announcement I decided to continue with data collection for them assuming that some of these hashtags might become trending between the announcement and the actual day of General Election. This was the case with all five of them, hence they were included in the new dataset even though the collection for them started prior to the announcement. After the Election day (8 June 2017) I kept collecting data for extra 3 days until 11 June 2017 and as a result data for five more trending hashtags were collected: #NotMyPrimeMinister, #TheLastLeg, #DUPCoalition, #hignfy and #WorstPrimeMinisterInHistory.

Once the collection started, Netlytic generated a dataset containing all collected posts for each hashtag. Each dataset contained numerous basic metrics such as: the full body of the post, timestamp, hashtags, author and so on. Netlytic also automatically generated Network properties (metrics) for each hashtag. These included: Diameter, Density, Reciprocity, Centralisation and Modularity.

Data limitations

Validity

The General Election in the UK became news globally almost immediately after its announcement. As a result, hashtags related to the event started trending in different parts of the world causing some immediate problems with data validity. For example, hashtag #GeneralElection\(^{67}\) became trending just a few minutes after May’s announcement in Latvia (at 11:17:05) and then in Algeria (at 11:21:57) and several locations in the US (i.e. Washington - at 11:42:11, Virginia Beach at 11:47:00) followed by Australia (Sydney at 12:02:09), Belarus (Minsk, Gomel and Grodno at 12:47:16), Switzerland (Zurich at 12:47:14) and several other locations around the world (in the

\(^{67}\) https://trendogate.com/search/?trend=%23generalelection&page=3
Netherlands, Italy, Germany, France and Ireland) until it finally became trending globally at 15:37:43. A similar pattern was followed by other election related hashtags such as #GeneralElection201768 or #GE1769.

The above examples show that from day 1 the same hashtags were used in different locations which raises questions about the validity of measurement. Do they all represent the same event? It is possible that all these hashtags were used exclusively to discuss the General Election in the UK but one needs to note that most likely it was not the case. All above mentioned hashtags started trending in Latvia and there were local elections happening in Latvia’s capital Riga at the same time (election day 3 June 201770). There were also parliamentary elections in Algeria on 4 May 2017, which could indicate that some of the early trends in Algeria were more to do with their own elections rather than the UK one.

Luckily this issue only applies to the most general election hashtags. The majority of other hashtags collected for this study were very UK specific e.g. #TheresaMayIn5Words, so the fact that they are popular/trending in other geographies was not an issue.

Representativeness

Collecting data from Trending Topics on Twitter using REST API raises some serious questions about data representativeness. REST API allows the collection of the 1000 most recent Tweets every 15 minutes. This is enough for most non-trending hashtags as there are usually less than 1000 tweets in every 15 minutes. Unfortunately, it becomes very problematic for trending hashtags - the 1000 posts per 15 minutes limit is not enough to collect all relevant data: not all data is collected and the collected data is not distributed equally during the collection period. The Table 19 below illustrates the problem:

68 https://trendogate.com/search/?trend=%23generalelection2017
69 https://trendogate.com/search/?trend=%23GE17
70 http://pv2017.cvkl.lv/
<table>
<thead>
<tr>
<th>First post</th>
<th>Last post</th>
<th># of posts</th>
<th>Duration (mins)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 18/04/2017 14:29:09</td>
<td>18/04/2017 14:32:59</td>
<td>990</td>
<td>0:03:50</td>
</tr>
<tr>
<td>2 18/04/2017 14:58:30</td>
<td>18/04/2017 15:03:20</td>
<td>999</td>
<td>0:04:50</td>
</tr>
<tr>
<td>3 18/04/2017 15:16:49</td>
<td>18/04/2017 15:18:42</td>
<td>396</td>
<td>0:01:53</td>
</tr>
<tr>
<td>4 18/04/2017 15:28:25</td>
<td>18/04/2017 15:33:02</td>
<td>999</td>
<td>0:04:37</td>
</tr>
<tr>
<td>5 18/04/2017 15:43:36</td>
<td>18/04/2017 15:48:29</td>
<td>999</td>
<td>0:04:53</td>
</tr>
<tr>
<td>6 18/04/2017 15:57:52</td>
<td>18/04/2017 16:03:09</td>
<td>999</td>
<td>0:05:17</td>
</tr>
<tr>
<td>7 18/04/2017 16:12:45</td>
<td>18/04/2017 16:17:58</td>
<td>999</td>
<td>0:05:13</td>
</tr>
<tr>
<td>8 18/04/2017 16:27:17</td>
<td>18/04/2017 16:33:03</td>
<td>999</td>
<td>0:05:46</td>
</tr>
<tr>
<td>9 18/04/2017 16:42:59</td>
<td>18/04/2017 16:48:20</td>
<td>999</td>
<td>0:05:21</td>
</tr>
<tr>
<td>10 18/04/2017 16:57:52</td>
<td>18/04/2017 17:03:17</td>
<td>999</td>
<td>0:05:25</td>
</tr>
<tr>
<td>12 19/04/2017 09:03:49</td>
<td>19/04/2017 09:48:03</td>
<td>2983</td>
<td>00:44:14</td>
</tr>
<tr>
<td>13 19/04/2017 10:04:15</td>
<td>19/04/2017 10:48:15</td>
<td>2927</td>
<td>00:44:00</td>
</tr>
<tr>
<td>14 19/04/2017 10:50:17</td>
<td>19/04/2017 11:33:02</td>
<td>2685</td>
<td>00:42:45</td>
</tr>
<tr>
<td>15 19/04/2017 11:58:06</td>
<td>19/04/2017 12:48:41</td>
<td>2340</td>
<td>00:50:35</td>
</tr>
<tr>
<td>16 19/04/2017 18:53:09</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 19: Data collected for #GeneralElection between 18/04/2017 14:29:09 and 19/04/2017 18:53:09

The table above shows how data was collected by Netlytic App in the first 24hrs of the data collection period at 14:32:59 on 18/04/2017. The data importer used by Netlytic used the Twitter REST API v1.1 search/tweets endpoint, which returns a collection of relevant Tweets matching a specified query (#GeneralElection).
I began data collection for #GeneralElection at 14:32:59 on 18/04/2017. At that time, the hashtag was already trending in numerous locations around the world and was just about to start trending globally. In the settings of Netlytic App I requested the repeated collection in 15-minute intervals of up to 1000 most recent Tweets as per Twitter API limitation. The first query (row 1) returned 990 Tweets covering 3mins and 50 seconds. The next collection started 30 minutes later at 15:03:20 (row 2) and returned 996 Tweets covering 4 minutes and 50 seconds. It is not clear why there was a gap of 30 minutes between collections, even though the settings were set to collect data every 15 minutes. Possibly there could have been a technical problem with the software. As a result, no data was collected for any Tweets posted between 14:32:59 and 14:58:30. After another 15 minutes, at 15:18:42 Netlytic collected another batch of Tweets - this time it was only 396 messages covering 1 minute and 53 seconds. Again, I am unable to explain why only 396 Tweets were collected, and not 1000 as per Twitter limit. As a result, no data was collected for any Tweets posted between 15:03:20 and 15:16:49.

The situation improved in the next two hours. Between 15:33:02 (row 4) and 17:03:17 (row 10) Netlytic collected 999 Tweets approximately every 15 minutes. Each collection covered approximately 5 minutes prior to the collection time. At that time #GeneralElection was trending and data suggests that there were about 1000 Tweets posted every 5 minutes. Netlytic kept hitting this limit, leaving the remaining 10 minutes of data uncollected.

After the 17:03:17 collection, Netlytic stopped collecting data until late in the evening. The first Tweet collected in the next batch is from 22:53:41, which leaves a gap of almost 6hrs between 17:03:17 and 22:53:41. Again, it is impossible to say why there is no data collected for this period. One possible explanation could be that on top of time intervals and number of Tweets per collection limits, Twitter also has a limit of how many searches can be made in a single time interval by a single user. Netlytic allows a search of 300 hashtags per user. All these can be set to collect data every 15 minutes. Assuming Twitter API has a limit of searches per 15-minute interval, this could explain why there are gaps in data collection. Possibly no data was collected for #GeneralElection between 17:03:17 and 22:53:41 because data for other hashtags was pulled from Twitter during this time and Twitter API simply blocked requests for #GeneralElection.
The first Tweet after the 6hr break was collected at 22:53:41, which indicates that the collection started later. Data indicates it started the next day (19 April 2017) at 00:18:00 and 999 Tweets were collected covering about 1hr and 30 minutes. Table 20 below shows how data collection was distributed throughout the entire period between 18/04/2017 22:53:41 and 19/04/2017 02:33:08 as shown in row 11 in the previous Table 19.

| #GeneralElection (data between 18/04/2017 22:53:41 and 19/04/2017 02:33:08) |
|---------------------------------|-----------------|----------------|----------------|
| First post                     | Last post       | # of posts     | Duration (mins) |
| 11-1 18/04/2017 22:53:41       | 19/04/2017 00:18:00 | 999            | 01:24:19       |
| 11-2 19/04/2017 00:18:04       | 19/04/2017 00:33:06 | 117            | 00:15:02       |
| 11-3 19/04/2017 00:33:17       | 19/04/2017 00:47:57 | 168            | 00:14:40       |
| 11-4 19/04/2017 00:48:25       | 19/04/2017 01:02:48 | 207            | 00:14:23       |
| 11-5 19/04/2017 01:03:11       | 19/04/2017 01:18:00 | 167            | 00:14:49       |
| 11-6 19/04/2017 01:18:19       | 19/04/2017 01:33:05 | 236            | 00:14:46       |
| 11-7 19/04/2017 01:33:10       | 19/04/2017 01:47:53 | 262            | 00:14:43       |
| 11-8 19/04/2017 01:47:58       | 19/04/2017 02:03:09 | 325            | 00:15:11       |
| 11-9 19/04/2017 02:03:10       | 19/04/2017 02:18:08 | 368            | 00:14:58       |
| 11-10 19/04/2017 02:18:16      | 19/04/2017 02:33:08 | 509            | 00:14:52       |

Table 20: data collected for #GeneralElection between 18/04/2017 22:53:41 and 19/04/2017 02:33:08

On 19 April 2017 the first data collection started at 00:18:00 and Netlytic collected 999 Tweets covering 1hr and 24 minutes. Netlytic continued collecting data almost exactly every 15 minutes, covering all Tweets covering the entire time interval. For example, between 00:18:04 and 00:33:06 117 Tweets were collected. The analysis of timestamps indicates that these are all available Tweets with this hashtag in this time interval. The latest hashtag from the previous interval had the timestamp of 00:18:00 and the earliest from this interval - 00:18:04, meaning that there was only a 4 second gap between them. The same pattern can be observed throughout the
entire data collection block - there are usually only a few seconds between the latest hashtag from the previous batch and the earliest of the following ones. This is a striking contrast in comparison to the previous table, where each collected batch only covered 5 minutes on average, and there was a 10-minute gap, for which no data was collected.

The table 20 data indicates that all available data was collected and Netlytic never hit the 1000 most recent posts limit. The most obvious explanation for this is the time of the day - not that many people were discussing this topic in the middle of the night. What cannot be explained easily is why Netlytic stopped collecting data for another 6 hours between 02:33:08 and 09:03:49. Most likely it was to do with the limit of search terms per account as described above.

The data collection process was then restarted at 09:18:17. Table 21 below presents the collection process. During the first collection (row 12-1) 999 posts were collected, covering just over 14 minutes. The second collection started at 09:33:00 and another 999 Tweets were collected. The earliest post from this collection had a timestamp of 09:18:33 and the latest from the previous - 09:18:17, which would indicate that there is only an 18 second gap between them, meaning that the second collection (row 12-2) collected all posts in that time interval. The only concern is that the entire limit of 1000 posts was used and it seems that the entire interval was covered, leaving a gap between the two collections. It is possible it was chance: that there were exactly 1000 Tweets posted between the two collections. There is a similar situation with the second and third collections - the last post of the second collection (row 12-2) has a timestamp of 09:33:00, which is identical to the first one of the third collection (row 12-3). This time however there were 984 posts collected, which could indicate that indeed the rate of posts at this time of the day was around 1000 per 15 minutes, and the 1000 posts limit was just sufficient to collect all data. This pattern is confirmed by the following rows 13-1 to 14-2 in which the collection covers the entire length of the 15-minute interval and there are usually approximately 1000 posts collected for the interval. Then clearly there was a decrease in the number of posts from 11:18:01 (row 14-3) onwards and each collection includes all posts (well below 1000 limit) from the interval.
The final issue that remains unexplained is collection gaps. The table 21 above shows two of them: between 09:48:03 and 10:18:08 there is one collection missing which should have appeared around 10:03, and then between 11:33:02 and 12:18:11 there are two collections missing, which should have happened around 11:48 and 12:03. Most likely these were caused by the limit of the number of searches per account.

This section has presented a detailed analysis of data generated by Twitter REST API and it is clear that there are serious issues with the sample's internal representativeness. This issue was discussed theoretically in Chapter Five. This section describes an example and identified two main problems: first, the collector hits the 1000 posts per 15 minutes limit for popular trending hashtags and as a result
is only able to collect data for a few minutes rather than the entire 15 minutes interval; second, there is an issue of unexplained gaps in data collection, when no data is collected at all.

The dataset

The dataset of collected hashtags contains 2,873,899 messages that were posted by 1,227,951 users. As a result of the extra 7 days prior to the announcement and 3 days after the actual election day, the dataset covers 63 days (exactly 9 weeks). During this time, the data for 114 hashtags were collected giving an average of 1.8 new hashtags per day or 12.6 per week (see Figures 51 and 52 below). This does not mean that there were only two trending hashtags per day during the analysed period: a large proportion of hashtags were trending several times, sometimes for several days in a row.

Figure 51: The number of trending hashtags per day (General Election 2017, UK)
Out of the 114 collected hashtags the first 57 were collected during the first 30 days (between 10 April and 9 May) giving an average of 1.9 hashtags per day. The collection of the remaining 57 hashtags took 33 days between (10 May and 11 June) giving an average of 1.72 hashtags per day. This shows that the rate of appearing of the new hashtags was slightly higher (4%) in the first half of the analysed period. It is clearly visible from the graph above that it was caused by the spike during the election announcement day.

**Categorisation**

Once all data was collected, 114 hashtags were manually categorised following Naaman et al’s (2011: 908) typology of exogenous and endogenous hashtag trends:
Trends in exogenous categories capture an activity, interest, or event that originated outside of the Twitter system (e.g., an earthquake). Trends in endogenous categories are Twitter-only activities that do not correspond to external events (e.g., a popular post by a celebrity) (Naaman et al 2011: 908).

Four coders categorised all 114 Election hashtags independently following the set of rules suggested by (Naaman et al. 2011: 908). For Exogenous Trends coders were looking for hashtags related to broadcast-media events (local and global), global news events both breaking e.g. terror attacks, and non-breaking e.g. health care reforms, local participatory and physical (planned and unplanned) political events. Each hashtag in this category was also compared to the hashtag lists generated by Gallacher at al. (2017) and Cram at al. (2017), who also studied this event but collected data predominantly for exogenous hashtags. For endogenous trends coders were looking for political memes, political hashtag games or any other hashtags that were not trending because of external-to-Twitter events.

The idea behind the use of this categorisation is that exogenous trending hashtags become trends because of external-to-Twitter events, so the likelihood of them being orchestrated is very low. Endogenous trends emerge on Twitter and there is no external reason/explanation why they became trending, hence it is possible they were orchestrated by groups of users as was described in Chapter Three and Four.

Once the initial, top level categorisation was performed and categorisation was agreed amongst the four coders, the ‘Posts over time’ graphs were generated for all 114 hashtags to visually check if they only had a single peak or multiple peaks during the collection period. Peaks are treated as indicators of trending, for example hashtag #bbcqt that is a backchannel for the BBC Question Time programme, had multiple peaks, usually linked to when the programme was broadcast on TV. On the other hand #CorbynHood only trended once and after the initial peak of the number of posts people stopped using it. Both top level categories were divided into two subcategories of single and multi-peak hashtag trends. The tables with all categorised hashtags are presented in Appendix I.
Findings and Analysis

During the analysed period 114 hashtags were identified as related to the General Election. 30 (26.32%) of them were then categorised as Endogenous, of which 23 (20.18% of the total) had a single peak and 7 (6.14% of the total) had multiple peaks. 84 hashtags (73% of the total) were coded as Exogenous, of which 40 (35% of the total) had a single peak and 44 (38.6%) had multiple peaks.

<table>
<thead>
<tr>
<th>Type of trend</th>
<th>% of hashtags</th>
<th>% of messages</th>
<th>% of Posters</th>
<th>hash/mess (ratio)</th>
<th>hash/poster (ratio)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total</td>
<td>100.00%</td>
<td>100.00%</td>
<td>100.00%</td>
<td>1.00</td>
<td>1.00</td>
</tr>
<tr>
<td>Endogenous</td>
<td>26.32%</td>
<td>10.48%</td>
<td>9.77%</td>
<td>2.51</td>
<td>2.69</td>
</tr>
<tr>
<td>Endogenous-1</td>
<td>20.18%</td>
<td>5.20%</td>
<td>5.67%</td>
<td>3.88</td>
<td>3.56</td>
</tr>
<tr>
<td>Endogenous-M</td>
<td>6.14%</td>
<td>5.28%</td>
<td>4.09%</td>
<td>1.16</td>
<td>1.50</td>
</tr>
<tr>
<td>Exogenous</td>
<td>73.68%</td>
<td>89.51%</td>
<td>90.23%</td>
<td>0.82</td>
<td>0.82</td>
</tr>
<tr>
<td>Exogenous-1</td>
<td>35.09%</td>
<td>19.50%</td>
<td>26.76%</td>
<td>1.80</td>
<td>1.31</td>
</tr>
<tr>
<td>Exogenous-M</td>
<td>38.60%</td>
<td>70.02%</td>
<td>63.47%</td>
<td>0.55</td>
<td>0.61</td>
</tr>
</tbody>
</table>

Table 22: Distribution of types of hashtags trends identified in the dataset (GE 2017 - UK)

Table 22 shows that 26.32% of hashtags in the dataset were classified as endogenous but they only contained 10.46% of all messages and had 9.77% of all posters. The ratio of the % of hashtag trends to the % of messages is 2.5, meaning that a relatively small number of messages (10.48%) is responsible for 2.5 times more hashtag trends of this type. The ratio of % of hashtags to the % of posters is 2.69.

Just under 74% of hashtags were classified as exogenous and they contain almost 90% of all messages and more than 90% of all posters, giving the ratio of the % of hashtag trends to the % of messages of 0.82 and the % of trends to the % of posters at 0.82 as well. The other way of looking at this is that 26.32% of Trend Box endogenous hashtags contain 10.48% of messages and 9.77% of posters. 73.68% of exogenous hashtags contain 89.51% of messages and 90.23% of posters. This confirms the findings of Recuero and Araújo (2012a) who argue that orchestrated trends (and all orchestrated trends are always endogenous) are usually created by fewer users in comparison to naturally occurring trends which result from many users tweeting about them.
This is a striking difference and suggests that there are significant differences between these two categories. The data becomes even more interesting, when controlling for the number of peaks in each category. The category of endogenous-1 (endogenous hashtags with a single peak) constitutes 20% of all trending hashtags in the dataset but only contains just over 5% of all messages and 5.67% of all posters. There is a similar situation with exogenous hashtag trends with a single peak - they constitute just over 30% of all hashtag trends in the dataset but contain just under 20% of messages and just under 27% of posters.

Top level categorisation revealed that hashtag trends classified as endogenous contain significantly fewer messages and posters on average than exogenous hashtag trends. This indicates that endogenous hashtag trends tend to be popular for shorter periods of time and attract significantly lower number of users. This confirms the findings of Huang et al. (2010) who argues that all micro-meme (endogenous) hashtags live relatively short lives: they very quickly get popular, get embraced by a critical mass of users and are disseminated through Twitter Trends, and then almost immediately get abandoned when a critical mass of users stop attaching a specific hashtag to their tweets. Single peak hashtag trends in both endogenous and exogenous categories have a higher ratio of hashtag trends to messages and hashtag trends to messages than hashtag trends with multiple peaks. This indicates that single peak hashtag trends in both categories attract significantly fewer users and generate significantly fewer messages than multiple peak hashtag trends but generate a high proportion of trends. In case of this study, single peak endogenous and exogenous hashtag trends constitute more than 55% of the trend box but contain less than 25% of messages and around 32% of posters. This is the main finding from the perspective of setting the agenda of the Trend Box.

Single peak trending hashtags do not generate a lot of engagement (in comparison to multiple peak hashtag trends) but they generate a lot of visibility in the trend box and are able to do so with relatively small numbers of users and content. For exogenous trending hashtags this visibility comes from external events, but for endogenous ones, it is generated entirely on Twitter and therefore whoever is able to generate such hashtags through orchestration is acquiring visibility but not engagement. The content of the examples of endogenous single peak hashtags (e.g. #BloodyDifficultWoman, #BoycottTheSun, #CurseTheToryParty, #MakeJuneTheEndofMay, #WorstPrimeMinisterInHistory) seem to confirm that.
these hashtags already have a message included in them. Assuming these were made trending via orchestration, the mere fact of being present in the Trend Box is the success. The other group of hashtags in this category are political hashtag games, for example #DontVoteToryBecause, #MayBondFilms, #SuggestapolicyforUKIP or #TheresaMayIn5Words, which encourage users to contribute or simply consume funny content related to the election.

Multiple peak exogenous hashtags are on the other side of the spectrum. They trended several times during the analysed period and tended to generate a lot of messages from a large group of users. These are usually general hashtags related to the event (#ge17, #ge2017, #GeneralElection), the main actors in the event (#theresamay, #farage, #Farron), political messages of the parties (#toriesout, #votelabour) and most importantly TV/Radio programmes (#BBCDebate, #bbcpm, #bbcqt, #bbcsp). Cram (2017: Online) calls the last type of hashtags broadcast-driven and argues they played a dominating role in the event (in terms of numbers) but not necessarily had any significant role in setting the agenda or shaping political debates. This is possible as they essentially act as backchannel for the TV programmes and provide means of tracking the audiences of particular media generated events. They generate volume but not because of the hashtag itself but because of the event that it describes. This is very different that endogenous hashtags that generate interest because of the message that is captured in the hashtag. The similar thing can be said about pollical hashtags operated by the parties. They clearly generate engagement - in 2017 election there was an overwhelming dominance of pro-Labour sentiment (Cram 2017: Online), but the result of the election showed that engagement not necessarily translates into winning. It is possible that using Twitter Trend box to simply gain the visibility for the message is more powerful than dominating the sentiment of a backchannel discussion.

**Network metrics**

Network metrics were defined and described in Chapter Six. This section looks at three Network properties available from Netlytic Application Diameter, Density and Reciprocity (see Table 23 below). All three describe network characteristics, such as information flows or how individuals interact with each other.
### Types of identified trends by network metrics (General Election UK 2017)

<table>
<thead>
<tr>
<th>Type of trend</th>
<th>Diameter (Ave)</th>
<th>Density (Ave)</th>
<th>Reciprocity (ave)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total</td>
<td>43.89</td>
<td>0.00041</td>
<td>0.0141</td>
</tr>
<tr>
<td>Endogenous</td>
<td>22.27</td>
<td>0.00064</td>
<td>0.0113</td>
</tr>
<tr>
<td>Endogenous-1</td>
<td>17.70</td>
<td>0.00077</td>
<td>0.0105</td>
</tr>
<tr>
<td>Endogenous-M</td>
<td>37.29</td>
<td>0.00020</td>
<td>0.0137</td>
</tr>
<tr>
<td>Exogenous</td>
<td>51.62</td>
<td>0.00032</td>
<td>0.0152</td>
</tr>
<tr>
<td>Exogenous-1</td>
<td>35.23</td>
<td>0.00043</td>
<td>0.0111</td>
</tr>
<tr>
<td>Exogenous-M</td>
<td>66.52</td>
<td>0.00023</td>
<td>0.0189</td>
</tr>
</tbody>
</table>

#### Diameter

As noted before, the diameter of a network measures the longest of all the calculated shortest paths between two network participants. In other words, it measures the longest distance between two participants or simply network’s size or the reach - how long it will take to reach any node in the network (Cheliotis, 2010). The average diameter for all trending hashtags in the data set is 43.89 and there are significant differences between endogenous (22.27) and exogenous (51.62) categories. The smallest diameter is observed for single peak endogenous trends and the largest for exogenous multi-peak ones. These results confirm the findings from the previous section that exogenous multi-peak networks are the largest in terms of user base (they have more than 63% of all posters).

#### Density

Density is the proportion of existing ties (edges) to the total number of possible ties in a network. To calculate it Netlytic divide the number of existing ties (connections) by the number of possible ties. The results in relation to the General Election data set show that density of endogenous trending hashtags is twice as high as density of exogenous hashtags. The application of this metric thus shows that posters in the first category form a more close-knit community and are talking with many others. (Cheliotis 2010). In comparison, posters in the exogenous category are less connected to each other in the network. The highest value of density can be observed
for a single peak endogenous category, which indicates a more close-knit community and most likely orchestration as a method to make the hashtag trending.

These findings are similar to the findings of Recuero and Araújo (2012a) and their study of orchestrated trends. They establish that orchestrated topics have much denser and clustered networks than naturally occurring ones, suggesting they are built on tight-knit communities. Recuero and Araújo (2012a) argue that these differences are also caused by the way trends spread through the network. Naturally occurring (exogenous) topics rely on values such as novelty and spread through bridging (weak) ties. They emerge naturally from discussions about events or celebrities. Orchestrated topics on the other hand rely on values such as engagement, cooperation and trust among the users and spread through bonding (strong ties). They are a form of collective action with a common goal which is easier to achieve via organised cooperation, hence they form denser networks. These findings seem to be confirmed by the reciprocity measure.

**Reciprocity**

Reciprocity is the ratio of the number of links between nodes pointing in both directions (also called reciprocal ties) to the total number of links (not all possible ties) (Cheliotis, 2010). A high reciprocity, as it is the case with exogenous multi peak category, indicates that many participants have two-way conversations, whereas a low value (endogenous, single peak category has the lowest value) suggests many one-sided conversations, with very little back and forth conversation. This is the outcome of techniques used by fans to orchestrate trends (Recuero and Araujo 2012b) which are not based on conversations but posting as many messages with the hashtag that needs to become trending. The reciprocity of such networks is relatively low in comparison with networks that occur naturally. In the field of politics, Bastos at al. (2013) argue that in order to make political hashtags trending, instead of relying on hubs (as it is the case with gatekeeping in traditional mass media) one should focus on highly active users who might have relatively few connections but are able to generate highly replicable posts. The levels of reciprocity for endogenous, single peak trends suggest it is very likely they were created via orchestration.

To sum up the analysis so far then, all three network metrics confirm that endogenous (especially single peak) Twitter trends generated during the campaign
for General Election display very similar characteristics to orchestrated fandom trends.

**Hashtag length**

Chapter Six analysed changes in hashtag length in Poland since their inception until recently and concluded that hashtags used as orchestrated political micro-memes tend to be longer than hashtags used for categorisation or as backchannels for TV discussions. In fact, all functions other than orchestration tend to produce short hashtags. Recuero and Araujo (2012b) have the same conclusions and argue that since orchestrated trending hashtags usually contain the full statement or even a phrase they are also usually longer. Their results from Brazil show that they contained 13.1 characters in comparison to naturally appearing ones that were on average 9.9 characters long.

<table>
<thead>
<tr>
<th>Type of trend</th>
<th>Length (Ave)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total</td>
<td>13.49</td>
</tr>
<tr>
<td>Endogenous</td>
<td>16.96</td>
</tr>
<tr>
<td>Endogenous-1</td>
<td>17.21</td>
</tr>
<tr>
<td>Endogenous-M</td>
<td>16.14</td>
</tr>
<tr>
<td>Exogenous</td>
<td>12.25</td>
</tr>
<tr>
<td>Exogenous-1</td>
<td>13.15</td>
</tr>
<tr>
<td>Exogenous-M</td>
<td>11.46</td>
</tr>
</tbody>
</table>

*Table 24: Hashtag Types by length (average number of letters) - GE 2017 UK Dataset*

The findings from the UK General Election 2017 dataset confirm these results (Table 24). The average length of the trending hashtag in Poland, measured as the number of letters was 15.24. In this dataset, it is 13.49 letters. Not surprisingly, endogenous, single peak hashtags are the longest (e.g. #LastMinuteCorbynSmears or #MakeJuneTheEndOfMay) and exogenous multi-peak (e.g. #GE17 or BBCQT) trends are the shortest. This is another metric that indicates that hashtags in the first category were orchestrated.
Conclusion and limitations

This chapter was guided by two questions posted by Aruguete (2017: 51). The first asked whether social networks can set conversation topics or repeat the agenda of topics proposed by elite media. The second one was concerned with the agenda setting power claimed by official information sources and asked if it persists in the new media environment.

The analysis revealed that just over 25% of the Trends surfaced by Twitter Trend Box during the campaign before the General Election 2017 was endogenous to Twitter, meaning that they did not reply to agenda set by traditional media. However, after looking deeper into the data it becomes clear that without knowing the actual time they were visible for, it is impossible to draw the full picture. Exogenous hashtag trends with a visibility of almost 75%, were trending multiple times during the campaign, which means their agenda setting power should be bigger than the discussed 75%. A high proportion of exogenous hashtags are simply backchannels for TV programmes or general categorisation hashtags such as #GE17. They create the awareness of the event (GE) or media programmes (#BBCQT) but do not set the agenda in the sense that they tell users what to think. In order to learn about opinions, users have to click the hashtag and explore all tweets that were tagged with it. On the other hand, endogenous hashtags do not require that. Their power is in the fact that the user does not even need to click on it, to know what to think. The message, the tone and the narrative are already present in the hashtag. In this way the visibility on its own in the Trend Box seems to be more important than the volume of the conversations they generate.

The question of how Twitter’s Trend Box can be studied as an algorithmic gatekeeper was answered methodologically, analytically and from the perspective of digital media. Methodologically, following Madsen’s (2012) notion of ‘screened visions’ the case study confirmed that third party Trend lists can be used to generate data to analyse Trend Box as an algorithmic gatekeeper. The method helped to surface more trending hashtags than was possible in other studies (Cram et al 2017: online and Gallacher at al. 2017: 1) that used methods which only surfaced exogenous hashtag trends.
One of the greatest limitations of this study is the issue with data representativeness. Twitter's REST API generated almost 3 million messages posted by more than 1 million of users but there were significant gaps in the data, especially for the most popular hashtags, which raises some questions about the internal representativeness. Another limitation is related to the way data collection was organised. It required the researcher to manually identify the trend and manually set up the search query in Netlytic. Unfortunately, it meant that often hashtags were trending for hours before the first 1000 Tweets (REST API Limit) were collected, meaning that the data for the initial stage of the trend was not collected. This limitation will be addressed in the next Chapter, in which I describe the development of Trend Catcher - a tool that captures all available data for a trend almost immediately after it is surfaced by Twitter.

Analytically, the use of basic and network metrics helped to establish clear differences between exogenous and endogenous trends, especially visible between two subcategories: exogenous multi peak trends and endogenous single peak ones. Most of the findings confirmed that the network behaviour of endogenous trends is similar to the behaviour of orchestrated fandom trends. This also indicates that endogenous trends that appeared during GE 2017 were orchestrated.

Finally, from the digital media perspective, this chapter shows that endogenous hashtag trends are not a marginal trend but are now becoming one of the main features of Twitter. They are the form of hashtagability realised through users who manipulate platform’s algorithm through Coordinated Inauthentic Behaviour. Most of the exogenous trends in the dataset have clearly identifiable algorithmic owners: for example, #BBCQT is owned algorithmically by the BBC as is the case with most of the hashtags linked to TV programmes. If they do not have institutional owners, e.g. #GE17 it is obvious that they are being used as naturally occurring categorisation tools. With endogenous trends it is different. One can treat orchestrated fan trends as innocent games of teenagers. The same can be said about hashtag games, which as argued in Chapter Three have their creators and ‘admins’. When it comes to political orchestrated hashtag trends the networks behind them behave in the same way as fan trends, but no one knows who is behind them. This is problematic as they have considerably more cultural and political significance than fan trends or hashtag games. They can help to set the agenda of the platform (25% of GE2017 trends were in this category) and give visibility to issues in ways that were previously only
possible through paid advertising with clearly defined organization behind them. With orchestrated endogenous trends we simply do not know who and why created them.

The next chapter will explore how the form of hashtagability that creates hashtag trends can be studied from the perspective of the knowledge they generate and what happens in the life of the trend before it becomes one. It will try to compare the before and after trend stages to see the impact of a hashtag becoming a trend on the behaviour of users and how they re-contextualise it.
Chapter 9: Hashtag Cloud Analysis

Introduction

This chapter addresses the becoming of hashtags trends by introducing Hashtag Cloud Analysis (HCA) - a novel method of investigating trending hashtags through the use of co-occurrence. It develops a tool for studying hashtagability, called Trend Catcher, which captures the ‘becoming’ of trends. HCA helps to explore hashtagability realized as the potential of hashtags to become trends by trying to capture the ‘becoming’ of the hashtag trend - the pre trending phase in the life of a hashtag, and comparing it with the phase of being a trend, when the potential is fully realized.

Methodologically, the Trend Catcher tool draws on Madsen’s (2012) concept of Screened Visions. It can be used to develop both myopic and hyperopic visions of trending and makes them publicly available at trend-catcher.tk. The myopic vision is operationalised as an interface generated by data from a Twitter API (list of trends, time and date of the hashtag becoming a trend) and a snapshot of Hashtag Cloud Average Score - a new metric developed in this chapter. The hyperopic vision developed in this chapter presents an extended quantitative and qualitative view of hashtags co-occurring with each other. The quantitative view is presented in the form of Hashtag Cloud Average Score (HCAS) broken down into pre- and post- Trend Box entry phases, respectively Phase 1 and Phase 2. HCAS as a metric aims to identify orchestrated trends by measuring hashtag co-occurrences. It is based on the observations of data from the previous chapter as well as previous research (Huang et al. 2010; Recuero and Araújo 2012a) that indicates that orchestrated trends should have fewer hashtags co-occurring with them in the ‘becoming trend stage’ (Phase 1) as the orchestrating teams are entirely focused on making a single hashtag trending and therefore do not use any other hashtags. The situation should be different with naturally occurring trends, which should have more co-occurring hashtags.
Analytically, the myopic vision helps to examine the life cycle of each hashtag trend and identifies the impact of the entry of a hashtag to a Trend Box on the associations it forms. It presents ranked lists of hashtags co-occurring with the one that is being analysed. This myopic vision is an analytical tool to study hashtagability - the potential of hashtags to do things realized by the users and the platform. It shows how hashtagability is realized by the function of becoming a trend and how these hashtag trends (generated by algorithms based on users’ behaviour) is informed by the co-occurrence of hashtags.

Finally, from the perspective of digital media, HCA shows what happens with the hashtag just before and immediately after it becomes a trend. It helps to identify possible orchestration and shows the agenda setting power of Twitter Trend Box by offering a clear view of the before and after associations of a hashtag. It is a practical contribution that reaches out beyond academia and has the potential to be developed further commercially and applied in business, policy or market research.

**Hashtag Clouds**

**Co-occurrence**

At a basic level, hashtags co-occurrence can be defined as two or more hashtags added to a single post. The historical #SanDiegoFire that introduced hashtags to Twitter got its first co-occurring hashtag (#openworld07) as early as December 2007. The practice of multi-tagging in emergency situations developed by Starbird and Stamberger as early as 2010, was the first coordinated attempt to make use of hashtag co-occurrences. Multi-tagging was later re-developed by Grasso et al (2017) for the Italian emergency situations.

This chapter uses Co-occurrence Analysis based on the frequencies of co-occurring hashtags to study the becoming of trends. Technically there is nothing, apart from word limit, that stops users from adding two or more hashtags into a single post. When this happens, an immediate bond is created between the hashtags. Rocheleau and Millette (2015) argue that hashtag co-occurrences can be understood as an organisational strategy, allowing users in a hashtag community to manage
information. Co-occurrence analysis was used by Marres and Gerlitz (2015), who used Twitter Streamgraph and Infomous tools to measure the co-occurrence of keywords in real time as a way to tell what was ‘happening’. They argue that Co-Occurrence Analysis based only on frequencies of co-occurring words helps to answer the question: ‘what is happening right now?’ They see the frequency of co-occurrence as a suitable indicator of what is becoming current or as they call it ‘happening issues’. This chapter uses co-occurrence to look at the life span of hashtags rather than ‘issues’ in the first instance; it helps to surface what is usually invisible - the ‘becoming trend stage’ of the hashtag. It thus contributes to an understanding of the overall lifespan of hashtags. It does this by developing a concept of a Hashtag Cloud that is then operationalised as a ranked list of co-occurring hashtags for qualitative analysis and Hashtag Cloud Average Score for quantitative analysis. These analyses enable a view on the happening of issues.

**Hashtag Cloud (HC)**

At the most basic level, a Hashtag Cloud (HC) is the group of hashtags present in a single Twitter post. For example, for the post ‘We had a great day in Paris! It’s a great city! #paris #beautiful #cathedral #architecture #france’ Hashtag Cloud consists of all co-occurring hashtags present in the post: ‘#paris #beautiful #cathedral #architecture #france’.

Things get a bit more complex, when one looks at co-occurring hashtags in Twitter search results, rather than at the level of an individual post. Twitter search for a hashtag creates two different types of possible networks. One of them was defined as ambient affiliative network by Zappavigna (2012) and consists of users who are co-present. The other possible network consists of hashtags that co-occur with each other and the search term (hashtag). For example, search for #London will bring all tweets that contain hashtag #London and these tweets will contain other hashtags as well. By collecting some (say 10) of these posts (manually or via API) and removing all non-hashtags, one is left with the list of hashtags that co-occurred in the search results with #London. This is the Hashtag Cloud for a search: it does not
represent a single post, but 10 posts. However, to enable this Cloud to reveal
something about trending, we need to analyse it further.

We know that #London was present in all these posts, so its frequency was most
likely 10 (or more). It is also possible that other hashtags co-occurred more than
once with #London. The below example of Twitter search result illustrates this
scenario:

Tweet 1: The Royal Exchange in the City of #london. #photography

Tweet 2: 400,000,000 #Snapchat's a Day! News from #contagiousNNW
#London

Tweet 3: Who is going to #london for #Easter?

Tweet 4: #london or #berlin? Where would you go?

Tweet 5: My mother was from #london but then my family moved to
#coventry because of house prices.

Tweet 6: On my way from #berlin. I'm landing in #London in 2hrs

Tweet 7: King's Cross bridge in 1953. #London

Tweet 8: Think I'll drop the vlog from #London now I know #AlsinaNation
been waiting for it... here it goes

Tweet 9: This is such a stunning setting for a show #sunset #London

Tweet 10: Thanks again to @LondonHistorian for opportunity to visit
archaeological dig at Liverpool Street - absolutely brilliant :-D #London
#history

To extract a Hashtag Cloud from the above search results, we need to remove all text
apart from hashtags. By doing that one ends up with the following list: #london
#photography #Snapchat #contagiousNNW #London #london #Easter #london
#berlin #london #coventry #berlin #London #London #London #AlsinaNation
#sunset #London #London #history. The list can now be ordered by frequency of
occurrence which creates a ranking: #London (occurs 10 times), #Berlin (2),
#photography (1), #Snapchat (1), #contagiousNNW (1), #Easter (1), #coventry (1),
#AlsinaNation (1), #sunset (1), #history (1). This ranking is what forms a Search
Level Hashtag Cloud. It is a list of hashtags co-occurring with the search term hashtag
ranked and ordered by the frequency of co-occurrence. This type of Hashtag Cloud is the main unit for the analysis in Hashtag Cloud Analysis as developed here for the purpose of analysing the life span of trends. The next section explains how Hashtag Clouds can be used to analyse different stages of the life of the trend.

**Hashtag Cloud Analysis**

Hashtag Cloud Analysis (HCA) is a fully automated process of analysing trending hashtags by studying their co-occurrences. It utilises a specially developed tool - Trend Catcher - to capture and then analyse trending hashtags in selected locations and in two different stages of a trend's life: 'Becoming Trend' and 'Being Trend'. This section firstly describes how the life cycle of trends has been theorised in academia and how these studies informed the data collection strategy used by the Trend Catcher application. Secondly, it shows how the collected data is then processed and made available for qualitative and quantitative analysis.

**The becoming of trends**

There is a relatively small literature that addresses the life span of trends. Yardi et al. (2009) argue that most activity around trending hashtags occurs during the 24 hours following the creation of the hashtag, with the first hours being the most significant. Asur et al. (2011) defined the three main stages of the life of the trend as: (1) formation, (2) persistence, that is, continued existence and (3) decay, the process of decomposition. They argue that the lifespan of a trend depends on the triggers and trends that originate in traditional media outlets (exogenous) usually last longer than the trends generated by Twitter users (endogenous) and that overall only a few topics last for a long time, while most disappear from the Trending Topics box in the order of 20-40 minutes. Huang et al. (2010) argue that all micro-meme hashtags live relatively short lives and they quickly go through two phases. The first is the adoption of a hashtag - the process by which a newly coined hashtag is embraced by a critical mass of users and disseminated through Twitter i.e. a hardly ever used hashtag suddenly becoming widely used. Then hashtags go into an abandonment phase - the process in which a critical mass of users stop attaching a specific hashtag to their tweets.
The speed of adoption of hashtags seems to depend on the topic of hashtags. Romero et al. (2011: 695) use the measure of ‘persistence’ defined as ‘the relative extent to which repeated exposures to a piece of information continue to have significant marginal effects on its adoption’ to see how different hashtags behave depending on their topic. They argue that politically controversial hashtags are particularly persistent and that repeated exposure to these hashtags has an unusually large effect on the adoption of a hashtag. In contrast hashtag idioms and neologisms (Huang et al call these micro-memes) are particularly non-persistent and multiple exposures have the opposite effect.

Finally, location and time zones are also known to play a role in the life span of a trend. Asur et al. (2011) notice that very often topics disappear from the Trending Topics box and then reappear there after a while: this is the case with around 34% of trends. Asur et al. (2011) think this could be caused by time zone differences and a topic entering and leaving trends as people are waking up/ going to bed at different times and this is reflected in their Twitter activity. They also observed that some topics that were trending in the evening might reappear in the Trending Box in the morning the next day in the same time zone. A similar situation was observed in the previous chapter, where 45% of trending hashtags had multiple peaks, meaning that they became trends multiple times during the analysed period.

The above studies show that the life cycle of a trending hashtag is relatively short and can usually be described by two or three distinctive periods: rapid adoption of a new hashtag, a period of relative stability and a rapid abandonment phase. Most trending hashtags become trends at some point during the first (rapid adoption) stage and then the fact of entering the trend box and getting the extra visibility increases that adoption even more. They then enter a period of stability and finally a rapid decline. From the research perspective, it is almost impossible to say what happens with the hashtag in the ‘becoming trend stage’, when it is undergoing this rapid adoption but it is still not recognised by the algorithm as a trend. I call it a ‘becoming trend’ stage. The process happens entirely at the back end of the Twitter platform and users or researchers have no visibility of it – there is no such thing as a Pre-Trend box that would give an indication of hashtags that could be potentially trending in 10-20 minutes. It is possible that there are hashtags that undergo a rapid adoption, for example via orchestration, and are identified by algorithm as
potentially trending but then never become trends as in the last few minutes they do not receive enough attention from the users or basically do not 'tick' all the boxes required by the algorithm to become a trend. These unsuccessful trends are never surfaced by Twitter.

In order to study the pre-trend Box life of a hashtag, it is crucial to be able to collect as much information about this period as possible. Unfortunately, the infrastructure of Twitter is not very helpful. The most popular hashtags already have thousands of posts when they become trends, so qualitative analysis of these posts using Twitter search would be very difficult. Twitter API could be helpful, but its most popular version (REST API) has a limit of 1000 most recent posts that can be downloaded using it. As a result if data collection is delayed the data that is captured is not from the 'becoming trend' stage of the hashtag but 'being trend' stage because almost immediately after a hashtag becomes a trend, it generates even more interest. This problem with data collection 'hides' the formation stage from the public eye and the more time passes from the surfacing of the trend the more difficult it is to capture the trend formation data. The next section describes how this problem can be solved with a specially designed automatic data collection tool.

**Trend Catcher: Data collection strategy**

Trend Catcher is a custom-built application that was developed especially for this study to enable data capture for a trending hashtag when it is still in the adoption phase and the trend has not been surfaced yet by Twitter Trend box. The two key features of the application are that it monitors all Twitter Trends for selected geographical regions (the USA, Poland and London) via Twitter Trends Search API and once a new trend has surfaced, it almost immediately starts data collection, allowing it to capture the pre-trend data.

The US was chosen as a high proportion of hashtag games originate there and then start trending in Britain and other English-speaking countries. Poland was chosen for its linguistic isolation that helps to identify trends in a single country. It is difficult for a Polish hashtag to start trending somewhere else in the world, without a group of Polish speakers in that region that could make it trending. Finally, London was chosen as the location where a significant number of British trends start. The choice of three locations was also dictated by the financial and capacity limitations of a PhD
study. It would not be possible for a single person to monitor thousands of trends around the world.

Trend Catcher application is constantly connected to Twitter Trends API and collects data for the above locations. Every ten minutes it sends a request to Twitter to obtain the list of all trending Topics. It then identifies all new Trends that are hashtags and immediately starts data collection for them to enable the capture of pre-trend data. Based on the findings from previous studies and the analysis of data downloaded for 114 hashtag trends in Chapter Seven, Trend Catcher collects 1 hours’ worth of posts from the 'becoming trend' stage and then another three hours’ worth of data after the hashtag is actively trending to cover the persistence and abandonment phases (Yardi et al. 2009). As a result, the data for each trend covers 4 hours of which the first hour is treated as pre-Trend Box phase and the remaining 3 hours as being trending. For ease of use, I am calling these 'Becoming trend' stage (or Phase 1) and 'Being Trend' stage (or Phase 2).

The data collected for the analysis of trends during GE 2017 campaign discussed in the previous chapter revealed that 45% of trends had multiple peaks, meaning that they were surfaced by the Twitter Box, then disappeared from it and then reappeared again after some time. As that analysis showed, this can happen more than once during the same day (Asur et al. 2011). In order to understand the life span of trends, the decision was made that all captured trends for the day should described not just as identified by a hashtag, but also with a timestamp. As a result, it is possible that the dataset for each day contains two or more trends for the same hashtag but with multiple timestamps. These are all treated separately and ‘Becoming Trend’ and ‘Being Trend’ data for each of these trends is collected separately.

Informed by the above design, the data collection application was developed with the help of Maciej Jarka71, a senior ETL engineer. Technically, the procedure is fully automated and no human intervention is required. The extraction of data is

71 Mr Jarka wrote the code following my instructions and has provided continuous support for the application since the first deployment in 2017.
operationalised using Twitter4J\textsuperscript{72} - a non-commercial Java library known for its reliability and coverage of a wide range of API methods which connects to ‘Get Trends near a location’ Twitter API \textsuperscript{73} using two search parameters: getPlaceTrends(WOEID)\textsuperscript{74}, which returns current trends for a selected locations (USA, Poland and London) and getTweets(Query), which returns tweets for a given query - a trending hashtag. All the API calls and load procedures are performed repeatedly by TrendCatcher ETL Java application deployed on AWS Cloud Stack. The application is a custom Java code, scheduled in 10-minute intervals on AWS EC2 Microsoft Windows 10 instance. The custom-made application was developed instead of using any existing ETL products, because of the very specific requirements imposed by the desire to analyse pre and post trend time, hashtags only etc., and the lack of available products on the market that could perform the task.

The data collected by the tool forms an archive which at the time of writing contains 118,000 hashtag trends captured between November 2017 and February 2020 for three locations (USA, Poland and London). For these hashtag trends, more than 100,000,000 Tweets and more than 160,000,000 co-occurring hashtags were collected (see table below).

<table>
<thead>
<tr>
<th></th>
<th>London</th>
<th>US</th>
<th>Poland</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of Tweets</td>
<td>55959244</td>
<td>47796996</td>
<td>110482165</td>
</tr>
<tr>
<td>Number of Hashtags</td>
<td>83499091</td>
<td>67072616</td>
<td>16339427</td>
</tr>
<tr>
<td>Number of Trends</td>
<td>50858</td>
<td>45748</td>
<td>21330</td>
</tr>
</tbody>
</table>

Table 25: Data Statistics for Trend Catcher (November 2017 - Feb 2020)

\textsuperscript{72}\url{http://twitter4j.org/}

\textsuperscript{73}\url{https://developer.twitter.com/en/docs/trends/trends-for-location/overview}

All data from the archive is made available for the analysis at www.trend-catcher.tk in the form of a dashboard. The following three sections will explore some of the qualitative and quantitative kinds of analysis that are possible using the collected data and observed limitations. It is hoped that the tool can be further developed for other kinds of analysis by other researchers.

**The qualitative Hashtag Cloud Analysis**

The trend-Catcher (www.trend-catcher.tk) website was developed as a dashboard to allow the analysis of the becoming of hashtag trends. The logic of the design follows Madsen's idea of screened visions and Hashtag Clouds enable both myopic and hyperopic visions. The home page creates a myopic vision presented as a list of all captured hashtags for a given location (USA, London or Poland). There is also an archive of all historical dates. It is the immediate vision of the Trend Box as ‘it is happening’ and is the starting point to further exploration via clickable hashtag hyperlinks. After clicking on any of the hashtags, the user is taken to a hyperopic vision for an individual hashtag. The design of the layout (see figure 53 below) was developed with the aim of presenting the results of both quantitative and qualitative analysis on a single page. The top two blocks of the hyperopic vision present Hashtag Cloud Average Scores (to be discussed in the next section), and the bottom two boxes show Hashtag Clouds in Becoming (Phase 1) and Being Trend (Phase 2) stages ordered by frequencies.
Based on the original design (Figure 53), I employed a web developer\textsuperscript{75} to create the front end for the Trend Catcher application. Figure 54 below shows how the design was implemented and trend-catcher.tk website was developed.

\textsuperscript{75} Frontend of Trend-Catcher.tk was developed by web developer Krzysztof Chojnowski
The best way to explore Trend Catcher as a dashboard is by accessing live applications at www.trend-catcher.tk. For the ease of reading, from now I will be pasting tables rather than screenshots from the website. The table below shows the Hashtag Clouds in two Phases (Becoming and Being Trend) generated for #BISEXUALMENEXIST in a format that is used on the website.
Table 26: Pre- (becoming) and post (Being)-trend Hashtag Clouds captured for #BISEXUALMENEXIST

The Table 26 above can be used to analyse what Marres and Gerlitz (2015) call ‘happening issues’. It shows a detailed, associative or distributed view of the analysed hashtag in two phases, and an aggregated view of all clickable issues (hashtags) that are related to the analysed term. Most importantly, it does this for the two distinctive stages, which helps to observe the effect of the hashtag becoming a trend. The ‘Becoming Trend’ stage shows how a focused discussion, with the co-occurring hashtags clearly related to the analysed term, got completely hijacked by spammers in the ‘Being Trend’ stage. The screenshot below (Figure 55) shows how spammers started using #BISEXUALMENEXIST when it became a trend. By making such shifts in conversations visible, Trend Catcher website offers a new and innovative way of exploring changes in Twitter conversations and identifying inauthentic behaviour in the happening of issues.

76 https://www.trend-catcher.tk/london/tag/BISEXUALMENEXIST/date/2020-02-25/
The table 26 above could be also analysed as a new way of looking at Twitter Search results. The usual way would include posts, images, usernames etc. This hyperopic vision removes all this from view and instead contextualises the search hashtag using other hashtags only to produce an associative view – this is the cloud. It is a new way to see what the discussion is ‘about’, making clear the dynamic, fluid and multiple nature of searchable talk without the need of extracting it from the large number of posts.

Finally, the visual exploration of Hashtag Clouds ranked by their frequencies, allows the researchers to notice that hashtags that could be described as orchestrated, for example micro-memes, fandom hashtag or hashtag games, or political memes usually have almost no other hashtags co-occurring with them in the pre-trend stage. It is only when they become trends, that other hashtags tend to start co-occurring with them.
An example is the Polish hashtag #KidawaTworzy which is a political micro-meme targeting the Malgorzata Kidawa Blonska - the candidate in the 2020 Presidential Campaign. The style of the hashtag is very similar to political micro memes that I identified in the historical analysis of Polish trending hashtags in Chapter Six, where I argued that such hashtags most likely are orchestrated. The analysis of Phase 1 and 2 Hashtag Clouds using Trend Catcher Tool allowed me to see that in the first stage this hashtag only co-occurred with three other hashtags and in the second stage the co-occurrence increased to 22. This was a striking contrast to exogenous TV programme hashtags such as #minela8 or naturally occurring ones such as #PancernyMarian, which had an almost identical distribution and number of co-occurring hashtags in Phase 1 and 2.

This analysis of orchestration builds on the observation and analysis of data collected in the previous chapter as well as the research of Huang et al. (2010) and Recuero and Araújo (2012a) which suggests that the practice of orchestrating trends requires the focus of the orchestrating group on a single hashtag. This would indicate that such hashtags should have almost no other hashtags co-occurring with them in the pre-trend stage. Then, once such hashtag becomes a trend and gets the visibility of other users, who are not members of the orchestrating team, new co-occurring hashtags should start appearing in the second phase. Based on these observations, I developed Hashtag Cloud Average Score - a new experimental metric that could further help to identify orchestrated trends.

**The Quantitative Hashtag Cloud Analysis**

The previous section showed how Hashtag Clouds could be explored qualitatively. This section explores the creation of a new metric - Hashtag Cloud Average Score (HCAS) based on hashtag co-occurrences. The logic behind this metric follows the findings from the qualitative exploration of Hashtag Clouds. The higher the average hashtag cloud score, the more likely the trend was orchestrated as there are fewer hashtags co-occurring with it, and the lower the score, the more likely that the

77 [https://www.trend-catcher.tk/poland/tag/KIDAWATWORZY/date/2020-02-17/](https://www.trend-catcher.tk/poland/tag/KIDAWATWORZY/date/2020-02-17/)

78 [https://www.trend-catcher.tk/poland/tag/MIN%5C4%98%5C5%81A8/date/2020-02-19/](https://www.trend-catcher.tk/poland/tag/MIN%5C4%98%5C5%81A8/date/2020-02-19/)

79 [https://www.trend-catcher.tk/poland/tag/PANCERNYMARIAN/date/2020-02-19/](https://www.trend-catcher.tk/poland/tag/PANCERNYMARIAN/date/2020-02-19/)
hashtag became a trend naturally, not by orchestration. Chapter Six explored hashtag length and user diversity to see if they are indicative of orchestration. Chapter Seven used user Network Metrics such as density or reciprocity to explore users’ behaviour around hashtags and proved that they were very indicative of possible orchestration. In this chapter I explore the co-occurrence of hashtags to see if it has the potential to identify orchestration.

Technically, the calculation of HCAS was fully automated based on hashtag frequencies. The calculation is triggered by the Trend Catcher ETL. It is then performed directly on Amazon RDS (Relational Database Service) as a SQL procedure. In 2017, at the beginning of the project PostgreSQL was used as an underlying RDS technology but due to the enormous monthly growth in size of collected data there were periodic outages of the application. The latest version of the application uses SQL procedure. The Figure 56 below is a diagram of how the Trend Catcher application operates.

Methodologically, Trend Catcher generates HCAS for each individual hashtag. Once a hashtag Trend is identified by the app, the tool immediately starts data collection. The first data set (known as Phase 1) is generated by downloading all tweets containing the search term (Trending hashtag) that appeared in the selected geographical region in the last hour prior to trend identification. The data is then immediately processed by the tool in a filtering box. All non-hashtags are removed.
by the filter and a Hashtag Cloud for Phase 1 is generated as a list of ranked, co-
occurring hashtags with their frequencies. The same procedure is then repeated for
the second dataset that consists of all Tweets posted in four hours after the trend
detection. The outcome of this process are the two (Phase 1 and Phase 2) lists of
hashtags co-occurring with the trending hashtag, that are published on Trend
Catcher website as described in the previous section.

In order to calculate HCAS, Trend Catcher performs a simple mathematical
procedure on the collected data. I will use the example of #GeneralElection to
illustrate the exact procedure. It starts by calculating the sum of all frequencies of co-
occurring hashtags. For #GeneralElection Trend Catcher identified 10197
occurrences of #GeneralElection and 640 other hashtags co-occurring with it. The
top co-occurring hashtag #ge17 had a frequency of 801, followed by the second
#theresamay with a frequency 395 and so on. At the bottom of the list there were
hundreds of hashtags with a frequency of 1. Trend Catcher can sum all frequencies
of co-occurring hashtags: in the case of #GeneralElection the sum was 5664. In the
next stage, it can remove 20% of hashtags with lowest co-occurrence - the long tail
following the running total of frequencies. The remaining 80% of hashtags (in the
case of #GeneralElection the sum of their frequencies was 4530) can then be divided
into quarters following the moving total of their frequencies. For example, the first
quarter of co-occurring hashtags for #GeneralElection contained two hashtags:
#ge2017 (frequency 801 - 17.7% of the total of 4530) and #theresamay (395 - 8.7%
of the total of 4530). The algorithm established that 1196 (the sum of 801 and 395)
constitutes 26.4% of the total 4530. This is Q1. The same procedure is then
performed for the remainder of the dataset.

The removal of 20% of hashtags with lowest co-occurrence is based on previous
studies, that looked at the distribution of hashtags on Twitter (Gerlitz and Rieder,
2013) or more precisely, the distribution of co-occurring hashtags on Twitter (Shah
and Joshi, 2013). Gerlitz and Rieder (2013) analysed the sample from 1 day of
Twitter activity (844,602 occurrences of 227,029 unique hashtags) and established
that the distribution of hashtags in their sample followed the typical power law and
only 25.8% of hashtag appeared more than once and only 0.7% more than 50 times.
Shah and Joshi (2013:2) came to the same conclusion (See Figure 57 below) based
on the sample of 465,832,570 occurrences of 24,792,561 hashtags. Both these
studies took different approaches to removing the long tail and these were determined by their objectives. Gerlitz and Rieder (2013) decided that their cut-off point was 50 occurrences as 96.6% of these hashtags could be considered as connected (mentioned in the same tweet with other hashtags). From that perspective the connectedness was only on the level of an individual Tweet. Shah and Joshi (2013) similarly to this study sorted the hashtags in descending order of co-occurrence counts but focused their analysis on pairs of hashtags with the strongest co-occurrences, which practically means they only analysed two hashtags at the time.

The two studies mentioned above show two extremes based on their respective objectives. Gerlitz and Rieder (2013) made their decision based on the connectedness of hashtags in the entire sample. They did not analyse connectedness of individual hashtags. On the other hand, Shah and Joshi (2013) analysed individual hashtags and made the decision to look at only a single hashtag with the highest co-occurrence. In this thesis, I attempted to do both - to establish the connectedness of the analysed, single hashtag (1) with all co-occurring hashtags (2) (HCS). To make it...
even more complicated my aim was also to present these co-occurring hashtags visually as an associative view, as described above, for the qualitative Hashtag Cloud Analysis. In practical terms, if I only focused on the pair with the strongest co-occurrence, the calculation of Hashtags Cloud Score would not be possible as the score would only be describing the relation between two hashtags. There would also be no possibility to present the list of other hashtags present in the cloud. On the other hand, if I included all hashtags in the calculation, the list of co-occurring hashtags for the most popular trends would be so long that I would not be able to present it on the website as it would take enormous computing power to generate it for each trend. I had to make a practical decision to strike a good balance between the quantitative view of the Cloud and the impact of the cut-off point on Hashtag Cloud Score (quantitative analysis).

As a result, I experimented with different cut-off points that included between 50 and 100% of co-occurring hashtags. As expected, the inclusion of all (100%) hashtags proved extremely difficult for the most popular hashtags. For example, hashtag #GeneralElection had 640 co-occurring hashtags which made it impossible to present these all on a single page in a way that would make it digestible for the user. On the other hand, there were less popular trending hashtags that only had 10 or 20 co-occurring hashtags, which could all be easily presented. After visually inspecting more than a hundred distributions and how these can be presented on the website, I established that the cut-off point should be at 70 co-occurring hashtags. This number ensured that all hashtags with significant co-occurrence with the most popular trending hashtags were surfaced. Gerlitz and Rieder (2013) in their study established that this number was 50 for their dataset, but they analysed only a single dataset. In case of this research, I had thousands of datasets for individual hashtags varying significantly in their respective frequency of co-occurring hashtags (from just a couple to more than a thousand). As a result, I had to set up a cut-off point as a percentage rather than a frequency. I analysed the initial 200 trends and established that keeping 80% of co-occurring hashtags ensured that there were no more than 70 of them even for the most popular trends. This approach has its limitations, which I discuss in the following section.

In the next stage, Trend Catcher algorithm calculates the average Hashtag Cloud Score for each quarter. In the example above it is calculated by dividing 26.4% by
two (because there are only two hashtags in this quarter), giving an Average Hashtag Score of 13.5% for Q1. The same procedure is then performed for the remaining three quarters. In the case of #GeneralElection these were 0.132 for Q1, 0.043 for Q2, 0.018 for Q3 and 0.007 for Q4. The Hashtag Cloud Average Score is calculated as the average of the scores for four quarters. In the case of #GeneralElection the Hashtag Cloud Average Score (HCAS) was 0.050. Then exactly the same procedure is performed for the dataset for Phase 2. As a result, two Scores are generated Phase 1 HCAS and Phase 2 HCAS.

In the final stage, both these scores need to be analysed in a search for the patterns described at the beginning of the section. Hashtags with low number of co-occurring hashtags get their HCAS closer to 1 and those with a large number of co-occurrences get the score closer to 0. These scores are then added to the website dashboard to both of the screened visions: the myopic vision, that lists all trending hashtags for the day in a given geography shows Phase 1 and Phase 2 Trend Hashtag Average Cloud Scores as HCAS-1 and HCAS-2. It offers a quick view and helps to identify hashtags that could be suspected of orchestration. Such a hashtag would have a high HCAS-1 and low HCAS-2. Table 27 below shows an example of how this works in practice.

The first column shows all identified hashtag trends in a given period of time. Column two shows the date when the hashtag was identified as a trend and column three gives a specific time. Columns four and five are Hashtag Cloud Average Scores (HCAS) in Phases 1 and 2. They provide an indication of the levels of co-occurrence of hashtags in both Becoming Trend (Phase 1) and 'Being Trend' (Phase 2) stages. Most non-orchestrated hashtags have both Phase 1 and 2 HCAS that are very similar, however #FILMSFARMERSWOULDMAKE was correctly identified as an orchestrated Hashtag Game in London in February 2020. The further qualitative analysis of its Hashtag Cloud revealed that there was only one hashtag co-occurring with it in Phase 1 and 5 in Phase 2.
Generally speaking, HCAS works well to identify orchestrated trends and is able to mathematically describe Hashtag Clouds and calculate the score based on co-occurrences created in relation to different lifespan stages. Hashtags with low number of co-occurring hashtags get a HCAS closer to 1 and those with a large number of co-occurrences get the score closer to 0. These scores are then presented in a table so just a quick look is enough to identify potentially orchestrated trends. Unfortunately, during the testing phase of the application I identified an issue that prevents Hashtag Cloud Analysis to predict trend orchestration based on HCAS for all hashtags. It is linked to the spatial distribution of trending hashtags.

### Issues with Hashtag Cloud Analysis

The main issue HCAS has with predicting orchestration is linked to access to Phase 1 data for hashtags that have already started trending somewhere else. The previous Chapter (GE 2017) provided an example of how a single hashtag can trend in different locations. Hashtag #GeneralElection became trending in Latvia (at 11:17:05) just a few minutes after Theresa May made an announcement about the election (around 11:00am UK time). Then it started trending in Algeria (at 11:21:57) and several locations in the US (i.e. Washington - at 11:42:11, Virginia Beach at 11:47:00) followed by Australia (Sydney at 12:02:09), Belarus (Minsk, Gomel and Grodno at 12:47:16), Switzerland (Zurich at 12:47:14) and several other locations around the world (in the Netherlands, Italy, Germany, France and Ireland) until it became trending globally at 15:37:43. Then it finally became a trend in the UK (first in London) 10 minutes later at 15:47:49. These trends that appeared in Latvia,...

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80 https://www.trend-catcher.tk/london/date/2020-02-20
81 https://trendogate.com/search/?trend=%23generalelection&page=3
Australia and in different parts of the world prior to appearing in the UK, have a significant impact on what data can be captured for a trend in the UK.

If Trend Catcher was set up to collect data in all the locations mentioned in the above example, it would collect multiple trends for the same hashtag #GeneralElection. It would then collect data for Phase 1 (1hr before trend identification in a location) and Phase 2 (3 hours' worth of data for the location). The problem with this approach is that the data which would be identified as Phase 1 in one location, would be treated as Phase 2 in the other. For example, data collected for Zurich, where #GeneralElection was identified as a trend at 12:47:14 would include Becoming Trend (Phase 1) data covering the period between 11:47:14 and 12:47:14 and as the above example suggests, this data would be treated as ‘Being Trend’ (Phase 2) in case of Latvia, Algeria and multiple other locations in the US, Australia and Belarus.

Ideally, Tweets that made #GeneralElection trending in Latvia should not be included in the dataset of tweets collected for Zurich as the search query is based on the location, but in practice it is impossible to determine if this is the case without having access to all signals that are used by Twitter’s trend algorithm (Seaver 2012, Kitchen 2014). The qualitative analysis of Hashtag Clouds show that the data is mixed, meaning that if a hashtag is trending somewhere in the world and then becomes trending in a second location, it is impossible to isolate co-occurring hashtags only for the second location. As a result, when collecting ‘Becoming Trend’ (Phase 1) data for location 2, we are also collecting Being Trend (Phase 2) data for location 1. In such cases data does not represent the real Phase 1 for the location, making it impossible to identify orchestration reliably as this makes the co-occurrence higher for the Phase 1 data, lowering the HCAS score and indicating that it is a naturally occurring trend, when in reality it was orchestrated an hour earlier but in a different location.

The table below for hashtag #IfImMadItsBecause illustrates how the issue presents itself in practice. Trend Catcher calculated the Phase 1 HCAS for #IFIMMADITSBECAUSE as very low (0.042) indicating there was no orchestration. However, as qualitative analysis reveals, it is very likely it was orchestrated somewhere else before it started trending in London. The hashtag is very likely a conversational micro-meme. The data captured for it as Phase 1 shows that the co-occurrence is extremely dispersed - there are a lot of co-occurring hashtags but they
are rather random, most likely used by spammers. This qualitative analysis shows that co-occurring hashtags in this Phase 1 Hashtag Cloud are very similar to Phase 2 Cloud of #BISEXUALMENEXIST, which was clearly attacked by spammers. The same thing must have happened in case of #IFIMMADITSBECause and even though the below data was captured as Phase 1, it is in fact very much a Phase 2 Hashtag Cloud.

<table>
<thead>
<tr>
<th>Trending Hashtag</th>
<th>Date</th>
<th>co-occurring hashtag</th>
<th>Quarter</th>
<th>cnt</th>
</tr>
</thead>
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<td>25/02/2020</td>
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<td>2</td>
</tr>
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<td>1</td>
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<tr>
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<td>1</td>
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<td>1</td>
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<td>#IFIMMADITSBECause</td>
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<td>1</td>
</tr>
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<td>1</td>
</tr>
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<td>25/02/2020</td>
<td>#STORY</td>
<td>4</td>
<td>1</td>
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<td>25/02/2020</td>
<td>#THEWALKINGDEADUK</td>
<td>4</td>
<td>1</td>
</tr>
</tbody>
</table>

Table 28: Becoming Trend Phase Hashtag Cloud for #IFIMMADITSBECause generated by Trend Catcher on 25/02/2020

On the other hand, the Phase 1 Hashtag Cloud generated for #TINYVOICETUESDAY (see table below) shows all co-occurring hashtags are relatively connected with the trending one and is very likely that in this case Trend Catcher captured the ‘becoming’ of this trend accurately.

82 https://www.trend-catcher.tk/london/tag/IFIMMADITSBECause/date/2020-02-25/
The two above examples of #IFIMMADITSBECAUSE and #TINYVOICETUESDAY show that even though the tool is able to capture the data relating to a trending hashtag before it becomes a trend in a specific location, it is unable to provide consistency of results. This is a serious limitation. While it can be addressed through qualitative analysis, it is a consequence of the fact that the data collection strategy had to be based only on selected locations through lack of resources. If HCAS could be applied to the very first instance of the trend for a given hashtag anywhere in the world, it could provide evidence to show whether a trend was orchestrated or not. The current application of the tool does not give this confidence as most of the trends it captures are in fact already trending elsewhere.

This problem is less visible for Polish hashtags, as it is less common for them to become trends somewhere else. English trending hashtags are truly global and trends can start anywhere in the world and appear in London or the US after a while. The method works, but in the context of global trends, that appear locally, the data collection strategy fails to capture the true 'Becoming Trend' stage (Phase 1). The only way to capture that data would be to get access to every single trend in the world and be able to say where it started trending first.

The final limitation is methodological and is linked to the removal of 20% of co-occurring hashtags with the lowest frequency. This was a practical decision dictated by the limitations imposed by the need to be able to present Hashtag Clouds on the website for qualitative analysis. As a result, it has implications for the calculation of HCS, especially for trending hashtags with low co-occurrence. Both Gerlitz and Rieder (2013) and Shah and Joshi (2013) confirm in their studies that hashtags that appear in the long tail were not significant from the perspective of their objectives. Gerlitz and Rieder (2013: Online) describe these as not connected with the more popular hashtags and define them as 'spam hashtags that are deployed by a single

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Table 29: Pre Trending Hashtag Cloud for #TINYVOICETUESDAY generated by Trend Catcher on 25/02/2020

<table>
<thead>
<tr>
<th>Trending Hashtag</th>
<th>Date</th>
<th>co-occurring hashtag</th>
<th>Quarter</th>
<th>cnt</th>
</tr>
</thead>
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<td>#TINYVOICETUESDAY</td>
<td>25/02/2020</td>
<td>#TRANSITION</td>
<td>4</td>
<td>1</td>
</tr>
</tbody>
</table>

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83 https://www.trend-catcher.tk/london/tag/TINYVOICETUESDAY/date/2020-02-25/
account only’. Shah and Joshi (2013:2) argue that such hashtags ‘are prone to very high levels of noise due to large numbers of personal, ambiguous or misspelled hashtags that do not add any meaningful information.’ They also add that ‘co-occurrence measure itself produces many noisy connections between hashtags (p.3)’ Nevertheless, the objective of this study, was to analyse these 'noise' or 'spam' hashtags as well, so not having them limits the power of both qualitative and quantitative analyses. This is especially so in relation to trending hashtags with low co-occurrence, in which case the 20% of removed hashtags could include relevant ones removing them from the qualitative view of Hashtag Cloud. It is possibly less concerning in the case of the most popular trends, which have hundreds of co-occurring hashtags and the visual analysis of all of them would be practically impossible. It also has implications for the calculation of HCAS, but this time is more significant for the most popular trends. Using the example of #GeneralElection, out of 645 co-occurring hashtags, only the top 58 were included in the calculation of HCAS. They represent 80% of hashtags based on frequency, but less than 10% of all captured hashtags.

It was outside the scope of this study to determine the statistical significance of the 80-20 cut-off decision. As described above, the decision was made because of practical reasons. Nevertheless, it must be noted, that the inclusion of all co-occurring hashtags for the calculation of HCAS would possibly produce more relevant results. The decision was determined by the objective of practically testing the new methodology and the tool rather than testing different data cut-off points. It was also heavily influenced by the need to be able to present the most popular trends as a Hashtag Cloud in a format that is user friendly and can be visually analysed.

The most logical step for the future research would be to separate the qualitative and quantitative parts of this analysis and create a tool that is able to present visually only the manageable number of co-occurring hashtags for qualitative analysis and analyse all co-occurring hashtags to calculate HCAS. The technical limitations and the cost of server did not allow for this in case of this study, and both were based on the same datasets with 20% of co-occurring hashtags removed. This limitation however offers a great starting point for the analysis of the significance of cut-off point in relation to HCAS and establishing if it is needed at all.
Conclusion

The primary contribution of Hashtag Cloud Analysis - at least so far - is that it adds to the understanding of happening or life span of trends by enabling identification of ‘Becoming Trend’ and ‘Being Trend’ stages. The results are not always valid because its reliance on Twitter Trend box requires identification of specific locations, and to study all or many was not possible because of financial limitations of this research. However, Hashtag Cloud Analysis points to the importance - possibly not fully acknowledged before methodologically - that happening of trends is distributed not just temporally but also spatially.

The Trend Catcher tool was much more successful in its contribution to the study of hashtagability when operationalized as a qualitative dashboard. The two Phase 1 and 2 lists of co-occurring hashtags offer a detailed context for each analysed trend. The ordering of co-occurring hashtags based on their frequency creates a hierarchy of hashtags which is not visible via Twitter’s native search. It helps to contextualize the trending hashtags in relation to an association, distribution or cluster of hashtags. It also offers a great way to compare Phase 1 and 2 co-occurrences for those hashtags, for which data for the ‘Becoming Trend’ phase was captured correctly. For such trends one can see the effect for the hashtag to become a trend - almost immediately the number of co-occurring hashtags increases and the new hashtags (in ‘Being Trend’ phase) become less associated with the trending hashtags in comparison to pre-trend stage. It clearly shows what it means for a hashtag to become a trend in terms of the changing structure of co-occurring hashtags or even being hijacked by spammers. This novel way of presenting the lifespan of a trending hashtag offers much greater visibility of the changes taking place over time and helps to provide additional insights, that are not visible on the surface. It is a very practical solution and could be used by organisations that monitor social media to enrich their analysis by adding this extra layer of change over time.

The chapter also suggests that hashtagability realised as the function of creating trends is by its nature an ongoing, never ending process that has no clear beginning or an end for the high proportion of hashtags. Chapter Six established that the majority of trending hashtags in Poland were entering and leaving Trend box on a regular basis every week or even every day. It might be the case that for such
hashtags it is not useful to establish the clear point when they started to form a trend as they are always 'on the move' - in one location they are in the trend abandonment phase and in the other they are only forming a trend. Trying to capture the 'beginning' is a complex task from the methodological point of view as they simply have no single beginning or end. Instead of fixating on capturing the becoming, it might make more sense to observe them as they are 'performing' the trend and consider what knowledge about hashtagability the trend generates as it is distributed in time and space. By following this approach, Trend Catcher could be seen as a starting point for the development of a tool for surfacing of 'Becoming Trend' data, not only for the identification of co-occurring hashtags but also co-present users, which could be a powerful combination for identifying Coordinated Inauthentic Behaviour, especially during elections.
Chapter 10: Conclusion

Introduction

This thesis explored hashtagability - the structural possibility of hashtags to do things or carry out functions that can be either realised by the users or the platform, most of the time by a combination of the two. The term hashtagability was coined by merging hashtags with Weber’s (2007:140) notion of -ability to emphasise their potential. It was explored in this interdisciplinary study by drawing from the traditions of media studies, data science, social science and digital methods studies. The thesis was guided by the question: how hashtagability, realised as the potential of hashtags to become trends, can be analysed and why should it be? More specifically, it aimed to develop new methods to analyse the realization of hashtagability as the performance of gatekeeping and agenda-setting by users and the platform on the Twitter platform.

There are two key findings of the thesis in relation to hashtagability. Firstly, it established that hashtagability, the potential of hashtags to acquire new functions, usually initially happens as the result of the activity of small groups of users, who in certain circumstances are able to introduce new functions to the platform. Trend orchestration with the use of hashtags is possibly the most significant realisation of hashtagability since this use of hashtags has the potential to reach millions of users. Hashtags themselves were introduced to the platform by orchestration and it is possible that orchestration to make hashtags trending is currently responsible for a large proportion of new trends. As a result, and has been documented, it is possible that anonymous users who are able to orchestrate political trends have a disproportionately high impact on Trending Topics on Twitter and therefore can set the agenda on the platform. The power of agenda setting through orchestration is not realised by being able to ‘flood’ the platform with large numbers of messages, but by intelligent coordination, that requires fewer users and messages, but offers the same visibility in the Trend Box as non-orchestrated trends. In this way, trend
orchestration offers a similar visibility as paid advertising but without the need to reveal the organization or person behind it.

Secondly, hashtagability realised as trending is, by its nature, an ongoing, never ending process that has no clear beginning or an end for the majority of trends. The lifespan of a trending hashtag can be divided into two distinctive stages: 'Becoming Trend' and 'Being Trend'. The making of this distinction helps to show the effect of the realisation of the potential of a hashtag to become a trend on the platform. The structure of co-occurring hashtags changes dramatically once a hashtag becomes a trend and the number of co-occurring hashtags increases almost immediately showing the power of Trend Box. However, this process is complex: as my analysis showed the becoming or happening of trends is distributed not just temporally but also spatially, which causes significant methodological issues.

In relation to the study of methods, this thesis tested several existing techniques and methods to study hashtagability, including different approaches to data collection ranging from manual collection using Twitter to bespoke, custom made solutions developed especially for this project. The study introduced an innovative data collection method for the study of historical hashtags, that deals with the problem of the lack of visibility of what was happening on the platform in the first few years after it was launched. The method was tested in the first empirical chapter about Polish hashtags. The thesis also introduced Hashtag Cloud Analysis - an innovative process of investigating trending hashtags through the use of co-occurrence which adds to the understanding of happening or life span of trends by enabling identification of the ‘Becoming Trend’ and ‘Being Trend’ stages.

The thesis also showed the significance of the study of trends. It showed how groups of users are able to exploit the hashtagability for their benefit by manipulating the Trending Topics algorithm and making their hashtag trending. As a result, a hashtag's ability to deliver a short message through trends that are visible to millions as part of the Trend Box should be treated seriously.

In sum, this thesis showed how hashtagability, realised as the function of creating trends, can be analysed. It also showed the significance of trending hashtags and their power to set the agenda of the platform. In short, the thesis addressed its primary research question by describing and analysing historical and current user
practices on Twitter and by developing new concepts (hashtagability, algorithmic ownership and hashtag clouds), new tools (Trend Catcher) and methods (Hashtag Cloud Analysis) to analyse hashtagability. Most importantly this thesis offered a new way of analysing hashtags and how they emerge on Twitter as Trends. On top of a theoretical contribution, it offered a very practical solution to real-life issues such as spread of disinformation or identification of Coordinated Inauthentic Behaviour.

The following section provides a chapter summary of how each chapter contributed to answering the research question.

**Chapter Summaries**

After the Introduction in Chapter One, Chapter Two elaborated a conceptual framework for the thesis. It started by positioning the thesis in the wider context of the digital age (Dewar 1998) and the digital economy, which it described in relation to cognitive capitalism - an economic system centred around the accumulation of immaterial assets protected through intellectual property rights (Boutang 2011; Thrift 2006). It introduced Twitter as one of the leading companies of the cognitive economy in which companies and other organisations provide platforms that organise their members in a network society (Castells, 1996:34). Such companies are organised so as extract value from the activity or ‘labour’ of their users. They do this by expanding the extent, nature and intensity of their networked interactions (Levy and Kerckhove, 1998 as cited in Flew (2007: 21). The chapter argued that these interactions are increasingly managed by algorithms which have acquired the ability to set the agenda of digital platforms (Aruguete 2017: 51) by acting as gatekeepers (Lewin 1947).

As a consequence of this shift towards algorithmic gatekeeping, new techniques, collectively known as Coordinated Inauthentic Behaviour (Weedon et al, 2017) have been developed to set the agenda of platforms. Hashtagability, realised as the potential of hashtags to become trends can happen through such coordination or orchestration. In short, orchestrated trends may take the form of Coordinated Inauthentic Behaviour. As a result, the chapter argued, the exploration of potentially orchestrated Twitter trends deals with a very current and pressing social issue,
which makes the study significant from the social, political and digital media perspectives. From the perspective of the aims of the thesis, the chapter explained why trends are worth studying.

Chapter Three laid out the groundwork for the concepts of hashtagability by looking at the lineage of hashtags and tracing their roots in information technology, digital media and social science traditions. Particular attention was paid to the changing role of metadata and the practice of tagging, suggesting that they contributed to the emergence of hashtags on Twitter. The chapter used Kehoe and Gee’s (2011) historical perspective to illustrate the radical changes in the ways tagging was performed online and how the distinction between authors and readers was blurred, with power gradually shifting from content authors to readers, who have come to be known as users. Social tagging, in which users perform the function of categorisation through the consumption of content, results in bottom-up categorisations, known as folksonomies (Vander Wal, 2004: Online).

Having described the roots of social tagging at the beginning of the XXI century, the chapter then argued that the emergence of hashtags on Twitter as a user-led innovation was a natural consequence of these processes rather than a surprising phenomenon that emerged as a revolutionary feature on the platform. It suggested that hashtags are the product of the evolutionary changes in the ways categorisation is performed online and showed the ever-increasing role of the user in the process of categorising. Chapter Three also traced the history of the use of #SanDiegoFire - the hashtag that is widely believed to have contributed to the adoption of hashtags on the platform. It shows that orchestration has been a feature of hashtags from the very beginning: in fact, hashtags were adopted on the platform only because of a successful coordinated action of a group of users. The adoption of hashtags, first by Twitter users and then their promotion by Twitter – through their introduction to the infrastructure of the platform - created hashtagability - the structural potential of hashtags to carry out functions not present at the time of their introduction.

Chapter Four continued the exploration of the history of hashtags by studying how hashtagability was realised through the activities of users, including how they developed new uses of hashtags, including hashtagging etiquette. It also described how the Twitter company made this possible by technically developing the platform. The emergence of numerous functions were described, starting with the function of
categorisation of content through social tagging, followed by the conversational function, in which a hashtag acts as a backchannel for external (exogenous) events such as sport events (Harrington, 2014; Highfield, 2014; Kroon, 2017), cooking game shows (Zappavigna, 2017), reality television (Lochrie and Coulton, 2012) or news (Deller, 2011) as well as Twitter internal (endogenous) events defined as micro-memes (Huang et al 2010) or ‘hashtag games’ (Wikström, 2014). Chapter Three also looked at how hashtagability was realised as a community building function, which combines the categorising power of hashtags and their ability to facilitate conversations. Using Zappavigna’s notion of ‘searchable talk’ (2012) and ambient affiliation the chapter showed how hashtags signal that there is a potential presence of other users to use the hashtag. Finally, Chapter Three described hashtagability as a performative vehicle that enables hashtags to become trends and to be used to create trends.

Chapter Five marked the beginning of a two-chapters long exploration into the methodological and epistemological challenges of hashtagability, with a focus on how to investigate the potential of hashtags to create trends in ways that are enabled by the platform through its algorithm. The structure of these two chapters is built around a review of approaches to study hashtag trends: the aims of such approaches, and their strengths and limitations.

Chapter Five covered research relating to the platform and the user using ethnographic and other qualitative methods. It looked at research investigating the platform from the perspective of Trend Box with its recommendation algorithm. It introduced trends, their social and cultural significance and the ways they can be accessed through different entry points to the Twitter platform: natively through Twitter, via third party application or by using API. The chapter argued that these entry points, theorised as delineation devices (Madsen, 2012) organise content and actors in different orders and create different spaces where information is arranged differently according to diverse relevance criteria. In short, they create different ‘screened visions’, described by Madsen (2012) as myopic - the immediate vision of topics that are relevant on Twitter, and hyperopic vision - the extended, more detailed visibility of a specific topic. This distinction was used in this thesis as a backbone for the three empirical chapters, which explored three different delineation devices as starting points for their data collection strategies.
Chapter Five explored the hyperopic vision created by Twitter Trends when used via native Twitter mobile or web app and introduced a new concept - algorithmic ownership. The concept was developed drawing on the account of the community building function of hashtags by Zappavigna (2015), Lury and Day's (2019) analysis of algorithmic personalisation, and Seaver's (2012) description of a collaborative filtering systems/algorithms. This original contribution to the fields of digital media and social science described algorithmic ownership as an associative, fluid connection, enabled by hashtags, which is performative, distributed, fluid and personalised, and that needs to be constantly renewed to exist. It contributes to an understanding of the significance of trending in renewing this association.

The second part of Chapter Five continued the exploration of the connection between users and hashtags through a review of the available literature and accounts of user practices on the platform that fall under the umbrella of Coordinated Inauthentic Behaviour. It showed how groups of users are able to exploit the hashtagability for their benefit by manipulating Trending Topics algorithm and making their hashtag trending. The exploration of trends as algorithmic effects was then continued in Chapter Six but this time from a quantitative data perspective. This chapter positioned the thesis methodologically in the field of data science and explored the benefits and limitations of research methods derived from the study of big data and Twitter Trend algorithms. It systematically described the tools that are currently available to study Twitter data and identified some possible problems with the internal and external representativeness of such data. These problems were later described and addressed in the three empirical case study chapters that follow. Most importantly, Chapter Six discussed a possible data collection methodology for the three empirical chapters that follow by exploring the limitations of Twitter APIs and discussing methodological problems with sampling. It also introduced Twitter’s basic metrics, more advanced network parameters and finally custom-made metrics - all of which were used in the three case studies.

The three empirical chapters, of which two were case studies, aimed to study hashtagability by developing new methods for data collection and analysis, testing the existing ones and building new tools. In doing so, they developed a methodology that showed how hashtag trends can be analysed in relation to the aims described earlier. The research design (historical analysis) used in Chapter Seven heavily relied
on the human researcher alone - all stages (the identification, collection and analysis of data) were performed by the researcher. Chapter Eight only relied on the human researcher at the data identification stage, while the other two stages made use of available tools: Twitter REST API to collect data and Netlytic platform to analyse the data. Chapter Nine described a fully automated tool that is able to identify hashtag trends, collect data and perform analysis using specially developed algorithms.

More specifically, Chapter Seven investigated the first decade of Polish trending hashtags. It can be seen as an empirical investigation of Chapters Three and Four which looked at the history and the developments of hashtagability - the potential of hashtags and their users to develop new functions on the platform. The chapter developed a novel strategy for historical data collection using the concept of ‘screened visions’ (Madsen, 2012) that was operationalised by using a third party trends archive (myopic vision) to identify trending hashtags and then searching for their first use directly on Twitter (hyperopic vision). This strategy allowed the collection of data for hashtags first used between 2008 and 2017 and their analysis in relation to their changing functions using three measures: the average number of trending hashtags per year, the average length of hashtag (in characters and words) and user’s diversity. This chapter also looked at the connection between hashtags and their creators to practically test the concept of algorithmic ownership developed in Chapter Five.

The analysis of the data in relation to three metrics accompanied by qualitative analysis of content surfaced three distinctive periods in hashtags development. The first one was described as an adoption phase (2008), in which there was a relatively low number of users and the vast majority of hashtags were very short. It was concluded that hashtags were being used more or less exclusively for content categorization in this period. This finding confirms that in Poland, similarly to the US, the first phase of hashtag use is primarily content categorisation. The second phase, known as slow (2009 - 2011) is characterised by the slow introduction of other functions. The qualitative data analysis revealed that hashtags used as comments started emerging which was accompanied by a significant increase in the average length of hashtags. The final identified phase - called creative (2012 - 2017) - showed a radical increase of the use of hashtags as comments or jokes and from 2015 onwards as political micro-memes. Hashtags created in this phase were characterised by an increase in average length and a decrease in creator diversity.
Overall Chapter Seven showed that hashtags’ average length increased over time in the analysed period, which is an indication of a change in functions. This change is especially visible in the final phase, which sees an increase in hashtags that could be identified as orchestrated with the goal of making them trending. Such hashtags, most of them being political micro-memes, had relatively fewer authors than hashtags used for categorization of content, which suggests the orchestration can be performed by relatively small number of users who exercise disproportionately high power over Trending Topics, at least in Poland during the period studied. Such users can use orchestration techniques to set the agenda of the platform, and as a result change the narrative around issues, people or topics on the platform.

This finding from Chapter Seven informed the selection of trending hashtags used during General Election 2017 in the UK to study the impact of orchestration on Trend Box in Chapter Eight. The context of this general election was especially interesting for this thesis as it happened less than a year after the Brexit referendum, Donald Trump being elected the president of the US and Rodrigo Duerte the president of the Philippines - events that triggered a discussion about the spread of disinformation in digital media space (Cadwalladr. 2017) (Online, 2017) (Corpus Ong and Cabanes, 2018). These events were responsible for the emergence of the term Coordinated Inauthentic Behaviour (Weedon et al. 2017), which describes disinformation campaigns that purposely entangle orchestrated action with organic activity.

The specific question this chapter asked was how Twitter’s Trend Box could be studied as an algorithmic gatekeeper that sets the agenda of the platform and influences users by establishing a hierarchy of news prevalence (McCombs and Shaw 2002). The question was triggered by Aruguete's (2017: 51) claim that although social networks have gained a lot of ground recently, it is not known to what extent they have the ability to set the agenda on their own rather than simply repeating the agenda of traditional media. Conceptually and methodologically, Chapter Eight drew on the research of Recuero and Araujo (2012b), Recuero et al (2012) and Huang et al. (2010) who described numerous orchestration techniques amongst fans or players of hashtag games, and how orchestration can be measured using network properties.

To investigate algorithmic gatekeeping, a Twitter data collection strategy was developed using a two stage (identification and collection) process which was a
version of Madsen's ‘screened visions’ approach. Similarly to the data collection strategy described in Chapter Six, a third party Twitter Trends tool, which created a myopic vision of the trend box, was used to identify trends related to the election. The identification made use of an almost live monitoring of the tool rather than retrospectively identifying related trends. This meant I was able to collect data with almost no delay using Twitter REST API via Netlytic Application, enabling me to capture the data almost as it was happening.

The analysis of the captured data was then developed by comparing the impact of exogenous and endogenous trends (Naaman et al. 2011: 908). Exogenous trends are those related to broadcast-media events (local and global), global news events or local participatory and physical political events. Endogenous trends are typically political memes, political hashtag games. By using this binary category, I intended to establish what types of hashtag trends get selected by the algorithm to be featured in the Trend Box, in what proportion and whether any could be seen as orchestrated.

The analysis was performed using Twitter's own metrics, including for the number of messages or posters, and social network properties such as diameter, density and reciprocity. Drawing on the findings from Chapter Seven, a new metric - a trend's average length - was created to identify differences between hashtag length between the two categories. The results revealed that Twitter's basic and network metrics can be used to illustrate differences between exogenous and endogenous trends and that the behaviour of endogenous trends is similar to the behaviour of orchestrated fandom trends. Another significant result was that endogenous trends constituted 25% of all trends in the analysed period, meaning that possibly one in four trends was generated internally on Twitter without any external triggers and that most likely a high proportion of these was orchestrated. The quantitative analysis revealed that exogenous trends tend to generate significantly more messages and more users take part in the discussions they triggered, but the relevance of this finding from the perspective of agenda setting is questionable. The qualitative analysis of hashtags showed that exogenous trends tend to create the awareness of events or TV programmes but are not able to set the agenda. They act as backchannels for discussions, e.g. #BBCQT, but do not provide they do not provide summary statements or encapsulations of particular positions, as it is the case with endogenous trends e.g. #MakeJuneTheEndofMay. The power of endogenous trends
is not in engagement numbers but in the ability to deliver a statement or message to an audience by simply being present in the Trend Box. In that sense, although endogenous trends constitute four times fewer trends than those related to external events, they qualitatively deliver a message through the Trend Box, without the need for the user to click and explore the trend. In that sense, their power lies in a visibility that can be compared to that previously achieved only through paid advertising.

The final empirical chapter continued the exploration of the form of hashtagability that creates hashtag trends, by introducing Hashtag Cloud Analysis (HCA) – a method to investigate trending hashtags through their co-occurrence. HCA helps to see the effect of Trend Box as an algorithmic gatekeeper in relation to changes in discussion dynamics by comparing pre- and post- Trend hashtag co-occurrences. In order to perform HCA, a new tool called Trend Catcher was developed for capturing the ‘becoming’ of trends by exploring ‘Becoming Trend’ and ‘Being Trend’ phases, so allowing an exploration of the lifespan or biography of trending hashtags. The design of the tool was informed by limitations observed in the first two empirical chapters. In terms of how the tool presents the results, the aim was to make it understandable by the general public, without a specialist knowledge of trends or hashtags.

Methodologically, the chapter introduced advanced data collection and analysis strategies but instead of relying on existing tools or human monitoring it automated the majority of these processes. Similarly to the other two empirical chapters, the Trend Catcher tool drew on Madsen’s (2012) concept of Screened Visions; however, as this chapter describes, these visions were presented in especially created environment that was made publicly available at www.trend-catcher.tk. Both myopic and hyperopic visions were presented as dashboards generated by data from a Twitter API and processed by the application’s own algorithm. The myopic vision presents a list of all available hashtag trends for a selected location on a selected day. By clicking on one of the trends, users are taken to the hyperopic vision, which presents an extended quantitative and qualitative view of hashtags co-occurring with each other broken down into pre- and post-Trend Box entry phases.

The dashboard supports the visual comparison of Hashtag Clouds in the ‘Becoming Trend’ and ‘Being Trend’ stages as lists of co-occurring hashtags ordered by their frequency. It creates a hierarchy of hashtags which is normally not visible via Twitter’s native search. By doing this it helps to contextualize the trending hashtags
in relation to an association, distribution or cluster of hashtags. Most importantly, for those hashtags for which data for Phase 1 was captured correctly, it made the effect of becoming a trend on the hashtag visible. The analysis of these examples showed how becoming a trend almost immediately increases the number of co-occurring hashtags and how the new, Phase 2 co-occurring hashtags become less associated with the trending one in comparison to the Phase 1.

The quantitative view of both myopic and hyperopic visions takes the form of a Hashtag Cloud Average Score (HCAS) also broken down into ‘Becoming Trend’ and ‘Being Trend’ phases. The aim of the HCAS metric was to identify orchestrated trends based on the findings from previous research (Huang et al 2010; Recuero and Araújo 2012a) as well as observations of data in the first two empirical chapters. The identification happens through the calculation of the average number of frequencies of the co-occurring hashtags in ‘Becoming Trend’ and ‘Being Trend’ stages and comparing them with each other. The orchestrated hashtags that were clearly identified as Twitter endogenous micro memes or hashtag games in the qualitative analysis, displayed a low level of co-occurring hashtags in the Becoming Trend stage and much higher after becoming a trend, indicating that orchestration requires a high levels of focus on a single hashtag during the pre-trend stage. This pattern was not observed for exogenous trends, which started as backchannels for TV programmes or as a reaction to external to Twitter events. In this case, ‘Becoming Trend’ and ‘Being Trend’ Hashtag Clouds had similar levels of co-occurrences.

The next section will describe methodological limitations faced by the three empirical chapters and how the results are not always valid.

**Methodological limitations**

This study sought to extend the current field of research on hashtags by introducing the concept of hashtagability, and to develop the study of hashtagability by exploring the potential of hashtags to become trends. I aimed to test the limitations of existing methods and develop my own to study trends in ways that show how they perform gatekeeping on Twitter. The major limitations of this study are linked to data collection strategies and the quality of data obtained from Twitter.
The first major two limitations were identified in Chapter Seven in relation to the internal representativeness of data. This limitation is a consequence of the lack of access of most researchers to more data, rather than the data collection strategy. In the study in Chapter Seven, there was a lack of access to data before 18 October 2014. Not much can be done about this, as access to historical Twitter trends is limited. It is possible that in the future more archives may be released by Twitter, which could help to address this issue. Looking into the future however, this should not be a problem with future applications of the method used in Chapter Seven, as all Twitter trends data is currently being collected on a daily basis by many archives.

The second limitation identified in Chapter Seven is related to the study of algorithmic ownership with the use of historical data. This limitation is a consequence of the time elapsing between the first usage of hashtags and the time when the analysis was performed. This limitation led me to develop a data collection strategy for the following two chapters, which addressed this problem by collecting data almost immediately (Chapter Eight) and immediately (Chapter Nine) after the emergence of a trend. These solutions are based on a change in the process of data collection, rather than on solving the problem in the context of historical data.

A third limitation of this study was identified in Chapter Eight and is linked to data representativeness. The chapter provided a detailed account of how data generated by Twitter's REST API contained several gaps in the coverage, especially for the most popular hashtags. Some of the gaps were random and it was difficult to explain them with the API limitations.

A fourth limitation, similarly to the second one, is linked to the temporal distribution of tweets for a trending hashtag and the limitations of collecting this data using REST API. In short, this limitation is caused by Twitter policy, which only allows the download of the latest 1000 Tweets: this is not enough time to capture data for the ‘Becoming Trend’ phase of the trend. This research solved this problem by developing Trend Catcher - a tool that captures all available data for a trend almost immediately after it is surfaced by Twitter and uses Streaming API for data collection.

The final limitation encountered while conducting this research has possibly not been fully acknowledged before methodologically (and in this sense is itself a
finding). It is related to the new dimension of the happening of trends that was identified in Chapter Nine which established that trends are not just distributed temporally but also spatially. As a result, the fact that hashtag becomes a trend in one location does not mean that it never became a trend in another location. The contrary is true - almost 50% of hashtags (as established in Chapter Eight) trend multiple times in different locations. As a result, without being able to capture the data for the very first trend for a hashtag, it is impossible to generate Hashtag Clouds for the 'Becoming Trend' phase as most of the time the data represents 'Being Trend' stage, but in different locations. The only solution to this problem is to expand data collection to every single geography where Twitter offers trends, which would allow the identification of the first time a hashtag became a trend.

Implications and future studies

In terms of how this research can affect policy and practice around algorithmic gatekeeping and the power of agenda setting on Twitter, this research has shown that although the majority of orchestrated trends are created for fun, e.g. hashtag games, there is also a possibility that the same techniques are used to create trends around more serious issues such as elections and important national/local events. This research showed that up to 25% of political micro memes created during the campaign before General Election 2017 in the UK could have been orchestrated. This is a significant finding not just from the perspective of digital media but also national security as well as public debate. Following their identification as conducted here, a more in-depth qualitative analysis could be performed to identify if these hashtags were targeting specific individuals or organisations.

Chapter Seven showed that a single user was responsible for the creation of almost 40 trends targeting selected individuals and political parties in Poland, meaning that the person/organisation behind this account had a disproportionately high impact on the Polish Trending Topics and could set the agenda of the platform. Such a situation is risky. It is impossible to establish the motivations of such accounts: is the author an “unwitting agent” who does not realise what is happening or do they orchestrate trends being fully aware of the consequences for the public debate? More research in this area should be conducted.
Such political memes have the potential to disturb democratic processes by promoting values that support only one side on the political spectrum and create an impression that values of their political opponents are less popular or less worthy. Orchestration of trends, when targeted at a specific person can be also seen as a form of orchestrated cyber bullying, which could and should be explored by specialists in the fields of psychology. Being regularly targeted by an unknown group of users for a long period of time can have significant mental health implications.

This thesis has demonstrated how hashtagability, specifically the potential of hashtags to become trends, can be analysed. Methodologically, this study identified what data collection strategies can be used and how data can be analysed to uncover orchestrated trends, which is not only a theoretical but also a practical contribution, that can be almost immediately applied in business i.e. for social media monitoring. Trend Catcher, using Hashtag Cloud Average Score (HCAS) is able to identify trends that are likely to be orchestrated but because of the lack of financial limitation of PhD research, the tool could not be deployed globally to solve the methodological problem of the identification of the first trending location and collecting data for it.

This research introduced the concepts of hashtagability and algorithmic ownership which could be developed further in the field of social science not only to study Twitter but also other platforms that have hashtags embedded in their infrastructure and rely on algorithms. Finally, I hope that this thesis will make a positive and useful contribution to the current literature and wider awareness of trend’s orchestration as well as the impact of orchestration on populations, Twitter users but also individual people who might become victims of cyberbullying. It is my hope that the creation and public availability of Trend Catcher will inspire other researchers to conduct more studies and gain valuable insight into orchestration practices.
Appendix I

The following four tables present the results of categorisation of 114 hashtags collected during and after General Election 2017 in the UK. There are four categories:

- Single peak Endogenous hashtag trends
- Multiple Peaks Endogenous hashtag trends
- Single Peak Exogenous hashtag trends
- Multiple Peaks Exogenous hashtag trends

The findings are presented in Chapter Eight.

**Single peak Endogenous hashtag trends**

<table>
<thead>
<tr>
<th>Hashtag</th>
<th>Categorisation</th>
<th>Started collection</th>
<th>Ended collection</th>
</tr>
</thead>
<tbody>
<tr>
<td>#AskTheresaMay</td>
<td>Endogenous</td>
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<td>11/07/2017</td>
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<td>28/06/2017</td>
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Multiple Peaks Endogenous hashtag trends
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<th>Ended collection</th>
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</thead>
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Multiple Peak Exogenous Hashtag Trends

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