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Future Research Directions in Demand Management

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Background

Pricing and revenue management faces new research challenges against the background of new markets for trading of personal data, new regulations on data privacy, opportunities for personalised pricing, demand learning and many more emerging trends and developments. In order to explore these challenges, the British *Engineering and Physical Sciences Research Council* funded an interdisciplinary workshop to identify future research directions in demand management². The workshop (led by the authors Strauss and Currie) took place in September 2017 in London, and brought together 33 academics and practitioners in demand management and related disciplines, including law, computer science, digital marketing and operational research.

In this article, we present an outline of the research directions that emerged at this event for the benefit of researchers interested in pricing and revenue management. The article is organised by the main topics that dominated the discussion.

Pricing of private data

Companies are sitting on a wealth of customer data that they could monetize internally by better exploiting it, or externally by trading it with third parties to generate additional income. There are specialised firms (e.g. Acxiom) that focus on trading consumer data and it has developed into a multi-billion dollar business.

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According to a recent report by the Direct Marketing Association (DMA, 2015), individuals themselves are becoming increasingly entrepreneurial, seeing their data as a personal commodity to be traded for their own advantage. They further find that consumers are seeking more direct incentives such as financial rewards for sharing their data, rather than indirect benefits such as personalised products.

This leads to the question of how such data should be priced. Ideally, the price should reflect the value of the data to the buyer. However, the value of a customer's data depends on the context that the buyer wants to use it for (which may not be known by the seller). If the seller is an individual, it would be interesting to propose a bidding strategy to determine the price that should be paid by the buyer to an individual to obtain their data, the expected value of which is likely to differ between buyers. Only a few papers have so far been published on the topic of pricing private data, e.g. Li and Raghunathan (2014) or Gkatzelis et al. (2015), so there appears to be scope for significant contributions.

Another research topic of interest is related to privacy. Although the DMA (2015) reports that overall privacy concerns are reducing, it nevertheless is an important factor in trading private data. Professor Graham Cormode highlighted at the workshop that anonymization does not work reliably as a guarantor of privacy, as illustrated by various infamous privacy breaches such as the NYC taxi data scandal (<https://research.neustar.biz/2014/09/15/>). Instead, workshop participants suggested research into construction of "personas" that represent specific customer types rather than individuals.

In summary, context-dependent pricing of private data and privacy-preserving techniques for data release are promising areas for future research.

Choice-based Revenue Management

During the workshop, a number of business experts from various industry discussed the background of having competing products in the marketplace for a customer to book. Today's revenue management systems often rely on the assumption that each product has its own self-contained market, which is independent of any other competing products. In the academic literature, this is typically referred to as the "independent demand assumption". Since 2004, an increasing volume of research has been devoted to working on choice-based RM, where customers' purchase decisions are influenced by the availability and attractiveness of several offerings. For a recent review, see Strauss et al. (2018). The representatives of the travel industry at the workshop see the further development and integration of such models into revenue management systems as key, where the main challenge lies in sufficiently accurate estimation of choice-based demand models as well as choice-based optimisation that can operate on large-scale problems.

Behavioural Pricing in RM

RM systems are usually built on the assumption of a rational customer, yet empirical research has shown that many psychological effects may have an influence on customer decisions. Examples include that a price of £999 will likely drive a significantly higher amount of demand than a price of £1000, or that the existence of a redundant option may increase sales of other options (decoy effect), etc. Yet, most revenue management systems today cannot model these

effects; there seems to be significant potential for improvements through quantifying these psychological effects and exploiting them in the optimisation.

Demand Learning

Disruption to the demand estimation and forecasting process does not only result from psychological effects, but also stems from external events that currently the analysts need to identify and quantify the impacts of. However, when managing a large number of product lines simultaneously, detecting these and estimating their effects can be difficult.

Therefore, developing algorithms that identify significant changes in the demand patterns and adjust the forecasts accordingly is an important research area. Much theoretical work has been done here but there seems to be a need for more of it to be translated into practice. Going one step further, there is a growing area of research developing algorithms which aim to balance learning and earning in such a way to maximise long-term revenue; e.g. see (Besbes and Zeevi 2012). These algorithms help to combine experimentation with exploitation, and find out more about customer behaviour without sacrificing income.

Personalisation

Within the travel industry, revenue management systems typically do not operate at a customer level and rather focus on segmenting demand based on the products they purchase, rather than the characteristics of the people making these purchasing decisions.

This leads to interesting research questions:

- How can we model unconstrained demand exploiting knowledge of customer profiles?
- What is the long-term value of a strategic customer versus a loyal customer?
- Should we be modelling consumers or products?
- Can we value the trade-off between granular demand management and privacy?

Personalisation moves one step beyond profiling or segmentation, segmenting the market into atoms (single customers) rather than groups of homogeneous customers. Such a practice is not entirely new; for example, it is prevalent in used-car markets, real estate markets and micro-financing in developing countries.

The discussion of personalisation at the workshop concentrated on personalised pricing rather than personalised offers. The latter practice is fairly well-established, particularly in industries where loyalty schemes are prevalent, but the former tends to raise more questions of ethics and image. Existing examples of price personalisation largely use soft information approaches, where the seller acquires knowledge about the buyer during personal vocal communications and then uses this acquired knowledge to price the good. Soft information approaches do not work for large online marketplaces however; as offering individual prices involves identification of the user before the price is displayed to them. This can be difficult online unless a user logs in first, particularly in the new era of the General Data Protection Regulation (GDPR) in which customers have more control over their data and strict data governance rules need to be followed.

In order to implement personalized pricing, the seller needs to learn the features of their potential customers, either by asking them directly or by using more sophisticated approaches, which are able to reveal customers' preferences from their purchasing behaviour. The first approach tends not to work because customers tend not to disclose their

true preferences. This means that sellers have to extract their customers' preferences and features by analysing their sales records.

The challenge of developing models which can learn customer features is multi-fold. For example, such models should be able to learn customers' opinions about different features of the product by analysing previous purchases, online searches, and other personal information such as age, gender, etc. This would require merging data from disparate sources and employing complex learning algorithms to extract insights about individual customer behaviours. Learning a customer's preferences is not as simple as looking at his/her previous purchases of similar products: it is also necessary to understand the customer's general preferences, which require development of algorithms using economic theories on rational consumption. For example, economists have long studied and developed models on household consumption (Chiappori, 1988). These models, coupled with algorithms that test revealed preference theories (Nobibon et al (2016); Diewart (1973)) can be powerful in understanding consumers' consumption behaviour.

In last few years, researchers have started to look into the development of algorithmic models in a step towards personalized pricing (Some references include Ban et al (2017), Golrezaei et al. (2014), Wittman and Belobaba (2017), Kallus and Udell (2017) and Chen et al (2015)).

One aspect of personalisation that is somewhat addressed by loyalty schemes is to consider the value of each individual customer as a whole, rather than considering each of their purchases separately. This combines revenue management and pricing with ideas from customer lifetime value and may suggest that offering a valuable customer better prices than one who uses the service infrequently is likely to result in a higher long-term revenue. These ideas of valuing loyal, high-value customers go back millennia, but perhaps need to be better incorporated into automated pricing models.

The main question that came out of the discussion was: How valuable and ethical is personalised pricing and how does it benefit overall social welfare? This suggests a need for an assessment of how much revenue could be gained from a perfect system of personalised prices and also a more qualitative study of how personalised pricing could be implemented in an ethical manner. There is perhaps a need for more regulation to determine which categories of products and services are amenable to personalised pricing.

Conclusion

To conclude, the key future directions for demand management fall into five main areas: trading of data; choice modelling; behavioural pricing; demand learning; and personalisation. A common theme of ensuring that academic research is translated into practice came out in all of these areas; and one of the conclusions of the workshop was a need for a better two-way communication between academia and practice. We hope that this article provides a starting point for a more involved conversation between researchers and practitioners.

References

- Ban, Gah-Yi and Keskin, N. Bora, Personalized Dynamic Pricing with Machine Learning (May 23, 2017). Available at: <http://dx.doi.org/10.2139/ssrn.2972985>
- Chen, X. and Owen, Z. and Pixton, C. and Simchi-Levi, D. A Statistical Learning Approach to Personalization in Revenue Management (March 15, 2015). Available at: <http://dx.doi.org/10.2139/ssrn.2579462>
- Chiappori, P. (1988) Rational Household Labor Supply. *Econometrica* 56(1): 63-90.
- Diewart, W. E. (1973) Afriat and Revealed Preference Theory. *The Review of Economic Studies* 40(3):419-425.
- DMA. Data privacy: what the consumer really thinks. (June 2015) Available at: https://dma.org.uk/uploads/ckeditor/Data-privacy-2015-what-consumers-really-thinks_final.pdf
- Gkatyelis, V., Aperjis, C. and Huberman, B.A. (2015) Pricing Private Data. *Electronic Markets* 25(2) pp. 109-123
- Golrezaei, N., Nazerzadeh, H. and Rusmevichientong, P. (2014) Real-Time Optimization of Personalized Assortments. *Management Science* 60(6):1532-1551.
- Kallus, N. and Udell, M. Dynamic Assortment Personalization in High Dimensions. (Sept 2016). Available at: <https://arxiv.org/abs/1610.05604>
- Li, X.-B. and Raghunathan, S. (2014) Pricing and disseminating customer data with privacy awareness. *Decision Support Systems* 59: 63–73
- Nobibon, F.T., Cherchye, L., Crama, Y., Demuynck, T., De Rock, B. and Spieksma, F.C.R. (2016) Revealed Preference Tests of Collectively Rational Consumption Behavior: Formulations and Algorithms. *Operations Research* 64(6):1197-1216.
- Strauss, A.K.; Klein, R. and Steinhardt, C. (2018) A Review of Choice-based Revenue Management: Theory and Methods. Forthcoming in *European Journal of Operational Research*
- Wittman, M. and Belobaba, P., (2017) Personalization in airline revenue management – Heuristics for real-time adjustment of availability and fares. *Journal of Revenue and Pricing Management* 16(4) pp. 376-396