Time Machine: Generative Real-Time Model For Failure (and Lead Time) Prediction in HPC Systems

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Abstract—**High Performance Computing (HPC) systems generate a large amount of unstructured/alphanumeric log messages that capture the health state of their components. Due to their design complexity, HPC systems often undergo failures that halt applications (e.g., weather prediction, aerodynamics simulation) execution. However, existing failure prediction methods, which typically seek to extract some information theoretic features, fail to scale both in terms of accuracy and prediction speed, limiting their adoption in real-time production systems. In this paper, differently from existing work and inspired by current transformer-based neural networks which have revolutionized the sequential learning in the NLP tasks, we propose a *novel* scalable log-based, self-supervised model (i.e., no need for manual labels), called *Time Machine*[1], that predicts (i) forthcoming log events (ii) the upcoming failure and its location and (iii) the expected lead time to failure. Time Machine is designed by combining two stacks of *transformer-decoders*, each employing the *self-attention mechanism*. The first stack addresses the failure location by predicting the sequence of log events and then identifying if a failure event is part of that sequence. The lead time to predicted failure is addressed by the second stack. We evaluate Time machine on four real-world HPC log datasets and compare it against three state-of-the-art failure prediction approaches. Results show that Time Machine significantly outperforms the related works on Bleu, Rouge, MCC, and F1-score in predicting forthcoming events, failure location, failure lead-time, with higher prediction speed.**

I. Introduction

Large-scale High Performance Computing (HPC) systems, such as supercomputers, execute resource-hungry applications such as weather forecasting, flow dynamics simulations among many others. These systems, consisting of sophisticated hardware (HW) and software (SW), often fail due to their scale and their design complexity. The SW components, such as OS and parallel file systems, typically generate log messages that capture the health of various components in the system, such as network and memory, and these log messages are recorded in a central repository[1], which we call a log file. As a result, system administrators find it a very useful source of information when trying to predict system failure because it contains rich information about normal behavior (i.e., informational messages) or abnormal behavior (i.e., error messages) of various system components. As such, failure log analysis of HPC systems is attracting more and more researchers from academia and industry in order to improve the reliability of such systems.

[1]A Time Machine allows us to travel into the future to observe the health state of HPC system and report back. Here, we travel into the log extension to report an upcoming failure.

When errors in the HPC system are not suitably handled, which can occur at specific components (e.g., nodes), then a failure of the system, i.e., more specifically, one or more affected components, may occur. A failure is a special event in the system and results in a special log (e.g., lockup log) to be recorded in the log file. The impact of such failures may be enormous on applications: drastic computational overhead could be introduced, such as through (partial) re-execution, thereby having severe impact on application execution. In an era of exascale computing (i.e., HPC systems executing 10^{18} floating point operations per second), failures are predicted to occur more frequently, exacerbating associated overhead.

To mitigate the impact of failure, efficient failure management strategies are required. Specifically, failure prediction is becoming a pressing work, especially when combined with proactive recovery management techniques such as checkpointing/restart or job migration [2], [3]. Unfortunately, the effectiveness of failure prediction tools is still insufficient, thereby necessitating the development of online failure prediction techniques to flag impending failures and their lead-times with high prediction accuracy and speed and with lesser computational overhead. Some works on failure prediction exists, e.g., [4], [5].

In this paper, we address this important problem of failure prediction by developing and applying *a transformer-decoder* model on HPC log data to build a generative self-supervised model, which we call **Time Machine**, to predict two important failure parameters: (i) the failure location, i.e., which nodes will crash, and (ii) the lead time to failure, i.e., how long is left before the predicted failure happens. Our designed Time Machine works as follows: (i) For the location problem, it first predicts the future sequence of logs (future health state) and then identifying if a failure event is part of the predicted sequence and (ii) for the lead time to failure problem, Time Machine reduces the time prediction problem (which is a regression problem) into a self-annotated multi-class classification problem, by predicting the class for the failure lead time. We discuss the motivation of modelling the failure lead time problem in the methodology section, Phase IV-B1. Note that our work introduces a novel method to construct (no need for manual labels) and augment a self-time annotated training dataset on sequential time-based (timestamps) raw data via an automatic accumulative and iterative process.

Transformers neural networks and transfer learning facilitate pre-training natural language processing (NLP) language models (e.g., GPT2/3, BERT[6]) on a huge dataset and fine-tuning the model to various standard NLP downstream tasks (e.g., text generation) which leads to typically much better performance. However, an area that has not been investigated for the utility of generative transformers is the failure prediction in high performance computing (HPC) systems. The use of generative models for failure prediction using HPC logs is very challenging: (i) erroneous states and failures are rare(r) events, (ii) logs are often incomplete, duplicate and (iii) messages are alphanumeric in nature and generally lack a proper structure [7], which is very different from the context of, say, text prediction application [8].

There are many state-of-the-art RNN-based failure prediction methods such as Long Short-term Memory (LSTM) [9] (Desh), Bidirectional Long Short Term Memory (Bi-LSTM) [10], and Gated Recurrent Unit (GRU) [11], which however suffer from non-trivial weaknesses: (i) long training time because of the absence of parallelization in recurrence learning, and (ii) the vanishing gradient problem with loss of earlier "memory", which may cause limited accuracy. Our Time Machine approach improves on the state-of-the-art failure prediction approaches through (i) self-attention mechanism and (ii) parallelization which are the crux of transformer neural networks and which are explained in detail in IV.

Additional failure prediction models are developed for HPC systems. However, these solutions are mainly based on supervised-learning, requiring extensive data labelling such as [12], [13], [14]. Furthermore, most unsupervised & self-supervised solutions do not address the problem of predicting the lead-time to failure, such as Clairvoyant [15]. Specifically, Clairvoyant used one stack transformer-decoder to predict failures only. To enable the prediction of failure lead time, there are several key innovative designs proposed in our solution. Our Time Machine framework adopts a two-stack transformer-decoder architecture to predict not only failures but their lead times. The adaptation of the transformer-decoder to predict the failure lead times is based on a novel approach to self-attention: Specifically, the Time Machine framework demonstrates how the self-attention mechanism developed for text prediction is used to predict the failure lead times, by encoding/decoding log events to map each log event onto its timestamp step during the training and prediction phases. In many domains (e.g., [16], [17]) except for fault tolerance, other transformer variants have been utilized for predicting time series as a regression task (i.e., supervised learning), which requires label data and results in limited accuracy. However, Time Machine is the first paper to overcome these limitations by formulating the time prediction as a self-annotated multi-class classification problem by predicting the class for the failure lead time. Moreover, the Time Machine can construct training instances in real-time because of our novel synthetic minority oversampling design. The Time Machine method can be generalized to other domains for similar time-based tasks (e.g., business, healthcare, booking business).

We evaluate Time Machine on four real-world HPC logs and we compare it against LSTM [9] (Desh), Bi-LSTM [10], and GRU [11]. Results show that Time Machine significantly outperforms the best of them: (I) **Log events prediction**: Time Machine obtains a Bleu and Rouge score of up to 0.79 and 0.77 respectively whereas best of the three techniques only has 0.47 and 0.34. (II) **Failure Location**: Time Machine obtains a MCC and F1-score of up to 0.80 and 0.87, respectively, while the best one of the three techniques only has 0.53 and 0.71 respectively. (III) **Failure lead time**: Time Machine is also the best in class, with MCC and F1-score of up to 0.87 and 0.95, respectively. (IV) **Speed-up of training and prediction**: Time Machine is significantly faster than other approaches in both training (5.4$\sim$9.4$\times$ speed-up on average) and chain prediction (over 15$\times$ faster than the related works), making Time Machine very suitable for online failure prediction in real-time production HPC systems.

II. System Model and Fault Model

In this section, we present the system model, fault model, and HPC system component (e.g., node) failure.

A. System Model

We describe the general HPC system model targeted by our research as follows: In the HPC system, there are a set of compute nodes $C = \{C_1, \ldots, C_m\}$ provided to execute user-submitted jobs $J = \{J_1, \ldots, J_n\}$ (e.g., weather forecasting, scientific application). A job scheduler is used to assign the jobs to different production time-slots $T = \{T_1, \ldots, T_p\}$ on specific nodes. As the system operates, a bunch of log messages are generated to capture the health of the system and collected on a central log server or file [15].

B. Fault Model

A fault model specifies the way a system is expected to be affected by faults. Our designed failure prediction framework can be applied on various types of discrete faults at different levels, such as hardware, system, application level, file system, and at an aggregate supercomputer level. As a fault occurs, the resulting errors will be manifested as error messages in the system log file. Overlooking the error messages will likely result in a system/application failure, which will also be logged. For simplicity of description, we consider node failures [8] without loss of generality, and focus on the prediction of node failure events as well as their failure lead-times through our proposed method (called *Time Machine*), which can also be applied to failures of other components (such as switches, GPUs).

C. HPC System Component Failure

HPC component (e.g., node) failure is a state in which the operating system kernel hang-up, becomes unresponsive, goes stuck, or loops loop without ends, blocking other processes from executing and ultimately causing the nodes to shutdown. In HPC systems, there could be many factors or different types of preceding errors (from hardware errors to software/application faults) that can result in node failures. The preceding errors that cause node failures are very diverse, including hardware issue (memory, GPU, network), OS process errors, file system errors, application errors, etc [15].

The consequence of these preceding errors may differ a lot. Some errors may induce failures very quickly because of their fast propagation: i.e., the sequence of log events between the first error message and the ending failure event could be very short. On the other hand, some other errors may take a long time before their corresponding failure occurs, corresponding to a lengthy sequence of log events with a relatively high delay between the first error message and the ending failure event. It is also worth noting that there could be many interleaved & irrelevant log events recorded between node failures and their preceding error events, for both short and long sequences. This makes the failure prediction process more challenging.

III. Problem Formulation

We formulate the research problem as below: Given a log dataset with a sequence of events, our objective is to predict the upcoming sequence of log events and determine if this sequence may contain a failure event; if yes, then predict the lead-time of the failure event as well.

Research challenges: There are two important attributes of failure prediction: (i) **Location**: the component (or node) that would fail/crash should be accurately predicted so that the failure recovery mechanism can be launched at proper "location" and (ii) **Failure lead time**: the time at which the failure log event is predicted to occur should be similar/accurate compared to the one in real-time, otherwise, the failure recovery mechanism would be triggered at wrong time.

We denote the set of log sequences by $\mathcal{L}^r$, where its length is at most r. Suppose we are given two sets: $\mathcal{L}^m$ and $\mathcal{L}^k (k \leq m)$, where the elements in the set $\mathcal{L}^k$ are possible extensions of the elements in $\mathcal{L}^m$. That is, each element in $\mathcal{L}^m$ can be assigned an element from $\mathcal{L}^k$ as an output. Accordingly, for each $e_i \in \mathcal{L}^m$, $e'_j \in \mathcal{L}^k$ indicates the true prediction outcome (i.e., the real sequence of log events following e_i). Our failure prediction research is to model a mapping $\mathcal{M} : \mathcal{L}^m \to \mathcal{L}^k$, in which $\mathcal{M}(e_i)$ is the predicted sequence which follows e_i, i.e., $e_i \cdot \mathcal{M}(e_i)$ is a predicted upcoming log sequence of length $(k+m)$, i.e., $e_i \cdot \mathcal{M}(e_i) \in \mathcal{L}^{m+k}$.

We formulate the two problems as follows:

Definition 1 (Log Events Prediction)**.** *For a sequence of log events $e_i \in \mathcal{L}^m$, a predictor $\mathcal{M}$ is expected to be with the minimal distance for the log sequences of length (m+k), i.e., $arg\ min_{\mathcal{M}}\ \mathcal{D}(e_i \cdot \mathcal{M}(e_i), e_i \cdot e'_j)$, where $\cdot$ indicates 'sequence concatenation' and $\mathcal{D} : \mathcal{L}^{m+k} \times \mathcal{L}^{m+k} \to \mathbb{R}$ is the distance measure. $\mathcal{D}$ is a distance metric on two log sequences; $\mathcal{D}$=0 means two logs are identical to each other. If the distance is 0, we claim "$\mathcal{M}$ correctly extends e_i"; or else, we say "$\mathcal{M}$ approximately extends e_i".*

Definition 2 (Failure Prediction)**.** *For a predictor $\mathcal{M}$ on a log sequence $e_i \in \mathcal{L}^m$ with an extension $e'_j \in \mathcal{L}^k$, we say "$\mathcal{M}$ accurately solves the failure prediction" iff $\mathcal{F} \in e'_j \Leftrightarrow \mathcal{F} \in \mathcal{M}(e_i)$. We say "$\mathcal{M}$ approximately solves the failure prediction problem" if $\mathcal{F} \in \mathcal{M}(e_i) \Rightarrow \mathcal{F} \in e'_j$.*

When $\mathcal{F} \in e'_j$, we say that the extension e'_j is a *failure extension* of e_i and when $\mathcal{F} \in \mathcal{M}(e_i)$, we say that $\mathcal{M}(e_i)$ is a *predicted failure extension* of e_i. We also say that e_i is a failure precursor sequence. Note that $\mathcal{D}(e_i \cdot \mathcal{M}(e_i), e_i \cdot e'_j)$=0 means that the predicted lead time of failure event is accurate perfectly, i.e., the failure event would occur right at the predicted moment. Also note that a small value of $\mathcal{D}$ indicates that the failure event occurrence moment is approximately correct in the sequence.

For the failure lead time [18], due to the non-determinism at the system level, it is difficult to accurately predict the *exact* failure lead time. To circumvent this challenge, we propose to model the failure lead time prediction as a multi-class classification problem. We propose a general formal definition of failure lead time as follows.

Definition 3 (Lead time to Failure)**.** *Given a log sequence $e_i \in \mathcal{L}^m$, its extension $e'_j \in \mathcal{L}^k$ which is a failure extension of e_i, the failure lead time of e_i is the difference between the timestamp of the last event in $e_i \in \mathcal{L}^m$ and the failure event in e'_j and is equal to $TS(\mathcal{F} \in e'_j) - TS(last(e_i))$, where TS denotes the timestamp function and last function returns the last element of a sequence respectively.*

Let $\mathcal{L}^m$ be the instance space. Every point $e_i \in \mathcal{L}^m$ is a potential state of the log. Given a pair $\langle e_i, F(e_i)\rangle$, where $e_i \in \mathcal{L}^m$ is a failure precursor sequence, e'_j is a failure extension of e_i and $F(e_i)$ denotes the failure lead time of e_i, we wish to learn an approximation of the unknown F, denoted by $\hat{F}$ and $\hat{F}(e_i) = TS(\mathcal{F} \in \mathcal{M}(e_i)) - TS(last(e_i))$, where $\mathcal{M}$ is a predictor that solves the failure prediction problem.

Definition 4 (Predicted Lead time to Failure)**.** *Given a failure precursor log sequence $e_i \in \mathcal{L}^m$, its failure extension $e'_i \in \mathcal{L}^k$, a set of non-overlapping p ranges $R = \{R_1, \ldots, R_p\}, R_i \in \mathbb{Z}^+ \times \mathbb{Z}^+, R_i \cap R_j = \emptyset$ and a predictor $\mathcal{M}$ which solves the failure prediction issue approximately, we say that the predicted failure lead time is correct if $\exists R_i \in R \cdot \hat{F}(e_i) \in R \Rightarrow F(e_i) \in R$.*

IV. Time Machine Methodology

Inspired by recent work in (NLP) tasks, we propose a transformer-decoder based sequential model to predict the forthcoming events, node failure, and failure lead-time in HPC systems. In general, we take the self-attention based language model as an estimator for the posterior probabilities, in which we consider the log events as input words, a sequence of log events as a sentence, and the probabilities of failure in HPC as a context-based generative probabilities. Furthermore, self-attention is friendly to *parallelization*, such that the training and prediction time can be significantly reduced by leveraging parallel techniques, compared to existing state-of-the-art failure prediction methods, such as RNN-based methods used in [9], [10], [11]. To this end, we develop a novel real-time online approach namely **Time Machine** which is fully self-supervised without the need for labeling by HPC system administrators. As shown in Figure 1, the architecture of our model consists of **two** transformer-decoder neural network components, and both of the two decoders are based on the transformer-decoder variant [19]. The **first** transformer component aims to predict HPC node failures with two major steps: (1) for each node, it predicts the sequence of future events (or future health state); (2) it determines weather a failure is included in the predicted sequence. The **second** transformer component aims to predict *lead times*, based on which one or more proactive fault-tolerant techniques can be accurately selected in time ahead of the failure occurrence.

As for the Time Machine methodology which adopts two stacks of transformer-decoder to predict HPC system failures and their lead-times, its framework design also includes three key innovative points:

- Transformer neural networks are employed originally for NLP tasks such as text classification, text generation, summarisation, while the **Time Machine** method is the first work utilizing transformer architecture to predict the lead-time to failures. This method can be generalized to other domains for time-based prediction tasks.
- Time Machine introduces a novel Synthetic Minority Oversampling Technique for online time-based tasks to construct the training instances in real-time from failure sequences.
- In the fault tolerance research, our Time Machine method is the first study to reduce/convert the time prediction problem (a regression problem) into a self-annotated multi-class classification problem, by predicting the class for the failure lead time.

We detail our proposed framework in the rest of this section.

A. Node Failure Prediction

*1) **Phase I. Log Event Prepossessing**:* In the first phase, similar to the tokenization in NLP task, we first convert the log message into an ID based log event sequence: $e_1, e_2, ..., e_m$, where m is the length of event sequence, $e_i \in \{t_j | j = 1, 2, ..., T\}$ represents the i-th event, and t_j stands for all possible event types in the log event prediction. Besides, we let $m < 1024$ in order to make it possible that all input event sequences share similar length for parallel processing, which is distinct from the existing RNN methods. Moreover, the Byte Pair Encoding (BPE) method is utilized to tokenize the input to encode any unusual tokens (IDs of log entries).

*2) **Phase II. Log Events Learning and Failure Prediction**:* Our proposed approach aims to take the self-attention mechanism to improve the connectivity among the events in log sequences. Accordingly, we utilise transformer-decoder architecture, a stack of decoder blocks preceded by an input layer to embed the real-time log events sequence logged by the HPC system component node, and then followed by linear and softmax layers to predict failures (e.g., node crashes, networks failures) by two steps: predicting the future sequence of events and then identifying if a failure is part of the predicted sequence. More details are described in the following text. We refer the readers to read [19] for detailed background of the *transformer variant* which we will use to build our model.

We summarize the current masked language (failure and lead-time prediction in our case) model as follows:

In a typical transformer block ℓ, assuming the input feature for token e_i in $l-1$-th layer of transformer is e_i^{l-1}, the information propagation process is given by:

$$v_i^{l-1} = \text{Self-Attention}(e_i^{l-1} | e_1^{l-1}, e_2^{l-1}, ..., e_m^{l-1}) \quad (1)$$

$$\Phi(v_i^l) = \varphi(W^l v_i^{l-1} + b^l) \quad (2)$$

$$e_i^l = \text{LayerNorm}(\Phi(v_i^l) + e_i^{l-1}) \quad (3)$$

where e_i^l is the learned feature for e_i in l-th layer, v_i^l is the corresponding value vector in the regard of the self-attention mechanism according to e_i^l, φ is an element-wise nonlinear function applied to a feed-forward layer, whose weight matrix, $W^l \in \mathbb{R}^{n_l \times n_{l-1}}$, transforms the feature dimension from n_{l-1} to n_l, Self-Attention(e^{l-1}) returns the weighted value vector of all input representations where weights are derived by multiplying the query vector of the current input e^{l-1} with the key vectors from other inputs. Between every two transformer blocks, there is a skip-connection and a layer normalisation. The former mechanism bypasses the transformer block ℓ and adds the input e^{l-1} directly to the output v^l of this block, while the latter normalises the input across the feature dimension.

STEP 1: Transfer Learning Based Sequence Prediction

The main idea in pre-trained language model, such as GPT-2/3 [19], aims to predict a particular word based on its context by: $P(e_i | e_1, e_2, ..., e_{i-1}, e_{i+1}, ..., e_m)$. However, in the HPC events prediction, the tokens after expected prediction e_i is unseen to the model. Furthermore, the vocabulary, which stands for the log events types, is much smaller than NLP task, which may lead to overfitting if we simply train an over-parameterised model.

Therefore, we propose to use pre-trained model (GPT-2) from NLP, which is almost isotropic, to initialise the transformer-decoder model to predict the future log event by fine-tuning the parameters on HPC dataset. Here, we define the probability of future log event by Softmax $P(\hat{e'}_{m+i} | e_1, e_2, ..., e_m) = \text{Softmax}(\text{FNN}(e_i^L | e_1, e_2, ..., e_m))$, where the FNN stands for the feedforward neural network and L is the last layer of transformer block.

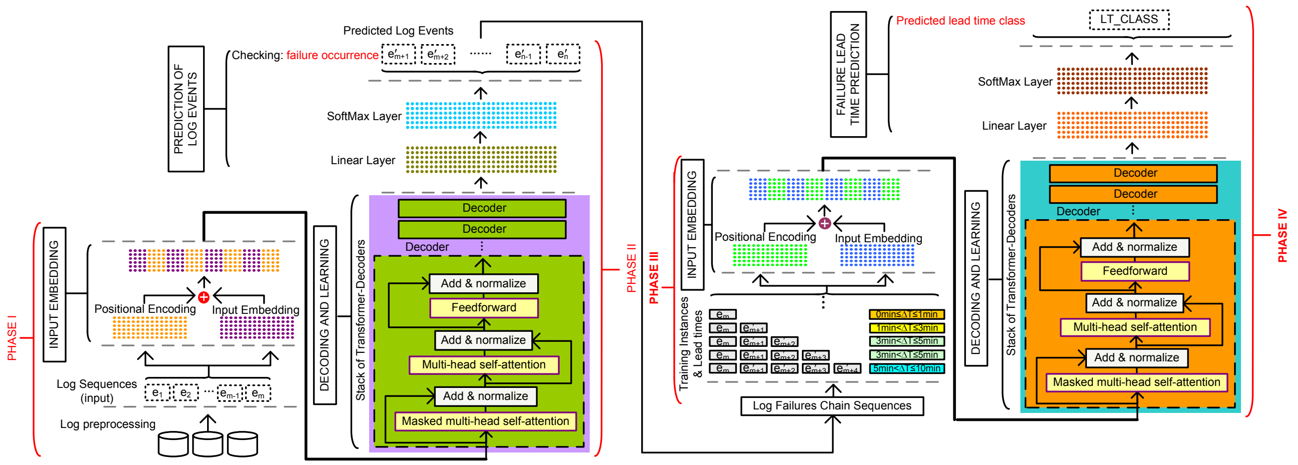
According to definition 1, we use the cross-entropy as the metric to measure the distance between distribution in loss function,

$$\mathcal{L} = \sum_{i=1}^{n-m} P(e'_{m+i}) \cdot \log(P(\hat{e'}_{m+i} | e_1, e_2, ..., e_m)) \quad (4)$$

where the estimated probabilities of $P(\hat{e'}_{m+i})$ are defined by the Softmax function with the learned vectors along to the last FNN layer, and the $P(e'_{m+i})$ is the true output from training corpus, which is an advantage that, in such learning architecture, we do not require a specific annotation for self-supervised learning. The sequence of log events can be generated from large scale of raw data automatically. In this way, the pre-trained language model can be easily adapted to the log events prediction task in real-time.

STEP 2: Failure Prediction

Based on the prediction of log events, we can generate a log events sequence by a given $\{e_1, e_2, ..., e_m\}$, marked as: $\{e_1, e_2, ..., e_m, e'_{m+1}, ...e'_n\}$, where $\{e_i | i \leq m\}$ is the



Predicted Log Events
PREDICTION OF LOG EVENTS
Checking: failure occurrence
e'_{m+1} e'_{m+2} ...... e'_{n-1} e'_n
SoftMax Layer
Linear Layer
Decoder
Decoder
Decoder
Add & normalize
Feedforward
Add & normalize
Multi-head self-attention
Add & normalize
Masked multi-head self-attention
Stack of Transformer-Decoders
DECODING AND LEARNING
PHASE II
INPUT EMBEDDING
Positional Encoding
Input Embedding
Log Sequences (input)
e_1 e_2 ... e_{m-1} e_m
Log preprocessing
PHASE I
FAILURE LEAD TIME PREDICTION
Predicted lead time class
LT_CLASS
SoftMax Layer
Linear Layer
PHASE III
INPUT EMBEDDING
Positional Encoding
Input Embedding
Training Instances & Lead times
e_m
e_m e'_{m+1}
e_m e'_{m+1} e'_{m+2}
e_m e'_{m+1} e'_{m+2} e'_{m+3}
e_m e'_{m+1} e'_{m+2} e'_{m+3} e'_{m+4}
$0min \le \Delta T \le 1min$
$1min < \Delta T \le 3min$
$3min < \Delta T \le 5min$
$3min < \Delta T \le 5min$
$5min < \Delta T \le 10min$
Log Failures Chain Sequences
DECODING AND LEARNING
Stack of Transformer-Decoders
Decoder
Decoder
Decoder
Add & normalize
Feedforward
Add & normalize
Multi-head self-attention
Add & normalize
Masked multi-head self-attention
PHASE IV

Fig. 1: Illustration of Health State/Failure/Lead Time Prediction Phases

given event and $\{e'_j | m+1 \le j \le n\}$ is the predicted event. According to definition 2, the failure prediction aims to identify if the e'_j is the failure extension of e_i. Hence, we can convert the generated event e'_j to the unique ID to check if it is the failure. Here, we suppose the whole vocabulary of log events is $\mathcal{V}$, which contains two subsets, the failure events $\mathcal{V}^f$, and the normal events $\mathcal{V}^n$, where $\mathcal{V}^f \cup \mathcal{V}^n = \mathcal{V}$ and $\mathcal{V}^f \cap \mathcal{V}^n = \emptyset$. Then, one can easily quantify that a predicted log event is a failure if it is a member of failure events set ($e'_j \in \mathcal{V}^f$).

B. *Predicting Lead Times to The Node Failure*

One key novelty that is significantly different from existing transformer based sequence models, is predicting lead times for the failure events such that appropriate proactive methods could be triggered in time, which is handled by the Phase III and Phase IV.

*1) **Phase III: Failure Sequences Construction for Lead-Time Prediction**:* In order to predict the node failures' lead times, the first and foremost step is establishing and preparing a dataset based on failure chains (i.e., the Phase III as presented in Figure 1). Our framework can be easily deployed for HPC systems in real-time, because the training/testing datasets from the failure chains and associated labels (i.e., lead times) are created automatically (**no need for manual labelling**) based on log events' timestamps.

We introduces a **novel Synthetic Minority Oversampling Technique** for online time-based tasks to construct the training instances in the real-time from failure sequences as follows. In our model, predicting a node's failures ahead is achieved through accurately predicting the forthcoming log events $\{e'_{m+1}, e'_{m+2}, ..., e'_n\}$. Without loss of generality, we assume that the predicted log events sequence ends with a failure event since the motivation of our proposed method aims to predict the failure. Hence, based on the given log events sequence $\{e_1, e_2, ..., e_m\}$ and the proposed events/failure prediction methods, we have a failure chain of $\{e'_{m+1}, e'_{m+2}, ..., e'_n\}$, where $\exists e'_j \in \mathcal{V}^f$.

To predict the lead time for any concrete failure chain, we then use the timestamp $TS(\cdot)$ to estimate the lead time when the failure appears for a given sequence of log events. Intuitively, we only need to predict the $TS(e'_j)$, where $\{e'_j \in \mathcal{V}^f\}$. However, considering that the size of $\mathcal{V}^f$ is limited, it is essential to design a smoothing method to overcome the potential risk caused by over-fitting. Hence, we propose to utilise the transformer-decoder based method to approximate the $TS(\cdot)$ for both $e'_j \in \mathcal{V}^n$ and $\mathcal{V}^f$, and take advantage of sequential model to guarantee the latent pattern $TS(e'_i) < TS(e'_j) (i < j)$ is true, to achieve both reasonable and stable lead-time prediction. Specifically, to make the trade-off between efficiency and accuracy, we convert the prediction of lead times from a regression problem to a multi-class classification problem which predicts the class for the failure lead time. Such a design is motivated by the fact that there are only a few proactive recovery techniques used in practice (e.g., less than 10 techniques), and each technique requires a specific lead time to launch. Moreover, the correction/proactive actions generally require approximately estimated lead times instead of the exact lead times. Accordingly, we define 6 lead-time classes $\hat{y}_j$ in our study: $\hat{y}_j \in \{$[0min,1min], (1min,3min], (3min,5min], (5min,10min], (10min,15min], (15min,∞)$\}$. Our model is flexible in increasing/decreasing lead time classes based on the system recovery mechanism.

We use an example to describe how to construct the training instances. Without loss of generality, suppose a failure chain contains 6 log events including the failure event with associated timestamps: $((e_m, 01{:}00{:}00), (e'_{m+1}, 01{:}00{:}30), (e'_{m+2}, 01{:}01{:}00), (e'_{m+3}, 01{:}03{:}10), (e'_{m+4}, 01{:}04{:}55), (e'_{m+5}, 01{:}07{:}16))$, where the $e'_{m+5} \in \mathcal{V}^f$ is the failure event. The training instances and their associated lead time classes are constructed automatically in terms of the failure chain iteratively, as illustrated in Figure 2.

As all log sequences training instances are created from the failure chains as described above, the lead-times have been associated/mapped to the corresponding lead-time classes. Note that this process is conducted during runtime model deployment, and all log event instances are assigned the same

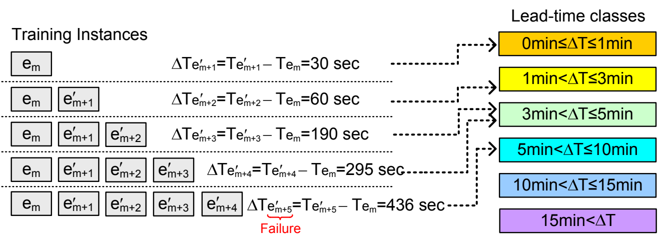

Training Instances
Lead-time classes
e_m
e'_{m+1}
e'_{m+2}
e'_{m+3}
e'_{m+4}
$\Delta Te'_{m+1}=Te'_{m+1}-Te_m$=30 sec
$\Delta Te'_{m+2}=Te'_{m+2}-Te_m$=60 sec
$\Delta Te'_{m+3}=Te'_{m+3}-Te_m$=190 sec
$\Delta Te'_{m+4}=Te'_{m+4}-Te_m$=295 sec
$\Delta T\underbrace{e'_{m+5}}_{\text{Failure}}=Te'_{m+5}-Te_m$=436 sec
0min≤ΔT≤1min
1min<ΔT≤3min
3min<ΔT≤5min
5min<ΔT≤10min
10min<ΔT≤15min
15min<ΔT

Fig. 2: Lead Time Training Instances Construction

tokens as discussed in IV-A2 before being embedded/fed into the second transformer-decoder stack.

2) ***Phase IV: Lead-Time Learning and Prediction***: Based on the prediction of log events, we can generate a log events sequence by a given $\{e_1, e_2, ..., e_m\}$, marked as: $\{e_1, e_2, ..., e_m, e'_{m+1}, ...e'_n\}$, where e_i is the given event and e'_j is the predicted event. According to sequence generation in section IV-B1, the lead-time prediction aims to identify the label of y_j for the failure extension of e_i with length j, a.k.a $\{e_1, e_2, ..., e_m, e_1, ...e_j\}$. Hence, we convert this task into sequence classification, in which we employ the fine-tuned transformer-decoder-based model to extract the last representation R_{e_j} of the token e_j, to approximate the posterior probability according to the failure label in real-world datasets, by a Softmax probability:

$$P(y_j) = \\ \text{Softmax}(\text{FNN}(\text{decoder}(R[e'_j]|e_1, ..., e_m, e'_{m+1}, ..., e'_j))) \tag{5}$$

In general, any loss function or pre-trained language model can be deployed for the approximation. Without loss of generality, we choose the cross-entropy as loss function and the GPT-2 as decoder in our implementation. In summary, $\forall$ log events sequence $e_1, e_2, ..., e_m$, we can predict the failure extension of $e'_{m+1}, ..., e'_n$ by minimising the loss function defined by equation.4. According to equation.5, we can then predict the lead time to failure of $TS(e'_j) - TS(e_m)$. This proposed framework requires no annotation or supervised signal but facilitates optimising the process which can select the lowest computation cost correction/recovery mechanisms to correct and fix HPC system errors before the failures occur.

C. *Featuring Real-Time in Time Machine*

Deploying the *Time Machine* online in real-time requires fine-tuning the model parameters in case new log sequences and failure patterns are encountered. Thus, the teacher forcing technique [20] is proposed to complement *Time Machine* in real-time. The integration between the *Time Machine* and teacher forcing approach enables online training, learning, and prediction by using ground truth input instead of our model output (the log events predicted by *Time Machine*) from a previous time step as an input. The truth input in our case is the actual log events generated by HPC system components (e.g., compute nodes). This integration can cope with any new types of log sequences and emerging failure patterns because of various cases, such as upgrade of the HPC system components (i.e., software, hardware, services). The new jobs (e.g., applications) running on HPC systems can also induce new log patterns that have not been met before. Moreover, the teacher-forcing technique forces the real-time log event learning/prediction under the *Time Machine* to be conducted on correct log events (i.e., the correct log sequences generated by the system) rather than log sequences predicted ahead by *Time Machine* (which may be incorrect prediction).

V. System, Datasets, and Evaluation Metrics

A. *Systems and Log Data*

Table I shows the the four **unlabeled** log datasets and their supercomputers characteristics which used in our study. The four data logs are generated from three different real-world supercomputers clusters. Specifically, these system are of various scales (from 200 nodes to 5600 nodes), various interconnects (Infiniband and Aries Dragonfly), different file systems (Luster, MarFS, etc.), different processors, and different logging mechanism. The log datasets are (i) Syslogs, (ii) Rationalized Logs (abbreviated as RatLogs). Both Syslogs and RatLogs are collected form Ranger supercomputer(operated by Texas Advanced Computing Center (TACC)) [21] at different time and have been widely used for failure analysis [22], [23], [8], [24]. Rationalized Logs is upgraded logs based on a new logging framework called Rationalized logging framework for Ranger supercomputer which replaced Sys logging framework. Unlike Syslogs, RatLogs has a few additional fields to record more information, for example, job-ID to identify each running job. (iii) Cray XC30 logs [18] generated by Cray XC30 supercomputer , and (iv) Cray XC40 logs [25] generated from Cray XC40 (Mutrino) supercomputer which was managed under a joint effort between Los Alamos National Laboratory (LANL) and Sandia National Laboraties (SNL). Mutrino, sited at SNL. Both Cray XC30 logs and Cray XC40 logs consist of two different types of logs (console and message).

B. *Evaluation Metrics*

Time Machine predicts (i) forthcoming log events (the entire health state of each node in the system) (ii) the node failure, and (ii) the expected lead time to failure. Therefore, our model is evaluated in three aspects. (1) We evaluate the accuracy by comparing the log events predicted by *Time Machine* versus the actual log events generated in reality by the four HPC systems using two text generation metrics (*Bleu* and *Rouge*). *Bleu* and *Rouge* metrics can complement each other for the NLP text generation (upcoming log events prediction in our case) tasks evaluation. Specifically, they correspond to the precision measure and recall measure, respectively. (2) We evaluate the prediction accuracy of our model regarding the nodes' failure events using several standard metrics including recall, precision, F1_score, Matthew's correlation coefficient (MCC), false-positive rate, and false-negative rate. We removed the log events predicted by our model (candidate) and the actual log events generated by the HPC system (reference) except failures in order to employ these metrics. (3) We evaluate the prediction accuracy of our model regarding the lead-time to node failures based on standard metrics: recall, precision, F1_score, and Matthew's correlation coefficient (MCC).

*1) **Log Events Prediction Evaluation Metrics**:* *Bleu* and *Rouge* are used to evaluate the prediction accuracy of the log events predicted by our model versus the actual log events generated by the four HPC systems in real-time as follows:
(i) ***Bleu*** (Bilingual Evaluation Understudy [26])

Bleu is an important indicator to measure the percentage of log events predicted by our model correctly (candidate) compared with the real log events as recorded by the HPC system (reference). A Bleu score is in the range of [0,1], where 0 indicates a mismatch and 1 means a perfect match.

The Bleu metric is defined in Equation 6 [26]:

$$\begin{gathered} Bleu = BP \times e^{(\sum_{n=1}^{N} w_n \log p_n)} \\ where \quad BP = \begin{cases} 1, & c > r \\ e^{1-r/c}, & c \leq r \end{cases} \\ p_n = \frac{\sum\limits_{C \in \{Candidates\}} \sum\limits_{n\text{-}gram \in C} Count_{clip}(n\text{-}gram)}{\sum\limits_{\acute{C} \in \{Candidates\}} \sum\limits_{n\text{-}gram \in \acute{C}} Count(n\text{-}gram)} \end{gathered} \tag{6}$$

where BP refers to *brevity penalty* , r refers to the length of the reference event sequence in the HPC system, c is the length of the candidate log sequence predicted by our model, N refers to the length of ngrams, $w_n = \frac{1}{N}$ means the positive weights. As for the formula of p_n in Equation 6, $Count(ngram)$ and $Count_{clip}(ngram)$ refer to the number of ngrams for the candidate in the test set and the number of clipped ngrams for the candidate log sequence, respectively.
(ii) ***Rouge*** (Recall-Oriented Understudy for Gisting Evaluation N-gram Co-Occurrence Statistics) [27])

We use Rouge to measure the recall – the percentage of the real log events (reference) overlapped with the log events predicted by our model (candidate). The rouge score is always in the range of 0 to 1, where 0 indicates a mismatch and 1 means a perfect match. We present its definition in Equation 7 [27]:

$$Rouge = \frac{\sum\limits_{S \in \{Reference\}} \sum\limits_{(gram_n) \in S} Count_{match}(gram_n)}{\sum\limits_{S \in \{Reference\}} \sum\limits_{(gram_n) \in S} Count(gram_n)} \tag{7}$$

where n refers to the number of ngrams, $Count(gram_n)$ is the number of ngrams in the reference, and $Count_{match}(gram_n)$ means the maximum number of ngrams included by both reference set and candidate set.

*2) **Node Failure and Lead-Time Evaluation Metrics**:* We use some other well-known metrics to evaluate node failure prediction, which are summarized in Equations (8) to (13), where TP, FP, FN, and TN refer to True Positives (failure events are predicted correctly), False Positives (failure events are predicted incorrectly), False Negatives (failure events are missed by our model) and True Negatives (normal events are predicted correctly by our model), respectively. Precision and recall are two typical widely measures for failure prediction accuracy. F1_score is an aggregated metric by merging precision and recall. Matthew's correlation coefficient (MCC) is another aggregated metric which returns a high score if and only if the model performs well in all the four categories (TP, FP, FN, and TN).

$$Precision = \frac{TP}{TP+FP} \tag{8}$$

$$Recall = \frac{TP}{TP+FN} \tag{9}$$

$$F1\ Score = 2\frac{Recall \cdot Precision}{Recall+Precision} \tag{10}$$

$$MCC = \frac{TP \times TN - FP \times FN}{\sqrt{(TP+FP)(TP+FN)(TN+FP)(TN+FN)}} \tag{11}$$

$$FPRate = \frac{FP}{FP+TN} \tag{12}$$

$$FNRate = \frac{FN}{TP+FN} \tag{13}$$

As for the evaluation of lead-time prediction, we also use the above standard metrics including recall, precision, F1_score, and Matthew's correlation coefficient (MCC).

VI. Performance Evaluation

To show the efficacy and applicability of our failure&lead-time prediction method, we carefully evaluate the performance of our model on four real-world supercomputer system logs: (i) SysLogs, (ii) Rationalized logs, (iii) Cray XC30 logs and (iv) Cray XC40 logs. They were logged by three different supercomputers and four different logging mechanisms at different operational times, which are all **unlabeled**. We compare our approach to three state-of-the-art deep learning prediction techniques (a.k.a., baselines in the following text): Desh (LTSM) [9], Bi-LSTM [10],and GRU [11]. These three related works employ LSTM, Bi-LSTM, and GRU neural networks to predict HPC failures, respectively, and they have been verified as the best in class. We do not compare our work to traditional machine learning (ML) (e.g., Random Forest, SVM, DT, KNN) for two reasons. First, our model is a self-supervised learning that does not need labels whereas ML methods depend on labeled data (i.e., supervised learning-based techniques). Second, even ML algorithms can be utilised for classification (e.g., anomaly detection) and regression tasks, however, they are not designed to resolve text generation (prediction) tasks which is our research problem. In what follows, we show and discuss the major evaluation results.

*A. **Log Data Preprocessing***

We preprocess the log data by sorting the log events according to timestamps, cleaning raw messages, and removing the duplicate messages in terms of the spatial and temporal correlations. Consequently, these log messages are converted to log sequences regarding their associated nodes, which corresponds to the phase I of our methodology. As shown in Table I, the quantities of the datasets' log messages are reduced significantly after the preprocessing step. Specifically, a total of 83087, 25272, 127161, and 49391 log sequences are constructed from Syslogs, Rationalized logs, Cray XC 30 logs, and Cray XC 40 logs, respectively. Each of the four logs is divided into training part and testing part. The training part accounts for 80% of the logs' data, while the testing part accounts for the remaining 20%.

TABLE I: Data Logs before and after the Preprocessing Phase

Log Name	# nodes	processors	Duration	# raw logs	# filtered logs
Syslogs	4,084	AMD Opteron	5 mon	43.6 m	2.3 m
RatLogs	4,084	AMD Opteron	6 mon	361 m	8.1 m
Cray XC30	5,600	IvyBridge	1 mon	133 m	15.3 m
Cray XC40	200	Haswell/KNL	16 mon	237 m	5.9 m

B. Training and Prediction Time Performance

Time Machine remarkably decreases the overall training time compared to the three state-of-the-art prediction approaches (LTSM (Desh), BiLSTM, and GRU). The overall training time includes two parts: (i) the training time in the regard of the prediction of the log event patterns and (ii) the training time for the prediction of the lead time to node failures. For the 4 HPC Systems Data Logs, *Time Machine* takes only 3.53 hours for the overall training on average, while other related works (LTSM, BiLSTM, and GRU) require 14.54 hours, 25.53 hours, and 13.22 hours, respectively. Also, our model is 15× faster over all baseline solutions in predicting the forthcoming log sequence of events. The training and prediction time speed-up results are detailed as follows.

*1) **Log Events Training Time Performance:*** The training time for learning to predict the log sequences and identifying failure patterns, which is addressed by the first transformer-decoder stack, is drastically reduced $5.4 \sim 9.4\times$ compared to three other state-of-the-arts on average as shown in Table II. *Time Machine* requires only 0.7∼3.83 hours in training, while LTSM, BiLSTM, and GRU require 3.79∼20.75 hours, 6.69∼36.66 hours, and 5.74∼18.88 hours, respectively.

TABLE II: Log Events Training Time Performance in Hours

	Time Machine	LSTM	Bi-LSTM	GRU
SysLogs	1.60	8.86	15.30	7.89
Rationalized Logs	0.70	3.79	6.69	3.66
Cray XC 30	3.83	20.75	36.66	18.88
Cray XC 40	1.17	6.31	10.33	5.74
Average	1.83	9.93	17.25	9.04

*2) **Lead Time Prediction Training Time Performance:*** The training time for learning to predict the lead time to node failures, which is addressed by the second transformer-decoder stack, also drastically decreased $3.74 \sim 7.23\times$ compared to three other state-of-the-arts, as illustrated in Table III. Based on all the 4 HPC Systems Data Logs, *Time Machine* requires only 1.71 hours of training on average, while the other related works (LTSM, BiLSTM, and GRU) require 4.61 hours, 8.29 hours, and 4.17 hours, respectively.

TABLE III: Lead Time Training Time Performance in Hours

	Time Machine	LSTM	Bi-LSTM	GRU
SysLogs	1.2	3.17	5.91	2.84
Rationalized Logs	0.54	1.49	2.69	1.34
Cray XC 30	3.86	10.42	18.32	9.44
Cray XC 40	1.24	3.35	6.24	3.09
Average	1.71	4.61	8.29	4.17

*3) **Log Events Prediction Time Speed-up Performance:*** Our model has the highest speed on the prediction of forthcoming log sequence of events (chain lengths), as shown in Figure 3. As evaluated in our experiments, the speedup of our model in predicting the forthcoming log sequence of events is 15× faster over all baseline solutions (LSTM (Desh), Bi-LSTM and GRU). The Figure 3 shows that only 5.78 secs are needed to predict a log sequence with the chain length of 1024, whereas state-of-the-art methods require 96∼167 secs.

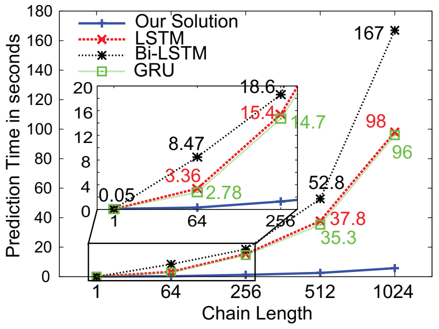
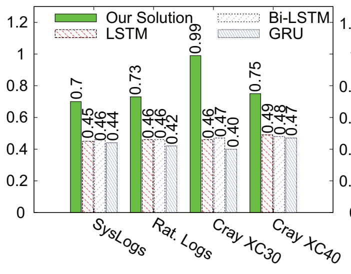


Fig. 3: Prediction Time of Chain Lengths

The low training time and high prediction performance of our model are attributed to the transformer-decoder mechanism's parallelization capability and positional encoding. More specifically, it takes considerably less time than the RNN models (baselines) because the RNN model lacks parallel training and requires sequential learning. On the one hand, optimization of training time in HPC systems is significant because deploying the model online in real-time requires multiple fine-tunings of the model parameters over time in case of new log sequences and failure patterns appear. HPC system operators frequently elevate system components (software/hardware) and services to add new components (i.e., hardware or software) to improve high-performance computing demands. The increased number of high-resources-hungry jobs (e.g., applications) scheduled day-to-day on HPC systems also induces the logging management systems to generate new log patterns that have not been learned. On the other hand, Machine Time is particularly suitable for real-time failure prediction because of the high-speed prediction of forthcoming log sequence of events (chain lengths). It is noted that the growth of the number of events in the log chain does not come up with higher prediction times using *Time Machine*, whereas the baselines consume a long time to predict the same log sequence, and the speedup turns more and more obvious with increasing log chain lengths. So, our model is suitable for the real-time use-case with vast amount of logs generated in a short time (seconds), especially when the HPC components face erroneous behaviors that may lead to component crashes. Consequently, the high-speed prediction achieved by our model can boost the selection of the most suitable failure recovery action.

C. Overall Learning & Log Events Prediction Performance

We also evaluate the overall accuracy of our model in predicting the forthcoming log events (e.g., normal, errors, or failures) before the actual events occur, with respect to predict the entire system health state.


(a) Bleu

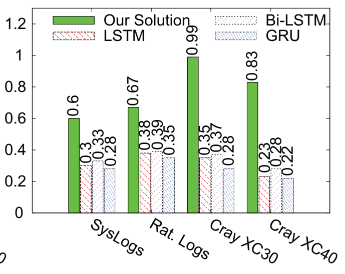

(b) Rouge

Fig. 4: Entire Health State Prediction Accuracy

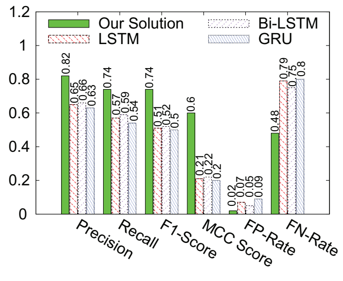
Figure 4 (a) and (b) show the Bleu measure and Rouge measure of the entire health state prediction. Bleu and Rouge measure the degree of similarity (overlapping) between the candidate solution (predicted log events by our model or the baselines (LSTM, Bi-LSTM and GRU)) and the reference (log events generated by the supercomputer system in realtime). As shown in the figure, our transformer decoder-based approach achieves a Bleu score of 0.70∼0.99 in predicting forthcoming log events based on the four system logs. In contrast, the other three state-of-the-arts have much lower Bleu scores (in the range of only 0.4∼0.5). On average, 79% of log events predicted by our model appeared in the events generated by the HPC system (the reference), compared to just 47% by Bi-LSTM (the best score from among the three baselines).

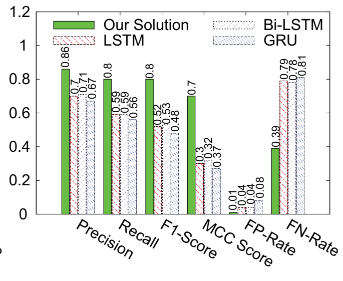
Also, our solution has a significantly higher Rouge score than the other three methods as depicted in Figure 4 (b). *Time Machine* obtains Rouge scores of 0.60, 0.67, 0.99 and 0.83 on the four system logs (SysLogs, Rationalized logs, Cray XC30 logs, and Cray XC40 logs), respectively. The Bi-LSTM baseline, however, obtains the Bleu scores of only 0.33, 0.39, 0.37 and 0.28, respectively. Similarly, both LSTM (Desh) and GRU based prediction solutions also have fairly low Rouge scores, which are in the range of 0.22 ∼ 0.39. On average, ≈ 77% of events generated by the supercomputer systems in real-time (the reference) appear in the log events predicted by *Time Machine* (candidate), compared to just ≈ 34% by the best state-of-the-art prediction solution (i.e., Bi-LSTM).

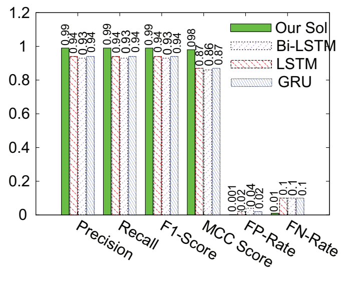
We note that all the baseline solutions (related works) can hardly capture long-range dependencies/correlations between the events of long sequences, because they all depend on RNN model, which suffers from the memory loss issue for earlier events because of the vanishing gradients. By comparison, our solution is able to predict the upcoming log event sequence as long as it correlates to the preceding log sequence, as manifested by a high match between the forthcoming log events under our prediction model, and the events generated on the real system. In particular, the masked self-attention mechanism can efficiently identify the log entries of important events while moving the focus away from irrelevant ones and capturing long-range dependencies/correlations between events in long sequences.

D. Node Failure Prediction Performance Evaluation

Figure 5 shows the prediction accuracy of failure events under our model and baselines. We apply six measurements (Recall, Precision, MCC Score, F1-score FP-Rate, and FN-Rate) to evaluate our candidate solution and reference, based on logs with removed non-failure events.


(a) SysLogs


(b) Rationalized Logs


(c) Cray XC30 Logs

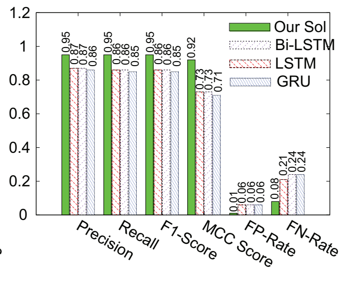

(d) Cray XC40

Fig. 5: Failure Prediction Performance

As presented in Figure 5, *Time Machine* predicts upcoming node failures with high average precision score (0.91) on the four HPC system logs. In comparison, the best baselines are LSTM and Bi-LSTM, whose average scores (0.79) are lower than our model. For example, 82% of Ranger SysLogs node failures predicted by *Time Machine* indeed appear in the actual events generated by Ranger HPC system, compared to only 66% by Bi-LSTM (the best score from among the three baselines). Also, the results show that our technique obtains a better recall accuracy with an average score of 0.87 on the four HPC system logs. In comparison, the best baseline (both LSTM and Bi-LSTM) obtains the average score of only 0.74. *Time Machine* achieves a recall score of 0.74 on Ranger SysLogs; Bi-LSTM (best-baseline score) obtains a recall score only 0.59. This means on average, 74% of actual node failures generated by Ranger appear in SysLogs can be predicted by *Time Machine*, compared to only 59% by Bi-LSTM.

According to Figure 5, our solution has much higher MCC scores and F1-scores than all other baselines. Specifically, our model achieves better prediction on the four system logs with MCC scores of 0.6∼0.92, and the f-scores reach 0.74∼0.99, which are both much higher than that of other baselines. For example, for SysLogs and Rationalized Logs, the MCC scores of our model can reach 0.6 and 0.7, respectively, which are much higher than the baselines' (0.2∼0.22 and 0.3∼0.37).

Furthermore, the significant improvement of our model over baselines is also manifested by false positive rate (FP-rate) and false negative rate (FN-rate) as as shown in Figure 5. For example, our model drives only 1% false failure alarms and only 24% false non-failure reports on average for all the four system logs, indicating fairly rare incorrect trigger recovery actions. However, the three baselines face higher FP-rate (5%) and FN-rate (47%), respectively.

We explain why our model significantly advances the baselines in the failure prediction as follows. As mentioned before, different lengths of log sequences are observed between the failure events and their associated errors and faults (such as software and kernel OS process, file-system errors, memory and storage errors, and network errors). Those sequences contain numerous interleaved and irrelevant log events, making the failure prediction process more challenging. For instance, some errors take many hours to trigger the associated failures, resulting in extended and lengthy log sequences (e.g., there are still 3000+ events after the logs filtering phase). In contrast, our transformer-decoder-based model leverages multi-head masked attention layers and the positional encoding technique, which can completely avoid recursion, processing log sentences as a whole and understands associations between log events, leading to higher prediction accuracy/capability.

*E. **Lead Time Prediction Performance Evaluation***

This section presents details about the performance of the prediction of lead-time to failure events. As mentioned previously, the second key primary goal is to predict not only node failures but their lead times, in order to choose appropriate recovery and correction techniques that can be executed in time based on the remaining time to the failures.

Three key points need to be clarified first as follows:

- The failure prediction techniques (Bi-LSTM approach [10] and GRU-based approach [11]) do not support lead-time prediction originally. In our research work, we implement a lead time component for each of them based on Bi-LSTM and GRU neural networks, respectively, so that they are enabled to predict lead-time classes.
- For fairness, we reduce the time-lead prediction problem into a self-annotated multi-class classification problem for all the baselines (RNN-based, Desh(LSTM based) [9], Bi-LSTM based [10], and GRU based [11]).
- We define 6 lead-time classes; however our model is flexible in increasing/decreasing lead time classes based on the HPC system recovery mechanisms.

Figure 6 shows the failure lead-time prediction results with two critical observations. On the one hand, our model always has the highest accuracy from among all the four solutions. In absolute terms, the MCC and F1-score under our model can reach up to 0.87 and 0.95, respectively, which are higher than the scores resulted from the three state-of-the-arts (0.87 and 0.94, respectively). In particular, for SysLogs and Rationalized Logs, the MCC scores of Time Machine can get up to 0.76 and 0.83, respectively, while the baselines' MMC scores are 0.74 and 0.78. On the other hand, all the four prediction methods have relatively high accuracy in predicting failure lead-times

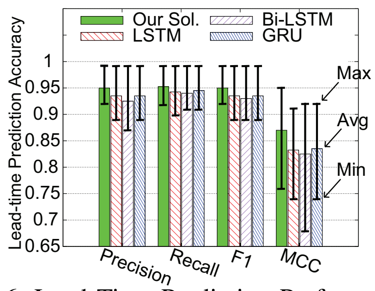


Fig. 6: Lead Time Prediction Performance

on the four real-world system logs. Such a high accuracy is primarily attributed to modelling the lead-time prediction as a classification task rather than a regression task. The reason we can model the lead-time prediction as a classification task is two fold: (i) there are only a few correction/recovery actions in total, and each action requires approximate lead times rather than exact lead times. The proactive recovery and error correction approaches may have largely different triggering/recovery costs. The typical proactive fault tolerance methods include job migration, checkpointing, process cloning, node quarantine, error correction code (ECC)), and so on. The generic live process migration technology, for example, may require a prior notice of less than 10 seconds according to the experiments conducted by [28], while similar OS virtualization technologies may call for much longer lead times (a warning of 13-24 seconds in general). To assist redundant execution during failures, Rezaei et al. [29] showed that node cloning requires less than 200 seconds. Gupta et al. [30] demonstrated 5-9% of future failures may be prevented when quarantining the blades/cabinets by stopping scheduling jobs on the nodes for a few hours after a failure is manifested.

There are four key points about predicting the lead-time analysis,which are noteworthy being mentioned as follows:

- Our model and baselines can all accurately forecast a variety of the lead times to different types of their associated failures. For example, the lead times (60 seconds, 80 seconds, 120 seconds, 160 seconds) of Cray supercomputer failures due to different errors of OS kernel panic, job scheduler Slurm, a hardware non-maskable interrupt (NMI), and Machine Check Exceptions, respectively).
- Our model predicts some failures of Ranger and Cray HPC systems that occurred with a very short lead time (only 5 seconds) after the occurrence of their associated errors. Some types of segmentation faults and memory corruption failures are examples of this class. Thus, In these cases, the HPC system management control should first quarantine the corresponding failure-prone nodes for a couple of hours to avoid waste of the compute resources. Second, the system should use a recovery action that takes less time (e.g., the generic live process migration) or avoid triggering any correction/recovery actions as most failures have already occurred in this case.
- Our model predicts accurately many failures with relatively long lead times. For instance, The lead times to

different node soft lockups failures in the TACC Ranger supercomputer are $\approx 100 minutes, \approx 125 minutes, \approx 300 minutes$ of their associated errors (general protection, page fault, loss of service connection by via Network Interface Device (NID)). In this case, our technique (Time Machine) can help the HPC system's administrator choose the best suitable lightweight error correction approach instead of an expensive solution. Also, it is practical to postpone triggering the recovery mechanism technique until a certain short period before the actual failure occurrence because most of these kinds of failures can be corrected themselves automatically.

- *Time Machine* can be considered the best optimization failure prediction solution since it reports the failures and their lead time at the same time their associated causes (i.e., errors) appear. That means our transformer neural networks based method exhibits the most efficient prediction of lead times to node failures solution.

VII. Related work

Log messages are utilized based on statistical and machine/deep learning approaches for the log based reliability analysis in today's HPC systems: log preprocessing/filtering, anomaly detection, and failure prediction.

First, multiple machine learning and deep learning techniques have been employed for log parsing/filtering, For example, **LogAider**[31], **Logram** [32], **DIP** [33], **LSWE**[34]. Recently, different parsers that rely on transformer variants have also been proposed, e.g., [35], [36].

Second, various machine and deep learning approaches (e.g., SVM, Random Forest, LSTM) are utilized for anomaly detection: classifying the log events or sequences as normal or anomaly (similar to anomaly classification in NLP). For instance, [8], **Logclass** [37], **Deeplog** [38], [39], **SiaLog** [40], **PLELog** [41], and CNN-based studies (e.g.,[42], [43], [44]). Some studies [45], [46], [47] proposed anomaly detection methods based on Generative Adversarial Networks (GANs). Several studies have proposed to use self-attention with different transformer variants to detect HPC anomalies. These approaches rely on self-attention-based transformer-decoder [48], self-attention with different transformer-encoder variants [49], [50]. Compared to these approaches, our Time Machine is a real-time generative model for predicting log events, components (e.g., node) failures, and the lead time to the predicted failures in HPC systems via utilizing two stacks of self-supervised transformer-decoders.

In order to ensure the mitigation techniques effective upon failures, the corresponding failures need to be predicted early enough compared with their occurrence moment. That is, it is critical to predict not only failure locations but also the lead times to these failures accurately, in order to trigger appropriate recovery and correction approaches in time. This makes this problem more complex than the previous three log analysis tasks (log parsing, anomaly detection, and failure diagnosis). Several failure prediction methods for HPC systems are proposed, including rule-based method and mathematics/analytics-based method (e.g., [51], [52], [53], [54], [55], [56], [57]). In comparison, our solution focuses on machine and deep learning categories. Many studies [58], [59], [14], [60], [61], [62], [63], [64], [65], [66], [67] leveraged ML techniques to predict the largescale systems failures based on calculating correlation association scores between the log events and failures, however extensive data engineering efforts and manual labelling are required to transform log messages to the numerical & statistical data before applying these solutions, and they are lack of predicting the failures' lead-time. Moreover, machine learning-based approaches generally lead to lower prediction accuracy compared to the deep learning methods which are the best related works. Different models have been proposed to predict failures in HPC systems based on deep learning algorithms. Similar to the ML-based methods, most of them do not perform inference leadtime analysis such as [68], [69], [10], [11], [15], and few frameworks include sub-models to predict the leadtime of failures such as **Desh** [9] and its extension **Aarohi** [5]. In comparison with deep learning methods, Time Machine is a more efficient failure and lead time prediction technique, which outperforms all RNN-based methods in all evaluation metrics based on our experiments. Clairvoyant [15] utilized transformer-decoder to predict only the soft lockup failures. In comparison, Time Machine uses two stacks of transformer decoders to predict any possible types of failures and the lead time of failures accurately as detailed in the introduction.

VIII. Conclusion

In this paper, we employ the transformer-decoder neural networks to build a novel real-time model called *Time Machine* to predict log events, failures, and their lead-times in HPC system's components (e.g, nodes). Time machine and three state-of-the-art techniques are evaluated on four HPC log data. Experiments show that our model significantly outperforms other state-of-the-arts in both accuracy and speed. Our model can trigger recovery solutions at right places and right time with substantially reduced cost. Note that this work introduces a novel method to automatically (no need for labels) construct and augment a self-time annotated training dataset on sequential time-based (timestamps) raw data via automatic accumulative and iterative process. Also, Time Machine is the first paper to formulate the time prediction (a regression problem) as a self-annotated multi-class classification problem by predicting the class for the failure lead time. Motivated by the promising results of our solution, in future, we will explore other generative models such as T5, GANs, BART for the prediction of HPC failures and lead-times.

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