

UniLog: Deploy One Model and Specialize it for All Log Analysis Tasks

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Abstract—Log analysis is vitally important for network reliability, and many log-based tasks are derived to analysis logs, such as anomaly detection, failure prediction, log compression, and log summarization. It is desired to have a unified log analysis framework to simultaneously run all these log analysis tasks on one model to achieve deployment convenience, superior task performance, and low maintenance cost. However, due to severe challenges about log data heterogeneity across devices, pioneer works design specialized algorithms for each task. In this work, we formulate the log analysis as a multi-task learning approach and propose to train a single model that can perform various log analysis tasks. We name this unified log analysis approach as *UniLog*. To effectively build an UniLog model, we propose a log data pretrained transformer to utilize the enormous unlabeled log data, and a corresponding multi-log-tasking finetune strategy for various log analysis tasks. Extensive experiments across seven datasets on four log analysis tasks demonstrate that UniLog achieves remarkable performance.

Index Terms—Log Analysis, Pretrained Model, Transformer

I. INTRODUCTION

Large-scale network services have been increasingly integrated into our daily lives. Most of them are expected to be available on a 24×7 basis, and any accidental downtime can lead to irreparable performance and significant revenue loss. For instance, a downtime in Amazon in 2017 led to a loss of around 150 million US dollars [1] [2]. Therefore, network service reliability becomes increasingly important. These network services continuously generate large amounts of logs (see Fig. 1 for examples), which describe a vast range of events and record run-time information. The huge volume of logs makes it impractical to manually inspect logs for key diagnostic information, even with “search” or “grep” toolkit. Thus there are fast-growing demands to design automatic log analysis frameworks.

Many automatic log analysis approaches have been proposed with the success of machine learning and deep learning, as shown in Fig. 2. Existing log analysis approaches can be classified into four tasks [1] (see Fig. 1), *i.e.*, anomaly detection aiming to proactively detecting anomalous service behaviors [3], failure prediction which predicts service failure according to omen patterns [4], log compression trying to save

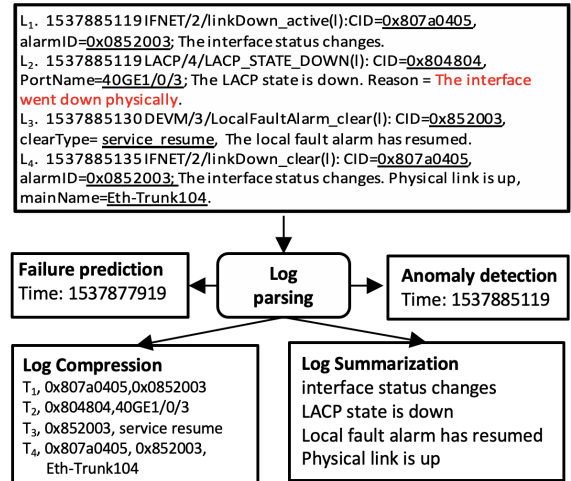


Fig. 1: Examples of log analysis tasks. Log parsing is a pre-processing step for automated log analysis.

the storage space of massive logs [5], and log summarization summarizing a series of logs [6].

Despite the tremendous success of the existing log analysis methods, these algorithms only specialize in one type of log analysis task. Nevertheless, real-life deployment constantly desired to do multiple log analysis tasks simultaneously. Imagine a scenario: the maintenance system localizes anomalous logs, and it warns the operators about a potential system failure that might happen very soon. Meanwhile, the system summarizes the unreadable logs into few words to let the operators examine the summarized logs and compress these vast amounts of real-time logs into lossless log data for future usage. More importantly, all these functionalities are performed via a single model, which is easy to debug and upgrade.

Such a model is appealing yet hard to accomplish due to the following challenges. First of all, log data are heterogeneous across domains (*i.e.*, datasets, devices, time.) because different datasets and devices are always filled with different rules to generate logs. Moreover, the style of generated logs from the network system can change from time to time (*i.e.*, due to system upgrade), makes even more challenging to design a

good model for log analysis tasks across domains. Secondly, there are many types of log analysis tasks; these tasks are not complemented from the perspective of algorithm design. For example, anomaly detection needs to reconstruct the origin piece of the log. In contrast, failure prediction needs to predict a specific time where failures might happen. Therefore, current methods design task-specific models for each log analysis task. Unifying these tasks into a single model is non-trivial.

In this paper, we present a novel approach, named as UniLog, which unified various log analysis tasks under a single framework, enables us to deploy a single model, and specialize it for all log analysis tasks. The UniLog has the following merits. First of all, it can generalize to log data from different or even unseen domains. This is achieved by leveraging the Transformer [7], a deep neural architecture that has been rapidly developed in recent years on natural language processing (NLP) [8], computer vision [9], and graph data [10]. We developed a large-scale unlabeled log data pretrain framework to mix up the log data from different domains and use these data to pretrain the Transformer neural networks. Such well designed pretrained Transformer can perform log analysis across different devices and different time periods effectively and consistently. Secondly, the UniLog is a framework to deploy one model and specialize it for all log analysis tasks. It unifies different log analysis tasks into a single framework. The UniLog would relieve the operators from debugging and upgrading the model to the log analysis tasks themselves. Last but not least, switching the UniLog model from one task to another does not involve prior knowledge from the professionals, enabling smooth and automatic workflow for maintaining the network log analysis system.

Extensive experiments are conducted to verify our proposed UniLog model. We evaluate our method on four log analysis tasks, including log anomaly detection, log failure prediction, log summarization, and log data compression. Our model performs competitively or outperforms state-of-the-art methods on seven public log datasets across these four log analysis datasets. For instance, we outperform PreFix [4] by an average of 5.46% F1 score on failure prediction tasks on Switch log dataset [4]. On log anomaly detection, we achieve better F1 scores on both HDFS and BGL datasets than state-of-the-arts. Furthermore, our experiments have shown that the UniLog can generalize on unseen log data, which overcome log data domain adaption and concept drift problem. We believe that UniLog offers an interesting and practical new perspective on designing the model for log analysis tasks.

II. RELATED WORK

A. Transformer

The Transformer is a type of deep neural network, which have been rapidly developed since Vaswani *et al.* [7] and gradually dominate multiple field and tasks, including natural language process (NLP) [8], computer vision [9], [11], [12] and graph [10]. BERT is the first pretrained model to pre-train the Bi-Directional Transformer on large-scale unlabeled WikiText2 [8] and achieved ground-breaking performance on

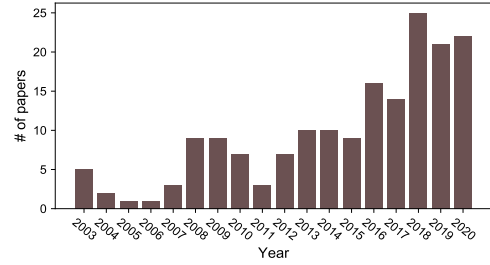


Fig. 2: The number of log analysis papers published since 2003. We observed that (1) automated log analysis has been continuously and actively investigated in the past two decades, and (2) the number of publications witnesses a sharp rise since 2016.

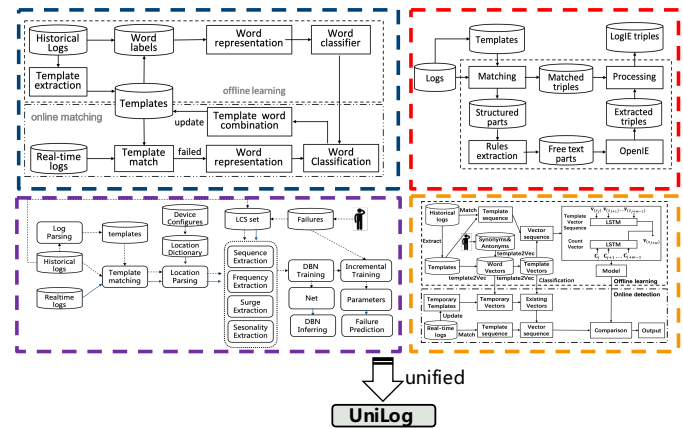


Fig. 3: An example of existing log analysis frameworks. The top left is a log compression framework. The top right is a log summarization framework. The bottom left is a log failure prediction framework. The bottom right are some log anomaly detection algorithms. These methods are designed specifically for a log analysis task. Our approach unified these log analysis tasks into a single model.

multiple NLP tasks. Liu *et al.* [13] present to add task-specific classification networks or different losses for each task. The T5 [14] is another multi-tasking transformer. They convert the NLP tasks to a text-to-text format, which enables to pretrain of the model. Their paradigm presents a new pretrained dataset called C4 and achieves state-of-the-art results in multiple NLP benchmarks. The Transformer has soon been expanded to a huge model that contains billions of parameters [15] and pretrained on enormous unlabeled data [16]. Some prior works adopt Transformer or BERT for log anomaly detection. For example, the LogBERT [17] use Transformer as a log feature extractor. Unlike previous works that only adopt the Transformer as a feature extractor and perform anomaly detection on log data, whereas, we train a single versatile Transformer model that is pretrained on log data and can do multiple log analysis tasks.

B. Log Analysis

This section briefly reviews prior works on four log analysis tasks, i.e., failure prediction, log anomaly detection, log compression, and log summarization.

Log Failure prediction. Network reliability is vital for IT service corporations, and any system failure could cause a significant loss. If the occurrence of system failure can be predicted in advance, then the engineers can take some proactive actions to prevent system collapse and avoid economic loss. The log failure prediction is a supervised binary classification task. Given a log sequence, we need to build a classifier to predict whether the system will corrupt. Existing approaches utilize machine learning algorithms such as XGBoost [4] to predict system failure.

Log Anomaly Detection. Detecting anomalies in logs is crucial for timely identifying malfunctions of system. Log anomaly detection has been the most active research field for log analysis. The log anomaly detection task is an unsupervised binary task, where each log need to be labeled as normal or abnormal. A conventional way to detect anomalous logs is to use reconstruction method, where log are first encoder into the feature embedding space through a mapping function, and then gradually recover the logs back from the embedding space. By measure the distance with a designed distance metric (i.e., l2 distance) between test data point and normal log feature embedding, we are able to detect the logs that cause system failure. If the calculated distance is larger than a predefined threshold, we will consider it as a anomaly sample. Existing works either use hand-crafted method, recurrent neural network or transformer [3], [17], [18] to extract log feature embedding. Note that failure prediction is a fundamentally different tasks than log anomaly detection. The anomaly detection aim to locate the anomalous sample in the existing data, whereas failure prediction need to predict the potential anomalous time period that can have anomalous samples in the future.

Log Compression. Logs often need to be stored for a long time in practice (i.e., a year) to analyze anomalous problems or root causes. However, storing logs consumes a large amount of storage space and computing resources, which incurs high operational costs. Log compression aims to compress massive log data lossless with the minimum amount of storage. The query time also matters since unzip all logs for a long period, and locating the target log is time-consuming. The compression rate is usually to measure how well an algorithm can compress a certain amount of data to minimize storage space. Log data can be compressed by popular data compression techniques, such as bzip [19], 7zip [20], or zip [21]. Logparse [22] is explicitly designed to do log data compression, which has achieved a notable compression rate. This paper integrates the log compression functionality into our framework, improving the compression

rate for log data.

Log Summarization. Logs record detailed run-time information of services. After a failure is detected, diagnosed, or predicted, operators still have to inspect the raw logs to gain a summarized view before taking action. However, manual or rule-based log summarization has become inefficient and ineffective. Log summarization aims to obtain the summarized information of necessary logs for a given log stream. The output is a human-readable sentence. The log summary task is similar to log compression. Nevertheless, the output of the log compression task is not necessary to be readable, as long as its information is lossless. In our case, it is necessary to keep the semantics presented in the logs for the output summary to be readable. Meng *et al.* [6] present a log summarization dataset and designed a log summary framework by using the rule-based algorithm to produce a triplet for each log data. We extend their work to the deep learning approach, which is more general and practical for cross-service log data.

III. DESIGN OF UNILog

In this section, we first introduce two critical components in our UniLog framework: log data pretrained Transformer and multi log analysis tasks finetune strategy. We then discuss some modifications we made in the Transformer neural network architectures.

A. Log Data Pretrained Transformer

Pretrained model is prevalent and it dominates many fields in recent years, for example, BERT [8] in NLP and ImageNet-pretrained backbone in computer vision [23]. When training a neural network that can handle various log analysis tasks, there are two significant challenges. First, log analysis tasks vary, and the desired feature representation of log data is also different for each sub task. Secondly, the log data are heterogeneous across different network devices and different periods. The pretrained Transformer can easily solve these two challenges via 1) the pretrained Transformer can extract *common* log data feature representation from extensive unlabeled data, and these feature representations can be a good initialization point to further finetune to a task-specific feature representation by learning task-specific training objective. 2) the Transformer architecture has been proven that can be effectively scaled up and beneficial when the scale of data increases [9], even when the data are noisy. For the log data, though the meaningful semantic in the log data are scarce, our empirical study demonstrates that it is effective to train the Transformer neural network on large-scale log data.

The pretrain steps are simple. Similar to the natural language, the order feature in the log sequence is important. For example, a system log cannot print “change state to down” before the message of “change state to up”, unless there are anomalous events. Because the pretrain stage do not involved in labels, we choose a self-supervised training objective as the first step to train a unsupervised transformer on log data, which enable the model to understand the importance of log order. A

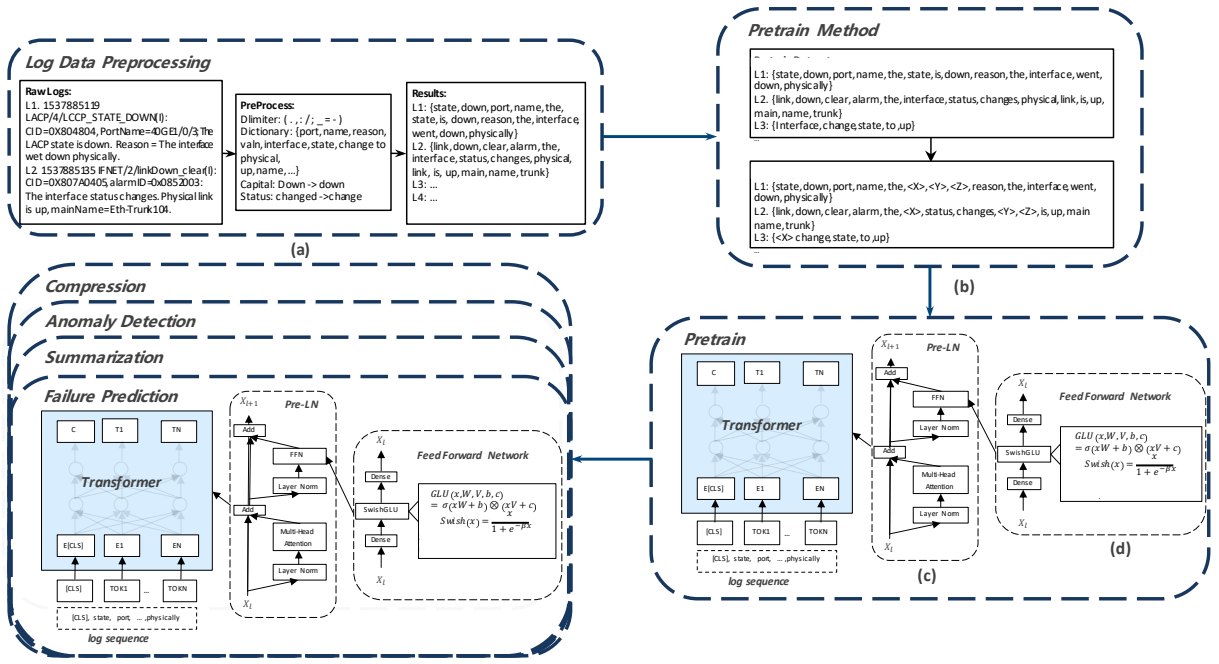


Fig. 4: The overview of UniLog. The (a) is the log preprocessing step to prepare the pretrained data. The (b) represents the pretrain method we used in UniLog. The (c) and (d) shows the modification we made in the Transformer neural network architecture.

common choice of the training objective is to use BERT-style objective, which randomly sample 15% of tokens in the input log sequence and then drop them. These dropped token are replaced by a sentinel token and assigned a special token ID to it. The token ID is a special token added to the vocabulary and does not correspond to any wordpiece. The unsupervised training objective thus can be formulated as predicting the dropped out tokens. The output should be the original log sequence.

The natural language is normally considered as structural text: the contexts between consecutive sentences are meaningful. Whereas the log data are unstructured, typically there is no correlation between consecutive log sequences. What matters to the log data is the consecutive words and sentences from long range. Therefore, we proposed a novel pretrain objective based on the particular property of log data. Specifically, we mask the tokens in the same as we did in the BERT-style pretext task, except that we only mask the consecutive words. We choose up to three consecutive tokens, where the token with largest random probability is chosen. We then mask subsequent two or three tokens. If the chosen token is the last token in the sequence, then we mask the previous two tokens. The output is also the original log sequence. An example of the pretrain objectives can be found in Table II. Secondly, we increase the number of input token to increase the receptive field of log data. As such, the Transformer is able to train with a large chunk of log sequence, and potential learn the long range dependency between two log sequences.

Log Data Preprocessing. The log preprocessing step is briefly shown in Figure 4(a). We define the word in a log is a token. Tokenization is a crucial step to build a successful log analysis model. However, the structure of the log sequence is quite different from the sentence in natural language. The top part of Figure 1 shows few examples of log sequence. Basically, the log sequence contains many meaningless separators and words. Therefore we first use a set of special delimiters (.,/:;_=-). These delimiters can primarily separate the log. However, this is insufficient since many words in the logs are not natural language texts, such as “LocalFaultAlarm_clear”. After using the delimiter, we still get “LocalFaultAlarm”. We then use wordninja, a text tokenizer based on English Wikipedia unigram frequencies, to separate meaningful text in a log sequence. In the end, we can get a set of tokens $\{tok_1, tok_2, \dots, tok_n\}$, where each token represents a word. For instance, the word “LocalFaultAlarm_clear” is separated into “Local”, “Fault”, “alarm”, “clear” by the first two steps. Additionally, we need to change the capital word to lower case and set a word with a different status, *i.e.*, change and changed, as the same token.

Input and Output. In order to train a single model on the diverse set of log analysis tasks, we reform the input and output format. We cast all of the tasks we consider into a log-to-log format. Specifically, the model is fed by log sequence and then returns some output logs. This framework provides a consistent training objective to pretrain the UniLog on unlabeled log data and then finetune to fit a specific task.

TABLE I: Description for the datasets.

Datasets	Description	# of logs	# of anomalies/failures	A.D.	Comp.	Summ.	Fail.
HDFS	Hadoop distributed system log	11,175,629	16,838 anomalies	✓	✓	✓	✗
BGL	Blue Gene/L supercomputer log	4,747,963	348,460 anomalies	✓	✓	✓	✗
HPC	High performance cluster log	433,489	-	✗	✓	✓	✗
Proxifier	Proxifier software log	21,329	-	✗	✓	✓	✗
Hadoop	Hadoop MapReduce job	394,308	-	✗	✓	✗	✗
ZooKeeper	ZooKeeper service	74,380	-	✗	✓	✗	✗
Switch	Switch hardware failures	29,174,680	2,204 failures	✗	✗	✗	✓

In this way, the UniLog will focus on extracting common feature representations in the log data. Then the model can switch to learn task-specific features by finetuning. To specify in which task the model should be finetuned or performed, we add a task-specific prefix to the input log data sequence before feeding it to our model. For example, we add “<anomaly>” before the log sequence if we desire to perform the log anomaly task. The model will then give the output to determine whether a log sequence is normal or anomalous. This holds the same for all tasks, thus allowing the model to handle multiple tasks. The list of a prefix we used is <anomaly>, <summarization>, <compression>, and <failure>, corresponding to log anomaly detection, log summarization, log compression, and failure prediction.

B. Log Analysis Task-Specific Finetune

Task-Specific Finetune Strategy. The pretrained log data-based Transformer provides us the common feature representations that universally exist on log data. In order to run specific log analysis tasks such as anomaly detection, we need to finetune our model based on the task training objective so that the model can learn task-specific feature representations. As the log analysis contains multiple sub-tasks, the pretrained model needs to conduct multi-log-tasking. However, perform multi-tasks on a single network can lead to suboptimal results, especially on low-resource tasks [24] due to the co-adaptation effect. UniLog aims to process a sequence of logs and then return the output for every log analysis task. The previous method [25] gradually unfreeze the parameters in the model to achieve this goal; however, it is sensitive to the size of the training dataset and the total number of training iterations [14]. We relax the multi-task finetune framework and introduce a straightforward checkpoint-based method. Specifically, we first record the checkpoint after the model finishes pretraining. Then we load this checkpoint every time a new task needs to be finetuned. During inference, we load the checkpoint for each finetuned task model and return the outputs. Therefore the engineers can simply deploy UniLog, which is a single, unified model, and perform multiple log analysis tasks at the same time. Since there is only one model for deployment, the maintenance cost can be very cheap, and model upgrading can be done under a single framework. The UniLog improves the system reliability, enables the engineers to free their hands on debugging the deployed model, and focuses on system maintenance itself.

Additionally, we introduce extra task-aware heads to finetune on the sub-tasks. Each task-aware head is attached with two consecutive multilayer perceptrons after the log feature embedding layers. A task-aware head is used to disentangle the feature representations that are learned between different log analysis tasks. For instance, there are four log analysis tasks in our framework; then, we will have four task-aware heads, where each head corresponding to a sub-task and return the task-specific results. We can jointly optimize the task-aware head with our pretrained model during finetuning to achieve better model performance.

For the log failure prediction, we use the softmax operation to return the probability of a network system failure shortly. We use the cross-entropy loss as our training objective. The log anomaly detection use l2 norm loss as the pretrain objectives. This heuristic way is very effective since the pretrain objective loss can represent how hard it is to reconstruct an input log sequence. Similar to the other reconstruction-based anomaly detection method, we set a predefined threshold as 1e-3 and assign the log sequence with validation loss higher than this threshold as the anomalous sample. We use the cross-entropy loss to train the log summarization task to output the summarized log given a sequence of the log. The log compression is more complex than the other tasks, thus we discuss it in a separate section.

Log Compression. Besides the transformer network that extracts the log feature embedding, the log compression requires an entropy coding scheme. We choose the arithmetic coding scheme [26] for simplicity. Specifically, given a log sequence $s = s_0, s_1, \dots, s_w$ of length w number of tokens, we first use the predictor \mathcal{T} to encode this stream of tokens and return the probability $P(s) = P(s_0), P(s_1), \dots, P(s_w)$ for each token, where $P(s) = P(s_w | s_{w-1}, \dots, s_0)$ is a token conditional probability depends on the past tokens. In our context, the transformer we describe above can be considered as a predictor. Then an entropy coding scheme is used to store the token into a lossless code of bit-length $\log_2 P(s_t | s_{t-1}, \dots, s_0)$ based on the token probability given by the predictor. We iteratively compress each token until all tokens are compressed. The decompression stage is similar to the compression stage, except that the entropy coding scheme generates the preceding tokens. Thus the transformer network does not involve in decompression, making the decompression efficient.

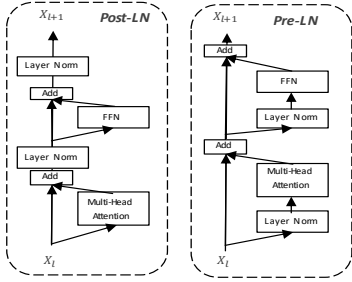


Fig. 5: The left is Post-LN and the right is Pre-LN structure which we used in our paper.

C. Details of the Transformer Architecture

The Transformer Model. After a log sequence is preprocessed into a sequence of log tokens, it is mapped to a sequence of embeddings and then passed into the encoder. The encoder is a stack of transformer blocks, and each block comprises a multi-head self-attention layer [7] followed by a shallow feed-forward network (FFN). We apply layer normalization to the input of each self-attention layer and FFN. We also apply Dropout [27] within the FFN, on the residual path, on the attention weights, and at the input and output of the entire stack. The decoder structure is similar to the encoder, except there is a standard attention layer after each self-attention layer. The self-attention layers in the decoder use a form of causal self-attention. Unlike self-attention in the encoder, which allows the model to attend to past outputs and future outputs, causal self-attention only allows the model to attend to past outputs. The decoder’s outputs are forward to a fully connected layer with softmax, whose weights are shared with the input embedding matrix. We apply relative position embedding and share this position embedding across all layers in our model. More detailed explanations of the Transformer neural network architectures can be found in [8]. In the next section, we introduce two modification on Transformer architecture to improve the model performance for log analysis tasks.

Pre-LN Structure. Layer normalization (LN) [28] is an essential building block of the transformer, and Post-LN architecture is a common choice. However, since we utilize long-range sequences to learn the feature representation of log data, the parameter gradients, which we used to update the model parameters, can be extremely high and cause gradient overflow. Previous study [29] on Pre-LN structure have shown to possess well-behaved properties on gradients at initialization, thus alleviate the large gradient during training. The comparison of Post-LN and Pre-LN structure are shown in Figure 5. In short, Post-LN places the LN on the main path so that the gradient of the parameters near the output layer are large [29]. Whereas the Pre-LN place on the residual path. An empirical study is performed in the Fig. 5.

LogAct. Feed-forward network (FFN) is another fundamental component of the Transformer. It is comprised of few stacks of multilayer perceptron followed by non-linear

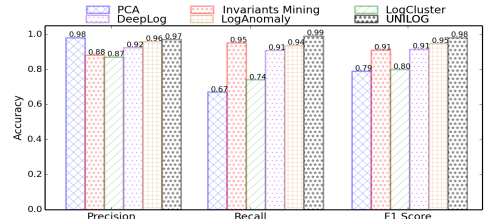


Fig. 6: Anomaly detection results on HDF5 dataset

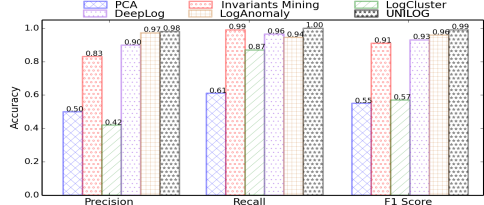


Fig. 7: Anomaly detection results on BGL dataset.

activation. The non-linear activation controls how much expressiveness [30] can a neural network represent. We introduce a novel non-linear activation function, named as *LogAct*, to enhance the expressive power of the Transformer, which is more suitable to deal with long-range, unstructured log data for log analysis tasks.

Inspired by [31] and [32], our *LogAct* combines the GLU activation function [31] and Swish activation function [32]. Specifically, the GLU unit can be formulated as:

$$GLU(x, W, V, b, c) = \sigma(xW + b) \otimes (xV + c) \quad (1)$$

where x is the input, W and V are weight matrix, b and c are bias. The Swish activation function can be formulated as:

$$Swish(x) = \frac{x}{1 + e^{-\beta x}} \quad (2)$$

where the β is a learnable parameters. In our paper, we combine the Swish function and GLU function as:

$$LogAct(x, W, V, b, c) = \frac{(xW + b)}{1 + e^{-\beta(xW+b)}} \otimes (xV + c) \quad (3)$$

In our experiment, we replace very ReLU layer in the FFN with *LogAct*. We conduct an ablation study on the effectiveness of *LogAct* in Table VII.

IV. EXPERIMENTS

In this section, we evaluate our methods on four log analysis tasks: log anomaly detection, log summarization, log compression, and log failure prediction. We briefly summarized the datasets in Table I. Note that for some tasks, the dataset may not have labels for evaluation; thus, we omit those experiments (denotes as cross-mark in the table). The details baseline and results will be introduced in the following sections for each task, respectively. Through our experiment section, we sometime use abbreviation for simplicity, i.e., "A.D." to denote anomaly detection, "Comp." to represent log compression, and "Summ." for log summarization.

TABLE II: Examples of different pretrained method. The BERT-style objective includes a corruption term, where some token are replace by a random token, in our example, the word link in the original text is replace by word *status*. The original text denote that the model predicts the original input based on the reconstruction objective.

Method	Input	Target
Prefix Language Modeling BERT-style [8]	The interface status changes The <M>status <M>Physical <i>status</i> is up	Physical link is up original text
UniLog	The <M><M><M>Physical status is up	original text

TABLE III: Comparison of model performance for failure prediction task.

Switch	Method	Precision	Recall	F1
M1	HSMM	32.27%	95.3%	48.21%
	SKSVM	8.25%	76.09%	14.89%
	PreFix	87.35%	74.36%	80.33%
	UniLog	84.25%	79.60%	81.86%
M2	HSMM	0.28%	60.58%	0.56%
	SKSVM	4.47%	8.72%	5.91%
	PreFix	59.79%	58.59%	59.19%
	UniLog	65.73%	63.24%	64.46%
M3	HSMM	26.32%	11.11%	15.63%
	SKSVM	0.79%	91.91%	1.58%
	PreFix	84.00%	52.50%	64.61%
	UniLog	87.90%	64.58%	74.46%

A. Setup

Implementation Details We follow the model design in Section 4. Specifically, we use 3 blocks for both in encoder and decoder. Each block consists of a multi-head self-attention layer, optional encoder-decoder attention layer, and a feed-forward network. We use 4 heads for self-attention, 32 inner dimensions for metrics in the attention layer, a hidden size of 128 for transformer blocks, and an output dimension of 512 for FFN. We apply Dropout with 0.3 probability in the model for regularization. Unlike This result modern network designed for NLP tasks, our model’s size is four numbers of magnitude smaller since the scale of the public dataset for log analysis is much smaller than those for NLP tasks. This enables us to achieve good performance for log analysis tasks without the overwhelming number of parameters.

All experiments are done on NVIDIA V100 GPUs 32 GB memory with Python 3.5 and Pytorch 1.3. We use NVIDIA Apex framework for distributed training. We use a batch size of 128, and trained with AdamW [33]. We use 180 as the maximum length of log sequence and pretrained with $2^{16} = 65,536$ step. We set the initial learning rate as $5e-4$ without learning rate warm-up stage and use exponential learning rate decays. We fine-tuned all tasks for $2^{11} = 2048$ steps to prevent over-fitting.

Datasets. We use the BGL [34], HDFS [35], HPC [36], ZooKeeper [37], Proxifier [38], Hadoop [39] and Switch [4] to conduct our experiments. We use the dataset split strategy from the prior works for fair comparison. For anomaly detection, failure prediction, summarization and compression we follows the LogAnomaly [3], PreFix [4], LogSummary [6],

TABLE IV: Comparison of model performance for log compression task.

Method	HPC	HDFS	Zoo	Hadoop	Avg.
bzip	5.7%	9.3%	3.0%	5.6%	6.1%
7zip	7.0%	8.5%	3.1%	5.0%	5.9%
zip	8.6%	11.4%	4.8%	8.0%	8.2%
LogParse	23.4%	14.1%	10.9%	42.4%	22.7%
LogParse + bzip	3.4%	3.2%	2.4%	3.6%	3.2%
LogParse + zip	4.4%	7.8%	2.8%	5.0%	5.0%
LogParse + 7zip	3.7%	6.3%	2.8%	3.4%	4.1%
UniLog	2.7%	2.9%	2.8%	3.3%	2.9%

and LogParse [5], respectively. For the pretrained dataset, We utilize all log datasets mentioned above to pretrain UniLog, except test data which we used for evaluation.

Evaluation Metrics. For anomaly detection, summarization, and failure prediction, A method’s capability is usually assessed by four metrics that have intuitive interpretation, *i.e.*, precision, recall, and F1 score, and thus we use these metrics to evaluate each method. For log compression, we use compression rate $C = \frac{\text{size of compressed logs}}{\text{size of original logs}}$, which indicates the model’s ability to store the same amount of logs with the number of storage space.

B. Results.

Log Anomaly Detection. Log anomaly detection is the most widely studied topic in the log analysis domain. In this section, we conduct experiments on two log anomaly detection benchmark: HDFS and BGL to demonstrate the effectiveness of our proposed framework. We compare UniLog to the following methods with 1) PCA [35], PCA-based anomaly detection method vectorize each log sequence as an event count vector and employed to find patterns between the dimensions of event count vectors. 2) Invariant Mining [40] which was the first applied to log- based anomaly detection in [40] based on the assumption that program invariants are the linear relationships that always hold during system running. 3) LogCluster [39] that determine the state of a new log sequence by computing its distance to representative vectors in knowledge base and report the log sequence as normal or abnormal based on representation vector distance. 4) DeepLog [39] is the first deep learning approach on log anomaly detection. 5) LogAnomaly [3], the state-of-the-art method on log anomaly detection, combines sequential patterns and quantitative patterns.

TABLE V: Comparison of model performance for log summarization task.

Logs	Method	Precision	Recall	F1
BGL	TextRank	0.893	0.238	0.347
	LogSummary	0.815	0.703	0.788
	UniLog	0.895	0.824	0.858
HDFS	TextRank	0.893	0.238	0.347
	LogSummary	0.759	0.432	0.538
	UniLog	0.876	0.650	0.746
HPC	TextRank	0.904	0.265	0.365
	LogSummary	0.819	0.911	0.840
	UniLog	0.835	0.911	0.871
Proxifier	TextRank	0.663	0.050	0.093
	LogSummary	0.879	0.857	0.864
	UniLog	0.925	0.877	0.900

TABLE VI: Comparison of compression rate for Log data compression task with Post-LN versus Pre-LN structure.

Task	Dataset	Method	Precision	Recall	F1
A.D.	BGL	Post-LN	0.95	0.94	0.94
		Pre-LN	0.98	1.00	0.99
Summ.	BGL	Post-LN	0.850	0.832	0.841
		Pre-LN	0.895	0.824	0.858

In Fig. 6 and Fig. 7 shows the experimental results for log anomaly detection on HDFS and BGL dataset. Our proposed UniLog achieves the best performance on both datasets. Specifically, on the HDFS dataset, UniLog achieved precision of 0.97, recall of 0.99, and f1 score of 0.98. The f1 score is 0.3% higher than LogAnomaly. On the BGL dataset, our method achieve precision of 0.98, recall of 1.00 and f1 score of 0.99. It further improve the f1 score 0.3% over LogAnomaly. This improvement is non-trivial, since reliability on the system is vital and an f1 score improve over 0.1% might save millions of dollars.

Log Summarization. After demonstrating the superiority of our method on log anomaly detection, we evaluate it for log summarization that requires refining the semantic information in the log sequence. We demonstrate the experimental results for log data summarization. We choose TextRank [41], a classic keyword extraction algorithm, and LogSummary [6] the state-of-the-art method design specifically to summarize log data. Table V reports the experimental results; it shows that the UniLog can significantly improve our log summarization performance: UniLog is improving the F1 score by 0.070 on BGL data, 0.031 on HPC data, and 0.036 on Proxifier over LogSummary. On hard task HDFS, the F1 score of UniLog is 0.208 higher than LogSummary, demonstrate that UniLog is more effective than the classic model and LogSummary in a real-world situation.

Log Failure Prediction. We now show UniLog can improve the performance on failure prediction tasks. As shown in Table III, we perform experiment on Switch log

TABLE VII: Comparison of model performance for Log data compression task with different activation layer.

Task	Dataset	Method	Precision	Recall	F1
A.D.	BGL	ReLU	0.97	0.99	0.98
		LogAct	0.98	1.00	0.99
Summ.	BGL	ReLU	0.866	0.815	0.840
		LogAct	0.895	0.824	0.858

datasets to compare UniLog against a) SKSVM [42], a log-based failure prediction system used in computer b) HSMM [43], a log-based failure prediction in ISP devices, and c) Prefix [4], the state-of-the-art log failure prediction algorithm for switch failure prediction. We can observe that, though both SKSVM and HSMM are failure prediction algorithms, their performance is relatively low. This is due to that these two methods are designed specifically for computer and ISP service. As a result, they fail to generalize on Switch log dataset. On the contrary, our UniLog achieves better performance on all three switches, despite the fact that UniLog is not being designed for switch failure prediction tasks. Particularly, on the M2 and M3 switch, the UniLog strongly outperforms these approaches notably, obtains a +5.27% and +9.85% F1 score improvement. This provides another indication that UniLog is able to capture generalizable knowledge in the cross-service log data.

Log Compression. We also conduct experiments on log compression. We compare our method to three popular data compression techniques that are widely used in the computer system, bzip [19], 7zip [20], zip [21]. We also compare to LogParse [22], a log parsing method that can adaptively classify log based on the word. The LogParse can effectively combine with existing data compression techniques to compress log data. We therefore compare our method to LogParse, which is followed by bzip, 7zip, and zip algorithm. The experimental results are shown in Table IV. Our method consistently improves the compression ratio over all baseline methods. Specifically, UniLog increase 2.1% on average compression rate on four datasets compare to the previous state-of-the-art, which results in an excellent storage reduction. Besides, as the number of samples in the target dataset increase, UniLog achieve more improvement on the performance. For instance, on the largest dataset HDFS, where the number of logs is over two orders of magnitudes larger than HPC and Hadoop, the UniLog improves the compression rate relatively up to 3.4%.

C. Ablation Study

Pretrain Objectives. We conduct experiments to validate the effectiveness of denoising objectives in our method. We compare with 1) Prefix Language Modeling, where log sequences are feed into the network and ask to return the next log sequence, 2) the BERT-style objective, where consecutive tokens are masked. In Table IX, we present the experimental results on BGL anomaly detection task and

TABLE VIII: Comparison of model performance for Log data compression task with different pretrain objectives.

Task	Dataset	Method	Precision	Recall	F1
A.D.	BGL	Prefix Language Model	0.65	0.68	0.66
		BERT-style	0.95	0.94	0.94
		UniLog	0.98	1.00	0.99
Summ.	HDFS	Prefix Language Model	0.325	0.739	0.451
		BERT-style	0.770	0.521	0.621
		UniLog	0.876	0.650	0.746

TABLE IX: Comparison of model performance for Log data compression task with different pretrain objectives.

Task	Dataset	Method	Precision	Recall	F1
A.D.	BGL	Prefix Language Model	0.65	0.68	0.66
		BERT-style	0.95	0.94	0.94
		UniLog	0.98	1.00	0.99
Summ.	HDFS	Prefix Language Model	0.325	0.739	0.451
		BERT-style	0.770	0.521	0.621
		UniLog	0.876	0.650	0.746

HDFS summarization task. The prefix language modeling is only obtained an F1 score of 0.66, which is not suitable for the log analysis task. On both tasks, the UniLog with our proposed pretrain objective achieve significantly better results than both prefix language modeling and BERT-style objective. On log summarization, which is a semantic essential task, our pretrain objective outperform BERT-style objective by 0.125 on F1 score, shows that our method is more suitable to extract representation in the unstructured log data.

Pre-LN. We evaluate the importance of Pre-LN architecture in Table VI. The experiments are conducted on BGL dataset with log anomaly detection and log summarization. We can observe that the experimental results on both tasks are improved. On the log summarization tasks, the F1 score of the model using LogAct is 0.018% higher than the model using ReLU. The improvement on precision is significant, which is over 0.031%.

LogAct. We verify the effectiveness of our proposed LogAct layer. We evaluate the model performance on the BGL dataset on log anomaly detection and log summarization tasks, and the result is shown in Table VII. The precision, recall, and F1 score on Summarization of LogAct is lifted by, respectively. On the other hand, the On log anomaly detection, the LogAct increases on all evaluation metrics by 1%. Because the performance on BGL dataset is already high, thus these improvement is non-trivial. The results indicate the complex feature representation that unstructured text may have and, therefore, can benefit from more non-linearity.

Does Transformer Really Benefit from More Unstructured Log Data? The log data is considered to be data-intensive yet lacks useful information. Hence we study that if massive log data can really achieve better performance than small-scale

TABLE X: Comparison of model performance on log anomaly detection, log compression, and log summarization on HDFS data.

Pretrain Dataset	Task	Precision	Recall	F1	Comp. Rate
HDFS	A.D.	0.94	0.96	0.95	-
	Comp.	-	-	-	3.5%
	Summ.	0.807	0.545	0.651	-
+ BGL	A.D.	0.90	0.93	0.91	-
	Comp.	-	-	-	5.6%
	Summ.	0.652	0.380	0.480	-
+ (Proxifier + ZooKeeper + Hadoop + HPC)	A.D.	0.94	0.94	0.94	-
	Comp.	-	-	-	5.6%
	Summ.	0.812	0.597	0.688	-
+ Switch	A.D.	0.97	0.99	0.98	-
	Comp.	-	-	-	2.9%
	Summ.	0.876	0.650	0.746	-

TABLE XI: Comparison of model performance for transfer learning to Hadoop.

Method	Precision	Recall	F1
LogTransfer	0.980	0.970	0.977
UniLog	1.000	0.986	0.993

log data. We evaluate our assumption by progressively adding more datasets into our pretrain model and then finetune on the task model. We linearly reduce the total training iterations based on the number of log data in the total pretrain dataset. The rest of the training strategy is kept the same. We evaluate on HDFS to validate our assumption. We provide the results on three tasks, log anomaly detection, log compression, and log summarization. The Table X shows the experimental results. We can observe that when the HDFS is the only pretrain dataset, the result on sub-tasks is relatively higher than using HDFS + BGL + Proxifier + ZooKeeper. This is intuitive since directly pretrain on the target data can certainly improve the performance on finetuning. This phenomenon is utilized in the self-training [44]. When the number of pretrain data is not large enough, the model’s eventual performance on target data may be bias towards other datasets. However, the performance is improved and eventually surpasses the performance on sole pretrained on HDFS. Especially when we add the Switch dataset, the F1 score on anomaly detection increases from 0.95 to 0.98, the compression rate increases from 3.5% to 2.9%, and the F1 score on summarization is achieved 0.651 compared to 0.746. This supports our assumption that the UniLog can indeed improve by training on more log data, though the information entropy provided by the log data is small.

Does UniLog generalize on unseen dataset? As we have previously stated that, UniLog can learn common features from massive log data via pretrain. In the real world, the algorithm running on the server can often feed with unseen data, which results in poor performance due to the *data domain shift*. Though our method does not target to solve domain adaptation problems, we evaluate the ability

of UniLog to generalize on unseen data. We pretrain our model on our pretrain dataset without the Hadoop dataset. Then, we evaluate our method on the Hadoop dataset by finding anomalous samples in the Hadoop. We compare our method with LogTransfer [45], a log-based domain adaptation method. The LogTransfer is trained on the HDFS dataset and then evaluate on the Hadoop dataset. Table XI shows that, with the pretrain-finetune paradigm, the transfer learning ability of UniLog is better than LogTransfer, outperforms the state-of-the-art method by 0.16 on the F1 score.

V. CONCLUSION

This work aim to build a unified framework for log analysis tasks. We propose *UniLog*, which enable the engineers to deploy one model that are specialized for all log analysis tasks. Our experiments have shown that UniLog perform competitively with, or outperform, SOTA methods on various log datasets across four log analysis tasks.

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