Log Parsing: How Far Can ChatGPT Go?

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Abstract-Software logs play an essential role in ensuring the reliability and maintainability of large-scale software systems, as they are often the sole source of runtime information. Log parsing, which converts raw log messages into structured data, is an important initial step towards downstream log analytics. In recent studies, ChatGPT, the current cutting-edge large language model (LLM), has been widely applied to a wide range of software engineering tasks. However, its performance in automated log parsing remains unclear. In this paper, we evaluate ChatGPT's ability to undertake log parsing by addressing two research questions. (1) Can ChatGPT effectively parse logs? (2) How does ChatGPT perform with different prompting methods? Our results show that ChatGPT can achieve promising results for log parsing with appropriate prompts, especially with few-shot prompting. Based on our findings, we outline several challenges and opportunities for ChatGPT-based log parsing.

Index Terms—Log analytics, Log parsing, Large language model, ChatGPT

I. INTRODUCTION

Large-scale software-intensive systems, such as cloud computing and big data systems, generate a large amount of logs for troubleshooting purposes. Log messages are produced during software runtime by the logging statements in source code. They record system events and dynamic runtime information, which can help developers and operators understand system behavior and perform system diagnostic tasks, such as anomaly detection [1]–[4], failure prediction [5], [6], and failure diagnosis [7], [8].

Log parsing is an important initial step of many downstream log-based system diagnostic tasks. Through log parsing, free-text raw log messages are converted into a stream of structured events [9]–[12]. To achieve better log parsing accuracy, many data-driven approaches, such as those based on clustering [13], [14], frequent pattern mining [15], [16], and heuristics [9], [10], [17], have been proposed to automatically distinguish the constant and variable parts of log messages [11], [12], [18]. Recent studies adopt pre-trained language models for representing [4], [18], [19] log data. However, these methods still require either training models from scratch [20] or tuning a pre-trained language model with labelled data [4], [18], which could be impractical due to the scarcity of computing resources and labelled data.

More recently, large language models (LLMs) such as ChatGPT [21] has been applied to a variety of software engineering tasks and achieved satisfactory performance [22], [23]. However, it is unclear whether or not ChatGPT can

effectively perform automated log parsing. More research is needed to determine its capabilities in this important area. Therefore, in this paper, we conduct a preliminary evaluation of ChatGPT for log parsing.

More specifically, we design appropriate prompts to guide ChatGPT to understand the log parsing task and extract the log event/template from the input log messages. We then compare the performance of ChatGPT with that of SOTA (state-of-the-art) log parsers in zero-shot scenario. We also examine the performance of ChatGPT with a few log parsing demonstrations (few-shot scenarios). Finally, we analyze the performance of ChatGPT to explore its potential in log parsing. Our experimental results show that ChatGPT can achieve promising results for log parsing with appropriate prompts, especially with few-shot prompting. We also outline several challenges and opportunities for ChatGPT-based log parsing.

In summary, the major contributions of this work are as follows:

- To the best of our knowledge, we are the first to investigate and analyze ChatGPT's ability to undertake log parsing.
- We evaluate ChatGPT-based log parsing on widely-used log datasets and compare it with SOTA log parsers.
- Based on the findings, we outline several challenges and prospects for ChatGPT-based log parsing.

II. BACKGROUND

A. Log Data

Large and complex software-intensive systems often produce a large amount of log data for troubleshooting purposes during system operation. Log data records the system's events and internal states during runtime. Figure 1 shows a snippet of log data generated by Spark.

A log message usually contains a header that is automatically produced by the logging framework, including information such as component and verbosity level. The log message body (log message for short) typically consists of two parts: 1) Template - constant strings (or keywords) describing the system events; 2) Parameters/Variables - dynamic variables, which reflect specific runtime status. Figure 1 shows an example of logs produced by Spark, where the header (including Datetime, Component, and Level) is generated by the logging framework and is generally easy to extract. The log event/template "Putting block <*> with replication took <*>" associated with parameters (e.g., "rdd_0_1", "0"), in contrast, is often difficult to identify.

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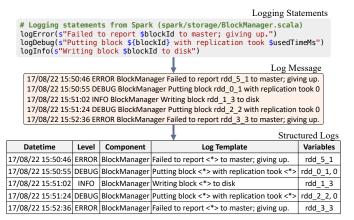


Fig. 1: An example of log data and log parsing from Spark

B. Log Parsing

Log parsing typically serves as the first step toward automated log analytics. It aims at parsing each log message into a specific log event/template and extracting the corresponding parameters. To achieve better performance compared to traditional regular expression-based log parsers, many data-driven approaches have been proposed to automatically distinguish template and parameter parts. These data-driven approaches can be categorized into several groups. 1) Similarity-based clustering: LKE [24], LogSig [13], and LenMa [14] compute distances between two log messages or their signature to cluster them based on similarity. 2) Frequent pattern mining: SLCT [25], LFA [16], and Logram [15] leverage frequent patterns of token position or n-gram information to extract log templates that appear constantly across log messages. 3) Heuristics-based searching: Drain [10], Spell [9], Swiss-Log [17], and SPINE [26] utilize a tree structure to parse logs into multiple templates. 4) Deep learning based parsing: UniParser [20] formulates log parsing as a token classification problem and LogPPT [18] leverages language models to perform log parsing in few-shot scenarios.

Structured log data, obtained after log parsing, can be used for many downstream log analytics tasks, such as anomaly detection [2], [3], [27], failure prediction [5], [28], and failure diagnosis [7], [8].

III. STUDY DESIGN

A. Research Questions

We aim at answering the following research questions through experimental evaluation:

- **RQ1.** Can ChatGPT effectively perform log parsing?
- **RQ2.** How does ChatGPT perform with different prompting methods?

RQ1 is to evaluate the effectiveness of ChatGPT in log parsing. To answer RQ1, we provide a basic definition of log parsing (i.e., abstracting the dynamic variables in logs [29]) and ask ChatGPT to extract the log template for one log message per request by using the following prompt template (where the slot '[LOG]' indicates the input log message):

Prompt Template (PT1)

You will be provided with a log message delimited by backticks. You must abstract variables with '{placeholders}' to extract the corresponding template. Print the input log's template delimited by backticks.

Log message: '[LOG]'

RQ2 aims at investigating the impact of prompting methods on ChatGPT-based log parsing. Specifically, we evaluate the performance of ChatGPT under two experimental settings:

1) **Few-shot scenarios:** Since log data is heterogeneous, we follow a recent study [18] to provide a few demonstrations (1, 2, and 4) of log parsing when applying ChatGPT to log data. Specifically, we use the following prompt template to ask ChatGPT to extract the log template of an input log:

Prompt Template (PT2)

You will be provided with a log message delimited by backticks. You must abstract variables with '{placeholders}' to extract the corresponding template.

For example:

The template of '[DEMO_LOG1]' is '[TEMPLATE1]'. The template of '[DEMO_LOG2]' is '[TEMPLATE2]'.

Print the input log's template delimited by backticks.

Log message: '[LOG]'

2) **Different prompts:** We evaluate the impact of different prompts on log parsing with ChatGPT. Specifically, along with PT1, we further evaluate a *simple* (PT3) and an *enhanced* (PT4) prompt as follows:

Prompt Template - Simple (PT3)

You will be provided with a log message delimited by backticks. Please extract the log template from this log message: '[LOG]'

Prompt Template - Enhance (PT4)

You will be provided with a log message delimited by backticks. You must identify and abstract all the dynamic variables in logs with '{placeholders}' and output a static log template. Print the input log's template delimited by backticks.

Log message: '[LOG]'

B. Benchmark and Setting

We conduct experiments on 16 datasets originated from the LogPai benchmark [11], [30]. This benchmark covers log data from various systems, including distributed systems, supercomputers, operating systems, mobile systems, server applications, and standalone software. Since there are multiple errors in the original benchmark, in this paper, we use the corrected version of this benchmark [31] in our evaluation. Each dataset contains 2,000 manually labelled log messages.

We build a pipeline for our experiments using the ChatGPT API based on the gpt-3.5-turbo model released by OpenAI [21]. To avoid bias from model updates, we use a snapshot of gpt-3.5-turbo from March 2023 [32].

TABLE I: Comparison with existing log parsers in zero-shot scenario

	AEL		Spell		Drain		Logram		SPINE			ChatGPT						
	GA	MLA	ED	GA	MLA	ED	GA	MLA	ED	GA	MLA	ED	GA	MLA	ED	GA	MLA	ED
HDFS	0.998	0.625	0.943	1	0.301	1.386	0.998	0.626	0.940	0.930	0.005	19.297	0.866	0.499	7.980	0.960	0.939	0.062
Hadoop	0.869	0.262	14.576	0.778	0.113	23.967	0.948	0.269	15.399	0.451	0.113	26.531	0.950	0.279	16.447	0.795	0.525	11.017
Spark	0.905	0.360	3.197	0.905	0.321	5.465	0.920	0.360	2.629	0.282	0.259	7.532	0.925	0.337	4.816	0.925	0.922	0.596
Zookeeper	0.921	0.496	2.672	0.964	0.452	3.188	0.967	0.497	2.288	0.724	0.474	5.534	0.989	0.502	3.541	0.667	0.233	5.460
BGL	0.957	0.344	5.057	0.787	0.197	7.982	0.963	0.344	4.973	0.587	0.125	10.021	0.923	0.376	5.081	0.878	0.790	5.258
HPC	0.903	0.678	0.959	0.654	0.530	4.630	0.887	0.654	1.534	0.911	0.665	2.278	0.945	0.667	1.980	0.807	0.497	3.498
Thunderb	0.941	0.036	14.731	0.844	0.027	15.684	0.955	0.047	14.632	0.554	0.004	16.208	0.665	0.051	18.331	0.568	0.808	5.933
Windows	0.690	0.153	10.767	0.989	0.004	3.200	0.997	0.462	4.966	0.694	0.141	6.700	0.684	0.151	12.379	0.686	0.301	17.623
Linux	0.405	0.174	15.633	0.152	0.088	16.256	0.422	0.177	15.534	0.186	0.124	17.857	0.545	0.108	11.145	0.910	0.635	3.328
Android	0.773	0.393	9.396	0.863	0.150	12.574	0.831	0.548	6.940	0.742	0.278	17.734	0.938	0.181	14.630	0.711	0.549	10.763
HealthApp	0.568	0.163	19.066	0.639	0.152	8.468	0.780	0.231	18.476	0.267	0.112	15.814	0.983	0.446	5.320	0.898	0.628	6.560
Apache	1	0.694	10.218	1	0.694	10.234	1	0.694	10.218	0.313	0.007	12.315	1	0.276	11.036	1	1	0
Proxifier	0.495	0.495	10.207	0.527	0.478	12.842	0.527	0.504	10.138	0.504	0	27.222	0.049	0.016	14.198	0.001	0.014	27.025
OpenSSH	0.537	0.246	4.976	0.556	0.191	7.331	0.789	0.508	7.543	0.611	0.298	6.220	0.676	0.253	8.018	0.659	0.170	7.854
OpenStack	0.758	0.019	19.559	0.764	0	30.400	0.733	0.019	30.759	0.326	0	64.057	0.384	0.011	48.025	0.449	0.433	7.440
Mac	0.764	0.169	18.902	0.757	0.033	23.390	0.787	0.230	20.365	0.568	0.182	21.517	0.761	0.204	19.334	0.619	0.248	25.530
Average	0.780	0.331	10.053	0.761	0.233	11.687	0.844	0.385	10.458	0.540	0.174	17.302	0.767	0.272	12.641	0.721	0.543	8.621

Note: Thunderb denotes Thunderbird; For Edit Distance (ED), the lower is the better.

C. Baselines

We compare our proposed method with five state-of-theart log parsers, including AEL [33], Spell [9], Drain [10], Logram [15], and SPINE [26]. We choose these five parsers in our evaluation since their source code is publicly available; and a prior study [11], [31] finds that these parsers have high accuracy and efficiency among the evaluated log parsing methods. For SPINE, we use the source code provided by its authors. For other baselines, we adopt the implementation of these methods from their replication packages [12], [34].

D. Evaluation Metrics

Following recent studies [12], [20], [35], we apply three metrics to comprehensively evaluate the effectiveness of log parsing, including:

- Group Accuracy (GA): Group Accuracy [11] is the most commonly used metric for log parsing. The GA metric is defined as the ratio of "correctly parsed" log messages over the total number of log messages, where a log message is considered "correctly parsed" if and only if it is grouped with other log messages consistent with the ground truth.
- Message Level Accuracy (MLA): The Message Level Accuracy [20] metric is defined as the ratio of "correctly parsed" log messages over the total number of log messages, where a log message is considered to be "correctly parsed" if and only if every token of the log message is correctly identified as template or variable.
- Edit Distance (ED): Edit Distance [35] measure the accuracy of log parsers in terms of lexical similarity between parsed results and ground truth, by computing the distance between parsed templates and ground truth templates.

IV. RESULTS

A. The Effectiveness of ChatGPT in Log Parsing

In this RQ, we evaluate the performance of ChatGPT-based log parsing in the zero-shot scenario. We compare the results of ChatGPT with baselines in terms of GA, MLA, and ED. Table I shows the results. For each dataset, the best accuracy is highlighted in boldface. The results show that, in terms of GA, ChatGPT achieves the best accuracy on three out of 16 datasets. On average, it achieves a GA of 0.721, which outperforms the average result of Logram by 33.5%, and is 0.85x of that of the best baseline Drain. Regarding MLA and ED, ChatGPT significantly outperforms the baselines with an improvement of 41.0% to 212.1% in MLA and 14.2% to 50.2% in ED. Specifically, it achieves the best results on 10 out of 16 datasets in terms of MLA and 8 out of 16 datasets in terms of ED. The results indicate that ChatGPT is able to distinguish variable and content tokens in log messages, as reflected by the high MLA values. However, there is much log-specific information (such as domain URLs, API endpoint addresses, block/task IDs, etc), which varies a lot across log data. ChatGPT has difficulties in correctly recognizing these log-specific information, leading to lower GA values. Figure 2 shows some examples of log templates generated by ChatGPT and Drain. We can see that ChatGPT correctly identifies variable values and types in the second log message (i.e., username and uid). However, it cannot recognize the whole address of "video.5054399.com: 80" as one variable in the first log message.

B. The Performance of ChatGPT-based Log Parsing under Different Prompting Methods

1) With few-shot scenarios: We evaluate the performance of ChatGPT in few-shot scenarios using PT2. For the 1-shot

	ChatGPT	Drain						
Log	video.5054399.com:80 o	pen through proxy						
Message	proxy.cse.cuhk.edu.hk:5070 HTTPS							
Parsed	video.{server} open through	<*> open through						
Template	proxy {proxy} HTTPS	proxy <*> HTTPS						
Log	session opened for use	or root by (wid=0)						
Message	session opened for use	er root by (uiu=0)						
Parsed	session opened for user	session opened for						
Template	{user} by (uid={uid})	user root by (uid=0)						

Fig. 2: Examples of log parsing with ChatGPT

scenario, we search for the most frequent log message and use it as the example for ChatGPT. For 2-shot and 4-shot scenarios, we apply a few-shot random sampling algorithm [18] to select 2 and 4 examples for ChatGPT. Table II shows the results. We observe a noticeable improvement of 19.5% and 29.9% in MLA and ED, respectively, with just one example of log parsing. With 4 examples, ChatGPT achieves the best MLA and ED on all 16 datasets and significantly outperforms the other log parsers. It also achieves a comparable GA to the second best log parser, SPINE. The results indicate that ChatGPT is able to learn log parsing from a few demonstrations and achieves good performance. It also shows that ChatGPT exhibits good generality to a variety of log data through few-shot learning.

TABLE II: The results in few-shot scenarios

Dataset		1-shot	t		2-shot	:	4-shot			
Dataset	GA	MLA	ED	GA	MLA	ED	GA	MLA	ED	
HDFS	0.903	0.939	0.063	0.960	0.993	0.007	0.845	0.993	0.105	
Hadoop	0.787	0.588	11.629	0.959	0.600	5.448	0.969	0.623	4.941	
Spark	0.910	0.880	1.186	0.873	0.865	2.080	0.887	0.925	0.622	
Zookeeper	0.842	0.666	1.500	0.779	0.663	1.588	0.842	0.545	2.021	
BGL	0.888	0.919	1.648	0.936	0.934	2.739	0.952	0.935	2.962	
HPC	0.872	0.897	1.029	0.930	0.935	0.675	0.932	0.938	0.461	
Thunderb	0.172	0.492	6.821	0.575	0.827	5.810	0.473	0.791	2.938	
Windows	0.567	0.638	6.853	0.566	0.483	9.120	0.982	0.979	0.727	
Linux	0.620	0.671	2.507	0.753	0.718	2.209	0.742	0.719	2.253	
Android	0.810	0.663	9.726	0.870	0.682	11.932	0.884	0.698	7.384	
HealthApp	0.908	0.657	5.952	0.920	0.742	3.408	0.920	0.747	3.211	
Apache	0.731	0.946	0.486	0.731	0.793	1.863	1	1	0	
Proxifier	0	0.329	6.621	0.024	0.315	11.631	0.050	0.781	2.379	
OpenSSH	0.240	0.374	4.742	0.544	0.209	5.860	0.523	0.512	4.210	
OpenStack	0.152	0.389	8.252	0.343	0.434	5.267	0.513	0.958	0.527	
Mac	0.577	0.342	27.687	0.653	0.503	16.486	0.670	0.500	15.166	
Average	0.623	0.649	6.044	0.713	0.668	5.383	0.761	0.790	3.119	

2) With different prompts: Different prompts could lead to different results when applying LLM. In this RQ, we evaluate the performance of ChatGPT on log parsing using (1) a simple prompt (PT3): we directly ask ChatGPT to return the template of a log message; and (2) an enhanced prompt (PT4): we specifically ask ChatGPT to follow three steps of log parsing: identify variables, abstract variables, and output a static template. Table III shows the results.

We notice that with a simple prompt, ChatGPT can hardly understand the concept of log parsing and thus achieve low accuracy (e.g., 0.493 GA). There are many cases where ChatGPT asks for more information when we use PT3. In

TABLE III: The results with different prompts

Dataset		PT1		PT	3 (Sim	ple)	PT4 (Enhance)			
Dataset	GA	MLA	ED	GA	MLA	ED	GA	MLA	ED	
HDFS	0.960	0.939	0.062	0.413	0.884	0.535	0.920	0.892	1.197	
Hadoop	0.795	0.525	11.017	0.740	0.450	11.556	0.801	0.449	10.709	
Spark	0.925	0.922	0.596	0.623	0.788	0.880	0.700	0.922	0.662	
Zookeeper	0.667	0.233	5.460	0.797	0.233	6.672	0.648	0.273	4.409	
BGL	0.878	0.790	5.258	0.243	0.686	8.512	0.947	0.863	3.329	
HPC	0.807	0.497	3.498	0.592	0.605	5.277	0.920	0.908	0.816	
Thunderb	0.568	0.808	5.933	_	_	_	0.255	0.505	3.395	
Windows	0.686	0.301	17.623	0.148	0.292	20.239	0.403	0.525	8.602	
Linux	0.910	0.635	3.328	0.286	0.657	3.428	0.445	0.594	3.448	
Android	0.711	0.549	10.763	0.754	0.574	12.087	0.922	0.652	7.349	
HealthApp	0.898	0.628	6.560	0.767	0.637	6.498	0.886	0.636	6.425	
Apache	1	1	0	0.984	0.708	4.955	1	1	0	
Proxifier	0.001	0.014	27.025	0	0.001	18.424	0.001	0.016	27.730	
OpenSSH	0.659	0.170	7.854	0.261	0.335	6.609	0.462	0.451	4.837	
OpenStack	0.449	0.433	7.440	0.355	0.315	10.670	0.524	0.433	7.004	
Mac	0.619	0.248	25.530	0.434	0.228	39.599	0.614	0.380	17.919	
Average	0.721	0.543	8.621	0.493	0.493	10.396	0.653	0.594	6.739	

contrast, with the aid of the enhanced prompt (PT4), ChatGPT can perform log parsing more effectively. Specifically, it achieves an improvement of 9.4% and 21.8% over PT1 in MLA and ED, respectively. Overall, the design of prompts has a large impact on the performance of log parsing with ChatGPT. Including a clearer intention in the prompt could enhance parsing accuracy.

V. DISCUSSION

Based on our findings, we highlight several challenges and prospects for ChatGPT-based log parsing.

- (1) Handling log-specific data. Our study on log parsing indicates that it is promising to analyze log data with ChatGPT. However, it also shows that ChatGPT still faces difficulties in recognizing log-specific information generated during runtime (e.g., domain URLs, API endpoint addresses, etc.). Since these information occur frequently in log data, it could hinder the ability of ChatGPT in understanding log data.
- (2) The selection of demonstrations. Our experimental results show that ChatGPT exhibits good performance with few-shot prompting. Overall, the performance of ChatGPT can be improved with more demonstrations. However, we observe that in some cases, these demonstrations could bring noise and confuse the model (see Table II). Therefore, it is necessary to ensure the quality of selected demonstrations. How to select a small yet effective set of examples is an important future work.
- (3) Designing better prompts. In this paper, we found that different prompts could have a big impact on the performance of ChatGPT-based log parsing. Although many prompting methods have been proposed [36]–[38], it remains to explore which prompting method is suitable for log parsing, how to systematically design prompts, and whether there are better prompting methods. Future work is required toward designing better prompts for log parsing.
- **(4) Toward semantic-aware log parsing.** We observe that ChatGPT is able to not only extract the template associated

with variables but also semantically identify the categories of variables (see Figure 2). This awareness of variables' semantics could improve the accuracy of downstream tasks such as anomaly detection [29], [39]. Although achieving good initial results, future studies should be conducted to comprehensively evaluate the ability of ChatGPT toward semantic-aware log parsing.

VI. CONCLUSION

The paper discusses the potential of using ChatGPT, a popular large language model, for log parsing. We have designed appropriate prompts to guide ChatGPT to understand the log parsing task and compared its performance with state-of-the-art log parsers in zero-shot and few-shot scenarios. Our experimental results show that ChatGPT can achieve promising results for log parsing with appropriate prompts, especially with few-shot prompting. We also outline several challenges and opportunities for ChatGPT-based log parsing. In our future work, we will comprehensively evaluate the performance of ChatGPT and other LLMs on more log analytics tasks.

Our experimental data are available at: https://github.com/LogIntelligence/log-analytics-chatgpt.

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