System Log Parsing: A Survey

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Abstract—Modern information and communication systems have become increasingly challenging to manage. The ubiquitous system logs contain plentiful information and are thus widely exploited as an alternative source for system management. As log files usually encompass large amounts of raw data, manually analyzing them is laborious and error-prone. Consequently, many research endeavors have been devoted to automatic log analysis. However, these works typically expect structured input and struggle with the heterogeneous nature of raw system logs. Log parsing closes this gap by converting the unstructured system logs to structured records. Many parsers were proposed during the last decades to accommodate various log analysis applications. However, due to the ample solution space and lack of systematic evaluation, it is difficult for practitioners to find ready-made solutions that fit their needs. This paper aims to provide a comprehensive survey on log parsing. We begin with an exhaustive taxonomy of existing log parsers. Then we empirically analyze the critical performance and operational features of 17 open-source solutions quantitatively and qualitatively and, whenever applicable, discuss the merits of alternative approaches. We also elaborate on future challenges and discuss the relevant research directions. This survey constitutes a helpful resource for system administrators and domain experts to choose the most desirable open-source solution or implement new ones based on application-specific requirements.

Index Terms—Log parsing, system logs, log template extraction, log analysis

1 Introduction

With the proliferation of the Internet of Things (IoT), Cloud/Edge computing, Industry 4.0, and Fifth-generation mobile networks (5G), modern computing and communication systems commonly incorporate a large variety of (distributed) components to provide diversified services with guaranteed performance [1]. Consequently, they have become increasingly complex and burdensome to manage. System administrators traditionally resort to runtime analysis such as code instrumentation and profiling for execution monitoring and problem diagnosis, but these techniques are non-trivial to configure and can incur non-negligible overhead in production environment [2]. Alternatively, many research endeavors seek to explore system logs to accomplish the same tasks in a much less intrusive manner. Indeed, since the advent of the BSD Syslog protocol [3] in the 1980s, information and communications technology (ICT) systems have widely employed log files to keep track of the execution states and system events at runtime. Log files usually contain rich runtime information that system administrators and domain experts can leverage to perform advanced analytics and are thus deemed a fundamental building block for the development, maintenance, and troubleshooting of the modern systems [4].

However, nowadays, as the volume, velocity, and variety of system logs keep exploding, manually inspecting log messages is mostly impractical [5]–[7]. Existing log management and analytic tools [8]–[19] follow the classic Expert Systems approach [20], which heavily relies on manually composing regular expressions or customized rules to filter the log messages of interest. This approach requires a thorough understanding of the system internals and continuous maintenance over system upgrades [21]. For example, composing sufficiently accurate rules for Logsurfer [14] can incur a steep overhead [22]. Some network and security service providers even have to operate large data engineering teams to manage the composed rules [23].

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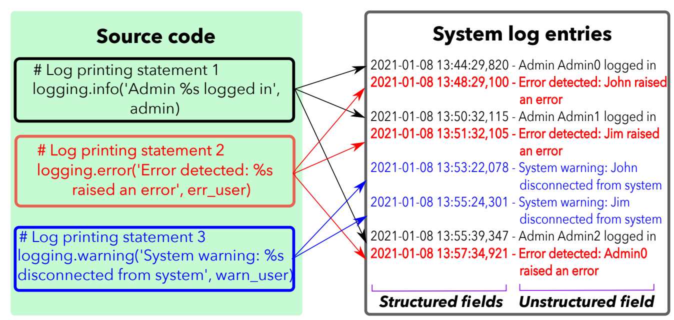


Fig. 1: A sample snippet of raw log entries along with the corresponding log printing statements in the source code.

To tackle this challenge, many end-to-end log analysis frameworks have been proposed. These frameworks employ many data mining and statistical analysis techniques to extract insights from system events [24]–[26]. In particular, with the rise of Artificial Intelligence (AI) and Machine Learning (ML) over the recent decades, there have been considerable activities towards enhancing IT operations analytics using AI/ML techniques (i.e., AIOps), which heavily rely on system logs to collect observational data [27]–[29]. Despite the optimistic outcomes, these frameworks mostly expect the input logs to have a normalized format (e.g., event types, message signatures, vectors, matrices) [30]–[33]. Nonetheless, raw logs generally record runtime system events, e.g., operations, warnings, and errors, as single-line

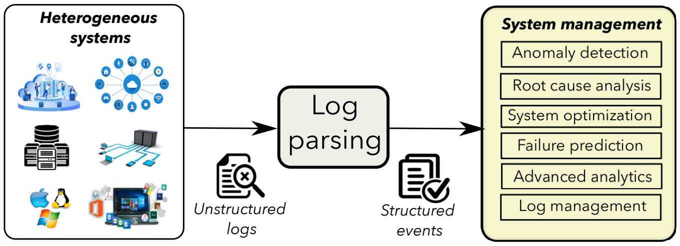


Fig. 2: The role of log parsing for system management.

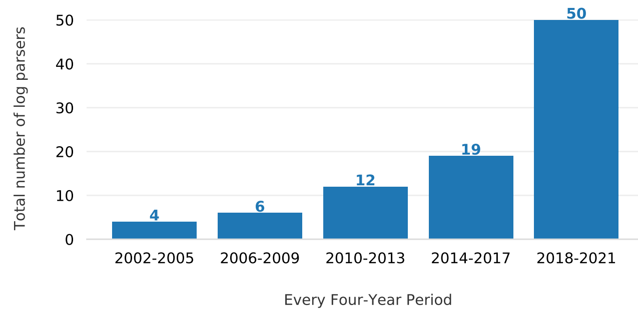


Fig. 3: Log parsers and the related works proposed during the past two decades.

or multi-line textual messages whose formats are solely decided by the log printing statements (e.g., *log.info()*, *printf()*). An illustrative example of 8 interleaved system log entries originated from 3 separate log printing statements in the program source code is shown in Fig. 1. Each entry consists of a timestamp and a free-text message with no event type or message signature. Such an issue is particularly obvious in large-scale systems [34]. There have been efforts towards log format unification [35]–[40], but most existing systems still generate log entries as unstructured (or semi-structured), free-text messages.

To close this gap, many research endeavors have been devoted to log parsing, which entails the fundamental step of automatically converting raw log entries into standard system events for high-level log analysis and system management. As depicted in Fig. 2, raw log entries originate from various real-world systems that are usually comprised of heterogeneous hardware devices (e.g., actuators, sensors, network equipment, end-user terminals) and software components (e.g., operating systems, applications). Log parsing eliminates the need to manually match and convert every entry of a system log, which can be otherwise extremely laborious and error-prone, and provides a unified data format for varied system management tasks, including anomaly detection [41]–[46], root cause analysis [47]–[49], failure prediction [50]–[52], and end-to-end log analysis [53]–[55]. Log parsing can also augment log management systems by converting raw log entries into compact representations and concise message types to save memory and facilitate data queries [56]–[59]. With the rapid expansion of modern ICT systems, log parsing keeps gaining momentum in recent years. According to our literature study, as synopsized in Fig. 3, many log parsers have been proposed during the last two decades, especially over the last four years. Nonetheless, despite the abundant solutions, their performance characteristics (e.g., parsing accuracy, runtime efficiency) and operational features (e.g., execution mode, accessibility) are still unclear, leading to the duplicated exertions of reinventing the wheel [60].

This paper provides a comprehensive review of existing log parsers and a detailed performance evaluation of open-source solutions. Some prior works are related to ours: Landauer et al. [61], Svacina et al. [62], He et al. [63], Bhanage et al. [64] and Skopik et al. [65], and Zheng et al. [66] investigated the impact of log mining for cybersecurity, reliability engineering, root cause analysis, anomaly detection, and failure prediction respectively. These works only covered specific log parsers relevant to each application domain. Instead, our taxonomy focuses on log parsing and targets all the existing solutions regardless of application domains. Besides the taxonomic reviews, some prior works focus on a specific collection of solutions and dive into their internals. El-Masri et al. [67] qualitatively discussed their performance and operational features of 17 log parsers. Zhu et al. [68] standardized the quantitative performance analysis process by evaluating 13 log parsers on 16 public datasets. Copstein et al. [69] validated the performance of the exact solutions and investigated their best practices to aid forensic analysis. Our work analyzes the performance and operational features of existing log parsers qualitatively and quantitatively. The novel aspects of this survey concerning the related work are outlined in Table 1.

TABLE 1: Comparison with the related works

Prior work	Taxonomy	Performance analysis	
		Quantitative	*Qualitative*
Landauer et al. [61]	✓		
Svacina et al. [62]	✓		
He et al. [63]	✓		
Bhanage et al. [64]	✓		
Skopik et al. [65]	✓		
Zheng et al. [66]	✓		
El-Masri et al. [67]			✓
Zhu et al. [68]		✓	
Copstein et al. [69]		✓	
Our work	✓	✓	✓

The main contributions of this paper are as follows:

- We review the literature and devise an exhaustive taxonomy of existing solutions based on their log parsing approaches.
- We collate the prior research endeavors and our benchmarking results on 17 open-source log parsers to empirically analyze the performance characteristics and operational features of parsing software.
- We envision future challenges for log parsing and discuss the possible research directions.

This paper is structured as follows: in Sec. 2, we give a general overview of log parsing. In Sec. 3, we present our taxonomy on existing log parsing solutions based on their parsing methodologies. Then we analyze the performance and operational features of the existing log parsers in Sec. 4, and discuss future challenges and research directions in Sec. 5 before concluding in Sec. 6.

TABLE 2: Table of terminology and definitions

Terminology	Definition
Log file/System log	A file of system execution records collected from any real-world systems.
Log parsing	The process of converting the unstructured entries in log files to structured event types.
Log entry/record	A single- or multi-line text record derived from a log printing statement. It is usually comprised of multiple fields.
Log message	The free-text field of a log entry. It describes a specific system event or status.
Event type	A notation marking a specific group of log entries from a log printing statement.
Event template	Denotes the format of an event type. It may consist of fixed tokens and variable tokens.
Preprocessing	The process of ruling out irrelevant raw log entries and tokenize the log messages.
Data classification	The process of organizing log messages based on specific metrics.
Template extraction	The process of identifying the correlative event template for each log message cluster.

2 Log parsing in a nutshell

In this section, we give a general definition of system logs and introduce the basic process of log parsing. We list all the relevant terminologies in Table. 2 for convenient reference.

2.1 What is a system log?

System logs are text files containing many single-line or multi-line log entries for modern computing and communication systems ranging from large-scale distributed clusters, supercomputers, end-user devices, and self-contained applications [70]. Each entry records a specific runtime system event. There is no universal standard to indicate its constituting fields. A log entry can contain multiple fields such as timestamp, severity level, logger name, message-id, and the actual log message expressing a semantic meaning. These fields are separated with delimiters like spaces, colons, or equal signs. While most fields, such as timestamps, have relatively standard formats, the log message field is usually in a free-text format, defined by individual developers through the log printing statements as illustrated in Fig. 1.

2.2 Log parsing process

The basic idea of log parsing is classifying the input log entries based on specific procedures and extracting the correct event types. We define a log file as a sequence of log entries: $L = (e_i : i = 1, 2, ...)$, where each entry l_i is generated by a log printing statement and can be represented as a sequence of tokens: $e_i = (t_j : j = 1, 2, ...)$. A token can be any combination of alphanumeric and special characters. A set of predefined delimiters separates tokens in each log entry. The length of each entry depends on the corresponding log printing statement and the parameters. Log entries generated by the same logging statement are of the same event type[1]. The free-text message field of a log entry usually consists of constant tokens that stay fixed for all messages

1. Note that the event types here do not necessarily map to the same set of actual system events, which the system developers solely defined. Instead, researchers commonly use them in the log parsing field to indicate the group of log messages generated by the same statement in the source code of system programs.

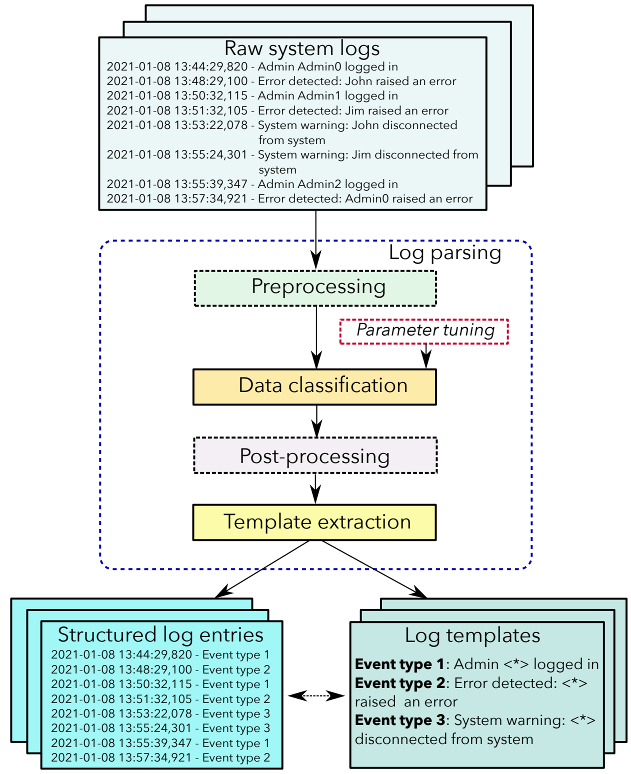


Fig. 4: A general overview of the log parsing process.

of the same event type and variable tokens corresponding to the parameters in the logging statement that may vary in each entry. A typical log template is extracted by keeping the constant parts and substituting the variable parts with predefined placeholders.

As shown in Fig. 4, a log parser commonly comprises four steps: preprocessing, data classification, post-processing, and template extraction. In the preprocessing step, the input log entries can be filtered, deduplicated, converted, or tokenized based on bespoke rules and predefined delimiters. The rules can be composed based on domain-specific knowledge or regular expressions [71]. We give a detailed discussion on preprocessing rules and delimiters in Sec. 4.2.3. After the preprocessing step, the log message field for each entry is extracted for further parsing. Although some log parsers consider this step optional, most existing solutions still heavily rely on preprocessing to reduce the input size and processing noises. Some log parsers can significantly benefit from fine-grained preprocessing. In the data classification phase, log entries are encoded with tailor-made data structures (e.g., numerical vectors, trees, dictionaries) and matched or grouped based on predefined similarity metrics (e.g., cosine similarity [72], Jaccard similarity [73], string edit distance [74]). Each resulting group constitutes a unique event type originating from a specific log printing statement. Many existing log parsers also optionally expose a set of tunable parameters to allow users to customize the subsequent log parsing process. For some solutions, parameter tuning can markedly improve their performance. We discuss the parameter tuning at length in Sec. 4.2.2. As log messages usually have heterogeneous characteristics, the data classification phase may fail to adapt to all the possible formats and lead to over- or under-parsing. Some solutions thus also adopt a post-processing phase to adjust the existing data classification results and avoid bias. Finally, each cluster's log template (or signature) is extracted to represent the log message field for all the enclosed entries. This process entails identifying constant and variable tokens for log messages in the same group. After log parsing, the initially unstructured log entries are converted into structured events with associated types, which can be leveraged by the ensuing applications to generate vectors, matrices, or sequences for advanced data analysis, insight extraction, and decision-making.

3 Log parsing solutions: A taxonomy

This section presents our taxonomy of existing log parsing solutions that employ different algorithms to interpret the free-text log messages and infer the corresponding event types. Among the different log parsing phases, we opt to classify existing solutions based on the methods for classifying log messages and extracting templates since these are the primary building blocks for any log parser. Based on our literature review, we categorize existing log parsing solutions into four categories: clustering-based approaches, frequent pattern mining-based approaches, heuristic approaches, and program analysis. Program analysis is a code-driven approach that primarily relies on the source code or the compiled executables to associate each log entry to the corresponding log printing statement, while solutions belonging to the other categories are data-driven. As most of the investigated log parsers mainly operate on the message field of each log entry, we thus refer to log messages as a general representation of log entries in this section. Due to the ample solution space, our classification method can partially overlap because a few log parsers might employ techniques from multiple categories. We classify them based on their *primary* log parsing method in this work. The goal is to categorize log parsing methods intuitively for IT professionals rather than provide a non-overlapping taxonomy of existing solutions.

Literature search

We collected the related works from prevalent scientific publications databases, including Google Scholar, IEEE eXplore, ACM Digital Library, SpringerLink, ResearchGate, and arXiv. The literature search consisted of two steps. We first explored these databases using the following keywords: log parsing, log template extraction, and log analysis. For each paper matching the keyword search, we checked its coherence with the log parsing process defined in Sec. 2.2. In this way, we derived the initial set of related works. Then we checked the references for each selected paper to search for related works. We also checked the works citing this paper whenever applicable. For newly obtained papers, we repeated this process iteratively. After almost one year of literature search, our paper covers the most exhaustive set of log parsing literature during the time of writing.

3.1 Clustering-based log parsing

Some log parsers are based on traditional clustering algorithms. For a given sequence of log entries L, a clustering-based log parsing method clusters them into a set of K clusters $\mathcal{C} = \{C_1, C_2, ..., C_K\}$, such that:

$$C_i \cap C_j = \emptyset, \forall i, j \in \{1, ..., K\}, i \neq j \tag{1}$$

$$C_i \neq \emptyset, \forall i \in \{1, ..., K\} \tag{2}$$

$$\bigcup_{i=1}^{K} C_i = \mathcal{C} \tag{3}$$

Log entries in the same cluster have high similarities, while entries across different clusters have low similarities. For each final cluster C_i, a log parsing method will extract a log template representing the event type of all the included entries. Note that the K can be specified beforehand or decided at runtime. According to our literature study, existing log parsers employ four clustering algorithms: hierarchical clustering, density-based clustering, online clustering, and other clustering methods.

3.1.1 *Hierarchical clustering*

A hierarchical clustering algorithm parses raw log messages into a hierarchy of clusters with different levels of similarities, i.e., dendrograms. Unlike other approaches that provide a definite set of clusters, it generates a collection of partitions with varying levels of details for users to select. Although the parsing results are more informative and flexible, it incurs a higher computation cost than the other clustering approaches [136]. Hierarchical clustering approaches can be either *agglomerative* or *divisive*.

Agglomerative clustering approaches begin with individual log messages and iteratively merge similar clusters until all the messages end up in the same cluster. **LogMine [7]** is a typical solution embracing this approach. It first executes a one-pass clustering algorithm to scan all the log messages sequentially and generate a set of dense clusters based on a distance function. The first message in each cluster is selected as the pattern of that cluster, and the resultant patterns form the bottom hierarchy. After this initial phase, LogMine repeats the clustering algorithm with a relaxed distance bound on the generated patterns. Then it applies a merging algorithm for each generated cluster to align and merge all the constituent patterns sequentially to generate a new pattern as a log template. These new patterns then form a new hierarchy level. The clustering and pattern recognition processes are iteratively invoked until the hierarchy is completed. Similarly, **Lin et al. [47]** convert raw log messages into sequences and iteratively merge them into new clusters using cosine similarity as the distance metric. The clustering process only terminates when all the newly merged clusters are far from each other. Afterward, the log message closest to each cluster's centroid is selected as that cluster's template. **LPV [75]**, **LogTree [24]**, and **LogOHC [76]** also belong to this category. LPV employs agglomerative hierarchical clustering (i.e., complete-linkage clustering) to incrementally group log messages based on Euclidean distance. LogTree employs single-linkage agglomerative clustering for multi-view event generation from

TABLE 3: Existing log parsers by category.

Category	Subcategory	Existing research items
Clustering	Hierarchical clustering	*LogMine [7], Lin et al. [47], LPV [75], LogTree [24], LogOHC [76], METING [77], HELO [78]*
	Density-based clustering	*STE [79], LTE [80], Pokharel et al. [81], Zou et al. [82], HLAer [83]*
	Online clustering	*LenMa [84], Guo et al. [85], LogSimilarity [52], Zhao et al. [86], StringMatch [87], FLP [88], Joshi et al. [89], One-to-one [90]*
	Other clustering methods	*LogSig [91], LKE [41], Pylogabstract [92]*
Frequent pattern mining	Apriori-based approach	*SLCT [93], LogHound [94], LogCluster [95], LFA [96], ENG [97]*
	Other approaches	*Signature Tree [98], DLog [99], FT-tree [50], Craftsman [100], Prefix-Graph [28], CAPRI [101] Logram [27], Liu et al. [102], Stearley et al. [103]*
Heuristic approaches	LCS-based approach	*Spell [104], SwissLog [43], Delog [105], Slop [106], Logan [107], LTmatch [108]*
	Parsing tree approach	*Drain [109], OLMPT [110], USTEP [111], AECID-PG [112], SHISO [113]*
	ML-based approach	*NLP-LP [114], Li et al. [34], Kobayashi et al. [115], McLean et al. [23], FastLogSim [116], NuLog [117] LogParse [118], Thaler et al. [119], Rand et al. [120], Ruecker et al. [121], LogDTL [122], LogStamp [29]*
	Other approaches	*Gao et al. [123], Chuah et al. [124], LEARNPADS [125], Baler [126], MoLFI [127], Lopper [128] CLF [129], POP [130], IPLoM [56], Paddy [131], AEL [2]*
Program analysis	Code analysis	*Xu et al. [132], Yuan et al. [48], Tak et al. [133]*
	Executable analysis	*Genlog [134], Zhao et al. [135]*

system logs. LogOHC proposes a customized online hierarchical clustering algorithm to aggregate similar log messages.

On the contrary, a divisive clustering approach considers the entire input dataset as a cluster and iteratively partitions it until all the resulting clusters contain a single log message. **METING [77]** and **HELO [78]** follow divisive hierarchical clustering. METING constructs a dendrogram by recursively bisecting existing clusters. At each partitioning step, logs containing the most common n-grams of a cluster are separated into one sub-cluster. The bisection only stops if a cluster reaches adequate homogeneity, assessed using a customized criterion. Similarly, HELO recursively partitions existing clusters by columns until each cluster's log messages have $\geq 40\%$ common tokens.

3.1.2 Density-based clustering

A density-based clustering algorithm explores the problem space and considers regions with *high point density* as clusters. Density-based algorithms, especially the Density-Based Spatial Clustering (DBSCAN) [137], have been widely used for log parsing. For instance, based on the assumption that log messages of the same type tend to have identical static tokens appear in the same position, **STE [79]** defines a scoring function to evaluate the tendency of a token being static. Then it employs the DBSCAN algorithm to identify static tokens based on the function. The log template is extracted from the top clusters. **LTE [80]** has three modules: information filter, message clustering, and template extraction. The information filter rules out timestamps and IP fields of the raw log messages based on pre-composed regular expressions. Then the clustering module employs the DBSCAN algorithm to group together messages with similar formats. Finally, the template extraction module obtains event types for each group using the Latent Dirichlet Allocation (LDA) [138] model integrated with the sampling algorithm. **Pokharel et al. [81]** convert each log message into bi-grams and cluster them directly using the DBSCAN algorithm. **Zou et al. [82]** also employ the DBSCAN algorithm along with a customized Levenshtein distance [139] to cluster log messages and extract the event templates. Besides the DBSCAN algorithm, **HLAer [83]** measures the similarities of the input logs and builds a clustering tree using the density-based OPTICS algorithm [140]. In the final phase, it extracts log formats via a sequential alignment scheme for each node in the clustering tree.

3.1.3 Online clustering

Online incremental clustering is another commonly adopted approach. Solutions in this category use explicit similarity metrics to cluster the continuously arriving logs. The most representative example is **LenMa [84]**, which incrementally clusters log messages based on positional token length. It converts each incoming log message into a vector of the constituent tokens' lengths. The vector is compared with the template of each existing cluster in terms of identical positional tokens and cosine similarity. The message is either appended to an existing cluster with the highest similarity or classified as a new cluster.

Some solutions follow this procedure but use distinct similarity metrics. For instance, **Guo et al. [85]** calculate message similarity based on the proportion of constant tokens. **LogSimilarity [52]** does this according to the weighted ratio of shared tokens. **Zhao et al. [86], [141]** clusters log messages based on the ratio of position-wise identical tokens and common sequences. **StringMatch [87]** clusters log messages based on cosine similarity and employs token position entropy to adjust existing clusters incrementally. **FLP [88]** incrementally clusters incoming logs based on message length, the first and last tokens, and a customized similarity metric. **Joshi et al. [89]** vectorize incoming logs with randomized hashing and employ a similarity search algorithm to cluster them through bitwise comparison incrementally. Messages with a common subsequence ratio beyond a threshold are clustered together. **One-to-one [90]** maintains a template list on-the-fly and follows three customized rules to cluster incoming logs incrementally.

3.1.4 Other clustering methods

Besides the preceding clustering approaches, there are three other clustering-based solutions. In particular, **LogSig [91]** customizes K-Means algorithm [142], a centroid-based clustering algorithm. LogSig converts input log messages into ordered word pairs and aggregates them into groups. Then it iterative moves log messages between groups to maximize the total number of common word pairs. Finally, it extracts the log template for each group based on common pairs. **LKE [41]** clusters log messages based on string edit distance. It calculates weights using a Sigmoid function and assigns them to different token positions to prioritize the leading tokens. Two messages with a distance smaller than a threshold are grouped, and a K-Means algorithm decides the threshold. Then it further splits each group by the least frequent token positions. The newly obtained groups constitute the final clustering results. **Pylogabstract [92]** employs a graph clustering approach. It firstly groups log messages by length and then employs Girvan-Newman community detection [143] and modularity value for log clustering.

3.2 Frequent pattern mining

Some log parsers employ Frequent Pattern Mining (FPM) [144], a traditional data mining approach to discover patterns that occur beyond a support value.

Some solutions mimic the classical Apriori algorithm [145] to extract frequent token sequences. **SLCT [93]** is the most representative solution adopting this approach. Its intuition originates from two fundamental properties of system logs: (i) most of the tokens occur only a few times, (ii) there are usually strong correlations between the frequent tokens. SLCT parses logs with three passes of the input dataset. The first pass extracts all the frequent words whose occurrences are larger than a predefined threshold. The second pass builds cluster candidates by matching the frequent words on each line. Finally, candidates with enough frequent words are identified as clusters.

SLCT lays the foundation for several other solutions: **LogHound [94]** considers input logs as database transactions and employs a breadth-first algorithm to extract frequent messages using an in-memory tree, which is built by layers until it includes all the frequent itemsets. **LogCluster [95]** locates the frequent words using a hash table. Then it extracts all the frequent words from each log message to build or update a candidate group. Candidates with smaller support than the threshold are dropped as outliers, and the remaining ones are selected as final clusters. **LFA [96]** scans over the input logs to build a word frequency table recording the position-wise occurrence of each word. Then it parses the log file by line and retrieves the frequency for every word in its corresponding position. LFA identifies the constant and variable parts based on the frequencies and builds an event type as a regular expression. **ENG [97]** extends LFA to support multiple delimiters for tokenization and multi-word variables.

Aside from the Apriori-based approaches, some works rely on tailored data structures to explore the frequency properties. The most commonly used structure is the prefix tree (also known as a trie), which is sequentially constructed from the input tokens to reduce index search complexities and identify frequent log sequences. For instance, **Signature Tree [98]** builds a prefix tree by recursively adding the most frequent combination of tokens as children until all the messages are associated with the tree. Then it prunes the tree by discarding all the nodes with more children than a threshold. After the pruning step, each remaining root-leaf path in the parsing tree constitutes a unique event template. **DLog [99]** constructs a prefix tree by recursively picking the same beginning tokens and employing a hashmap to store token occurrences. Event templates are extracted by comparing the root node with subtree nodes. **FT-tree [50]** scans the input logs to calculate token frequencies and uses a heuristic algorithm to construct a prefix tree. Newly learned log templates could also be incrementally added into the tree by only parsing the recently arrived logs. **Craftsman [100]** employs a dynamic prefix tree to parse logs and extract templates. First, it scans the whole dataset to derive the token frequency list ranked in descending order. Then it parses each log message to add a new branch to the tree incrementally according to the frequency list and the common subsequence with existing nodes. The obtained tree is pruned following a node degree constraint. **Prefix-Graph [28]** extends a probabilistic graph structure from the prefix tree. It begins with a directed acyclic graph and iteratively merges branches with similar frequency vectors. Finally, it uses a template extraction algorithm to retrieve the message signatures from the graph.

Besides prefix trees, some solutions choose other ways to discover frequent sequences. **CAPRI [101]** adopts the type-casting technique and bitmap multiplication algorithm to extract log events with different frequency properties and support incremental log mining. It also generates rules to reflect the contextual relationship between sequential messages. **Logram [27]** relies on n-gram dictionaries for log parsing. The n-grams with occurrence below a threshold are recursively transformed to $(n-1)$-gram until a list of infrequent 2-grams is obtained. Overlapping tokens in the list are identified as variables. **Liu et al. [102]** propose an approach that scans the input logs to build a word-counting table. Subsequently, a log dictionary mapping each keyword to a set of clusters is constructed. Each log message is parsed by extracting the most frequent token from the word-counting table and retrieving the most related log templates from the dictionary. The message is added to the dictionary by measuring the edit distance with the templates. **Stearley et al. [103]** maps each input token to an integer and employs a matching algorithm to locate all the patterns with a user-given specificity and support. Then it employs a set of conversions to classify log messages.

3.3 Heuristic approach

Aside from the more conventional frequent pattern mining and clustering algorithms, many log parsers employ different heuristic algorithms and data structures for log encoding, data parsing, and template extraction. The most adopted approaches include *longest common subsequence (LCS)*, *Parsing tree* and *Machine Learning (ML)*, which are discussed in Sec. 3.3.1, Sec. 3.3.2, and Sec. 3.3.3. Some other log parsing methods are based on more customized rules and data structures. We present them in Sec. 3.3.4.

3.3.1 LCS-based approach

Longest Common Subsequence (LCS) [146] is a popular approach widely adopted in log processing. Given two log messages $l_1 = \{x_1, x_2, ..., x_n\}$ and $l_2 = \{y_1, y_2, ..., y_m\}$, with $x_i (1 \leq i \leq n)$ and $y_j (1 \leq j \leq m)$ being arbitrary tokens in each message. A token sequence $s = \{z_1, z_2, ..., z_k\}$ is considered a common sequence of l_1 and l_2 iff $s \subseteq l_1$ and $s \subseteq l_2$. Intuitively, any pair of log messages can have multiple common sequences. The LCS of l_1 and l_2 is defined as a sequence of tokens with the value of k maximized.

Spell [104] is a typical solution that embraces an LCS-based approach. It maintains an LCS map for already parsed log entries, and each map consists of a group of log entry lineIDs, and the corresponding parsed LCS sequence (or message type). Spell searches through the map for an incoming log entry m to find the mapping e whose sequence has the maximum LCS length with m. If the length is longer than $\frac{|m|}{2}$, the LCS sequence of e is updated based on m with the lineID of m appended. Otherwise, a new mapping is created for m. In a later extension **[147]**, the authors augmented Spell with more efficient search algorithms, parallel execution, and semantic recognition.

Similar to Spell, **SwissLog [43]** relies on a dictionary to parse logs in four steps that involve multiple common heuristic approaches. It first tokenizes raw logs to build a valid *wordset*, which is then used to classify input logs. An LCS-based algorithm is then invoked to identify and mask the variable parts. Finally, it constructs a prefix tree to merge groups with common subsequences to avoid over-parsing. **Delog [105]** adopts a hash-based searching and an LCS-matching algorithm to partition similar input logs into groups. Each group is adjusted using a sequence alignment algorithm to cope with the inaccuracy caused by messages of the same types with variable parameter lengths. **Slop [106]** partitions incoming logs by lengths. For each message, Slop matches it to existing logs in the same partition and employs an LCS-based algorithm to extract templates. As messages with the same type can have different lengths, Slop uses another algorithm to identify and merge existing templates from all the partitions. **Logan [107]** defines a length-based method to rule out irrelevant templates and an LCS-based algorithm to match log messages with similar patterns. It also performs post-filtering constraints and periodical merging to improve parsing accuracy. **LTmatch [108]** also relies on LCS for its online processing pipeline. It calculates its word-matching rates with existing templates for each new log using an LCS-based algorithm. The log is added to the most matching group, and the corresponding template is updated using a proposed template extraction algorithm.

3.3.2 Parsing tree

Another commonly adopted heuristic method is the parsing tree. Unlike the prefix trees in Sec 3.2, a parsing tree approach employs bespoke encoding rules to match the incoming logs. **Drain [109], [148]** is an archetypal example in this vein. It relies on a fixed-depth parsing tree to cluster raw log messages into groups. Each leaf contains a set of log groups. Instead of comparing with all the groups, the tree structure effectively bounds the number of log groups each new message needs to traverse. A set of filtering rules are configured in the internal nodes to guide the search of the most suitable leaf node: the first-tier nodes match incoming messages by their lengths, and the following n tier nodes match messages by their preceding n tokens. When a message reaches a leaf node, it is assigned to the group with the highest per-token similarity.

Like Drain, **OLMPT [110]** proposes a two-level parsing tree to match logs. First-level children store the message length starting from the root, while second-level children sequentially store the initial token characters. OLMPT traverses the tree for each new log message and matches the most similar template by a character-wise score. Instead of fixed depth and encoding rules, **USTEP [111]** relies on an evolving parsing tree for log parsing. It dynamically encodes rules on the intermediate nodes and incrementally matches each incoming log message to a leaf node. **AECID-PG [112], [149]** constructs a parsing tree on-the-fly following four predefined rules. Each node is assigned a set of path frequencies to reflect different token sequences. It also allows defining a list of delimiters to flexibly tokenize the raw log messages. **SHISO [113]** also adopts a parsing tree to classify incoming logs based on token-wise Euclidean distance. Based on the search result, the log message is either merged into an existing node or added as a new node. After that, a format search algorithm is instantiated to refine existing cluster templates.

3.3.3 Machine learning

In recent years, Machine Learning (ML) has experienced unprecedented success in Natural Language Processing (NLP). As logs have similar features to natural languages, some solutions explore ML/NLP techniques.

NLP-LP [114] applies tokenization, semantic processing, vectorization, model compression, and classification techniques to find the optimal combination. According to the experimental results, it combines Latent Dirichlet Allocation and bi-gram to achieve high-quality log parsing. **Li et al. [34]** employs Hidden Markov Models (HMM) and a modified Naive Bayesian Model to classy logs and capture their temporal characteristics. **Kobayashi et al. [115]** employ the Conditional Random Fields [150] model to infer event templates by learning the structure of log message and exploring positional relations of words. **McLean et al. [23]** advocate adopting named entity recognition and NLP operations to train models on historical log data and incrementally learn the patterns and attributes therein. The trained models can then be utilized or customized to parse new logs. **FastLogSim [116]** trains a TF-IDF model [151] to identify similar log patterns, which are then merged with their templates extracted. **LogParse [118]** leverages the templates extracted by existing log parsers and uses an ML model (e.g., SVM) to train a classifier that can incrementally identify constant tokens and learn new log formats.

Some solutions employ the more sophisticated Neural Network (NN) models to augment existing NLP models. **Thaler et al. [119]** employ a five-layer neural language model to rebuild the original characters and predict the constant/variable parts of log messages. Then in [152], the same authors explore the recurrent neural networks (RNNs) with an LSTM encoder [153], which uses an RNN auto-encoder for log message embedding and an algorithm to classify messages in the embedding space and infer the event templates. **Rand et al. [120]** and **Ruecker et al. [121]** also employ LSTM to parse unseen log formats. In particular, FlexParser [121] employs stateful LSTM to capture parsing patterns across the training epochs and extract templates from the evolving log messages. **LogDTL [122]** constructs a deep transfer neural network model for log template generation. The model employs a transfer learning method to augment data training. **LogStamp [29]** treats log parsing as a sequential labeling problem. Given the historical logs, it employs a pre-trained bidirectional transformer to extract the relevant features. Then it employs a dual-path framework to extract the word embedding and labels, which are used to train a classifier that can perform online log parsing. **NuLog [117]** embraces self-supervised learning. It employs masked-language modeling to randomly mask the input tokens, vectorized and positionally encoded to be fed to a two-layer NN encoder. A final linear layer takes the resultant matrix and maps the log messages to their vector representation. Then the model dynamically processes new logs by masking each token to identify variables and generate the corresponding event templates.

3.3.4 Other heuristic approaches

Besides the LCS, parsing tree, and ML/NLP approaches, another group of log parsers uses other specialized heuristic approaches. Some of these solutions parse logs using a single heuristic algorithm, while others apply multiple heuristic algorithms to explore log features. We present all of them in this part.

Several solutions parse logs using a single heuristic algorithm: **Gao et al. [123]** propose a search-based algorithm to browse the raw messages and extract event templates from multi-line log messages; **Chuah et al. [124]** propose to construct event templates based on the simple assumption that the variable parts of a log message are composed of alphanumerics; **LEARNPADS [125]** employs a learning algorithm to refine log formats iteratively until all the log messages are successfully parsed; **Baler [126]** employs a heuristic algorithm to extract log templates based on token-integer hash mapping and predefined attributes; **MoLFI [127]** models log parsing as a multi-objective optimization problem and solve it with an evolutionary algorithm. It employs a two-level encoding schema to represent the event templates and applies the uniform crossover and random mutations to obtain new templates. Ultimately, it returns a Pareto Optimal partition with different trade-offs for the users to select.

Other solutions employ multi-step partitioning with different rules or heuristic algorithms to fully explore various characteristics of the input logs. For instance, **Lopper [128]** first groups logs by length and then by the similarity ratio of identical positional tokens. Then the obtained groups are merged according to a similarity function. In the final step, the template for each group is extracted. Two templates are combined if they share the constant parts. **CLF [129]** follows a two-step approach to partition input logs by the initial token and length. Then it counts the occurrence of tokens on each position to identify the constant parts. Each partition splits the log messages based on the previously identified constant token positions and extracts the corresponding templates. **POP [130]** first partitions input logs by length, and then it employs a heuristic method to partition by token position recursively. Templates for each group are generated by counting the distinct positional tokens. **IPLoM [56], [154]** employs a three-step approach for log parsing. First, it scans all the log messages and partitions them by message length. The resultant partitions are further divided by positional token frequency and a bijection search algorithm. Finally, the template of each group is extracted by checking the tokens on each column. A column with only a unique token is considered constant; otherwise, it is regarded as a variable piece. **Paddy [131]** parses logs using an inverted index dictionary that maps existing tokens to a list of log templates. Tokens of each new log message are used as reference keys to retrieve candidate templates from the inverted index. The candidates are then ranked and selected based on the Jaccard similarity and length. **AEL [2], [155]** is based on the clone detection technique [156]. It employs several heuristics to identify variable tokens for each log message and group messages with similar tokens and parameters into bins. Finally, it extracts the event template for each bin.

3.4 Program analysis

Besides the aforementioned data-driven solutions, program analysis is another broadly adopted approach by different log analysis applications [157], [158]. Although solutions based on program analysis are less practical than data-driven ones, we include them in our survey for completeness. Some log parsers also extend *source code analysis* of system programs to pinpoint the related logging printing statements. For example, **Xu et al. [132]** convert raw logs into a schema with message type and message variables. Then they get all the logging statements from the source code to match each log message. **Yuan et al. [48]** leverage source code with the related abstract syntax tree to generate regular expressions to parse log messages. Developers must annotate the logging statements and complex format strings to facilitate the process. **Tak et al. [133]** employ code analysis to identify the logging statements and compose regular expressions for log parsing. They also devise a text clustering algorithm to expand the parsing coverage. Although this approach renders optimistic results, the logging statements are not always easy to locate since developers may employ convoluted function calls. Moreover, the source code of many systems is usually unavailable due to intellectual property restrictions.

Some solutions further perform *executable analysis* to cope with these issues. For instance, **Genlog [134]** disassembles the target executable code and finds all the related log functions through a hybrid slicing approach. Then it reconstructs the log messages and employs data flow and taint propagation analysis to generate log templates. **Zhao et al. [135]** analyze the binary code and find all the logging statements through a keyword search. The signature of each statement is represented as regular expressions that are used to identify the event template of each log message.

4 Performance and operational features

Despite the abounding solutions, correctly choosing and configuring the most suitable ones is still a daunting task. As existing log parsers are implemented with different algorithms, they have divergent performance features and configuration complexities. Misconfigured parsers can lead to severe performance degradation for the ensuing log mining and analytic tasks. As a result, we devote this section to empirically analyzing the performance (Sec. 4.1) and operational features (Sec. 4.2) of the existing solutions.

4.1 Performance features

We review two key quantitative features in this work, namely the *parsing accuracy* and *execution time* of the existing solutions in Sec. 4.1.1 and Sec. 4.1.2. Due to the abounding solutions and the absence of source code for a subset of them, quantitatively comparing the performance of all the existing solutions is impractical. Therefore, we conduct our empirical analysis in a hybrid fashion, combining the available literature results and the quantitative evaluation of open-source log parsers.

4.1.1 Parsing accuracy

Conventionally, there are three traditional metrics to measure the effectiveness of information retrieval, i.e., **Precision, Recall**, and **F-Measure (FM)**. The precision is the ratio of correctly parsed log pairs over the total pairs generated by a log parser. By definition, recall is the ratio of correctly parsed log pairs over the actual total log pairs. Precision and recall are calculated as follows:

$$Precision = \frac{TP}{TP + FP} \tag{4}$$

$$Recall = \frac{TP}{TP + FN} \tag{5}$$

In the context of log parsing, given N raw input log entries (i.e., $\frac{N(N-1)}{2}$ message pairs), a true positive (TP) decision correctly identifies two log messages of the same type, a false positive (FP) decision arbitrates two log messages of different types to the same group. In contrast, a false negative (FN) decision parses two log messages of the same type to different groups. Precision and recall can reflect the effectiveness of existing solutions. Under-parsing can produce more false positives and degrade precision, while over-parsing can lead to more false negatives and hurt recall. F-Measure (or F-score) is purposed to balance these two metrics, and it is calculated as follows:

$$FM = \frac{(\beta^2 + 1) \cdot Precision \cdot Recall}{\beta^2 \cdot Precision + Recall} \tag{6}$$

where β is conventionally set to 1. Although FM can reflect log parsing accuracy, it only accounts for the correctly parsed log pairs, which is insufficient for log parsing. According to the definition of FM, two log messages of the same type are still considered a correct pair even if they are parsed into a group different from the rest of the same-typed log messages. Instead of FM, Du et al. [147] proposed the **Parsing Accuracy (PA)** to account for the ratio of correctly parsed log messages over the total number of log messages. PA is formally calculated as:

$$PA = \frac{\#Correct\_Messages}{\#Total\_Messages} \tag{7}$$

For the numerator in equation 7, log messages belonging to the same event type are considered correctly parsed if and only if all of them are parsed to the same group; otherwise, none of these messages is regarded as correct. Therefore, PA is more strict than FM and is more suitable for evaluating log parsing accuracy. We thus choose PA as the accuracy metric for our experiments.

According to our literature review, approximately 50 papers evaluated the performance of different log parsers.

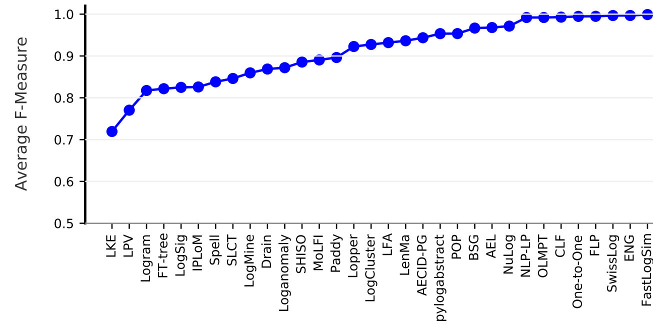


Fig. 5: The average F-Measure for some log parsers extracted from the literature

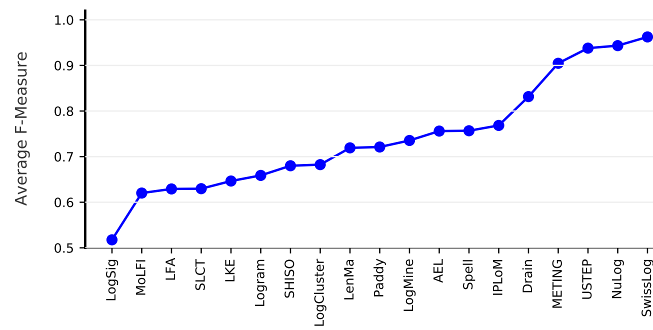


Fig. 6: The average PAs for some log parsers over heterogeneous logs evaluated in prior works

These works used a variety of public/proprietary log datasets to compare the selected log parsers in terms of standard or customized performance metrics. Most of these related works used FM and PA to characterize the accuracy of existing log parsers[2]. Therefore, we first capitalize on the numerical results in the literature to empirically understand the achievable accuracy for existing solutions. We thus collect all the numerical results and calculate the average FM and PA of existing log parsers in Fig. 5 and Fig. 6. Although the comparisons are biased because the evaluation datasets and runtime configurations were not precisely the same for all the log parsers, they can still help us develop a general idea. As we can observe, most log parsers can achieve $\geq 80\%$ FM, and some can even reach $\geq 90\%$.

Although PA is more strict than FM (as explained before), most of the parsers can still attain $\geq$ 60% PA, which is reasonable given the heterogeneity of the validation logs. Their accuracies are expected to improve with proper parameter tuning and preprocessing (which will be discussed later). In general, state-of-the-art solutions such as SLCT [93], LogMine [7], LogSig [91], LKE [41] generally perform worse than newly proposed ones, partially because they are more widely evaluated than the latter. Although some newly proposed solutions, such as FastLogSim [116], ENG [97], FLP [88], and One-to-One [90], can achieve near

2. Note that some related works evaluated log parsing accuracy with *Rand Index (RI)*, is calculated as $\frac{TP+TN}{TP+FP+FN+TN}$. We omit RI in our study since it is not as commonly employed as the FM and PA. Please refer to [29], [50], [90], [100], [129] for RI-related evaluation.

TABLE 4: Main characteristics of LogHub's 16 datasets

Dataset	#Log entries	Message length (2k) (min/avg/max)	#Templates (2k)
BGL	4,747,963	14/47/409	120
HDFS	11,175,629	8/57/425	14
HPC	433,490	6/24/326	46
Proxifier	10,108	32/52/125	8
Zookeeper	74,380	7/42/295	50
Linux	25,567	8/57/138	118
HealthApp	253,395	7/48/141	75
Apache	56,481	22/47/62	6
Spark	33,236,604	17/49/152	36
Hadoop	394,308	12/82/437	114
OpenSSH	655,146	23/64/106	27
OpenStack	207,820	51/76/178	43
Windows	114,608,388	16/88/297	50
Android	1,555,005	7/78/320	166
Thunderbird	211,212,192	7/62/761	149
Mac	117,283	9/94/1138	341

100% FM, their high accuracies can be biased since they were only tested with a few datasets.

Although the results are favorable, some solutions were only evaluated on a few datasets, and it is unclear if they can sustain similar effectiveness on other system logs. Therefore, we complement existing works by thoroughly evaluating the open-source log parsers. We specifically measure the PA of 17 open-source log parsers, namely LogSig [91], LKE [41], SLCT [93], LFA [96], MoLFI [127], SHISO [113], LogClusterr [95], LogMine [7], AEL [155], Spell [104], LenMa [84], IPLoM [56], Drain [109], Logram [27], Paddy [131], NuLog [117], and SwissLog [43]. The first 13 solutions' source code is provided by the LogPAI team [60], [68]. Note that other projects such as amuLog [58] and LogParse [118] also provided implementations for some of these log parsers (e.g., Drain, LogSig). We decided to stick to LogPAI's solutions as they are more adopted in the community. There are several other open-source solutions (e.g., FLP [88], Pylogabstract [92], and LogDTL [122]). We exclude them from our evaluation due to a lack of information or limited customizability, and integrating them is left for future work. Note that for all the experiments in the following sections, we opt to reuse the benchmarking procedure of LogPAI [159] because of its superior completeness and accessibility.

We reuse the 16 datasets of LogHub [70] to validate the PA of these solutions. The main characteristics of these datasets are shown in Table 4. Each dataset has 2k log entries randomly sampled from the original system logs, and the ground-truth event types and log templates have already been manually extracted for validation. These datasets cover a variety of ICT systems, including distributed computing, operating systems, supercomputers, and software apps, and performance evaluations across this dataset ensemble can reasonably validate the effectiveness of a log parser over heterogeneous logs [70]. Following the approaches by Zhu et al. [68], We measure the PAs of the 17 log parsers on all datasets. To ensure the optimality of the obtained results, we extensively tune the parameters of each log parser. We repeat the experiments ten times to obtain the averages for non-deterministic solutions like LKE, MoLFI, and NuLog. Note that NuLog was only evaluated on 10 of the 16 datasets because the authors did not provide the related regex rules and parameters. We will discuss preprocessing and parameter tuning at length in the next section.

We plot the distribution of PA all the log parsers under test in Fig. 7, ranked from left to right in ascending order of the median. In general, no solution can consistently prevail in all the test scenarios. Based on our observation, the accuracy of each log parser varies on different datasets, which is quite intuitive since each solution was designed to explore specific features of system logs. The accuracy will decrease if the input logs deviate from the expected formats. For relatively simple datasets like Apache, almost all the solutions can achieve 100% PA (except LogSig, which presents the lowest overall accuracy, as it is challenging to specify the cluster numbers beforehand). As the log complexities increase, the accuracies of these solutions begin to diverge. As we observe, the accuracy of IPLoM degrades on system logs with highly varied message lengths; SLCT and LFA cannot identify patterns below the threshold. The most extreme case is MoLFI, which achieves only 0.8% PA on the Proxifier dataset since it has difficulty distinguishing event types with highly similar formats. MoLFI does achieve 74% FM on the same dataset, which means it under-parses the identified messages, leading to extremely low PA. This case also validates the necessity of using PA as the accuracy metric over FM. Even the overall performant solutions still possess deficiencies on specific logs, e.g., Drain performs poorly on datasets with many leading variable tokens (e.g., Mac). NuLog and SwissLog achieve the best overall accuracy based on the obtained result. Other heuristic solutions, such as Drain and AEL, also show promising results. In general, heuristic solutions outperform the clustering- and FPM-based approaches in log parsing accuracy.

4.1.2 Parsing time

Besides accuracy, parsing time is another critical performance criterion, especially for real-time log analysis tasks. Although users can estimate a log parser's run time by analyzing its time complexity concerning the number of input log entries, this is inadequate in practice since there can also be other impactful factors for each log parser.

We devote this section to characterizing the execution time of 16 open-source log parsers with real system logs. All the experiments are conducted on a commodity server equipped with Intel Xeon CPU E5-2670 @ 2.3GHz (48 cores across two NUMA nodes) and 64GB RAM. Each experiment is executed on an isolated CPU core to reduce system-level interference. Since the log parsers under tests are implemented as single-thread applications, we assign one CPU core to each solution for the latency test. Similar to prior works, we keep the default parameters and preprocessing rules. To ensure fairness, we use the online version of Logram (without the Spark acceleration). We exclude NuLog from this evaluation as its neural network training is way slower than other solutions, even with GPU acceleration. We select 12 datasets from LogHub, i.e., the first 12 datasets in Table 4, and randomly sample log entries to compose the validation datasets. The sample sizes include 4k, 10k, 16k, 20k, 30k, 40k, 50k, 60k, 70k, 80k, 90k, and 100k. We measure the execution time for each solution on all the datasets and illustrate the results in Fig. 8. As some log parsers, especially LKE, require excessively long execution time to parse large

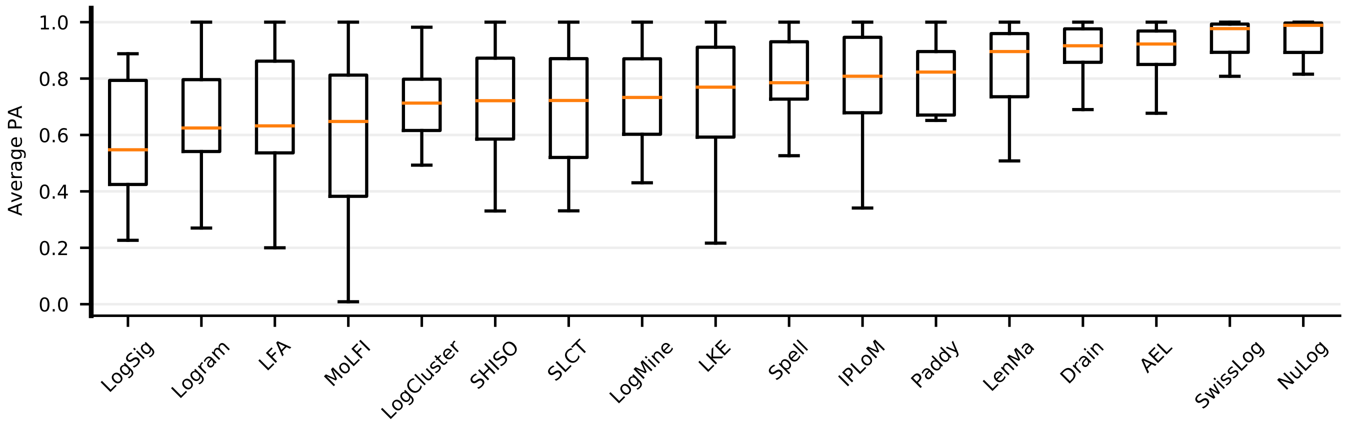


Fig. 7: The Parsing Accuracy distribution for some log parsers over heterogeneous logs.

log samples, we skip the experiments at some point to save time, yet the general trend still holds.

As we observe from Fig. 8, the execution time of most solutions can approximately scale linearly with the sample size. The heuristic solutions achieve lower overall execution time than other solutions. In particular, IPLoM, SwissLog, AEL, and Spell consistently achieve low execution times, and they can finish parsing 100k log files in around 10 seconds. These heuristic solutions use simple data structures and control logic that significantly reduces the parsing time. FPM-based solutions, such as LFA, LogCluster, and Logram, achieve comparable execution efficiency to the preceding heuristic solutions. The execution time of clustering-based solutions, i.e., LKE, LogMine, and LogSig, also scales linearly with sample size, but they take considerably longer to finish. LKE presents the highest parsing time due to its $O(n^2)$ time complexity, making it incapable of processing large datasets in a reasonable time. LogMine is also slow, mainly because of its vast message merging overhead. LogSig performs slightly better, but its clustering method is still slow to converge, and its execution time also depends on the starting point.

The execution times of other solutions are divergent across different datasets even with the same number of log entries, which means other factors can also impact their execution time. For instance, LenMa is slower than other heuristic solutions as it is less performant on datasets with highly varied message lengths. MoLFI has comparable results to LenMa on most datasets, but its execution time increases significantly on distributed systems (e.g., Hadoop, HDFS, Spark, and OpenStack) with more diversified log formats. SLCT is the only solution that scales less linearly on most datasets because it relies on frequent tokens to match the log messages for pattern mining. As the sample size increases, so is its frequent vocabulary set, which consequently increases the computation overhead of SLCT. This phenomenon is particularly obvious on complex datasets that contain large vocabularies, which explains the SLCT's sudden jump on complex datasets such as Spark, Hadoop, and HPC.

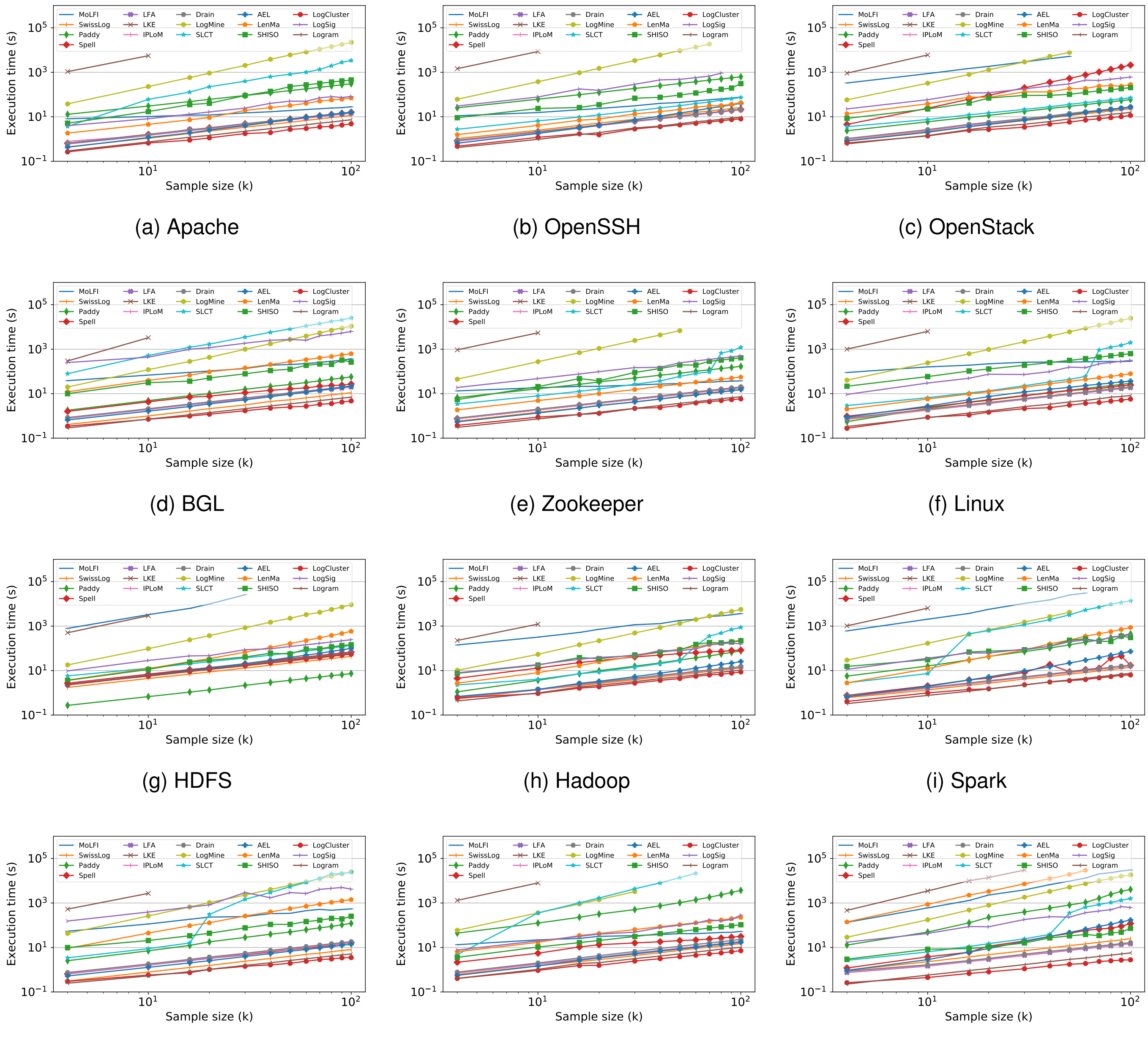
4.2 Operational features

Besides the performance indicators, there are also several noteworthy operational features, i.e., the parsing mode, preprocessing, and parameter tuning. The parsing mode alludes to a log parser's compatibility with the ensuing log analytics applications, while preprocessing and parameter tuning reveal a log parser's accessibility to average users. This section summarizes and discusses these features combining the benchmark results for the open-source solutions. When applicable, we also discuss some alternative methods we derived from the related works.

4.2.1 Parsing mode

Existing log parsers can operate in three different modes, namely *online*, *offline*, and *hybrid*. Offline log parsers need to process all the log messages in batches. Most early log parsers, such as SLCT, LKE, LogMine, and IPLoM, operate in offline batch processing mode. Intuitively, offline parsing mode should lead to satisfactory performance as it allows log parsers to scan all the messages and parse the logs with a global view. However, offline log parsers cannot allow real-time analytics, making them ill-suited for hyper-scale distributed systems.

Many log parsers embrace the online streaming mode to cope with this challenge. In fact, with the emergence of more specialized heuristics, online log parsers have attained comparable (if not better) performance than their offline counterparts [27], [147], [148]. Online parsers such as Spell, Drain, and SHISO operate on streams and can readily be adapted for real-time data-driven analysis. They have two significant advantages over offline solutions. First, online parsers can interpret newly collected logs on the fly and incrementally refine their internal parsing results without going through the offline training phase, making them ideal for real-time tasks such as system monitoring and fault diagnosis. Offline log parsers generally fall short in this regard. Some solutions, such as LKE and LogSig, can take days to parse large datasets. Second, unlike offline solutions, online parsers do not need to load the entire input data (which can be prohibitively huge) into the memory space, making them more accessible to users that do not possess enough resources.



(a) Apache (b) OpenSSH (c) OpenStack (d) BGL (e) Zookeeper (f) Linux (g) HDFS (h) Hadoop (i) Spark (j) HPC (k) Proxifier (l) HealthApp

Fig. 8: The log parsing time of 16 open-source log parsers on sample datasets with different numbers of log entries.

Besides these two standard modes, some log parsers operate in a hybrid mode, which entails an offline training phase and an online parsing phase, just like a typical ML pipeline. For instance, NuLog requires offline training to populate the model parameters via backward propagation. After that, it serves the model and parses the input logs online. This self-supervised approach can better learn the characteristics of logs from different sources and overcome the limitations of heuristic approaches that fail to generalize for unobserved log formats. According to our benchmarking results, NuLog presents the highest overall parsing accuracy on ten datasets. Such advantages have also been observed by other hybrid-mode log parsers [75], [77], [122]. Although more extensive evaluations are still needed to prove the validity of these solutions, the hybrid mode presents an intriguing future direction.

4.2.2 *Parameter tuning*

Many existing log parsers expose some parameters to allow users to fine-tune the performance. Nonetheless, for three reasons, correctly tuning these parameters is a non-trivial task. First, the exposed parameters usually have distinct sensitivities on the input logs, which can only be understood through extensive benchmarking. For example, SLCT exposes a support threshold to locate frequent words from the input logs. An overly strict threshold cannot identify all the relevant tokens and their associated patterns, while an overly loose threshold furthers the computation overhead

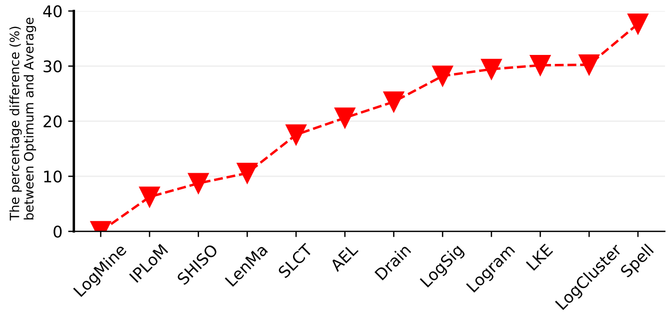


Fig. 9: The general impact of parameter tuning.

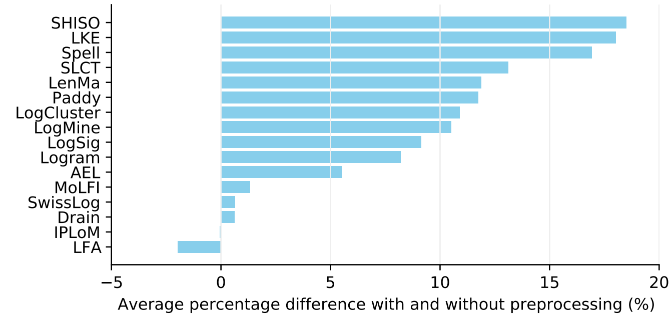


Fig. 10: The general impact of preprocessing

and may cause overfitting [95]. Second, the tunable parameters may implicitly impact each other, which requires a joint evaluation campaign to find the most suitable combination of parameters. Third, the tuning process must be repeated for new logs to guarantee the best log parsing results [68].

We devote this section to investigating the impact of parameter tuning. Starting from the default values, we sensibly perturb the parameters for each solution and collect the obtained PA. The same procedure is repeated on all the labeled 2k datasets in Sec. 4.1.1. To reflect the impact in a general sense, we calculate the ratio of optimal PA over the average PA, as illustrated in Fig. 9. We notice that some solutions from the LogPAI team slightly differ from the original papers. In this case, we opt to use LogPAI's implementations. According to our study, more tunable parameters do not necessarily mean higher tuning overhead. Some log parsers are relatively easy to tune because their parameters have negligible sensitivity. For instance, SHISO exposes four tunable parameters, i.e., the maximal child nodes and three format thresholds, that have little impact on the accuracy. IPLoM has five tunable parameters, but these parameters also have a minimal impact.

Conversely, some log parsers only expose a few parameters that require considerate tuning. For instance, Spell's message type threshold can strikingly impact accuracy ($\approx 40\%$). According to our experience, NuLog has the highest parameter tuning overhead. It exposes three parameters, i.e., #epochs, k, #samples, that can cover a vast range of values. The #epoch value has to be carefully tuned across different datasets, and k can only be fixed via cross-validation. We failed to attain even 20% PA on the Linux dataset. These solutions require a deep understanding of their design internals and data characteristics, which can be highly challenging for average users. One way to reduce this overhead is to tune parameters on small samples and directly apply them to larger datasets. Although this transferred parameter tuning performs decently in some cases, many solutions still fail to sustain satisfactory performance on large system logs with more disparate data attributes [60].

Some solutions are designed without requiring manual parameter tuning. For example, LFA, SwissLog, and Paddy automatically shield users from this potentially overwhelming undertaking. Other solutions have also embraced such an approach: Slop [106] defines a non-linear threshold criterion that can adapt to several system logs and thus does not require manual parameter tuning; LogSimilarity [52] employed an online classification algorithm to adjust the involved parameters incrementally. Although present research on automatic parameter tuning is still limited, it is a promising direction to implement new solutions that can be adaptive to different settings without human intervention.

4.2.3 Preprocessing

Besides parameter tuning, existing solutions rely heavily on human involvement for preprocessing, which may include interpreting raw log messages, removing irrelevant segments, and substituting redundant tokens (e.g., timestamps, IP addresses, unique identifiers) to reduce the parsing noise. All the open-source solutions we have evaluated rely on empirically composing regular expressions for preprocessing. According to prior research, log parsers can generally benefit from fine-grained preprocessing based on the characteristic of the input logs. However, this has to be conducted with caution, as incorrect preprocessing may inversely lead to performance degradation [60], [116], [130]. It is thus necessary to understand the impact of preprocessing on existing log parsers.

In this part, we rerun the accuracy tests without the preprocessing process on all the 2k datasets and compare the difference with the original accuracy. The regular expressions were empirically composed by the LogPAI team for each dataset. These rules only perform basic textual processing and can exhibit the bottom-line impact on each solution. The average PA difference with and without preprocessing for each solution is depicted in Fig. 10. According to the results, preprocessing has little impact on Drain, SwissLog, and IPLoM, making them more accessible to average users without prior knowledge. On the contrary, SHISO, LKE, and Spell show the highest overall difference ($\geq 15\%$). SLCT, Paddy, Lenma, and LogCluster are also sensitive to preprocessing ($\geq 10\%$). In particular, Lenma and LogCluster can only achieve 0.1% PA without preprocessing on the Proxifier dataset. NuLog's preprocessing requires specialized tokenization and masking filters, which require prior knowledge of the log formats. We do not present NuLog's result in Fig. 9, as we are uncertain of the filters for all test datasets. These solutions require more specialized preprocessing rules to unleash their full potential. We have also found a negative result for LFA's accuracy, reflecting its particular preprocessing rules requirement.

TABLE 5: A summary of the 17 open-source log parsers under evaluation

		Performance features				Operational features					
	Log parsers	Average accuracy		Parsing time		Parsing mode			Parameter Tuning		Preprocess.
		FM (%)	PA (%)	Complex.	Latency	Offline	Online	Hybrid	Parameters	Impact	Impact
FPM	**SLCT [93]**	88.98	62.94	$O(n)$	*medium*	✓			*support*	*medium*	*high*
FPM	**LFA [96]**	93.20	64.33	$O(n)$	*low*	✓			–	*zero*	*high*
FPM	**LogCluster [95]**	92.77	65.25	$O(n)$	*low*	✓			*rsupport*	*high*	*high*
FPM	**Logram [27]**	81.73	53.57	$O(n)$	*low*			✓	*double-/tri-Threshold*	*high*	*medium*
Clustering	**LogSig [91]**	90.03	52.93	$O(n)$	*medium*	✓			*groupNum*	*high*	*medium*
Clustering	**LKE [41]**	78.80	61.33	$O(n^2)$	*high*	✓			*split_threshold*	*high*	*high*
Clustering	**LenMa [84]**	93.63	76.64	$O(n)$	*medium*		✓		*threshold*	*medium*	*high*
Clustering	**LogMine [7]**	93.62	73.52	$O(n)$	*high*	✓			*max_dist,k,level*	*low*	*medium*
Heuristic approaches	**AEL [2], [155]**	96.81	79.12	$O(n)$	*low*	✓			*minEventCount, merge_percent*	*low*	*medium*
Heuristic approaches	**MoLFI [127]**	88.94	60.67	$O(n^2)$	*high*	✓			–	*zero*	*low*
Heuristic approaches	**IPLoM [56]**	96.76	75.66	$O(n)$	*low*	✓			*CT,FT,PT lowerbound/upperbound*	*low*	*low*
Heuristic approaches	**SHISO [113]**	92.09	67.80	$O(n)$	*medium*		✓		*maxChildNum mergeThreshold formatLookupThreshold superFormatThreshold*	*low*	*high*
Heuristic approaches	**Drain [148]**	97.74	86.54	$O(n)$	*low*		✓		*st, depth*	*medium*	*low*
Heuristic approaches	**Spell [104]**	96.07	79.26	$O(n)$	*medium*		✓		*tau*	*high*	*high*
Heuristic approaches	**NuLog [117]**	97.13	94.31	–	*high*			✓	*#epochs, #samples, k*	*high*	*high*
Heuristic approaches	**Paddy [131]**	89.63	71.43	$O(n)$	*medium*		✓		–	*zero*	*high*
Heuristic approaches	**SwissLog [43]**	99.56	93.29	$O(n)$	*low*			✓	–	*zero*	*low*

Although existing solutions widely use regular expressions, they are too general and fail to provide customized preprocessing for individual log parsers. We have even observed sightly decreased accuracy in some rare cases due to improper preprocessing (e.g., LFA). To this end, some other log parsers propose more advanced preprocessing procedures. For example, POP [130] provides two types of preprocessing functions for users to trim redundant fields and prioritize specific log events. Aside from the empirical understanding of input data, some solutions can benefit from detailed knowledge of the target systems. For instance, LogTree [24] relies on grammar parsers to preprocess log data and build the hierarchical message segments. These grammar parsers are highly dependent on specific system programs and usually require prior knowledge of the relevant domains. Users can also specify different clustering algorithms based on their needs, e.g., LEARNPADS [125] requires a user-specified log format description to preprocess log entries. Although these solutions enable more sophisticated parsing by consolidating user experiences and domain-specific knowledge, they are also more difficult for average users to master.

Another critical aspect of preprocessing, as pointed out by existing works [67], is how to handle the delimiters for heterogeneous logs. Most existing solutions, such as Spell, consider the commonly used signs such as space and equal as delimiters. Nonetheless, such an assumption does not always hold due to the free-text nature of system log messages, which can result in unexpected parsing errors [56]. Some solutions try to tackle this issue by simultaneously considering multiple signs as delimiters [43], [97], [112]. For instance, SwissLog employs a set of 5 delimiters ({, . ; : ”}) to tokenize the raw log messages more precisely. One-to-One allows users to specify the delimiters based on knowledge of the input log formats. Although these methods can alleviate the tokenization mistake, they cannot altogether avoid it since log entries can always employ more distinctive characters as delimiters. To overcome this limitation, Wurzenberger et al. [160] proposed a character-based log parser that performs a character-wise comparison to evaluate the similarity of two log messages, avoiding the entire tokenization step. Although their evaluation results were promising, this novel approach is still in its infancy, and more extensive benchmarking is needed to validate its applicability and performance thoroughly.

Summary

To sum up, we epitomize all the relevant performance and operational features of the 17 open-source solutions in Table 5. In particular, we list the average FM and PA for each solution for parsing accuracy. For the parsing time, we list both the time complexity and the general latency (derived from the evaluation of Sec. 4.1.2). For parameter tuning, we enumerate all the parameters and their overall impact on the final results. We have also shown the impact of preprocessing on the outcome. Although we cannot comprehensively evaluate all the existing solutions due to the lack of information, our benchmarking campaign can guide IT professionals in choosing the most suitable open-source solutions. Whenever applicable, we have also discussed the operational features of some closed-source solutions, which can be reused to implement new solutions.

5 Challenges and future directions

Despite the manifold solutions and overall robust outcomes, log parsers still face limitations that prevent them from pervasive deployment in a production environment. This section contemplates future challenges for log parsing technology and discusses the potentially relevant directions from the systems perspective.

5.1 The scarcity of public datasets

Like any data-driven approach, log parsers require abundant labeled datasets to validate and optimize performance. Unfortunately, Although these datasets have tremendously boosted the advancement of log parsing, real-world system logs (especially those from production environments) are still sought to increase the diversity of available data [60]. Since the performance of log parsers fluctuates substantially across datasets, the lack of data diversity hinders the continuous improvement of log parsing solutions. He et al. [130] tried to mitigate this problem by procedurally generating derivative samples with diversified properties from original public datasets, and Nguyen et al. [122] explored transfer learning techniques to alleviate data scarcity. However, these are not sustainable solutions in the long run. It is critical to collect, label, and disclose more logs from real systems, services, and applications to facilitate the design and validation of novel log parsers, which calls for a concerted effort from industry and academia.

5.2 Limited generalizability

Albeit existing log parsers can generally achieve sound outcomes, they still inevitably suffer from inaccuracies on most log datasets. As discussed in Sec. 4.1.1, these effects are caused by the intrinsic limitations of each existing solution with specific log properties such as the log size, message length, event distribution, and vocabulary size. Although the accuracy of a log parser can always be improved with more specialized heuristic algorithms and optimization techniques, it is challenging to keep pace with the rapid emergence of new log types induced by system requirement evolution.

As each log parser has specific performance characteristics on different datasets, one possible direction is to combine multiple parsers to compensate for the drawbacks of a single solution and thus enhance the overall performance. For instance, Xie et al. [161] proposed a p-value guided approach that aggregates all the templates extracted by four state-of-the-art log parsers, including IPLoM [56], LogCluster [95], AEL [155], and Spell [104] to improve the effectiveness of anomaly detection for the industrial IoT systems. According to their evaluation results, the proposed method achieved higher accuracy than any single log parser.

Another orientation is to exploit advanced Machine Learning (especially Deep Learning (DL)) techniques for sustainable performance. Our taxonomy involves some ML-based log parsers, as discussed in Sec. 3.3.3. These solutions have already shown encouraging outcomes. In particular, as one of the 17 evaluated open-source solutions, NuLog [117] achieves the highest accuracy on ten public datasets. Although the effectiveness of these solutions still requires further validation, we believe they can deliver more promising results with the rapid advancement of DL techniques. Based on our experience with NuLog, the high configuration difficulty and slow training process are two potential drawbacks for the DL-based solutions. They can be alleviated via system-level automation and acceleration, which will be thoroughly discussed in the following two subsections.

5.3 Lack of automation

Although existing log parsing solutions aim to enable automatic log analysis, most still rely heavily on human intervention to achieve satisfactory performance. As discussed in the previous section, empirical and domain-specific knowledge can play a decisive role for a log parser, especially during the parameter tuning and preprocessing phases. Also, as modern ICT systems are highly dynamic and constantly evolving, log parsers must deal with a perpetual shift in concepts and data contents. Existing solutions usually neglect this level of automation, which hinders their adoption in real systems.

In AI/ML domain, MLOps frameworks such as Airflow [162], Kubeflow [163], and MLflow [164] can automatically manage the end-to-end orchestration of machine learning workloads. As log parsers have a similar workflow, they can significantly benefit from a functionally equivalent framework that automates their delivery process, including log collection, data preprocessing, parameter tuning, algorithm training, continuous validation, and incremental deployment. Such a framework can significantly expedite the integration of log parsers in the production environment to facilitate advanced analysis and management.

5.4 Insufficient system-level acceleration

Existing log parsers have incorporated many algorithmic techniques to accelerate processing. However, they need to consider system-level acceleration more to scale up the operation in real-world scenarios.

As the volume of system logs increases, so does the resource footprint for log parsers. We believe log parsing can further benefit from system-level support for handling big data [165]. For example, LogMine augmented with MapReduce [166] can achieve up to $5\times$ speedup with multiple parallel workers [7]. Similarly, POP [130], Logram [27], Delog [105], and Logan [133] were built on Spark clusters [167] to benefit from the large-scale data processing capabilities. Ren et al. [168] computed the weighted edit distance for LKE using GPUs and reduced the processing time by roughly 90%. With the explosion of log data and the urgent need for real-time analytics, log parsers must extend the necessary support for heterogeneous accelerators (e.g., APIs, SDKs, and GUIs). Such an extension can also smooth their integration with the ensuing log analytics applications already popularly deployed on GPU and Big Data clusters.

6 Conclusion

This paper aims to provide a comprehensive survey of log parsers. According to their log data classification and template extraction methods, we exhaustively investigate existing solutions and organize them in an easily-accessible taxonomy. Then we systematically analyze their performance metrics (accuracy and parsing time) and operational features (parsing mode, parameter tuning, and preprocessing), extracting a consistent set of benchmark results on the most prevalent open-source solutions. This survey provides a reasoned first-hand guideline of the entire research space of log parsing. This work can also help practitioners select the most appropriate open-source solutions. We also envision future directions to promote the continued development of novel parsing techniques that may befit the evolution of log analysis requirements in modern ICT systems.

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