

1 AgenticNorm: Multi-Agent Lightweight Anomaly Detection 2 for Web Applications 3

4 ANONYMOUS AUTHOR(S) 5

6 Web applications support important areas such as finance, e-commerce, and healthcare, making their reliability
7 and security of paramount importance. However, web frontends are inherently manipulable, and abnormal
8 client behaviors may evade backend checks, creating exploitable vulnerabilities. Log analysis has emerged as
9 an effective defense by capturing client-server interactions. Two main categories of log analysis methods exist:
10 model-learning-based approaches that train predictive models from normal logs, and rule-learning-based
11 approaches that mine logical constraints from logs. However, these two categories have their limitations.
12 Model-learning-based methods detect anomalies by training predictive models on normal logs, but they suffer
13 from poor interpretability, high false positive rates, and difficulty in capturing subtle attacks. Rule-learning-
14 based methods provide stronger interpretability by extracting explicit constraints, as exemplified by WebNorm,
15 but they rely heavily on program instrumentation, closed-source large models, and manually engineered
prompts.

16 In this paper, we present AgenticNorm, a lightweight anomaly detection framework built upon compact,
17 locally deployable LLMs. AgenticNorm avoids program-analysis dependence, removes reliance on heavyweight
18 proprietary models, and mitigates prompt fragility through three innovations: (1) eliminating source-code
19 dependence via frequency-based inter-API relation discovery, (2) reducing log complexity through field
20 clustering into semantically coherent groups, and (3) iteratively refining prompts with adversarially generated
21 abnormal logs. These components are integrated into a multi-agent workflow that progressively improves
22 anomaly detection without extensive human intervention.

23 We implement and evaluate AgenticNorm on popular benchmarks, including TrainTicket and NiceFish.
24 Results demonstrate that AgenticNorm achieves effective and interpretable anomaly detection while requiring
significantly less contextual information compared to existing approaches.

25 **CCS Concepts:** • Security and privacy → Intrusion/anomaly detection and malware mitigation; Web
26 application security; • Software and its engineering → Software verification and validation.

27 Additional Key Words and Phrases: Web application security, Log anomaly detection, Rule learning

28 **ACM Reference Format:**

29 Anonymous Author(s). 2018. AgenticNorm: Multi-Agent Lightweight Anomaly Detection for Web Applications.
30 In *Proceedings of Make sure to enter the correct conference title from your rights confirmation email (Conference*
31 *acronym 'XX)*. ACM, New York, NY, USA, 17 pages. <https://doi.org/XXXXXXX.XXXXXXX>

32 **1 Introduction**

33 Web applications play a critical role in modern infrastructures, supporting domains such as fi-
34 nance [13, 45], e-commerce [38], and healthcare [22]. Their reliability and security are of paramount
35 importance. Unfortunately, web frontends are inherently manipulable: attackers can alter client-side
36 code or parameters to bypass validations, tamper with workflows, or inject abnormal behaviors.

37 In principle, backend applications implement authorization checks and other safeguards to
38 prevent such manipulations. However, because abnormal behaviors are often difficult to exhaustively

39 Permission to make digital or hard copies of all or part of this work for personal or classroom use is granted without fee
40 provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the
41 full citation on the first page. Copyrights for components of this work owned by others than the author(s) must be honored.
42 Abstracting with credit is permitted. To copy otherwise, or republish, to post on servers or to redistribute to lists, requires
43 prior specific permission and/or a fee. Request permissions from permissions@acm.org.

44 *Conference acronym 'XX, Woodstock, NY*

45 © 2018 Copyright held by the owner/author(s). Publication rights licensed to ACM.

46 ACM ISBN 978-1-4503-XXXX-X/2018/06

47 <https://doi.org/XXXXXXX.XXXXXXX>

50 cover through conventional frontend testing, certain anomalous actions may escape detection by
 51 the backend, leaving exploitable vulnerabilities.

52 To mitigate such risks, log analysis has become an effective defense mechanism. Logs in web
 53 systems typically record detailed interactions between clients and servers, including API calls,
 54 request parameters, and response statuses. Analyzing these logs enables the identification of
 55 anomalous interaction patterns that may signal security threats [2, 50]. Current state-of-the-
 56 art log analysis methods can be broadly classified into two categories: (1) *model-learning-based*
 57 *approaches*, which train predictive models from normal logs and use them to detect anomalies [1-
 58 3, 6, 7, 20, 21, 25, 27, 32, 36, 41-43, 46, 47], and (2) *rule-learning-based approaches*, which mine
 59 logical constraints from logs and detect violations [23].

60 The first category, model-learning-based approaches, typically employ deep learning models to
 61 classify logs as normal or abnormal [8, 10]. While effective in many scenarios, these approaches
 62 suffer from limited interpretability: the output is often a binary decision without clear explanations
 63 of the underlying cause. Given the large volume of logs in practice, even a small false positive rate
 64 can result in overwhelming numbers of alerts, complicating deployment. Moreover, these methods
 65 often struggle to detect subtle anomalies [34]; when malicious modifications closely mimic normal
 66 behaviors, the models tend to misclassify them, leading to missed detections.

67 To address these limitations, rule-learning-based approaches attempt to extract explicit log-
 68 ical constraints from logs and use them for anomaly detection [23]. Such approaches provide
 69 better interpretability, as the violated constraint reveals the concrete reason for detection. For
 70 example, WebNorm detects anomalies like the TrainTicket case by learning cross-API constraints
 71 (e.g., cancelOrder.arguments.orderId must appear in queryOrders.results[].id). Despite
 72 its effectiveness, however, WebNorm suffers from three critical limitations:

- 73 • **Dependence on program analysis and source code:** it requires access to frontend/backend
 74 code and additional instrumentation to align logs with code-level workflows, which is costly,
 75 brittle under rapid iteration, and infeasible for closed-source or third-party components.
- 76 • **Reliance on heavyweight proprietary LLMs:** constraint confirmation and synthesis depend
 77 on large closed-source models, which introduce latency, cost, and compliance/privacy risks.
 78 Furthermore, real logs are long and deeply nested, often exceeding the context windows of
 79 compact models and forcing reliance on heavyweight remote services.
- 80 • **Prompt sensitivity:** generating correct constraints often requires carefully crafted prompts. This
 81 results in project-specific manual engineering with poor transferability and unstable outcomes.

83 In this paper, we propose AgenticNorm, a lightweight anomaly detection framework designed
 84 around compact, locally deployable LLMs. Unlike WebNorm, AgenticNorm avoids dependence on
 85 program analysis, removes the need for heavyweight proprietary models, and mitigates prompt
 86 fragility through three key techniques:

- 87 • **Eliminating source-code dependence.** Instead of relying on program instrumentation to build
 88 log–code mappings, AgenticNorm directly infers constraints from raw logs. It discovers inter-API
 89 relationships using frequency-based analysis of co-occurring calls and derives constraints purely
 90 from runtime behaviors, enabling applicability even when source code is unavailable.
- 91 • **Field clustering for context reduction.** To overcome compact models’ limitations on long
 92 and nested logs, AgenticNorm expands JSON entities into flattened fields and groups them into
 93 semantically coherent clusters. Each cluster is processed independently, greatly reducing context
 94 length while preserving meaningful comparisons. This allows lightweight models to handle
 95 large-scale logs without resorting to heavyweight external LLMs.
- 96 • **Prompt refinement via generated abnormals.** To address prompt fragility, AgenticNorm
 97 introduces an iterative loop where adversarial logs are automatically generated to expose missing

<pre> 99 ① /api/v1/queryOrders 100 time: 2025-03-02 16:22 101 sessionId: eae15f87 102 { status: 1 103 results: [..... 104 { id: "fe9c72d9", travelDate: "2024-12-02", 105 trainNumber: "G6352", to: "taiyuan", }, 106 { id: "c256dcca", travelDate: "2024-08-09", 107 trainNumber: "G6686", to: "changsha", }, 108 { id: "a5365782", travelDate: "2024-06-05", 109 trainNumber: "G3508", to: "tianjin", }, 110 111] </pre>	<pre> ② Normal /api/v1/cancelOrder time: 2025-03-02 16:23 sessionId: eae15f87 arguments: { orderId: "fe9c72d9", loginId: "df27e80f" } </pre>	<p style="text-align: right;">Invariant</p> <p>"cancelOrder.arguments.orderId" matches one of "queryOrders.results.id"</p>
---	--	--

Fig. 1. A motivating example from the TrainTicket dataset illustrates a ticket refund workflow, where the user first retrieves a list of orders using `queryOrders` and then requests a refund through `cancelOrder`. The blue highlights indicate identifiers that should match across the two APIs, while the red highlight marks an abnormal tampering, where the `orderId` is replaced with a value not present in the queried list.

constraints. These logs guide the refinement of prompts, producing project-specific instructions that are both stable and transferable across iterations. This enables compact models to progressively capture robust invariants without manual prompt engineering.

AgenticNorm integrates these components into a multi-agent workflow, where agents for invariant generation, attack generation, and prompt refinement cooperate iteratively. The result is a system that adapts and self-improves with minimal human intervention.

This paper makes the following contributions:

- We propose AgenticNorm, a multi-agent framework for web anomaly detection that eliminates dependency on application source code.
- We implement the AgenticNorm framework and evaluate it on real-world benchmarks, including TrainTicket and NiceFish.
- Experimental results show that AgenticNorm achieves more effective anomaly detection with reduced contextual requirements compared to existing approaches.

2 Motivating Example

To illustrate the challenges of detecting anomalies from API logs, we examine a case from the TrainTicket dataset [31] involving a compromised ticket refund process. In a normal workflow, cancellation requires two steps. First, the user retrieves a list of refundable tickets. This list is displayed on the frontend, allowing the user to select which ticket to cancel. Second, the user selects one of these tickets and submits a cancellation.

APIs serve as the communication interface between frontend and backend components, typically defined by a request path and a payload format. Logs record the actual data exchanged through these APIs, usually including the request path and a JSON object for both request and response. Thus, logs are commonly represented in structured JSON format.

Figure 1 shows a simplified version of the relevant log entries, while the full logs are available in our anonymous artifact [4]. In our example, when the user retrieves refundable tickets, the frontend calls the `/api/v1/queryOrders` (abbreviated as `queryOrders`) API (① step in Figure 1), which returns a list of ticket orders. When the user selects a ticket to cancel, the frontend calls the `/api/v1/cancelOrder` (abbreviated as `cancelOrder`) API (② step in Figure 1). During invoking the `queryOrders` API, the backend returns a list of refundable tickets in the `results` field, each identified by a unique `id`. When invoking the `cancelOrder` API, the frontend provides an `orderId` in the request arguments to specify which ticket to cancel.

Table 1. Number of Input Tokens for WebNorm

Dataset	Mean	GeoMean	Median
TrainTicket	2.4×10^5	4.3×10^4	2.4×10^4
NiceFish	1.5×10^4	6.9×10^3	4.5×10^3

In normal operation, the frontend only shows tickets that can be legitimately canceled, and the user can only select from this list. So the `orderId` provided in the `cancelOrder` request must match one of the `id` values returned by the preceding `queryOrders` call. So there is a consistency constraint between these two APIs:

`cancelOrder.arguments.orderId` must appear in `queryOrders.results[].id`.

However, because frontend code executes entirely on the client side, a malicious user can tamper with browser data and forge unauthorized requests. For example, the attacker may replace the valid `orderId` with an arbitrary identifier not returned by `queryOrders` (e.g., `418ea03c`). This manipulation allows the attacker to cancel a ticket they do not own or to repeat a cancellation that should not be permitted. Such behavior can cause duplicate refunds and financial losses, creating significant risks to system security and integrity.

2.1 Existing Approaches

Existing log-based anomaly detection methods fall into two categories: (1) **Model-learning-based detectors**, which learn embeddings or features from normal and abnormal logs to classify anomalies; and (2) **Invariant-learning-based detectors**, which derive semantic invariants from logs and flag violations.

Model-learning-based detectors struggle in this scenario because normal and abnormal logs differ in only a few fields, making them nearly indistinguishable in embedding space. Furthermore, anomalies may be buried within long sequences of interleaved events, diluting the anomaly signal.

WebNorm [23] addresses this limitation by learning semantic invariants from logs with the help of LLMs. For example, it can infer the constraint that `cancelOrder.arguments.orderId` must match one of `queryOrders.results[].id`. By mapping code-level data flows to log fields and validating them as invariants, WebNorm can flag any violations as anomalies. In our motivating case, WebNorm successfully learns the cross-API dependency and detects the abnormal cancellation attempt.

Despite its effectiveness, WebNorm suffers from three key limitations:

- **Dependence on program analysis and source code:** WebNorm requires access to and instrumentation of frontend/backend code, which is costly, fragile under rapid iteration, and infeasible for closed-source or third-party systems.
- **Reliance on heavyweight proprietary LLMs:** invariant synthesis depends on remote, closed-source models, leading to cost and privacy risks. However, if directly replaced with a local deployable model, the long and nested logs often exceed the ability of small models, reducing effectiveness. Table 1 shows the number of input tokens for two datasets. The mean input length for TrainTicket is 2.40×10^5 tokens, far exceeding the context window of compact models due to very lengthy logs. Even for NiceFish, which has shorter logs, the mean input length is 1.50×10^4 tokens, still too long for compact models.
- **Prompt sensitivity:** correct invariants often appear only with carefully engineered prompts, making the process labor-intensive, project-specific, and difficult to generalize. Figure 2 illustrates the direct mapping between prompt instructions and generated invariants. The generated

```
197 # Datatype check
198 if not isinstance(instance['orderId'], str):
199     raise ValueError("orderId must be a str")
200 if not isinstance(instance['userId'], str):
201     raise ValueError("userId must be a str")
202 if not isinstance(instance['price'], float):
203     raise ValueError("price must be a str")
204
205 # Range Check
206 price_value = float(instance['price'])
207 if price_value <= 0:
208     raise ValueError("price must be a positive number")
209
210
211 Based on the logs, infer the valid values for each field by
212 referencing these common types of data validation:
213 1. Data Type Check: .....
214 2. Range Check: does the value fall within a logical numerical
215    range? (e.g., temperature, latitude, price).
216 3. Format Check: .....
```

(a) Prompt

(b) Corresponding Generated Constraints

Fig. 2. An illustration of relation between prompt and generated invariants in WebNorm. The left panel shows the prompt, which relies on manually crafted instructions and examples. Adjusting such prompts is labor-intensive and they often lack generalizability across diverse scenarios. The right panel illustrates the corresponding invariants generated from the prompt. The highlighted regions reveal the direct mapping between the prompt instructions and the generated constraints. Importantly, the generated invariants strictly adhere to the specified prompt and are limited to the constraint types explicitly mentioned.

invariants strictly adhere to the specified prompt and are limited to the constraint types explicitly mentioned. As a result, WebNorm may miss important invariants not covered by the prompt, leading to undetected anomalies.

2.2 Our Approach

We aim to preserve WebNorm’s strength in capturing *consistency constraints* while addressing its limitations. Unlike WebNorm, our approach relies only on logs (without program analysis), operates primarily with compact, locally deployable LLMs, and mitigates prompt fragility by automatically refining prompts through generated abnormal logs.

Specifically, we propose two techniques to enable anomaly detection with compact models:

- **Eliminating source-code dependence.** Instead of relying on program instrumentation to build log–code mappings, AgenticNorm directly infers constraints from raw logs. It discovers inter-API relationships using frequency-based analysis of co-occurring calls and derives constraints purely from runtime behaviors, enabling applicability even when source code is unavailable.
 - **Field Clustering.** Each JSON log entity is expanded into flattened fields and grouped into small, semantically coherent clusters. Instead of feeding the full log into the model, each cluster is processed independently. This reduces context length, highlights meaningful field-level relationships, and allows compact models to handle long and complex logs more effectively.
 - **Prompt Refinement via Generated Attacks.** To reduce reliance on manual prompt engineering, we design prompts that guide the LLM to generate abnormal logs. These generated logs expose missing constraints, which are then used to refine the prompts. The refined prompts enable compact models to capture project-specific invariants more accurately and robustly.

Field Clustering. To efficiently adapt logs for compact models, we expand each JSON record into individual fields and then group comparable ones into clusters. Figure 3 illustrates this process. Each cluster is given as a separate input to the LLM, ensuring that related fields are explicitly compared while avoiding unnecessary context.

Prompt Refinement via Generated Attacks. Compact models generally lack strong reasoning ability and cannot reliably infer constraints from fixed prompts. Manual prompt adjustment is time-consuming and project-specific. Figure 4 (left) shows the original WebNorm prompt, which

```
246
247     JSON Fields (cancelOrder - queryOrders)
248
249     time: "2025-03-02 16:22"
250     sessionId: "eae15f87"
251     { status: 1,
252      arguments: { orderId: "fe9c7d29", loginId: "df27e80f" },
253      env: { user_id: "df27e80f", is_user: true,
254            is_admin: false },
255      oj: { loginId: "0x1234", state: 0, accountId: "0x2345" },
256      results: [
257        { id: "1bf1bf21le", boughtDate: "2024-11-27
258         19:59:00", travelDate: "2024-12-02", travelTime:
259         "2024-11-21 10:12:00", accountId:
260         "df27e80f", ... },
261        ...
262      ]
263    }
```

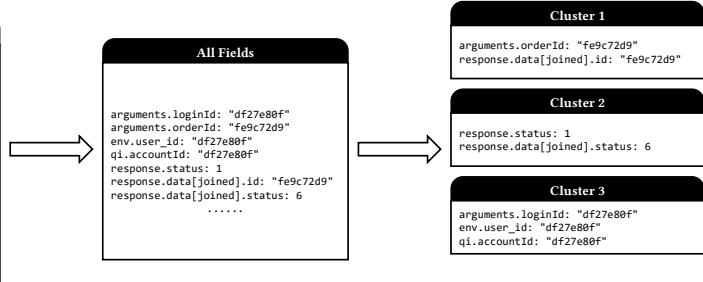


Fig. 3. An illustration of *Field Clustering* on the motivating example from the TrainTicket dataset. The original log entity is decomposed into flatten fields and then clustered into clusters, each containing only related and comparable fields.

261 Manually Written Prompt from WebNorm
262 Based on the logs, infer the valid values for each field by referencing these common types of data validation:
263 1. **Data Type Check:** can the string value be converted to a correct data type? (e.g., "0.0" -> float 0.0)
264 2. **Code Check:** does the value fall within a valid range? (e.g., postal codes, country codes, industry codes)
265

Refined Prompts by AgenticNorm

- * **Consistency**
 - If a field appears in both the main and related namespaces, their values must be identical.
 - If a joined value and an original value have corresponding field names, their values must be identical.
 - For dictionary fields, all subfields must be identical.

Invariant Generated by AgenticNorm

Fig. 4. An illustration of different prompts. The left panel shows the original prompt used in WebNorm, which relies on manually crafted instructions and examples, making prompt adjustment highly labor-intensive. The middle panel adds new instructions to the original prompt, guiding the LLM to generate abnormal logs. The right panel presents the refined prompt, which is able to capture a broader set of invariants.

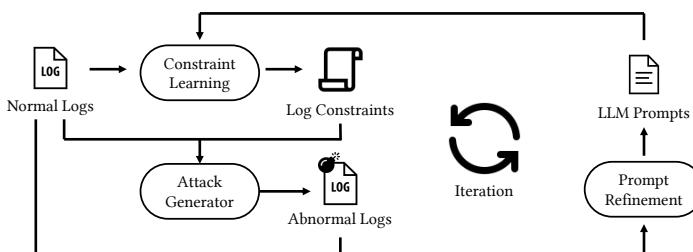


Fig. 5. Method Overview

depends on handcrafted instructions and examples. Our approach (middle) augments the prompt with additional instructions that guide the model to generate abnormal logs. These abnormal logs force the model to reason about field relationships—for example, checking consistency between joined fields and their originals. As shown in Figure 4 (right), the refined prompt enables the compact model to generate invariants that successfully capture the required field-level constraints.

3 Method

In this section, we present AgenticNorm, a lightweight multi-agent anomaly detection framework for web applications. AgenticNorm is designed to overcome the limitations of prior solutions such

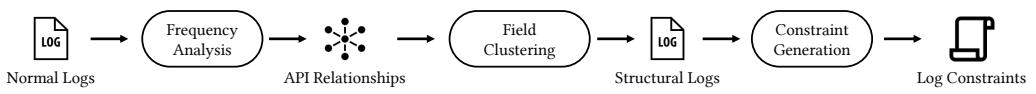


Fig. 6. Constraint Learning

as WebNorm, namely the reliance on heavyweight closed-source models, sensitivity to prompt engineering, and difficulty in handling long log contexts. Figure 5 provides an overview of the workflow.

3.1 Workflow

A central challenge in log-based anomaly detection is that prompt quality strongly influences detection results. Fixed prompts are brittle and may fail to capture certain invariants, leading to missed anomalies. To address this limitation, we propose an iterative loop in which attack generation and prompt adjustment are tightly coupled. The loop continuously strengthens prompts by exposing them to adversarial scenarios that exploit their current weaknesses. This process consists of three main modules, forming an iterative loop (Figure 5):

AgenticNorm consists of three main modules:

- **Constraint Learning:** derives invariants from normal logs.
- **Attack Generation:** synthesizes abnormal logs that break or bypass the learned invariants.
- **Prompt Refinement:** updates LLM prompts using feedback from undetected attacks.

AgenticNorm begins by deriving invariants from normal logs using an initial prompt in the **Constraint Learning** module. Then, the **Attack Generation** module synthesizes abnormal logs that break or bypass the learned invariants. Finally, the **Prompt Refinement** module updates LLM prompts using feedback from undetected attacks.

This adversarial loop allows prompts to evolve dynamically. Each cycle expands the attack space by introducing logs that specifically target the weaknesses of the current invariants, and in turn strengthens the prompts by incorporating counterexamples. Over time, this reduces reliance on manual intervention and improves robustness against both known and novel attacks.

Next, we break down each module in detail.

3.2 Constraint Learning

AgenticNorm generally follows the idea of WebNorm, but differs in that it does not rely on source code or data-flow analysis. This requires us to replace several of its original components. Figure 6 illustrates the process of constraint learning. First, AgenticNorm discovers relationships between APIs through frequency-based analysis. Next, to adapt to lightweight LLMs, AgenticNorm applies *Field Clustering*, which reduces the length of the input context per query, thereby lowering the workload of the model while improving its ability to identify constraints. Finally, AgenticNorm adopts a similar approach to WebNorm for detecting both intra-API and inter-API constraints, using an LLM to extract invariants and generate corresponding Python checking code. Unlike WebNorm, however, the prompts employed here are not manually designed; instead, they are obtained from the iterative refinement process described later, making them better suited for lightweight LLMs.

3.2.1 Frequency Analysis. AgenticNorm employs a frequency-based method to identify related APIs, eliminating the need for program analysis. Specifically, for a given API, it scans the surrounding window of log entries and counts the frequency of co-occurring API calls. The top- K most frequent

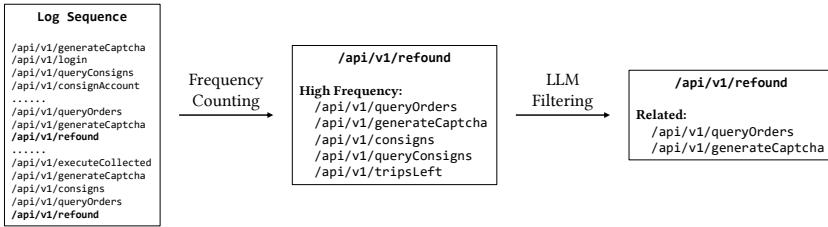


Fig. 7. An example of frequency-based analysis.

co-occurrences are considered related APIs, thus establishing inter-API relations. After this step, we utilize an LLM to verify and filter out spurious relations.

Figure 7 shows an example of frequency-based analysis on the TrainTicket dataset. Given a list of API calls, we slide a window of size K and count the frequency of co-occurring APIs. For instance, in this case, CreateOrder and AddPassenger frequently appear together, indicating a potential relationship. Then, the LLM is used to verify and filter out spurious relations.

3.2.2 *Field Clustering*. Lightweight LLMs are constrained by limited context windows, making it infeasible to directly process lengthy and complex logs. To address this limitation, we introduce *field clustering*, a technique that decomposes log entries into semantically related groups. This allows invariants to be extracted while ensuring that the input remains within the restricted context length.

To this end, AgenticNorm first analyzes the structure of logs, which often contain nested dictionaries and arrays. It then applies a set of expansion rules to flatten these structures into atomic fields. Finally, it employs an LLM to cluster the expanded fields based on semantic relatedness, forming compact groups that can be processed within the context limits.

Figure 3 provides an example of the field clustering process. The original log contains nested dicts (e.g., arguments, qi, etc.) and arrays (e.g., results). These structures are first expanded into flat fields (e.g., arguments.loginId, arguments.orderId, etc.). Finally, the expanded fields are clustered into semantically related groups (e.g., the cluster of arguments.loginId, env.userId, qi.accountId represents user identifiers).

Formally, we show the field clustering process in three steps: Log Structure Discovery, Expansion, and Clustering. Log Structure Discovery identifies the schema of logs and their data types. Expansion applies a set of rules to flatten nested structures into atomic fields. Clustering groups the expanded fields into semantically related clusters using an LLM.

4 Experiments

We focus on the following research questions.

- **RQ1: Overall Performance.** How effective is AgenticNorm in detecting web tamper attacks compared to state-of-the-art baselines and WebNorm? We evaluate its precision, recall, and F1-score on standard benchmarks.
- **RQ2: Ablation Study.** How do the core components of AgenticNorm contribute to its performance? We conduct ablation experiments on field clustering, attack generation, and prompt refinement to measure their individual impact.
- **RQ3: Model Scalability.** How does AgenticNorm perform when deployed with different scales of lightweight, locally deployable LLMs? We assess the trade-offs between detection accuracy, efficiency, and resource consumption across small, medium, and larger models.

Table 2. Overall evaluation of AgenticNorm

Model	TrainTicket			NiceFish		
	Precision	Recall	F1	Precision	Recall	F1
LogRobust [52]	0.12	0.65	0.20	0.21	0.54	0.30
LogFormer [15]	0.27	0.76	0.40	0.30	0.70	0.42
RAPID [33]	0.11	0.90	0.20	0.04	1.00	0.08
FastLogAD [24]	0.04	0.20	0.07	0.01	0.05	0.01
WebNorm [23]	1.00	0.80	0.88	1.00	0.75	0.86
AgenticNorm (Ours)	1.00	0.86	0.92	1.00	0.92	0.95

- **RQ4: Direct Substitution.** What happens if WebNorm is directly replaced with a smaller LLM without architectural modifications? This comparison highlights the necessity of our proposed techniques over naïve model substitution.

4.1 Experimental Setup

Benchmarks. We evaluate our approach on two widely-used benchmarks of web application logs: TrainTicket and NiceFish. Both datasets contain normal and attack traces derived from real-world systems, with injected tampering behaviors that allow controlled evaluation. Following prior work, we split logs into fixed-size windows of 20 entries, and assign binary labels at the window level.

Baselines. To demonstrate the effectiveness of AgenticNorm, we compare against three categories of methods: (1) *learning-based baselines*, including LogRobust [52], LogFormer [15], and RAPID [24], which rely on supervised or semi-supervised learning of log sequences; (2) *rule-based approaches*, represented by WebNorm [23], the current state-of-the-art interpretable system for normality modeling. These baselines cover both predictive and rule-driven paradigms in log anomaly detection.

Evaluation Metrics. We adopt precision and recall as the primary metrics. For windows of normal logs, if any attack is incorrectly flagged, the window is counted as a false positive (FP); otherwise it is a true negative (TN). For attack-containing windows, the detection of any injected attack is considered a true positive (TP), otherwise it is a false negative (FN). Formally, precision, recall, and F1-score are computed as

$$\text{Precision} = \frac{TP}{TP + FP}, \quad \text{Recall} = \frac{TP}{TP + FN}, \quad F1 = \frac{2 \cdot \text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}.$$

4.2 Results and Analysis

RQ1: Overall Performance. Table 2 summarizes the overall comparison¹. AgenticNorm achieves the highest F1-scores on both TrainTicket (0.92) and NiceFish (0.95). Some baselines, such as LogFormer and RAPID, obtain relatively high recall (e.g., 0.90 on TrainTicket and 1.00 on NiceFish for RAPID), but this comes at the cost of extremely low precision (0.11 / 0.04), leading to many false alarms. LogFormer offers a more balanced trade-off, but its F1-scores (0.40 / 0.42) remain far lower than ours. By contrast, WebNorm achieves perfect precision (1.00) but suffers from lower recall (0.80 on TrainTicket and 0.75 on NiceFish), missing many real attacks due to its reliance on fixed

¹We note that our reproduced results of WebNorm differ slightly from those reported in the original paper. After contacting the authors, we confirmed that they updated their dataset, which improveded precision but reduced recall. The results shown here reflect this corrected version.

Table 3. Ablation Study

Model	TrainTicket	NiceFish
Original (AgenticNorm)	0.92	0.95
w/o API relation prediction	0.67	0.50
w/o field clustering	0.60	0.83
w/o prompt refinement	0.61	0.83

Table 4. Comparison between Number of Tokens with and without Clustering

	With Clustering	Without Clustering
TrainTicket	7.2×10^3	2.4×10^5
NiceFish	6.0×10^3	1.5×10^4

Table 5. Comparison of Different LLMs

	TrainTicket		NiceFish	
	Precision	Recall	Precision	Recall
DeepSeek-V3	1.00	0.86	1.00	0.95
Gemma 3 4B	1.00	0.86	1.00	0.95
GPT-OSS 20B	1.00	0.83	1.00	0.90
GPT-OSS 120B	1.00	0.83	1.00	0.95

rules. AgenticNorm preserves the perfect precision of WebNorm while substantially improving recall (0.86 / 0.92), thus delivering the strongest overall detection performance.

RQ1: AgenticNorm surpasses state-of-the-art baselines, achieving the best F1-scores across both benchmarks.

RQ2: Ablation Study. Table 3 reports the impact of removing each component. All three modules contribute to performance improvements, but their effects differ in magnitude. Field clustering proves most critical: removing it reduces the F1-score from 0.92 to 0.60 on TrainTicket and from 0.95 to 0.83 on NiceFish. Prompt refinement has a comparable impact, with F1 dropping to 0.61 and 0.83, respectively. By contrast, removing API relation prediction leads to smaller but still notable degradation (0.92 → 0.67 on TrainTicket and 0.95 → 0.50 on NiceFish), showing that it provides complementary benefits.

To further evaluate the effectiveness of field clustering, we analyze the total number of input tokens in the prompts, comparing settings with and without clustering. Table 4 reports the token counts for each invariant generation task. The reduction is particularly pronounced on TrainTicket, as its logs contain more fields, and clustering eliminates a larger portion of redundancy. By shortening the token length, the model can process inputs more efficiently, which in turn leads to higher-quality invariants.

RQ2: Each component of AgenticNorm improves performance, with field clustering and prompt refinement being especially crucial.

491		
492		
493	/api/v1/preserveTicket	
494	arguments.oti.assurance: -2	
495	Simplified Log Entity	Range Constraints: - All numeric fields must be within a valid domain depending on type: - IDs, counters, quantities, prices, and assurance-like fields must be non-negative. - Percentages/probabilities must be within [0, 1] or [0, 100].
496		assert log["arguments.oti.assurance"] > 0
497	Refined Prompt	Learned Constraint

Fig. 8. An example from TrainTicket illustrating how prompt refinement improves the quality of generated invariants. The left panel shows a simplified version of the log entity, the middle panel presents the refined prompt with the additional range constraints compared to the original prompt, and the right panel displays the generated invariant.

RQ3: *Comparison between Different LLMs.* Table 5 shows results when varying the LLM used for the *Constraint Learning* module, while keeping *Attack Generation* and *Prompt Refinement* fixed to DeepSeek-V3. Across all four models (DeepSeek-V3, Gemma 3 4B, GPT-OSS 20B, GPT-OSS 120B), precision remains consistently perfect (1.00), and recall varies only slightly (0.83–0.86 on TrainTicket and 0.90–0.95 on NiceFish). This indicates that the effectiveness of AgenticNorm is not tied to a specific model scale in the constraint learning stage. The invariants derived through clustering and refinement are robust across models, demonstrating that smaller and more efficient LLMs can be deployed in practice without sacrificing detection accuracy.

RQ3: AgenticNorm maintains high performance across different LLMs, confirming its adaptability to smaller, locally deployable models.

RQ4: *Direct Substitution.* To further validate our design, we directly substitute WebNorm’s backbone with a smaller LLM (e.g., DeepSeek V3), without applying any of our proposed architectural modifications. Performance drops sharply in recall: on TrainTicket, recall falls from 0.92 to 0.60, and on NiceFish, from 0.95 to 0.50. This experiment shows that naïvely replacing large models with smaller ones is insufficient. While WebNorm functions well with powerful external LLMs, its invariants are too brittle when scaled down. By contrast, our techniques—field clustering, attack generation, and prompt refinement—enable small models to remain competitive, supporting practical local deployment.

RQ4: Simply substituting smaller LLMs into WebNorm leads to severe performance degradation, highlighting the necessity of our architectural innovations for making lightweight deployment viable.

5 Discussion

5.1 Impact of Adversarial Attacks on Prompt Refinement

Adversarial attacks play a crucial role in refining the prompts used for invariant generation. At the initial stage (Round 0), the prompt may fail to capture critical invariants, leading to missed detections for certain types of tamper attacks. However, when we introduce adversarial attacks that exploit these weaknesses, the system is forced to adapt: the failure cases serve as concrete counterexamples that guide the prompt-refinement process. After just one refinement iteration (Round 1), the updated prompt can successfully detect the previously missed anomaly.

For example, in Round 0, AgenticNorm fails to detect an attack where `arguments.oti.assurance` is set to a negative value (-2). After one iteration of adversarial attack-guided refinement, the refined prompt introduces explicit range constraints on numeric fields, which leads to the learned

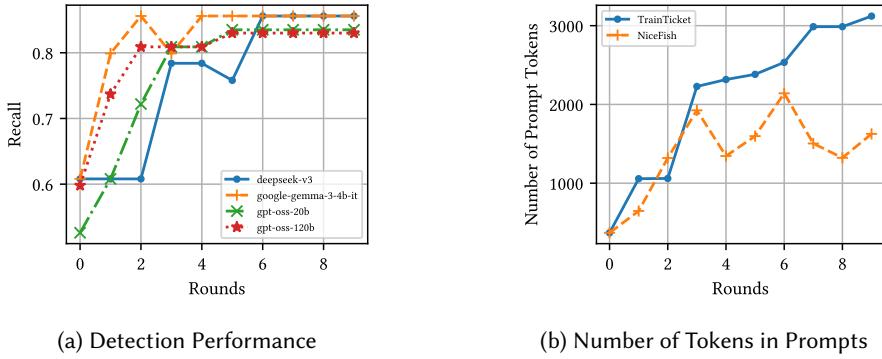


Fig. 9. Different Rounds of Prompt Refinement

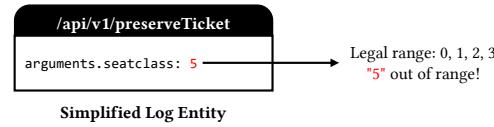


Fig. 10. An example from TrainTicket that cannot be detected by AgenticNorm. In this example, the range of a given field should be 0, 1, 2, 3 according to the system documentation. However, AgenticNorm do not know this information and thus cannot detect the tampering when the field is set to 5.

invariant assert log["arguments.oti.assurance"] > 0. This invariant enables the system to identify the anomaly that was previously overlooked. More detailed examples can be found in our repository [4].

This self-improving loop demonstrates how adversarial attacks not only test the robustness of the system but also actively drive the enhancement of detection accuracy, ultimately reducing the need for manual intervention and improving efficiency in practice.

5.2 Effect of Iterative Prompt Refinement

Figure 9a shows the effect of iterative prompt refinement on detection performance across different models. Recall improves consistently in the early rounds, with most models reaching their highest performance by Round 5–6. After this point, additional refinements no longer yield noticeable gains, and performance stabilizes at a plateau.

This trend aligns with Figure 9b, which shows that the number of tokens in the refined prompts continues to increase with each round. While longer prompts provide more detailed constraints, they eventually add little marginal benefit, indicating that the models have already captured the critical invariants needed for detection. Beyond this stage, further refinement mainly increases prompt complexity without improving effectiveness.

5.3 False Negatives

While AgenticNorm achieves high precision and recall, some false negatives remain. Figure 10 illustrates a case from TrainTicket that AgenticNorm fails to detect. In this example, the field arguments.oti.assurance should only take values in the range {0, 1, 2, 3} according to the system documentation. However, since AgenticNorm does not have access to this external knowledge, it

cannot identify the tampering when the field is set to an out-of-range value (e.g., 5). Currently, our approach relies solely on patterns learned from the logs, which may not cover all domain-specific constraints. More detailed examples can be found in our repository [4].

5.4 Limitations

Despite the promising results of AgenticNorm, several limitations remain.

Benchmark Selection. Our evaluation is restricted to two benchmarks (TrainTicket and NiceFish). While these datasets are widely used in prior work, they may not fully reflect the diversity of real-world applications, especially in large-scale industrial or domain-specific systems. Moreover, our attack synthesis is guided by the OWASP API Security Top 10, which provides strong coverage of common vulnerabilities but may overlook emerging or highly specialized attack patterns.

Model Dependencies. Although AgenticNorm is designed for lightweight deployment, certain modules (e.g., attack generation and prompt refinement) still rely on larger open-source models. This hybrid strategy ensures effectiveness but may limit applicability in environments with strict computational or resource constraints. In addition, the iterative prompt refinement process increases prompt length and complexity, which may reduce efficiency and introduce difficulties in maintaining refined prompts at scale.

6 Related Work

Log Anomaly Detection. Early attempts at anomaly detection from logs were largely based on analyzing execution traces of systems or individual APIs, with the goal of spotting deviations from expected behaviors [49]. Classical approaches mostly relied on manually written rules or statistical thresholds [18, 35, 37, 39, 40, 48, 50]. While useful in certain domains, these methods require expert-crafted specifications and often fail to generalize across applications.

With the development of machine learning, researchers began to explore learning-based approaches that automatically infer normal patterns from logs. Such methods can be broadly categorized into two groups: (1) *model-learning-based approaches*, which train predictive models from normal logs and use them to identify anomalies, and (2) *rule-learning-based approaches*, which mine logical constraints from normal logs and detect violations against them.

Model-learning-based approaches emerged with the advent of data-driven methods, where models are trained to capture behavioral patterns directly from log data [1–3, 6, 7, 20, 21, 25, 27, 32, 36, 41–43, 46, 47]. A large body of work in this direction adopts deep learning models to classify log sequences as normal or anomalous. Recurrent architectures have been widely used to capture sequential dependencies [8, 10], while CNN-based solutions exploit local contextual signals [14, 26]. Recent advances leverage Transformers [15, 19], graph neural networks [51], or pretrained language models tailored for log data [16, 17]. In addition, training-free retrieval methods have been proposed to exploit pre-trained models without fine-tuning, thereby reducing training costs and emphasizing token-level semantics [34]. Other works focus on improving data efficiency, for example by employing pseudo anomaly generation to augment scarce training data [24] or by integrating active learning into retrieval-augmented generation frameworks for anomaly detection [12]. Despite their predictive strength, these neural methods often act as black boxes, providing little insight into the root cause of anomalies and occasionally overlooking subtle yet critical deviations.

To address the limitations of black-box models, a complementary research direction emphasizes *explainability* through rule-learning-based methods. This line of work constructs explicit normality constraints that enable both anomaly detection and interpretable explanations. The most prominent example is WebNorm [23], which encodes behavioral invariants of web systems as first-order

638 logic rules derived from logs. While effective, WebNorm relies heavily on source code analysis
639 and large external models, and it does not explicitly enforce the consistency between logs and
640 their underlying data sources. Our work builds on this direction, proposing techniques that refine
641 normality inference with lightweight, deployable models and enhanced relational reasoning.
642

643 *RESTful API Security.* RESTful APIs, by virtue of their statelessness and ubiquity, have become an
644 essential surface for attacks in modern web systems. Prior research has extensively explored auto-
645 mated vulnerability discovery through API testing and fuzzing [5, 9, 11, 29, 30, 44]. These methods
646 typically mutate request sequences or payloads to trigger failures, guided by API specifications,
647 dependency constraints [30, 44], or machine learning predictions [28]. Enhanced strategies further
648 refine the fuzzing process to target specific classes of vulnerabilities such as injection attacks or
649 cross-site scripting [9, 11].

650 While fuzzing uncovers flaws through active probing, our approach takes a complementary
651 perspective: we aim to strengthen API security by learning invariants that characterize normal
652 interaction patterns. By detecting deviations from these learned normalities, we provide a systematic
653 way to capture tampering behaviors that bypass conventional fuzzing-based detection.
654

655 *Comparison to Our Work.* Existing solutions for log anomaly detection and RESTful API security
656 either emphasize predictive accuracy through deep learning or rely on fuzzing techniques to expose
657 vulnerabilities. While effective to some extent, these approaches face notable limitations: deep
658 neural methods lack interpretability and often miss subtle invariants, whereas fuzzing uncovers
659 vulnerabilities opportunistically but does not generalize to unseen tampering strategies. WebNorm
660 represents an important step toward explainable anomaly detection, but its reliance on heavyweight,
661 closed-source models and program source code restricts its applicability in practice.
662

663 In contrast, our approach focuses on lightweight, locally deployable models integrated into a
664 multi-agent framework. By introducing field clustering, we address the long-context challenge
665 inherent in compact models, and by leveraging an iterative attack-driven prompt refinement loop,
666 we enable the system to self-improve without extensive manual intervention. This combination
667 not only preserves explainability but also ensures that detection can be deployed securely and
668 efficiently in real-world settings.
669

7 Conclusion

670 In this paper, we presented AgenticNorm, a lightweight and locally deployable framework for
671 detecting web tamper attacks from logs. By combining field clustering, adversarial attack generation,
672 and iterative prompt refinement in a multi-agent workflow, AgenticNorm addresses key limitations
673 of prior approaches, including dependence on source code, reliance on heavyweight proprietary
674 models, and sensitivity to prompt design. Our evaluation on TrainTicket and NiceFish demonstrates
675 that AgenticNorm achieves state-of-the-art performance while remaining robust across different
676 LLM scales.
677

678 Looking ahead, we aim to enable AgenticNorm to adapt continuously as web applications evolve,
679 allowing it to handle changing APIs and attack patterns with minimal retraining. We also plan
680 to explore transfer and meta-learning techniques so that invariants and refined prompts learned
681 from one system can be effectively reused in new applications, improving both efficiency and
682 generalization across domains.
683

References

- 684 [1] Mithun Acharya, Tao Xie, Jian Pei, and Jun Xu. 2007. Mining API patterns as partial orders from source code: from
685 usage scenarios to specifications. In *ESEC/FSE*. <https://doi.org/10.1145/1287624.1287630>

- [2] Md Rakibul Alam, Ilias Gerostathopoulos, Christian Prehofer, Alessandro Attanasi, and Tomas Bures. 2019. A framework for tunable anomaly detection. In *2019 IEEE International Conference on Software Architecture (ICSA)*. IEEE, 201–210.
- [3] Hen Amar, Lingfeng Bao, Nimrod Busany, David Lo, and Shahar Maoz. 2018. Using finite-state models for log differencing. In *ESEC/FSE*. <https://doi.org/10.1145/3236024.3236069>
- [4] Anonymous Authors. 2025. *Details of AgenticNorm*. <https://sites.google.com/view/agenticnorm/home>
- [5] Vaggelis Atlidakis, Patrice Godefroid, and Marina Polishchuk. 2019. RESTler: Stateful rest api fuzzing. In *ICSE*. <https://doi.org/10.1109/ICSE.2019.00083>
- [6] Ivan Beschastnikh, Yuriy Brun, Sigurd Schneider, Michael Sloan, and Michael D Ernst. 2011. Leveraging existing instrumentation to automatically infer invariant-constrained models. In *ESEC/FSE*. <https://doi.org/10.1145/2025113.2025151>
- [7] Jakub Breier and Jana Branišová. 2015. Anomaly detection from log files using data mining techniques. In *Information Science and Applications*. 449–457. https://doi.org/10.1007/978-3-662-46578-3_53
- [8] Andy Brown, Aaron Tuor, Brian Hutchinson, and Nicole Nichols. 2018. Recurrent neural network attention mechanisms for interpretable system log anomaly detection. In *MLCS*. <https://doi.org/10.1145/3217871.3217872>
- [9] Gelei Deng, Zhiyi Zhang, Yuekang Li, Yi Liu, Tianwei Zhang, Yang Liu, Guo Yu, and Dongjin Wang. 2023. NAUTILUS: Automated RESTful API Vulnerability Detection. In *USENIX Security*. <https://www.usenix.org/conference/usenixsecurity23/presentation/deng-gelei>
- [10] Min Du, Feifei Li, Guineng Zheng, and Vivek Srikumar. 2017. DeepLog: Anomaly detection and diagnosis from system logs through deep learning. In *CCS*. <https://doi.org/10.1145/3133956.3134015>
- [11] Wenlong Du, Jian Li, Yanhao Wang, Libo Chen, Ruijie Zhao, Junmin Zhu, Zhengguang Han, Yijun Wang, and Zhi Xue. 2024. Vulnerability-oriented testing for restful apis. In *USENIX Security*. <https://www.usenix.org/conference/usenixsecurity24/presentation/du>
- [12] Chiming Duan, Tong Jia, Yong Yang, Guiyang Liu, Jinbu Liu, Huxing Zhang, Qi Zhou, Ying Li, and Gang Huang. 2025. EagerLog: Active Learning Enhanced Retrieval Augmented Generation for Log-based Anomaly Detection. In *ICASSP 2025-2025 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*. IEEE, 1–5.
- [13] Erik Feyen, Jon Frost, Leonardo Gambacorta, Harish Natarajan, and Matthew Saal. 2021. Fintech and the digital transformation of financial services: implications for market structure and public policy. *BIS papers* (2021).
- [14] Yuanyuan Fu, Kun Liang, and Jian Xu. 2023. Mlog: Mogrifier lstm-based log anomaly detection approach using semantic representation. *IEEE Transactions on Services Computing* 16, 5 (2023), 3537–3549. <https://doi.org/10.1109/TSC.2023.3289488>
- [15] Hongcheng Guo, Jian Yang, Jiaheng Liu, Jiaqi Bai, Boyang Wang, Zhoujun Li, Tieqiao Zheng, Bo Zhang, Junran Peng, and Qi Tian. 2024. Logformer: A pre-train and tuning pipeline for log anomaly detection. In *AAAI*. <https://doi.org/10.1609/aaai.v38i1.27764>
- [16] Haixuan Guo, Shuhan Yuan, and Xintao Wu. 2021. Logbert: Log anomaly detection via bert. In *IJCNN*. <https://doi.org/10.1109/IJCNN52387.2021.9534113>
- [17] Xiao Han, Shuhan Yuan, and Mohamed Trabelsi. 2023. LogGPT: Log anomaly detection via GPT. In *BigData*. <https://doi.org/10.1109/BigData59044.2023.10386543>
- [18] Stephen E. Hansen and E. Todd Atkins. 1993. Automated System Monitoring and Notification With Swatch. In *LISA*. <https://dl.acm.org/doi/10.5555/1024753.1024780>
- [19] Shaohan Huang, Yi Liu, Carol Fung, Rong He, Yining Zhao, Hailong Yang, and Zhongzhi Luan. 2020. HitAnomaly: Hierarchical transformers for anomaly detection in system log. *IEEE transactions on network and service management* 17, 4 (2020), 2064–2076. <https://doi.org/10.1109/TNSM.2020.3034647>
- [20] Qiao Kang, Ankit Agrawal, Alok Choudhary, Alex Sim, Kesheng Wu, Rajkumar Kettimuthu, Peter H Beckman, Zhengchun Liu, and Wei-keng Liao. 2019. Spatiotemporal real-time anomaly detection for supercomputing systems. In *2019 IEEE International Conference on Big Data (Big Data)*. IEEE, 4381–4389.
- [21] Ivo Krka, Yuriy Brun, and Nenad Medvidovic. 2014. Automatic mining of specifications from invocation traces and method invariants. In *FSE*. <https://doi.org/10.1145/2635868.2635890>
- [22] Athina A Lazakidou. 2009. *Web-based applications in healthcare and biomedicine*. Vol. 7. Springer Science & Business Media.
- [23] Yifan Liao, Ming Xu, Yun Lin, Xiwen Teoh, Xiaofei Xie, Ruitao Feng, Frank Liaw, Hongyu Zhang, and Jin Song Dong. 2024. Detecting and Explaining Anomalies Caused by Web Tamper Attacks via Building Consistency-based Normality. In *ASE*. <https://doi.org/10.1145/3691620.3695024>
- [24] Yifei Lin, Hanqiu Deng, and Xingyu Li. 2024. Fastlogad: log anomaly detection with mask-guided pseudo anomaly generation and discrimination. *arXiv preprint arXiv:2404.08750* (2024).
- [25] Davide Lorenzoli, Leonardo Mariani, and Mauro Pezzè. 2008. Automatic generation of software behavioral models. In *ICSE*. <https://doi.org/10.1145/1368088.1368157>

- [26] Siyang Lu, Xiang Wei, Yandong Li, and Liqiang Wang. 2018. Detecting anomaly in big data system logs using convolutional neural network. In *DASC*. <https://doi.org/10.1109/DASC/PiCom/DataCom/CyberSciTec.2018.00037>
- [27] Scott Lupton, Hironori Washizaki, Nobukazu Yoshioka, and Yoshiaki Fukazawa. 2021. Literature review on log anomaly detection approaches utilizing online parsing methodology. In *2021 28th Asia-Pacific Software Engineering Conference (APSEC)*. IEEE, 559–563.
- [28] Chenyang Lyu, Jiacheng Xu, Shouling Ji, Xuhong Zhang, Qinying Wang, Binbin Zhao, Gaoning Pan, Wei Cao, Peng Chen, and Raheem Beyah. 2023. MINER: A Hybrid Data-Driven Approach for RESTAPI Fuzzing. In *USENIX Security*. <https://www.usenix.org/conference/usenixsecurity23/presentation/lyu>
- [29] Alberto Martin-Lopez. 2020. Automated analysis of inter-parameter dependencies in web APIs. In *Proceedings of the ACM/IEEE 42nd International Conference on Software Engineering: Companion Proceedings*. 140–142.
- [30] Alberto Martin-Lopez, Sergio Segura, and Antonio Ruiz-Cortés. 2020. RESTest: Black-box constraint-based testing of RESTful web APIs. In *Service-Oriented Computing: 18th International Conference, ICSOC 2020, Dubai, United Arab Emirates, December 14–17, 2020, Proceedings 18*. Springer, 459–475. https://doi.org/10.1007/978-3-030-65310-1_33
- [31] MicroserviceSystem.Benchmark. 2018. *TrainTicket*. <https://github.com/FudanSELab/train-ticket/>
- [32] Anthonia Njoku, Heng Li, and Foutse Khomh. 2025. Kernel-Level Event-Based Performance Anomaly Detection in Software Systems under Varying Load Conditions. In *Companion of the 16th ACM/SPEC International Conference on Performance Engineering*. 26–30.
- [33] Gunho No, Yukyung Lee, Hyeongwon Kang, and Pilsung Kang. 2023. RAPID: Training-free Retrieval-based Log Anomaly Detection with PLM considering Token-level information. *arXiv preprint arXiv:2311.05160* (2023).
- [34] Gunho No, Yukyung Lee, Hyeongwon Kang, and Pilsung Kang. 2024. Training-free retrieval-based log anomaly detection with pre-trained language model considering token-level information. *Engineering Applications of Artificial Intelligence* 133 (2024), 108613.
- [35] Alina Oprea, Zhou Li, Ting-Fang Yen, Sang H Chin, and Sumayah Alrwais. 2015. Detection of early-stage enterprise infection by mining large-scale log data. In *DSN*. <https://doi.org/10.1109/DSN.2015.14>
- [36] Michael Pradel and Thomas R Gross. 2009. Automatic generation of object usage specifications from large method traces. In *ASE*. <https://doi.org/10.1109/ASE.2009.60>
- [37] James E Prewett. 2003. Analyzing cluster log files using logsurfer. In *Proceedings of the 4th Annual Conference on Linux Clusters*. Citeseer State College, PA, USA, 1–12.
- [38] Shati Sarmin Rahman and Sreekanth Dekkati. 2022. Revolutionizing commerce: The dynamics and future of E-commerce web applications. *Asian Journal of Applied Science and Engineering* 11, 1 (2022), 65–73.
- [39] John P Rouillard. 2004. Real-time Log File Analysis Using the Simple Event Correlator (SEC). In *LISA*. <https://dl.acm.org/doi/10.5555/1052676.1052694>
- [40] Sudip Roy, Arnd Christian König, Igor Dvorkin, and Manish Kumar. 2015. PerfAugur: Robust diagnostics for performance anomalies in cloud services. In *ICDE*. <https://doi.org/10.1109/ICDE.2015.7113365>
- [41] Vilc Queuepe Rufino, Mateus Schulz Nogueira, Alberto Avritzer, Daniel Sadoc Menasche, Barbara Russo, Andrea Janes, Vincenzo Ferme, Andre Van Hoorn, Henning Schulz, and Cabral Lima. 2020. Improving predictability of user-affecting metrics to support anomaly detection in cloud services. *IEEE Access* 8 (2020), 198152–198167.
- [42] Sigurd Schneider, Ivan Beschastnikh, Slava Chernyak, Michael D Ernst, and Yuriy Brun. 2010. Synoptic: Summarizing system logs with refinement. In *Workshop on Managing Systems via Log Analysis and Machine Learning Techniques (SLAM! 10)*.
- [43] Andrea Stocco and Paolo Tonella. 2020. Towards anomaly detectors that learn continuously. In *2020 IEEE international symposium on software reliability engineering workshops (ISSREW)*. IEEE, 201–208.
- [44] Emanuele Viglianisi, Michael Dallago, and Mariano Ceccato. 2020. Resttestgen: automated black-box testing of restful apis. In *ICST*. <https://doi.org/10.1109/ICST46399.2020.00024>
- [45] Darko B Vuković, Senanu Dekpo-Adza, and Stefana Matović. 2025. AI integration in financial services: a systematic review of trends and regulatory challenges. *Humanities and Social Sciences Communications* 12, 1 (2025), 1–29.
- [46] Neil Walkinshaw and Kirill Bogdanov. 2008. Inferring finite-state models with temporal constraints. In *ASE*. <https://doi.org/10.1109/ASE.2008.35>
- [47] Xingfang Wu, Heng Li, and Foutse Khomh. 2023. On the effectiveness of log representation for log-based anomaly detection. *Empirical Software Engineering* 28, 6 (2023), 137.
- [48] Kenji Yamanishi and Yuko Maruyama. 2005. Dynamic syslog mining for network failure monitoring. In *KDD*. <https://doi.org/10.1145/1081870.1081927>
- [49] Wenqian Ye, Guangtao Zheng, Xu Cao, Yunsheng Ma, and Aidong Zhang. 2024. Spurious correlations in machine learning: A survey. *arXiv preprint arXiv:2402.12715* (2024). <https://arxiv.org/abs/2402.12715>
- [50] Ting-Fang Yen, Alina Oprea, Kaan Onarlioglu, Todd Leetham, William Robertson, Ari Juels, and Engin Kirda. 2013. Beehive: Large-scale log analysis for detecting suspicious activity in enterprise networks. In *ACSAC*. <https://doi.org/10.1145/2523649.2523670>

- 785 [51] Chenxi Zhang, Xin Peng, Chaofeng Sha, Ke Zhang, Zhenqing Fu, Xiya Wu, Qingwei Lin, and Dongmei Zhang.
786 2022. DeepTraLog: Trace-log combined microservice anomaly detection through graph-based deep learning. In *ICSE*.
787 <https://doi.org/10.1145/3510003.3510180>
- 788 [52] Xu Zhang, Yong Xu, Qingwei Lin, Bo Qiao, Hongyu Zhang, Yingnong Dang, Chunyu Xie, Xinsheng Yang, Qian Cheng,
789 Ze Li, et al. 2019. Robust log-based anomaly detection on unstable log data. In *ESEC/FSE*. <https://doi.org/10.1145/3338906.3338931>

790
791 Received 20 February 2007; revised 12 March 2009; accepted 5 June 2009

792

793

794

795

796

797

798

799

800

801

802

803

804

805

806

807

808

809

810

811

812

813

814

815

816

817

818

819

820

821

822

823

824

825

826

827

828

829

830

831

832

833