

# 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, heavyweight proprietary models, and manually engineered  
prompts.

16 In this paper, we present AgenticNorm, a lightweight anomaly detection framework built upon lightweight,  
17 locally deployable LLMs. AgenticNorm avoids program-analysis dependence, removes reliance on heavyweight  
18 proprietary models, and mitigates prompt sensitivity 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 attack logs. These components are integrated into a multi-agent workflow that progressively improves anomaly  
22 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, 21 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, 44], e-commerce [37], 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 attack behaviors.

37 In principle, backend applications implement authorization checks and other safeguards to  
38 prevent such manipulations. However, because attack 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 covered through conventional frontend testing, certain attack actions may escape detection by the  
 51 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 attack  
 55 interaction patterns that may signal security threats [2, 49]. Current state-of-the-art log analysis  
 56 methods can be broadly classified into two categories: (1) *model-learning-based approaches*, which  
 57 train predictive models from normal logs and use them to detect anomalies [1–3, 6, 7, 20, 21, 25, 27,  
 58 32, 35, 40–42, 45, 46], and (2) *rule-learning-based approaches*, which mine logical constraints from  
 59 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 attack [8, 10]. While effective in many scenarios, these approaches suffer  
 62 from limited interpretability: the output is often a binary decision without clear explanations of  
 63 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 [33]; 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 logical  
 68 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 heavyweight proprietary models, which introduce latency, cost, and compliance/privacy  
 78 risks. Furthermore, real logs are long and deeply nested, often exceeding the context windows of  
 79 lightweight 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 lightweight, locally deployable LLMs. Unlike WebNorm, AgenticNorm avoids dependence  
 85 on program analysis, removes the need for heavyweight proprietary models, and mitigates prompt  
 86 sensitivity 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 input context reduction.** To overcome lightweight models’ limitations on  
 92 long and nested logs, AgenticNorm expands JSON entities into flattened fields and groups them  
 93 into semantically coherent clusters. Each cluster is processed independently, greatly reducing  
 94 input token length while preserving meaningful comparisons. This allows lightweight models to  
 95 handle large-scale logs without resorting to heavyweight LLMs.
- 96 • **Prompt refinement via generated attacks.** To address prompt sensitivity, AgenticNorm intro-  
 97 duces 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: <b>eae15f87</b> 102 { status: 1 103 results: [ ..... 104   { id: "<b>fe9c72d9</b>", 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: <b>eae15f87</b> arguments: { orderId: "<b>fe9c72d9</b>", loginId: "df27e80f" } </pre>	<p style="text-align: center;"><b>Constraints</b></p> <pre> "cancelOrder.arguments.orderId"   matches one of   "queryOrders.results.id" </pre>
---	--	--

Fig. 1. A motivating example from the TrainTicket dataset illustrating 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 attack case, 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 lightweight models to progressively capture robust constraints without manual prompt engineering.

AgenticNorm integrates these components into a multi-agent workflow, where agents for constraint 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 popular 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	$2.4 \times 10^5$	$4.3 \times 10^4$	$2.4 \times 10^4$
NiceFish	$1.5 \times 10^4$	$6.9 \times 10^3$	$4.5 \times 10^3$

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 attack logs to classify anomalies; and (2) **Rule-learning-based detectors**, which derive semantic constraints from logs and flag violations.

Model-learning-based detectors struggle in this scenario because normal and attack 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 constraints 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 constraints, WebNorm can flag any violations as anomalies. In our motivating case, WebNorm successfully learns the cross-API dependency and detects the attack 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:** constraint synthesis depends on remote, proprietary LLMs, 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  $2.40 \times 10^5$  tokens, far exceeding the context window of lightweight models due to very lengthy logs. Even for NiceFish, which has shorter logs, the mean input length is  $1.50 \times 10^4$  tokens, still too long for lightweight models.
- **Prompt sensitivity:** correct constraints 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 constraints. The generated

```

197
198
199
200
201 Based on the logs, infer the valid values for each field by
202 referencing these common types of data validation:
203 1. Data Type Check: .....
204 2. Range Check: does the value fall within a logical numerical
205 range? (e.g., temperature, latitude, price).
206 3. Format Check: .....
207
208
209
210
211
212
213
214
215
216
217
218
219
220
221
222
223
224
225
226
227
228
229
230
231
232
233
234
235
236
237
238
239
240
241
242
243
244
245

```

```

# Datatype check
if not isinstance(instance['orderId'], str):
    raise ValueError("orderId must be a str")
if not isinstance(instance['userId'], str):
    raise ValueError("userId must be a str")
if not isinstance(instance['price'], float):
    raise ValueError("price must be a float")

# Range Check
price_value = float(instance['price'])
if price_value <= 0:
    raise ValueError("price must be a positive number")
.....

```

(a) Prompt

```

# Datatype check
if not isinstance(instance['orderId'], str):
    raise ValueError("orderId must be a str")
if not isinstance(instance['userId'], str):
    raise ValueError("userId must be a str")
if not isinstance(instance['price'], float):
    raise ValueError("price must be a float")

# Range Check
price_value = float(instance['price'])
if price_value <= 0:
    raise ValueError("price must be a positive number")
.....

```

(b) Corresponding Generated Constraints

Fig. 2. An illustration of relation between prompt and generated constraints 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 constraints generated from the prompt. The highlighted regions reveal the direct mapping between the prompt instructions and the generated constraints. Importantly, the generated constraints strictly adhere to the specified prompt and are limited to the constraint types explicitly mentioned.

constraints strictly adhere to the specified prompt and are limited to the constraint types explicitly mentioned. As a result, WebNorm may miss important constraints 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 lightweight, locally deployable LLMs, and mitigates prompt sensitivity by automatically refining prompts through generated attack logs.

Specifically, we propose two techniques to enable anomaly detection with lightweight 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 lightweight 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 attack logs. These generated logs expose missing constraints, which are then used to refine the prompts. The refined prompts enable lightweight models to capture project-specific constraints more accurately and robustly.

*Field Clustering.* To efficiently adapt logs for lightweight 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.* Lightweight models generally lack strong reasoning ability and cannot reliably infer constraints from fixed prompts. Manual prompt adjustment is both time-consuming and highly project-specific. Figure 4 (left) shows the original WebNorm prompt,

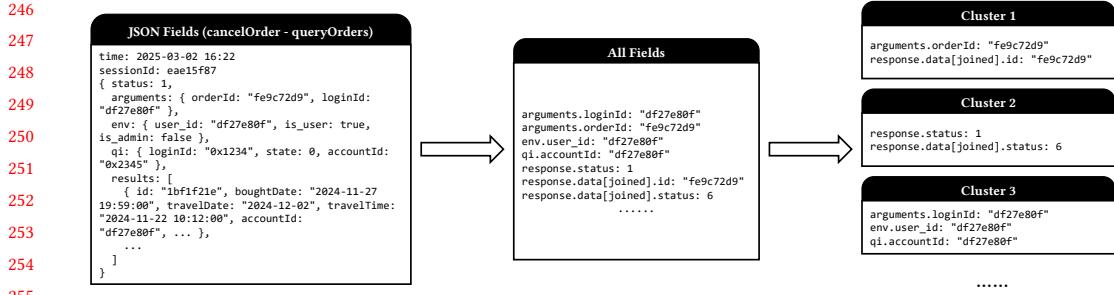


Fig. 3. An illustration of *Field Clustering* on the motivating example from the TrainTicket dataset. The original log entity is decomposed into flattened fields and then clustered into clusters, each containing only related and comparable fields.

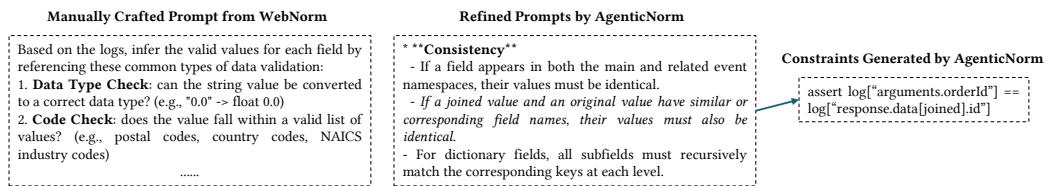


Fig. 4. An illustration of different prompts. The left panel shows the original prompt used in WebNorm, which relies on manually crafted instructions and examples, making prompt adjustment highly labor-intensive. The middle panel adds new instructions to the original prompt, guiding the LLM to generate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

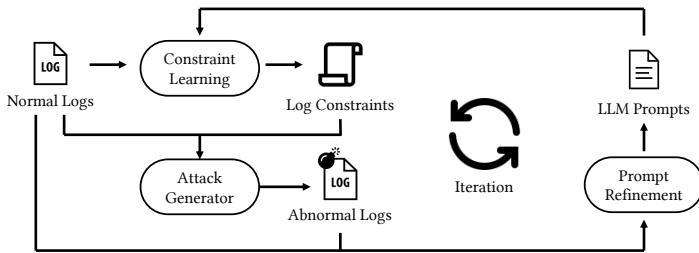


Fig. 5. Method Overview

288 which depends on handcrafted instructions and examples. Our approach (middle) augments the  
289 prompt with additional instructions that guide the model to generate attack logs. These attack  
290 logs force the model to reason about field relationships—for example, checking consistency be-  
291 tween joined fields and their originals. As shown in Figure 4 (right), the refined prompt enables  
292 the lightweight model to generate constraints that successfully capture the required field-level  
293 constraints.

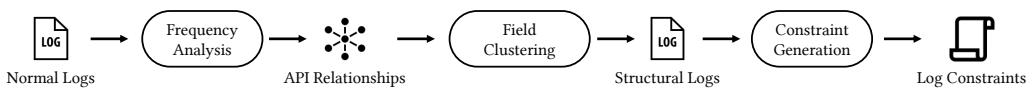


Fig. 6. Constraint Learning

### 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 as WebNorm, namely the reliance on heavyweight proprietary 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 constraints, 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 constraints from normal logs.
- **Attack Generation:** synthesizes attack logs that break or bypass the learned constraints.
- **Prompt Refinement:** updates LLM prompts using feedback from undetected attacks.

AgenticNorm begins by deriving constraints from normal logs using an initial prompt in the **Constraint Learning** module. Then, the **Attack Generation** module synthesizes attack logs that break or bypass the learned constraints. 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 constraints, 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 constraints 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.

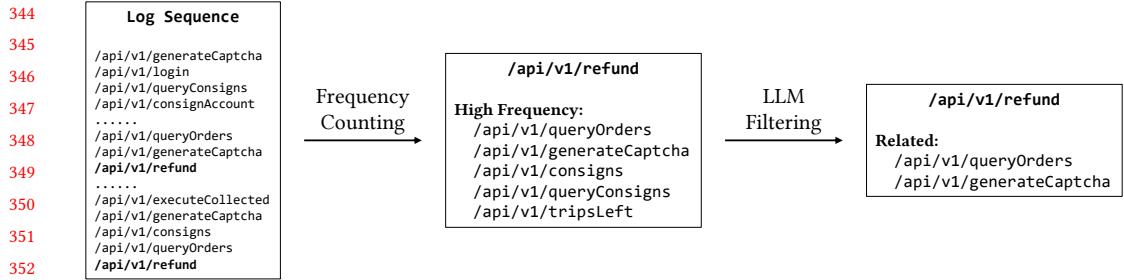


Fig. 7. An example of frequency-based analysis.

354     3.2.1 *Frequency Analysis*. AgenticNorm employs a frequency-based method to identify related APIs,  
 355     eliminating the need for program analysis. Specifically, for a given API, it scans the surrounding  
 356     window of log entries and counts the frequency of co-occurring API calls. The top- $K$  most frequent  
 357     co-occurrences are considered related APIs, thus establishing inter-API relations. After this step,  
 358     we utilize an LLM to verify and filter out spurious relations.

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

367     3.2.2 *Field Clustering*. Lightweight LLMs are constrained by limited context windows, making it  
 368     infeasible to directly process lengthy and complex logs. To address this limitation, we introduce  
 369     *field clustering*, a technique that decomposes log entries into semantically related groups. This  
 370     allows constraints to be extracted while ensuring that the input remains within the restricted  
 371     context length.

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

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

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

386     387     *Log Structure Discovery*. Each API may produce logs with diverse structures, including nested  
 388     dictionaries and arrays. We first parse the logs to uncover their structural schema and data types.  
 389     For each API, AgenticNorm analyzes all log entries and infers a unified schema that captures the  
 390     common structure, represented as fields and their associated types. Formally, we define a recursive  
 391     grammar for data types shown in Figure 8.

```

393     Data := unknown
394         | bool
395         | number
396         | string
397         | dict[key1 : Data, key2 : Data, ...]
398         | array[Data]
399
400

```

Fig. 8. Grammar for Log Data Types

405 Here, unknown denotes cases where the log structure cannot be precisely determined (e.g., due  
406 to ambiguity or inconsistency). By aggregating logs across APIs, AgenticNorm derives unified  
407 schemas that reconcile structural variations.

408 *Expansion.* After schema discovery, we apply a set of expansion rules to transform nested  
409 structures into flat fields. This ensures that all relevant information is explicitly represented,  
410 thereby facilitating clustering and constraint generation.

411 The rules are as follows:

- 412 • **Dict Expansion:** For a dictionary value, each key is concatenated with its parent field using a  
413 dot “.” separator. Formally,  $d: \text{dict}[\text{key}: \text{value}]$  is expanded into “ $d.\text{key}": \text{value}$ ”.
- 414 • **Array of Dict Expansion:** For an array of dictionaries, each dictionary key is expanded  
415 to a new array field. Formally,  $a: \text{array}[\text{dict}[\text{key}: \text{value}]]$  is expanded into “ $a[].\text{key}": \text{array}[\text{value}]$ ”.
- 416 • **Field Joining:** In certain cases, meaningful semantics emerge when fields from different struc-  
417 tural levels are *joined*. Specifically, if an outer field and an inner field share a common key (e.g.,  
418 an identifier), we match the entry and promote it as a new joined field.

419 Here are some examples of the expansion rules in motivating example:

- 420 • **Dict Expansion:**  $\text{arguments: dict}[\text{loginId: string, orderId: string}]$  is expanded into  
421 “ $\text{arguments.loginId}": \text{string, "arguments.orderId}": \text{string}$ ”.
- 422 • **Array of Dict Expansion:**  $\text{results: array}[\text{dict}[\text{id: number, status: string}]]$  is ex-  
423 panded into “ $\text{results}[].\text{id}": \text{array[number], "results}[].\text{status}": \text{array[string]}$ ”.
- 424 • **Field Joining:**  $\text{arguments.orderId}$  can be joined with the elements of  $\text{results}$  via the  $\text{id}$   
425 field. The result is a newly joined field: “ $\text{results}['\text{joined}']": \text{dict}[\text{id: number, status: string}]$ ”.

426 *Clustering.* The expansion step yields a large set of atomic fields, which are then organized into  
427 semantically coherent groups. To manage context length effectively, we cluster fields based on  
428 semantic relatedness. Instead of relying on hand-crafted heuristics, we employ an LLM to partition  
429 the expanded fields into clusters. For example, identifiers such as `user_id`, `session_id`, and joined  
430 fields with matching IDs form one cluster, while numerical values such as `price`, `amount`, and  
431 `discount` form another. This LLM-based clustering leverages semantic knowledge to generate  
432 meaningful and task-relevant partitions.

433 Through this pipeline, lengthy and complex logs are transformed into compact, semantically orga-  
434 nized structures, enabling lightweight LLMs to effectively generate constraints without exceeding  
435 context limitations.

442 Table 2. OWASP API Security Top 10 categories used in our framework. We exclude API4 (Unrestricted  
 443 Resource Consumption) and API9 (Improper Inventory Management) because both rely on frequency or  
 444 large-scale traffic/endpoint modeling, which is beyond the scope of our log-based analysis

446 Broken Object Level Authorization	Broken Authentication
447 Broken Object Property Level Authorization	Broken Function Level Authorization
448 Unrestricted Access to Sensitive Business Flows	Server-Side Request Forgery
450 Security Misconfiguration	Unsafe Consumption of APIs

453 *3.2.3 Constraint Generation.* The constraint generation process of AgenticNorm closely resembles  
 454 that of WebNorm, with the key distinction that its prompts are not manually crafted but auto-  
 455 matically derived through the subsequent attack-generation and prompt-refinement loop, making  
 456 them more suitable for lightweight LLMs. Given the structured logs, AgenticNorm first instructs  
 457 the LLM to produce candidate constraints in the form of executable rules that capture constraints  
 458 across different fields. These candidates are then iteratively evaluated against training logs, and any  
 459 violations on normal cases are fed back to the LLM along with contextual information, prompting it  
 460 to revise or discard the problematic constraints. Through this feedback loop, the system gradually  
 461 converges to a compact and reliable set of constraints that preserve both structural correctness and  
 462 semantic consistency.

### 463 3.3 Attack Generation

465 Based on the extracted constraints and a pool of normal logs, we deliberately synthesize attack log  
 466 entries that are difficult for the current constraints to capture. The attack generation process is  
 467 anchored in the *OWASP API Security Top 10*, one of the most authoritative industry standards for  
 468 categorizing API vulnerabilities. To align with our log-based setting, we exclude categories that  
 469 depend primarily on traffic volume or usage frequency (e.g., excessive resource consumption).

470 The *OWASP API Security Top 10*, maintained by the Open Worldwide Application Security Project  
 471 (OWASP), serves as the de facto reference for identifying and evaluating API vulnerabilities. It  
 472 is widely adopted by practitioners, penetration testers, and auditors as a standard checklist for  
 473 assessing the security of modern web APIs. Its categories are derived from extensive industry data  
 474 and community feedback, collectively covering the vast majority of real-world API attacks observed  
 475 in practice.

476 In our framework, we adopt the OWASP API Security Top 10 as the foundation for guiding attack  
 477 synthesis. Because our anomaly detection operates at the log level rather than the traffic level,  
 478 frequency-dependent categories (e.g., rate limiting and resource exhaustion) are excluded. For the  
 479 remaining categories, we refine them into finer-grained subcategories using LLM-based analysis,  
 480 ensuring that each synthesized attack corresponds to the log semantics of the target system. Table 2  
 481 summarizes the OWASP API Security Top 10 categories and indicates their usage in our pipeline.  
 482 Due to space limit, detailed descriptions can be found in our artifact repository [4].

483 Concretely, for each API and each API pair, we first sample a set of normal log entries. Guided  
 484 by the OWASP classification and the descriptions of each attack category, we then prompt an LLM  
 485 to generate corresponding attack log entries. The generated logs are required to bypass the existing  
 486 constraints whenever possible. These attack entries, together with the sampled normal logs, form  
 487 a labeled dataset that is subsequently used for prompt refinement. The prompt used for attack  
 488 generation is shown in Figure 9, with detailed attack strategies and input/output examples provided  
 489 in our artifact repository [4].

```

491 ** Identify ** You are a security testing expert. To ensure system security, your task is to generate
492 attack logs for a given API or API pair based on the OWASP API Security Top 10 categories. [Attack
493 Strategies from OWASP] [Input/Output Format] [Example]
494 ** Input ** [Normal Log Entries] [Constraints Conditions]
495 ** Output ** [Attack Log Entries]
496

```

Fig. 9. Abbreviated version of the LLM prompt for attack generation. Attack strategies and detailed examples are omitted here for brevity; the complete prompt is available in our artifact repository [4].

---

### Algorithm 1 Prompt Refinement via Log-Guided Feedback

---

```

502 Require: Dataset  $D$  containing pairs of normal logs  $N$  and attack logs  $A$ 
503 Require: Original prompt  $P$ 
504 Ensure: Refined prompt  $P'$ 
505 1:  $M_s \leftarrow []$  {Initialize list of modification suggestions}
506 2: for each  $(N, A) \in D$  do
507 3:    $M \leftarrow \text{LLM}(\text{"Generate modification suggestion"}, N, A, P)$  {Generate modification sug-
508   gesions based on a normal-attack log pair}
509 4:    $M_s.append(M)$ 
510 5: end for
511 6:  $P' \leftarrow \text{LLM}(\text{"Refine prompt"}, P, M_s)$  {Refine the original prompt by incorporating aggregated
512   suggestions}
513 7: return  $P'$ 

```

---

By grounding attack generation in this taxonomy, our framework inherits both breadth and credibility: it covers a wide spectrum of realistic API threats while remaining fully compatible with our log-based constraints detection setting.

### 3.4 Prompt Refinement

After attack generation, we obtain a labeled dataset consisting of both normal and attack logs. Our next task is to refine the prompts used in constraint generation, so that they can better capture the constraints needed to detect the synthesized attacks. The refinement process is similar to learning a model from labeled data, where the input dataset is the logs and the labels are whether each log is normal or attack. The difference is that instead of adjusting model parameters by policy gradient or backpropagation, we update the prompt text itself using an LLM.

Algorithm 1 outlines the prompt refinement process. For each normal-attack log pair in the dataset, we feed it into an LLM along with the current prompt, asking it to generate a modification suggestion. The LLM analyzes the pair and identifies what changes to the prompt could help distinguish between the normal and attack cases. This may involve adding new clauses, modifying existing ones, or removing irrelevant parts. Figure 10 shows an abbreviated version of the prompt used for refinement, with the complete version available in our artifact repository [4].

### 3.5 Implementation Details

*LLMs Used.* AgenticNorm is designed to work with lightweight, locally deployable LLMs. In our study, we observed that the tasks of *Attack Generation* and *Prompt Refinement* place heavier demands on the neural models, as they require more complex reasoning and creative generation. Therefore, we employ larger-scale models for these two tasks, specifically the open-source DeepSeek-V3.

540     \*\* Identify \*\* You are an expert in prompt engineering and constraints design for API logs. Your  
541     role is to iteratively refine prompts so they generate stronger constraints and corresponding  
542     Python detection functions. Your should output modification suggestions for the current prompt.  
543     [*Input/Output Format*] [*Example*]  
544     \*\* Input \*\* [*Normal Log Entries*] [*Attack Log Entries*] [*Current Prompt*]  
545     \*\* Output \*\* [*Modification Suggestions*]

#### (a) Modification Suggestions

**\*\* Identify \*\*** You are an expert in prompt engineering and constraints design for API logs. Your role is to iteratively refine prompts so they generate stronger constraints and corresponding Python detection functions. You should apply the suggested modifications to the current prompt.

[Input/Output Format] [Example]

**\*\* Input \*\*** [Current Prompt] [Modification Suggestions]

**\*\* Output \*\*** [Refined Prompt]

(b) Refined Prompt

Fig. 10. Abbreviated version of the LLM prompt for prompt refinement. The complete prompt is available in our artifact repository [4].

For *Constraint Learning*, the requirements are relatively lower, and we adopt smaller models to balance efficiency and effectiveness. In this work, we experimented with multiple models for constraint learning, including GPT-OSS-120B, GPT-OSS-20B, Gemma-3-4B, and DeepSeek-V3. This hybrid strategy allows us to maintain strong performance while reducing overall system resource consumption and deployment complexity.

*Hyperparameters.* For frequency-based API relation extraction, we set the sliding window size to 20 and select the top-5 most frequent APIs as related APIs. In field clustering, the maximum expansion depth for nested dictionaries is limited to 3, in order to avoid field explosion from excessive expansion. For each API, we generate up to 10 normal logs and 10 attack logs for use in prompt refinement. Prompt refinement is iterated for 10 rounds to ensure that the prompts sufficiently adapt to the synthesized attack scenarios. Further experimental details can be found in our code repository [4].

## 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 3. Overall evaluation of AgenticNorm

Model	TrainTicket			NiceFish		
	Precision	Recall	F1	Precision	Recall	F1
LogRobust [51]	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
<b>AgenticNorm (Ours)</b>	1.00	0.86	<b>0.92</b>	1.00	0.92	<b>0.95</b>

- **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.

*Baselines.* To demonstrate the effectiveness of AgenticNorm, we compare against three categories of methods: (1) *model-learning-based baselines*, including LogRobust [51], LogFormer [15], and RAPID FastLogAD [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

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

#### 4.2 Results and Analysis

*RQ1: Overall Performance.* Table 3 summarizes the overall comparison<sup>1</sup>. 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 rules. AgenticNorm preserves the perfect precision of WebNorm while substantially improving recall (0.86 / 0.92), thus delivering the strongest overall detection performance.

<sup>1</sup>We 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 led to improved precision but reduced recall. The results shown here reflect this corrected version.

Table 4. Ablation Study

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

Table 5. Comparison between Number of Tokens with and without Clustering

	With Clustering	Without Clustering
TrainTicket	$7.2 \times 10^3$	$2.4 \times 10^5$
NiceFish	$6.0 \times 10^3$	$1.5 \times 10^4$

Table 6. 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

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

**RQ2: Ablation Study.** Table 4 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 (in Constraint Learning) leads to smaller but still notable degradation ( $0.92 \rightarrow 0.67$  on TrainTicket and  $0.95 \rightarrow 0.50$  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 5 reports the token counts for each constraint 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 constraints.

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

**RQ3: Comparison between Different LLMs.** Table 6 shows results when varying the LLM used for the *Constraint Learning* module, while keeping *Attack Generation* and *Prompt Refinement* fixed to

687		
688		
689	/api/v1/preserveTicket	Range Constraints:
690	arguments.oti.assurance: -2	<ul style="list-style-type: none"> <li>- All numeric fields must be within a valid domain depending on type:           <ul style="list-style-type: none"> <li>- IDs, counters, quantities, prices, and assurance-like fields must be non-negative.</li> <li>- Percentages/probabilities must be within [0, 1] or [0, 100].</li> </ul> </li> </ul>
691	Simplified Log Entity	assert log["arguments.oti.assurance"] > 0
692	Refined Prompt	Learned Constraint

Fig. 11. An example from TrainTicket illustrating how prompt refinement improves the quality of generated constraints. 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 constraints.

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 constraints 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 an open-source 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 simply replacing heavyweight proprietary models with smaller ones is insufficient. While WebNorm functions well with powerful heavyweight LLMs, its constraints 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.

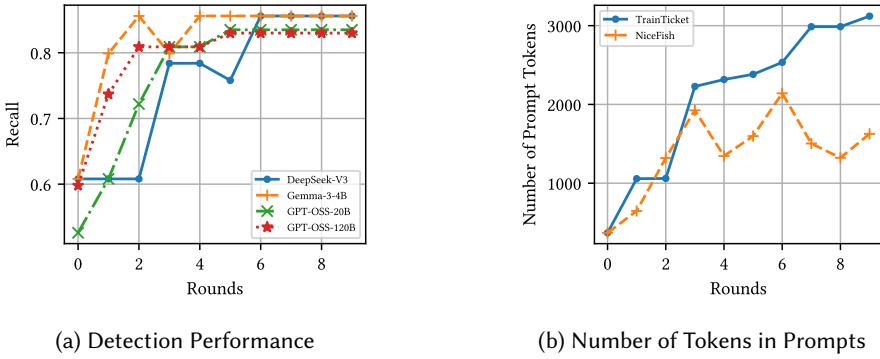
**RQ4:** Simply substituting smaller LLMs into WebNorm leads to severe performance degradation, highlighting the necessity of our architectural innovations for making lightweight deployment viable.

## 5 Discussion

### 5.1 Impact of Adversarial Attacks on Prompt Refinement

Adversarial attacks play a crucial role in refining the prompts used for constraint generation. At the initial stage (Round 0), the prompt may fail to capture critical constraints, 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 constraint `assert log["arguments.oti.assurance"] > 0`. This constraint enables the system



(a) Detection Performance

(b) Number of Tokens in Prompts

Fig. 12. Different Rounds of Prompt Refinement

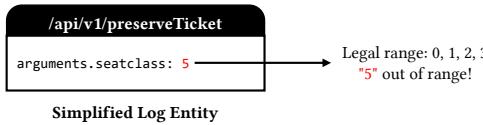


Fig. 13. An example from TrainTicket that cannot be detected by AgenticNorm. In this example, the range of a given field should be 0, 1, 2, 3 according to the system documentation. However, AgenticNorm does not know this information and thus cannot detect the tampering when the field is set to 5.

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 12a 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 after 5–6 rounds.

This trend aligns with Figure 12b, 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 constraints 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 13 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

785 approach relies solely on patterns learned from the logs, which may not cover all domain-specific  
 786 constraints. More detailed examples can be found in our repository [4].  
 787

#### 788 5.4 Limitations

789 Despite the promising results of AgenticNorm, several limitations remain.  
 790

791 *Benchmark Selection.* Our evaluation is restricted to two benchmarks (TrainTicket and NiceFish).  
 792 While these datasets are widely used in prior work, they may not fully reflect the diversity of  
 793 real-world applications, especially in large-scale industrial or domain-specific systems. Moreover,  
 794 our attack synthesis is guided by the OWASP API Security Top 10, which provides strong cover-  
 795 age of common vulnerabilities but may overlook emerging or highly specialized attack patterns.  
 796 This suggests that future work should consider integrating adaptive or domain-specific attack  
 797 taxonomies.  
 798

799 *Model Dependencies.* Although AgenticNorm is designed for lightweight deployment, certain  
 800 modules (e.g., attack generation and prompt refinement) still rely on larger open-source models.  
 801 This hybrid strategy ensures effectiveness but may limit applicability in environments with strict  
 802 computational or resource constraints. In addition, the iterative prompt refinement process increases  
 803 prompt length and complexity, which may reduce efficiency and introduce difficulties in maintaining  
 804 refined prompts at scale.  
 805

## 6 Related Work

806 *Log Anomaly Detection.* Early attempts at anomaly detection from logs were largely based on  
 807 analyzing execution traces of systems or individual APIs, with the goal of spotting deviations  
 808 from expected behaviors [48]. Classical approaches mostly relied on manually written rules or  
 809 statistical thresholds [18, 34, 36, 38, 39, 47, 49]. While useful in certain domains, these methods  
 810 require expert-crafted specifications and often fail to generalize across applications.  
 811

812 With the development of machine learning, researchers began to explore learning-based ap-  
 813 proaches that automatically infer normal patterns from logs. Such methods can be broadly cate-  
 814 gorized into two groups: (1) *model-learning-based approaches*, which train predictive models from  
 815 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.  
 816

817 Model-learning-based approaches emerged with the advent of data-driven methods, where  
 818 models are trained to capture behavioral patterns directly from log data [1–3, 6, 7, 20, 21, 25,  
 819 27, 32, 35, 40–42, 45, 46]. A large body of work in this direction adopts deep learning models to  
 820 classify log sequences as normal or anomalous. Recurrent architectures have been widely used  
 821 to capture sequential dependencies [8, 10], while CNN-based solutions exploit local contextual  
 822 signals [14, 26]. Recent advances leverage Transformers [15, 19], graph neural networks [50],  
 823 or pretrained language models tailored for log data [16, 17]. In addition, training-free retrieval  
 824 methods have been proposed to exploit pre-trained models without fine-tuning, thereby reducing  
 825 training costs and emphasizing token-level semantics [33]. Other works focus on improving data  
 826 efficiency, for example by employing pseudo anomaly generation to augment scarce training  
 827 data [24] or by integrating active learning into retrieval-augmented generation frameworks for  
 828 anomaly detection [12]. Despite their predictive strength, these neural methods often act as black  
 829 boxes, providing little insight into the root cause of anomalies and occasionally overlooking subtle  
 yet critical deviations.  
 830

831 To address the limitations of black-box models, a complementary research direction emphasizes  
 832 *explainability* through rule-learning-based methods. This line of work constructs explicit normality  
 833 constraints that enable both anomaly detection and interpretable explanations. The most prominent

example is WebNorm [23], which encodes behavioral constraints of web systems as first-order logic rules derived from logs. While effective, WebNorm relies heavily on source code analysis and large proprietary models, and it does not explicitly enforce the consistency between logs and their underlying data sources. Our work builds on this direction, proposing techniques that refine normality inference with lightweight, deployable models and enhanced relational reasoning.

*RESTful API Security.* RESTful APIs, by virtue of their statelessness, simplicity, and ubiquity, have become a critical component of modern web systems as well as an essential surface for attacks. Prior research has explored automated vulnerability discovery through API testing and fuzzing [5, 9, 11, 29, 30, 43], where request sequences or payloads are systematically mutated to reveal abnormal behaviors. These methods are often guided by API specifications, dependency constraints [30, 43], or machine learning predictions [28], reducing the need for manual rule design. More recent approaches further refine fuzzing strategies to target specific classes of vulnerabilities, such as injection attacks and cross-site scripting [9, 11], thereby improving the precision and effectiveness of automated security testing.

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

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

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

## 7 Conclusion

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

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

## 883 Data Availability

884 All source code, illustrative examples, detailed prompts, datasets, and experimental results related  
 885 to AgenticNorm are publicly available at <https://sites.google.com/view/agenticnorm/home> [4].  
 886

## 887 References

- 888 [1] Mithun Acharya, Tao Xie, Jian Pei, and Jun Xu. 2007. Mining API patterns as partial orders from source code: from  
 889 usage scenarios to specifications. In *ESEC/FSE*. <https://doi.org/10.1145/1287624.1287630>
- 890 [2] Md Rakibul Alam, Ilias Gerostathopoulos, Christian Prehofer, Alessandro Attanasi, and Tomas Bures. 2019. A  
 891 framework for tunable anomaly detection. In *2019 IEEE International Conference on Software Architecture (ICSA)*. IEEE,  
 892 201–210.
- 893 [3] Hen Amar, Lingfeng Bao, Nimrod Busany, David Lo, and Shahar Maoz. 2018. Using finite-state models for log  
 894 differencing. In *ESEC/FSE*. <https://doi.org/10.1145/3236024.3236069>
- 895 [4] Anonymous Authors. 2025. *Details of AgenticNorm*. <https://sites.google.com/view/agenticnorm/home>
- 896 [5] Vaggelis Atlidakis, Patrice Godefroid, and Marina Polishchuk. 2019. RESTler: Stateful rest api fuzzing. In *ICSE*.  
<https://doi.org/10.1109/ICSE.2019.00083>
- 897 [6] Ivan Beschastnikh, Yuriy Brun, Sigurd Schneider, Michael Sloan, and Michael D Ernst. 2011. Leveraging existing  
 898 instrumentation to automatically infer invariant-constrained models. In *ESEC/FSE*. <https://doi.org/10.1145/2025113.2025151>
- 899 [7] Jakub Breier and Jana Branišová. 2015. Anomaly detection from log files using data mining techniques. In *Information  
 900 Science and Applications*. 449–457. [https://doi.org/10.1007/978-3-662-46578-3\\_53](https://doi.org/10.1007/978-3-662-46578-3_53)
- 901 [8] Andy Brown, Aaron Tuor, Brian Hutchinson, and Nicole Nichols. 2018. Recurrent neural network attention mechanisms  
 902 for interpretable system log anomaly detection. In *MLCS*. <https://doi.org/10.1145/3217871.3217872>
- 903 [9] Gelei Deng, Zhiyi Zhang, Yuekang Li, Yi Liu, Tianwei Zhang, Yang Liu, Guo Yu, and Dongjin Wang. 2023. NAU-  
 904 TILUS: Automated RESTful API Vulnerability Detection. In *USENIX Security*. <https://www.usenix.org/conference/usenixsecurity23/presentation/deng-gelei>
- 905 [10] Min Du, Feifei Li, Guineng Zheng, and Vivek Srikumar. 2017. DeepLog: Anomaly detection and diagnosis from system  
 906 logs through deep learning. In *CCS*. <https://doi.org/10.1145/3133956.3134015>
- 907 [11] Wenlong Du, Jian Li, Yanhao Wang, Libo Chen, Ruijie Zhao, Junmin Zhu, Zhengguang Han, Yijun Wang, and Zhi  
 908 Xue. 2024. Vulnerability-oriented testing for restful apis. In *USENIX Security*. <https://www.usenix.org/conference/usenixsecurity24/presentation/du>
- 909 [12] Chiming Duan, Tong Jia, Yong Yang, Guiyang Liu, Jinbu Liu, Huxing Zhang, Qi Zhou, Ying Li, and Gang Huang. 2025.  
 910 EagerLog: Active Learning Enhanced Retrieval Augmented Generation for Log-based Anomaly Detection. In *ICASSP  
 911 2025-2025 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*. IEEE, 1–5.
- 912 [13] Erik Feyen, Jon Frost, Leonardo Gambacorta, Harish Natarajan, and Matthew Saal. 2021. Fintech and the digital  
 913 transformation of financial services: implications for market structure and public policy. *BIS papers* (2021).
- 914 [14] Yuanyuan Fu, Kun Liang, and Jian Xu. 2023. Mlog: Mogrifier lstm-based log anomaly detection approach using  
 915 semantic representation. *IEEE Transactions on Services Computing* 16, 5 (2023), 3537–3549. <https://doi.org/10.1109/TSC.2023.3289488>
- 916 [15] Hongcheng Guo, Jian Yang, Jiaheng Liu, Jiaqi Bai, Boyang Wang, Zhoujun Li, Tieqiao Zheng, Bo Zhang, Junran  
 917 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>
- 918 [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>
- 919 [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>
- 920 [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>
- 921 [19] Shaohan Huang, Yi Liu, Carol Fung, Rong He, Yining Zhao, Hailong Yang, and Zhongzhi Luan. 2020. HitAnomaly:  
 922 Hierarchical transformers for anomaly detection in system log. *IEEE transactions on network and service management*  
 923 17, 4 (2020), 2064–2076. <https://doi.org/10.1109/TNSM.2020.3034647>
- 924 [20] Qiao Kang, Ankit Agrawal, Alok Choudhary, Alex Sim, Kesheng Wu, Rajkumar Kettimuthu, Peter H Beckman,  
 925 Zhengchun Liu, and Wei-keng Liao. 2019. Spatiotemporal real-time anomaly detection for supercomputing systems.  
 926 In *2019 IEEE International Conference on Big Data (Big Data)*. IEEE, 4381–4389.
- 927 [21] Ivo Krka, Yuriy Brun, and Nenad Medvidovic. 2014. Automatic mining of specifications from invocation traces and  
 928 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](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] 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>
- [35] 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>
- [36] 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.
- [37] 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.
- [38] 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>
- [39] 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>
- [40] 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.
- [41] 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 (SLAML 10)*.
- [42] 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.
- [43] 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>
- [44] 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.
- [45] Neil Walkinshaw and Kirill Bogdanov. 2008. Inferring finite-state models with temporal constraints. In ASE. <https://doi.org/10.1109/ASE.2008.35>
- [46] 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.

- 981 [47] Kenji Yamanishi and Yuko Maruyama. 2005. Dynamic syslog mining for network failure monitoring. In *KDD*.  
982 <https://doi.org/10.1145/1081870.1081927>
- 983 [48] Wenqian Ye, Guangtao Zheng, Xu Cao, Yunsheng Ma, and Aidong Zhang. 2024. Spurious correlations in machine  
984 learning: A survey. *arXiv preprint arXiv:2402.12715* (2024). <https://arxiv.org/abs/2402.12715>
- 985 [49] Ting-Fang Yen, Alina Oprea, Kaan Onarlioglu, Todd Leetham, William Robertson, Ari Juels, and Engin Kirda. 2013.  
986 Beehive: Large-scale log analysis for detecting suspicious activity in enterprise networks. In *ACSAC*. <https://doi.org/10.1145/2523649.2523670>
- 987 [50] Chenxi Zhang, Xin Peng, Chaofeng Sha, Ke Zhang, Zhenqing Fu, Xiya Wu, Qingwei Lin, and Dongmei Zhang.  
988 2022. DeepTraLog: Trace-log combined microservice anomaly detection through graph-based deep learning. In *ICSE*.  
989 <https://doi.org/10.1145/3510003.3510180>
- 990 [51] Xu Zhang, Yong Xu, Qingwei Lin, Bo Qiao, Hongyu Zhang, Yingnong Dang, Chunyu Xie, Xinsheng Yang, Qian Cheng,  
991 Ze Li, et al. 2019. Robust log-based anomaly detection on unstable log data. In *ESEC/FSE*. <https://doi.org/10.1145/3338906.3338931>

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

993

994

995

996

997

998

999

1000

1001

1002

1003

1004

1005

1006

1007

1008

1009

1010

1011

1012

1013

1014

1015

1016

1017

1018

1019

1020

1021

1022

1023

1024

1025

1026

1027

1028

1029