AgenticNorm: Multi-Agent Lightweight Anomaly Detection for Web Applications

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

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

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

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

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

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1 Introduction

Web applications play a critical role in modern infrastructures, supporting domains such as finance [13, 44], e-commerce [37], and healthcare [22]. Their reliability and security are of paramount importance. Unfortunately, web frontends are inherently manipulable: attackers can alter client-side code or parameters to bypass validations, tamper with workflows, or inject attack behaviors.

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

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

To mitigate such risks, log analysis has become an effective defense mechanism. Logs in web systems typically record detailed interactions between clients and servers, including API calls, request parameters, and response statuses. Analyzing these logs enables the identification of attack interaction patterns that may signal security threats [2, 49]. Current state-of-the-art log analysis methods can be broadly classified into two categories: (1) *model-learning-based approaches*, which train predictive models from normal logs and use them to detect anomalies [1–3, 6, 7, 20, 21, 25, 27, 32, 35, 40–42, 45, 46], and (2) *rule-learning-based approaches*, which mine logical constraints from logs and detect violations [23].

The first category, model-learning-based approaches, typically employ deep learning models to classify logs as normal or attack [8, 10]. While effective in many scenarios, these approaches suffer from limited interpretability: the output is often a binary decision without clear explanations of the underlying cause. Given the large volume of logs in practice, even a small false positive rate can result in overwhelming numbers of alerts, complicating deployment. Moreover, these methods often struggle to detect subtle anomalies [33]; when malicious modifications closely mimic normal behaviors, the models tend to misclassify them, leading to missed detections.

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

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

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

- **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 for input context reduction.** To overcome lightweight models' limitations on long and nested logs, AgenticNorm expands JSON entities into flattened fields and groups them into semantically coherent clusters. Each cluster is processed independently, greatly reducing input token length while preserving meaningful comparisons. This allows lightweight models to handle large-scale logs without resorting to heavyweight external LLMs.
- **Prompt refinement via generated attacks.** To address prompt sensitivity, AgenticNorm introduces an iterative loop where adversarial logs are automatically generated to expose missing

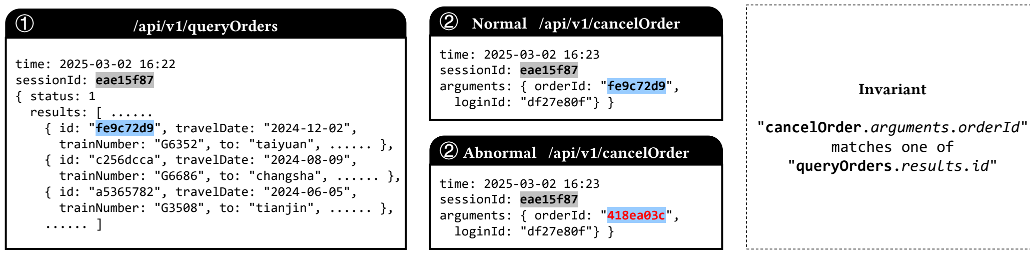


Fig. 1. A motivating example from the TrainTicket dataset illustrating a ticket refund workflow, where the user first retrieves a list of orders using `queryOrders` and then requests a refund through `cancelOrder`. The blue highlights indicate identifiers that should match across the two APIs, while 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 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 attack logs to classify anomalies; and (2) **Invariant-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**: 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 lightweight 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 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

```
Based on the logs, infer the valid values for each field by
referencing these common types of data validation:
1. Data Type Check: ......
2. Range Check: does the value fall within a logical numerical
range? (e.g., temperature, latitude, price).
3. Format Check: ......
```

(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 str")

# 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 time-consuming and project-specific. Figure 4 (left) shows the original WebNorm prompt, which

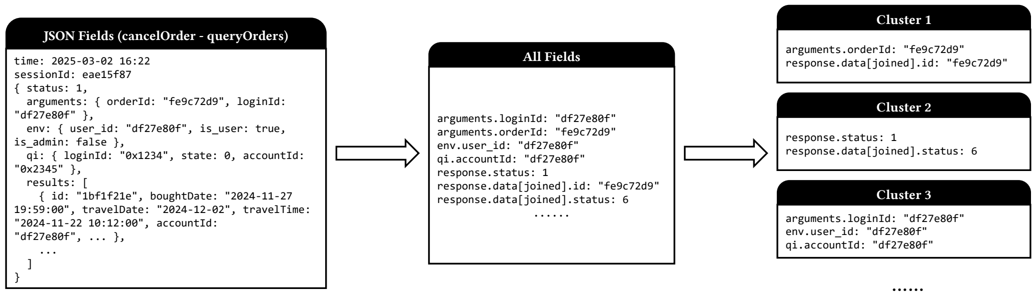


Fig. 3. An illustration of *Field Clustering* on the motivating example from the TrainTicket dataset. The original log entity is decomposed into flatten fields and then clustered into clusters, each containing only related and comparable fields.

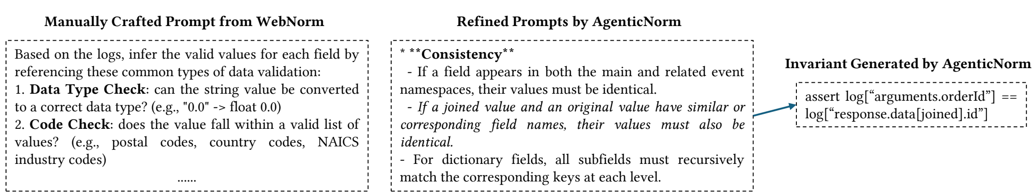


Fig. 4. An illustration of different prompts. The left panel shows the original prompt used in WebNorm, which relies on manually crafted instructions and examples, making prompt adjustment highly labor-intensive. The middle panel adds new instructions to the original prompt, guiding the LLM to generate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

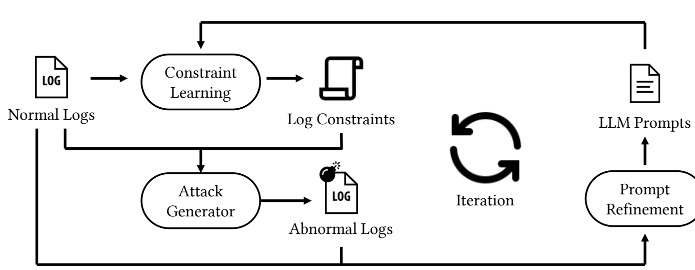


Fig. 5. Method Overview

depends on handcrafted instructions and examples. Our approach (middle) augments the prompt with additional instructions that guide the model to generate attack logs. These attack 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 lightweight model to generate constraints 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

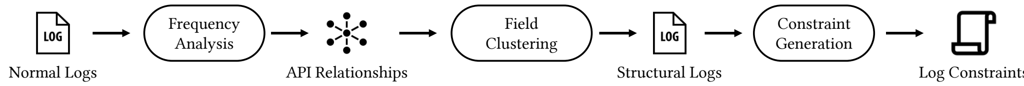


Fig. 6. Constraint Learning

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 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.

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

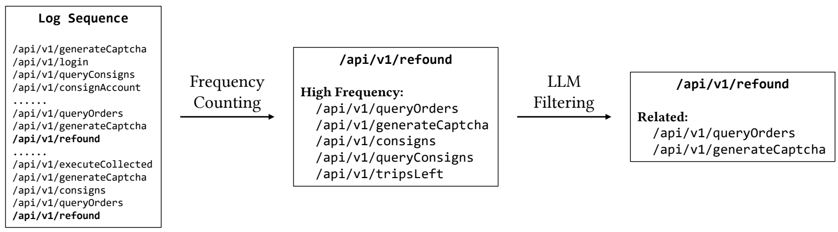


Fig. 7. An example of frequency-based analysis.

$$
\begin{aligned}
\text{Data} := \ & \texttt{unknown} \\
\mid\ & \texttt{bool} \\
\mid\ & \texttt{number} \\
\mid\ & \texttt{string} \\
\mid\ & \texttt{dict}[key_1 : \text{Data}, key_2 : \text{Data}, \ldots] \\
\mid\ & \texttt{array}[\text{Data}]
\end{aligned}
$$

Fig. 8. Grammar for Log Data Types

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 constraints 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 lightweight 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.

Log Structure Discovery. Each API may produce logs with diverse structures, including nested dictionaries and arrays. We first parse the logs to uncover their structural schema and data types.

For each API, AgenticNorm analyzes all log entries and infers a unified schema that captures the common structure, represented as fields and their associated types. Formally, we define a recursive grammar for data types shown in Figure 8.

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

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

The rules are as follows:

- **Dict Expansion**: For a dictionary value, each key is concatenated with its parent field using a dot "." separator. Formally, `d: dict[key: value]` is expanded into `"d.key": value`.
- **Array of Dict Expansion**: For an array of dictionaries, each dictionary key is expanded to a new array field. Formally, `a: array[dict[key: value]]` is expanded into `"a[].key": array[value]`.
- **Field Joining**: In certain cases, meaningful semantics emerge when fields from different structural levels are *joined*. Specifically, if an outer field and an inner field share a common key (e.g., an identifier), we match the entry and promote it as a new joined field.

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

- **Dict Expansion**: `arguments: dict[loginId: string, orderId: string]` is expanded into `"arguments.loginId": string, "arguments.orderId": string`.
- **Array of Dict Expansion**: `results: array[dict[id: number, status: string]]` is expanded into `"results[].id": array[number], "results[].status": array[string]`.
- **Field Joining**: `arguments.orderId` can be joined with the elements of `results` via the `id` field. The result is a new joined field: `"results['joined']": dict[id: number, status: string]`.

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

Through this pipeline, lengthy and complex logs are transformed into compact, semantically organized structures, enabling lightweight LLMs to effectively generate invariants without exceeding context limitations.

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

Table 2. OWASP API Security Top 10 categories and their usage in our framework. Frequency-dependent categories are excluded.

ID	Category	Usage in Our Framework
API1	Broken Object Level Authorization	Used. generates attack logs where access control constraints are bypassed.
API2	Broken Authentication	Used. simulates login/session anomalies not captured by current constraints.
API3	Broken Object Property Level Authorization	Used. focuses on tampering with specific fields in objects.
API4	Unrestricted Resource Consumption	Excluded. requires modeling frequency/traffic features.
API5	Broken Function Level Authorization	Used. attack logs where high-privilege functions are exposed to low-privilege actors.
API6	Unrestricted Access to Sensitive Business Flows	Used. simulates bypasses of workflow constraints.
API7	Server-Side Request Forgery	Used. generates adversarial logs where external calls are injected.
API8	Security Misconfiguration	Used. models cases where abnormal settings or defaults appear in logs.
API9	Improper Inventory Management	Excluded. relies on large-scale endpoint enumeration patterns.
API10	Unsafe Consumption of APIs	Used. synthesizes attack logs involving unvalidated or malicious upstream data.

3.3 Attack Generation

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

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

In our framework, we adopt the OWASP API Security Top 10 as the foundation for guiding attack synthesis. Because our anomaly detection operates at the log level rather than the traffic level, frequency-dependent categories (e.g., rate limiting and resource exhaustion) are excluded. For the remaining categories, we refine them into finer-grained subcategories using LLM-based analysis, ensuring that each synthesized attack corresponds to the log semantics of the target system. Table 2 summarizes the OWASP API Security Top 10 categories and indicates their usage in our pipeline.

Concretely, for each API and each API pair, we first sample a set of normal log entries. Guided by the OWASP classification and the descriptions of each attack category, we then prompt an LLM to generate corresponding attack log entries. The generated logs are required to bypass the existing invariants whenever possible. These attack entries, together with the sampled normal logs, form a labeled dataset that is subsequently used for prompt refinement. The prompt used for attack

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

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

Require: Dataset D containing pairs of normal logs N and attack logs A
Require: Original prompt P
Ensure: Refined prompt P'

```
M_s ← [ ] {Initialize list of modification suggestions}
for each (N, A) ∈ D do
    M ← LLM("Generate modification suggestion", N, A, P) {Generate modification suggestions based on a normal-attack log pair}
    M_s.append(M)
end for
P' ← LLM("Refine prompt", P, M_s) {Refine the original prompt by incorporating aggregated suggestions}
return P'
```

generation is shown in Figure 9, with detailed attack strategies and input/output examples provided in our artifact repository [4].

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 invariant 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 invariant 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

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

(a) Modification Suggestions

** *Identify* ** You are an expert in prompt engineering and invariant 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].

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. 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
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 [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[1]. 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

[1]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 improved precision but reduced recall. The results shown here reflect this corrected version.

Table 4. Ablation Study

Model	TrainTicket	NiceFish
Original (AgenticNorm)	**0.92**	**0.95**
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	7.2×10^3	2.4×10^5
NiceFish	6.0×10^3	1.5×10^4

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

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 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 → 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 5 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 constraints.

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

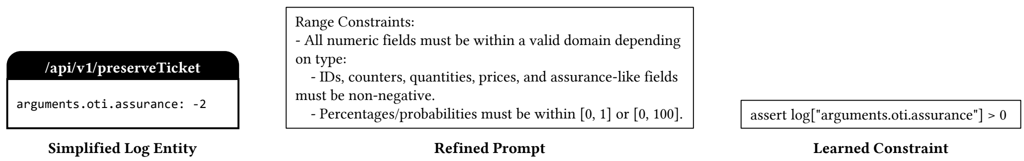


Fig. 11. An example from TrainTicket illustrating how prompt refinement improves the quality of generated constraints. The left panel shows a simplified version of the log entity, the middle panel presents the refined prompt with the additional range constraints compared to the original prompt, and the right panel displays the generated invariant.

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 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 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 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.

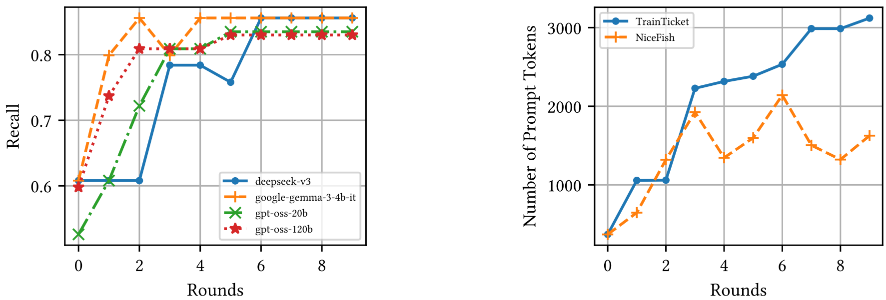
RQ4: Simply substituting smaller LLMs into WebNorm leads to severe performance degradation, highlighting the necessity of our architectural innovations for making lightweight deployment viable.

5 Discussion

5.1 Impact of Adversarial Attacks on Prompt Refinement

Adversarial attacks play a crucial role in refining the prompts used for invariant 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



(a) Detection Performance (b) Number of Tokens in Prompts

Fig. 12. Different Rounds of Prompt Refinement

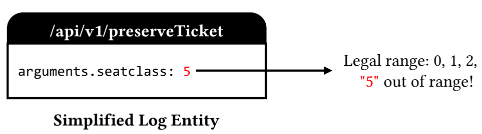


Fig. 13. An example from TrainTicket that cannot be detected by AgenticNorm. In this example, the range of a given field should be 0, 1, 2, 3 according to the system documentation. However, AgenticNorm does not know this information and thus cannot detect the tampering when the field is set to 5.

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 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 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 [48]. Classical approaches mostly relied on manually written rules or statistical thresholds [18, 34, 36, 38, 39, 47, 49]. 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, 35, 40–42, 45, 46]. 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 [50], 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 [33]. 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 constraints of web systems as first-order logic rules derived from logs. While effective, WebNorm relies heavily on source code analysis and large external 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 and ubiquity, have become an essential surface for attacks in modern web systems. Prior research has extensively explored automated vulnerability discovery through API testing and fuzzing [5, 9, 11, 29, 30, 43]. These methods typically mutate request sequences or payloads to trigger failures, guided by API specifications, dependency constraints [30, 43], or machine learning predictions [28]. Enhanced strategies further refine the fuzzing process to target specific classes of vulnerabilities such as injection attacks or cross-site scripting [9, 11].

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, closed-source 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.

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