Detecting and Explaining Anomalies Caused by Web Tamper Attacks via Building Consistency-based Normality

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ABSTRACT

Web applications are crucial infrastructure in the modern society, which have high demand of reliability and security. However, their frontend can be manipulable by the clients (e.g., the frontend code can be modified to bypass some validation steps), which incurs the runtime anomaly when operating the web service. Existing state-of-the-art anomaly detectors largely learn a deep learning model from the collected logs to predict abnormal logs with a probability. While effective in general, those approaches can suffer from inaccuracy (e.g., caused by subtle difference between the normal and abnormal/attack logs) and need additional efforts for root cause analysis.

In this work, we propose WebNorm, an anomaly detection approach to detecting and explaining the attack-caused anomalies on web applications in a unified way. Our rationale lies in learning the behaviorial normalities of a running web application as invariants. The normalities are designed regarding data normality (e.g., what information shall be consistent across different events), flow normality (e.g., what events shall happen under certain circumstances), and common-sense normality (e.g., what is the normal range of some parameter). The violation of the invariants indicates both the alarm and its explanation. WebNorm monitors the application behaviors by capturing the information flows between entities such as frontend, service, and database. Further, it learns the behaviorial normalities in terms of logical rules so that it can detect and explain behaviorial anomaly by the inconsistency between the normalities and the runtime application behaviors. We model the invariants as first-order logics, transferrable to executable Python scripts to generate alarm with explainable root cause. Our extensive experiment showing that, on the benchmark of *TrainTicket*, *NiceFish*. WebNorm improves the precision and the recall of the baselines such as LogAnomaly, LogRobust, DeepLog, NeuralLog, PLELog, ReplicaWatcher by more than 52.3% and 37.7% respectively, serving as a new state-of-the-art anomaly detection solution.

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1 INTRODUCTION

Web applications play a significant role in modern Information Technology infrastructure across core industries, such as government, banking, medical, and even the military [13, 14, 35, 40, 45], The sensitivity and criticality of its use cases call for high levels of security, i.e. Confidentiality, Integrity and Availability of the web application's data. However, functional bugs and security vulnerabilities introduced through insecure coding practices or security misconfiguration can undermine the security of the web application, with the potential to cause tremendous loss or repercussions for its stakeholders.

Web applications can be loosely divided into the frontend (running in a client browser) and backend (running in a server) components that communicate through well-established protocols, such as HTTP and WebSocket. Once it is deployed and made accessible to the public via the Internet, curious and knowledgeable users (or attackers) can extract, examine, and modify the frontend code freely, including tampering with business logic encoded in the frontend components of the web application, resulting to the web application behaving in unexpected ways. For example, member of public [37] discovered that Vistara Airlines suffered from payment bypass attacks where an attacker can manipulate input parameters to bypass the payment stage of transactions to obtain free goods or services.

This class of vulnerabilities are typically undetected by existing out-of-band security tools such as Web Application Firewalls as existing tools are (1) stateless, i.e. they are effective against well-known injection patterns but ineffective when the attack does not employ such patterns, (2) have no knowledge of what a normal sequence of requests to a web application and the corresponding data payloads should look like, beyond mere conformance to protocol standards.

The ability to detect and observe similar exploratory code-tampering activities, even failed ones, is invaluable to operators of web applications to (1) understand segments of the application which are actively being enumerated for vulnerabilities by threat actors, and (2) identify, investigate and respond to potential tampering activities where backend defences may have been insufficient.

As frontend code can be tampered, the interface between the frontend and backend components make for a trust boundary: runtime logs generated by backend components from interactions with the frontend is a reliable source of data for anomaly detection.

Log monitoring solutions that are widely adopted in the real world, such as Splunk [9], Elastic Stack [11] and IBM QRadar [18] detect anomalies based on predefined and customized rules (e.g., HTTP status, log keywords, and statistical deviation). Similar to Web Application Firewalls, most log monitoring solutions are stateless, with its knowledge of the web application being safeguarded limited to manually crafted rulesets that are not scalable nor adaptive as the application evolve. To capture abnormalities more effectively and with less manual effort, many researchers adopt deep-learning based solutions such as deep (graph) neural network models [10, 16, 30, 54] to learn the abnormal logs by preparing a training dataset in an either supervised or unsupervised ways. While existing solutions are more effective than mere rule-based log monitoring solutions, they still struggle to detect tamper-attack-triggered anomalies:

- **C1 (Subtle change of abnormality):** Firstly, unprecedented attacks can cause the generated logs to change in a very subtle way, which can be easily ignored by conventional deep-learning solutions. Given that the frontend code can be tampered in a multitude of unexpected ways, it is challenging to decide the granularity of the log features (e.g., tokenization [27], normalization [8], and word embedding [47]). Consequently, discriminative information could be abstracted away, or noisy information could be learned, resulting in overfitting of the resulting model.
- **C2 (Distribution-shift):** Secondly, explorative code tampering tactics can evolve quickly, making it challenging to collect new datasets to update the learned model, especially false-negative logs.
- **C3 (Explainability):** Finally, the state-of-the-art deep learning models usually project a sequence of logs into a suspiciousness score, which necessitates the response teams to triage the validity of an alert, which is not straightforward as it requires understanding what normal behaviour looks like and careful examination of the log sequence to identify anomalies due to the lack of explainability. This also delays downstream post-mortem response efforts such as root cause analysis and counter-measure deployment, should the alert be valid.

In this work, we propose, WebNorm, a LLM-based anomaly detection approach for web applications that detects and explains tamper attack-triggered anomalies in an unified way. Our approach assumes that (1) any web applications need to be tested before their deployment and (2) the *normality* of the application is much more stable than a novel attack. Thus, we collect the runtime logs of a target application in the testing-stage to construct their behavioral normalities in the form of first-order logic. The normalities include data normality (e.g., what information shall be consistent across different events), flow normality (e.g., what events shall happen under certain circumstances), and common-sense normality (e.g., what is the normal range of some parameter). For example, WebNorm can infer an invariant that "*the price of an item retrieved from the database should be consistent with the price passed from the front end*". Any violation of the invariant (e.g., the price tampered in the frontend) can raise an alarm with an explanation (e.g., the price inconsistency in this case).

We construct extensive facilities for our evaluation of WebNorm on state-of-the-art benchmarks *TrainTicket* [55] and *NiceFish* [38]:

- **Seeding/Testing Scenarios**: A set of pre-defined seeds (i.e., normal scenarios) in addition to Industry Fault to benchmark our reference behavioral model.
- **Abnormal Scenarios**: An attack toolkit towards the *TrainTicket* and *NiceFish* benchmark, called `TT-Attack` dataset, consisting of over 40 types of tamper attacks.

We evaluate the performance of WebNorm by comparing its precision, recall, and F1-scores with state-of-the-art baselines such as LogAnomaly [36], LogRobust [53], DeepLog [10], NeuralLog [28], PLELog [50], ReplicaWatcher [21]. The results show that (1) WebNorm exhibits significant improvement over the baseline by 73.6% increase in precision and 40.7% increase in recall over the state of the art methods at reasonable cost of runtime overhead, (2) WebNorm achieves the explanation accuracy of 92.3%, demonstrating its effectiveness for root cause analysis, and (3) the precision of WebNorm is robust against the perturbation of the number of seeding scenarios, and its recall is largely preserved as long as the seeding scenarios achieve a minimum coverage of 50% of the system.

In summary, we make the following contributions:

- We propose, WebNorm, a solution for detecting and explaining the tamper-attack triggered anomalies of a web application, by addressing the challenge of subtle changes of abnormalities and explainability. WebNorm learns the invariants on raw logs as consistency rules (i.e., data consistency, flow consistency, and common-sense consistency) in the form of first-order logic. Any violation of the invariant indicates both the alarm and the explanation.

- We make a comprehensive evaluation upon the state-of-the-art *TrainTicket* and *NiceFish* benchmark. We identify more than 40 types of tamper attack towards the benchmark based on its vulnerabilities, which can lay a foundation for the follow-up anomaly detection in the community.
- We deliver WebNorm as a deployable tool to help practitioners detect anomalies and identify corresponding root causes in practice. A demonstration of WebNorm is available at [39].
- Our extensive experiments show the precision and soundness of the WebNorm. Specifically, WebNorm significantly reaches a high accuracy on the anomlay detection.

More of the tool's videos and experimental data are available at [39].

2 MOTIVATING EXAMPLE

Figure 1 shows the log examples, normal and abnormal, on a ticket rebooking scenario in the *TrainTicket* system [55], a popular web application used as benchmark for various DevOps tasks.

Normal Scenario. In such a ticket-rebooking scenario, a user can change its reservation after he or she has booked a ticket. If the new ticket has a different price, he or she need to pay extra price (line 8-13). Otherwise, the system just update the order information without charging the user with extra payment. As showed in the Figure 1, the frontend code can be summarized into three steps (in red circules):

- **Step 1: Load Price (Backend to Frontend).** The system loads the price information and send the calculated extra price to the frontend.
- **Step 2: Payment (optional, Frontend to Backend).** The frontend check whether the extra price is larger than 0. If yes, it invokes the payment service, asking the user to accomplish the additional payment.
- **Step 3: Update Order Information (Frontend to Backend).** The system update the rebooking information (including the extra price information) in the system.

In Figure 1, each interaction between the frontend and the backend derives a log at the backend. We can see that the detailed rebooking information is logged, including the order id (i.e., `orderId=9115`), trip id (i.e., `tripID=D1345`), extra price to pay (i.e., `orderMoneyDifference=27.5`). [1] Next we illustrate how the logs can happen when the curious user explores and modifies the frontend code to avoid the extra payment.

Abnormal Scenario 1 (Tampered Data Consistency). The first tamper can change line 8 in Figure 1 by setting the price of the extra price to be 0 (i.e., `res.data['differenceMoney']=0`). In this case, even if the payment service is invoked (line 9), the user still pays no extra price. The resulted logs is showed in Figure 1, leaving the logs very similar to that in normal scenario, expect that the `price` parameter in the log is recorded as 0.

Abnormal Scenario 2 (Tampered Flow Consistency). The second tamper can change line 5 in Figure 1 by setting the condition in Javascript code (i.e., `res.data['differenceMoney'] != 0`). By this means, the frontend code can no longer exercise the branch to invoke the payment service. As a result, in comparison to the logs in the normal scenario, the resulted logs in the backend miss one log on invoking the payment service.

Challenges. The above examples render very high similarity between logs in normal and abnormal scenarios. Their discriminative features can involve either very detailed parameter value such as `price=0` and `orderMoneyDifference=27.5`, or the existence of *log flows* conditioned on the valuation of specific parameter such as whether the parameter `price` is larger than 0. Those features is domain-specific and logical. Even worse, there could be many logs happen in between those steps, which incurs a long context between critical events. All the above incur great challenges for any inductive approach, for example, to learn a deep (language) model in either supervised or unsupervised way.

Solution and its Rationale. In this work, we propose WebNorm to learn *logical* normality to infer the abnormalities, based on the expected *data consistency*, *flow consistency*, and *common-sense consistency* when the web application is operating, which is more deductive approach in comparison to the state-of-the-arts. Our approach consists of a learning phase and a deployment phase. By mapping the static code and their derived logs, WebNorm learns the potential relation between the parameters across different logs. The code analysis allows us to associate the logs (and their events) even if there are a large number of logs happen in-between them. For example, we can infer that the parameter `orderMoneyDifference` (passed from the backend to the frontend) is semantically equivalent to the parameter `price` (passed from the frontend to the backend). In addition, we confirm with LLM on the potential consistency relation between the parameters. As a result, we can build an invariant such as "$\forall s, s.orderMoneyDifference = s.price$" where s is a rebooking session. Similarly, by building the conditional flow consistency relationship between the frontend code and the backend logs in the learning phase, we can build an invariant such as "$\forall s, s.orderMoneyDifference > 0 \rightarrow e.payDifference$", indicating that a log event of paying extra price should happen if the parameter `orderMoneyDifference` is greater than 0.

Note that, those invariants are learned for just once. Then, we can validate the logs in the deployment phase. In addition, the violation of the learned invariants can serve as both the alarm and the explanation to facilitate the follow-up root cause analysis.

3 APPROACH

Figure 2 shows the overview of WebNorm to report runtime anomalies, consisting of a learning phase and a deployment phase. We assume that a web application (especially in the industrial settings) can have a set of representative (GUI) test cases (or seeds) to test its normal functionalities. Thus, given a target web application, we run the (GUI) test cases against its instrumented version[2] to collect the raw logs (**Log Collection**). For necessary observability, we instrument the application to capture the interaction between the web components such as service, database, and frontend. Technically, each called API with their runtime parameter values is instrumented to record an *event*, as showed in Figure 3 (**Application-specific**

[1]We will discuss how we address the observability challenges in generating the logs via program analysis in Section 3.1

[2]The implementation of instrumentation (e.g., AOP [3]) is transparent to the developers of the target web application.

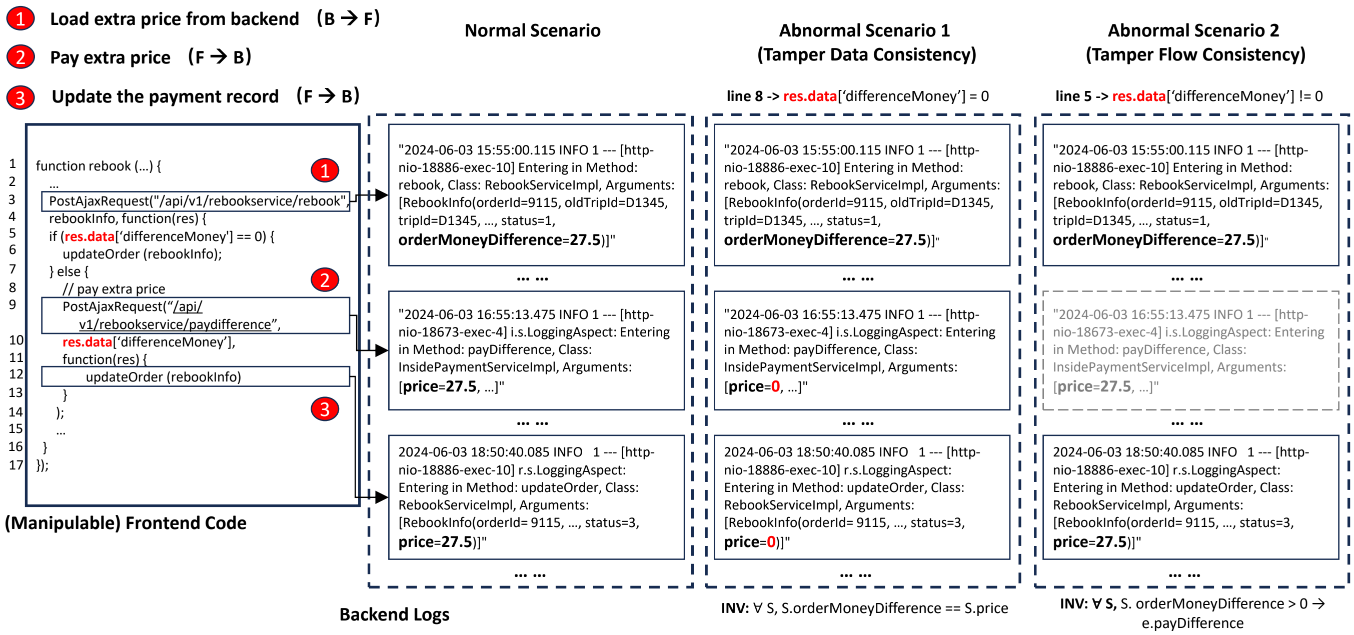

Figure 1: A motivating example showing how the backend anomalies can happen when a curious user (or attacker) explores and modifies the frontend code. The example is taken from the scenario of rebooking a ticket to pay extra price in the *TrainTicket* system. The difference between the logs in the normal scenario and that in the attack scenario is very subtle. In *Abnormal Scenario 1* where the user avoids paying extra price by changing a variable in the frontend, the log difference is a change of integer number (from 27.5 to 0, in red).

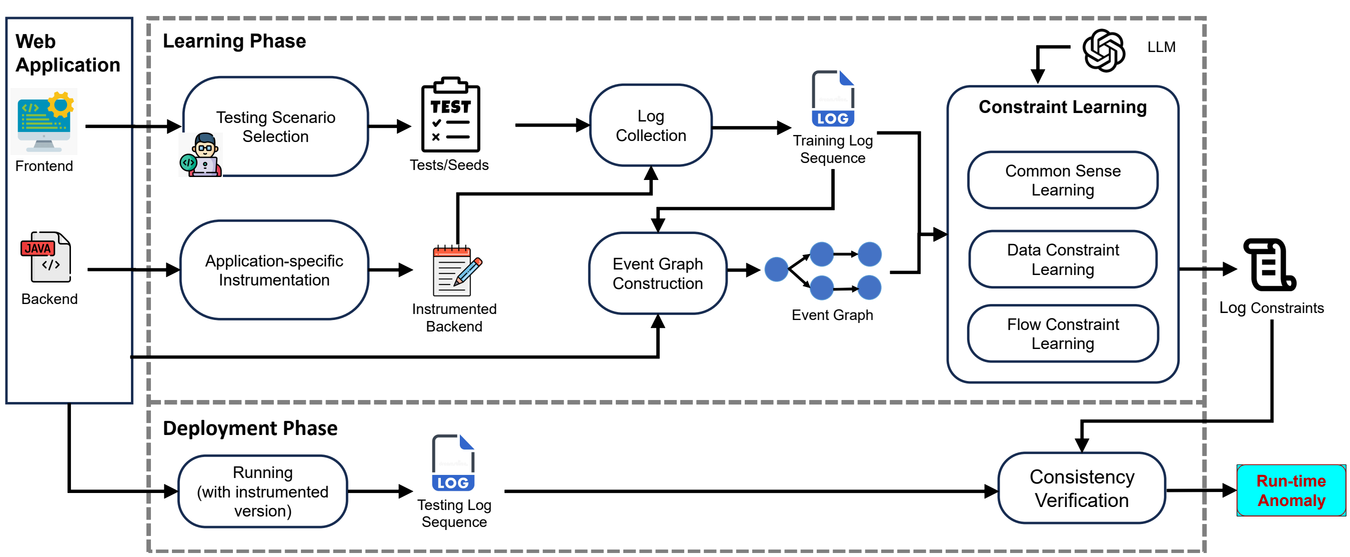

Figure 2: Overview of the design of WebNorm, which extracts the log normalities as first-order logic constraints in the learning phase. The log constraints are used to validate the runtime logs in the deployment phase.

Instrumentation). As a result, one GUI test case can result in a sequence of event as raw logs. Then, we analyze the source code of both frontend and backend to *link* the relevant events by attaching the control and data flow to convert the event sequence to an event graph (**Event Graph Construction**). Subsequently,

Instrumented Logs (Rebook Service as an Example)

Input = RebookInfo (oldTripId=D1345, tripId=D1345, seatType=2, date=2024-06-03)
API = Rebook.service.RebookServiceImpl
Output = Response (orderMoneyDifference=27.5)

Figure 3: An example of instrumented logs for the Rebook API as an event, consisting of API name, and the runtime valuation of the input and the output when it is called.

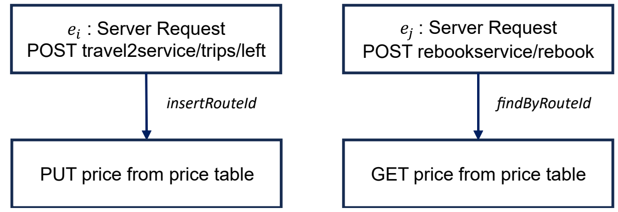

Figure 4: The example of two database sharing events ($e_i \preceq e_j$)

we parse the structured log information to derive a list of log constraints in the form of first-order logics (**Constraint Learning**). Each log constraint can be translated to executable Python script to detect and explain the runtime anomalies in the deployment phase (**Consistency Verification**).

3.1 Event Graph Construction

An event graph captures a variety of relations between the events of an operating web application. Formally, an event graph can be defined as $G = \langle Evt, R \rangle$ where (1) each $e \in Evt$ is an API call with runtime valuation of its input and output, and (2) each $r \in R$ ($R \leftarrow Evt \times Evt$) is a relation defined between two events. Further, we denote the set of input and output of an event e as $e.in$ and $e.out$ respectively. For example, in Figure 3, the input is a `RebookInfo` object (consisting of `oldTripId`, `tridId`, `seatType`, and `date`) and the output is a `Response` object with the extra payment information (i.e., `orderMoneyDifference`). We define three types of relations as follows.

- **DB Sharing:** Given two events (i.e., API call), denoted as e_i and e_j on an event sequence, we call e_i and e_j have a relation of *DB sharing* if e_i writes a data item to DB and e_j query the DB for the same data item, where $e_i \prec e_j$. Here, we use $\prec$ indicates the e_i happens before e_j. The relation demonstrates that there could be a read/written relation between these events.
- **Data Transition:** Given two events e_i and e_j, we call e_i and e_j have a relation of *data transition* if $\exists p \in e_i.out, q \in e_j.in$ ($e_i \prec e_j$) and $p = q$ and there $\nexists e_k(e_i \prec e_k \prec e_j)$ so that $\exists x \in e_k.out, q \in e_j.in, x = q$.
- **Trigger Condition:** Given two events e_i and e_j on an event sequence, we call e_i and e_j have a relation of *trigger condition* if $\exists p \in e_i.in$ can decide whether e_j can happen or not.

Metaphorically speaking, the relation of *DB sharing* and *data transition* is similar to the concept of data dependency in program analysis. In contrast, the relation of *trigger condition* is similar to that of control dependency. In this work, we conduct program analysis to parse the data and control dependency from the backend code, and map the dependency relations to their corresponding events on the logs. Note that, program analysis has its limitation to achieve precise results. Therefore, we conduct may-analysis to ensure that we can complete but unsound results. Based on the potential relation, we extract more precise invariants by interacting with LLM (see Section 3.2).

Shared Database Extraction. We first identify whether an event is database-relevant by defining a list of DB library calls (e.g., JDBC [19], JPA with Hibernate [49], and Spring Data JPA [20]). Then, given two events e_i and e_j, we parse the calls by tracking whether they share a relation by tracking whether they are processing a table column with the same name. For example, as shown in Figure 4, there are two event calling different APIs, i.e., e_i = `POST /api/v1/rebookservice/rebook` and e_j =`POST /api/v1/travel2service/trips/left`. Both events query from the same table `price`, by `insertRouteIds` and `findByRouteId`) respectively. Note that, the table column name (i.e., `price`) accessed by those services should be identical, ensuring the events query the same database.

Data Transition Extraction. We first parse the backend code into static data flow graph, where the nodes of API call are particularly labelled. Specifically, we denote the data flow graph as $G_d = \langle I, V, R, W \rangle$ where each node $n \in I$ represents a program instruction, each node $v \in V$ represents a local or global variable defined or used in the program, each edge $r \in R$ ($R \leftarrow N \times V$) represents that a *read* relation between an instruction and a variable, and each edge $w \in W$ ($W \leftarrow N \times V$) represents that a *write* relation between an instruction and a variable. Then, we map the those API call nodes (or instruction) back to the raw event sequence. Note that, each node in the event sequence is derived by executing an API call. Assume that e_i is mapped to an instruction node i_a, e_j is mapped to an instruction node i_b. If $\exists v \in V$ so that $(i_a, v) \in W$ and $(i_b, v) \in R$, we build a *data transition* relation for e_i and e_j.

Trigger Condition Extraction. We analyze the trigger condition from the frontend code, to identify the if an API call belongs to another API's trigger. For example, as shown in Figure 5, the output of `POST /api/v1/getUserInfo` (i.e., `userInfo.role`) should serve as a trigger condition to the API calls of `POST /api/v1/showContext` and `POST /api/v1/showPaywall`. To this end, we build the link between the frontend code (i.e., ground truth workflow) and the event sequence derived by its execution.

Given two event sequences s_1 = ⟨`getUserDetail`, `getPostDetail`, `showPaywall`⟩ and s_2 = ⟨`getUserDetail`, `getPostDetail`, `showContent`⟩, each derived by executing different branches in the frontend code in Figure 5. Note that, for each event, we also include its runtime parameters and values. Then, we compare s_1, s_2, and the frontend code snippets, to infer if there is a trigger condition relationship between two events. We locate the code snippets where the branch occurs and then use GPTs to determine the trigger relationships between `getUserInfo` and `showContent` or `showPaywall`. In this case, we can build the relation between the event `getUserDetail` (with parameter `role`) and the event `showContent`. By this means, we build the relation for any pairs of the events in the sequence, as the event graph. Note that, those coarse relations are the result of *may*-analysis.

```
function loadArticle(userId, articleId) {
try {
    const userInfo = getUserDetail(userId);
    const articleContent = getPostDetail(articleId
        );
    // Check user's role
    if (userInfo.role === "Premium") {
        showContent(articleContent);
    } else {
        showpaywall(mainPage);
    }
}
```

Figure 5: A code example at the frontend on Nicefish

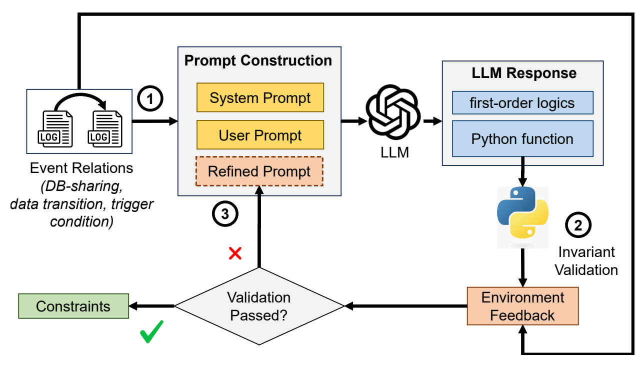

Figure 6: Constraint learning process of WebNorm, consisting of event relation selection, invariant generation, and invariant validation.

3.2 Constraint Learning

Figure 6 shows how we parse event relations into executable invariants with LLM for runtime validation. The process serves two goals, i.e., (1) relevant parameter discrimination and (2) invariant generation. As for parameter discrimination, given a subset of events (or logs) annotated with a relation (e.g., *DB-sharing*, *data transition*, or *trigger condition*), we use LLM to select the most relevant and useful parameters in the event to construct the invariant of different types (i.e., data consistency, flow consistency, and common-sense consistency). As for the invariant generation, we adopt the practice of chain-of-thought to derive the invariant in the form of both first-order logics and Python script. The generated Python scripts are used to run against the prompt-constructing logs to see whether the scripts can parse them to be the normal logs. If not (because of either the runtime exception or failed instances), we can refine the prompt and ask LLM to regenerate the invariants. Note that, the prompt-refining step can be regarded as few-shot learning for the most *fit* Python script given a subset of events. Given a predefined iteration number and a selected subset of logs, the prompt-refining loops will either end up with a confirmed constraint, or report no constraint for the log subset.

3.2.1 Constraint Types. Given that each event e has its own corresponding API, we denote the API signature of e as $e.API$ (see Figure 3 as an example), which is called as *event type*.

Data Consistency. We say there is a **data consistency** between two event types API_1 and API_2 if $\forall \langle e_i, e_j \rangle$, $e_i \prec e_j$, $e_i.API = API_1$, $e_j = API_2$, $\exists p \in e_i.out, q \in e_j.in$, so that $value(p) = value(q)$. Here $value(.)$ is a valuation function to have the runtime value of a parameter. The data consistency is denoted as $DC(API_1(p), API_2(q))$. For example, in Figure 1, in all the events, we can observe that the value of `price` and that of `orderMoneyDifference` always share the same value in the normal scenarios.

Note that, the data consistency exists for those relations of type *DB-sharing* or *data transition* relations. *DB-sharing* or *data transition* relations are defined on event instances, while the data consistency relation is defined on event types. Further, the data consistency is transitive because of the equality relation in its definition.

Flow Consistency. We say there is **flow consistency** between two event types API_1 and API_2 if $\forall \langle e_i, e_j \rangle$, $e_i \prec e_j$, $e_i.API = API_1$, $e_j = API_2$, $\exists cond$ as a condition defined on $e_i.in$ so that if $cond(e_i.in) = true$, e_j need to appear in the log sequence within k events after e_i appears. We denote it as $FC(API_1, API_2, k)$

Common-sense Consistency. We say there is **common-sense consistency** on an event type API if $\forall e$, $e.API = API$, $\exists cond$ as a condition defined on $e.in$ so that $cond(e.in)$ is always true. We denote it as $CSC(API)$.

The above definition allows us to filter candidate sets of event instances or event relations, which are potentially generated because of an invariant (of type of data consistency, flow consistency, and common-sense consistency). We first narrow down the scope of candidates by tracking their relation on event instances. Specifically, given a relation $r = \langle e_i, e_j \rangle$ $(e_i \prec e_j)$, r can only contribute to learn data consistency if it is *DB-sharing* or *data transition* relation, and learn flow consistency if it is *condition trigger* relation. Then, we filter the candidate sets according to the above definition on event types.

3.2.2 Prompt Construction to Generate Invariants. Then, we synthesize different prompts for different types of invariants. Given a candidate set, we parse its relevant code information and log samples to fill in our pre-defined prompt template.

Table 1 shows our prompt template to generate data consistency invariants. We adopt the practice of chain-of-thought and in-context learning to derive both the first-order logic and a Python script. As for the chain-of-thought design, we provide the *step-wise* thought instruction (see <Background> in Table 1) and ask LLM to generate the first-order logics followed by the Python scripts. As for the in-context learning, we provide examples (of both first-order logics and Python scripts) under a variety of scenarios to help LLM to output the results following strict format. As a result, LLM can output the response as showed in Figure 7.

Similarly, we construct prompt template for flow consistency and common-sense consistency invariants as showed in Figure 8 and Figure 9. In both figures, we use <> (e.g., `<class attributes>`) as the placeholder to fill in relevant code and log information. Given the space limit, interested audience can refer to [39] for more detailed prompt templates. As for the common-sense constraints, we ask LLM to focus on the following perspectives:

Table 1: The prompt template for generating data consistency invariants, the code (in red text) and the log samples (in blue text) are to be filled.

<Background>:
You are a software engineer that is extremely good at modelling entity relationships in databases. You SHOULD first provide your step-by-step thinking for solving the task. Your thought process should be enclosed using "<thought>" tag.
<Task>:
Here are the definition of two classes [A] and [B] :
Class [A] and its attributes: {class_definition1}
Class [B] and its attributes: {class_definition2}
Instances of both classes [A] and [B] can be found in these logs:
{log samples}

<Guidelines>:
Based on the logs, infer the possible relationships of attributes in [A] and [B] by referencing these common types of relationships: 1. Foreign key: an attribute in an entity that references the primary key attribute in another entity, both attributes must be the same data type. 2. Primary key: attribute(s) that can uniquely identify entities in an entity set. 3. Matching: an attribute(E.g: Price, ID) in an entity that must have the same value as an attribute in another entity, both attributes must be the same data type. (E.g: Price, ID)
You SHOULD construct as many of the most important first-order logic constraints and output it in general format. Examples:
- ∀ x (isDog(x) ⟵ hasFourLegs(x)
- ∀ x (isPerson(x) ⟵ ∃ y (isDog(y) ∧ owns(x, y)))
- ∀ x ∃ y ((isParent(x, y) ∧ isMale(x)) ⟵ isFather(x, y))
- ∃x (isHuman(x) ∧ loves(x, Mary))
- ∀ x (isStudent(x) ∧ studiesHard(x) ⟵ getsGoodGrades(x))
- ∀ x (isAnimal(x) ⟵ (∃ y (isFood(y) ∧ eats(x, y))))
Then, write a function that determines if instances of [A] and [B] are related to each other using their attributes.

<Few-shot Examples>:
```
def is_related(instance_A: dict, instance_B: dict) -> bool:
if instance_A.conditionA != instance_A.conditionB:
raise ValueError('instance_A and instance_A should have the same condition A and B')
return True
```

<Expected Results>: //to-be-generated results

Agent Response

Given the attributes: <class attributes>
We can construct the following first-order logic constraints

$\forall x\, \forall y\, (isRebookInfo(x) \wedge isPaymentInfo(y) \rightarrow (tripId(x) = tripId(y)))$

$\forall x\, \forall y\, (isRebookInfo(x) \wedge isPaymentInfo(y) \rightarrow (orderId(x) = orderId(y)))$

Implement a function is_related that checks if instances of RebookInfo and PaymentInfo are related based on the identified attributes.

```python
def is_related(A: dict, B: dict) -> bool:
    if A.get('orderId') != B.get('orderId'): return False
    if A.get('tripId') != B.get('tripId'): return False
    return True
```

Figure 7: Data constraint prompt and an example of a agent-environment interaction turn.

- **Presence check**: important fields should not be empty (e.g., ID)
- **Data Type Check**: is the field a valid data type? (e.g., integer for numbers)
- **Code Check**: does the value fall within a valid list of values? (e.g., postal codes, country codes, NAICS industry codes)

After calling *<parent API>*, the application flow can branch to A or B
Branch A: *<branch A API>* produces these logs: *<logs A>*
Branch B: *<branch B API>* produces these logs *<logs B>*
Based on the logs, identify variables that influence branching.
Next, construct first-order logic constraints with the variables.
Then, write a Python function
`def is_branch_a(log: str) -> bool`
that determines which branch a log belongs to. *<code requirements>*

Figure 8: Simplified prompt to generate flow consistency invariants

- **Range Check**: does the value fall within a logical numerical range? (e.g., temperature, latitude, price).
- **Format Check**: does the value follow a predefined format? (e.g., UUID, email, phone number, country codes).
- **Consistency Check**: are two or more values logically consistent with each other? (e.g., delivery date must be after shipping date).
- **Length Check**: does the value contain a correct number of characters? (e.g., password).

3.2.3 Invariant Refinement. To improve the quality of learned constraints and reduce hallucination, we design a test-driven approach

Here is the code definition of a class: <*class definition*>
Instances of this class can be found in these logs: <*logs*>
Based on the logs, infer the valid values for each field by referencing these common types of data validation: <*validation requirements*>
Then, write a Python function

```
def is_valid(instance: dict) -> bool
```

that determines if an instance of the class is valid (all fields have valid values). <*code requirements*>

Figure 9: Simplified prompt to generate common-sense constraints

for the agent to self-correct its code iteratively. Given a candidate set of events and relations C, we divide it into C_1 (for generating invariants, similar to the concept of training dataset) and C_2 (for validating and correcting invariants, similar to the concept of testing/validation dataset) where $C = C_1 \cup C_2$. The LLM agent interacts with the environment in a multi-turn setting, where the environment is a Python code interpreter equipped with a unit testing toolkit. The agent submits the generated code to the environment for testing.

We can translate C_2 to a set of test cases T. Then, $\forall t \in T$, we run t against the generated python script *code*, to derive the runtime message $msg(t)$. If any of the test cases have a failure message, we append its failure message as a part of the prompt to ask LLM to regenerate the results. In the meantime, we can have one more element in C_1 and one less in C_2. Given a threshold th, we interactively and iteratively run the procedure up to th times. We do not generate any invariants if the budget of all th times are used up. Otherwise, we record the generated invariants as consistency valuation rules in the deployment time.

4 EVALUATION

In this section, we aim to evaluate our WebNorm's performance, focusing on the following research questions.

- **RQ1**: How is the performance of WebNorm to detect attack-triggered anomalies comparing to the state-of-the-art anomaly detectors?
- **RQ2**: What is the cost of WebNorm to learn invariants and detect anomalies?
- **RQ3**: Whether WebNorm provide accurate explanations to pint point the root cause?
- **RQ4**: How does seed in the learning phase impact the performance of WebNorm?

4.1 Experiment Setup

Baselines. We compare WebNorm with 6 state-of-the-art log-based anomaly detectors (see Table 3) to evaluate the effectiveness of our WebNorm. We show our implementations of our baseline methods as follows and show the basic information in Table 3. Then, we select the existing anomaly detection methods from the similarity-based and deep-learning-based perspective. In the similarity-based approach, we select the recent proposed ReplicaWatch, which features as a training-less method and detects anomalies in containerized microservices. Their principle is to compare the similarity between the microservice's several replicas (i.e., sub microservices), and output an alarm when the inconsistency within the internal replicas reaches a certain threshold, highlighting a training-less manner. To compare with this approaches, we regard the log from an API function as a replica's log, and follow the same threshold 0.5 in our experiment, enabling the observation of performance in training-free rational approaches. We also select five deep-learning based approach, whose principle predicts the next normal events of a log based on the previous events of a log.

Table 2: The size of the evaluation logs in two platforms. All training logs are normal logs. N refers to normal, A refers to attack in seconds.

TrainTicket			*NiceFish*		
Training (N)	Testing (N)	Testing (A)	Training (N)	Testing (N)	Testing (A)
183,232	72,611	892	74,288	34,555	318

These approaches are proposed from between 2017 to 2021. For example, LogRobust [53], proposed in 2019, utilizes an attention-based Bi-LSTM model to identify the varying importance between different log events, providing robust anomaly detection in dynamic log environments. Similarly, DeepLog [10] uses similar methodology with the LSTM. LogAnomaly [36], proposed in 2019, shares similar principle with the DeepLog. LogAnomaly treats a log as an event sequence and considers the counts of different log events as an additional feature. It adopts an LSTM model to learn sequential and quantitative patterns. We follow the same parameter selection as the open-source code **??**.

Benchmark. Our evaluation is based on two real-world web applications, i.e., (1) one is *TrainTicket* v1.0.0 [55], a popular benchmark used in many DevOps tasks and (2) the other is the digital services platform *NiceFish* [38], which are commonly-used open-source platform. To collect the training dataset for all the baselines, we manually define 22 normal scenarios (i.e., seeds) in *TrainTicket* and 11 normal scenarios in *NiceFish*. Then we construct the testing dataset (with both normal and abnormal logs). As for the normal logs, we generate the normal scenarios by employing GPT-4 to simulate user interactions based on different pre-defined tasks [56]. As for the abnormal logs (i.e., attack logs), we refer to the literature [24] and the OWASP [3] to simulate the relevant attack scenarios in two websites. Specifically, we simulate 40 attack scenarios in *TrainTicket* and 14 scenarios in *NiceFish*. Table 2 shows the details of our benchmark. More of the details (e.g., dataset, replication package, and runtime configurations) are available at [39].

In the experiment, we employ the same sliding window (k=20) to segment logs and feed them to train deep-learning-based baseline models. In the similarity-based baseline models and our approach, we input all logs, given that the LLM-agent-based and similarity-based models can capture a log.

Evaluation metrics. We use the precision, recall, and F1-score to measure the effectiveness of anomaly detection based on TP (True Positive), FP (False Positive), and FN (False Negative).

- **Precision:** the percentage of anomalous logs out of all logs detected as anomalies, represented as precision = $\frac{TP}{TP+FP}$.

[3]https://owasp.org/www-community/attacks/Web_Parameter_Tampering

Table 3: The description of baseline models.

	Baseline Approach	Year	Model
Similarly Based [4]	Replica	2024	Training-less
Deep Learning Based [5]	LogRobust	2019	Bi-LSTM
	NeuralLog	2019	Transformer
	PLELog	2021	HDBSCAM+Cluster
	DeepLog	2017	LSTM
	LogAnomaly	2019	LSTM

- **Recall:** the percentage of all anomalous logs that are detected as anomalies, represented as recall = $\frac{TP}{TP+FN}$.
- **F1-Score:** the harmonic mean of precision and recall, represented as $F_1 = 2 \cdot \frac{\text{Precision}\cdot\text{Recall}}{\text{Precision}+\text{Recall}}$.

Further, given an abnormal log (or event sequence) in the ground-truth testing dataset, we can compare it with its normal version. Note that, the abnormal logs are achieve by applying tamper attacks. Then, we can manually compare the log difference with the reported explanation. Thus, we calculate the explanation accuracy rate by $\frac{M}{N}$, where M is the number of reported true anomalies and N is the number of the true anomalies with the true explanation.

4.2 RQ1: The Effectiveness of WebNorm

Table 4 shows the results where we can find that WebNorm can significantly outperform the baseline models. Overall, WebNorm outperforms all the other approaches in terms of precision and recall. We observe that all the baselines generally suffer from the limited abstraction from logs and context of relevant events to report the anomalies. Note that, many attack-triggered anomalies render very subtle difference from the normal logs, which incurs challenges for all the inductive solutions. In contrast, WebNorm is designed based on a deductive principle, which can well capture the appropriate log granularity and is sensitive to the subtle changes of the abnormal logs. Further, some anomalies are rendered in a long context, in this sense, the program analysis can well capture the relevant events even if there are a number of irrelevant events happen in between.

Table 5 breaks down the detailed comparison in different consistency-based invariants. We observe that WebNorm achieves the best performance on detecting flow consistency. In addition, the performance of WebNorm is still acceptable for generating the common-sense consistency invariants.

We further investigate when WebNorm failed to report false anomalies. In general, the general reason lies in that the hallucination caused by LLM. In this case, despite that Python scripts can pass all the test cases, the condition is trivial (see [39]) so that it can pass in the limited set of logs but cannot generalize well. In addition, the false negative lies in that we feed too long logs to LLM (i.e., GPT-4o) in this experiment. Therefore, it fail to recognize a few critical variables and parameters.

4.3 RQ2: Cost of WebNorm

In this experiment, the total cost of using third-party LLM API services to learn all constraints in *TrainTicket* is $13.59 for parsing 183K logs (see Table 2). Note that, the cost is incurred only during the learning phase. Table 6 and Table 7 further break down the details of runtime overhead, computationally and financially. We can see that, in comparison to the other consistency invariants, the data consistency invariants makes more runtime overhead. In general, it appears more often in the normal scenarios, which makes us to feed more logs to LLM, incurring more failures (and iterations) of the generated test cases.

Furthermore, we observe in Table 6 that the testing time is acceptable across these extremely large logs. Given that we only need to train the LLM-agents only once that can be deployed, the training time is acceptable in real-world settings, although it seems to take a longer time in our learning approach.

Table 4: The effectiveness of WebNorm.

Approach	*TrainTicket*			*NiceFish*		
	F1	Precision	Recall	F1	Precision	Recall
WebNorm	**0.914**	**0.906**	**0.924**	**0.922**	**0.928**	**0.917**
LogRobust	0.558	0.477	0.671	0.605	0.500	0.765
ReplicaWatcher	0.169	0.098	0.593	0.012	0.382	0.012
NeuralLog	0.103	0.522	0.057	0.042	0.772	0.022
PLELog	0.099	0.055	0.485	0.091	0.049	0.700
DeepLog	0.098	0.595	0.053	0.025	0.072	0.015
LogAnomaly	0.094	0.593	0.051	0.025	0.072	0.015

Table 5: The effectiveness of each scenario on *TrainTicket*.

Scenarios	F1	Precision	Recall
Data consistency	0.916	0.923	0.909
Flow consistency	0.930	0.928	0.933
Common sense consistency	0.897	0.867	0.929

Table 6: The total training and testing time on *TrainTicket*, training logs are over 180,000 logs, testing logs are over 70,000 logs.

Approach	Training Time (s)	Testing Time (s)
WebNorm	1050.1	21.6
LogRobust	407.1	0.4
ReplicaWatcher	N/A	1.7
NeuralLog	165.0	31.8
PLELog	148.9	9.9
DeepLog	16.2	2.8
LogAnomaly	32.0	7.6

4.4 RQ3: The Explainablity of WebNorm

WebNorm is expected to perform more reasonable traces to the developers. We show the performance of WebNorm's explainability in Table 8. We observe that WebNorm can overall locate the specific abnormal events, providing a intuitive feedback to the developers. For example, we can locate whether an event is triggered by the admin, or locate the abnormal events of *paydifference* and *rebook*

Table 7: The overhead comparison on *TrainTicket* based on over 180,000 logs.

Scenarios	Num. Constraints	Training Time	Cost
Data consistency	31	648.81s	$12.91
Flow consistency	10	108.14s	$2.87
Common Sense consistency	24	293.15s	$6.78

and its suspicious relations, allowing the developers to directly look into the relevant information about the tamper attacks, enabling to make a quick response to these attacks. We empirically observe that the false explanation largely lies in the hallucination of generated Python code. More interested audience can check our examples in [39]. We will leave the challenges in our future work.

4.5 RQ4: The Seed Coverage of WebNorm

Table 10 generally shows how the change of normal seeds can affect the performance of WebNorm. While the precision keeps intact when the normal seeds are reduced to 10%, 30%, 50%, 70%, and 90% respectively. The recall is largely affected. Generally, those normal seeds serve as the "training dataset" for generating the WebNorm constraints and invariants. We suggest that the practitioners to prepare more representative seeds to apply WebNorm.

5 RELATED WORKS

In this section, we illustrate the relevant works about the detection of tamper attacks on web applications. Existing detection methods generally rely on sequence-based manners [10, 17, 36, 50, 53], which mainly assume the linear and sequential execution of events. However, these approaches are not well-suited for detecting tamper attacks in web applications. This is because web applications typically exhibit varying data and multiple operational flows, which lack sequential events that can be specifically monitored. Here, we mainly summarize two categories of tamper attacks and their corresponding detection solutions.

Log-based Anomaly Detection. Many literature focus on dealing with inferring models from systems' execution logs [1, 4, 32, 41, 44, 46]. Wang et al. [48] use the sets of temporal invariants to distingwish the difference between the logs. Goldstein et al. [15] compare the path of 2 logs then visulized the differences. 2kdiff [2] was the first to incorporate log modeling into log analysis. Nonetheless, the models developed by these works are coarse-grained, which results in a detection precision that is inferior to that of WebNorm. Besides, Some literatures on program analysis [5, 12, 26] incorporate invariants into their models; in the context of microservices. But in microservices, the larger amount and complexity of logs and invariants make it hard for these methods to track and analyze effectively. On the DevOps part, DeepTraLog [52] utilizes a Graph Gated Neural Networks (GGNNs)-based deep SVDD [42] model for identifying anomalies in both traces and corresponding logs. SCWarn [54] utilizes multimodal learning from diverse, heterogeneous data sources to detect problematic software changes. Khairi [21] proposed a training-less approach to resist run-time replica faults.

Log Instrumentation. Current detection models are generally based on log instrumentation. Yuan et al.[51] proposed the software logging practices in large open-source software projects. Then, based on an observation of seven open-source systems, Li et al. [29] present a deep learning framework that automatically suggests logging locations in source code. Liu et al. [31] propose an approach to recommend logging variables for developers during software development by learning from existing logging statements. Among them, LANCE [33] is the most recent and valuable research, it utilizes a Text-To-Text-Transfer-Transformer (T5) model [34] trained on several Java projects to assist developers in instrumenting logs. However, it has not been trained to run against our custom instrumented logs, so it cannot fully replace our existing instrumentation rules.

Tamper Attack Detection. Data tamper attacks refer to that an malicious web user modifies the client-side data, for example, the database in the server-end neglect the price validation. To detect such attacks, studies [43] always focus on detecting data tamper attacks on E-Commerce Applications. Parameter tamper attacks refer to that an malicious user manipulates the returned parameters, responses from a client-side, for example, the server-end only considers the positive or negative value of several returned parameter, and ignores specific returned value like the pieces of the clothing purchased. To detect such attacks, Bisht [6] proposed NoTamper detection framework based on client-side javascript code analysis techniques specialized to form validation code. Later, Bisht [7] also optimized the NoTamper with the white-box manner. Khodayari [22] also claimed the current Content Security Policy (CSP) and Cross-Origin Opener Policy (COOP) defense strategies are not sufficient to detect request hijacking attacks. Moreover, JSFlowTamper [25] and BFTDETECTOR [23] employ DOM monitoring for flow tamper detection. However, these methods fail when there are no significant DOM changes before and after the tamper attacks. In contrast, our approach leverages instrumented logs to provide comprehensive monitoring of web applications.

Many web applications suffer from the data and parameter tamper attacks simultaneously, which means that, only detecting one kind of tamper attacks can still lead to serious finial losses. However, few works propose a detection method capable of detecting both data and parameter tamper attacks. We, in this paper, for the first time propose a comprehensive detection framework to systemically detect multiple tamper attacks in the run-time. By addressing both data and parameter tamper attacks, organizations can significantly reduce the risk of security breaches and financial losses in their web applications architectures.

6 CONCLUSION AND FUTURE WORK

We introduce the WebNorm framework, designed to enhance existing microservice anomaly detection algorithms and generate explanatory models for various anomalies. We demonstrate that WebNorm is able to detect a range of network attacks and industrial faults more effectively than other methods on the train-ticket platform. Additionally, WebNorm allows for customizing rules for log instrumentation within microservices. Our extensive experiments indicate that WebNorm can improve existing microservice

Table 8: The explainable examples for three constraints.

Constraints	Event1	Event2	Relation	Explanation Description
Flow Constraint	Rebook.service. paydifference	Rebook.service. rebook	Event2 riggers Event1	Paydifference should be triggered if differenceMoney returned by rebook is positive.
	User.service. getAllUsers	Auth.service. getToken	Event2 triggers Event1	GetAllUsers should be triggered if the role returned by getToken equals admin.
Data Constraint	Order.service. queryOrdersForRefresh	Inside_payment.service. pay	Event2 transfer price to Event1	QueryOrdersForRefresh and pay should have the same price
	contacts.service. findContactsByAccountId	preserve.service. preserve	Event2 transfer ContactId to Event1	FindContactsByAccountId and preserve should have the same contactId
Common Sense Constraint	Consign.service. updateConsignRecord	N.A	N.A	UpdateConsignRecord's weight must be a non-negative number

Table 9: *TrainTicket*'s explanation precision.

	Explanation Precision
Data consistency	0.933
Flow consistency	0.875
Common Sense consistency	0.961

Table 10: *TrainTicket*'s seeds coverage impact on the final result.

Seed Coverage	10%	30%	50%	70%	90%
Recall	0.367	0.559	0.752	0.838	0.902

detection frameworks, with rule-based logs effectively monitoring internal microservice activities.

In future work, we plan to train a large language model tailored explicitly for microservices to reduce false positives. Furthermore, we aim to fully automate the generation of normal seeds, thereby enabling the complete automation of the WebNorm system.

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