AIOpsLab: A Holistic Framework to Evaluate AI Agents for Enabling Autonomous Clouds

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Abstract

AI for IT Operations (AIOps) aims to automate complex operational tasks, such as fault localization and root cause analysis, to reduce human workload and minimize customer impact. While traditional DevOps tools and AIOps algorithms often focus on addressing isolated operational tasks, recent advances in Large Language Models (LLMs) and AI agents are revolutionizing AIOps by enabling end-to-end and multitask automation. This paper envisions a future where AI agents autonomously manage operational tasks throughout the entire incident lifecycle, leading to self-healing cloud systems, a paradigm we term *AgentOps*. Realizing this vision requires a comprehensive framework to guide the design, development, and evaluation of these agents. To this end, we present AIOpsLab, a framework that not only deploys microservice cloud environments, injects faults, generates workloads, and exports telemetry data but also orchestrates these components and provides interfaces for interacting with and evaluating agents. We discuss the key requirements for such a holistic framework and demonstrate how AIOpsLab can facilitate the evaluation of next-generation AIOps agents. Through evaluations of state-of-the-art LLM agents within the benchmark created by AIOpsLab, we provide insights into their capabilities and limitations in handling complex operational tasks in cloud environments.

1 Introduction

The rapid evolution of IT applications and services has led enterprises to increasingly depend on hyper-scale, cloud-based systems. These systems are often distributed, employing architectures such as microservices and serverless computing, enabling scalability but also adding complexity and introducing new operational challenges. In such cloud environments, issues can cascade into large-scale outages. For instance, an Amazon outage can result in losses of $100 million in just one hour (Wolfe, 2018).

To address the challenges of managing incidents in such complex infrastructures, there is a movement towards the adoption of AIOps (Artificial Intelligence for IT Operations), within the context of DevOps (Development and Operations). The ultimate goal of AIOps is to create autonomous self-healing clouds, where AI-driven approaches can detect, localize, and mitigate faults with minimal human intervention. Although such a concept has existed for over a decade (Li et al., 2012; Dai et al., 2009), the recent advancements of AIOps and Large Language Model (LLM) agents have brought this vision closer to reality (Zhao et al., 2023; He et al., 2022; Ma et al., 2018; Zhang et al., 2018; Ganatra et al., 2023; Somashekar et al., 2024; Zhang et al., 2024a; Chen et al., 2024). Large Language Model (LLM) agents (Mialon et al., 2023; Schick et al., 2024) integrate external tools to dynamically interact with their environment (Wei et al., 2022a), enabling them to autonomously manage the entire incident lifecycle, as shown in Figure 1.

To realize this autonomous self-healing cloud vision, we propose a new paradigm called *AgentOps* (Agent for Operations). In this paradigm, agentic approaches are not limited to isolated operational tasks but are capable of seamlessly managing multiple, cross-layer tasks across the entire operational stack. AgentOps represents an evolution where autonomous agents can make real-time decisions and end-to-end actions to ensure system reliability. This aligns with recent advancements in AI, as highlighted by a post:

> *"State-of-the-art AI results are increasingly obtained by compound systems with multiple components, not just monolithic models ... compound AI systems will likely be the best way to maximize AI results in the future"* – The Shift from Models to Compound AI Systems (Zaharia et al., 2024)

AI-driven tools and benchmarks like WebArena (Zhou et al., 2023), R2E (Jain et al., 2024b), HumanEval (Chen et al., 2021), LiveCodeBench (Jain et al., 2024a), and SWE-bench (Jimenez et al., 2024) have significantly advanced the

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'Dev' side of DevOps by accelerating software development. However, progress in AI for 'Ops', particularly AgentOps, remains limited, due to the lack of high-quality benchmarks for diverse, realistic scenarios. Addressing this gap requires *a framework that aids the design, development, and evaluation of AIOps agents* within an interactive environment, a key contribution of this paper.

Challenges and contributions. Building a holistic benchmark framework that can allow agents to interact dynamically with the cloud poses several challenges. The first challenge is to manage an evaluation flow that is generally applicable to diverse agents and clouds, powerful enough to evaluate agents by complex and realistic operational tasks, and valuable enough to provide different feedback or observability, together with extensibility that make it possible to accommodate new tasks and agents by the users. While existing tools address individual components of the AIOps evaluation, such as observability (He et al., 2023; Simonsson et al., 2021), application suites (Gan et al., 2019; Zhou et al., 2021; Sriraman and Wenisch, 2018) and chaos engineering (Netflix, 2011; ChaosBlade Team, 2019; ChaosMesh Authors, 2022), they lack the integration necessary to support a unified AIOps evaluation.

We present **AIOpsLab**, a holistic framework that can automatically manage the entire end-to-end evaluation process for AIOps solutions. This involves deploying services, fault injection, workload generation, orchestrating the agent-cloud interaction, and analyzing results. Specifically, AIOpsLab features the *Agent-Cloud Interface (ACI)*, a unified interface that enables agents to interact with the cloud. ACI allows agents to communicate, take action, and receive feedback, orchestrating these interactions to detect and resolve issues in dynamic and interactive environments.

Moreover, a common challenge in operation benchmarks is the lack of realistic evaluation scenarios, as existing approaches often rely on static datasets, such as system metrics (Han et al., 2022; Jacob et al., 2020) that are typically time series data, or on fixed question-answer format (Liu et al., 2023). Such setups do not capture the dynamic, unpredictable, and evolving nature of real-world cloud environments, where workloads and incidents fluctuate over time. To make matters worse, recent efforts on AgentOps (Wang et al., 2023; Zhang et al., 2024a) use proprietary services and datasets. Furthermore, existing AIOps approaches and their benchmarks often focus only on isolated aspects of the incident lifecycle, such as anomaly detection (Yu et al., 2024b) or fault localization (Sun et al., 2024). This lacks a cohesive framework to evaluate AIOps agents comprehensively. Moreover, it limits support for decision-making that could assist in chaining algorithms or selecting the most suitable agent for a given operation scenario.

To address these limitations, we designed a set of evaluation scenarios, referred to as *problems*, which replicates realistic incidents within the microservice system. AIOpsLab's problem pool is structured around a task-level taxonomy that categorizes tasks of different problems across the incident management lifecycle. Our approach ensures that evaluation scenarios go beyond simple performance or crash failures (that cannot be further analyzed or mitigated by the agents), incorporating fine-grained root causes to fully assess the diagnostic and mitigation abilities of AIOps agents.

Implementation. We developed AIOpsLab, an innovative framework for building AgentOps benchmarks to evaluate LLM-based AIOps agents. AIOpsLab utilizes two microservice applications from DeathStarBench (Gan et al., 2019) as testbeds, along with their workload generators. An extensible fault library, integrated with ChaosMesh (ChaosMesh Authors, 2022), enables diverse fault injections into the system. A telemetry observer, incorporating Prometheus (Prometheus Authors, 2024) for metrics, Jaeger (Jaeger Authors, 2024) for tracing, and Filebeat (Elasticsearch, 2024b) and Logstash (Elasticsearch, 2024a) for logging, supports on-disk storage of telemetry data, facilitating evaluations of both traditional AIOps algorithms and agentic solutions. We also integrate Helm and Kubernetes APIs into the AIOpsLab's orchestrator implementation.

To demonstrate the application of our framework in evaluating LLM-based agents as the benchmark, we use AIOpsLab to create 48 problems as evaluation scenarios covering different types of AIOps tasks, and register four agents from different types on those problems. The agent registration is lightweight, with less than a hundred lines of code to implement. Our evaluation process reveals distinct challenges agents face across tasks.

Summary. This paper makes the following contributions:

- We unravel the requirements and challenges of achieving a holistic framework that supports the design, development, and evaluation of autonomous AIOps agents;
- We develop a framework, AIOpsLab, which can not only deploy microservice cloud environments, inject faults, generate workloads, and export telemetry data but also orchestrate these components and provide agent-cloud interfaces for interacting with and evaluating agents.
- We leverage the AIOpsLab framework to construct a benchmark suite with 48 problems across different AIOps tasks in an interactive environment and evaluate four LLM-based agents.
- We provide a detailed analysis of the agents' performance and limitations by evaluating them on AIOpsLab.
- We will make AIOpsLab publicly available.[1]

[1]The link will be provided.

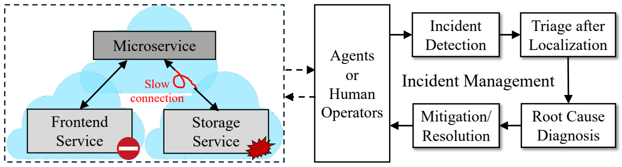


Figure 1. Microservice incident and its management lifecycle.

2 AIOpsLab

In this section, we discuss the design and implementation of AIOpsLab and its components, as illustrated in Figure 2.

2.1 Problem Definition

To support a wide range of evaluation scenarios (referred to as *problems*), which replicate realistic incidents within the microservice system, we first formalize an AIOps problem P as a tuple: $P = \langle T, C, S \rangle$, where T represents a *task*, C represents a *context*, and S represents the expected *solution* (oracle). The task T defines the specific AIOps operation to be performed, categorized into four types: detection, localization, (root cause) analysis, and mitigation. We define these tasks in Table 1. Each task type is associated with success criteria and evaluation metrics. For instance, the detection task employs Time-to-Detect (TTD) to measure the time taken to detect a fault.

The *context* C can be further formalized as a tuple: $C = \langle E, I \rangle$, where E is the *operational environment* in which the problem occurs, and I is the *problem information* used to describe the problem to the agent. The operational environment includes the cloud service, the fault model, and the workload model used to generate the problem, which is not shared with the agent. The problem information comprises of information such as service descriptions, task descriptions, and documentation about available APIs that is directly shared with the agent. It also subsumes indirect information (including logs, metrics, and traces observed in the operational environment) that is queryable by the agent at runtime. Finally, S is the expected outcome of the task, which is used to evaluate the agent's performance. The solution is typically problem and task-specific and is carefully designed for evaluation. Note that some problems, e.g., mitigation tasks, can be solved in multiple ways. In such cases, AIOpsLab evaluates the general state of the entire system, e.g., check whether all of the services are up and running, after the problem is resolved, rather than solely on the targeted resource where the fault was injected, because other services or resources may have been inadvertently affected during the mitigation process.

Example 2.1. Consider the problem of localizing a Kubernetes target port misconfiguration in a social network application. AIOpsLab makes it easy to define this problem in just a few lines by extending the `LocalizationTask` interface.

```python
from aiopslab import LocalizationTask, SocialNetwork
from aiopslab import Wrk, VirtFaultInjector
class K8STargetPortMisconf(LocalizationTask):
    def __init__(self):
        self.app = SocialNetwork()
        self.ans = "user-service"

    def start_workload(self):
        wrk = Wrk(rate=100, duration=10)
        wrk.start_workload(url=self.app.frontend_url)

    def inject_fault(self):
        inj = VirtFaultInjector(self.app.ns)
        inj.inject([self.ans], "misconfig_k8s")

    def eval(self, soln, trace, duration):
        res["TTL"] = duration
        res["success"] = is_exact_match(soln, self.ans)
        return res
```

Here, the task T is fault localization, and the solution S is the microservice named "user-service", which is also the fault injection target. The context C includes the social network application, a misconfiguration fault from AIOpsLab's fault library, and a standard workload using the `wrk` tool. AIOpsLab provides several such interfaces for all AIOps tasks (Section 2.4.1) and allows users to add new problems by extending them. Once problems are defined, AIOpsLab can instantiate them and allow agents to interact with them using an Orchestrator that we describe next.

2.2 Orchestrator

AIOpsLab's Orchestrator strictly enforces the separation of concerns between the agent and the service, using a well-defined central piece, the Orchestrator. It provides a robust set of interfaces that allow seamless integration and extension of various system components.

2.2.1 Agent Cloud Interface

A key responsibility of the Orchestrator is to provide a well-defined interface for the agent to interact with the cloud environment. Typically, developers operate clouds and services with various programming (e.g., APIs, CLIs) and user interfaces (incident portals, dashboards, etc.). However, existing interfaces to the cloud are not well-designed for LLMs and agents. For instance, humans can reliably ignore irrelevant information, which can prove distracting for agents and hamper performance.

The ACI specifies (1) the set of valid actions available to the agent 7 9, and (2) how the service's state is conveyed back to the agent as the observation of its actions 8.

In doing so, the ACI abstracts the cloud environment's complexity, simplifying the agent's decision-making process. The ACI is designed to be intuitive and easy to use, with a concise list of APIs, each documented to ensure that agents can make meaningful progress towards their objectives. Some APIs that AIOpsLab provides by default include `get_logs` (fetch logs), `get_metrics` (fetch metrics), `get_traces` (fetch traces), and `exec_shell` (execute shell commands after applying security policy filters).

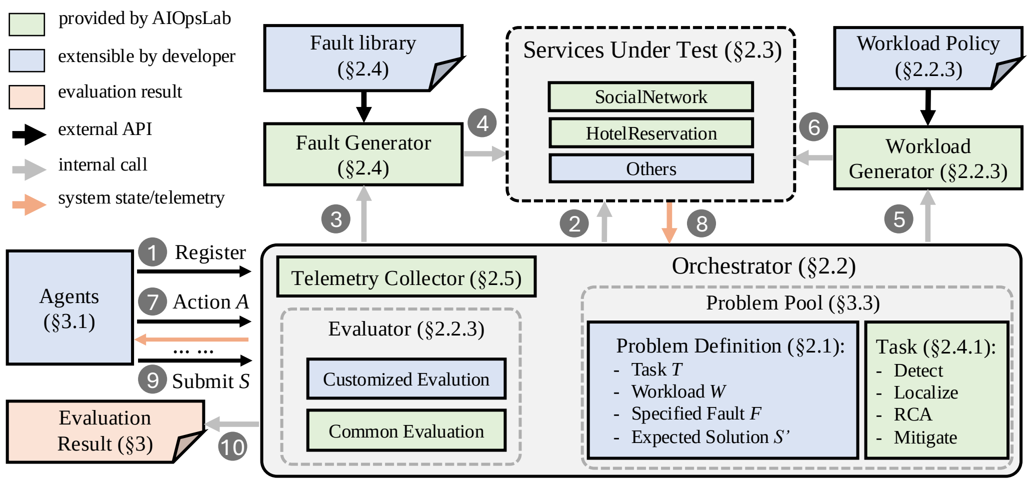


Figure 2. **Overview of AIOpsLab.** The Orchestrator coordinates interactions between various system components and serves as the Agent-Cloud-Interface (ACI). Agents engage with the Orchestrator to solve tasks, receiving a problem description, instructions, and relevant APIs. The Orchestrator generates diverse problems using the Workload and Fault Generators, injecting these into applications it can deploy. The deployed service has observability, providing telemetry such as metrics, traces, and logs. Agents act via the Orchestrator, which executes them and updates the service's state. The Orchestrator evaluates the final solution using predefined metrics for the task.

Example 2.2. This example illustrates how the ACI is defined in AIOpsLab as APIs that agents can use.

```
class TaskActions:
    def get_traces(ns: str, duration: int = 5) -> str:
        """
        Collects trace data of the services from Jaeger.
        Args:
            ns (str): The K8S namespace.
            duration (int): Duration to collect traces.
        Returns:
            str: Path to the directory where traces saved.
        """
        trace_api = TraceAPI(ns)
        end_t = datetime.now()
        start_t = end_t - timedelta(duration)
        traces = trace_api.extract_traces(start_t, end_t)
        return trace_api.save_traces(traces)
```

As shown, the ACI encapsulates complex operations behind simple APIs like `get_traces`. On initializing a problem, the Orchestrator automatically extracts documentation from these APIs to provide as *context* C to the agent. At runtime, agents can specify a wide range of actions on the service (e.g., scaling, redeploying, patching) by way of the Orchestrator's privileged access. Finally, the Orchestrator conveys the service's state after each action with high-quality feedback to the agent, including outputs, error messages, and tracebacks.

2.2.2 *Session Interface*

Another key responsibility of the Orchestrator is to manage the lifecycle of the agent and the service. We implement the Orchestrator as a session-based system, where a `Session` is created for each instance of an agent solving a problem. Agents are registered with the Orchestrator, and a session starts with simple API calls passing a unique problem identifier 1. AIOpsLab's design is highly flexible and integrates with the growing LLM and agent framework space. Our only requirement is that the agent must implement a `get_action` method with the following signature: `async def get_action(state: str) -> str`. It takes the service's state as input from the Orchestrator and returns the next action the agent wants to take. Note that this could be a simple wrapper function around any existing agent framework.

Example 2.3. In this simplified example, we illustrate how an Agent can be onboarded to AIOpsLab.

```
from aiopslab import Orchestrator
class Agent:
    def __init__(self, prob, instructs, apis):
        self.prompt = self.set_prompt(prob, instructs, apis)
        self.llm = GPT4()

    async def get_action(self, state: str) -> str:
        return self.llm.generate(self.prompt + state)

#initialize the orchestrator
orch = Orchestrator()
pid = "misconfig_app_hotel_res-mitigation-1"
prob_desc, instructs, apis = orch.init_problem(pid)
#register and evaluate the agent
agent = Agent(prob_desc, instructs, apis)
orch.register_agent(agent, name="myAgent")
asyncio.run(orch.start_problem(max_steps=10))
```

As shown on initializing a problem, the Orchestrator shares *context* necessary for the agent to solve the problem. It then polls (via `get_action`) for the agent's next action.

2.2.3 *Other Interfaces*

Problem Initializers. As described in Section 2.1, each problem is defined with a *context* C which includes its operational environment. This environment is the service, fault, and workload conditions under which the problem occurs. Here, the Orchestrator deploys services and uses infrastructure-as-code tools like (Helm, 2024) to deploy the required cloud service for each problem. We describe services already integrated into AIOpsLab in Section 2.3.

As shown in Figure 2, to create realistic benchmark scenarios, the Orchestrator then interfaces with two entities: (1) a *workload generator* 5 and (2) a *fault generator* 3. These generators introduce controlled service disruptions that simulate live benchmark problems. As the workload generator, AIOpsLab currently uses the `wrk2` tool (Gan et al., 2019), which supports several workload policies and also replays industry workloads 6. However, the AIOpsLab is extensible to other workload generators. For fault generation, AIOpsLab uses a custom fault library that instantiates faults across different levels of the system stack 4, such as application and virtualization. The library contains and extends to several fine-grained and parametric faults that go beyond surface-level symptoms and engage deeper into more complex resolution strategies. We describe the fault library in detail in Section 2.4.

Problem Evaluators. Finally, the Orchestrator plays a critical role in evaluating the agent's performance on a problem. It compares the agent's solutions against predefined success criteria and evaluation metrics specific to each task 10. AIOpsLab supports several default and common metrics for each task (e.g., Time-to-Detect for detection, number of steps taken, and tokens produced by an LLM-powered agent sent to AIOpsLab). Additionally, AIOpsLab provides an optional qualitative evaluation of agent trajectories using LLMs-as-Judges (Zheng et al., 2024). Beyond that, all user-defined evaluation metrics specific to the problem are run. For instance, for the localization problem in Example 2.1, the metric `success` is defined by the agent's submission matching the fault microservice's name. Lastly, the Orchestrator maintains comprehensive logs of all agent trajectories, including actions taken and resulting system states, facilitating detailed analysis and debugging. All of the evaluation results will be automatically collected.

2.3 Cloud Services

AIOpsLab deploys live microservice applications as cloud environments 2. AIOpsLab is currently integrated with the HotelReservation and SocialNetwork from DeathStarBench (Gan et al., 2019). The SocialNetwork application has 28 microservices, including Memcached, MongoDB, and Redis, that together implement several features of real-world social networking applications. The HotelReservation application, implemented with Go and gRPC, supports services like recommending and reserving hotels.

2.4 Task-oriented Fault Library

2.4.1 *Task Taxonomy*

We present a task-level taxonomy (Table 1) that categorizes the tasks that AIOps agents should accomplish according to the different stages of the incident management lifecycle, with progressively increasing complexity. In Table 1, a higher level indicates a harder and more impactful task to evaluate agents.

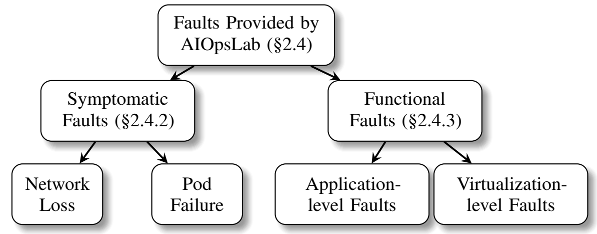


Figure 3. Fault categories to instantiate problems in AIOpsLab.

Table 1. Task taxonomy for AIOps agent evaluation. The lower the level, the easier the task. AIOpsLab aims to evaluate agents across all task levels with its problems.

Level	Task (# sub tasks)	Evaluation Focus
1	Detection (1)	Can the approach accurately detect anomalies or deviations?
2	Localization (1)	Can the approach pinpoint a fault's exact source (e.g., microservice)?
3	Root Cause Analysis (RCA) (2)	Can the approach determine the underlying cause of the fault?
4	Mitigation (1)	Can the approach give effective solutions to recover the environment?

Level 1 focuses on the preliminary identification of unusual behavior within the system, for example, detecting a malfunctioning Kubernetes pod of a microservice. Also, users can define more complex tasks or create sub-tasks. The root cause analysis task has both the system level and fault type prediction sub-tasks to be solved.

To instantiate problems across different task levels, we use fault injection to inject faults into the system, and construct a problem pool for AIOpsLab. We classify them into two main types, symptomatic faults and functional faults, as shown in Figure 3.

2.4.2 *Symptomatic Faults*

Symptomatic faults, such as performance degradation and crash failures, manifest as observable symptoms, such as increased latency, resource exhaustion, or service outages. These faults typically help to construct Level 1 and Level 2 tasks in the taxonomy, which can create problems that evaluate AIOps approaches' detection and localization ability. These faults provide an overview of potential problems but do not necessarily reveal the deeper, underlying root causes of issues (since they do not have one). AIOpsLab integrates the fault injection tool, Chaos-Mesh (ChaosMesh Authors, 2022), to inject symptomatic faults into microservice applications.

2.4.3 *Functional Faults*

Though there are many fault injection tools for testing the resilience of cloud systems (Marinescu and Candea, 2009; Banabic and Candea, 2012; Christakis et al., 2017; Zhang and Elbaum, 2012; Kingsbury, 2022; Pillai et al., 2014;

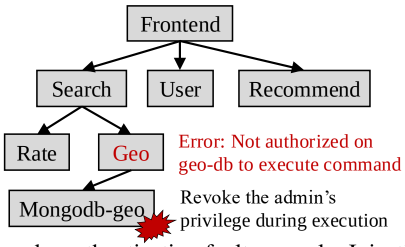


Figure 4. Revoke authentication fault example. Injection happens at Mongodb-geo service, while Geo service will be abnormal and generate error logs.

Alquraan et al., 2018; Lu et al., 2019; Chen et al., 2020; Leesatapornwongsa et al., 2014; Gunawi et al., 2011; Majumdar and Niksic, 2018; Ju et al., 2013; Heorhiadi et al., 2016; Alagappan et al., 2016; Mohan et al., 2018; Sun et al., 2022; Canini et al., 2012), most of them focus solely on injecting system symptoms. These coarse-grained faults can only disrupt without modeling the underlying, fine-grained root causes, e.g., misconfigurations or software bugs, and hence are unable to evaluate the capabilities of AIOps agents to diagnose and mitigate root causes.

The failure scenarios to evaluate AIOps agents across tasks must go beyond simple performance or crash failures, and reflect realistic cases that challenge agents, where functional faults come into play. Functional faults require approaches to not only detect (Level 1) and localize (Level 2) the failure but also diagnose the root cause (Level 3), such as incorrect deployment or operations, and apply the correct mitigation strategies (Level 4). For instance, the fault in Figure 4 revokes the admin authentication for the MongoDB database of the geographic microservice (Mongodb-geo). Since the Geo service relies on its backend database, errors will appear during its invocation.

Example 2.4. In the following example, we illustrate the structure of the application-level fault injector for a revoke authentication fault and its usage example in AIOpsLab.

```
from aiopslab.generators.fault.base import FaultInjector
from aiopslab.service.apps.hotelres import HotelReservation
class ApplicationFaultInjector(FaultInjector):
    def inject_revoke_auth(self, microservices: list[str]):
        """Revoke MongoDB admin privileges."""
        ...
    def recover_revoke_auth(self, microservices: list[str]):
        """Recover the revoke admin privileges fault."""
        ...
# Usage Example
class MongoDBRevokeAuth:
    def __init__(self):
        self.app = HotelReservation()

    def inject_fault(self):
        injector = ApplicationFaultInjector(ns)
        injector._inject(["mongodb-geo"], "revoke_auth")
```

Users can define problems using the existing fault library. For instance, users can specify different faulty services or even construct a task that injects multiple faults into multiple services concurrently. Users can also customize their faults to generate various problems. AIOpsLab provides the injection function for its associated failure scenarios and offers the corresponding mitigation mechanism to recover the system from the erroneous state. In Section 3.3, we will discuss the current problem pool we implement.

2.5 Observability

AIOpsLab is equipped with an extensible observability layer to provide comprehensive monitoring capabilities. AIOpsLab collects a wide array of telemetry data by its telemetry collector, including (1) traces from Jaeger (Jaeger Authors, 2024) detailing the end-to-end paths of requests through distributed systems, (2) application logs retrieved by Kubectl, or formatted and recorded by Filebeat (Elasticsearch, 2024b) and Logstash (Elasticsearch, 2024a), and (3) system metrics monitored by Prometheus (Prometheus Authors, 2024). AIOpsLab not only supports data collection during the interaction with the LLM agent but can also export the data offline to facilitate evaluating other traditional AIOps approaches. Besides, AIOpsLab is designed to capture information from other dimensions, e.g., codebase, configuration, and cluster information. Developers can also design and expose low-level system information (such as syscall logs) to agents using AIOpsLab's interface.

3 Evaluation

This section begins by outlining the evaluation setup and metrics employed within AIOpsLab. We then delve into the selected faults listed in Table 2, which serve as diverse evaluation scenarios within AIOpsLab. Following this, we evaluate the performance of the AIOps agents solving these problems, and then analyze the cost of the agents. We also dig into the reasons behind the performance differences to understand the challenges and potential agent improvements. Note that, all of the results are automatically collected and recorded by the problem evaluators (Section 2.2.3).

3.1 Evaluation Setup

We evaluate four LLM-based agents with AIOpsLab. Note that, for a fair comparison, we register the naive agent in AIOpsLab without any fine-tuning or modifications. We use GPT-3.5-Turbo and GPT-4-Turbo (Achiam et al., 2023) that have access to only a secure shell as baselines (GPT-w-Shell). In addition, we also evaluate the performance of ReAct (Yao et al., 2023), which extends chain-of-thought reasoning (Wei et al., 2022b) by integrating reasoning and acting in an interleaved manner,

As for cloud operation-specific agents, we choose Flash (Zhang et al., 2024b). Flash employs a workflow automation system that monitors execution status and decomposes complex instructions into manageable, conditional segments. It incorporates hindsight generation to learn from past interactions. As Flash was not publicly available at the time of writing, we develop a simplified version that retrospectively generates insights after each step.

Table 2. **Selected faults used to instantiate the problems for evaluation in AIOPSLAB.** Ext. stands for extensibility. ● denotes the fault can be easily used to construct other problems; ◐ denotes there is some manual effort needed to create new problems; while ○ means the fault is specific to some problems and cannot be applied to create other problems.

No.	Name	Application	Task Level	Category	Ext.	# Problem	Description
1	AuthenticationMissing	HotelReservation	1, 2, 3, 4	Functional Virtualization	◐	4	Missing authentication credentials cause access denial to MongoDB.
2	TargetPortMisconfig	SocialNetwork	1, 2, 3, 4	Functional Virtualization	●	12	The service cannot connect to the specified port due to misconfiguration.
3	RevokeAuth	HotelReservation	1, 2, 3, 4	Functional Application	◐	8	Revoked authentication causes database connection failure.
4	UserUnregistered	HotelReservation	1, 2, 3, 4	Functional Application	◐	8	The database service has access failures after the user was unregistered.
5	BuggyAppImage	HotelReservation	1, 2, 3, 4	Functional Application	○	4	Connection code bug in the application image causes access issues.
6	ScalePod	SocialNetwork	1, 2, 3, 4	Functional Virtualization	●	4	Incorrect scaling operation makes the number of pod zero for a service.
7	AssignNonExistentNode	SocialNetwork	1, 2, 3, 4	Functional Virtualization	●	4	Pod in a pending a failure status due to wrong assignment to a non-existent node.
8	NetworkLoss	HotelReservation	1, 2	Symptomatic	●	2	Network loss causes communication failures for a specific service.
9	PodFailure	HotelReservation	1, 2	Symptomatic	●	2	Service interruption due to a pod failure.
10	Noop	HotelReservation SocialNetwork	1	-	●	2	No faults injected into the system.

To compare with other AIOps approaches specific to a certain type of task, we evaluate three state-of-the-art, non-LLM-based AIOps algorithms on AIOPSLAB, using (multi-modal) telemetry data as input. They are: MKSMC (Çetin and Tasgin, 2020) for detection, RMLAD (Wang et al., 2020) and PDiagnose (Hou et al., 2021) for localization.

3.2 Metrics

Correctness. This metric measures the accuracy of the agent's response to problems. It evaluates whether the agent successfully detects, localizes, analyzes and resolves the problems as expected.

Time/Steps. These metrics evaluate the efficiency of the AIOps agent for each type of task. For example, Time-to-Detect (TTD) is the time elapsed from the occurrence of a fault to its detection, and Time-to-Mitigate (TTM) is the time taken from detection to complete mitigation of the fault. The number of steps or actions taken to solve the problem is also recorded. Note that this is the number of times the agent interacts with the AIOPSLAB instead of the number of requests sent to the backend LLM.

Cost. We use the number of tokens, including both the input token and output tokens, generated by the agents/environment as an indicator of the cost.

3.3 Problem Pool of AIOPSLAB Benchmark

Currently, AIOPSLAB benchmark consists of 48 problems in its problem pool. With six agents, we evaluate a total of 288 cases. Table 2 lists the faults used to instantiate the problems. As shown in Table 2, all functional faults (including Fault 1-7) are used to create problems at all of the four task levels; while the symptomatic faults (including Fault 8-9) can only be used to create problems at the detection and localization levels (Level 1 and Level 2). In the detection-level task, the agents must identify the presence of faults in real-time. This task is a binary classification, where the agents have to respond either "yes" if a fault is present or "no" on the contrary. The detection task (Level 1) can be made more complex, e.g., by asking the agents to label the abnormal telemetry data; however, we keep it simple here and leave the complex tasks to other levels. The localization (Level 2) task asks the agents to specify the exact location of the fault, usually a service or pod name in Kubernetes. The RCA task (Level 3) requires the agents to identify (1) the system layer the fault affects and (2) the type of the fault, e.g., misconfiguration or operation error. The mitigation task (Level 4) requires the agents to *interact with the environment* to fix the fault with a series of actions, such as updating the configuration, or rollback to a previous version, etc.

Most faults enable users to extend and create new problems easily by injecting the fault into other targets, such as services. For example, Fault 2 in AIOPSLAB can be injected into 10 services by simply configuring the injection target. We select the "user-service", "text-service", and "post-storage-service" from SocialNetwork as injection targets. Injecting faults into different targets is crucial because each service may have distinct dependencies, resulting in varied fault "blast radius" or failure propagation topologies. Consequently, faults can manifest at different locations within the microservice architecture to help evaluate the ability of the AIOps agents since different locations may indicate distinct difficulties. Applying some faults to construct problems may require additional effort. For example, Fault 3 and Fault 4 require the users to not only prepare the scripts to trigger the admin privilege revoke or user unregisteration during the testing, but also update the config map of the application in Kubernetes; and Fault 1

Table 3. **Overall performance of different agents.** We show the lines of code (LoC) to register the agent in AIOpsLab, average running time in seconds, average number of steps taken, average tokens used, and accuracy across all problems.

Agent	LoC	Time (s)	# Steps	Tokens	Acc.
GPT-4-w-Shell	41	28.61	6.44	6,394.5	49.15%
GPT-3.5-w-Shell	41	12.44	14.70	2,557.95	15.25%
ReAct	49	43.79	11.50	16,941.46	55.93%
Flash	60	99.64	8.48	6,484.25	59.32%

needs to enforce its TLS requirements through a Helm configuration update. Furthermore, some faults are designed for specific problems and are not readily adaptable, such as Fault 5, which involves an application-level code bug in the microservice's image.

3.4 Performance Results

The overall performance of the agents is summarized in Table 3, with task-specific results in Table 4. As illustrated in Table 3, Flash achieves the highest accuracy among all agents. Although GPT-3.5-turbo completes the tasks the fastest, it has the lowest accuracy at 15.25%.

The detection task, being a binary choice question, should be the simplest task and the first step an AIOps agent performs. However, as shown in Table 4(a), only Flash answers all the detection problems correctly. For localization task, agents are allowed to come up with a list of potential faulty services as their answers (since there could be multiple faults happenning in the system at the same time). To evaluate their accuracy, we consider both the top 1 and top 3 answers. In Table 4(b), ReAct performs best when evaluated using the top 3 answers, but its accuracy drops when considering the top 1. The RCA and mitigation tasks prove to be the most challenging for the agents. GPT-3.5-w-Shell fails to recover any failure in its mitigation attempts.

Problem difficulty differs across task levels. Despite showing promise in addressing realistic operational tasks, none of the agents consistently achieve high problem-solving accuracy across four task categories in AIOpsLab benchmark. Even the top-performing agents, such as Flash, exhibit limitations, particularly when tackling more complex tasks like mitigation. In Section 3.6, we will explore in detail the failure modes and challenges contributing to these performance limitations of agents, and opportunities for improvement.

3.5 Influence of the Step Limit

We examine the impact of the maximum number of allowed steps on the agent's performance, with the results shown in Figure 5. The step limit significantly affects the performance of certain agents. For instance, ReAct and Flash show improved accuracy with more steps, with Flash reaching the highest accuracy of 59.32% when the step limit is set to 20. However, for GPT-3.5-turbo, increasing the step limit beyond 5 does not yield better performance but merely

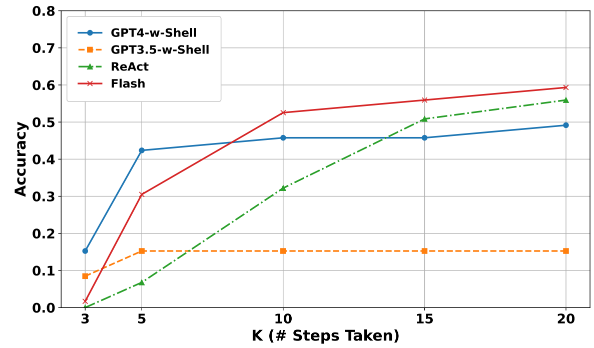


Figure 5. Agent performance vs. number of steps taken.

increases the token consumption. Notably, the plateauing of accuracy after a certain number of steps indicates that *self-repair with environment feedback can saturate quickly for AIOps problems*. On the contrary, in development tasks (Dev), such as code generation, feedback via various compositional tools such as linters, type checkers, and test cases help agents continuously improve. This suggests the need for (1) better task decomposition for AIOps problems using planning, (2) improved feedback mechanisms for intermediate steps, and (3) solutions that go beyond environment feedback and self-repair.

3.6 Agent Behavior: The Good, the Bad and the Gaps

We now delve into the behaviors of the agents and analyze the good, the challenges, and opportunities for improvement. In Table 4, we see that all agents perform better than the traditional non-LLM AIOps methods in terms of the problems for detection and localization tasks. Figure 6, shows the telemetry API usage patterns among agents. The `get_logs` API is the most frequently used API across all agents, then the `get_metrics`, and the `get_traces` APIs. However, agents also diverge in their patterns of API usage. For example, Flash does not use the `get_traces` API at all. We present the occurrences of other system commands for each agent in Table 5. We next discuss the underlying reasons and patterns contributing to the agents' poor performance.

3.6.1 *Wasting steps on unnecessary actions*

We observe that agents often waste steps on unnecessary actions, such as repeatedly calling the same API, generating non-existent APIs, or spending excessive steps in multi-agent communication. Specifically, the GPT-3.5-w-Shell agent often generates incorrect API commands in loops, leading to repeated errors in execution. For instance, setting `speaker_selection_method` as `round_robin` allows every agent to speak in every step, but this often prevents decisive, efficient decisions, as agents repeatedly resort to telemetry APIs for more information. Even with the `speaker_selection_method` set to `auto`, where the next speaker is automatically chosen, a selected agent always

Table 4. **Agent performance by task.** This table summarizes the performance of different agents across various tasks including detection, localization, RCA, and mitigation. Acc. stands for accuracy. Input/Output represents the number of tokens given to and produced by the agent, respectively.

(a) Detection Task

Agent	Accuracy	Time (s)	# Steps	Input	Output
GPT-4-w-Shell	69.23%	7.08	3.85	5,492	132
GPT-3.5-w-Shell	23.07%	11.05	13.60	1,940.44	385.56
ReAct	76.92%	39.00	11.46	15,608.08	933.15
Flash	100%	78.27	6.77	12,869.08	125.69
MKSMC	15.38%	1.00	N/A	N/A	N/A

(b) Localization Task

Agent	Acc.@3	Acc.@1	Time (s)	# Steps	Input	Output
GPT-4-w-Shell	61.54%	61.54%	7.04	4.23	4,588.07	133.23
GPT-3.5-w-Shell	30.77%	30.77%	6.26	11.92	1,784.23	217.08
ReAct	69.23%	53.85%↓	38.65	11.08	4,760.77	880.92
Flash	61.54%	46.15%↓	56.60	5.77	1,875.08	123.31
PDiagnose	15.38%	15.38%	1.02	N/A	N/A	N/A
RMLAD	7.69%	7.69%	1.98	N/A	N/A	N/A

(c) Root Cause Analysis (RCA) Task

Agent	Accuracy	Time (s)	# Steps	Input	Output
GPT-4-w-Shell	40.90%	8.68	4.81	4,297.91	176.18
GPT-3.5-w-Shell	9.09%	10.06	14.00	1,495.55	406.27
ReAct	45.45%	32.16	8.00	16,276.09	757.27
Flash	36.36%	59.00	6.09	1,193.90	152.45

(d) Mitigation Task

Agent	Accuracy	Time (s)	# Steps	Input	Output
GPT-4-w-Shell	27.27%	99.47	13.72	10,142.55	1,060.00
GPT-3.5-w-Shell	0%	23.78	20.00	3,178.33	967.71
ReAct	36.36%	67.18	15.54	29,211.90	1,464.90
Flash	54.55%	216.41	16.09	8,469.00	760.36

Table 5. Occurrences of system commands.

Agent	`find`	`echo`	`py`	`awk`	`mongo`	`grep`	`ls`	`cat`	`ip`
ReAct	0	0	0	3	0	1	26	30	0
Flash	0	3	0	0	0	0	8	10	0

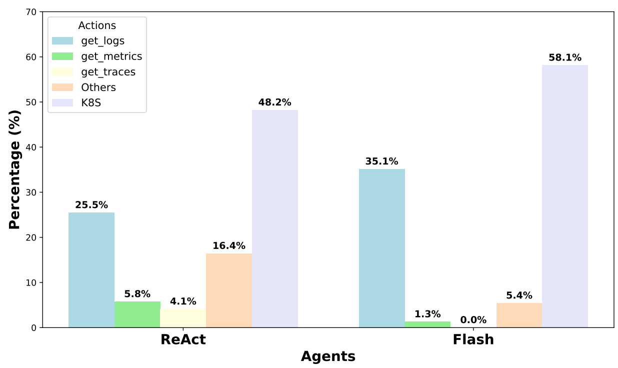
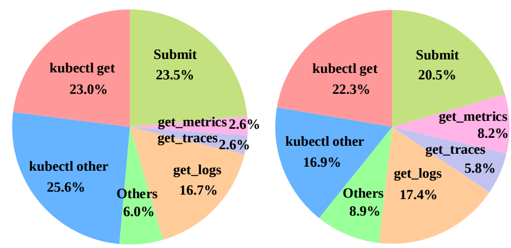


Figure 6. Total percentage of actions taken by different agents.



(a) Successful cases. (b) Failure cases.

Figure 7. Action distribution by success and failure cases.

speaks ten times in a step without communication (with a maximum of ten communication rounds per step).

3.6.2 *Overloaded information when consuming data*

To dig deeper into the agent failure modes, we analyze the correlation between the agents' actions and the success or failure of problem-solving, as well as the distribution of actions across steps. In Figure 7, we present the distribution of actions for both successful and failed cases. Agents tend to use `get_metrics` and `get_traces` APIs sparingly in successfully resolved problems, typically only when necessary. This is understandable, as the metrics data, e.g., CPU and memory usage have numerous values, which are hard to directly interpret, and trace data are descriptive records of the system's dependencies, which are more comprehensible when visualized. However, agents may subsequently consume these data with a `cat` command directly, which can overwhelm the model's input context window and cause distraction and more tokens to be consumed. Consequently, using these telemetry APIs without careful consideration or analysis can add more noise into the agents' reasoning, possibly leading to token exhaustion. We expect more refined telemetry data processing and filtering mechanisms to be implemented in the agents to avoid this issue in the future.

3.6.3 *Invalid API usage*

We notice that agents can struggle with improper formatting of API calls. For instance, GPT-3.5-w-Shell consistently generates incorrect command formats (though the API name is correct), such as malformed parameters, and repeat the error in subsequent steps. In many cases, GPT-3.5-w-Shell repeatedly responds with: "I apologize for the error. Here is the API call again:" followed by the same/similar mistake. This issue is observed as many as 14 times within a 20-step problem-solving case.

Similar issues with invalid API usage are also observed in other agents. For instance, the ReAct agent occasionally generates incorrect API commands, but typically recovers by reasoning through the errors and self-correcting its commands. In the following example, ReAct uses an incorrect parameter for the `get_logs` API, but subsequently corrects it by checking the existing services in its next step.

REACT: `get_logs("test-social-network", "Social Network")`
AIOPSLAB: Error: Your service/namespace does not exist.
REACT:
Thought: I should check the services deployed within the test-social-network namespace to ensure I use the correct service name.
Action: I will list the services in the test-social-network namespace to confirm the correct name of the service.
```
exec_shell("kubectl get services -n test-social-network")
```

3.6.4 *False positive detection issues*

To further evaluate the agents' performance, we set up two detection problems for the two microservice applications where no faults exist, referred to as no operation (Fault 10 – Noop in Table 2) problems. Only GPT-4-W-SHELL correctly identify these cases as normal system execution, while the others report false positives, misinterpreting normal activities (e.g., standard workload generation) as faults.

4 DISCUSSION

AIOPSLAB helps engineers to easily create customized incident scenarios for evaluating agents. By providing Agent Cloud Interfaces (ACIs) as guard-rails, AIOPSLAB ensures that agents are tested within a controlled environment, allowing users to focus on designing scenarios that accurately represent incidents in their systems and defining the specific problems their agents should solve.

AIOPSLAB is also adaptable to other fault types. For example, an anomaly detection workload scenario can be introduced for detection tasks. Further, users can create problems where agents are required to label the workload or telemetry data to identify anomalies.

When implementing problem evaluators, fine-grained evaluation oracles, or AIOPSLAB's optional LLM-as-Judge, may be necessary. For instance, in the binary-choice detection task, agents may answer correctly but provide incorrect interpretations or reasoning. In one case, an agent claimed to detect an abnormal system behavior, but its explanation referenced a workload that was, in fact, normal and unrelated to the injected fault. Leveraging AIOPSLAB's LLM-as-Judges can help address this issue by comparing the LLM reasoning chains with the problem description (including the fault, workload, and environment setup).

5 RELATED WORK

AgentOps. Recent advancements in cloud management have increasingly incorporated LLMs to enhance operational tasks. Approaches such as fine-tuned GPT models (Ahmed et al., 2023), RCACopilot (Chen et al., 2024), RCAgent (Wang et al., 2023), MonitorAssistant (Yu et al., 2024a), and Xpert (Jiang et al., 2024) illustrate the effectiveness of LLMs in monitoring and analyzing complex system behaviors. However, beyond the lack of publicly available implementations and associated private datasets, there is a notable gap: the absence of a unified benchmark capable of providing realistic evaluation scenarios to assess agents' performance across operational tasks.

AIOps benchmarks. Existing AIOps benchmarks primarily rely on static or text-based datasets, such as system metrics (Han et al., 2022; Jacob et al., 2020), typically time series data, or fixed question-answer format (Liu et al., 2023). These benchmarks, together with the general Language Model benchmarks (Hendrycks et al., 2021b;a; Liang et al., 2023; Lee et al., 2024; BIG-bench authors, 2023; Huang et al., 2023), do not simulate the dynamic and complex cloud environments, not to mention allowing agents to interact with them to solve operational tasks.

6 CONCLUSION

In this paper, we unravel the requirements and challenges for a comprehensive framework that supports the design, development, and evaluation of autonomous AIOps agents. We develop a framework, AIOPSLAB, which combines a fault injector, workload generator, cloud-agent orchestrator, and telemetry observer to simulate cloud incidents and provide an agent-cloud interface for orchestrating and evaluating AIOps agents. We leverage AIOPSLAB to construct a benchmark suite with 48 problems and evaluate four agents to demonstrate the application of AIOPSLAB in evaluating LLM-based agents across different types of AIOps tasks.

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