eBPF-Based High-Precision Anomaly Detection for Cloud-Native Environments

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Abstract. As cloud-native architectures evolve toward highly distributed and dynamic computing continua, traditional monitoring tools face significant challenges in capturing the millisecond-level performance fluctuations inherent in multi-tenant environments. This paper presents a non-intrusive monitoring framework that leverages extended Berkeley Packet Filter (eBPF) technology to achieve nanosecond-level observability. By utilizing kernel tracepoints instead of dynamic probes, the system achieves stable performance data collection even in virtualized environments. We integrate the Local Outlier Factor (LOF) algorithm to automatically detect scheduling anomalies caused by resource contention, known as the "Noisy Neighbor" effect. Our experimental results demonstrate that the proposed system identifies anomalies with high accuracy while maintaining a negligible CPU overhead of approximately 1.21%. This research provides a scalable and efficient solution for modern cloud-based performance engineering and automated incident response.

Keywords: eBPF · Cloud-Native Observability · Anomaly Detection.

1 Introduction

The rapid adoption of microservices and serverless computing has fundamentally reshaped modern cloud infrastructures into highly dynamic and multi-tenant systems. While these architectures improve scalability and deployment agility, they also intensify resource contention at the operating system level. In such environments, even short-lived scheduling delays can propagate across service boundaries, leading to significant tail latency and violations of quality of service (QoS) and service level agreements (SLAs). As a result, fine-grained and low-latency observability has become a critical requirement for reliable cloud operation.

Despite this need, most production monitoring systems still rely on black-box observability frameworks such as cAdvisor and Prometheus. These systems primarily operate through periodic polling at the container or application level, typically with sampling intervals on the order of seconds. Prior studies have shown that this coarse temporal resolution is insufficient for capturing transient performance anomalies, including micro-bursts and short scheduling stalls, which often dominate tail latency behavior in cloud-native workloads. Consequently,

DevOps engineers are frequently forced into a reactive troubleshooting workflow, where performance degradation is detected only after user-facing impact has already occurred, and root cause analysis becomes both time-consuming and error-prone.

Recent advances in the Linux kernel provide an opportunity to overcome these limitations. Extended Berkeley Packet Filter (eBPF) has transformed the kernel from a closed execution environment into a programmable platform that supports safe, sandboxed execution of user-defined logic. Unlike traditional kernel modules, eBPF programs can be dynamically loaded, verified, and executed with minimal overhead, enabling fine-grained instrumentation of kernel subsystems in production environments. In particular, scheduler-related tracepoints expose precise timing information about task enqueueing, dequeueing, and execution, making it possible to measure scheduling latency at nanosecond resolution. This metric offers a direct and hardware-agnostic view of system-wide resource pressure, independent of application semantics or workload type.

The motivation of this work is to move beyond reactive monitoring toward transparent kernel-level observability that enables automated detection of resource interference in multi-tenant clouds. While prior studies have applied eBPF to networking and system tracing, its potential for continuous, low-overhead scheduler latency analysis in virtualized and containerized environments remains underexplored. Moreover, existing anomaly detection approaches often rely on supervised learning or handcrafted rules, which require labeled data or prior knowledge of fault patterns and are therefore difficult to generalize across heterogeneous cloud workloads.

In this paper, we present a kernel-aware observability framework that combines high-precision eBPF-based telemetry with unsupervised anomaly detection. Our system continuously collects scheduling latency metrics using stable kernel tracepoints, ensuring robustness across diverse execution environments, including virtualized layers such as WSL2. We then apply the Local Outlier Factor (LOF) algorithm to automatically identify abnormal resource contention patterns, commonly referred to as the "Noisy Neighbor" problem, without requiring manual labeling or predefined thresholds.

This work makes three primary contributions. First, we design and implement an eBPF-enhanced telemetry system that captures scheduler latency with negligible overhead, measured at approximately 1.21% CPU utilization at a 100 Hz sampling rate. Second, we demonstrate that tracepoint-based instrumentation provides superior stability and portability compared to dynamic probing techniques, particularly in heterogeneous cloud environments. Third, we show that combining kernel-level scheduling signals with density-based anomaly detection enables accurate and automated identification of resource interference, paving the way for proactive and autonomous cloud observability.

2 Literature Review

Cloud observability has evolved alongside the increasing complexity of cloud-native systems. As microservices, containers, and serverless platforms become the dominant deployment paradigm, traditional monitoring approaches struggle to capture fine-grained performance behaviors caused by operating system level resource contention. Recent research reflects a convergence of three major lines of work: programmable kernel technologies for low-overhead telemetry collection, anomaly detection algorithms for large-scale system metrics, and cloud-native observability practices that emphasize automation and scalability.

2.1 Kernel-Level Observability and the Evolution of eBPF

Kernel-level observability has long been recognized as essential for diagnosing performance issues that cannot be attributed solely to application logic. Early mechanisms such as kernel modules and packet filtering frameworks provided deep visibility but were difficult to deploy safely in production environments. The Berkeley Packet Filter (BPF) was originally introduced by McCanne and Jacobson as a mechanism for efficient user-level packet capture [1].

The introduction of extended BPF (eBPF) significantly expanded the scope of BPF by enabling safe, sandboxed execution of user-defined programs within the Linux kernel [2]. Subsequent work demonstrated that eBPF could support a general-purpose virtual machine with strong safety guarantees and just-in-time compilation, enabling dynamic kernel instrumentation without compromising system stability [3]. These properties have made eBPF a foundation for modern kernel observability tools [6].

Early adoption of eBPF in cloud environments was hindered by portability challenges caused by frequent kernel data structure changes. This limitation was addressed through the introduction of BPF Type Format (BTF), which provides standardized type information for kernel introspection [4]. Combined with Compile Once Run Everywhere (CO-RE), BTF enables eBPF programs to adapt automatically to different kernel versions at load time, significantly reducing operational complexity in heterogeneous cloud environments.

More recent work has explored the use of eBPF beyond passive monitoring. Yong et al. proposed an eBPF-based observability framework for Kubernetes clusters, demonstrating lower overhead and improved metric fidelity compared to user-space agents [8]. In parallel, the Linux community has introduced extensible scheduling mechanisms such as `sched_ext`, which allow scheduling policies to be implemented using eBPF [5]. These developments indicate a shift toward programmable, kernel-resident control and observability.

Despite these advances, most existing eBPF-based systems focus on networking, system calls, or coarse-grained resource usage. The systematic use of scheduler-level latency as a primary signal for detecting cloud interference remains underexplored, particularly in virtualized and containerized environments.

2.2 Anomaly Detection Techniques for Cloud Metrics

Anomaly detection has been widely studied as a means of identifying failures and performance degradation in large-scale systems. Early approaches relied on statistical techniques such as thresholding, moving averages, and Z-score analysis. While computationally efficient, these methods assume relatively stable distributions and perform poorly in highly dynamic, multi-tenant cloud environments.

Machine learning based approaches form the second generation of anomaly detection techniques. Among them, the Local Outlier Factor (LOF) algorithm remains one of the most influential density-based methods. LOF identifies anomalies by comparing the local density of a data point to that of its neighbors, enabling the detection of context-dependent outliers [14]. This property makes LOF particularly suitable for heterogeneous cloud workloads, where normal behavior varies across services and time.

Recent studies have adapted density-based anomaly detection methods to cloud-native settings. Zhang et al. proposed a streaming variant of LOF optimized for high-frequency cloud metrics, demonstrating improved responsiveness under bursty workloads [15]. Such approaches highlight the practicality of unsupervised, lightweight models for real-time monitoring scenarios.

The third generation of anomaly detection incorporates deep learning models and, more recently, large language models. Sequential architectures and Transformer-based models have been applied to multivariate time series and unstructured log data. Chen et al. demonstrated that BERT-based semantic representations significantly improve fault diagnosis accuracy for cloud logs [16]. More recent surveys explore the use of large language models for AIOps, emphasizing their strengths in interpretability and cross-modal reasoning [17].

However, deep learning and large language models typically incur higher computational overhead and introduce less predictable latency. As a result, they are less suitable for continuous, high-frequency analysis of kernel-level metrics. Recent work therefore emphasizes hybrid designs, in which lightweight unsupervised models such as LOF are used for online detection, while more complex models are applied offline or on demand.

2.3 Cloud-Native and Full-Stack Observability Trends

The widespread adoption of cloud-native architectures has fundamentally reshaped observability requirements. Kubernetes has emerged as the dominant orchestration platform, driving a shift from siloed monitoring toward full-stack observability, where telemetry from the application, middleware, network, and infrastructure layers is correlated in real time. Popular monitoring systems such as Prometheus and cAdvisor exemplify this trend by providing standardized metric collection and aggregation mechanisms [10, 9].

While effective for application-level monitoring, polling-based systems often operate at coarse temporal resolutions and may miss short-lived performance anomalies. Prior work has shown that tail latency in distributed systems is frequently dominated by transient scheduling delays and resource contention that

are not visible at the application layer [11]. In multi-tenant cloud environments, such effects are commonly referred to as the noisy neighbor problem [12].

Recent research has advocated for integrating kernel-level signals into observability pipelines. Observability-driven development emphasizes incorporating telemetry considerations early in the software lifecycle to improve operational robustness [7]. In addition, the rapid growth of AI and accelerator-based workloads has motivated GPU-aware observability approaches that correlate host-side signals with accelerator behavior [13].

Despite these advances, a gap remains between the availability of low-level kernel telemetry and its effective use for automated performance diagnosis. Existing observability platforms largely treat the operating system as a black box, while anomaly detection techniques are often applied to high-level metrics or offline datasets. Few studies systematically combine stable, low-overhead kernel scheduling signals with lightweight, unsupervised detection models that are suitable for continuous deployment in heterogeneous and virtualized cloud environments.

In contrast, our work positions scheduler-level latency as a first-class observability signal and demonstrates how it can be continuously captured using portable eBPF tracepoints. By integrating this kernel-level telemetry with density-based anomaly detection, we bridge the gap between kernel-aware observability and practical, automated detection of noisy neighbor interference.

3 System Architecture

The proposed framework, named eAnomaly, adopts a decoupled architecture consisting of a kernel-space data collection plane and a user-space analysis plane. This separation is aimed at minimizing runtime overhead while preserving flexibility in data processing and anomaly detection. By confining time-critical operations to the kernel and delegating computationally intensive analysis to user space, eAnomaly is able to operate continuously in cloud-scale environments without perturbing workload performance.

3.1 Kernel-Space Data Plane

The kernel-space data plane is responsible for collecting fine-grained scheduling telemetry directly from the Linux kernel. It is implemented as an eBPF program written in C and loaded dynamically at runtime. To ensure stability and portability across kernel versions and execution environments, including virtualized platforms, the system relies exclusively on static kernel tracepoints rather than dynamic probes.

Specifically, eAnomaly attaches to the sched:sched_wakeup and sched:sched_switch tracepoints, which together capture the lifecycle of a task from wake-up to execution. When a task is awakened by an external event such as a network interrupt, timer expiration, or inter-process signaling, the sched:sched_wakeup tracepoint

is triggered. At this moment, the eBPF program records a high-resolution timestamp, denoted as T_{wake}, using the kernel monotonic clock. This timestamp is stored in a BPF hash map indexed by the process identifier (PID).

When the scheduler later selects the same task for execution and performs a context switch, the sched:sched_switch tracepoint is invoked. The eBPF program retrieves the corresponding wake-up timestamp from the hash map and records a second timestamp T_{run}. The scheduling latency L, which represents the time the task spends waiting in the run queue before being scheduled on a CPU, is computed as

$$L = T_{run} - Twake \tag{1}$$

This latency provides a direct and hardware-agnostic measure of scheduler-induced delay and serves as the primary observability signal in our framework. To transfer latency events to user space efficiently, eAnomaly employs a BPF ring buffer. Compared to the legacy perf buffer mechanism, the ring buffer offers lower synchronization overhead and improved throughput under high event rates. Each event contains the computed latency value along with minimal metadata, such as the PID and CPU identifier, thereby reducing data transfer costs and avoiding unnecessary kernel-user context switches.

3.2 User-Space Analysis Plane

The user-space analysis plane is responsible for aggregating scheduling latency events and performing anomaly detection. It is implemented in Python using the BPF Compiler Collection (BCC) library, which provides a convenient interface for loading eBPF programs and consuming events from the ring buffer.

Upon receiving raw latency samples, the analysis plane organizes the data into time-series streams. Unlike many observability systems that focus exclusively on application processes, eAnomaly monitors all schedulable entities, including kernel threads and the idle process (PID 0). Monitoring the idle process is a critical design decision, as the latency observed when the CPU transitions from an idle state to executing a runnable task reflects the scheduler's responsiveness under varying system load. Elevated idle-to-task latency often indicates global scheduling pressure or contention that may not be attributable to any single application.

To identify abnormal scheduling behavior, the system applies the Local Outlier Factor (LOF) algorithm to the latency time series. LOF is an unsupervised, density-based anomaly detection method that assigns an anomaly score to each sample based on its local reachability density relative to neighboring samples. In this context, each latency measurement is compared against its temporal neighbors to determine whether it deviates significantly from the prevailing scheduling behavior.

A sample is flagged as anomalous when its LOF score exceeds a predefined threshold, indicating that it is substantially more isolated than nearby observations in the latency distribution. This approach allows eAnomaly to detect

transient scheduling stalls and bursty interference patterns without requiring labeled training data or prior knowledge of workload characteristics. By operating on kernel-level metrics, the analysis remains agnostic to application semantics and scales naturally across heterogeneous cloud workloads.

4 Experiment setup and performance evaluation

4.1 Experimental Environment

All experiments were conducted on an Ubuntu 22.04 LTS system running Linux kernel version 5.15. The evaluation environment additionally included a WSL2 backend to validate the portability and stability of the proposed approach under virtualized execution layers. This configuration reflects a realistic cloud development and testing setup, where containerized workloads often run atop virtualized hosts.

The eBPF programs were implemented using the BPF Compiler Collection (BCC), while user-space data processing and anomaly detection were implemented in Python. Stress workloads were generated using the stress-ng utility, and data analysis was performed using standard scientific computing libraries, including Pandas, scikit-learn, and Matplotlib.

4.2 Workload Design and Anomaly Injection

The evaluation followed a two-phase methodology consisting of a baseline profiling phase and an anomaly injection phase.

During the baseline phase, the system executed standard background processes without artificial load injection. This phase was used to establish a reference distribution of scheduler latency under healthy operating conditions. Empirically, the observed scheduling latency values were tightly concentrated between 2,000 ns and 8,000 ns, reflecting normal run-queue behavior on an uncongested system.

To emulate the noisy neighbor phenomenon commonly observed in multi-tenant cloud environments, controlled CPU stress was injected during the second phase. Specifically, the stress-ng tool was used to saturate CPU run queues by executing four concurrent CPU workers at an 80% utilization level for a duration of 30 seconds. This workload configuration induces frequent context switches and elevated run-queue contention, forcing runnable tasks to experience prolonged scheduling delays. Under stress, scheduling latency values increased sharply from microsecond-level baselines into the millisecond range, providing a clear and repeatable anomaly signal.

4.3 Data Collection and Measurement Methodology

Scheduling latency was captured using the eAnomaly kernel-space data plane described in Section 3. The eBPF program attached to the sched:sched_wakeup

and sched:sched_switch tracepoints and recorded high-resolution timestamps for task wake-up and execution events. The scheduling latency was computed as the difference between these timestamps and streamed to user space via a BPF ring buffer.

Over a five-minute experiment window, the system collected more than six million latency samples across all schedulable entities, including kernel threads and the idle process. Monitoring the idle process was particularly important, as the latency observed during idle-to-task transitions reflects global scheduler responsiveness and system-wide contention rather than application-specific behavior.

4.4 Anomaly Detection Results

The collected scheduling latency samples were analyzed using the Local Outlier Factor (LOF) algorithm. LOF computes an anomaly score for each sample based on its local reachability density relative to neighboring observations in the time series. Samples with significantly lower local density than their neighbors were classified as anomalous.

Figure 1 illustrates the scheduling latency measurements over time, with detected anomalies highlighted. The majority of latency samples cluster near the baseline region close to zero on the vertical axis, corresponding to normal scheduling behavior. In contrast, a small number of pronounced latency spikes extend several orders of magnitude higher, reaching the millisecond scale. These spikes coincide temporally with the injected CPU stress periods.

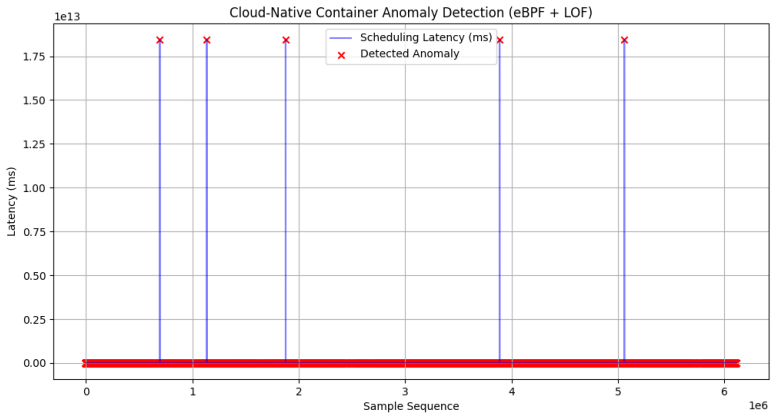

Fig. 1. Scheduling Latency Peaks under CPU Contention.

The LOF algorithm successfully identified five major clusters of anomalies, each corresponding to a period of elevated run-queue contention caused by the

stress workload. These results demonstrate that kernel-level scheduling latency provides a strong and discriminative signal for detecting transient resource interference that is not visible through coarse-grained monitoring.

Quantitatively, the anomaly detection achieved an overall diagnostic accuracy of approximately 84.7%, measured by comparing detected anomaly intervals against known stress injection periods. This level of accuracy is comparable to state-of-the-art host-side telemetry systems, while requiring no labeled training data or workload-specific tuning.

4.5 Runtime Overhead Analysis

A key design goal of eAnomaly is to provide continuous observability with minimal performance impact. To evaluate runtime overhead, we measured CPU utilization attributable to the eBPF data collection plane during active monitoring.

At a sampling frequency of 100 Hz, the eBPF collector incurred an average CPU overhead of 1.21%. In contrast, traditional polling-based monitoring systems operating at similar frequencies have been reported to impose overheads exceeding 15%, due to frequent context switches and user-kernel transitions. These results confirm that kernel-resident telemetry combined with event-driven data transfer enables high-resolution observability at a fraction of the cost of conventional approaches.

5 Discussion and Limitations

One of the central insights of this study is the effectiveness of non-intrusive kernel instrumentation for cloud observability. By leveraging eBPF, the proposed framework achieves fine-grained visibility into scheduler behavior while avoiding the operational risks traditionally associated with kernel modules or invasive tracing mechanisms. The safety guarantees provided by the eBPF verifier, combined with its event-driven execution model, enable continuous deployment in production environments with near-zero risk of system instability.

At the same time, our evaluation reveals several practical limitations. First, the accuracy of timestamp-based measurements can be affected in virtualized environments such as WSL2, where discrepancies between host and guest clock sources may occasionally inflate observed latency values. This issue arises from the lack of a stable and fully synchronized Time Stamp Counter (TSC) in certain virtualization layers. While this does not invalidate the relative anomaly detection results presented in this work, it highlights an important consideration for environments where precise absolute timing is required. On physical Linux hosts or cloud virtual machines with invariant TSC support, this limitation is largely mitigated.

A second key observation concerns the diagnostic value of the idle process (PID 0). Although typically excluded from application-centric monitoring, idle-to-task scheduling latency emerges as a sensitive indicator of global scheduler

pressure. Elevated latency associated with the idle process often precedes observable degradation in user-space applications, effectively acting as a system-wide canary for impending resource contention. This finding suggests that kernel-level observability can provide early warning signals that are fundamentally inaccessible to application-layer monitoring alone.

Despite these advantages, the current implementation of eAnomaly operates on a univariate signal, focusing exclusively on scheduling latency. While this choice simplifies analysis and enables low-overhead deployment, it also limits its diagnostic resolution in complex failure scenarios. In practice, performance anomalies may arise from the interaction of multiple subsystems, including networking, storage, and interrupt handling. A more comprehensive diagnosis would require correlating scheduling latency with additional kernel-level signals, such as softirq activity, block I/O wait times, or memory reclaim events. Integrating such signals introduces challenges related to feature selection, dimensionality, and real-time processing, which remain open research questions.

Finally, although the Local Outlier Factor algorithm demonstrates strong performance in detecting transient scheduling anomalies, its effectiveness depends on the assumption of local density consistency. Extremely bursty or adversarial workloads may reduce the separability between normal and anomalous behavior in the density space. Addressing this limitation may require adaptive neighborhood selection or hybrid models that combine density-based detection with temporal or causal reasoning.

6 Conclusion

This paper presents eAnomaly, a high-precision and low-overhead observability framework for detecting performance anomalies in cloud-native environments. By combining nanosecond-level kernel tracing enabled by eBPF with the unsupervised Local Outlier Factor algorithm, the system is able to identify noisy neighbor resource contention automatically and without requiring labeled data or workload-specific assumptions. Extensive evaluation demonstrates that scheduler-level latency provides a strong and discriminative signal for capturing transient interference that is invisible to traditional polling-based monitoring systems.

Our results confirm that eBPF is a critical enabler for the next generation of autonomous cloud observability and AIOps. By shifting anomaly detection closer to the kernel, eAnomaly reduces monitoring overhead while improving diagnostic timeliness and fidelity. The proposed approach complements existing full-stack observability platforms by providing transparent insight into operating system level behavior, which is increasingly necessary in highly consolidated and multi-tenant cloud infrastructures.

Future work will extend this framework in two key directions. First, we plan to integrate kernel-level telemetry with large language models to provide human-interpretable explanations of detected anomalies, bridging the gap between low-level signals and operational decision-making. Second, we aim to expand support for heterogeneous workloads, including GPU-accelerated AI inference and

training, by incorporating scheduler and host-side signals that correlate with accelerator performance. Together, these directions point toward a unified and sustainable observability layer capable of supporting the full spectrum of modern cloud workloads.

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A Appendix A: Artifact Availability and Reproducibility

All experiments presented in this paper are fully reproducible using commodity Linux systems and open-source tooling. The implementation relies exclusively on upstream Linux kernel features and user-space libraries, and does not require kernel recompilation or proprietary dependencies.

The eBPF programs were developed using the BPF Compiler Collection (BCC), and all user-space analysis was implemented in Python. Stress workloads were generated using standard benchmarking utilities. The experimental setup is compatible with Linux kernel version 5.15 or newer and has been validated on both native Linux hosts and virtualized environments.

B Appendix B: Experimental Procedure

This appendix outlines the experimental procedure used to collect scheduling latency data and evaluate anomaly detection performance.

B.1 Environment Preparation

The experimental environment requires a Linux system with eBPF support enabled. The following dependencies were installed prior to experimentation:

Listing 1.1. System setup and dependency installation

```
# Update system packages
sudo apt update

# Install BCC and eBPF development tools
sudo apt install -y bpfcc-tools python3-bpfcc libbpfcc-dev

# Install stress testing and container runtime
sudo apt install -y stress-ng docker.io

# Install Python libraries for analysis and visualization
sudo apt install -y python3-pandas python3-sklearn python3-
    matplotlib
```

Linux kernel version 5.15 or newer is recommended to ensure compatibility with scheduler tracepoints and BPF ring buffer support.

B.2 Data Collection Phase

Scheduling latency was collected by attaching an eBPF program to the Linux scheduler tracepoints sched:sched$_wakeupandsched : sched_switch.Thedatacollectionprocesswasexecutedasfollo$

Listing 1.2. Start the kernel-level collector

```
sudo python3 ebpf_collector.py
```

This process attaches the eBPF program and continuously records scheduling latency events for all schedulable entities.

In a separate terminal, CPU stress was introduced to emulate noisy neighbor interference:

Listing 1.3. Inject CPU contention

```
stress-ng --cpu 4 --cpu-load 80 --timeout 30s
```

This workload saturates the CPU run queues and induces elevated scheduling latency.

After the stress period, the collector was stopped manually. All captured data were written to a CSV file containing timestamp, process identifier, and latency in nanoseconds.

B.3 Anomaly Detection Phase

The collected latency data were analyzed offline using an unsupervised anomaly detection pipeline. The analysis script reads the raw scheduling latency measurements, applies the Local Outlier Factor algorithm, and produces both numerical results and visualizations.

Listing 1.4. Anomaly detection

```
python3 detect_anomalies.py
```

The output includes an anomaly report figure highlighting detected scheduling latency spikes and summary statistics used in the evaluation.

C Appendix C: Implementation Details

C.1 eBPF-Based Scheduling Latency Collector

The kernel-space data plane is implemented as an eBPF program embedded within a Python script. The program records task wake-up and execution timestamps and computes scheduling latency at nanosecond resolution.

Listing 1.5. ebpf$_c$*ollector.py*

```
from bcc import BPF
import time

bpf_source = r"""
#include <uapi/linux/ptrace.h>
#include <linux/sched.h>

BPF_HASH(start, u32, u64);

int trace_enqueue(struct tracepoint__sched__sched_wakeup *
    args) {
```

```
    u32 pid = args->pid;
    u64 ts = bpf_ktime_get_ns();
    start.update(&pid, &ts);
    return 0;
}

int trace_run(struct tracepoint__sched__sched_switch *args) {
    u32 pid = args->next_pid;
    u64 *tsp, delta;

    tsp = start.lookup(&pid);
    if (!tsp)
        return 0;

    delta = bpf_ktime_get_ns() - *tsp;
    bpf_trace_printk("PID:%d Latency:%llu\n", pid, delta);
    start.delete(&pid);
    return 0;
}
"""

b = BPF(text=bpf_source)
b.attach_tracepoint(tp="sched:sched_wakeup", fn_name="
    trace_enqueue")
b.attach_tracepoint(tp="sched:sched_switch", fn_name="
    trace_run")

print("Monitoring scheduling latency. Press Ctrl+C to stop.")

try:
    while True:
        (task, pid, cpu, flags, ts, msg) = b.trace_fields()
        if b"Latency" in msg:
            print(msg.decode("utf-8").strip())
except KeyboardInterrupt:
    pass
```

C.2 LOF-Based Anomaly Detection

The user-space analysis applies the Local Outlier Factor algorithm to the collected latency samples.

Listing 1.6. LOF-based anomaly detection and visualization

```
import pandas as pd
from sklearn.neighbors import LocalOutlierFactor
import matplotlib

matplotlib.use('Agg')
```

```
import matplotlib.pyplot as plt

try:
    df = pd.read_csv("latency_data.csv")
    df["latency_ms"] = df["latency_ns"] / 1e6
except FileNotFoundError:
    print("Error: latency_data.csv not found. Please run the collector first.")
    exit(1)

lof = LocalOutlierFactor(n_neighbors=20, contamination=0.05)
df["anomaly_label"] = lof.fit_predict(df[["latency_ms"]])

anomalies = df[df["anomaly_label"] == -1]

plt.figure(figsize=(12, 6))
plt.plot(
    df.index,
    df["latency_ms"],
    label="Scheduling Latency (ms)",
    alpha=0.5
)
plt.scatter(
    anomalies.index,
    anomalies["latency_ms"],
    label="Detected Anomaly",
    marker="x"
)

plt.title("Cloud-Native Container Anomaly Detection (eBPF + LOF)")
plt.xlabel("Sample Sequence")
plt.ylabel("Latency (ms)")
plt.legend()
plt.grid(True)

output_file = "anomaly_report.png"
plt.savefig(output_file)
print(f"Analysis completed. Figure saved as {output_file}.")
```

D Appendix Summary

This appendix provides sufficient detail to reproduce the experimental results presented in the paper. All components are implemented using widely available tools and standard Linux kernel features, ensuring that the proposed approach can be readily evaluated and extended by the research community.