BSODiag: A Global Diagnosis Framework for Batch Servers Outage in Large-scale Cloud Infrastructure Systems

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Abstract*—Cloud infrastructure is the collective term for all physical devices within cloud systems. Failures within the cloud infrastructure system can severely compromise the stability and availability of cloud services. Particularly, batch servers outage, which is the most fatal failure, could result in the complete unavailability of all upstream services. In this work, we focus on the batch servers outage diagnosis problem, aiming to accurately and promptly analyze the root cause of outages to facilitate troubleshooting. However, our empirical study conducted in a real industrial system indicates that it is a challenging task. Firstly, the collected single-modal coarse-grained failure monitoring data (i.e., alert, incident, or change) in the cloud infrastructure system is insufficient for a comprehensive failure profiling. Secondly, due to the intricate dependencies among devices, outages are often the cumulative result of multiple failures, but correlations between failures are difficult to ascertain. To address these problems, we propose BSODiag, an unsupervised and lightweight diagnosis framework for batch servers outage. BSODiag provides a global analytical perspective, thoroughly explores failure information from multi-source monitoring data, models the spatio-temporal correlations among failures, and delivers accurate and interpretable diagnostic results. Experiments conducted on the Alibaba Cloud infrastructure system show that BSODiag achieves 87.5% PR@3 and 46.3% PCR, outperforming baseline methods by 10.2% and 3.7%, respectively.

I. Introduction

Cloud systems have gained great popularity in a variety of applications such as computing, storage, and e-commerce, owing to their superiority in deployment, migration, and scalability, when compared to traditional systems [1]. Cloud service providers (CSPs) like AWS, Azure, and Alibaba Cloud, offer both private and public cloud services to their clientele by leasing cloud devices or selling cloud products [2]. Cloud infrastructure, constructed from essential physical equipment such as computing units, networking devices, and power components, forms the backbone of the cloud system. Due to its vast system scale and intricate architecture, failures and faults within the cloud infrastructure system severely undermine the stability and availability of upstream services, potentially leading to customer attrition and revenue loss. It is thus an important task to diagnose failures and faults within the cloud infrastructure system promptly and accurately.

In a cloud infrastructure system, a *batch servers outage*, i.e., the simultaneous breakdown of a cluster of related servers, is often considered as one of the most fatal failures. Such a failure could typically result in the complete unavailability of all upstream services. For instance, an actual batch servers outage occurred at the Alibaba Cloud Hong Kong data center on December 18, 2022, causing a catastrophic interruption in elastic container service (ECS), PolarDB, and networking service, lasting for over 12 hours [3].

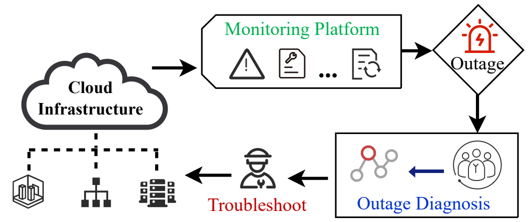

Figure 1: The life cycle of a batch servers outage diagnosis.

A cloud infrastructure system is a large-scale system comprising thousands to millions of devices. In practice, the devices within a cloud infrastructure system are usually grouped into several domains according to their physical functionalities, e.g., Internet data center (IDC), cloud networking, and cloud servers, to facilitate the dispatching and diagnosis of failures [4]. Fig. 1 shows the typical life cycle of a batch servers outage diagnosis. An online monitoring platform tracks and records the cloud infrastructure system status continuously. When a batch servers outage event is reported, experts from different domains are dispatched to meticulously analyze the monitoring data and diagnose the cause of the batch servers outage. On-site engineers (OSEs) then use these diagnostic results to troubleshoot and restore system availability. In this process, the unique domain-specific failure knowledge from different expert teams is crucial for an accurate diagnosis. Despite the widespread use of this standardized diagnosis workflow, our observations from real-world industrial practice reveal that, since it entails manually analyzing the monitoring data and intensive collaboration among different specialties, this makes diagnosis time-consuming and labor-intensive. This substantially hampers the ability to respond quickly to failures.

In recent years, many efforts have been devoted to providing an automatic failure diagnosis strategy for microservice systems [5]–[8]. As small-scale systems that typically only involve at most dozens of components, microservice systems extensively collect fine-grained machine data such as metrics [9], logs [10], and traces [11] to diagnose failures and model the correlations between failures [12]. In contrast, in a large-scale cloud infrastructure system, the monitoring platform is constrained by storage and computing resources, allowing only the recording of coarse-grained monitoring data

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such as alerts [13], incidents [14], and changes [15]. Significant disparities in data formats make the existing methods tailored for microservice systems entirely inapplicable to our batch servers outage diagnosis problem. Some recent methods attempt to address the large-scale system failure diagnosis problem through failure graph analysis [4,16,17]. However, due to the inability to accurately measure the correlation between failures, these methods suffer from the underreporting and misreporting issues. This motivates us to propose a novel solution.

In this work, we study the problem of *batch servers outage diagnosis in large-scale cloud infrastructure systems*, where the goal is to accurately and promptly locate the root cause of an outage, and facilitate troubleshooting. Our in-depth empirical study conducted on Alibaba Cloud reveals pivotal challenges to solve this problem. First, coarse-grained monitoring data collected in the cloud infrastructure system only provides a cursory aggregation for suspicious anomalies and system status changes, rendering them insufficient for comprehensive failure profiling. Second, the correlations among various failures vary significantly across domains. For example, network failures often exhibit a hierarchical structure, while IDC failures often propagate through resource sharing among devices. This makes it difficult to provide an accurate global measure of failure correlation. Third, due to the intricate dependencies among devices, outage is frequently the outcome of the cumulative effect of multiple failures. This not only makes it challenging to accurately identify the root cause, but also results in locating a single root cause that fails to provide OSEs with a holistic perspective of the failure propagation. Therefore, an accurate and interpretable failure root cause analysis method is desired.

Motivated by these observations, we propose BSODiag, an *unsupervised* and *lightweight* framework designed for diagnosing a batch servers outage. The core ideas of BSODiag are: (i) fully exploiting multi-source monitoring data via modality-specific failure detection and a unified failure event representation to provide a more comprehensive failure profiling; (ii) synergistically examining the spatio-temporal information in failures, utilizing the failure knowledge contained in historical outages and the device dependencies reflected in current outage, to accurately quantify the correlation between failures. Based on this global analytical perspective, BSODiag combines the two diagnostic tasks, i.e., root cause localization and failure propagation path inference, to enhance the accuracy and interpretability of diagnosis results. Moreover, the lightweight design of BSODiag ensures a rapid response to outages.

In more detail, BSODiag comprises three pivotal modules to tackle the aforementioned challenges individually. First, a *multi-source failure detection* module employs modality-specific components to simultaneously detect outage-related failures from alerts, incidents, and changes. Alerts are converted into time series through a serialization strategy, enabling unsupervised anomaly detection methods to pinpoint authentic failures. Changes are filtered using an expert-provided whitelist, and only high-risk actions are retained. The related failures are uniformly integrated into events, and further represented as attribute tuples. Subsequently, a *failure correlation mining* module combines failure knowledge mining and knowledge verification to discern the failure correlations reflected in historical data, and integrate them into a failure knowledge graph. Finally, an *outage root cause analysis* module constructs an event cause graph using the failure knowledge graph and a device dependency graph, and delivers interpretable diagnostic results through a customized random walk and a propagation probability-based path inference.

Our contributions can be summarized as follows:

- To the best of our knowledge, we are the first to study the batch servers outage diagnosis problem, which demands urgent resolution in the industry. We conducted an empirical study on a large-scale cloud system, and the observations uncover the key insights of this problem.
- We propose BSODiag, an unsupervised and lightweight batch servers outage diagnosis framework to address the problem. BSODiag thoroughly explores failure information from multi-source monitoring data, models the spatio-temporal correlations among failures, and delivers accurate and interpretable diagnosis results.
- To evaluate the effectiveness of BSODiag, we collected real-world failure monitoring data from Alibaba Cloud infrastructure system. Our extensive experiments conducted on this industrial dataset show that BSODiag achieves 87.5% on PR@3 and 46.3% on PCR, outperforming baseline methods by 10.2% and 3.7%, respectively.

II. Background and Empirical Observations

In this section, we first describe related background about the cloud infrastructure system and the collected failure monitoring data to facilitate a comprehensive understanding of the proposed batch servers outage diagnosis problem. Then, we conduct an in-depth empirical study in a real-world industrial context to elicit crucial insights for addressing this problem.

A. Cloud Infrastructure System

A cloud infrastructure system (CIS) refers to the collective term for all physical devices utilized in a cloud system. In current industrial practice, devices in a cloud infrastructure system are categorized into distinct domains based on their physical functionalities, maintained by experts with domain-specific knowledge to facilitate failure management and diagnosis. The Alibaba Cloud infrastructure system, as discussed in this paper, is grouped into three primary domains: Internet data center, cloud networking, and cloud servers.

Internet Data Center (IDC). The primary role of an IDC is to maintain standardized rooms to ensure the operation of servers and network devices. It primarily comprises an uninterrupted power supply (UPS) system and a temperature and humidity control system. Owing to the inherent physical propagation mechanisms, a failure within the IDC domain commonly results in extensive batch failures [18]. For instance, a power failure in a server rack can cause all servers on that rack to go offline, and a temperature control system failure can result in malfunctioning of all the devices in this room.

ID	Occurence Time	Device SN	Anomaly Type	Anomaly Content
66	22/03/25 21:12:06	XX_632	server temperature anomaly	temperature: 42.5°C
67	22/03/25 21:12:07	XX_225	circuit group interrupt	partial interrupt
68	22/03/25 21:13:22	XX_764	network device state anomaly	psw offline
69	22/03/25 21:13:22	XX_046	high cpu utilization	cpu utilization: 77%
69	22/03/25 21:13:22	XX_046	high cpu utilization	cpu utilization: 82%

(a) An Alert Sequence

Batch Servers Outage Incident

Incident ID: 1633525
Occurence Time: 22/03/25 21:33:26 - 22/03/25 21:57:48
Location: RACK: R.43-A.22-HZ.116
Relative Devices SN: XX_6389, XX_7200, XX_1573,XX_4532,...
Description: 26 servers are unreachable, suspected to be a batch servers outage failure.

(b) A Batch Servers Outage Incident

AC Refrigerant Replace Change

Change ID: 23665
Operation Time: 22/03/25 18:25:30 - 22/03/25 18:27:55
Location: ROOM-A.22-HZ.116
Relative Devices SN: XX_302,XX_306
Change Content: Replace the refrigerant of the air conditioner
Change Reason:Abnormal cooling of air conditioner

(c) A Refrigerant Replace Change

Figure 2: Different failure monitoring data collected in cloud infrastructure system.

Cloud Networking. Cloud networking devices, such as switches, and load balancers, provide connectivity among servers, and between servers and the backbone network. Owing to hierarchical structure and redundant design, networking devices exhibit complex interdependencies, causing failures within the network domain to manifest significant cascading effects. For example, a congestion failure in a top-layer load balancer can disrupt the operation of mid-layer switches, and ultimately cause bottom-layer servers to go offline.

Cloud Servers. Cloud servers are essential devices that provide computing and storage capabilities within CIS. It comprises numerous individual servers which are centrally deployed and configured into a cluster using virtualization and resource management techniques. Each server is equipped with computing units (e.g., CPU and GPU), storage units (e.g., SSD), and power supply components. Notably, the failure occurring within each server's component only impacts the status of the corresponding single server and does not cause a batch servers outage failure. Therefore, within the server domain, our focus is solely on batch failures related to outages.

B. Coarse-grained Failure Monitoring Data

To enable the timely detection and diagnosis of failures, cloud infrastructure systems are equipped with an automated monitoring platform [19] that continuously collects failure monitoring data, such as alerts, incidents, and changes, to document all anomalies, failures, and configuration changes. In Fig. 2, we present the different types of failure monitoring data collected in the Alibaba CIS.

Alert. Alert data is the structured table that chronologically records anomalies detected in a CIS. Each alert, i.e., each row in Fig. 2a, comprises a timestamp, device serial number, anomaly type, and a concise anomaly description. It is important to note that an alert simply reports an anomaly and does not equate to a failure. For example, an alert for "high CPU utilization" may be triggered by server CPU utilization exceeding a predetermined threshold since increased service traffic, which does not necessarily imply an actual CPU failure. This threshold-based triggering mechanism makes alerts sensitive to minor anomalies but also prone to significant false positives and alert flooding [1,13].

Incident. An incident is a textual ticket that aggregates relevant failures into an event. Each incident details the failure's start time, end time, device serial numbers, failure type, and a description. Incidents serve as the most direct evidence for experts to comprehend and diagnose failures. However, their intrinsic aggregation mechanism results in two notable shortcomings, i.e., delayed reporting and omissions.

Change. A change records a configuration change event in the CIS, such as manual hardware replacement, software update, or automated migration of virtual resources. Industry experiences have shown that changes are commonly high-risk factors leading to system failures [15]. Following a failure, the change data can assist engineers in checking for configuration errors and performing rapid rollbacks.

C. Empirical Observations

In this section, we conduct an in-depth empirical analysis on Alibaba CIS to answer the following research questions:

- **RQ1**: Can coarse-grained monitoring data collected in a CIS adequately describe all failures, if not, how to obtain a more comprehensive failure profiling?
- **RQ2**: What is the cause of batch servers outage, and what is the correlation mechanism between failures?
- **RQ3**: What are the necessary diagnostic results for real-world applications?

Analysis of Data Quality (RQ1). Constrained by storage and computational resources, large-scale cloud infrastructure systems collect only coarse-grained monitoring data to diagnose system failures. Existing methods usually analyze alert, incident, and change data independently to pinpoint the root cause. To evaluate the representational efficacy of these monitoring data for all failures, we collected real-world data from Alibaba CIS and conduct a qualitative analysis. Specifically, we select a batch servers outage case and trace six types of failures occurred near to the outage (i.e., within two hours before the outage and 15 minutes after the outage).

Table I: Analysis of monitoring data quality.

Failure Type	Incident	Change	Alert	#Failures
Switch Reboot	✓			4
Temperature Anomaly	✓		✓	126
Refrigerant Replacing		✓		1
PSU Power Outage	✓			2
High CPU Utilization			✓	305
Partial Network Loss			✓	206

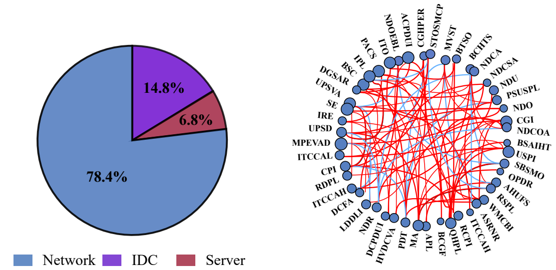
We observe that single-source monitoring data are insufficient to reveal all suspicious failures. For instance, incidents are adept at detecting significant failures, such as "Switch Reboot" and "PSU Power Outage", yet they may overlook minor failures like “High CPU Utilization”. In contrast, alarms are sensitive to these minor failures, but their “sensitivity" also leads to a large number of false positives regarding “Partial Network Loss”. Hence, for a comprehensive and accurate detection of all potential failures, *synchronous analysis of multi-source monitoring data is imperative*.

Analysis of Failure Correlation (RQ2). In a CIS, intricate interdependencies exist among devices. A failure can trigger a cascade of related failures on adjacent devices. These failures gradually propagate throughout the cloud infrastructure, ultimately becoming potential factors leading to batch servers outage. When a batch servers outage failure is detected, the diagnosis system is expected to accurately identify the root cause of these outage-related failures. In this process, accurately measuring the correlation among failures is essential. To gain a comprehensive understanding of the outages and related failures, we conducted an analysis of the root cause distribution and the failure correlation patterns.

We built a large-scale testing platform in Alibaba CIS for outage data collection and verification. Figure 3a depicts the distribution of root causes of 95 outage cases that were collected on this testing platform. Our observation reveals that cross-domain network failures (accounting for 78.4%) and IDC failures (accounting for 14.8%) are the primary root causes of batch servers outage. Furthermore, Fig. 3b illustrates the correlation patterns among 48 failures selected at random, where two connected nodes represent two related failures. Our analysis indicates that failure correlations are intricate, encompassing both intra-domain (blue connection lines) and cross-domain (red connection lines) correlations. These findings imply that a batch servers outage often results from concurrent multi-domains failures. Hence, *it is crucial to develop a failure correlation measurement technique that can model failure correlations from a global perspective* for accurately tracing the root causes of outage.

Analysis of Efficient Troubleshooting (RQ3). Following an outage, the outage diagnosis system delivers diagnosis outcomes to OSEs to facilitate rapid troubleshooting and system restoration. Existing methods for failure diagnosis in microservice systems predominantly employ root cause ranking or supervised learning approaches to predict the top-k root causes directly. Nevertheless, these methods neglect the significant gap between diagnosis outcomes and the troubleshooting process required in the real-world industrial systems. To illustrate the inadequacies of these methods in practical applications, we present a troubleshooting analysis in Fig. 4.

In the practical troubleshooting process, to prevent the recurrence of failures [8], OSEs systematically check all related devices along the failure propagation path, ensuring that all potential failures are repaired. For example, in the case presented in Fig. 4, OSEs need to investigate three suspicious paths. In this process, OSEs discover that, in addition to the root cause (i.e., power outage), aging of the PSW (Polymerize Switch) is another reason for this outage. The aged PSW’s tolerance for high temperatures decreased, leading to multiple automatic reboots and causing the batch servers outage,



(a) Root Causes Distribution (b) Failure Correlation Patterns

Figure 3: Analysis of root causes and failure correlations.

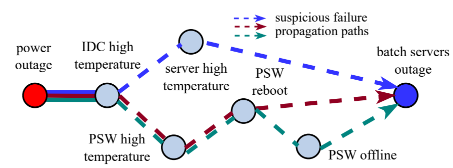


Figure 4: Analysis of real-world troubleshooting process

ultimately. Consequently, in addition to repairing the power components, replacing the PSW is also necessary. However, prior diagnosis methods focus solely on pinpointing the root cause failure of outage, without providing insight into how the root cause failure propagated step by step. This limitation leads to the oversight of potential failures, posing a threat to system stability. Hence, *providing the interpretable diagnosis results that include both root cause failure and failure propagation path is necessary for efficient troubleshooting.*

III. Batch Servers Outage Diagnosis

In this section, we first give the related definitions, and then provide a formal description of our problem.

Anomaly, Failure, Event. We use anomaly, failure, and event to refer to abnormalities at various levels, respectively. An *anomaly* refers to an abnormal observation in device metrics, but does not necessarily cause system failure. A *failure* is a more serious malfunction that affects the system operation. An *event* denotes an aggregation of similar failures or system changes that occur nearby in time and on neighboring devices, typically sharing the same triggering mechanism.

Outage Snapshot. An outage snapshot refers to the collection of monitoring data related to the outage. Formally, let us set the outage occurrence time as the time origin, and use a negative (positive) value to indicate the time amount before (after) the outage. Then the outage snapshot is defined as $U \equiv \{\mathcal{A}_{-L:T'}, \mathcal{I}_{-T:T'}, \mathcal{C}_{-T:T'}\}$, where $\mathcal{A}$, $\mathcal{I}$, and $\mathcal{C}$ represent the collected alerts, incidents, and changes, respectively; L, T, and T' denote pre-set timestamps for data collection.

A. Problem Formulation

Problem 1 (The Batch Servers Outage Diagnosis Problem)**.** *Given an outage case with outage snapshot U, we want to provide accurate and interpretable outage diagnostic results. Specifically, we have two sub-problems, i.e., failure detection and outage root cause analysis.*

- *Failure detection sub-problem takes the outage snapshot U as input, detects all outage-related* events *E in U through a discriminator $\mathcal{F}\colon U \mapsto E = \{e_1, \dots\}$.*

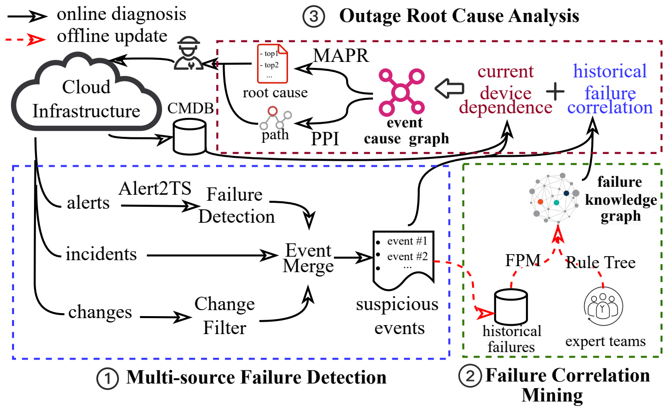


Figure 5: The overview of BSODiag

- *Outage root cause analysis sub-problem takes E as input, locates the top-k root cause set S_U of the outage and infers the failure propagation path p_U through a localizer $\mathcal{M}\colon E \mapsto \{e_r, p_U\}$.*

IV. Methodology

The empirical observations in Section II-C reveal three challenges in batch servers outage diagnosis problem: (i) low-quality failure monitoring data, (ii) intricate failure correlations, and (iii) lack of interpretability in root cause localization results. In this section, we propose an unsupervised global diagnosis framework called BSODiag. Fig. 5 provides an overview of BSODiag, illustrating its three core modules, i.e., *multi-source failure detection*, *failure correlation mining*, and *outage root cause analysis*, which are designed to address these respective challenges. In what follows, we elaborate on each module in proposed BSODiag.

A. Multi-source Failure Detection (MFD)

When the monitoring platform detects a batch serves outage, BSODiag is immediately activated. The MFD module takes the outage snapshot U as input, detects all suspicious outage-related failures, and treats them as candidates for root cause analysis. Our quality analysis in Section II-C indicates that single-source coarse-grained monitoring data used by existing methods [1,17] exhibits significant omissions (mainly from incidents) or false positives (mainly from alerts) in characterizing failures. A direct solution to address this problem is to simultaneously collect and analyze multi-source monitoring data [20,21]. However, the inherent differences in data forms and attributes in multi-source data hinder the direct application of this approach. Therefore, in the MFD module, we first use modality-specific failure detection components to detect genuine outage-related failures from different data sources separately, then aggregate related failures and uniformly represent them as events. Considering that incidents have already been aggregated into high-risk events, we only process alerts and changes during this stage.

1) Alert2Event

Alerts meticulously document all device-level anomalies, providing detailed failure information. However, we observe that due to the inherent triggering mechanism, alert processing faces two significant challenges, i.e., false positives and alert flooding. False positive alerts are reports of abnormal device states, but actually not related to the outage. They are caused by the empirical thresholding based triggering mechanism employed by the alert system. On the other hand, alert flooding occurs from the repeated reporting of the same failures, causing critical failures to be buried and difficult to identify. Therefore, we design the Alert2Event sub-module to efficiently detect genuine outage-related failures from the original alerts. The core idea of Alert2Event is to compare the differences of alert patterns (i.e., frequency and intensity of alerts) across different time periods before and after an outage. Intuitively, if a failure's alert pattern changes suddenly near the outage occurrence time, it is likely to be related to the outage. In contrast, if an alert pattern remains stable and consistent over time, it is likely to be noise and unrelated to the outage. Therefore, the Alert2Event sub-module consists of two components, namely *Alert2TS* and *Failure Detection*, where Alert2TS converts raw alert data into *alert sequences* to reflect the failure's alert pattern, and failure detection identifies genuine outage-related failures from them.

Alert2TS. We observe that a faulty device (i.e., one appearing in the outage snapshot) may trigger alerts with different failure types and exhibit different alert patterns. Therefore, the Alert2TS component is designed to transform the raw alerts of each faulty device into a multivariate time series, where each dimension of the time series quantifies the alert pattern for a specific failure on that device. Formally, for an alert set $\mathcal{A}$ from the outage snapshot U, we first divide $\mathcal{A}$ into multiple alert subsets $\{\mathcal{A}_1, \mathcal{A}_2, \ldots, \mathcal{A}_S\}$ according to their unique device serial number. Each alert subset is defined as $\mathcal{A}_s \equiv \{a_s^{k,t} \colon k \in \mathcal{K}, t \in [-L, T']\}$, recording all alerts that occurred on device s in time range $t \in [-L, T']$ in chronological order, where $a_s^{k,t}$ represents an alert that appeared at time t with failure type k, and $\mathcal{K}$ represents all of the failure types. Next, we uniformly divide the timeline of outage snapshot into time slots of length δ, and aggregate the homogeneous alerts within each time slot. Each alert subset $\mathcal{A}_s$ is thus converted into an equidistant multivariate time series $X_s \in \mathbb{R}^{K \times N}$, where $K = |\mathcal{K}|$ and $N = (L + T')/\delta$. In the aggregation process, for a numerical alert, we extract the numerical value $v_s^{k,t}$ from its description fields through regular expression matching and set the alert intensity $r_s^{k,t} = v_s^{k,t}$; for non-numerical alerts, we simply set $r_s^{k,t} = 1$ if failure type k occurs at time slot t on device s. Finally, each numerical point $x_s^{k,i}$ in the alert sequence X_s is defined as the cumulative alert intensity within the corresponding time slot, i.e., $x_s^{k,i} = \sum_{t \in l_i} r_s^{k,t}$, where l_i represents time slot $[(i-1)\delta - L, i\delta - L]$.

Failure Detection. To accurately identify outage-related failures, the failure detection component employs SPOT [22] algorithm for outlier detection in alert sequences. SPOT is an unsupervised anomaly detection algorithm that can efficiently identify outliers in a time series. In our case, for an alert sequence X_s, SPOT considers the alert sequence within the *initial window*, i.e., $t \in [-L, -T]$, as the normal alert pattern to establish the extreme value boundaries. It then dynamically updates these boundaries in the *diagnosis window*, i.e., $t \in [-T, T']$, and identifies outliers in it. Outliers appearing in the same dimension are further consolidated into a single failure f along with an attribute tuple $(sn, type\_failure, type\_device, start\_time, end\_time)$, which describes the device serial number, failure type, device type, start and end times of this failure. Finally, each alert sequence X_s is mapped to a failure set $\{f_1, f_2, \dots, f_H\}$ that contains H genuine failures discovered on device s.

2) Change Filter

Different from alerts and incidents, changes record alterations in the system status. The changes attended within a CIS can be classified into two categories, i.e., *proactive changes* and *passive changes* according to the difference in trigger mechanism. Proactive changes are initiated by OSEs or software engineers and include actions such as hardware replacements, software fixes, or upgrades. In contrast, passive changes are automatically triggered by external factors such as automated virtual resource migrations. Our empirical observations indicate that only proactive changes have the potential to cause other failures. Therefore, for the changes in the outage snapshots, we employ a rule-based whitelist to remove irrelevant changes, retaining only the proactive changes for subsequent outage investigation.

3) Event Merge

The failure detection component picks out the outage-related failures and changes from multi-source monitoring data as candidates for further root cause analysis. However, these results are not immediately usable due to two issues, i.e., the redundant records of the same failure across different monitoring sources and the inconsistencies in the granularity of failure descriptions. To address these issues, we employ an event merge component to integrate failures from alerts, original incidents, and proactive changes. Specifically, we segment the diagnosis window $[-T, T']$ into multiple time windows of length η. Within each time window, similar failures (those with the same failure type and occurring on similar devices) are merged into an event, uniformly represented as an attribute tuple $(sns, type\_failure, type\_device, start\_time, end\_time)$, where sns denotes the serial numbers of the failure devices. The start and end times of an event correspond to its earliest and latest occurrence times.

B. Failure Correlation Mining (FCM)

After detecting all outage-related events E in U, BSODiag is expected to further identify the root cause of the outage. However, accurately modeling the correlations between failures from a global perspective is a challenging task. Although these failures appear simultaneously in the outage snapshot, their correlations may differ significantly. For instance, given a failure pair $\langle f_a, f_b \rangle$ from U, if f_b is caused by f_a, a strong causal correlation $f_a \rightarrow f_b$ exists between them. If f_a and f_b are simultaneously caused by another failure f_c, just a concurrent correlation is present. Conversely, if f_a and f_b merely coincidentally appear together, they are unrelated. In traditional industrial diagnosis scenarios, failure correlations are stored as domain knowledge in the minds of different experts. However, manual diagnosis is time-consuming and labor-intensive. The FCM module aims to thoroughly explore failure information in historical data, mining stable failure mechanisms to measure the correlations between failures.

The basic idea of FCM module is to mine failure pairs with a high concurrent frequency from historical data to represent the influence mechanisms between failures. For a failure pair $\langle f_a, f_b \rangle$, if we observe a high conditional probability $P(f_b|f_a)$ in the historical data, it means that there is likely a causal correlation $f_a \rightarrow f_b$. These high-frequency failure pairs are further abstracted as failure knowledge, serving the subsequent root cause diagnosis.

FCM module employs the classic association mining algorithm Apriori [23] to mine high-frequency failure pairs from historical data. We gather historical failure data to construct an *event set* $\mathcal{T}$. The events in $\mathcal{T}$ are then divided into multiple *event groups* $\mathcal{T} = \{\mathcal{T}_1, \mathcal{T}_2, \dots\}$, where each group $\mathcal{T}_i = \{e_1, e_2, \dots\}$ shares the same spatio-temporal characteristics, indicating they occur on the same day and within the same data center. The event group is the maximum scope within which two failures can influence each other. It should be noted that when we focus only on the failure type attribute of events, events and failures are equivalent. Therefore, for convenience, we refer to $\langle e_a, e_b \rangle$ as a failure pair. For a failure pair $\langle e_a, e_b \rangle$, the metrics *support* and *confidence* are used to measure the reliability of their correlation and are calculated as:

$$\text{support}(\langle e_a, e_b \rangle)) = P(e_a, e_b) = \frac{num(\langle e_a, e_b \rangle)}{num(failure\ pairs)},$$

$$\text{confidence}(\langle e_a, e_b \rangle)) = P(e_b|e_a) = \frac{num(\langle e_a, e_b \rangle)}{num(e_a)}.$$

We note that both high-frequency *causal* failure pairs and *concurrent* failure pairs are discovered in this process, but only causal correlations are necessary for root cause analysis. Consequently, we further constrain the association mining using an expert-provided failure rule tree, which depicts the hierarchical relationships among failures from a macro perspective. Only upper-level failures can trigger lower-level failures. Therefore, we retain only high-frequency failure pairs that satisfy these hierarchical relationships.

Algorithm 1 gives the pseudo-code of the high-frequency failure pairs mining (FPM) algorithm. In Lines 1–7, high-frequency failures in the historical data are initially filtered from the event set $\mathcal{T}$. Subsequently, in Line 11, candidate failure pairs are constructed, and those that meet the failure hierarchical relationships (in Line 12) and support thresholds (in Line 16) are further picked out. Finally, all high-frequency failure pairs set $\mathcal{Q}_2$ and their confidence values are output and stored in the failure knowledge graph G_f.

C. Outage Root Cause Analysis (ORCA)

In a CIS, the interconnections between devices are intricate, involving correlations such as physical connections, resource sharing, and service dependencies. Failures propagate

Algorithm 1: Failure Pairs Mining (FPM)

Input: Event Set $\mathcal{T} = \{\mathcal{T}_1, \mathcal{T}_2, \dots\}$, Support Threshold α
Output: Frequent Failure Pairs Set $\mathcal{Q}_2$

// frequent failures initialization
$\mathcal{Q}_1 \leftarrow \emptyset$;
for *each event* $e \in \mathcal{T}$ **do**
  if $e \in \mathcal{Q}_1$ **then** $e.count \leftarrow e.count + 1$;
  else
    $\mathcal{Q}_1 \leftarrow e$;
    $e.count \leftarrow 0$;
  $\mathcal{Q}_1 \leftarrow \{e \in \mathcal{Q}_1 \mid e.count \geq |\mathcal{Q}_1| \cdot \alpha\}$;
// frequent failure pair mining
$\mathcal{Q}_2 \leftarrow \emptyset$;
for $i \leftarrow 1, \dots, |\mathcal{Q}_1|$ **do**
  for $j \leftarrow i, \dots, |\mathcal{Q}_1|$ **do**
    $p_{ij} \leftarrow \langle e_i, e_j \rangle$;
    if $e_i.level > e_j.level$ **then**
      $\mathcal{Q}_2 \leftarrow p_{ij}$;
      for *each failures group* $\mathcal{T}_l \in \mathcal{T}$ **do**
        if $p_{ij} \in \mathcal{T}_l$ **then**
          $p_{ij}.count \leftarrow p_{ij}.count + 1$;
$\mathcal{Q}_2 \leftarrow \{p_{ij} \in \mathcal{Q}_2 \mid p_{ij}.count \geq |\mathcal{Q}_2| \cdot \alpha\}$;

gradually along these inter-device dependencies, ultimately leading to a batch servers outage. The ORCA module aims to comprehensively analyze the correlations between outage-related failures, accurately locate the root cause of outage, and infer the failure propagation path, providing OSEs with interpretable diagnosis results. ORCA mainly consists of three components, i.e., event cause graph construction, outage root cause location, and failure propagation path inference. The detailed descriptions of each component are as follows.

1) Event Cause Graph Construction

To provide a comprehensive view for failure analysis, we construct an event cause graph G_e for each outage case to describe the correlations between failures. G_e is a directed graph where each node e_i represents an outage-related event in the failure snapshot U. The direction of the edges indicates the triggering correlation between failures, and the edge weight ω_{ij} represents the correlation strength of a failure pair $\langle e_i, e_j \rangle$.

The failure knowledge graph G_f models failure correlations within historical data. Intuitively, the failure knowledge in G_f can be used to construct the event cause graph G_e. For example, for two events e_i and e_j, a naive strategy to measure their correlations is to search the failure pair $\langle e_i, e_j \rangle$. If the edge $e_i \rightarrow e_j$ exists in G_f, we set $w_{ij} = 1$; otherwise, $w_{ij} = 0$. However, this approach has two significant drawbacks. First, such binary edges cannot accurately model the varying propagation capabilities between different failures. Second, it relies entirely on historical information and cannot apply to new failures that have never appeared before.

To address these issues, we further propose a spatio-temporal failure correlation strategy that analyzes failure information from both historical and current perspectives simultaneously. Specifically, we obtain historical failure correlations from the constructed fault knowledge graph G_f, using the confidence of failure pair $\langle e_i, e_j \rangle$, denoted as $e_{ij}.conf$, as the measure of reliability of failure correlation $e_i \rightarrow e_j$. Additionally, we utilize a configuration management database (CMDB) that records detailed system configurations and architectural information to assess the current physical connectivity of failures. For an event e_i, we let $e_i.sn$ denote the devices affected by e_i, and let $(e_i.out).sn$ denote all peripheral devices connected to $e_i.sn$. We define the connectivity strength between two events e_i, e_j as $dist(e_i, e_j) = |(e_i.out).sn \cap e_j.sn| / |e_i.sn|$. Particularly, when e_i and e_j are the same type of device, the connectivity strength is simplified to $dist(e_i, e_j) = |e_i.sn \cap e_j.sn| / |e_i.sn|$. Finally, we combine the spatio-temporal information of the failures to calculate the causal strength of each failure pair $\langle e_i, e_j \rangle$ as $w_{ij} = \exp(p_{ij}.conf) \cdot dist(e_i, e_j)$.

2) Outage Root Cause Location

The event cause graph preliminarily reveals the correlations between failures from a global perspective. In real industrial diagnostics, expert teams jointly analyze multiple factors such as the occurrence time, severity, and propagation capability of failures, gradually deducing the propagation process between failures to identify the root cause. Inspired by this, we propose a customized multi-attribute event graph random walk algorithm (MAPR) to locate the outage root cause.

MAPR first introduces the time priority and impact on the outage of each event into the node attribute initialization, defining node personalization score as $u_i = exp(-t) \cdot dist(e_i, e_o)$, where e_o is the outage node. Subsequently, it uses the failure correlation w_{ij} as the failure transition probability of $e_i \rightarrow e_j$, and performs multiple walks on the event graph, continuously updating the node personalization score u_i. It is worth noting that to prevent the walk from getting stuck in outage nodes, we add an incoming edge $e_o \rightarrow e_i$ to each outage-related node e_i and set the edge weight $w_{oi} = \frac{1}{|E|-1}$. After L iterations, the personalization score of each node e_i converges to a constant $\bar{u}_i$. We then remove the outage nodes and determine the top-k root cause nodes set S_U by ranking the personalization scores of the remaining nodes.

3) Failure Propagation Path Inference

Although we have identified root cause node $e_r = S_U[1]$, i.e., top-1 node in S_U, the propagation path from e_r to e_o remains unclear. The empirical analysis in Section II-C indicates that providing interpretable failure propagation paths is crucial for enhancing the troubleshooting efficiency of OSEs. To this end, we further propose a propagation probability based failure propagation path inference method (PPI). The basic principle of PPI is to select the path with the highest cumulative propagation probability from the root cause node to the outage node on the event causality graph. Specifically, we first search all connected paths $\mathcal{P} = \{p_1, p_2, \dots\}$ from e_r to e_o. Then, we calculate the cumulative propagation probability of each path and select the one with the highest probability:

$$p_U = \arg\max_{p_i \in \mathcal{P}} \text{TransPr}(p_i) = \arg\max_{p_i \in \mathcal{P}} \prod_{j \in |p_i|} \bar{u}_j,$$

where $|p_i|$ indicates the number of nodes in each path p_i.

V. Experiments

In this section, we perform experiments on real-world diagnosis data to evaluate the performance of the proposed BSODiag method.

A. Experimental Setting

1) Dataset Collection

We built a large-scale testing platform in Alibaba CIS and collected all monitoring data in this testing platform from January 2022 to December 2023. This dataset includes alerts, incidents, and changes, encompassing 95 batch server outages, each affecting dozens to hundreds of servers. We divided the collected monitoring data into four distinct datasets. The initial dataset, $\mathcal{D}_{init}$, comprises all monitoring data from 2022 and serves to initialize BSODiag. The remaining three datasets, i.e., $\mathcal{D}_{idc}$, $\mathcal{D}_{net}$, and $\mathcal{D}_{all}$, contain monitoring data from 2023 and are used to validate the diagnostic performance. Specifically, $\mathcal{D}_{all}$ includes data from all outage cases in 2023, while $\mathcal{D}_{idc}$ and $\mathcal{D}_{net}$ are subsets focusing on outages caused by IDC failures and network failures, respectively. The detailed statistics of these datasets are presented in Table II.

Table II: Datasets statistics

Dataset	#Incident	#Alert	#Change	#Failure Types	#Outage Cases
$\mathcal{D}_{init}$	$19,020$	$879,870$	$3,255$	62	27
$\mathcal{D}_{idc}$	173	$256,212$	$1,657$	31	19
$\mathcal{D}_{net}$	478	$774,638$	$5,091$	44	47
$\mathcal{D}_{all}$	665	$1,032,851$	$7,644$	56	68

In the experiment, based on the diagnostic experience, we set the initial window for outage snapshots to $[-4, -2]$, indicating the range from 4 hours to 2 hours before the outage. The diagnosis window is set to $[-2, 0.25]$, spanning from 2 hours before the outage to 15 minutes after the outage. Additionally, the time slot length δ and the event merge time window η are set to 1 minute and 5 minutes, respectively. Support threshold α in Algorithm 1 is set to 0.001, and the number of iterations L for MAPR is set to 100.

2) Compared Baselines

We compare BSODiag with three rule based methods, two machine learning (ML) based methods, and two failure graph based methods. Rule based and ML based methods are prevalent in industrial settings for their straightforward implementation, while failure graph based methods are state-of-the-art approaches in current microservices outage diagnosis.

• *Rule based methods*. We employ two widely used root cause diagnosis strategies: **Hierarchy-First** and **Time-First**. The hierarchy-first strategy [24] determines the hierarchy of suspicious failures based on a failure rule tree and considers the failure with the highest hierarchy as the root cause. In contrast, the time-first strategy [25] identifies the earliest occurring failure as the root cause. In addition, we adopt a **Random Selection** strategy to simulate the diagnosis process without any domain knowledge. To improve diagnosis accuracy, we apply these strategies on the output of MFD module.

• *Machine learning based methods*. These methods model the root cause location problem as a supervised classification problem, and address it using machine learning techniques. We implement this approach by combining the MFD module with a ML-based classifier. Each event output by the MFD module is initially represented as a multi-attribute vector encompassing failure time, failure hierarchy, and its connectivity strength with outage event. Subsequently, an **SVM** or **Random Forest** classifier is utilized to identify the root cause.

• *Failure graph based methods*. **AirAlert**[1] and **COT** [4] are state-of-the-art methods in microservices outage diagnosing problem. AirAlert leverages the Fast Causal Inference algorithm [26] to discern causal relationships between alert sequences and outages, constructing a failure graph, then using an XGBoost model to pinpoint the root cause. COT constructs an incident correlation graph using historical incident data, models the connections between failure based on this, and uses an SVM classifier to determine the root cause.

3) Evaluation Metrics

In outage diagnosis, BSODiag performs two tasks, i.e., root cause localization (RCL) and failure propagation path inference (PPI). For RCL task, we use two metrics PR@k and MAP to assess the performance of BSODiag and other baselines. We use $\mathcal{U}$ to denote all outage cases in $\mathcal{D}_{diag}$, where each outage case $U \in \mathcal{U}$ is represented by the corresponding outage snapshot. PR@K is defined as $PR@k = \frac{1}{|\mathcal{U}|}\sum_{U\in\mathcal{U}} \mathbf{1}[r_U \in S_U[1:k]]$, where r_U is the true root cause of outage case U, and $S_U[1:k]$ represents the top-k root causes predicted by the diagnosis method. Considering that accurately locating the top-1 root cause is challenging, we set $k = \{1, 2, 3\}$. MAP further evaluates the average performance for different k, calculated as $MAP = \frac{1}{k}\sum_{1\leq i\leq k} PR@i$.

For PPI task, we define path coverage rate (PCR) to evaluate the explainability of the inferred propagation paths. PCR is defined as $PCR = \frac{1}{|\mathcal{U}|}\sum_{U\in\mathcal{U}} \frac{|p_U \cap \hat{p}_U|}{|p_U|}$, where p_U and $\hat{p}_U$ denote the predicted failure propagation path and its ground truth, respectively. $|p_U \cap \hat{p}_U|$ represents the longest common subpath of p_U and $\hat{p}_U$. For all three metrics, larger values indicate better performance.

B. Performance

We first examine the performance of BSODiag and other baselines on the RCL task. As shown in Table III, BSODiag significantly outperforms all other baselines across all metrics. In dataset $\mathcal{D}_{all}$, compared to the most competitive baseline, i.e., COT, BSODiag improved by 9.3%, 8.4%, 10.2%, and 9.3% on the PR@1, PR@2, PR@3, and MAP, respectively. Similar advantages are also observed in $\mathcal{D}_{idc}$ and $\mathcal{D}_{net}$ datasets. This indicates that BSODiag can more accurately locate the root cause of outages. Additionally, we observe that although rule-based methods are straightforward, their performance is suboptimal because they only consider the failures attributes superficially and cannot fully perceive the correlation between failures. Meanwhile, for ML-based methods, the rarity of outage cases makes it difficult to sufficiently optimize the model. This further illustrates that our proposed unsupervised diagnosis strategy based on the event cause graph is more suitable for the outage diagnosis problem.

Table III: Comparison of different methods for RCL task

Methods	$\mathcal{D}_{idc}$				$\mathcal{D}_{net}$				$\mathcal{D}_{all}$			
	PR@1	PR@2	PR@3	MAP	PR@1	PR@2	PR@3	MAP	PR@1	PR@2	PR@3	MAP
Random Selection	14.3%	31.2%	42.6%	39.4%	8.7%	23.8%	36.4%	23.0%	10.4%	28.8%	39.6%	25.4%
Hierarchy-First	12.6%	27.5%	46.3%	28.8%	13.9%	37.8%	66.4%	39.4%	12.5%	35.4%	62.5%	36.8%
Time-First	22.5%	42.6%	53.8%	39.6%	41.2%	56.0%	73.7%	57.0%	35.0%	52.0%	70.1%	52.4%
SVM	32.0%	44.6%	62.5%	46.4%	27.4%	44.2%	65.3%	45.6%	27.8%	43.9%	66.1%	45.9%
Random Forest	39.2%	58.8%	72.0%	56.7%	41.4%	57.9%	71.4%	56.9%	42.6%	58.7%	74.3%	58.5%
AirAlert	18.5%	30.9%	41.0%	30.1%	28.0%	43.2%	53.6%	41.6%	24.5%	38.7%	48.8%	37.3%
COT	46.3%	66.0%	82.7%	65.0%	40.8%	57.5%	72.2%	56.8%	44.9%	62.4%	77.3%	61.5%
BSODiag (**ours**)	**56.1%**	**72.9%**	**88.2%**	**72.4%**	**52.4%**	**70.7%**	**86.7%**	**69.9%**	**54.2%**	**70.8%**	**87.5%**	**70.8%**

Comparing the performance of all methods on $\mathcal{D}_{idc}$ and $\mathcal{D}_{net}$, we observe that rule based and failure graph based baselines exhibit obvious performance fluctuations. Notably, rule based methods demonstrate a performance difference of approximately 20% on $\mathcal{D}_{net}$ compared to $\mathcal{D}_{idc}$. This phenomenon stems from inherent differences in failure propagation mechanism across various domains. IDC failures typically span multiple domains, whereas network failures present a more straightforward hierarchical structure, facilitating root cause localization. Although ML-based methods show consistent performance across different domains, their root cause diagnosis capabilities remain suboptimal due to their inability to model the intrinsic correlations between failures. In contrast, our method, i.e., BSODiag, comprehensively models failure correlations by incorporating historical knowledge and current device dependencies, demonstrating consistent superiority across various domains.

Table IV: Comparison of different methods for PPI task.

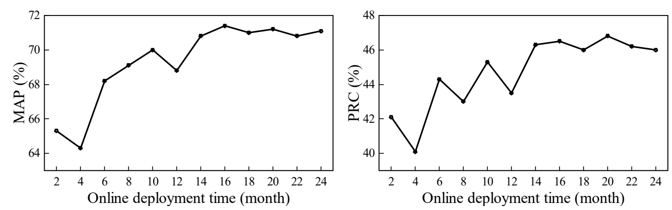
Dataset	Methods			
	DPS	SPS	FHM	BSODiag(**ours**)
$\mathcal{D}_{idc}$	38.0%	35.2%	41.8%	**45.6%**
$\mathcal{D}_{net}$	41.6%	32.4%	43.3%	**46.8%**
$\mathcal{D}_{all}$	40.2%	33.8%	42.6%	**46.3%**

For the PPI task, due to the absence of directly comparable baselines, we compare BSODiag with several straightforward path inferring strategies, i.e. **deepest path search** (DPS), **shortest path search** (SPS), and **Failure Hierarchy Matching** (FHM). DPS and SPS, respectively, search for the longest and shortest path between the top-1 root cause node e_r and outage node e_o as the failure propagation path. The failure hierarchy matching strategy strictly follows the "upstream-downstream" propagation policy described in the failure rule tree to infer failure propagation path. The results, exhibited in Table IV, indicate that BSODiag achieves 46.3% PCR, showing an improvement of 6.1%, 12.5%, and 3.7% compared to the other baselines, respectively.

C. Online Evolution

In BSODiag, the failure knowledge graph, constructed from historical data, is essential for accurately measuring failure correlations. The scale of historical data directly determines the quality of the constructed failure knowledge graph, thereby affecting the diagnosis performance of BSODiag. In actual online deployment, as more failure data are collected, we can continuously update BSODiag to optimize its performance.

Figure 6 illustrates the online evolution of BSODiag's performance over two years. Despite minor fluctuations in root cause diagnosis performance due to the deployment of differentiated services in real cloud systems, BSODiag's overall performance exhibits an initial increase followed by stabilization. In the early stages, when failure data are sparse, BSODiag's diagnostic accuracy is limited due to insufficient fault knowledge. As more data accumulates, the quality of the failure knowledge graph gradually improves, resulting in enhanced diagnostic performance. In the later stages, the failure knowledge graph reaches a quality plateau, leading to a steady state in BSODiag's performance.



(a) MAP (b) PCR

Figure 6: The online deployment performance of BSODiag.

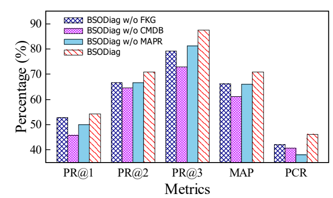


Figure 7: Ablation study

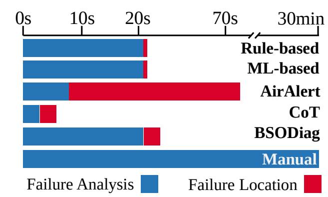


Figure 8: Time Consumption

D. Ablation Study

In this section, we conduct an ablation study on $\mathcal{D}_{all}$ dataset to provide a better understanding of the proposed BSODiag. In the experiment, we remove each of the three core modules separately: the failure knowledge graph, the configuration management database, and the event cause graph multi-attribute random walk. These are denoted as "BSODiag w/o FKG", "BSODiag w/o CMDB", and "BSODiag w/o MAPR", respectively. The results are shown in Fig. 7.

We observe that when the corresponding components are removed, the performance of BSODiag on both RCL and PPI tasks significantly declines. This indicates that 1) the proposed spatio-temporal failure correlation analysis strategy can provide more accurate failure correlation modeling; and 2) the proposed global analysis perspective can better understand the propagation process of failures, thereby improving the ability to locate root causes and infer failure propagation path.

E. *Efficiency Analysis*

To further evaluate the diagnosis efficiency of BSODiag, we conduct an efficiency analysis in this section. Fig. 8 compares the root cause diagnosis efficiency of BSODiag with all baselines and expert maintenance technicians in the Alibaba on $\mathcal{D}_{all}$ dataset. The total time consumption is divided into two stages, i.e., failure analysis and failure localization.

The results demonstrate that BSODiag achieves a single diagnosis of an outage case in 24.5 seconds, marking a substantial improvement over the traditional manual diagnosis, which typically requires an average of 30 minutes. Additionally, we note that the most time-consuming part of the diagnosis process is the MFD module, as it involves complex failure analysis operations including both failure detection and failure merging. Similarly, rule-based and ML-based methods primarily consume time during the failure analysis process. In contrast, AirAlert's time consumption is mainly in the failure localization phase, as it necessitates the computation of pairwise correlations among alert sequences, a process that demands significant computational resources. While COT exhibits the highest diagnostic efficiency by processing only incident data, our findings in Table III suggest that this approach may overlook certain outage-related failures, potentially compromising the accuracy of root cause localization.

VI. Related Work

Failure Detection. Failure detection [27,28] aims to promptly identify anomalies using monitoring data generated by hardware devices or service nodes. Depending on the type of data required, existing methods can be categorized as metric based, log based, trace based, and multi-modal based methods.

Metric based methods identify failures by modeling both the normal and abnormal sequential patterns in metrics using traditional statistical methods [29] or end-to-end learnable neural networks [9]. *Log based* methods transform logs into keyword index sequences [30,31] or natural language [10], and detect failures by combining the sequential and semantical information of logs. *Trace based* methods are mainly used for detecting invocation anomalies in microservice systems. Such methods typically use historical traces to model the normal response pattern, and then during the detection phase, traces that deviate from the normal pattern are identified as anomalies [11,32]. Multi-modal based methods jointly model metrics, logs, and traces, mining failure patterns from multiple data modalities and reducing the rate of missed failure detection [20,21].

Root Cause Analysis. Due to the complex correlations between devices or services in cloud service systems, a single failure often triggers multiple related failures. Root cause analysis (RCA) [6,7,33] aims to locate the root cause failures [34]. The existing RCA methods can be divided into search based, learning based, and causality graph based methods.

Traditional *search based* RCA methods [22,35] identify root causes by searching for attribute combinations with the highest commonality in failure. For example, HotSpot [35] uses a potential score to measure the correlation of different attribute combinations within failures and employs a heuristic strategy to reduce the search space of attribute combinations. These methods are the easiest to deploy. However, it should be noted that they are only applicable to scenarios with discrete failure attributes due to their reliance on restricted attribute space.

Learning based methods [8,20] typically model RCA as a supervised graph node classification problem. These methods first construct a component dependency graph, where each node represents a device or service node, and the edges represent the inherent connections between corresponding components. Graph neural networks are then used to aggregate failure information among different nodes. For example, Eadro [20] first builds a node dependency graph through component interaction information and then uses a GAT-based status learning approach to accomplish failure detection and root cause localization tasks, simultaneously. Due to the requirement of a large amount of labeled data, these methods are difficult to deploy in real industrial environments.

Causality graph based RCA methods [17,36] have been extensively studied in recent years. These methods typically contain two core steps, i.e., failure causality reasoning and root cause localization [17,25,37,38]. The failure causality reasoning constructs a failure causality graph that directly reflects the failure propagation process by mining the correlation between failures through their own information. For instance, MicroCause [25] proposes a path condition time series algorithm to learn the causal relationships between failures from the metrics of microservice nodes. COT [4] obtains the correlations between failures from historical incidents and constructs a failure causality graph based on this. Subsequently, on the failure causality graph, these methods use random-walk based or search based approaches to locate the root cause.

VII. Conclusion

The failure diagnosis capability of cloud infrastructure systems is crucial for maintaining system availability. In this paper, we propose an unsupervised lightweight diagnosis framework BSODiag to address the batch servers outage diagnosis problem. BSODiag comprehensively detects system failures by fully utilizing multi-source failure monitoring data, including alerts, incidents, and changes. Subsequently, failure spatio-temporal information reflected in historical data and current devices is used to measure the correlation between failures. Finally, BSODiag analyzes the failure propagation process from a global perspective, accurately locates the root causes of the outage, and infers failure propagation paths. Experiments on real industrial data demonstrate that BSODiag significantly outperforms existing baseline methods.

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