# MicroRes: Versatile Resilience Profiling in Microservices via Degradation Dissemination Indexing

#### Tianyi Yang

The Chinese University of Hong Kong Hong Kong SAR tyyang@cse.cuhk.edu.hk

# Yuxin Su\*

Sun Yat-Sen University Zhuhai, China suyx35@mail.sysu.edu.cn

# Cheryl Lee

The Chinese University of Hong Kong Hong Kong SAR cheryllee@link.cuhk.edu.hk

## Cong Feng

Computing and Networking Innovation Lab, Huawei Cloud Computing Technology Co., Ltd Shenzhen, China fengcong5@huawei.com

## Michael R. Lyu

The Chinese University of Hong Kong Hong Kong SAR lyu@cse.cuhk.edu.hk

# Jiacheng Shen

The Chinese University of Hong Kong Hong Kong SAR jcshen@cse.cuhk.edu.hk

## Yongqiang Yang

Computing and Networking Innovation Lab, Huawei Cloud Computing Technology Co., Ltd Shenzhen, China yangyongqiang@huawei.com

## ABSTRACT

Microservice resilience, the ability of microservices to recover from failures and continue providing reliable and responsive services, is crucial for cloud vendors. However, the current practice relies on manually configured rules specific to a certain microservice system, resulting in labor-intensity and flexibility issues, given the large scale and high dynamics of microservices. A more labor-efficient and versatile solution is desired. Our insight is that resilient deployment can effectively prevent the dissemination of degradation from system performance metrics to user-aware metrics, and the latter directly affects service quality. In other words, failures in a nonresilient deployment can impact both types of metrics, leading to user dissatisfaction. With this in mind, we propose MicroRes, the first versatile resilience profiling framework for microservices via degradation dissemination indexing. MicroRes first injects failures into microservices and collects available monitoring metrics. Then, it ranks the metrics according to their contributions to the overall service degradation. It produces a resilience index by how much the degradation is disseminated from system performance metrics to user-aware metrics. Higher degradation dissemination indicates lower resilience. We evaluate MicroRes on two open-source and one industrial microservice system. The experiments show MicroRes' efficient and effective resilience profiling of microservices. We also showcase MicroRes' practical usage in production.

ISSTA '24, September 16-20, 2024, Vienna, Austria

## CCS CONCEPTS

• Computer systems organization  $\rightarrow$  Reliability; Maintainability and maintenance; Cloud computing; • Software and its engineering  $\rightarrow$  Software testing and debugging.

#### **KEYWORDS**

Microservices, resilience profiling, fault injection

#### **ACM Reference Format:**

Tianyi Yang, Cheryl Lee, Jiacheng Shen, Yuxin Su, Cong Feng, Yongqiang Yang, and Michael R. Lyu. 2024. MicroRes: Versatile Resilience Profiling in Microservices via Degradation Dissemination Indexing. In *Proceedings of the 33rd ACM SIGSOFT International Symposium on Software Testing and Analysis (ISSTA '24), September 16–20, 2024, Vienna, Austria.* ACM, New York, NY, USA, 13 pages. https://doi.org/10.1145/3650212.3652131

#### **1** INTRODUCTION

Nowadays, an online service is usually developed as a bunch of fine-grained and independently-managed microservices and then deployed as a microservice system [19]. Microservice systems exhibit three prominent attributes [5]. First, they are highly decoupled and usually contain many microservices, e.g., Netflix's system has hundreds to thousands of microservices [31]. Second, microservices are dynamic. New features and updates are delivered continuously and frequently. Last, microservices are specialized. Each microservice only processes a single type of request. Microservices interact with each other and serve users' requests together.

Resilience, i.e., the ability to maintain performance at an acceptable level and recover the service back to normal under service failures [51], is essentially one of the desired abilities of online services. Figure 1 illustrates a non-resilient example by plotting the request throughput of an online service during the normal and the faulty period. Intuitively, the resilience of the service is low because the failure causes service degradation, reflected by the throughput decrement. Resilience profiling is thereby crucial as

<sup>\*</sup>Yuxin Su is the corresponding author.

Permission to make digital or hard copies of all or part of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. Copyrights for components of this work owned by others than the author(s) must be honored. Abstracting with credit is permitted. To copy otherwise, or republish, to post on servers or to redistribute to lists, requires prior specific permission and/or a fee. Request permissions from permissions@acm.org.

<sup>© 2024</sup> Copyright held by the owner/author(s). Publication rights licensed to ACM. ACM ISBN 979-8-4007-0612-7/24/09...\$15.00 https://doi.org/10.1145/3650212.3652131

faults and failures are unavoidable [33, 40] and a resilient system can be commissioned to users by ensuring service reliability. Without sufficiently high resilience, a new or updated microservice system should not be directly deployed in the production environment.



Figure 1: The monitoring metrics during the normal period (the green area) and the failure injection period (the red area). "rx\_bytes" and "tx\_bytes" indicate network receive and transmit rate.

The current practice [39] for resilience profiling is to set resilience rules manually, including the concerned failure types, the metrics to monitor, the measure of degradation, and the criteria for passing or failing the tests. However, such a method is highly time-consuming and labor-intensive, all the while lacking flexibility to adapt to different microservice systems.

First, manual rule identification relies heavily on domain expertise to define the rules that can represent the degradation caused by failures. Defining proper rules is very burdensome because 1) the number of microservices is usually huge (up to tens of thousands), and so are their failures since microservices are highly decoupled [54]; 2) the dynamism of microservices requires frequent updates of the rules [5]. In Huawei Cloud, it usually takes two manmonths of discussion before the test engineers reach a consensus on the rules according to our survey, and the update requirement even worsens this situation.

Second, rule-based resilience profiling can not fit in different microservice systems. The reason is two-fold: 1) Microservices are specialized for different business applications, making the failures and their resulting manifestations manifold [40]. 2) Fixed PASS/FAIL results obtained from resilience test rules fail to discriminate the subtle difference in an online service's resilience when the boundary between "resilient" and "non-resilient" becomes less absolute. This is because various refined resilience mechanisms (e.g., circuit breakers, replications, and node auto-scaling) are applied in existing platforms, such as Kubernetes, so the system can be in a "gray-failure" status that can not be fully depicted by a few common metrics like mean time to recover (MTTR) used in the test rules.

An intuitive idea to mitigate the two issues is to propose a versatile resilience profiling technique with smooth criteria. However, designing such an approach is non-trivial. The critical challenge is how to determine to what extent a microservice system is resilient. To address the challenge, we investigate the failure impact on two deployments of Train-Ticket [57], an open-source microservice benchmark system, with and without common resilience mechanisms (Section § 3.2). We find that failures affect system performance metrics (e.g., memory usage, network throughput) such as memory usage and network throughput, but a resilient service can prevent the impact from disseminating to user-aware metrics such as response latency and MTTR. Based on the observation, our insight is that we can measure microservice resilience by comparing the degree of degradation dissemination from system performance metrics to user-aware metrics. *If the degradation cannot disseminate from system performance metrics to user-aware metrics, the resilience is high. Otherwise, the resilience is low.* 

Motivated by this insight, we present **MicroRes**, the first versatile resilience profiling framework for microservice systems. MicroRes consists of three phases, i.e., *failure execution, disseminationbased metric lattice search*, and *resilience indexing*. *Failure execution* comprises two phases: *failure injection* and *failure clearance*. Given a specified failure and a predefined *load generator*, MicroRes collects the service's monitoring metrics in the normal and faulty period. For the *dissemination-based metric lattice search*, we propose a dissemination-based algorithm that ranks all the monitoring metrics according to their contributions to the overall service degradation. We construct a metric lattice from the power set of the monitoring metric set. The ranking is based on a degradation-based path search in the metric lattice. Lastly, for *resilience indexing*, we index the resilience in (0, 1) by how much the degradation in system performance metrics is disseminated to the user-aware metrics.

Experiments on two open-source (Train-Ticket [57] and Social-Network [24]) and one industrial (Huawei Cloud) microservice system demonstrate the effectiveness of MicroRes. We inject failures into all systems and compare the performance of resilience profiling under MicroRes and several baselines. The experimental results demonstrate that our proposed method accurately quantifies the system resilience and outperforms the baselines. Specifically, in terms of cross-entropy, MicroRes achieves the best performance of 0.3246 on the Train-Ticket benchmark, 0.3766 on the Social-Network benchmark, and 0.2977 on the industrial benchmark. In terms of accuracy, MicroRes also achieves the best performance of 0.9012, 0.8611, and 0.8929 on the Train-Ticket, Social-Network, and industrial benchmarks. Furthermore, we showcase the successful usage of MicroRes in the production cloud system of Huawei Cloud. We make the code and dataset publicly available<sup>1</sup>.

The contributions of this work are highlighted as follows:

- We identify the labor-intensity and flexibility issues for the current rule-based practice for resilience profiling. Then we conduct the first investigation on how degradation disseminate from system performance metrics to user-aware metrics in resilient and non-resilient microservice systems, which demonstrates the viability of versatile resilience measuring.
- We propose MicroRes, the first versatile resilience profiling framework that can automatically index the resilience of a microservice system to different failures. MicroRes measures the dissemination of degradation from system performance metrics to user-aware metrics. The higher the dissemination, the lower the resilience.
- Evaluation of MicroRes on two open-source and one industrial microservice systems indicates its effectiveness and efficiency. The industrial case study also confirms the practical usage of MicroRes.

<sup>&</sup>lt;sup>1</sup>https://github.com/yttty/MicroRes

## 2 BACKGROUND

This section first briefly describes the metrics of a microservice system. Then we present the necessity and procedure for resilience profiling that underpins our approach.

## 2.1 Metrics of Microservices

In the contemporary landscape, large-scale online services such as Netflix and Twitter adopt microservices [19] to achieve scalability, robustness, and agility. This architectural approach involves breaking down a monolithic online service into fine-grained components known as microservices [48]. These microservices are highly decoupled and can be numerous in a system; for instance, Netflix employs hundreds to thousands of microservices [31]. Virtualized infrastructure, like virtual machines and containers, is commonly used for deploying microservices. To facilitate service decoupling and orchestration, additional components like API gateways, service registries, and databases are employed.

As a result of this complex setup, microservice systems generate extensive and diverse monitoring metrics [17], which can vary based on the system's architecture and implementation. Broadly, these monitoring metrics fall into two categories: *system performance metrics* and *user-aware metrics*.

System performance metrics directly reflect the runtime status of microservices and the underlying orchestration system. Microservice orchestration platforms like Kubernetes [20] use multi-level isolation to manage containers in isolated pods on nodes, either virtual or physical machines. Components for network management, proxy, and task scheduling are also monitored for various system performance metrics, including CPU and memory usage, network throughput, disk I/O, TCP connections, etc., at both the infrastructure and container levels. As any failure of these components may possibly result in the degradation of service, all the pods, nodes, and other components are monitored, producing various system performance metrics, e.g., CPU and memory usage, network throughput, network transmit and receive rate, disk I/O speed and error rate, number of TCP connections, etc. The system performance metrics are collected at different virtualization levels, i.e., the infrastructure level (machines) and the container level (microservices).

User-aware metrics, in addition, reflect the quality of service in a specific time period from the users' aspect. User-aware metrics, such as response latency, error rate, throughput, mean time to recovery, and availability rate, are also crucial system indicators. Different online services value different user-aware metrics. For example, availability and error rate are common performance attributes of transactional services, while video streaming services are usually based on throughput.

## 2.2 Microservice Resilience Testing

Resilience in a microservice system pertains to its capacity to sustain service performance at an acceptable level and efficiently recover from failures that lead to service degradation [51, 55]. The construction of robust online services becomes imperative, given the inevitability of faults and failures [33, 40]. The ability to withstand unexpected failures is crucial for minimizing downtime, upholding service quality, and fulfilling service-level agreements, which is crucial for user experience. Resilience testing [44] is a primary method for ensuring software resilience, demanding that all new or updated microservices undergo these tests to validate the resilience of online services. Unlike functional correctness tests [4], which focus on core application functions and data integrity, resilience tests deliberately introduce failures into the system under stress or chaotic conditions to assess how the microservice system performs [31]. Test engineers then use the observed flaws to refine the architectural design. The passing criterion involves the online service continuing to deliver acceptable performance despite the induced failures. In real-world scenarios, industrial practitioners also employ chaos engineering [7, 12] to assess software resilience within production environments with live traffic. The resilience testing procedure encompasses *failure injection* and *test results determination* [39].

As an example, testing the resilience of an online service when facing high network packet loss involves several steps. First, test engineers introduce network packet loss failures by utilizing appropriate tools. Next, they collect relevant monitoring metrics based on the engineers' domain knowledge. In this sample case, monitoring metrics like network transmit and receive rate and request throughput will be selected. Once the metrics are gathered and visualized (Figure 1), engineers can examine the data, with the green area representing the normal period and the red area signifying the faulty period. By comparing the duration and magnitude of the monitoring metrics, the engineers can draw conclusions about the online service's resilience to network packet loss. If the throughput experiences a significant drop during the faulty period, it indicates that the online service has failed this resilience test.

While automation of resilience testing is feasible, it remains cumbersome, necessitating the definition of test rules. To standardize the procedure, test engineers manually determine a set of rules for each failure type, consisting of five components: failure type, load, monitored metrics, degradation profiling, and pass criteria. The fail*ure type* denotes the specific failure to inject, with the expectation that the tested service should demonstrate resilience to this failure. Load is determined based on the maximum load the service can handle without performance issues. Monitored metrics are selected to clearly manifest the degradation caused by the injected failure, encompassing I/O rates, throughput, mean time to recovery, latency, and other relevant metrics. Degradation profiling quantifies the degree of degradation, often considering the duration and magnitude changes of the target metrics. Pass criteria are then established to determine the resilience test result, involving the analysis of monitoring metrics under normal and faulty conditions, leading to a PASS/FAIL conclusion. These criteria should be based on the anticipated service quality. For each failure type, test engineers need to adhere to the outlined procedure to conduct resilience tests.

## **3 MOTIVATION**

In the current industrial practice, test engineers conduct resilience profiling by manual configuration of rules. This section first points out that the current resilience testing practice suffers from laborintensity and flexibility issues due to the decoupled, dynamic, and specialized nature of microservices (§ 3.1). To keep up with the fast-evolving microservices, automated and versatile resilience profiling is desired. To explore the opportunity to automate resilience profiling, we compare the differences of failures' manifestations in the monitoring metrics between resilient and non-resilient deployments of an open-source benchmark microservice system (§ 3.2). Our insight is that versatile resilience profiling can be automated by quantifying the degradation disseminated from the system performance metrics to the user-aware metrics.

## 3.1 Issues of Current Practice

Currently, test engineers manually set resilience test rules for each service and each failure type. Setting the rules heavily depends on human expertise. As demonstrated below, such a practice suffers from labor-intensity and flexibility issues, especially when evaluating the resilience of an online service composed of multiple fast-evolving microservices.

3.1.1 **Labor-intensity Issue**. Cloud providers are increasingly becoming worried of relying on manual labor and expertise for resilience profiling. This is partly because the process of creating rules is time-consuming and labor-intensive. The problem of labor intensity is especially pronounced in microservices, primarily due to two specific reasons.

- 1) *Decoupled, massive components.* Since microservice systems are highly decoupled, the number of microservices is very large. Due to the complex dependency [54, 56] and system architecture [37], the number of failures increases exponentially with the number of microservices in the system. Making proper rules under such massiveness is really challenging.
- Dynamics. Microservices encourage seamless updates and flexible deployment of services [5], so the failure rule sets should be updated accordingly, incurring lots of burden on test engineers.

Our investigation into a cloud service provider, Huawei Cloud, reveals that each service has around 26 microservices on average, with the largest having over 190 microservices. Each microservice generates over 40 metrics, resulting in approximately 1040 monitoring metrics per cloud service. Despite the possibility of automating the analysis of monitoring metrics, manual resilience rule definition and updating remain labor-intensive, taking about two person-months per cloud service. As a result, the manual identification of resilience test rules is not too time-consuming and labor-intensive for large-scale microservices.

*3.1.2* **Flexibility Issue**. Fixed resilience test rules cannot fit different microservice systems, as well as microservices with various refined resilience mechanisms, lacking the desired adaption to different systems. We attribute this flexibility issue to two reasons.

- 1) *Diversity exists in micoservices and their failures.* Microservices are specialized and may fail in different ways [40], so the manifestations of failures are also manifold. The current practice requires per-system and per-fault re-configurations on test rules.
- 2) Resilience sometimes is not an either-or thing. The boundary between "resilient" and "non-resilient" in certain cases is less absolute due to the presence of refined resilience mechanisms. Fixed resilience test rules with binary PASS/FAIL results may not adequately capture the subtle differences in an online service's resilience for two main reasons. First, the impact of failures in a microservice system is diverse, as the decoupled architecture [37] often leads to partial failures of microservices [22].

Second, online services adopting the microservice architecture commonly employ multiple ways for fault tolerance, e.g., multiple replications and active traffic control [38]. With these fault tolerance mechanisms, the online service can be in a gray-failure status [33].

For example, suppose we conduct resilience tests on an online service. The passing criteria require the mean time to recovery to be 5 minutes, which means the microservice should recover to the normal status in 5 minutes after the failure injection. Given the throughput of a microservice's two versions A and B under the same failure, the only difference is that version A takes 5 minutes to recover while version B only takes 2 minutes. Version B has higher resilience than A. However, both versions PASS the resilience test and we cannot explicitly know which one is more resilient. Thus, fixed rules cannot reflect the subtle difference in resilience.

Compared with traditional monolithic applications, the metric analysis for a microservice system becomes more complex because (1) the decoupled and specialized nature of microservices makes the number of monitoring metrics explode, and (2) the mutual influence between monitoring metrics becomes exquisite [23, 25].

To sum up, the current manual test rule configuration suffers from the labor-intensity issue due to the decoupled and dynamic attributes of microservices. The impact of failures is diverse. The fixed test rules cannot adapt to different microservice systems and cannot depict the subtle difference in an online service's resilience, which results in the flexibility issue. Thus, it is necessary to design a framework for resilience testing that can automatically adapt to different failures without defining the rules manually.

#### 3.2 Investigation on Failures' Impact

Microservice resilience is frequently compromised due to ubiquitous failures [55, 56], including the inherent bugs [57, 58], unstable message passing [34], and unreliable cloud infrastructure [40, 52]. Even routine operations, such as software upgrades and configuration file changes, can lead to significant service disruption [29].

To identify microservice resilience failures, we analyzed incident reports from 2020 to 2022 at Huawei Cloud. Two senior Ph.D. students, familiar with the cloud computing system, classified each failure by level (infrastructure or container) and type (e.g., memory, network, machine). We collected failures that occurred one or more times and were related to service resilience, with input from an experienced cloud system architect. The analysis yielded 27 relevant failures, categorized by virtualization level and type of failed resource. Software bugs were excluded as they are typically detected through functional testing. Table 1 lists these failures.

To comprehend the impact of failures, we conduct an empirical study on two different deployments of the Train-Ticket open-source microservice benchmark system [57]. One deployment is configured with common resilience mechanisms (load balancing and two replications for each microservice), while the other lacks these mechanisms. The study takes place on a Kubernetes cluster with 128 GB memory and 24 CPU cores, and monitoring metrics are collected and visualized using cAdvisor [27] and Prometheus [21].

We inject the failures listed in Table 1 into the Kubernetes cluster using ChaosBlade [2] and record and analyze the system's response. Finally, we compare the impacts with and without the common resilience mechanisms. MicroRes: Versatile Resilience Profiling in Microservices via Degradation Dissemination Indexing

Table 1: Failures and the correspond	ng degrad	lation with and	l without the resi	ilience mec	hanisms	mentioned	in §	3.2	2
1	0 0								

XY: . 1: .: X 1	- m	- T - 1				
Virtualization Level	Type	Failure	Degradation w/o resilience mechanisms	Degradation w/ resilience mechanisms		
	CPU	CPU overload	High physical CPU usage, slow response speed	Decreased but acceptable response speed		
	Memory	Memory overload	High physical memory usage, slow response speed	Decreased but acceptable response speed		
		Disk partition full	Unable to read/write, internal error (500)	Normal response		
		High disk I/O throughput	High physical I/O throughput	Normal response		
	Storage	High disk I/O latency	Slow I/O	Normal response		
		High disk I/O error	Slow and erroneous I/O	Normal response		
		Block storage service stopped	I/O rate drop to zero, internal error (500)	Normal response		
		High HTTP packet loss rate	High retransmission rate	Normal response		
Infrastructure		High HTTP request latency	High connection latency, slow response	Return to normal response speed shortly		
	Natural	TCP disconnection	Connection error, disconnected	Return to normal response speed shortly		
	INCLWOIK	Port in use	Connection initialization error	(same as left)		
		NIC down	Connection error, unreachable network	(same as left)		
		Running out of network connections	Unable to create new connections	Normal response		
	Process	Critical process killed	Unresponsive process, existing connection down	Normal response after some time		
	Machine	Unplaned reboot	Machine offline	Normal response after some time		
		Power outage	Machine offline	Normal response after some time		
		System time shift	Process error	Automaitc time correction		
	CPU	Container CPU overload	High container CPU usage, slow response speed	Decreased but acceptable response speed		
	Memory	Container memory overload	High container memory usage, slow response speed	Decreased but acceptable response speed		
		Container TCP disconnection	Connection error within container	Return to normal response speed shortly		
Container		Unreachable network	Network unreachable error in container	Return to normal response speed shortly		
	Network	Container port in use	Connection initialization error	(same as left)		
		Container network packet loss	High retransmission rate	Return to normal response speed shortly		
		Container virtual NIC down	Connection error	Return to normal response speed shortly		
	Storage	Container disk full	Unable to read/write, internal error (500)	Normal response after some time		
	Instance	Container instance killed	Instance offline, unresponsive microservice endpoint	Normal response after some time		
	instance	Container instance suspended	Instance offline, unresponsive microservice endpoint	Normal response after some time		

The impact of the injected failures becomes evident through service degradation. This degradation is quantified by measuring how much the service's performance deviates from the benchmark [55]. We herein use the service's average performance without injected failures as the benchmark. The service degradation is determined by comparing the performance during the normal period with that during the fault-injection period. Table 1 contains the failure manifestations without applying the described resilience mechanisms in the penultimate column, while the last column shows the failure manifestations with the resilience mechanisms applied. It's worth noting that the same failure may cause different degrees of degradation depending on the employed resilience mechanism.

Through a comparative analysis of the last two columns in Table 1, we observe that failures can exhibit diverse impacts and resilient services can mitigate the impact of failures on system performance metrics, while user-aware metrics are less affected. For instance, when there is only one container, the container CPU overload failure leads to 100% CPU usage remaining for an extended duration and affects the end user's experience negatively. Nevertheless, when multiple replications are employed, the impact on user-aware metrics, such as throughput, becomes less severe. Another example is that microservices with two active replications can rapidly recover from a "container instance killed" failure. Conversely, microservices lacking such replication mechanisms will experience extended recovery times or even break down entirely.

## 3.3 Our Insight

In this paper, we define **degradation dissemination** as *the process by which degradation in system performance metrics spreads or disseminates to affect user-aware metrics in a microservice system.* When a failure causes degradation in the system performance metrics, it can have an impact on user-aware metrics, leading to less resilient services.

As evidenced by our empirical study on failures' impact, we suggest that versatile and labor-efficient resilience profiling can be achieved by analyzing the dissemination of degradation from system performance metrics to user-aware metrics. When the degradation of user-aware metrics mirrors system performance metrics, the failure's impact spreads from the system to the user-aware level, resulting in less resilient services. Conversely, lower dissemination of degradation implies higher microservice system resilience. This finding highlights the possibility of creating a versatile framework for assessing a microservice system's resilience to different failures, eliminating the need for manually defining resilience test rules.

**Insight**: Microservices exhibit diverse failure patterns, resulting in various impacts on metrics. The primary consequence of these failures is service degradation. Higher resilience is associated with limited dissemination of degradation from system performance metrics to user-aware metrics.

## 4 METHODOLOGY

We propose MicroRes, a versatile microservice resilience profiling framework via degradation dissemination indexing. Figure 2 illustrates the overall workflow of MicroRes. It consists of three phases, i.e., failure execution, dissemination-based metric lattice search, and resilience indexing. The failure execution is composed of failure injection and failure clearance. Given a specified failure and a predefined load generator, MicroRes collects the to-be-tested service's monitoring metrics in the normal and faulty period. For the disseminationbased metric lattice search, we propose a dissemination-based metric selection algorithm. We organize all possible metric subsets of the monitoring metrics as a huge lattice. Then MicroRes searches the lattice while reducing the dimension by gradually selecting and removing the metric that contributes most to the overall degradation. In this way, the search path naturally forms a ranked list of monitoring metrics along with their contribution to the overall degradation. Lastly, for resilience indexing, we calculate the resilience index by

ISSTA '24, September 16-20, 2024, Vienna, Austria



Figure 2: Overall framework of MicroRes.

how much the degradation disseminates from system performance metrics to user-aware metrics.

MicroRes measures the performance loss (i.e., the degree of service degradation) by comparing the metrics' difference between normal and faulty periods. It quantifies the degradation dissemination by ranking the monitoring metrics' contribution to the overall degradation. In short, if system performance metrics contribute more to overall degradation than user-aware metrics, degradation dissemination is less, indicating higher resilience.

Such design addresses the labor-intensity and flexibility issues. First, MicroRes automatically produces resilience indices by measuring the degradation dissemination from system performance metrics to user-aware metrics, significantly alleviating human labor and saving time. Second, as MicroRes uses ranking, it is agnostic to the system architecture or adopted resilience mechanisms, allowing for flexible adoption to different microservice systems without system-dependent or fault-specific configurations.

#### 4.1 Failure Execution

The *failure execution* consists of the *failure injection* and the *failure clearance* phases. First, a test engineer needs to provide a *load generator* to the online service being tested. The load generator should mimic real-world requests from users. Second, the test engineer selects a list of failures to test. The failure can be injected at the infrastructure level or at the container level. Then, MicroRes automatically generates a failure injection pipeline. For each failure, MicroRes injects the failure, clears the failure, and collects the service's monitoring metrics in the meantime. The duration of failure injection and failure clearance are the same for each failure.

During the two phases, MicroRes collects two types of metrics, i.e., user-aware metrics and system performance metrics. Suppose  $\mathcal{B}$  is the user-aware metrics set and  $\mathcal{P}$  is the system performance metrics set in the system. We denote the set of all the useraware metrics and system performance metrics as  $\mathcal{M} = \mathcal{B} \cup \mathcal{P}$ . Suppose  $card(\mathcal{M}) = \mathcal{M}$ , we can index all the monitoring metrics from  $m_1$  to  $m_M$ . In other words,  $\mathcal{M} = \{m_1, m_2, \cdots, m_M\}$ . Thus, for any  $i \in [1, \mathcal{M}]$ , either  $m_i \in \mathcal{B}$  or  $m_i \in \mathcal{P}$ . We denote the monitoring metrics during the failure injection period as  $\mathcal{M}^f = \{m_1^f, m_2^f, \cdots, m_M^f\}$ . For each  $i, m_i^f$  is a univariate time series denoting the monitoring metrics during the failure injection (faulty) period. Likewise, we denote the monitoring metrics during the failure clearance (normal) period as  $\mathcal{M}^n = \{m_1^n, m_2^n, \dots, m_M^n\}$ . Also, for each *i*,  $m_i^n$  is a univariate time series denoting the monitoring metrics during the failure clearance (normal) period. We ensure that  $length(m_i^f) = length(m_i^n) = T$ .

## 4.2 Dissemination-based Metric Lattice Search

The dissemination-based metric lattice search aims at comparing and ranking the contribution of different monitoring metrics to the overall service degradation caused by the failure. Algorithm 1 shows the procedure for dissemination-based metric lattice search. We introduce the dissemination-based metric lattice search from the following three aspects, i.e., *metric lattice construction, disseminationbased metric selection*, and *metric lattice search*.

Algorithm 1: Dissemination-based Metric Lattice Search						
<b>Input:</b> The monitoring metrics $\mathcal{M} = \{m_1, m_2, \cdots, m_M\}$ ; The						
monitoring metrics during the failure injection period						
$\mathcal{M}^f = \{m_1^f, m_2^f, \cdots, m_M^f\}$ ; The monitoring metrics during						
the failure clearance period $\mathcal{M}^n = \{m_1^n, m_2^n, \cdots, m_M^n\}$						
<b>Output:</b> An ranked list of metrics $\hat{\mathcal{M}}$						
1 Construct the metric lattice (Section § 4.2.1)						
$\mathcal{L} = EmptyList()$						
$_{3}M = M$						
4 while $M \neq \emptyset$ do // Metric Lattice Search						
$_{5}$ cmax, $m_{imax} = MetricSelection(M)$						
6 $\mathcal{L}.append((cmax, m_{imax}))$						
7 $M = M - \{m_{imax}\}$						
8 end						
9 return $\mathcal L$						

4.2.1 Metric Lattice Construction. Formally, a lattice is a partially ordered set in which each pair of elements has a least upper bound and a greatest lower bound. Inspired by the frequent itemset mining algorithm [30, 45], we construct a lattice from the power set (i.e., the set of all subsets) of all the available monitoring metrics (denoted as  $\mathcal{M}$ ). Let each subset of  $\mathcal{M}$  be a node in the metric lattice  $\mathcal{L}$ . We define the order between any two nodes of the lattice as the subset-superset relation. Formally, suppose we have  $a, b \subseteq \mathcal{M}$  and  $a \neq b$ , then  $a \subset b(\subseteq \mathcal{M})$  (in the monitoring metric set) indicates  $a \leq b$  ( $b \rightarrow a$  in the metric lattice). Given the definition, for any

*a* and *b*, the least upper bound is  $\mathcal{M}$ . The greatest lower bound is  $\emptyset$ . Hence, the correctness of the generated lattice is theoretically guaranteed. The metric lattice will be searched starting from the node  $\mathcal{M}$  in later steps.

Figure 3 illustrates an example metric lattice constructed from  $\mathcal{M} = \{m_1, \dots, m_4\}$ . Each directed edge indicates a subset-superset relation, pointing from the metric superset to the metric subset. Note that we set the number of monitoring metrics as a small value, 4, for a clear illustration.



Figure 3: An example metric lattice constructed from  $\mathcal{M} = \{m_1, \cdots, m_4\}$ . We set the number of monitoring metrics as a small value, 4, for a clear illustration. The path of all solid red edges forms a ranked list.

4.2.2 Dissemination-based Metric Selection. As mentioned in Section § 3.2, service degradation is the primary manifestation of the failures' impact. We propose to measure the service degradation via the fluctuation of system performance metrics and user-aware metrics. If the degradation of system performance metrics, resilience is higher. Otherwise, the resilience is lower. Therefore, the key is to select the monitoring metric that contributes most to the overall service degradation among all the monitoring metrics.

Algorithm 2 shows how to select the metric that contributes most to the overall service degradation. Expressly, given a subset of the entire monitoring metrics set  $\mathcal{M}' \subseteq \mathcal{M}$  and the metrics during the faulty and normal period  $\mathcal{M}'^f$  and  $\mathcal{M}'^n$ . We first compute the performance difference  $\delta_i$  of each monitoring metric  $m_i$  (Line 7). The computation involves determining the absolute difference for each specific metric during the failure injection period, paired with the metrics during the failure clearance period. This absolute difference serves as a measure of the influence of injected failures on each metric. All metrics' performance difference naturally forms a performance difference matrix **D** (Line 10). Subsequently, we identify the metric that has the most significant impact on the performance difference, as outlined in Lines 12 to 18.

We apply Principal Component Analysis (PCA) [30, 53] on the performance difference matrix **D** to reduce **D** to 1 dimension. PCA is a statistical technique for simplifying and understanding complex data by reducing its dimensionality while preserving most of its variability. In our case, we have a bunch of metrics' performance differences in a high-dimensional space. Each dimension represents

Algorithm 2: Dissemination-based Metric Selection								
<b>Input:</b> The monitoring metric subset $\mathcal{M}'$ ; The monitoring metrics								
during the failure injection period $\mathcal{M}'^f$ ; The monitoring								
metrics during the failure clearance period $\mathcal{M}'^n$								
<b>Output:</b> The metric $m_i \in \mathcal{M}'$ where $m_i$ contribute most to the								
overall service degradation								
1 Function MetricSelection $(M', M'^{j}, M'^{n})$ :								
T = length of the monitoring metrics								
$3 \qquad D = []$								
4 for $m_i \in \mathcal{M}'$ do								
5 // Compute the performance difference of each individua								
metric								
6 for $t = 1 \dots 1$ do								
7 $\left  \delta_{i}(t) = \left  m_{i}^{\prime}(t) - m_{i}^{\prime\prime}(t) \right  \right $								
8 end								
9 $\delta_i = \delta_i - \delta_i // \text{Normalize } \delta_i$								
10 $\mathbf{D} = [\mathbf{D}; \hat{\delta}_i] // \text{Concatenate the normalized performance}$								
difference								
11 end								
12 $\delta_{PC1} = \text{PCA}(\mathbf{D}, dim = 1) // \text{Reduce to one dimension via}$								
Principal Component Analysis								
13 // Select the metric that contributes most to the performance								
$for \hat{\delta} \in D$ do								
$\frac{14}{10}  \frac{10}{0_i} \in D \text{ do}$								
$c_i = \text{contribution}(op_{C1}, o_i)$								
16 end $16$ end $16$								
17 $cmax = \max(c_i)$								
18 $imax = \arg\max_i(c_i)$								
19 return $cmax$ , $m_{imax}$								
20 End								

a different attribute of degradation, e.g., disk I/O, network, response latency, etc. We use PCA to find a new dimension, called the principal component, that captures the most important performance difference. The principal component, of length T (Line 12), denoted as  $\delta_{PC1}$ , is a linear combination of the original metrics principal components. Let  $\delta_{PC1}$  represent the overall service degradation caused by the injected failure. We compute the contribution of each metric to the overall degradation via a contribution measure Contribution() (Line 15). The higher the similarity between  $\delta_{PC1}$ and  $\delta_i$ , the larger the Contribution() outputs. Contribution() can be a correlation coefficient (e.g., Pearson correlation coefficient) or any other distance measure (e.g., Euclidean distance or dynamic time warping distance) deemed appropriate. We discuss the selection of Contribution() in Section § 5.3. In the end, the function returns the metric *m<sub>imax</sub>* that contributes most to the overall service degradation, along with its contribution cmax. mimax will guide the metric lattice search, and *cmax* will be used to calculate resilience in Section § 4.3.

4.2.3 Metric Lattice Search. The metric lattice search is straightforward with the dissemination-based metric selection. As shown in Algorithm 1, the search starts from the node of the entire metric set  $\mathcal{M}$ . At each node  $\mathcal{M}' \in \mathcal{M}$ , we select the metric  $m_{imax}$  that contributes most to the service degradation on the metric set  $\mathcal{M}'$ . We then eliminate the monitoring metric  $m_{imax}$  from  $\mathcal{M}'$  and proceed to the next node until all the monitoring metrics are eliminated.

ISSTA '24, September 16-20, 2024, Vienna, Austria

Table 2: Effectiveness Comparison (RQ1) and Ablation Study (RQ2) of MicroRes

Category	Method	Train-Ticket				Social-Network				Industry						
		CE	MAE	RMSE	Acc	F1	CE	MAE	RMSE	Acc	F1	CE	MAE	RMSE	Acc	F1
	SVC	0.8830	0.3497	0.5267	0.5802	0.7018	1.2608	0.3908	0.5657	0.5278	0.6383	0.6743	0.3786	0.4627	0.6786	0.7273
RQ1	RF	0.9399	0.3507	0.5277	0.5802	0.7018	0.6708	0.2358	0.4063	0.5833	0.6809	0.7477	0.4012	0.4865	0.5000	0.5882
	ET	0.8163	0.2999	0.4771	0.5926	0.7227	0.9160	0.3135	0.4927	0.6111	0.6818	0.5340	0.3100	0.3814	0.5714	0.6842
	MicroRes-euc	0.4464	0.1868	0.3384	0.6543	0.7846	0.7199	0.2861	0.4640	0.6389	0.7451	0.4409	0.3036	0.3729	0.6071	0.7027
RQ2	MicroRes-corr	0.3629	0.1730	0.3174	0.6914	0.8092	0.5969	0.2201	0.3865	0.6111	0.7407	0.4049	0.2882	0.3516	0.5714	0.6842
	MicroRes-cid	0.3725	0.1645	0.3037	0.8148	0.8966	0.5154	0.1851	0.3326	0.8333	0.9091	0.3855	0.2737	0.3304	0.8571	0.9130
	MicroRes	0.3246	0.1618	0.2993	0.9012	0.9481	0.3766	0.1814	0.3382	0.8611	0.9231	0.2977	0.2436	0.2812	0.8929	0.9362

The path from  $\mathcal{M}$  to  $\emptyset$  naturally forms an ordered list of all the monitoring metrics m and their contribution value c, denoted as  $\mathcal{L}$ . For example, in Figure 3, the path of all solid red edges forms the ordered list  $[m_2, m_4, m_1, m_3]$ .

#### 4.3 **Resilience Indexing**

Section § 3.2 finds that resilience can be inferred from whether the degradation in system performance metrics disseminates to the degradation in user-aware metrics. To quantify the degradation dissemination, we calculate the degradation in system performance metrics and user-aware metrics with Equation 1 and Equation 2, respectively. Equation 1 and 2 are derived from the Discounted Cumulative Gain [16], which initially measures the quality of search engines' results from the aspect of both the order and the content relevance.

$$D_{\mathcal{P}} = \sum_{m_i \in \mathcal{P}} \frac{c_i}{\log_2(rank(m_i; \mathcal{L}) + 1)}$$
(1)

$$D_{\mathcal{B}} = \sum_{m_i \in \mathcal{B}} \frac{c_i}{\log_2(rank(m_i; \mathcal{L}) + 1)}$$
(2)

In the end, we utilize the sigmoid function to map the difference between  $\mathcal{B}$ 's and  $\mathcal{P}$ 's contribution to a float value  $r \in (0, 1)$ , as shown in Equation 3.

$$r = \frac{1}{1 + e^{D_{\mathcal{B}} - D_{\mathcal{P}}}} \tag{3}$$

where *r* measures the degradation dissemination from the system performance metrics to the user-aware metrics. Larger *r* means higher resilience. In practice, engineers can set a resilience threshold  $\tau$  to get binary PASS/FAIL results, i.e.,  $r > \tau \Rightarrow$  PASS and  $r < \tau \Rightarrow$  FAIL.

## **5 EVALUATION**

This section evaluates MicroRes by answering the following research questions:

- **RQ1.** How effective is MicroRes in evaluating the resilience of online services?
- **RQ2.** How do different contribution measures affect the performance of MicroRes?
- RQ3. How efficient is MicroRes?

#### 5.1 Experiment Settings

5.1.1 Dataset. To illustrate the practical effectiveness of MicroRes, we carried out experiments on two simulated datasets and one

industrial dataset. Since there is no existing dataset for resilience testing, we conducted resilience tests on two open-source microservice systems and one industrial microservice system. We collected the monitoring metrics and manually labeled the resilience testing results to build the three datasets. We release all datasets with the paper to facilitate future research in this field.

**Table 3: Dataset Statistics** 

Dataset	$ \mathcal{B} $	$ \mathcal{P} $	#Microservices	#Failures	Failure Duration
Train-Ticket	30	195	15	24	10 minutes
Social-Network	50	325	25	10	5 minutes
Industry	2	12	(Undisclosed)	28	20 minutes

Simulated Datasets: For collecting the first simulated dataset, we deploy Train-Ticket [57], an open-source microservice system, with Kubernetes, a popular microservice orchestrator. Train-Ticket is a web-based ticketing system with 15 microservices. For load generation, we develop a request simulator to simulate the access of ordinary users to the ticketing system. The simulator will log in to the system, search for tickets, order tickets, food, insurance, and make the payment. We inject 24 failures listed in Table 1 into the benchmark microservice system with ChaosBlade. (We omit the three failures in "Infrastructure - Machine" as we do not have any access to the physical server.) For each failure, the failure injection period and failure clearance period both last for 10 minutes, during which the simulator continuously sends requests to the system. cAdvisor [27] is used to collect 13 system performance metrics. The system performance metrics cover all major aspects of the microservice system, including CPU, file system, memory, and network. As for the user-aware metrics, we use Jaeger, an open-source tracing framework, to trace all the API calls. Following the existing research [54], we calculate the average response time and the request error rate in seconds as the user-aware metrics.

Similarly, we collected the second simulated dataset on another widely used microservice orchestrator "docker-compose". Different from "Kubernetes", "docker-compose" orchestrates microservices on a single host. The resilience of a "docker-compose" microservice system depends more on the microservice developer. We use the Social-Network [24] microservice system. It includes 12 microservices for processing user requests and 13 microservices for data storage. Its user-aware metrics include the average response latency and the request error rate. As "docker-compose" employs few resilience mechanisms at the infrastructure level, we only inject 10 failures at the container level with ChaosBlade. Each failure lasts for 5 minutes since the Social-Network benchmark responds faster than Train-Ticket.

*Industrial Dataset*: To illustrate the practical usage of MicroRes, we collected an industrial dataset from the production cloud system of Huawei Cloud. Serving tens of millions of users worldwide, Huawei Cloud provides many cloud services to users, including cloud virtual machines, cloud databases, edge computing, data analytics, etc. The data analytic service adopts the microservice architecture. We inject 27 container-level and infrastructure-level failures into the data analytic service using the proprietary fault injection tool. As the production system takes roughly half a minute to complete one request, we let each failure last for 20 minutes. Limited by the production system, we collected 12 performance metrics and 2 user-aware metrics in total. The user-aware metrics of the dataset include the latency and the error rate.

Manual labeling: As MicroRes is unsupervised, labels are only for evaluation. We adopt the criteria in Section § 3 for resilience, i.e., whether the degradation in system performance metrics disseminates to the degradation in user-aware metrics. Following the existing work [54], we adopt binary PASS/FAIL labels since it is easier for annotators to reach an agreement. For the industrial dataset, test engineers from Huawei Cloud investigate the monitoring data and annotate PASS/FAIL labels according to the criteria and their expertise. For the simulated datasets, industrial engineers were not available to develop all the ground truth. Thus, we invited two senior Ph.D. students to inspect the collected monitoring metrics and give PASS/FAIL labels on each injected failure. Since the two benchmarks are open source and easy to follow, experienced Ph.D. students could produce accurate labels. In case of disagreement, which turns out to be rare, they will invite industrial engineers to judge and verify difficult cases. In particular, to address discrepancies in the impact assessment of Container CPU overload and Container memory overload failures, engineers must reconcile differences between the two Ph.D. student annotators, as the impact of these failures appears somewhat ambiguous. Resolving these discrepancies involves consulting the SLA to determine the final label. For other failures, the two PhD student annotators consistently reach an agreement. Lastly, we convert PASS to 1 and FAIL to 0 before quantitatively comparing them with the resilience values.

Table 3 shows the statistics of the three datasets. As the number of monitoring metrics varies with the microservice system architecture, we list the number of system performance metrics (denoted as  $|\mathcal{P}|$ ) and user-aware metrics (denoted as  $|\mathcal{B}|$ ) in Table 3. "# Microservices" and "# Failures" mean the number of microservices, and the number of injected failures in the dataset, respectively.

5.1.2 Baselines. As MicroRes is the first automatic data-driven approach to compute resilience indices, few existing approaches could serve as baselines. Since metrics are time series data and the nature of testing is classification, we resort to commonly-used classification algorithms as baselines, i.e., Support Vector Machine Classifier [15] (denoted as SVC), Random Forest [13] (denoted as RF), and Extra Trees [26] (denoted as ET). For the baselines, we directly use the implementation from the Python package sklearn.

Since MicroRes does not require training, to ensure fairness, we only use the classification baselines to compute the contribution of different metrics to the overall degradation. Specifically, let the input  $X_t$  be all the monitoring data at time t, and the output  $y_t$  be whether t is in the failure injection period, we train the predictive baselines with all  $X_t$  and  $y_t$ . No testing data is needed, as we directly use the rank of feature importance (for ET and RF) and the rank of coefficient (for SVC) as the ordered sequence of the monitoring metrics. In RF and ET, feature importance describes the relevance of features [13]. The meaning of coefficients in SVC is in line with feature importance [49]. As the baselines already consider the relevance of features, we set the contribution  $c_i = 1$  and calculate the resilience indices the same way as MicroRes.

5.1.3 Evaluation Metrics. Since the label is binary, but the resilience index of MicroRes is a decimal value, we employ two types of evaluation metrics. First, we follow existing work [54] and employ Mean Absolute Error (MAE)  $MAE = \frac{\sum_{i=1}^{N} |y_i - p_i|}{n}$ , Root Mean Squared Error (RMSE)  $RMSE = \sqrt{\frac{\sum_{i=1}^{N} (y_i - p_i)^2}{N}}$ , and Cross Entropy (CE)  $CE = \frac{1}{N} \sum_{i=1}^{N} -[y_i \log(p_i) + (1 - y_i) \log(1 - p_i)]$  to directly compare binary labels and decimal outputs. Specifically, CE calculates the difference between the label and the probability distribution of the produced resilience indices. MAE and RMSE measure the absolute and root-mean-squared differences between the produced resilience indices and the ground truth labels. Lower CE, MAE, and RMSE values indicate better prediction results. Second, to show the practical usage in practice, we set the resilience threshold  $\tau$  to convert the decimal outputs to binary predictions, then use accuracy and f1-score indicate better prediction results.

5.1.4 Experimental Environments. We deployed the Train-Ticket benchmark in a Kubernetes cluster of two physical servers. Both servers have 128 GB RAM and 24 CPU cores. The Social-Network benchmark was deployed in a t2.2xlarge EC2 instance of AWS with 8 GB RAM and 8 CPU cores. The Industry dataset was collected in proprietary servers in Huawei Cloud. For all datasets, we run the degradation-based metric lattice search and the resilience indexing on a laptop with 4 Intel CPU cores and 8 GB RAM.

#### 5.2 RQ1: Effectiveness

To study the effectiveness of MicroRes, we compare its performance with the baseline models on both datasets. For the contribution measure of MicroRes, we employ dynamic time warping (DTW) [35] algorithm. Specifically, for the parameters of DTW, we set the warping window to be 5 seconds (for Train-Ticket) and 2 seconds (for Social-Network), and use the square of the absolute difference as the distance measure. We do this because the Social-Network benchmark is deployed in a single server, and it responds faster than the Train-Ticket benchmark. Moreover, real-world industrial data often contains noise and variability. Setting a bigger window helps filter out irrelevant fluctuations and focus on meaningful patterns or trends within the data. We also use the moving average of a window size 3 to smoothen the monitoring metrics for the baselines and our method. We set the resilience threshold  $\tau = 0.4$  for the Train-Ticket and Social-Network datasets and set  $\tau = 0.75$  for the industrial dataset. The thresholds differ between simulated and industrial datasets because Train-Ticket and Social-Network are equipped with very few resilience measures, but the industrial system has many resilience measures, such as replications and better error tolerance in code. The overall performance is shown in Table 2, where we mark the best result for each metric and dataset. MicroRes achieves the best performance on all the datasets. Notably, compared with the best baseline, MicroRes reduces the loss by 44.3%, 21.4%, and 26.3% in terms of CE, MAE, and RMSE on the industrial dataset. Moreover, MicroRes achieves the best accuracy (0.8929) and F1-score (0.9362) on the industrial dataset. The performance on the industrial dataset highlights the effectiveness of MicroRes in production. The improvement of MicroRes on the industrial dataset is smaller than on the simulated datasets. The industrial microservice system incorporates more fault tolerance mechanisms, making it harder for MicroRes to discriminate between PASS/FAIL. Moreover, since the interactions of the TT benchmark are very fast, the statuses of TT's services are relatively similar, making simple baselines and our approach perform similarly.

#### 5.3 RQ2: Ablation Study

In RQ2, we focus on comparing the performance of various MicroRes variants to assess how different contribution measures affect MicroRes' overall performance. To achieve this, we keep the primary framework, namely the Dissemination-based Metric Lattice Search, and employ diverse contribution measures for the performance evaluation. In particular, we conduct experiments with varying contribution measures, i.e., Euclidean Distance (denoted as "MicroRes-euc"), Pearson Correlation (denoted as "MicroRes-corr"), Complexity Invariant Distance [9, 10] (denoted as "MicroRes-cid"), and keep other parameters identical. Our method, which uses DTW as the contribution measure, is denoted as "MicroRes" in the table. Table 2 shows the performance under different contribution measures. We marked models with the best performance in terms of CE, MAE, RMSE, and F1-score. The results indicate that the impact of different contribution measures in a reasonable range is small, but "MicroRes" gives the overall best performance.

#### 5.4 RQ3: Efficiency

The efficiency of MicroRes is composed of three parts, including (1) the duration of failure execution, the time complexity of (2) the degradation-based metric lattice search, and (3) the resilience indexing. The required duration of failure execution varies dramatically for different systems, and we will discuss the suggested duration in Section § 7. Among the remaining two phases, the most timeconsuming phase is the degradation-based metric lattice search. Theoretically, the time complexity of Algorithm 2 depends on the length T of the monitoring metrics, the number of monitoring metrics  $|\mathcal{M}|$ , and the time complexity of Cont(). Since  $|\mathcal{M}| \ll T$  in practice, we treat  $|\mathcal{M}|$  as a constant. The computation of performance difference costs O(T), and the dimension reduction with PCA costs  $O(T^3)$ . As dynamic time warping can be easily parallelized, we treat the time complexity of Contribution() as O(T). Merging together, the upper bound of the time complexity is  $O(T^3)$ . Considering the average time of failure injection is usually several hours, the time complexity of  $O(T^3)$  will not be a problem. On average, the latter two phases take 302 seconds to process a failure test case of T = 1200 on a laptop.

## 6 SUCCESSFUL CASES

MicroRes has been integrated into the resilience testing procedure of Huawei Cloud. This section demonstrates two cases to show the flexibility of MicroRes and the practical usage of the resilience index. In Figure 4, Case 1 shows the monitoring metrics during "Process Killed" failure in the Industry dataset. Case 2 shows the monitoring metrics during "High I/O Throughput" failure in the Industry dataset. "Success Rate" and "Avg. Delay" are user-aware metrics. "Proc. No." and "I/O Rate" are system performance metrics. Other unaffected system performance metrics are omitted for clear presentation. In the first case, the killed process cannot respond to user requests. Consequently, the success rate drops significantly, and the resilience index is low, making it FAIL MicroRes's test. In contrast, in the second case, although the I/O rate is high, the average delay and the success rate remain stable. Hence, the "I/O Rate" ranked much higher than the two user-aware metrics, and the resilience index is high, so the test result is PASS. Note that no separate configuration is needed for the two test cases. Thus, MicroRes can be adopted flexibly for different failures. Moreover, by inspecting the resilience index and the ranked metrics, engineers can quickly identify the impacted metrics, showing the practicality of MicroRes.



Figure 4: Two successful cases in the industrial dataset. The green area means the normal period and the red area means the failure injection period.

## 7 DISCUSSION

#### 7.1 Practiccal Usefulness

MicroRes's practicality lies in its minimal human configuration requirements. There is no need for engineers to configure individual systems and their faults. Instead, engineers only have to choose the desired faults and examine the generated resilience indices. Resilience indices play a crucial role in helping engineers comprehend the extent of degradation propagation from system performance metrics to business metrics during a specific fault. For instance, if the degradation in the network received bytes (rx\_bytes) has a more significant impact on request throughput, engineers can improve fault tolerance in the network accordingly.

Notably, MicroRes has already been integrated into the production system of Huawei Cloud, contributing to a reduction in the average time for resilience testing from 2 days to 4 hours. According to our practical usage in Huawei Cloud, we suggest during the failure execution phase, at least 40 requests (20 requests during the failure injection and 20 requests during the normal period) should be processed. In industrial cloud systems, a complex API request usually takes 10 seconds to finish, so the failure execution phase should last for less than 8 minutes, as a rule of thumb. Compared with the frequency of microservice updates, i.e., usually, once a week, the failure execution phase will not burden test engineers too much with the help of MicroRes.

# 7.2 Limitation

The major limitation lies in the fact that MicroRes still requires bootstrapping manual configurations on the categorization of useraware metrics and system performance metrics to facilitate resilience indexing. It is important to highlight, however, that these two manual tasks only need to be done once, as subsequent executions of MicroRes do not rely on human intervention. Hence, the bootstrapping manual configurations will not hinder the practical usage of MicroRes.

## 7.3 Threat to Validity

Labeling Accuracy. The major threat to validity is labeling accuracy. To evaluate MicroRes, we conduct experiments on two simulated datasets. The evaluation on two simulated datasets requires labeling the resilience test results, but the labels may not be 100% accurate. However, the resilience mechanisms and deployment environment of the benchmark systems are clear to all the annotators, so the resilience test results are straightforward. Moreover, when disagreements arise, the annotators will consult experienced test engineers who are in charge of the resilience assurance of the cloud services of Huawei Cloud. The number of inaccurate labels should be small.

Insufficiency of Simulation. For the evaluation, we deploy opensource benchmark microservice systems to simulate real-world services. Compared with real-world services, the open-source benchmarks do not fully consider fault tolerance, resulting in poor resilience in the simulation. Hence, the simulated dataset may not exhibit some common attributes of real online services. However, we deploy the benchmark microservice systems with two widelyused microservice orchestrators to show the practical usefulness of MicroRes in different environments. We also simulate concurrent and varying user requests to mimic the real-world scenario. Most importantly, we also employ the experiments on an industrial dataset from Huawei Cloud, which contains more metrics and complex degradation dissemination. The experiment results make MicroRes stand out among the baselines. In summary, the simulated and industrial datasets can accurately reflect the theoretical and practical superiority of MicroRes.

## 8 RELATED WORK

*Resilience Testing of Online Services.* To ensure the ability of the system to minimize the impact of potential failures, considerable attention has been paid to resilience testing of microservices, including model-based resilience representation and analysis [43, 55], non-intrusive and automated fault injection [3, 8, 31, 41], scalability resilience testing [1]. [43] used the PRISM probabilistic model checker to analyze the behavior of the Retry and Circuit Breaker resiliency patterns. [55] proposed a Microservice Resilience Measurement Model (MRMM) to represent the resilience requirements

of MSA Systems. [3] proposed a lineage-driven fault injection approach to infer whether injected faults can prevent correct outcomes by exploring historical data lineage and satisfiability testing. [31] presented a non-intrusive resilience testing framework that injects faults by manipulating the network packets between microservices. [1] simulated delay latency injection to assess the fault scenario's impact on the cloud software service's scalability resilience. [1, 3, 31] all require test engineers to write test descriptions and manually check assertions. Netflix proposed chaos engineering [8] to inject faults in the system randomly. A recent study [41] proposes automatically generating resilience test cases by inferring whether the injected faults can result in severe failures.

Instead of resilience profiling, most prior works mainly concern fault injection into microservices with minimal system intrusion. Additionally, the existing approaches rely heavily on human labor or historical cases, making them less practical in cloud-scale service systems with high dynamism and complex failure models. In contrast, MicroRes primarily emphasizes resilience profiling with minimal manual configuration, which is dispensed with historical testing cases.

*Combination Searching.* Many combination searching techniques [6, 14, 28] have shown its promise in reducing information redundancy and enhancing the performances of data-driven models. The combination searching approaches fall into three categories: score-based [14] and embedding-based [18, 32, 36, 42], and wrapper-based [11, 46, 47, 50]. Specifically, wrapper-based approaches use different combinations of features to train the same downstream model. Some heuristic approaches [11, 50] have also been developed to narrow the searching space due to the high searching complexity. MicroRes employs a wrapper-based method and overcomes the demerits of high computation cost and over-fitting by proper pruning.

#### 9 CONCLUSION

This paper intends to mitigate the labor-intensity and flexibility issues of the current practice of resilience profiling that relies on manually making rules. We propose the first versatile resilience profiling framework, MicroRes, for microservice systems via degradation dissemination indexing. Our insight behind MicroRes, motivated by the investigation on the impact of common failures, is that resilient deployment can effectively prevent the dissemination of degradation from system performance metrics to user-aware metrics. MicroRes quantifies the dissemination of degradation from system performance metrics to user-aware metrics, which is a one-sizefits-all solution without architecture knowledge, thereby adaptable to different systems. Evaluations on open-source and industrial microservice systems show that MicroRes can accurately and efficiently measure the resilience of microservice systems, outperforming all baseline methods in terms of cross-entropy.

#### ACKNOWLEDGMENTS

The work was supported by the Guangdong Key Research Program (No. 2020B010165002), the Research Grants Council of the Hong Kong Special Administrative Region, China (CUHK 14206921), and the National Natural Science Foundation of China (No. 62202511).

ISSTA '24, September 16-20, 2024, Vienna, Austria

#### REFERENCES

- Amro Al-Said Ahmad and Peter Andras. 2022. Scalability resilience framework using application-level fault injection for cloud-based software services. J. Cloud Comput. 11 (2022), 1. https://doi.org/10.1186/S13677-021-00277-Z
- [2] Alibaba. 2022. ChaosBlade: An easy to use and powerful chaos engineering experiment toolkit. https://github.com/chaosblade-io/chaosblade
- [3] Peter Alvaro, Joshua Rosen, and Joseph M. Hellerstein. 2015. Lineage-driven Fault Injection. In Proceedings of the 2015 ACM SIGMOD International Conference on Management of Data, Melbourne, Victoria, Australia, May 31 - June 4, 2015. ACM, 331–346. https://doi.org/10.1145/2723372.2723711
- [4] Paul Ammann and Jeff Offutt. 2008. Introduction to Software Testing. Cambridge University Press. https://doi.org/10.1017/CBO9780511809163
- [5] Michael Armbrust, Armando Fox, Rean Griffith, Anthony D. Joseph, Randy H. Katz, Andrew Konwinski, Gunho Lee, David A. Patterson, Ariel Rabkin, Ion Stoica, and Matei Zaharia. 2009. Above the Clouds: A Berkeley View of Cloud Computing. Technical Report UCB/EECS-2009-28. EECS Department, University of California, Berkeley. http://www2.eecs.berkeley.edu/Pubs/TechRpts/2009/ EECS-2009-28.html
- [6] Anna E. Bargagliotti and Raymond N. Greenwell. 2015. Combinatorics and Statistical Issues Related to the Kruskal-Wallis Statistic. Commun. Stat. Simul. Comput. 44, 2 (2015), 533–550. https://doi.org/10.1080/03610918.2013.786781
- [7] Ali Basiri, Niosha Behnam, Ruud de Rooij, Lorin Hochstein, Luke Kosewski, Justin Reynolds, and Casey Rosenthal. 2016. Chaos Engineering. *IEEE Softw.* 33, 3 (2016), 35–41. https://doi.org/10.1109/MS.2016.60
- [8] Ali Basiri, Niosha Behnam, Ruud de Rooij, Lorin Hochstein, Luke Kosewski, Justin Reynolds, and Casey Rosenthal. 2016. Chaos Engineering. IEEE Softw. 33, 3 (2016), 35–41. https://doi.org/10.1109/MS.2016.60
- [9] Gustavo E. A. P. A. Batista, Eamonn J. Keogh, Oben Moses Tataw, and Vinícius M. A. de Souza. 2014. CID: an efficient complexity-invariant distance for time series. *Data Min. Knowl. Discov.* 28, 3 (2014), 634–669. https://doi.org/10.1007/ S10618-013-0312-3
- [10] Gustavo E. A. P. A. Batista, Xiaoyue Wang, and Eamonn J. Keogh. 2011. A Complexity-Invariant Distance Measure for Time Series. In Proceedings of the Eleventh SIAM International Conference on Data Mining, SDM 2011, April 28-30, 2011, Mesa, Arizona, USA. SIAM / Omnipress, 699–710. https://doi.org/10.1137/1. 9781611972818.60
- [11] Pablo Bermejo, Luis de la Ossa, José A. Gámez, and José Miguel Puerta. 2012. Fast wrapper feature subset selection in high-dimensional datasets by means of filter re-ranking. *Knowl. Based Syst.* 25, 1 (2012), 35–44. https://doi.org/10.1016/J. KNOSYS.2011.01.015
- [12] Aaron Blohowiak, Ali Basiri, Lorin Hochstein, and Casey Rosenthal. 2016. A Platform for Automating Chaos Experiments. In 2016 IEEE International Symposium on Software Reliability Engineering Workshops, ISSRE Workshops 2016, Ottawa, ON, Canada, October 23-27, 2016. IEEE Computer Society, 5–8. https: //doi.org/10.1109/ISSREW.2016.52
- [13] Leo Breiman. 2001. Random Forests. Mach. Learn. 45, 1 (2001), 5–32. https: //doi.org/10.1023/A:1010933404324
- [14] Henry D. Chadwick and Ludwik Kurz. 1969. Rank permutation group codes based on Kendall's correlation statistic. *IEEE Trans. Inf. Theory* 15, 2 (1969), 306–315. https://doi.org/10.1109/TIT.1969.1054291
- [15] Corinna Cortes and Vladimir Vapnik. 1995. Support-Vector Networks. Mach. Learn. 20, 3 (1995), 273–297. https://doi.org/10.1007/BF00994018
- [16] W Bruce Croft, Donald Metzler, and Trevor Strohman. 2010. Search engines: Information retrieval in practice. Vol. 520. Addison-Wesley Reading.
- [17] Caskey L. Dickson. 2013. A Working Theory-of-Monitoring. Technical Report. Google, Inc. https://www.usenix.org/conference/lisa13/working-theorymonitoring
- [18] Robin Dillon and Yacov Y. Haimes. 1996. Risk of extreme events via multiobjective decision trees: application to telecommunications. *IEEE Trans. Syst. Man Cybern. Part A* 26, 2 (1996), 262–271. https://doi.org/10.1109/3468.485753
- [19] Microsoft Azure Doc. 2019. Microservices architecture style. https://docs.microsoft.com/en-us/azure/architecture/guide/architecturestyles/microservices
- [20] The Linux Foundation. 2022. Kubernetes. http://kubernetes.io/
- [21] The Linux Foundation. 2022. Prometheus. https://prometheus.io/
- [22] Jacob Gabrielson. 2022. Challenges with distributed systems. https://aws.amazon. com/builders-library/challenges-with-distributed-systems/
- [23] Yu Gan, Mingyu Liang, Sundar Dev, David Lo, and Christina Delimitrou. 2021. Sage: practical and scalable ML-driven performance debugging in microservices. In ASPLOS '21: 26th ACM International Conference on Architectural Support for Programming Languages and Operating Systems, Virtual Event, USA, April 19-23, 2021. ACM, 135-151. https://doi.org/10.1145/3445814.3446700
- [24] Yu Gan, Yanqi Zhang, Dailun Cheng, Ankitha Shetty, Priyal Rathi, Nayan Katarki, Ariana Bruno, Justin Hu, Brian Ritchken, Brendon Jackson, Kelvin Hu, Meghna Pancholi, Yuan He, Brett Clancy, Chris Colen, Fukang Wen, Catherine Leung, Siyuan Wang, Leon Zaruvinsky, Mateo Espinosa, Rick Lin, Zhongling Liu, Jake

Padilla, and Christina Delimitrou. 2019. An Open-Source Benchmark Suite for Microservices and Their Hardware-Software Implications for Cloud & Edge Systems. In Proceedings of the Twenty-Fourth International Conference on Architectural Support for Programming Languages and Operating Systems, ASPLOS 2019, Providence, RI, USA, April 13-17, 2019. ACM, 3–18. https://doi.org/10.1145/3297858.3304013

- [25] Yu Gan, Yanqi Zhang, Kelvin Hu, Dailun Cheng, Yuan He, Meghna Pancholi, and Christina Delimitrou. 2019. Seer: Leveraging Big Data to Navigate the Complexity of Performance Debugging in Cloud Microservices. In Proceedings of the Twenty-Fourth International Conference on Architectural Support for Programming Languages and Operating Systems, ASPLOS 2019, Providence, RI, USA, April 13-17, 2019. ACM, 19–33. https://doi.org/10.1145/3297858.3304004
- [26] Pierre Geurts, Damien Ernst, and Louis Wehenkel. 2006. Extremely randomized trees. Mach. Learn. 63, 1 (2006), 3–42. https://doi.org/10.1007/S10994-006-6226-1
- [27] Google. 2022. cAdvisor: Analyzes resource usage and performance characteristics of running containers. https://github.com/google/cadvisor
- [28] Quanquan Gu, Zhenhui Li, and Jiawei Han. 2011. Generalized Fisher Score for Feature Selection. In UAI 2011, Proceedings of the Twenty-Seventh Conference on Uncertainty in Artificial Intelligence, Barcelona, Spain, July 14-17, 2011. AUAI Press, 266–273. https://dslpitt.org/uai/displayArticleDetails.jsp?mmnu=1&smnu=2& article\_id=2175&proceeding\_id=27
- [29] Haryadi S. Gunawi, Mingzhe Hao, Riza O. Suminto, Agung Laksono, Anang D. Satria, Jeffry Adityatama, and Kurnia J. Eliazar. 2016. Why Does the Cloud Stop Computing? Lessons from Hundreds of Service Outages. In Proceedings of the Seventh ACM Symposium on Cloud Computing, Santa Clara, CA, USA, October 5-7, 2016. ACM, 1–16. https://doi.org/10.1145/2987550.2987583
- [30] Jiawei Han, Micheline Kamber, and Jian Pei. 2011. Data Mining: Concepts and Techniques, 3rd edition. Morgan Kaufmann. http://hanj.cs.illinois.edu/bk3/
- [31] Victor Heorhiadi, Shriram Rajagopalan, Hani Jamjoom, Michael K. Reiter, and Vyas Sekar. 2016. Gremlin: Systematic Resilience Testing of Microservices. In 36th IEEE International Conference on Distributed Computing Systems, ICDCS 2016, Nara, Japan, June 27-30, 2016. IEEE Computer Society, 57–66. https://doi.org/10. 1109/ICDCS.2016.11
- [32] Tin Kam Ho. 1998. The Random Subspace Method for Constructing Decision Forests. *IEEE Trans. Pattern Anal. Mach. Intell.* 20, 8 (1998), 832–844. https: //doi.org/10.1109/34.709601
- [33] Peng Huang, Chuanxiong Guo, Lidong Zhou, Jacob R. Lorch, Yingnong Dang, Murali Chintalapati, and Randolph Yao. 2017. Gray Failure: The Achilles' Heel of Cloud-Scale Systems. In Proceedings of the 16th Workshop on Hot Topics in Operating Systems, HotOS 2017, Whistler, BC, Canada, May 8-10, 2017. ACM, 150–155. https://doi.org/10.1145/3102980.3103005
- [34] Lalita Jategaonkar Jagadeesan and Veena B. Mendiratta. 2020. When Failure is (Not) an Option: Reliability Models for Microservices Architectures. In 2020 IEEE International Symposium on Software Reliability Engineering Workshops, ISSRE Workshops, Coimbra, Portugal, October 12-15, 2020. IEEE, 19–24. https: //doi.org/10.1109/ISSREW51248.2020.00031
- [35] Eamonn J. Keogh. 2002. Exact Indexing of Dynamic Time Warping. In Proceedings of 28th International Conference on Very Large Data Bases, VLDB 2002, Hong Kong, August 20-23, 2002. Morgan Kaufmann, 406–417. https://doi.org/10.1016/B978-155860869-6/50043-3
- [36] Yongdai Kim and Jinseog Kim. 2004. Gradient LASSO for feature selection. In Machine Learning, Proceedings of the Twenty-first International Conference (ICML 2004), Banff, Alberta, Canada, July 4-8, 2004 (ACM International Conference Proceeding Series, Vol. 69). ACM. https://doi.org/10.1145/1015330.1015364
- [37] Kubernetes. 2022. Kubernetes Documentation: Cluster Architecture. https://kubernetes.io/docs/concepts/architecture/
- [38] Kubernetes. 2022. Kubernetes Documentation: Disruptions. https://kubernetes. io/docs/concepts/workloads/pods/disruptions/
- [39] Sarah Lewis. 2021. Software Resilience Testing. https://www.techtarget.com/ searchsoftwarequality/definition/software-resilience-testing
- [40] Haopeng Liu, Shan Lu, Madan Musuvathi, and Suman Nath. 2019. What bugs cause production cloud incidents?. In Proceedings of the Workshop on Hot Topics in Operating Systems, HotOS 2019, Bertinoro, Italy, May 13-15, 2019. ACM, 155–162. https://doi.org/10.1145/3317550.3321438
- [41] Zhenyue Long, Guoquan Wu, Xiaojiang Chen, Chengxu Cui, Wei Chen, and Jun Wei. 2020. Fitness-guided Resilience Testing of Microservice-based Applications. In 2020 IEEE International Conference on Web Services, ICWS 2020, Beijing, China, October 19-23, 2020. IEEE, 151–158. https://doi.org/10.1109/ICWS49710.2020. 00027
- [42] Sebastián Maldonado and Julio López. 2018. Dealing with high-dimensional class-imbalanced datasets: Embedded feature selection for SVM classification. *Appl. Soft Comput.* 67 (2018), 94–105. https://doi.org/10.1016/j.asoc.2018.02.051
- [43] Nabor C. Mendonça, Carlos Mendes Aderaldo, Javier Cámara, and David Garlan. 2020. Model-Based Analysis of Microservice Resiliency Patterns. In 2020 IEEE International Conference on Software Architecture, ICSA 2020, Salvador, Brazil, March 16-20, 2020. IEEE, 114–124. https://doi.org/10.1109/ICSA47634.2020.00019
- [44] IBM Garage Methodology. 2022. Test software resiliency. https://www.ibm.com/ garage/method/practices/manage/practice\_resiliency/

MicroRes: Versatile Resilience Profiling in Microservices via Degradation Dissemination Indexing

- [45] Shinichi Morishita and Jun Sese. 2000. Transversing itemset lattices with statistical metric pruning. In *Proceedings of the Nineteenth ACM SIGMOD-SIGACT-SIGART Symposium on Principles of Database Systems*. Association for Computing Machinery, 226–236. https://doi.org/10.1145/335168.335226
- [46] Werner Mostert, Katherine M. Malan, and Andries P. Engelbrecht. 2018. Filter versus wrapper feature selection based on problem landscape features. In Proceedings of the Genetic and Evolutionary Computation Conference Companion, GECCO 2018, Kyoto, Japan, July 15-19, 2018. ACM, 1489–1496. https: //doi.org/10.1145/3205651.3208305
- [47] Kourosh Neshatian and Mengjie Zhang. 2009. Pareto front feature selection: using genetic programming to explore feature space. In *Genetic and Evolutionary* Computation Conference, GECCO 2009, Proceedings, Montreal, Québec, Canada, July 8-12, 2009. ACM, 1027–1034. https://doi.org/10.1145/1569901.1570040
- [48] Sam Newman. 2015. Building microservices designing fine-grained systems, 1st Edition. O'Reilly. https://www.worldcat.org/oclc/904463848
- [49] John Platt et al. 1999. Probabilistic outputs for support vector machines and comparisons to regularized likelihood methods. Advances in large margin classifiers 10, 3 (1999), 61–74.
- [50] Muhammad Summair Raza and Usman Qamar. 2016. A hybrid feature selection approach based on heuristic and exhaustive algorithms using Rough set theory. In Proceedings of the International Conference on Internet of Things and Cloud Computing, Cambridge, UK, March 22-23, 2016. ACM, 47:1-47:7. https://doi.org/ 10.1145/2896387.2896432
- [51] Nasser Samir and Brown Kyle. 2020. PRODUCTION SOFTWARE APPLICATION PERFORMANCE AND RESILIENCY TESTING. https://lens.org/094-261-625-935-507
- [52] Amazon Web Services. 2022. AWS Post-Event Summaries. https://aws.amazon. com/premiumsupport/technology/pes/

- [53] Michael E. Tipping and Christopher M. Bishop. 1999. Mixtures of Probabilistic Principal Component Analysers. *Neural Comput.* 11, 2 (1999), 443–482. https: //doi.org/10.1162/089976699300016728
- [54] Tianyi Yang, Jiacheng Shen, Yuxin Su, Xiao Ling, Yongqiang Yang, and Michael R. Lyu. 2021. AID: Efficient Prediction of Aggregated Intensity of Dependency in Large-scale Cloud Systems. In 36th IEEE/ACM International Conference on Automated Software Engineering, ASE 2021, Melbourne, Australia, November 15-19, 2021. IEEE, 653–665. https://doi.org/10.1109/ASE51524.2021.9678534
- [55] Kanglin Yin and Qingfeng Du. 2021. On Representing Resilience Requirements of Microservice Architecture Systems. Int. J. Softw. Eng. Knowl. Eng. 31, 6 (2021), 863–888. https://doi.org/10.1142/S0218194021500261
- [56] Ennan Zhai, Ang Chen, Ruzica Piskac, Mahesh Balakrishnan, Bingchuan Tian, Bo Song, and Haoliang Zhang. 2020. Check before You Change: Preventing Correlated Failures in Service Updates. In 17th USENIX Symposium on Networked Systems Design and Implementation, NSDI 2020, Santa Clara, CA, USA, February 25-27, 2020, Ranjita Bhagwan and George Porter (Eds.). USENIX Association, 575-589. https://www.usenix.org/conference/nsdi20/presentation/zhai
- [57] Xiang Zhou, Xin Peng, Tao Xie, Jun Sun, Chao Ji, Wenhai Li, and Dan Ding. 2021. Fault Analysis and Debugging of Microservice Systems: Industrial Survey, Benchmark System, and Empirical Study. *IEEE Trans. Software Eng.* 47, 2 (2021), 243–260. https://doi.org/10.1109/TSE.2018.2887384
- [58] Xiang Zhou, Xin Peng, Tao Xie, Jun Sun, Chao Ji, Dewei Liu, Qilin Xiang, and Chuan He. 2019. Latent error prediction and fault localization for microservice applications by learning from system trace logs. In Proceedings of the ACM Joint Meeting on European Software Engineering Conference and Symposium on the Foundations of Software Engineering, ESEC/SIGSOFT FSE 2019, Tallinn, Estonia, August 26-30, 2019. ACM, 683–694. https://doi.org/10.1145/3338966.3338961

Received 16-DEC-2023; accepted 2024-03-02