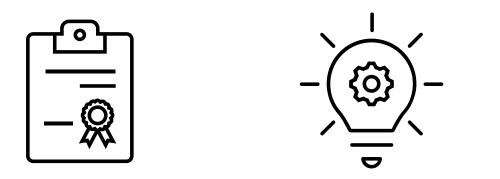
### Guardian of the Resiliency: Detecting Erroneous Software Changes Before They Make Your Microservice System Less Fault-Resilient

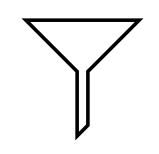
Guanglei He<sup>1, 4</sup>, Xiaohui Nie<sup>2</sup>, Ruming Tang<sup>3</sup>, Kun Wang<sup>1, 4</sup>, Zhaoyang Yu<sup>1, 4</sup>, Xidao Wen<sup>3</sup>, Kanglin Yin<sup>3</sup>, Dan Pei<sup>1, 4</sup>



21 June 2024 // Guangzhou, IWQoS 2024

### OUTLINE







BACKGROUND

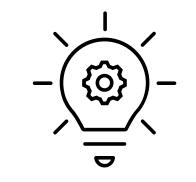
FRAMEWORK

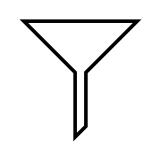
**EVALUATION** 

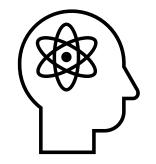
SUMMARY

### OUTLINE









BACKGROUND

FRAMEWORK

EVALUATION

SUMMARY

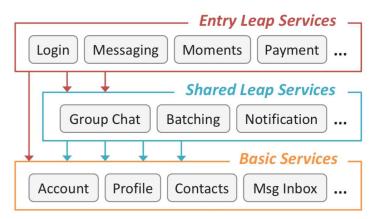
### **Microservice Architecture**

Microservice architecture has become a staple in production.

#### **Microservice Architecture**

Arrange an application as a collection of loosely coupled, fine-grained services

#### Advantage: Scalability, Flexibility



#### Example: WeChat's microservice architecture\* 3,000 services, over 20,000 nodes

\*: Zhou, Hao, et al. "Overload control for scaling wechat microservices." Proceedings of the ACM Symposium on Cloud Computing. 2018.



### **Microservice Architecture**

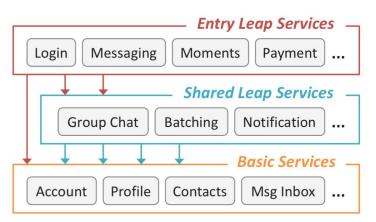
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#### **Microservice Architecture**

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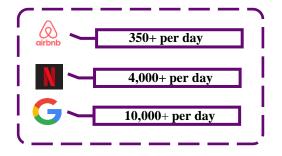


Software changes in a microservice system

- Frequent but error-prone
- Google:

**70%** of incidents were attributed to erroneous software changes

#### **Software Change** Bug fixes, configuration adjustments, etc.



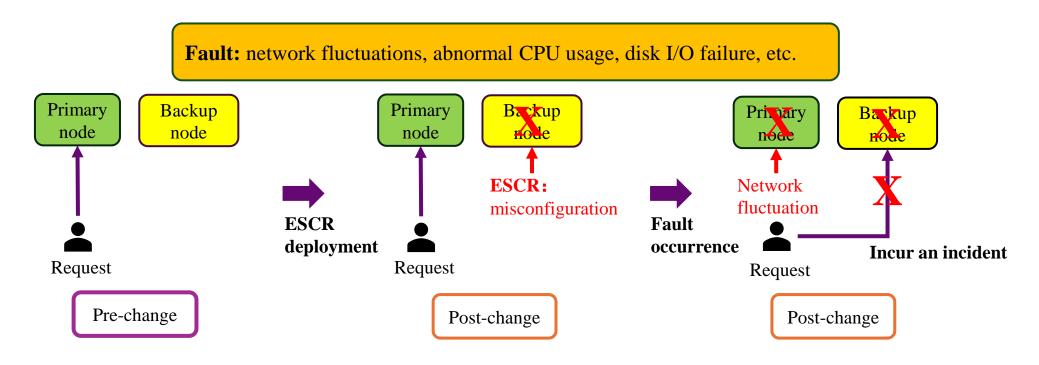
### **Example:** WeChat's microservice architecture\* **3,000** services, over **20,000** nodes

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### **Erroneous Software Changes that Reduce fault Resilience**

Some Erroneous Software Changes Reduce the fault Resilience (ESCR) of microservice systems.

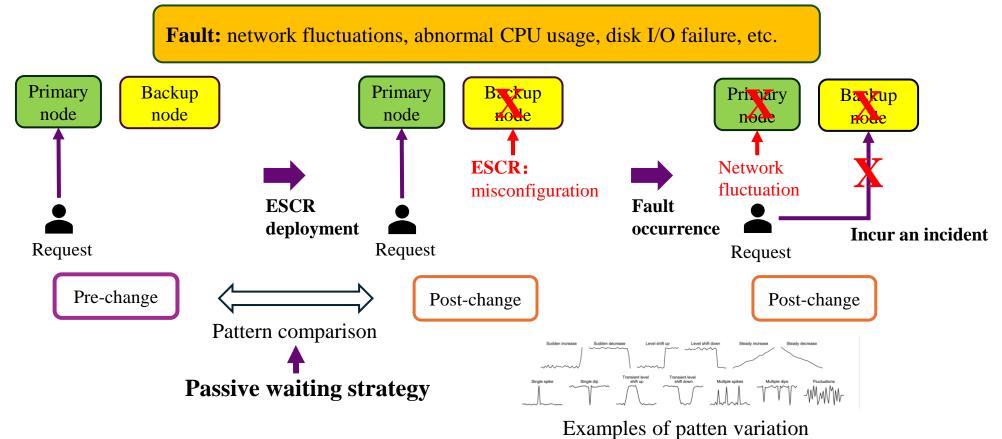
• ESCRs incur incidents when faults occur in systems.



### **Erroneous Software Changes that Reduce fault Resilience**

Some Erroneous Software Changes Reduce the fault Resilience (ESCR) of microservice systems.

- ESCRs incur incidents when faults occur in systems.
- Our empirical study reveals that **37.87% of the erroneous software changes qualified as ESCRs.**



### Challenge

Lack of training data

- Insufficient real-world abnormal data
- The high labeling cost of data generated through fault injection

#### **Complex KPI patterns**

- **Dozens of faults** should be injected to test the fault resilience
- Faults can **affect** the pattern of KPIs

#### Significant overhead

- Millions of KPIs to be checked in real-world microservice systems
- Training overhead & Detection overhead

### Challenge

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- The high

#### Complex

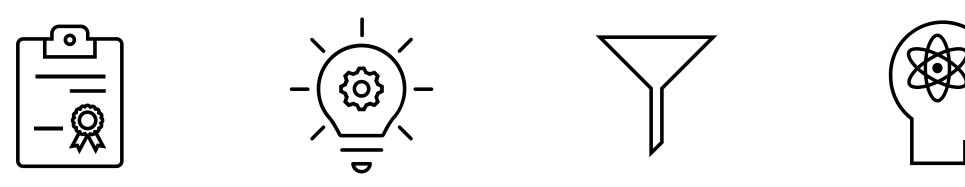
# **ResilienceGuardian!**

- Dozens of faults should be injected to test the fault resilience
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### OUTLINE



BACKGROUND

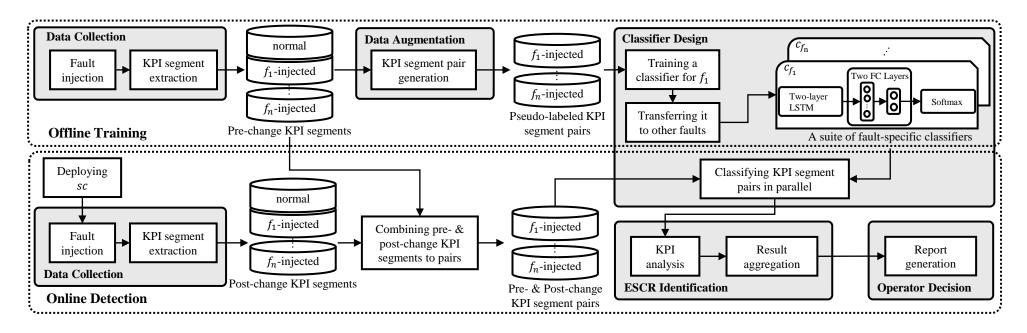
### FRAMEWORK

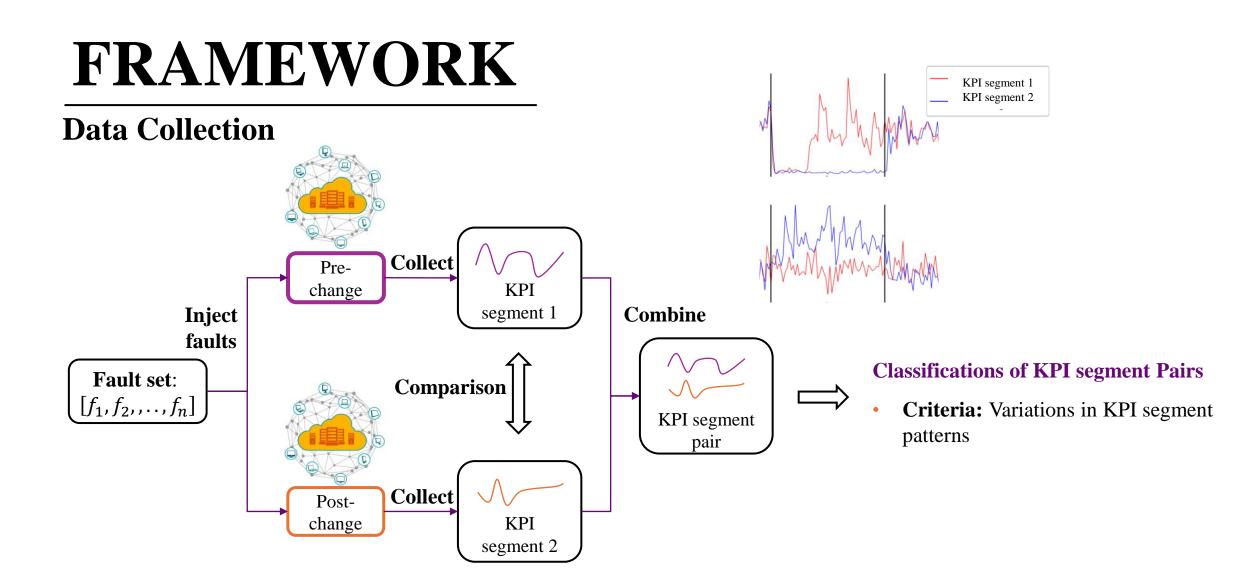
### EVALUATION

SUMMARY

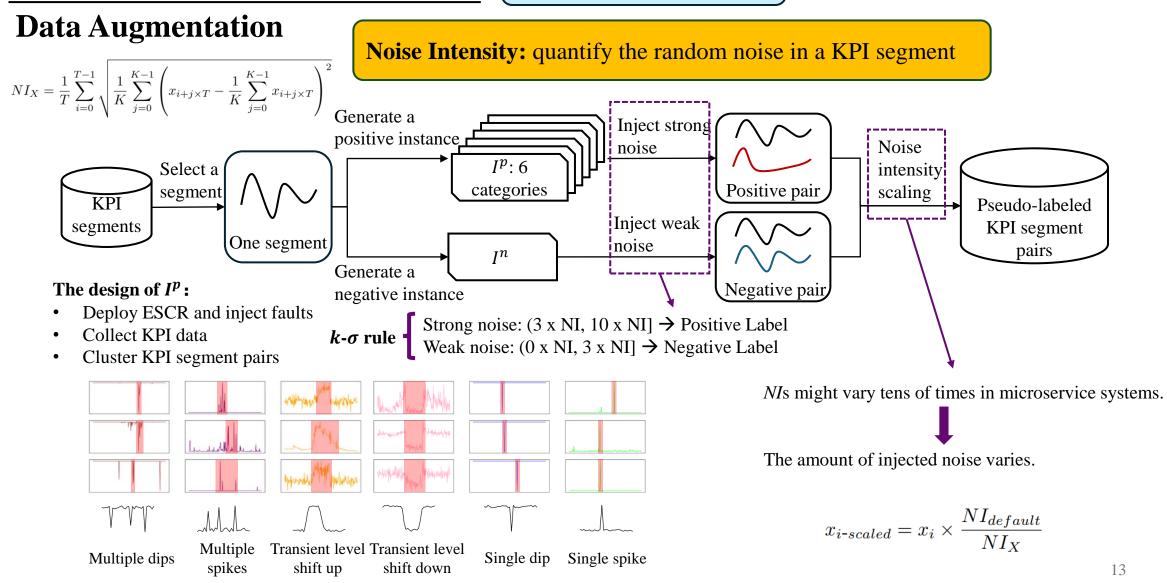
### ResilienceGuardian

- Deploy the software change in the **staging environment**.
- Perform **fault injection** to test the resilience.
- Utilize machine learning models to process KPI data, aiming to assess the fault resilience.



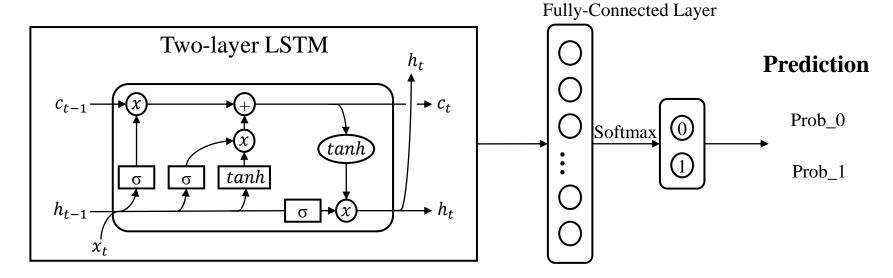


Lack of training data



### **Classifier Design: Model**

- A **fault-specific** strategy: train individual classifiers for each fault.
- A **lightweight** deep-learning model



#### **Feature Extraction Layers**

#### Significant overhead

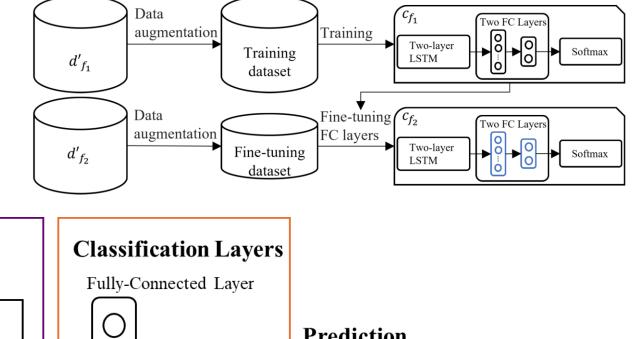
**Complex KPI patterns** 

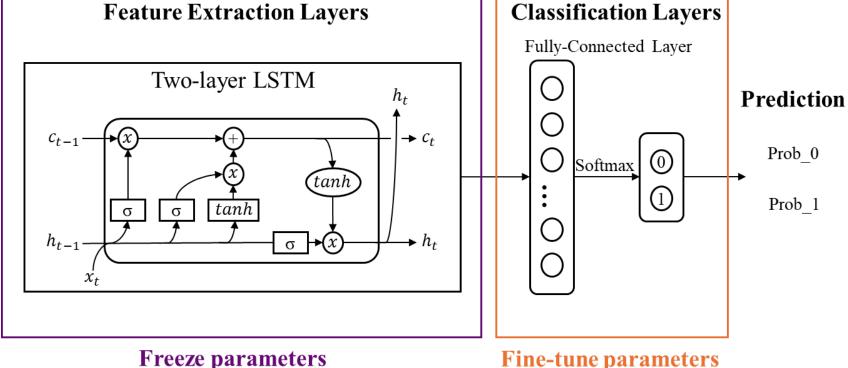
#### **Classification Layers**



### **Classifier Design: Transfer Learning**

**Significant training overhead** 

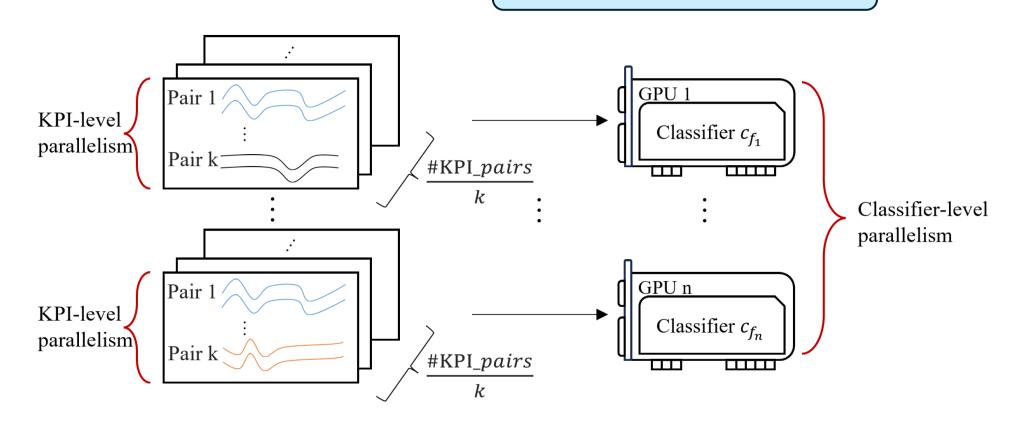


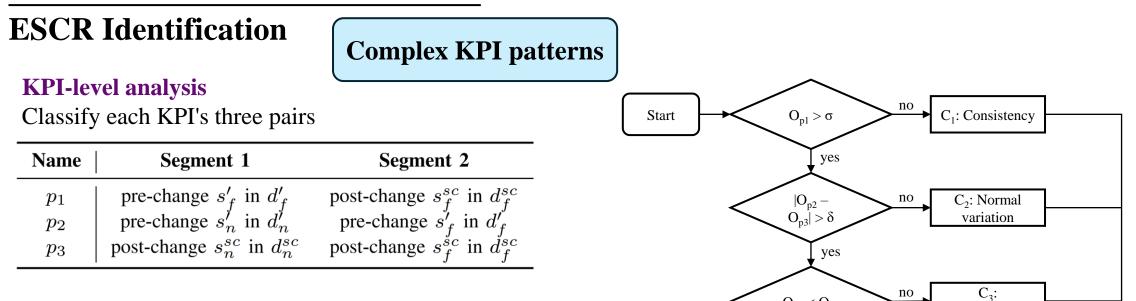


### **Classifier Design: Parallelism Strategy**

Strategy configuration: a 2-tuple (k, n)

Significant detection overhead





 $O_{p2} < O_{p3}$ 

C<sub>4</sub>: ESCR

yes

Improvement

End

#### **Result aggregation:**

Calculate a vulnerability score  $vs_f$  for each fault f

$$vs_f = \sum_{\sigma}^{KPI \in C_4} \frac{|O_{p_2} - O_{p_3}|}{\sigma} O_{p_1}$$



### **Operator Decision**

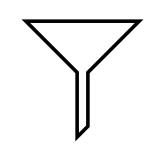
- **Operator** should **confirm** these results.
- **Detection report**: records the KPI-level analysis and the aggregation result

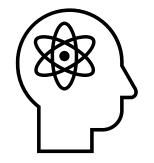
Software Change Ticket								ision Panel
Service Operation Submit Time Recommendation		HipsterShop-AdService Backup node modification of the 'testbed-worker1' server 2023-09-30 17:00:00 ESCR					Accept	Reject
Detection Result								
Rank	1 <b>Vul</b>	nerability Score 21.32 F	ault Network	_Packet_Loss-5	0%_testbed-woker1	Start 2023-09	9-30 21:00:00	Duration 15 min
Index	Туре	КРІ	Category			Visualization		
1	Business KPI	adservice-request_count	4	pre-change — post-change	100 50 0	~~~~	mayoun	mannam
2	Machine KPI	adservice-net_send_packet	4	pre-change — post-change	100 50 1 Armana	maynum	m My Maradas	have the the the the the the the the the th
Rank 2       Vulnerability Score 9.67       Fault Abnormal_CPU_Usage-80%_testbed-woker1       Start 2023-09-30 22:00:00       Duration 15 min								
Index	Туре	KPI	Category			Visualization		
1	Machine KPI	adservice-cpu_usage	4	pre-change — post-change	0.15 0.10	bergengengerete	mappe	An and another and an
2	Business KPI	adservice-request_duration	4	pre-change post-change	1.5 1.0	non-many-maked M	mM	la strong and and an

### OUTLINE









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SUMMARY

### **Datasets**

#### Dataset A & Dataset B

- Deploy ESCRs and perform fault injection ۲
- **Dataset** *A*: HipsterShop (**80** instances) **Dataset** *B*: Train-Ticket (**120** instances) •
- •

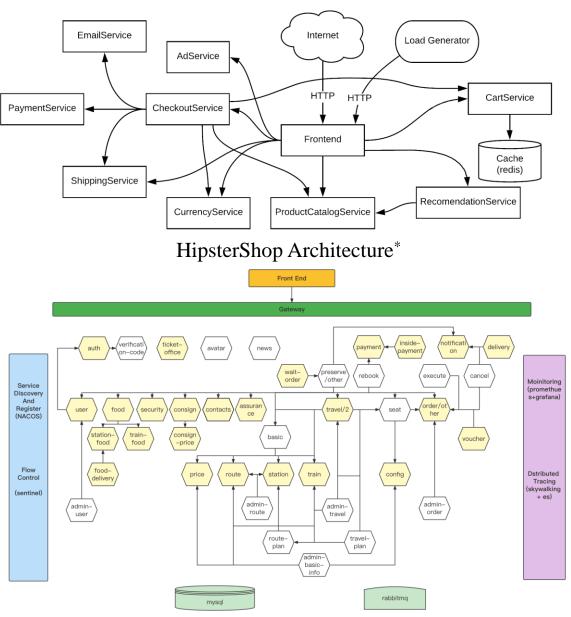
Category	Description			
Ι	<i>E1</i> - Reducing CPU resources improperly <i>E2</i> - Reducing memory resources improperly			
II	<i>E3</i> - Configuring insufficient CPU resources <i>E4</i> - Configuring insufficient memory resources			
III	<ul> <li>E5 - Permitting expired requests to access invalid databases</li> <li>E6 - Permitting expired requests to invoke death loops</li> </ul>			
IV	<ul><li><i>E7</i> - Interrupting the forwarding of requests</li><li><i>E8</i> - Forwarding requests to invalid backup nodes</li></ul>			

#### **Dataset C**

The UEA Archive •

\*: https://github.com/lightstep/hipster-shop

#: https://github.com/FudanSELab/train-ticket



#### Train-Ticket Architecture<sup>#</sup>

### **ESCR Identification & Ablation Study**

Datase	t Approach	Р	R	<b>F1</b>	Training (min)	Detection (s)
	Gandalf	0.74	0.68	0.71	87.32	34.32
	SCWarn	0.64	0.59	0.61	23.91	9.35
	Kontrast	0.88	0.81	0.84	290.74	0.10
$\mathcal{A}$	Lumos	0.55	0.70	0.62	-	15.12
	Donut	0.78	0.54	0.64	327.86	17.24
	Telemanom	0.59	0.67	0.63	197.31	5.24
	ResilienceGuardian	0.91	0.89	0.90	8.32	0.12
	Gandalf	0.72	0.66	0.69	355.21	31.09
	SCWarn	0.69	0.65	0.67	77.36	38.18
	Kontrast	0.82	0.79	0.80	693.33	0.11
В	Lumos	0.63	0.59	0.61	-	19.07
	Donut	0.72	0.67	0.69	1368.57	21.38
	Telemanom	0.55	0.58	0.56	814.89	5.32
	ResilienceGuardian	0.87	0.92	0.89	33.86	0.12

**Dataset** *A*: collected from **HipsterShop Dataset** *B*: collected from **Train-Ticket** 

#### **ESCR Identification**

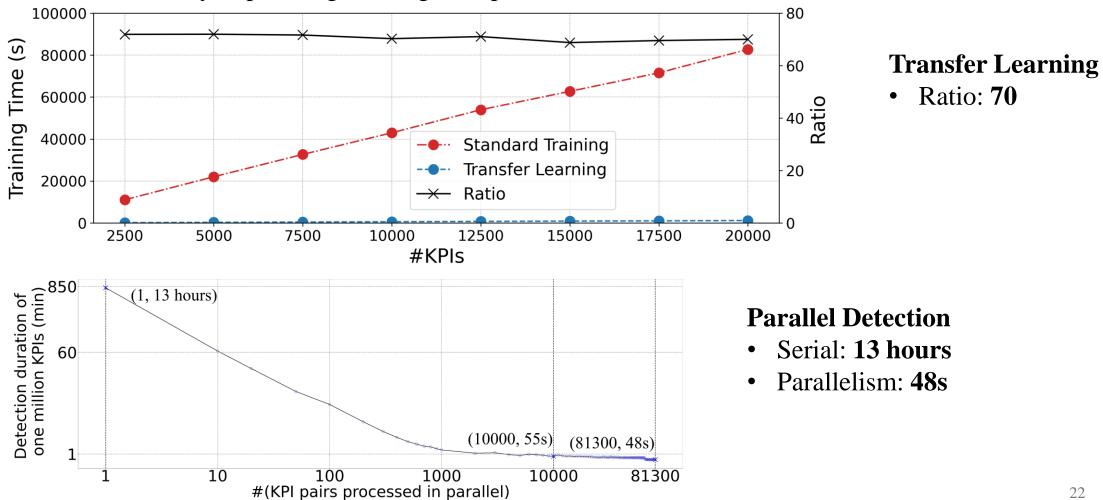
- F1 score: 0.91
- Training time: a reduction of 56.23% 97.53%
- Detection time: 0.12s

#### **Ablation Study**

- Verify the contribution
  - Data augmentation
  - Transfer learning

Dataset	Approach	Р	R	F1	Training (min)	Detection (s)
	ResilienceGuardian	0.91	0.89	0.90	8.32	0.12
	ResilienceGuardian <sub>pre</sub>	0.79	0.83	0.81	9.42	0.12
$\mathcal{A}$	$ResilienceGuardian_{cate}$	0.77	0.87	0.82	20.85	0.13
	$ResilienceGuardian_{one}$	0.83	0.77	0.80	6.88	0.12
	$ResilienceGuardian_{all}$	0.94	0.91	0.92	68.79	0.12
	ResilienceGuardian	0.87	0.92	0.89	33.86	0.12
	ResilienceGuardian <sub>pre</sub>	0.81	0.78	0.79	35.61	0.12
В	$ResilienceGuardian_{cate}$	0.83	0.80	0.81	68.54	0.14
	$ResilienceGuardian_{one}$	0.76	0.87	0.81	31.09	0.13
	$ResilienceGuardian_{all}$	0.93	0.95	0.94	310.92	0.12

### **Scalability**

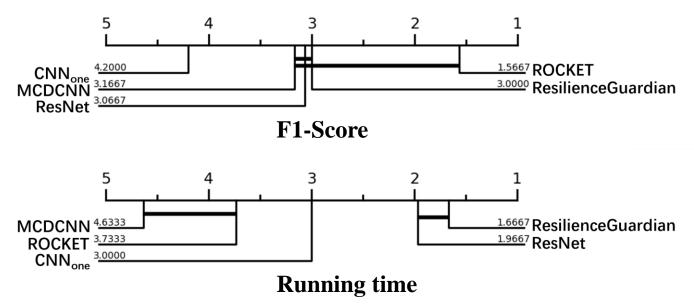


Scale the dataset by duplicating KPI segment pairs.

### Classification

#### **Critical Difference Diagram**

• Coordinate: the mean rank of the model for all datasets



Dataset C: The UEA archive

#### Effectiveness

• F1-Score: Similar to ROCKET

#### Efficiency

• **Running time: Outperform** ROCKET

#### Conclusion

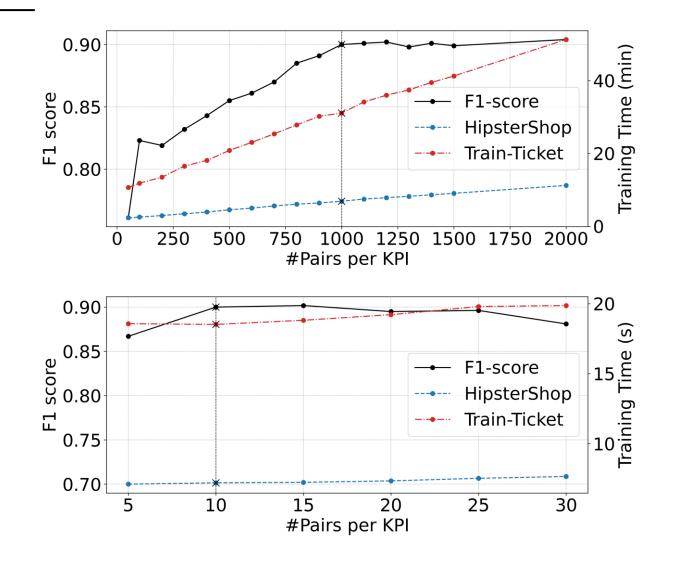
• A **satisfying balance** between effectiveness and efficiency

**Hyperparameter Configuration** 

*α*: #Pairs per KPI for Training *α* == 1000

β: #Pairs per KPI for Transfer Learning

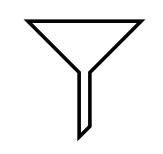
• β == 10

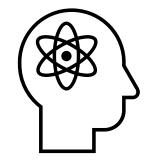


### OUTLINE









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**SUMMARY** 

# Summary

- To the best of our knowledge, this paper is **the first attempt** to address **Erroneous Software Changes that Reduce fault Resilience** (ESCR) identification.
- Our framework, ResilienceGuardian, enables **the early detection** of ESCRs before they impact the **fault resilience** of microservice systems in production.
- ResilienceGuardian is systematically evaluated on **two well-known microservice systems**, achieving an average **F1-score** of **0.90** in identifying ESCRs.

# Thank you! Q&A

hgl21@mails.tsinghua.edu.cn IWQoS 2024