Practical Root Cause Localization for Microservice Systems via Trace Analysis

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[4] 必示 BIZSEER

June 26 2021. IWQoS 2021

Outline

Background

Approach

Evaluation

Summary

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Microservice Systems

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- Microservice architecture: the lasted trend to build systems

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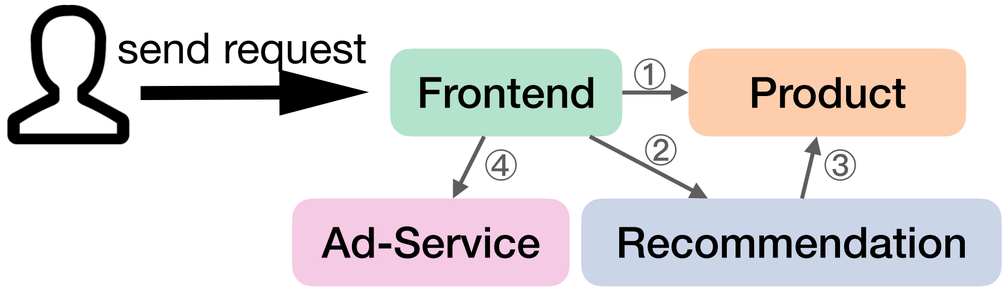
- Microservice architecture: the lasted trend to build systems
- What is microservice architecture?
  - Loosely coupled and independently deployed ‘micro’ services
  - Communicating with other services to realize a user request



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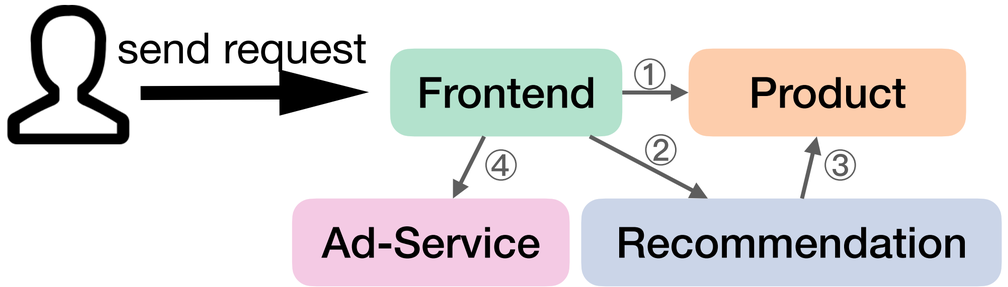
Microservice Systems

- Microservice architecture: the lasted trend to build systems
- What is microservice architecture?
  - Loosely coupled and independently deployed ‘micro’ services
  - Communicating with other services to realize a user request
- Benefits:
  - Fast delivery
  - Better scalability
  - Greater autonomy



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Root-Cause Service Localization

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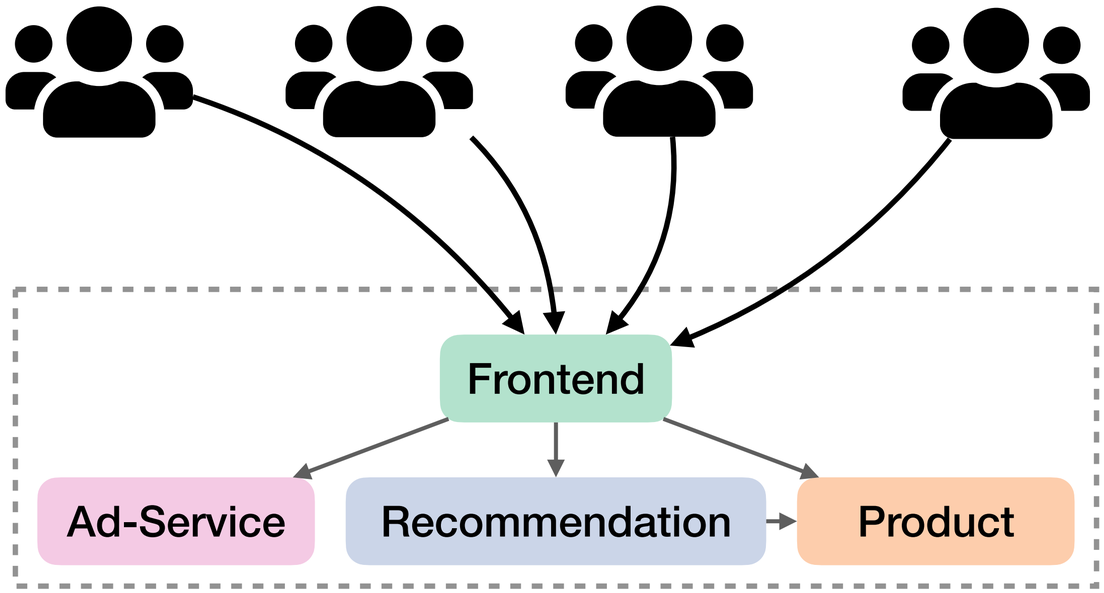

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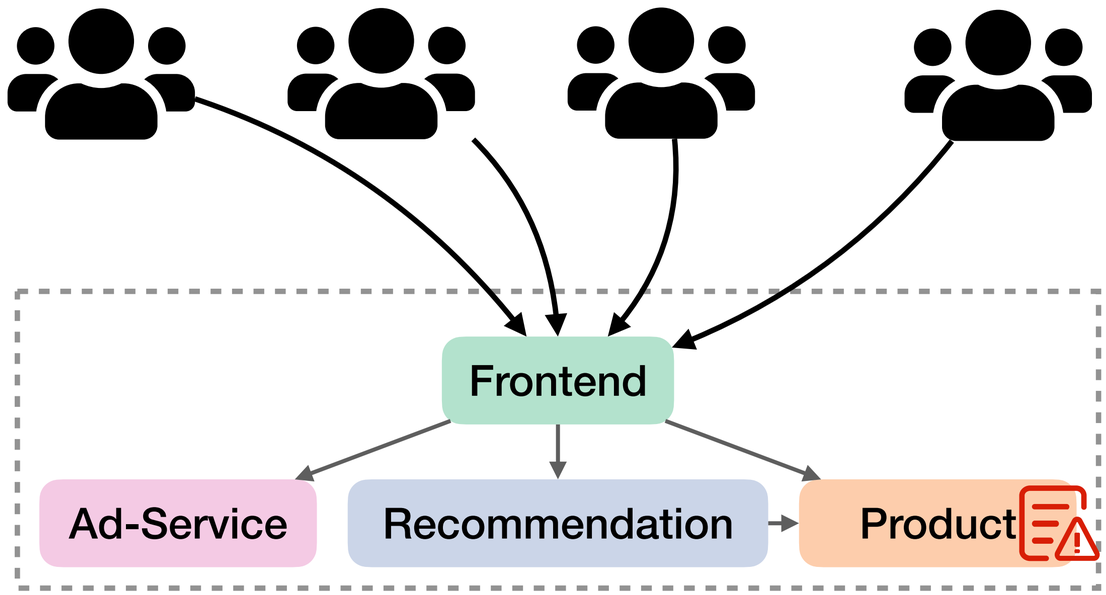

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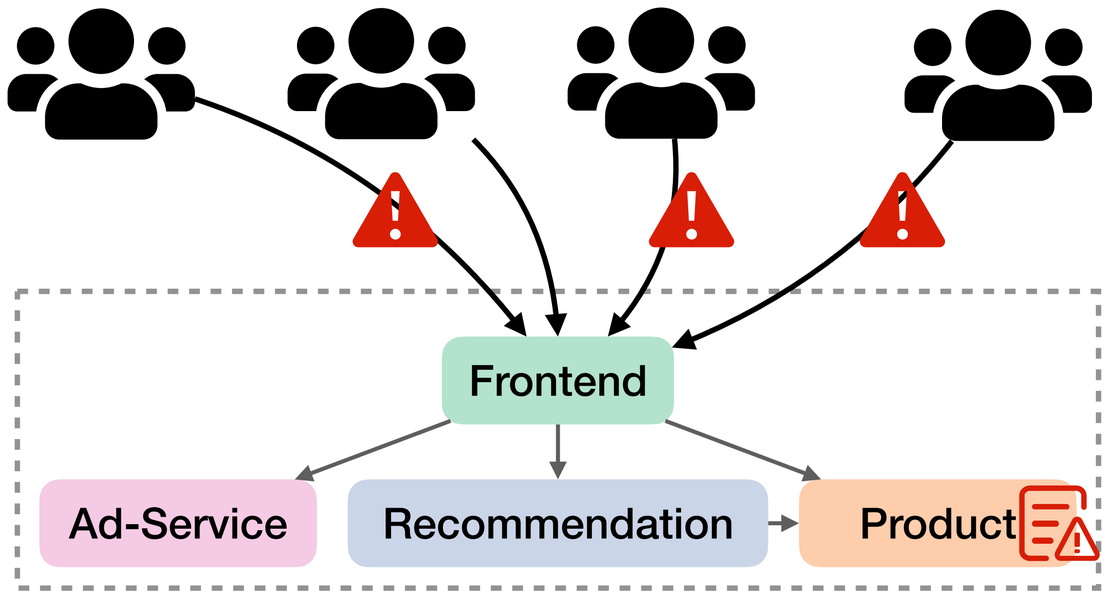

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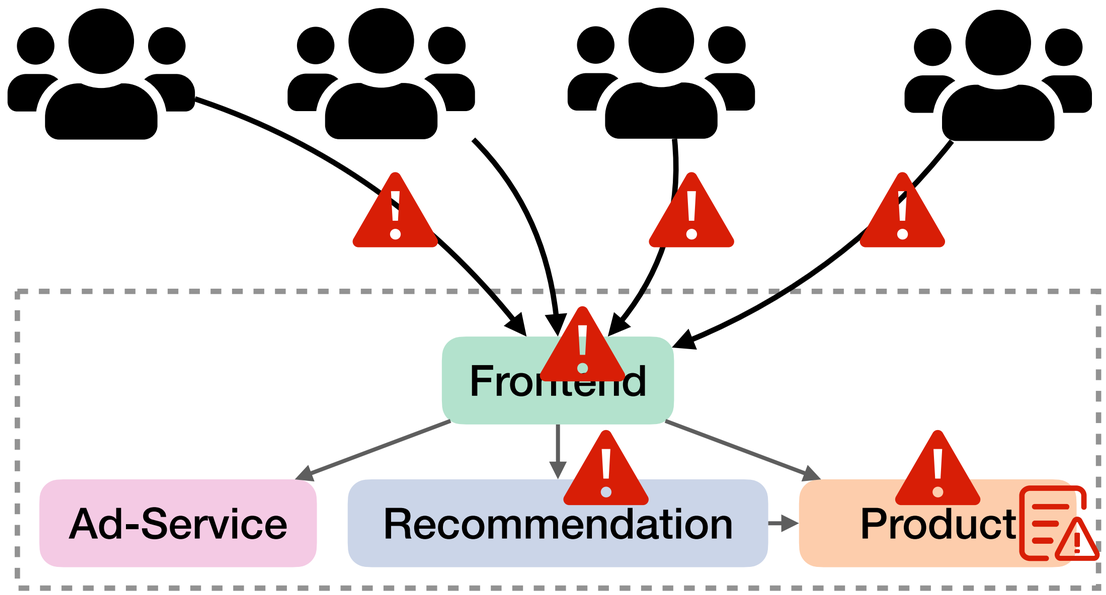

Many related services also behave abnormally due to the dependency among services

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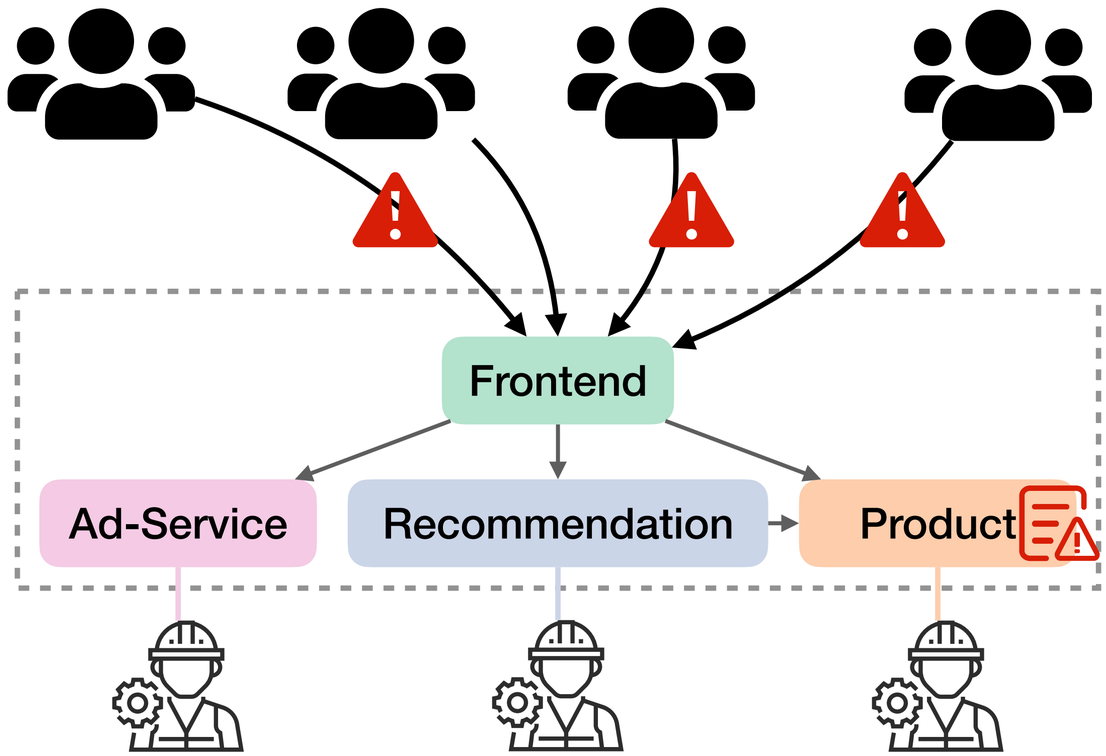
Root-Cause Service Localization



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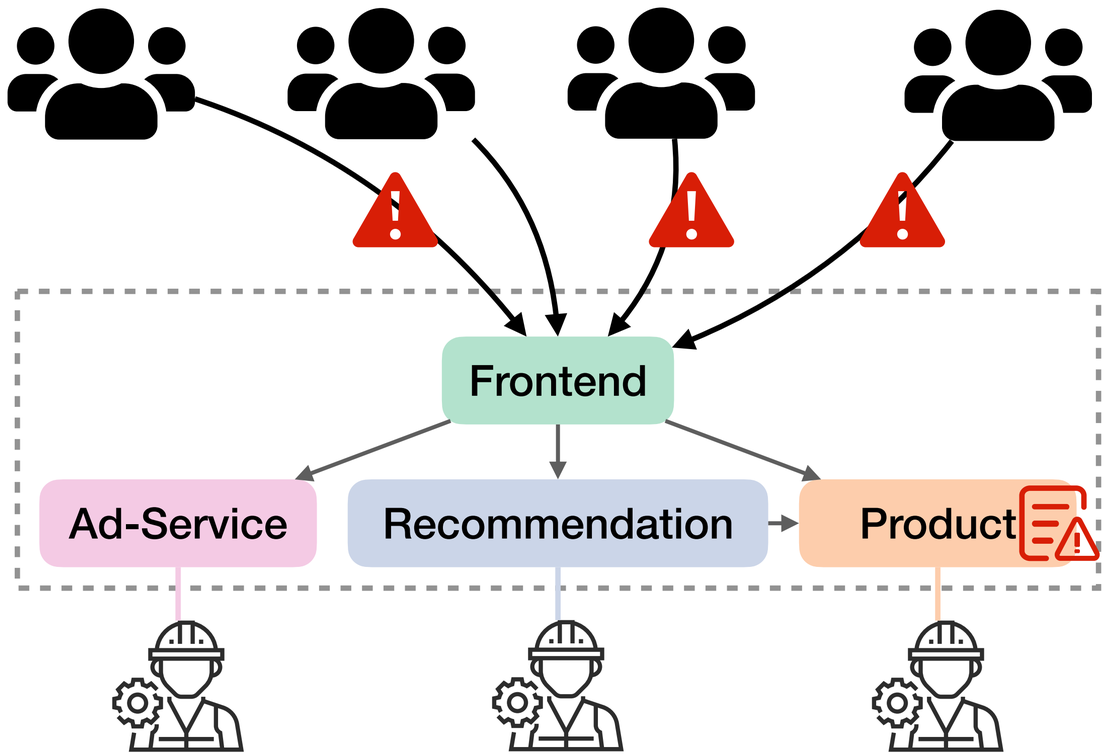


Many related services also behave abnormally due to the dependency among services

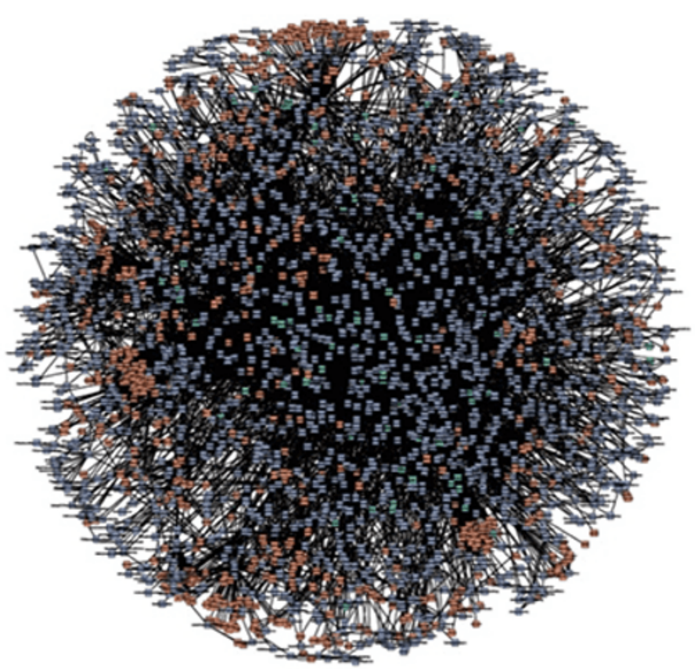
Different services are developed and maintained by different teams

When a fault happens, we need to localize the root-cause service at first before the corresponding team's further investigation

Background

Challenges in Microservice Systems

1. Complex dependencies among services



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Background

Challenges of Root Cause Localization in Microservice Systems

2. Dynamic runtime environments

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AMAZON	23.000/day	minutes	high	high
GOOGLE	5.500/day	minutes	high	high
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FACEBOOK	1/day	hours	high	high
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TYPICAL ENTERPRISE	once every 9 months	months or more	low/medium	low/medium

From "The Phoenix Project"

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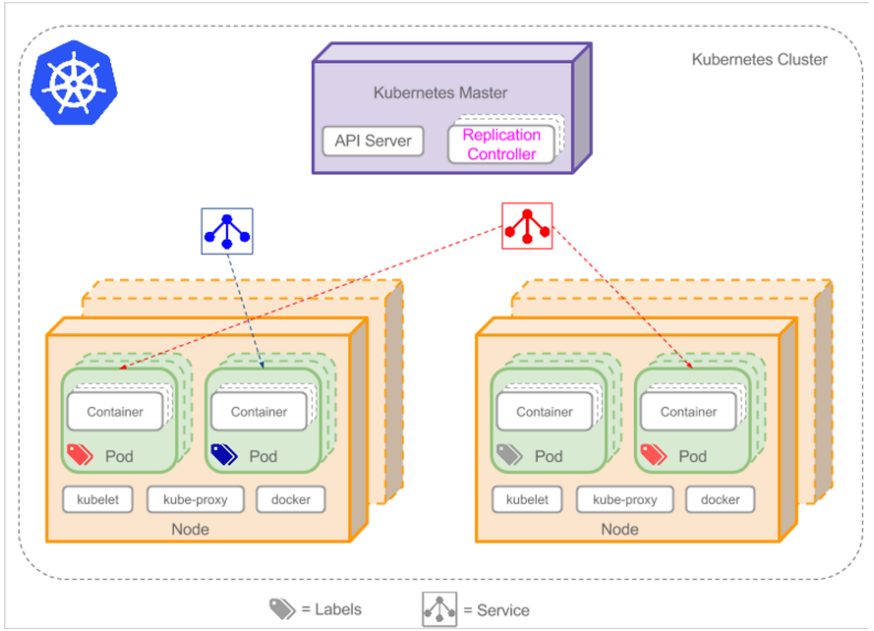

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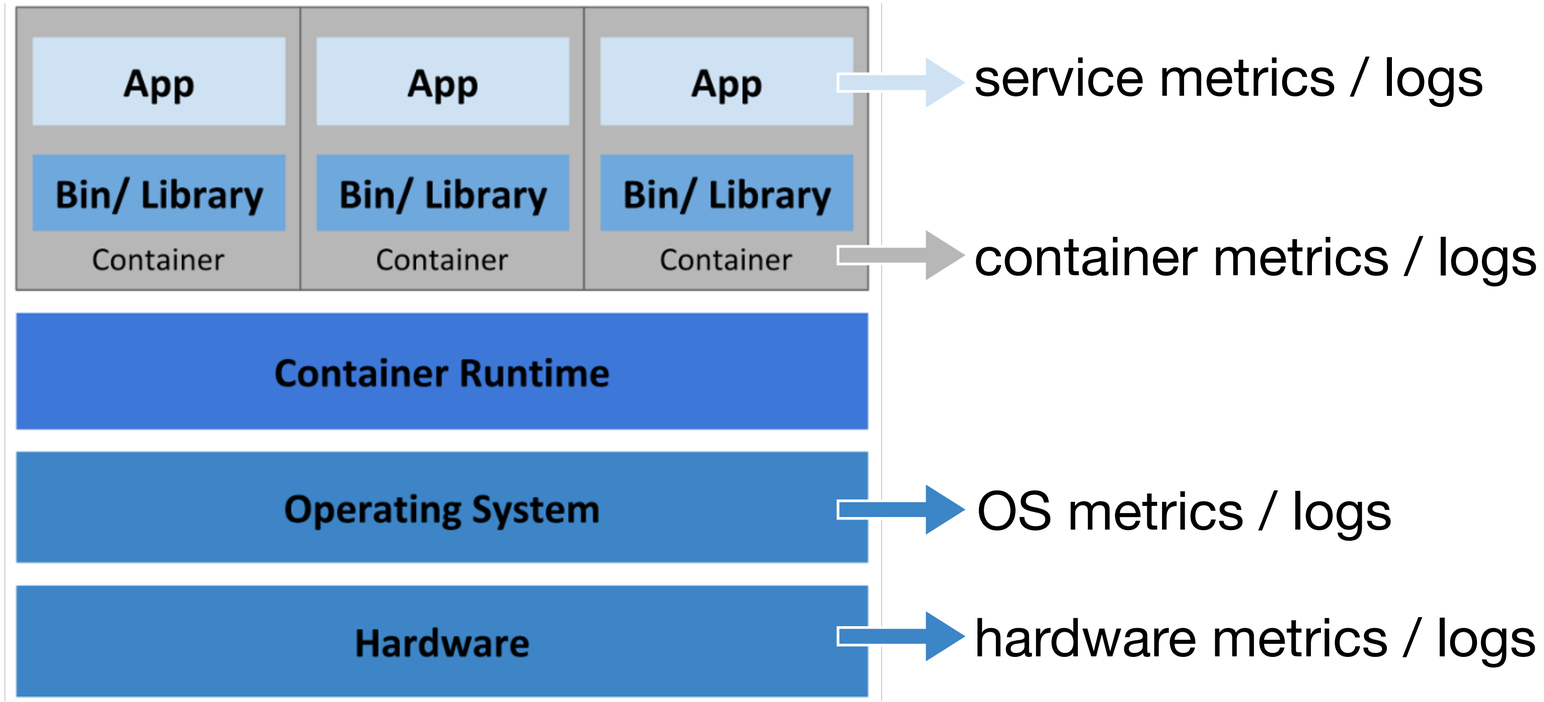
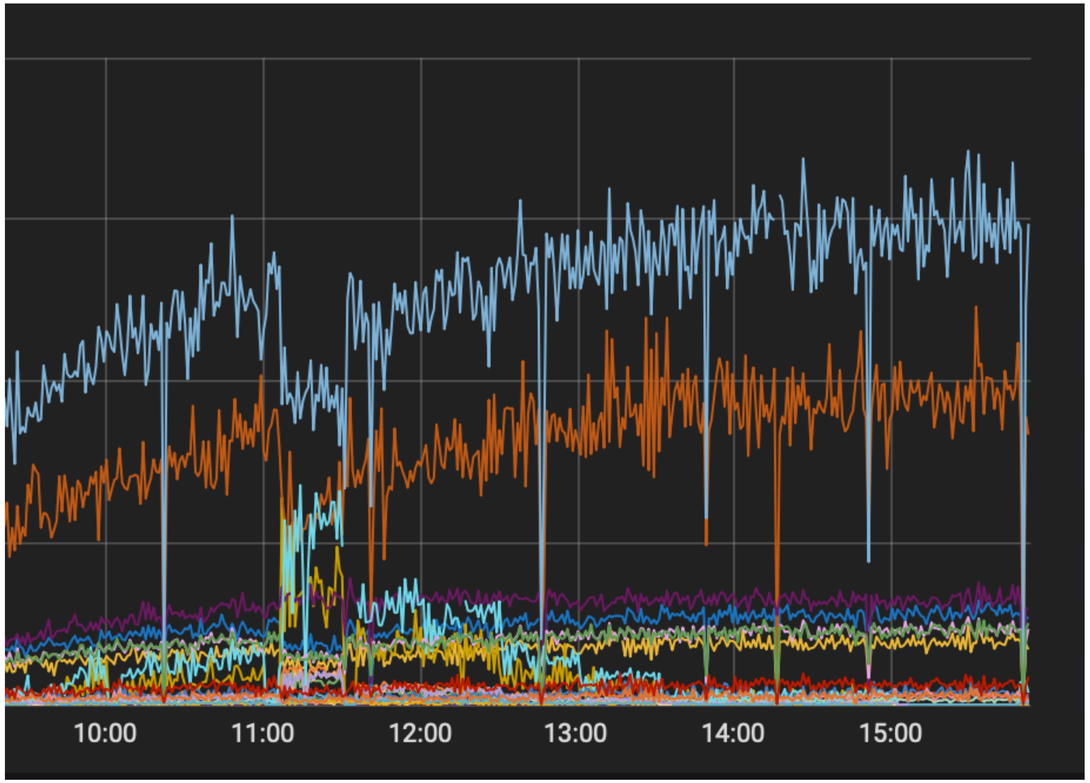
Challenges of Root Cause Localization in Microservice Systems

3. Various types and huge volumes of monitoring data



Background

Metrics or Logs Based Localization Approaches



Metrics lack detailed contextual information and fine-grained dependencies of invocations

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Logs are usually generated in an arbitrary manner and most log messages contain little information for root cause localization

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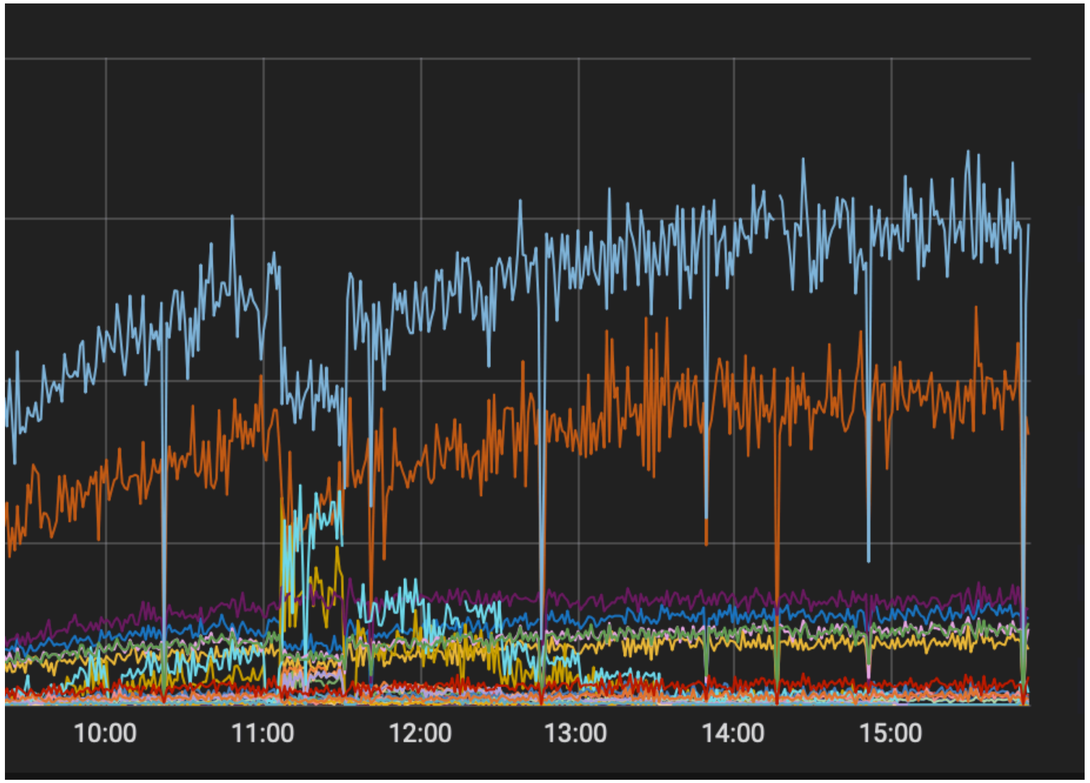

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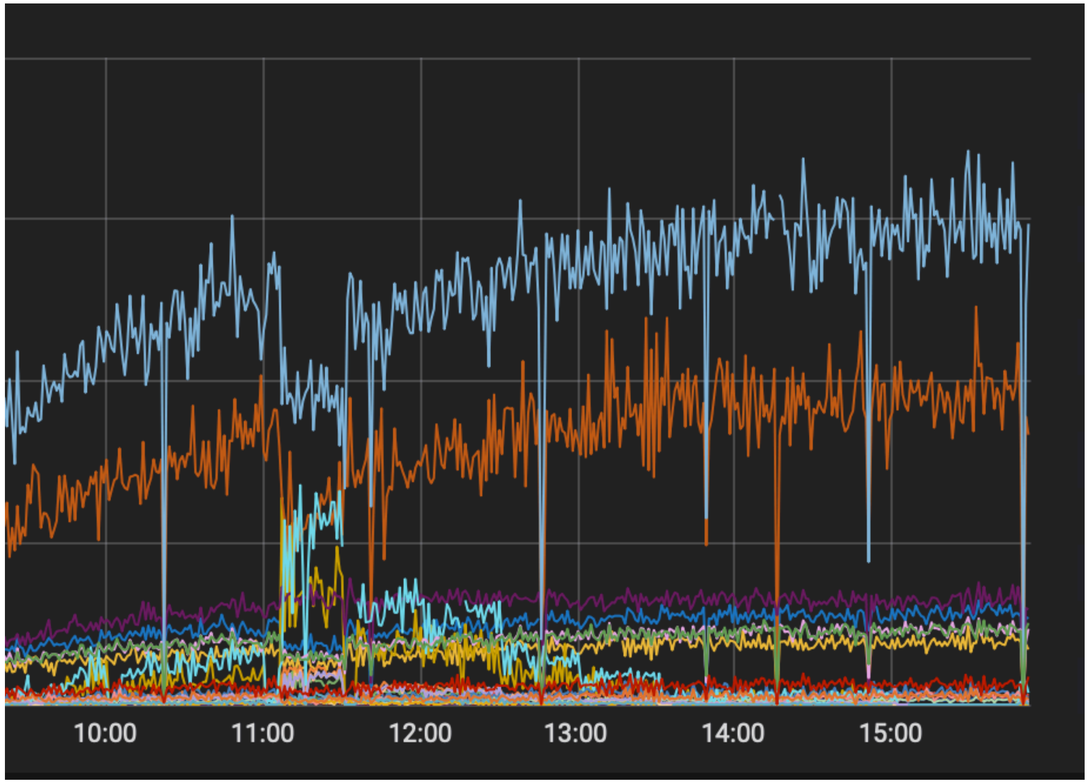

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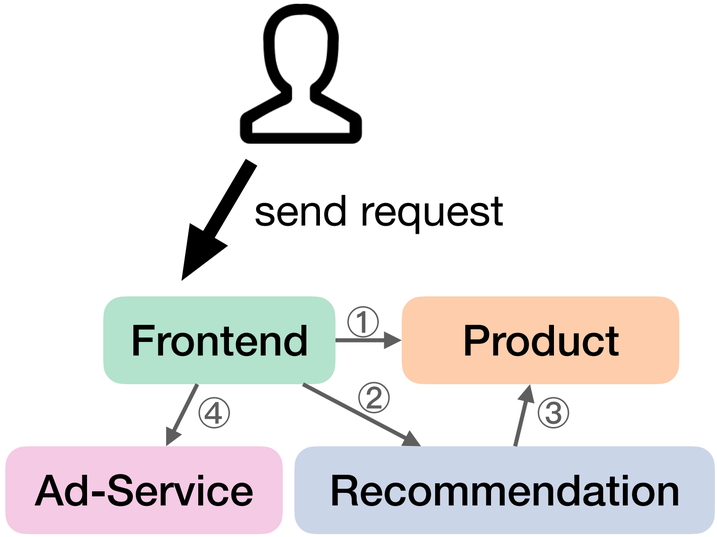
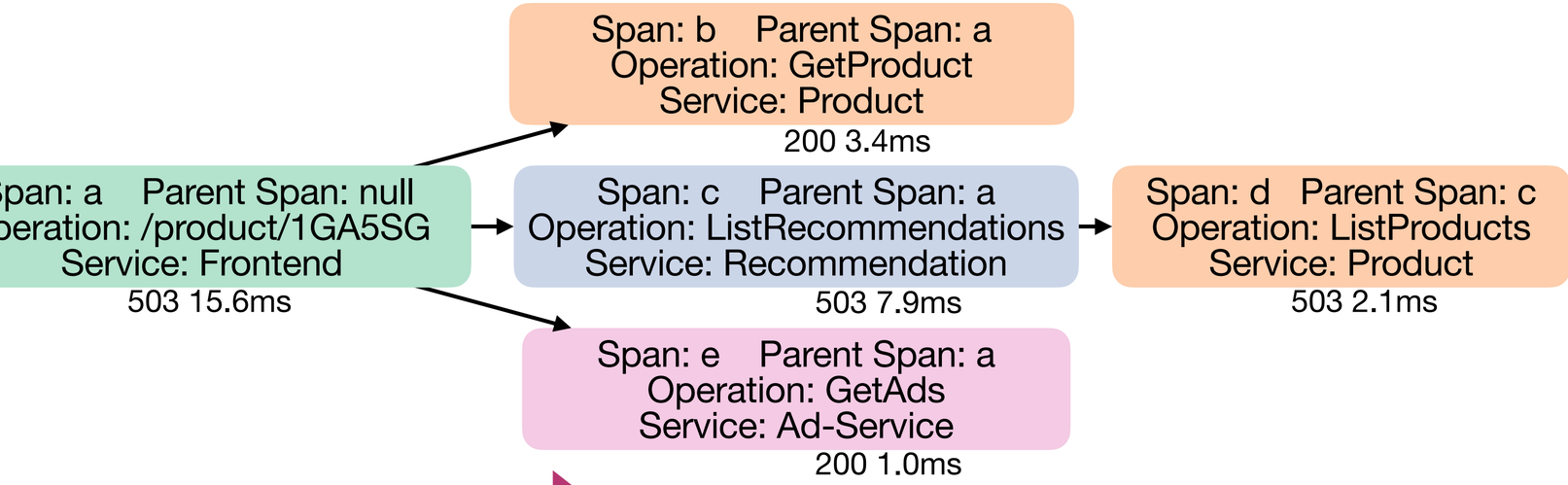
Trace-Based Localization Approaches

A trace is the whole execution process invoked by a user request on services



Service Dependency Graph



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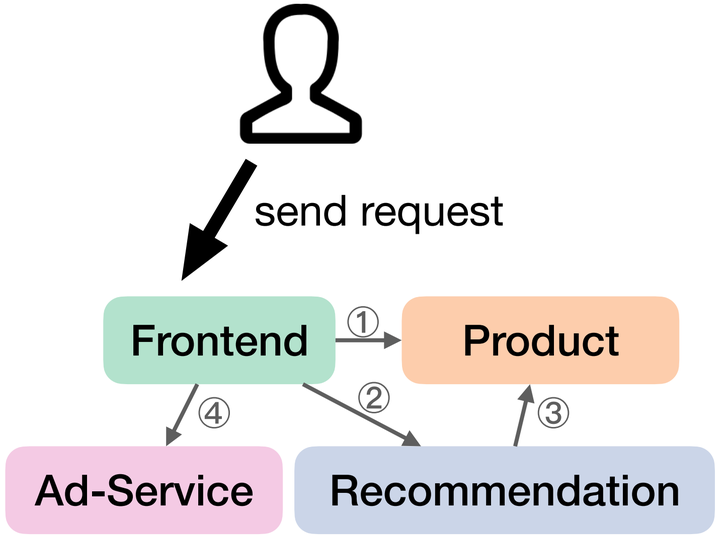

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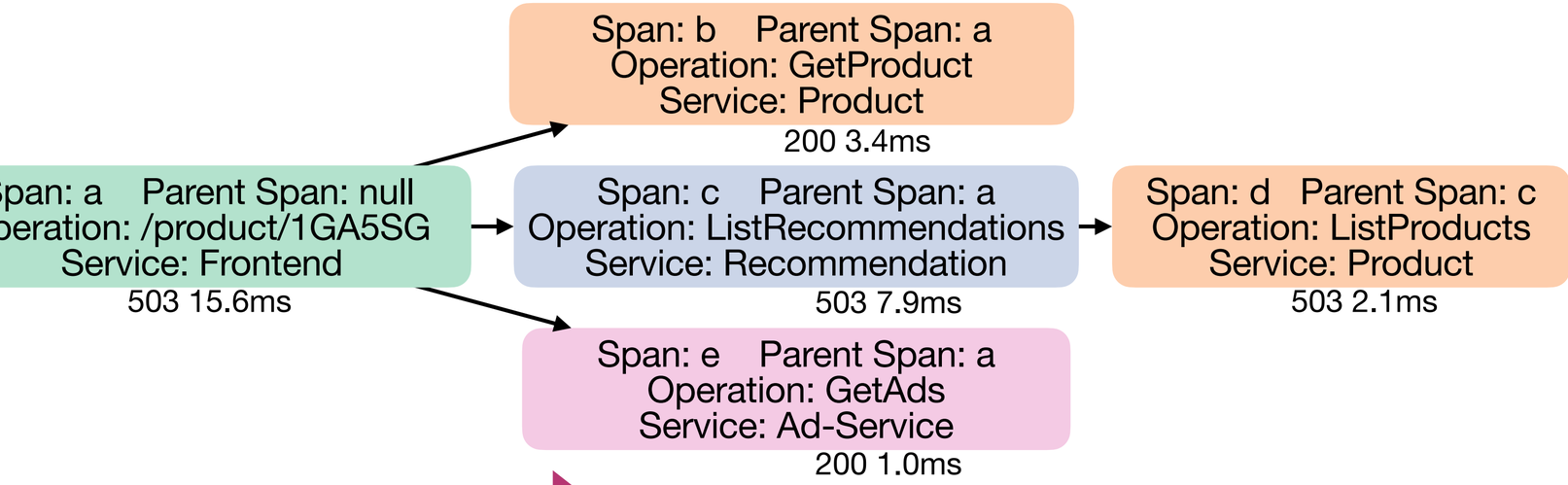

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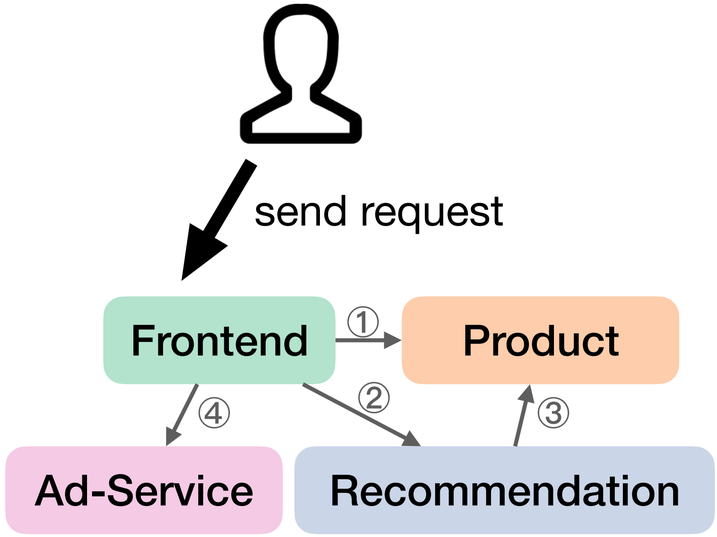

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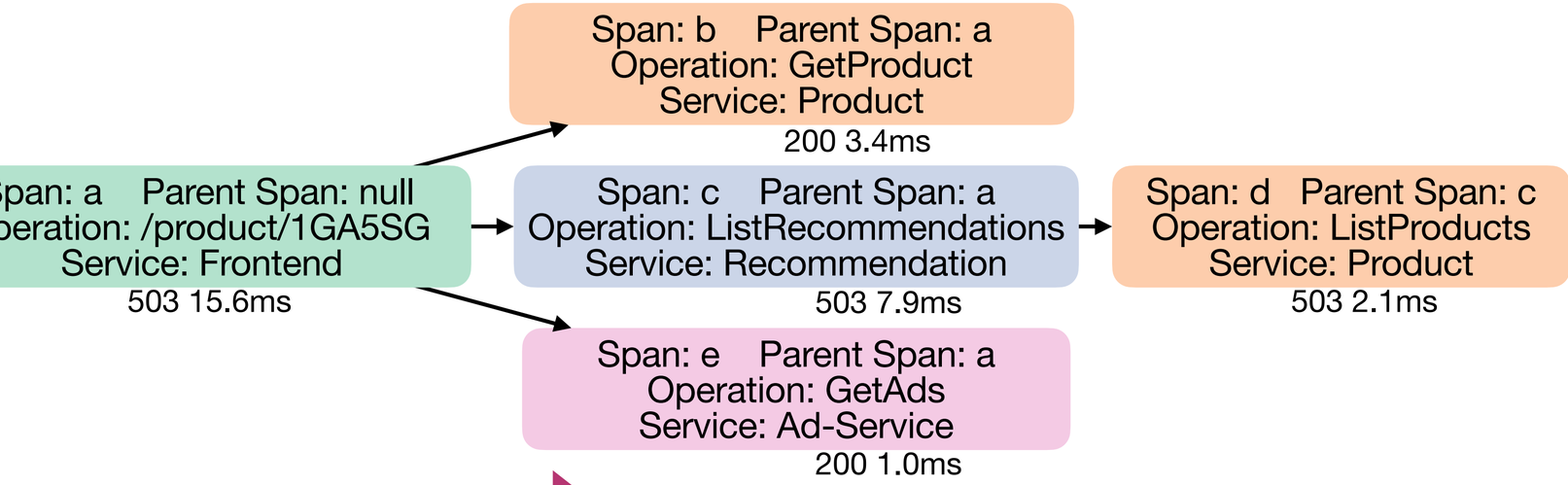

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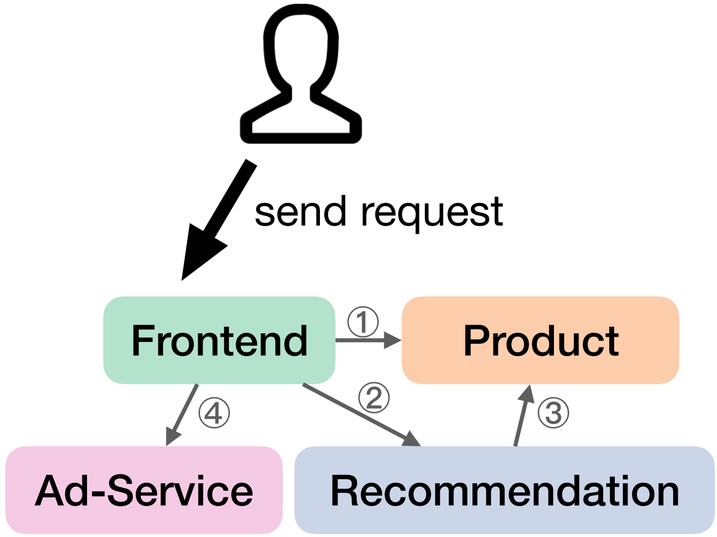

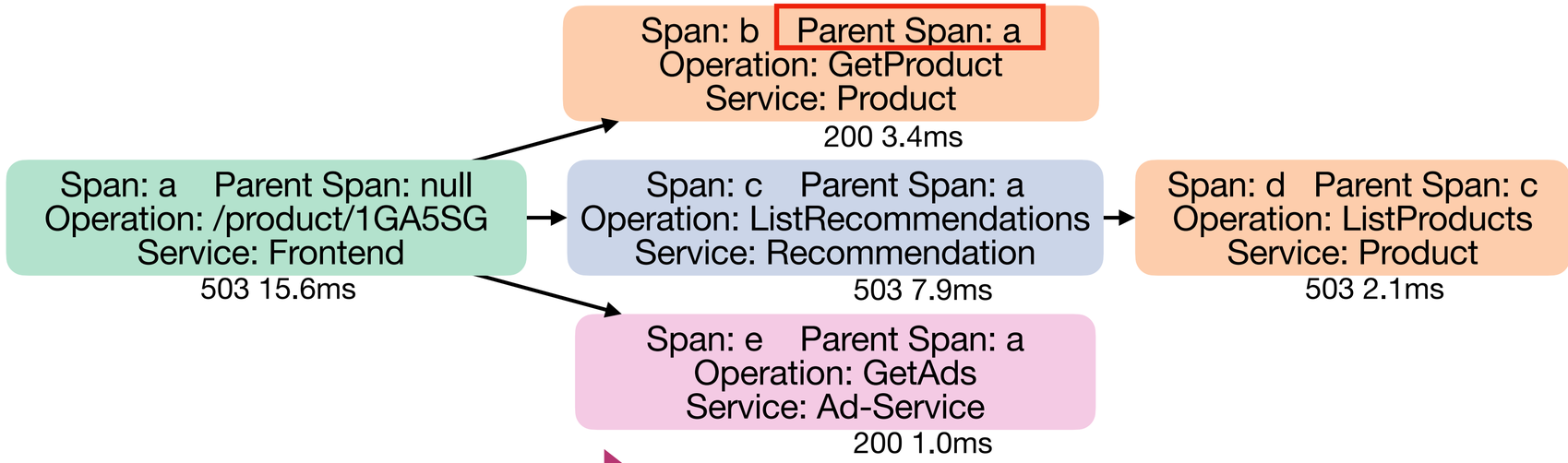

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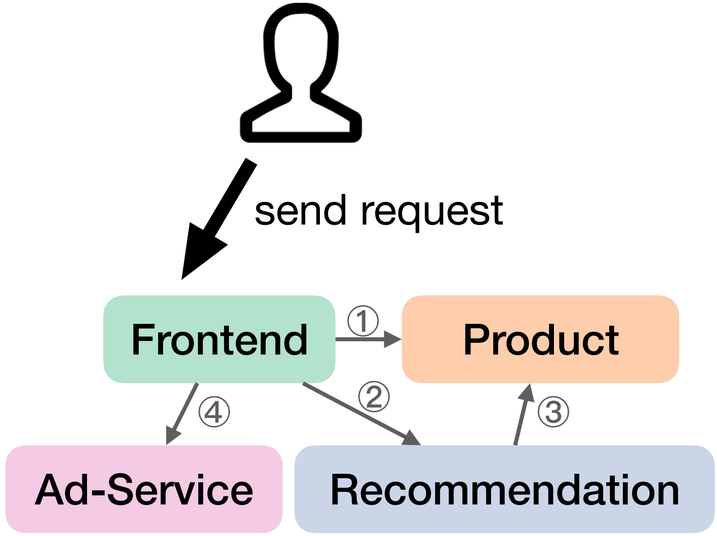

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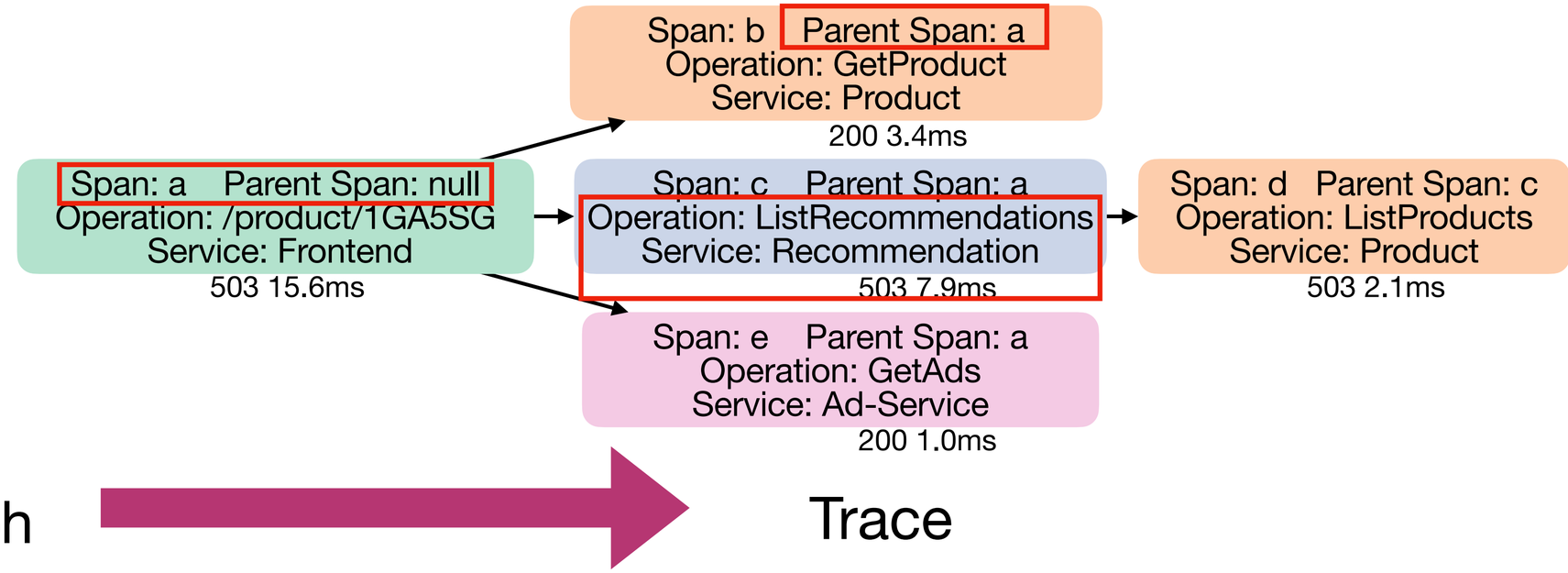

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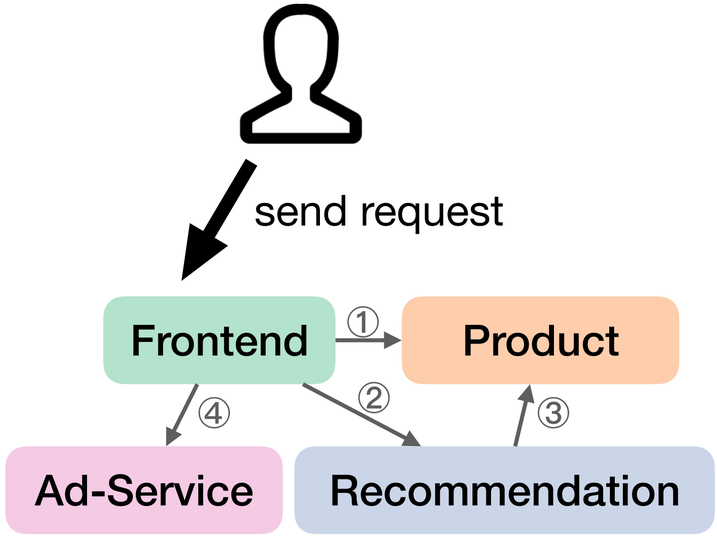

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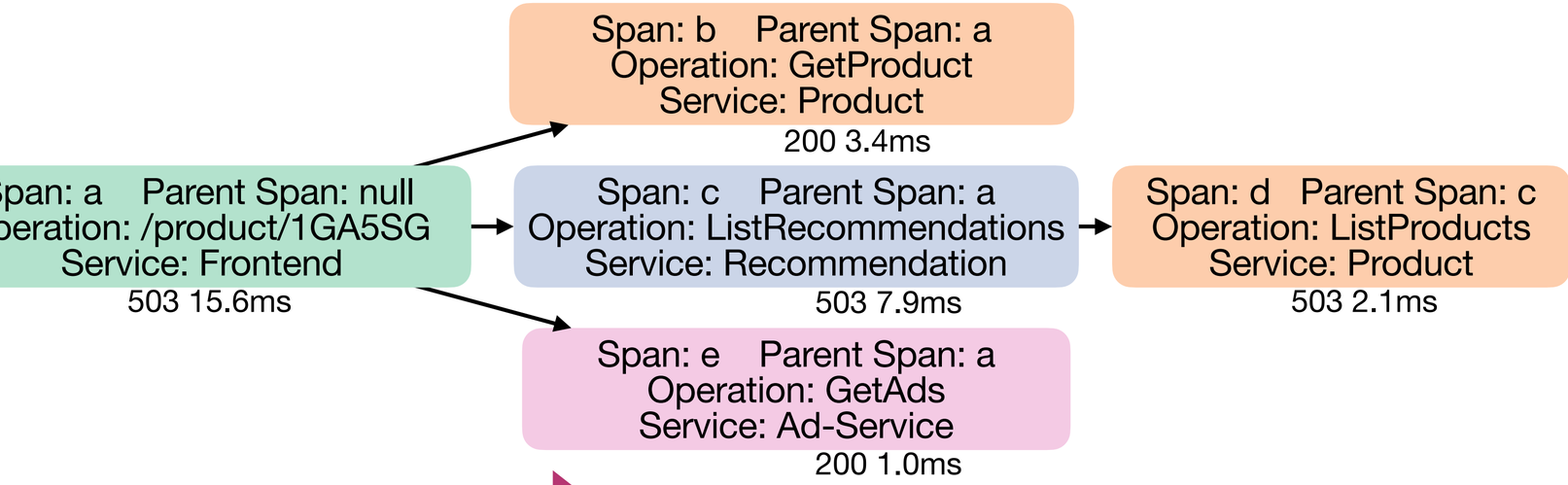

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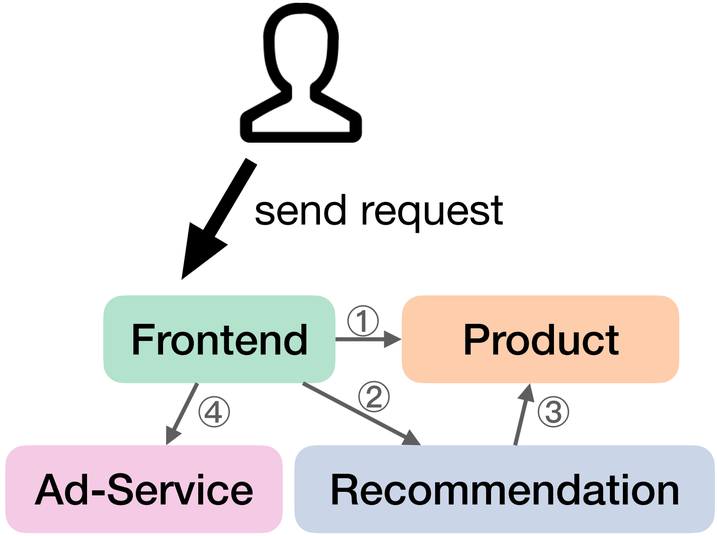

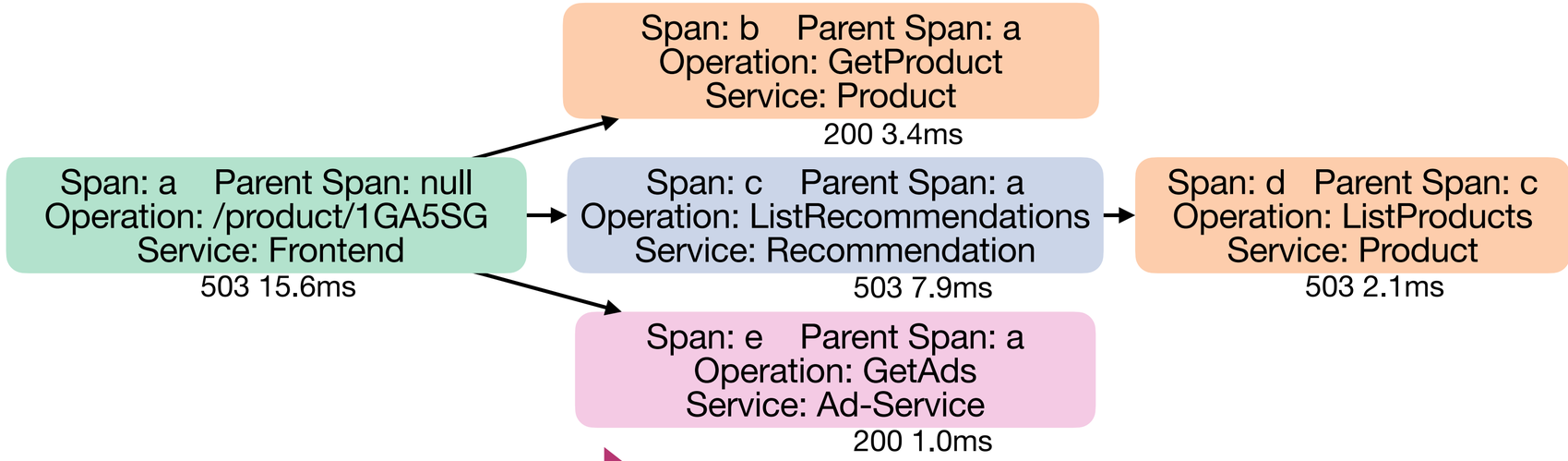

Service Dependency Graph → Trace

Traces record **detailed dependencies** and enough **contextual information** for root-cause service localization

Motivation

Existing Trace-Based Localization Approaches

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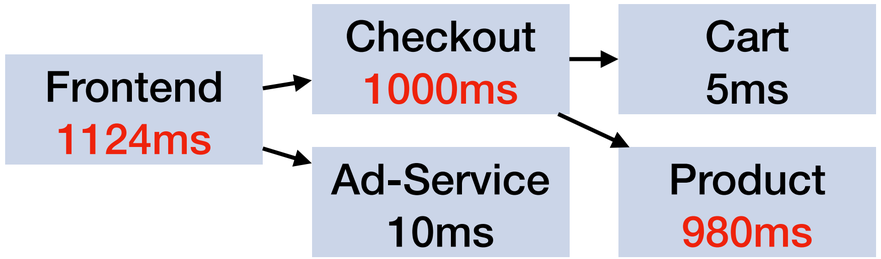
- MicroScope[ICSOC'18] and TraceAnomaly[ISSRE'20] take the most upstream abnormal invocation of an abnormal trace as the root cause.



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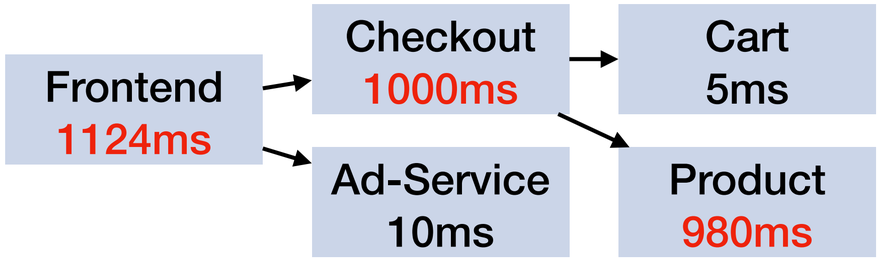

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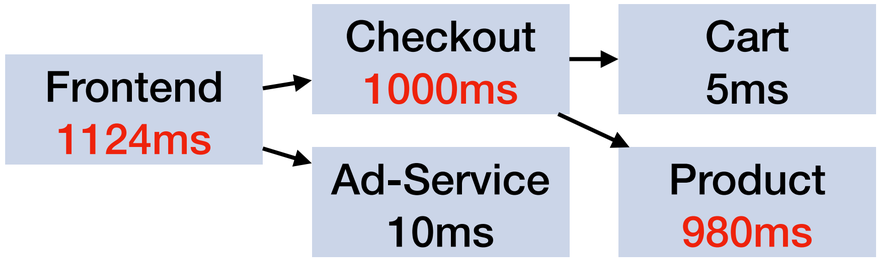

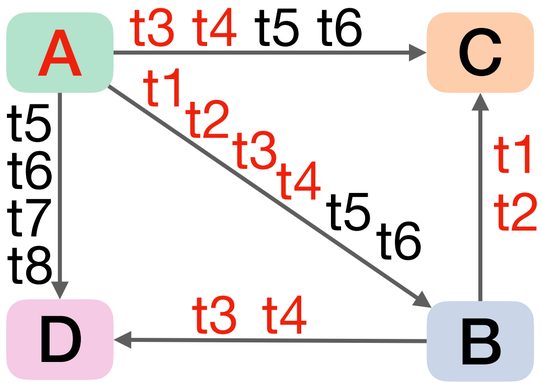

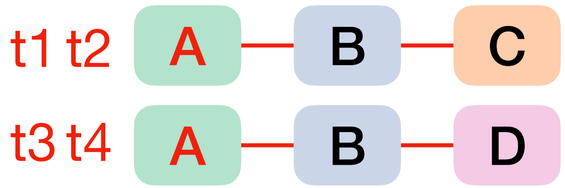

The implementation bug of API /a1 in service A makes further invocations from /a1 abnormal

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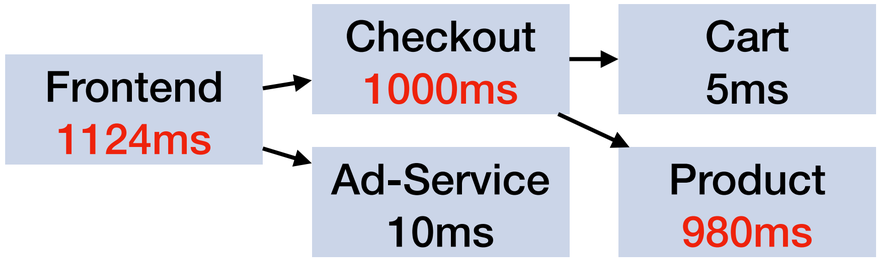
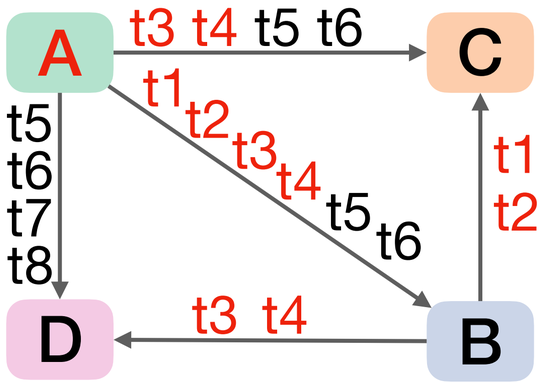
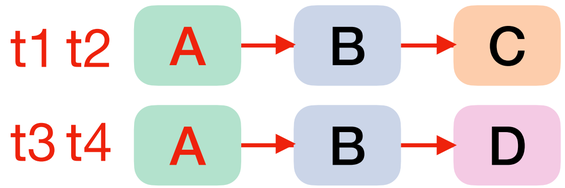




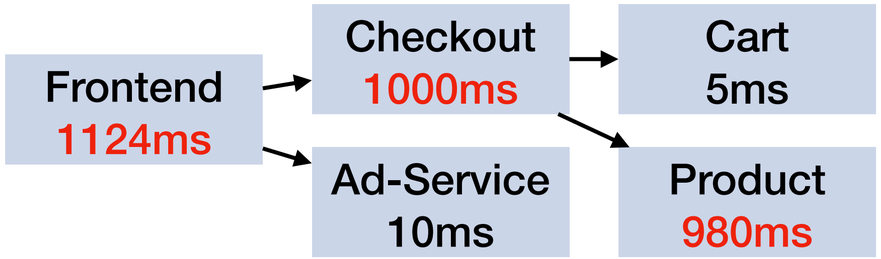


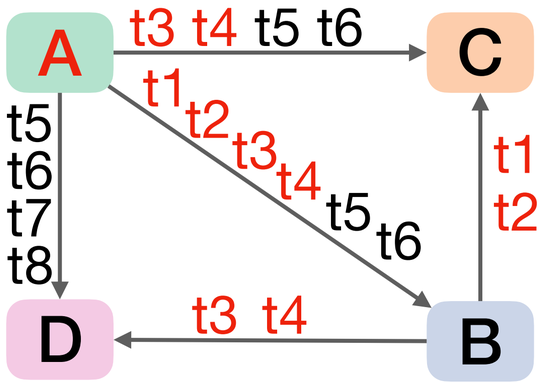
The implementation bug of API /a1 in service A makes further invocations from /a1 abnormal

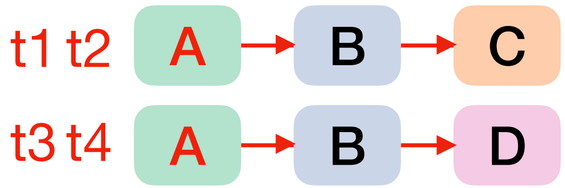
Motivation

Existing Trace-Based Localization Approaches

- MicroScope[ICSOC'18] and TraceAnomaly[ISSRE'20] take the most upstream abnormal invocation of an abnormal trace as the root cause.







The implementation bug of API /a1 in service A makes further invocations from /a1 abnormal

The root-cause service is not the most upstream one

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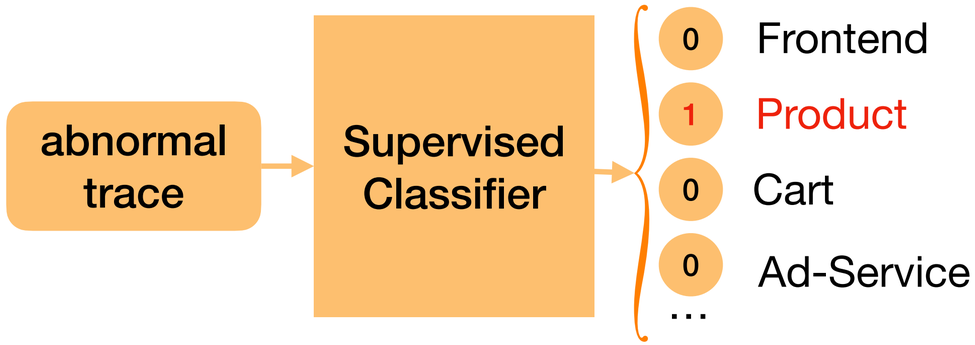
- MEPFL[FSE'19] uses a supervised machine learning model to "classify" the root-cause service for an abnormal trace.



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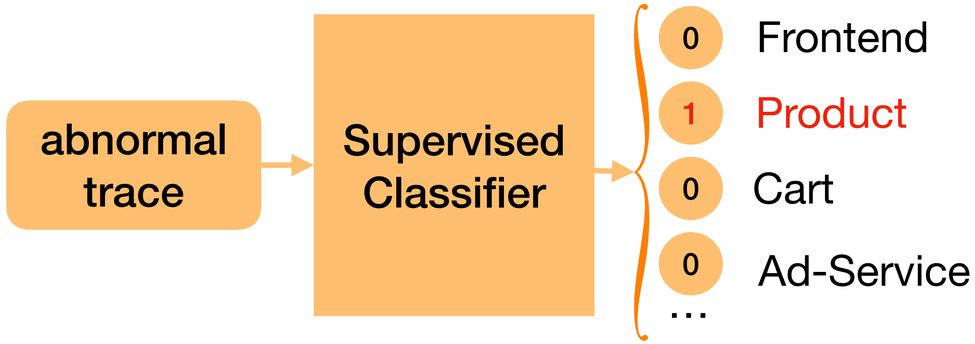

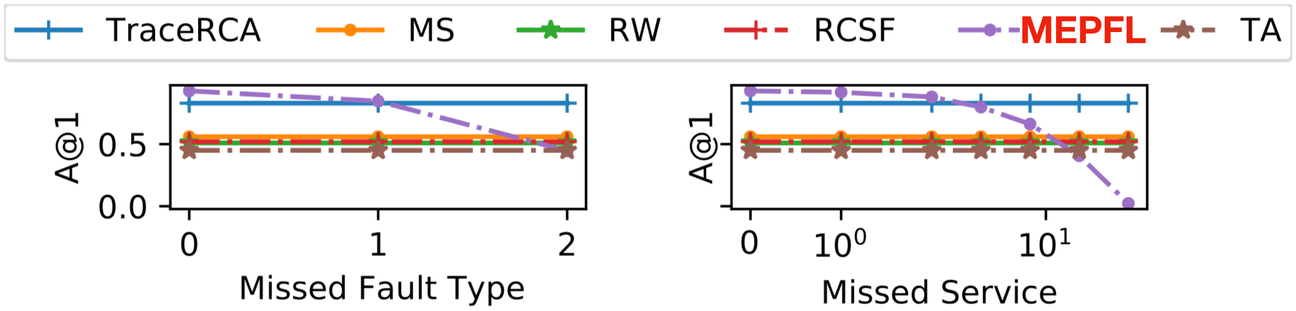

Supervised approaches rely on training data with high coverage on all fault types and microservices

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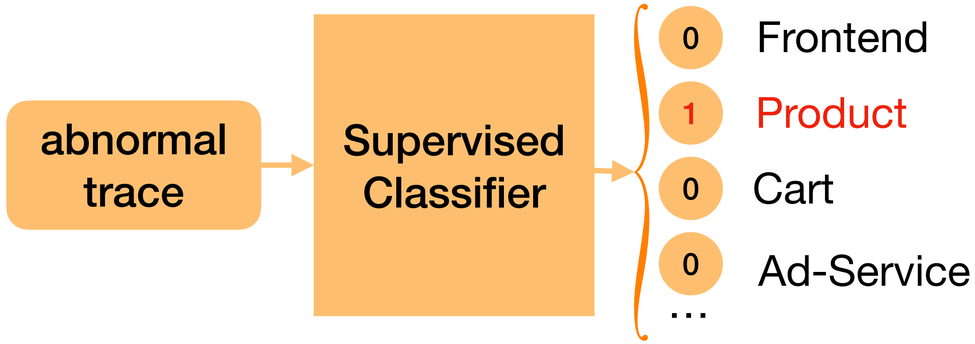

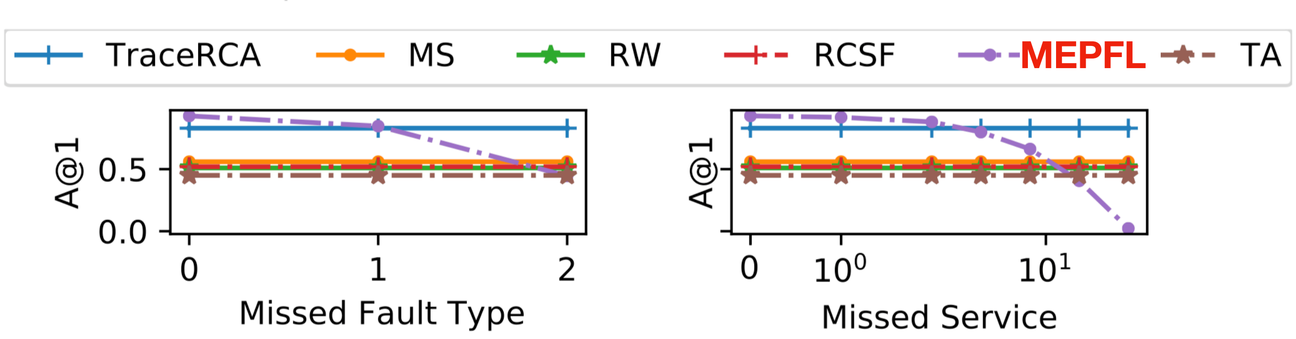

Supervised approaches rely on training data with high coverage on all fault types and microservices

It is hard for supervised approaches to handle new faults

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Our insight utilizes the ***statistical information*** based on ***both normal and abnormal traces***

Motivation

Key Metrics

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support $\uparrow$ $\Rightarrow$ “more abnormal traces”

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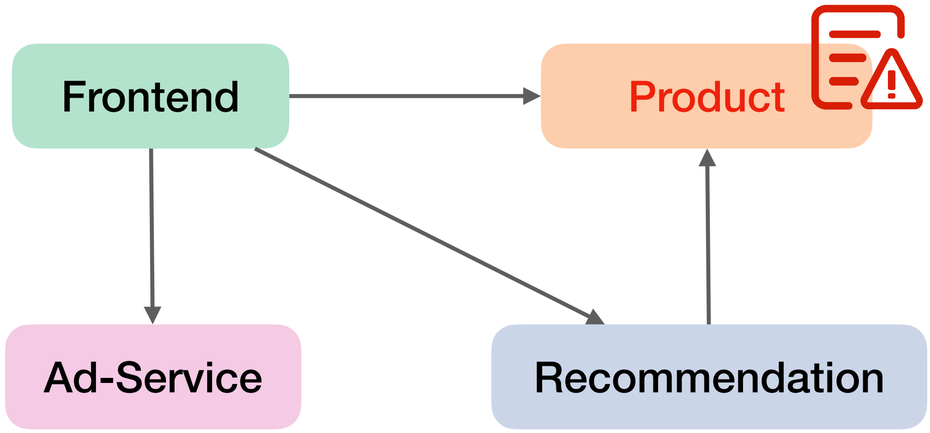

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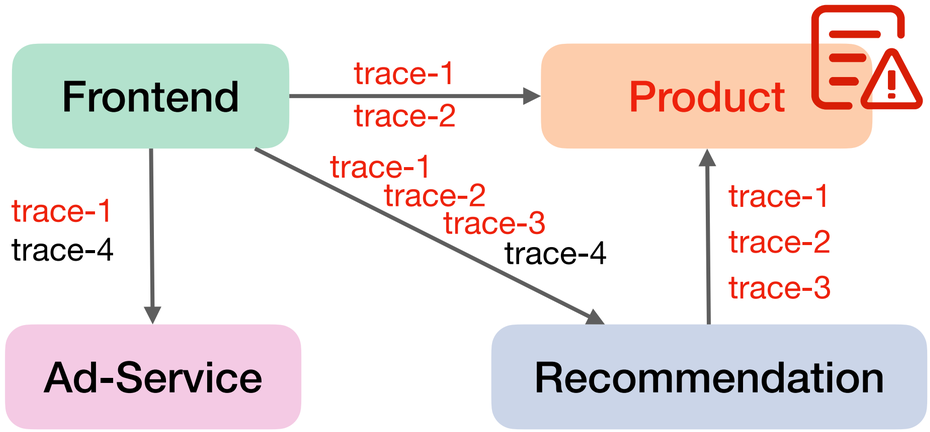

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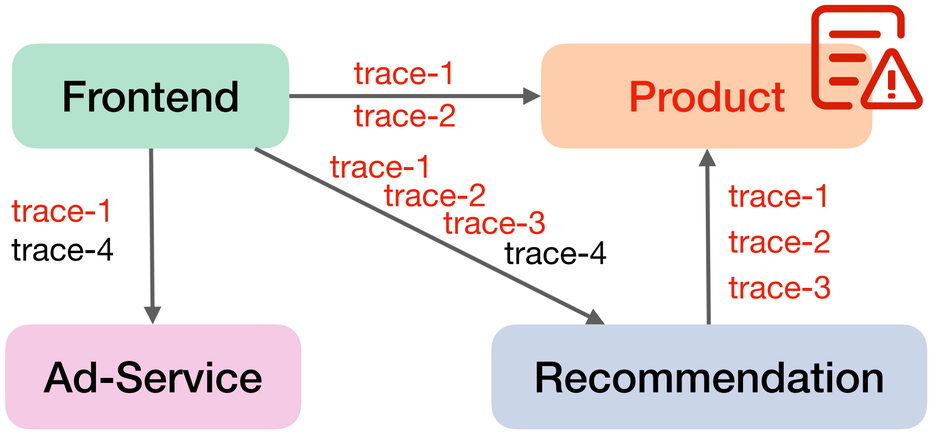

	support	confidence
Frontend		
Product		
Recommendation		
Ad-Service		

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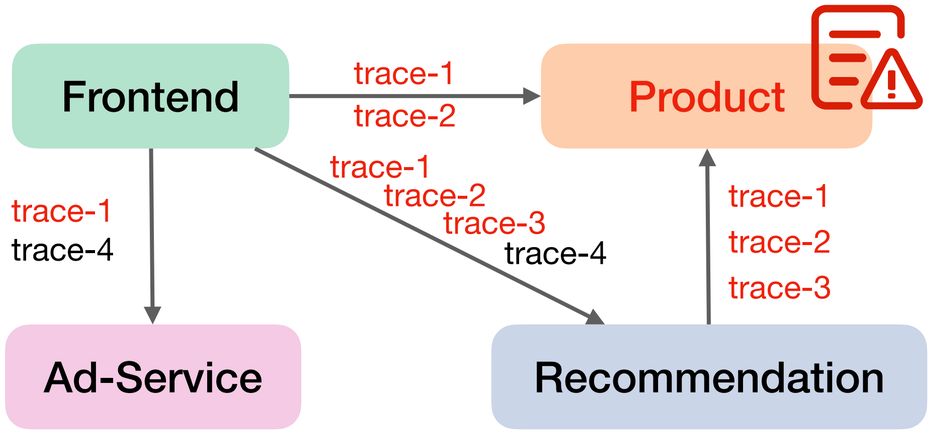

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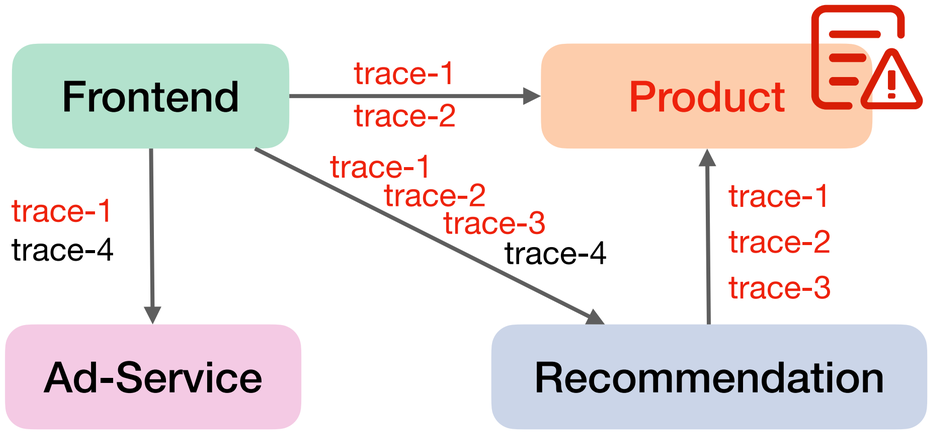

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Product		
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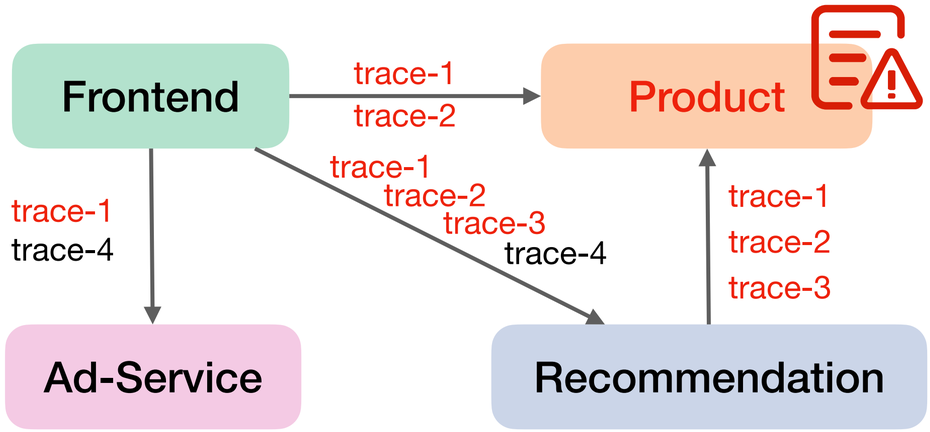

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Frontend	3/3	
Product		
Recommendation		
Ad-Service		

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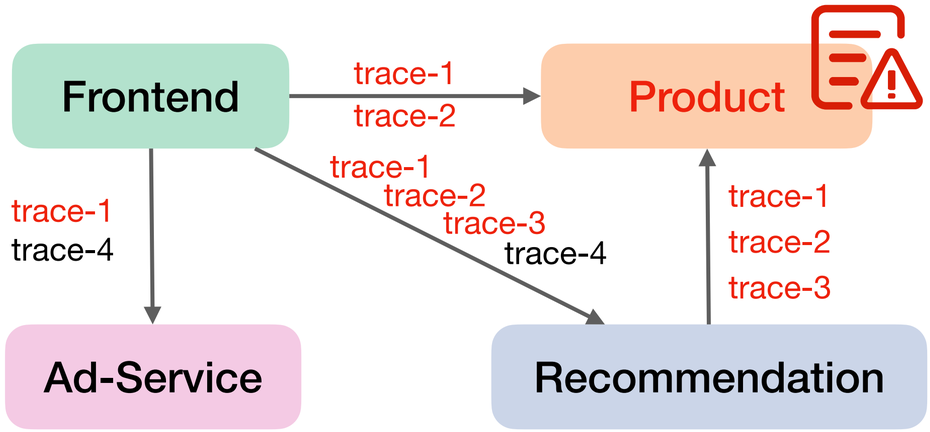

	support	confidence
Frontend	3/3	3/4
Product		
Recommendation		
Ad-Service		

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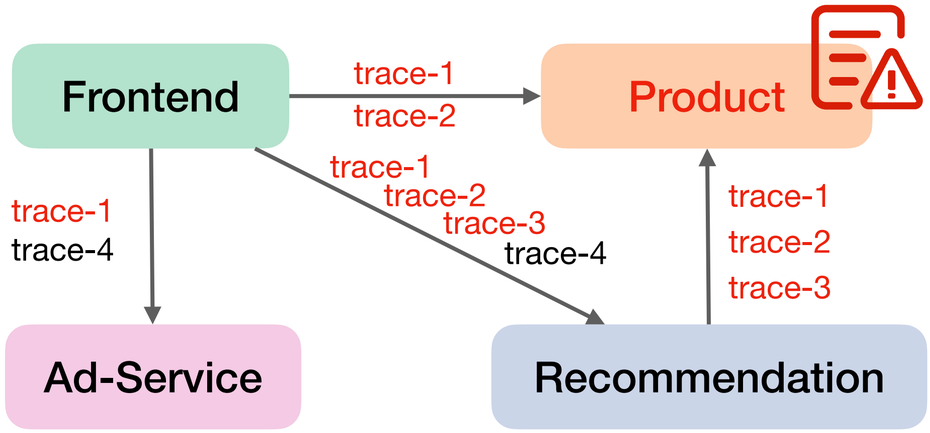

	support	confidence
Frontend	3/3	3/4
Product	3/3	3/3
Recommendation	3/3	3/4
Ad-Service	1/3	1/2

Core Idea

1. Multi-Feature Anomaly Detection

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We need to detect abnormal traces

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Multi-feature anomaly detection is necessary

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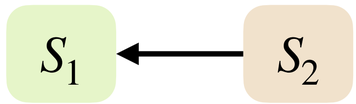

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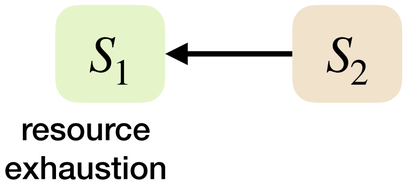

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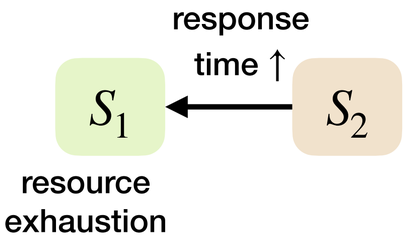

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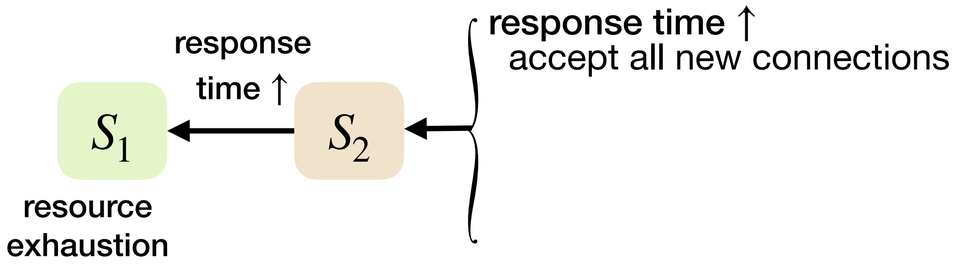

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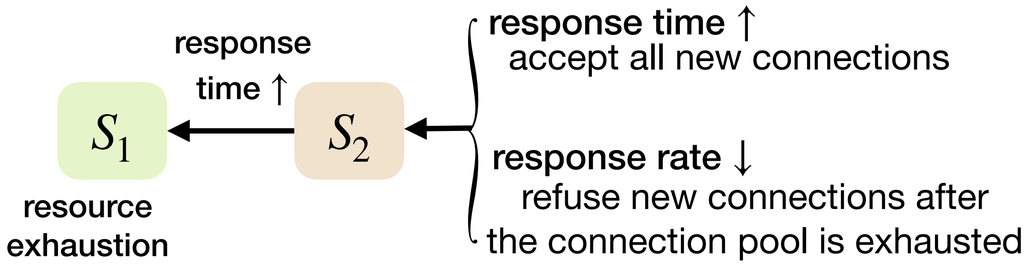

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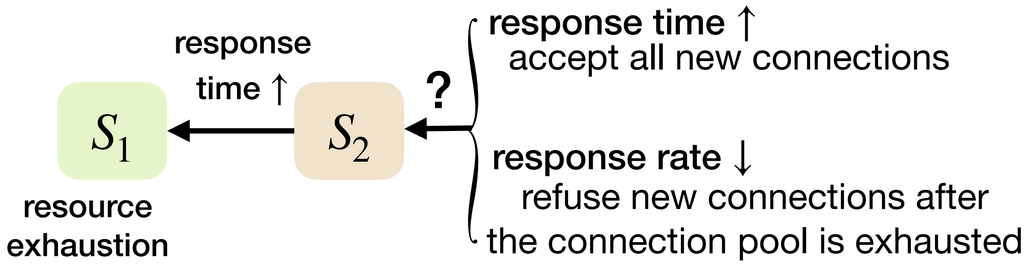

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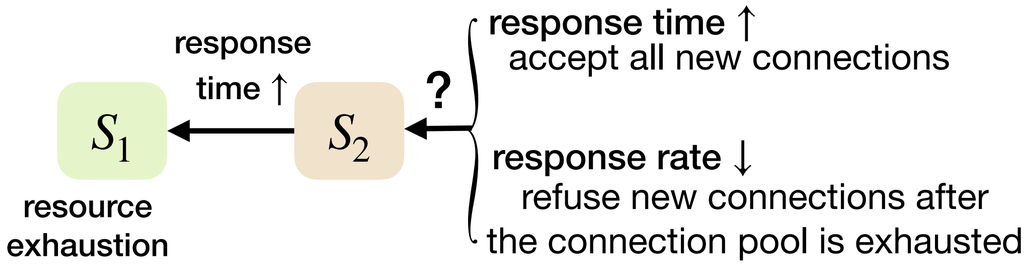

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Only some features are related to the concerned fault, but there could be also anomalies in other irrelevant features

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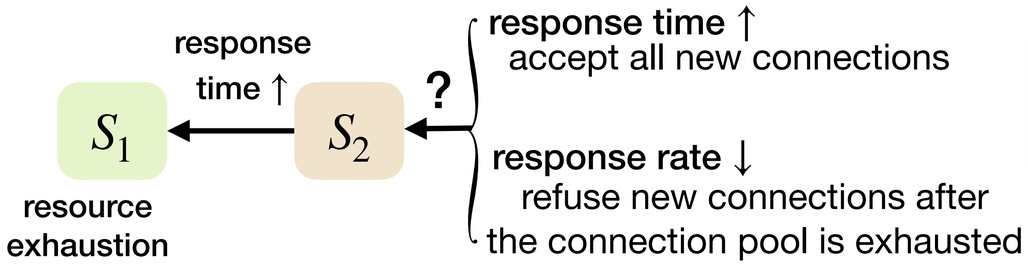

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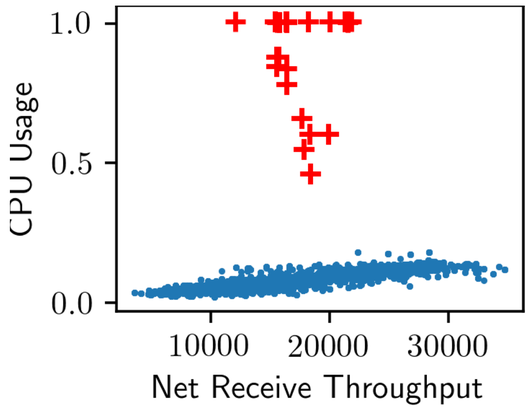

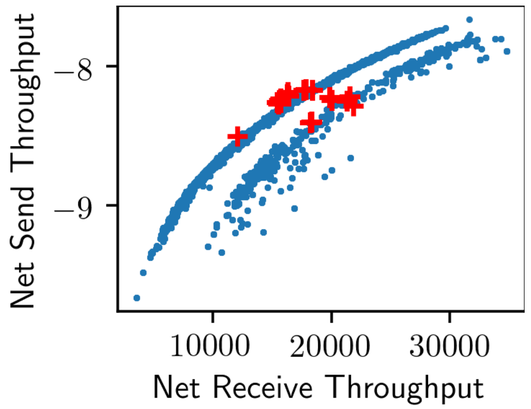

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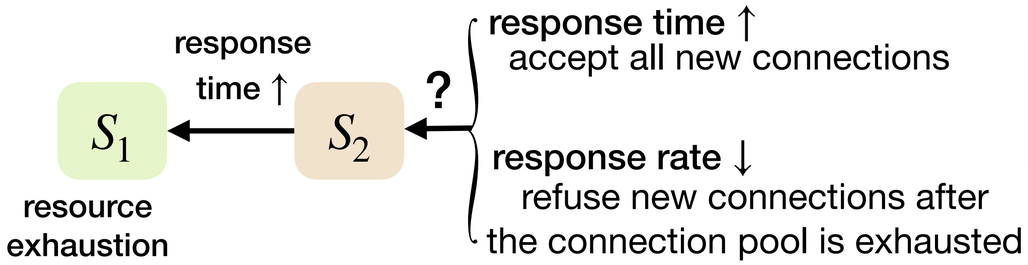

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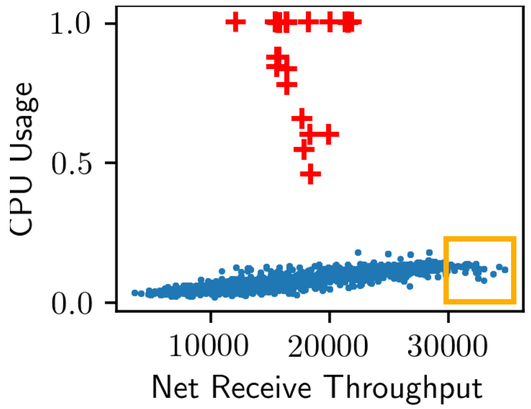

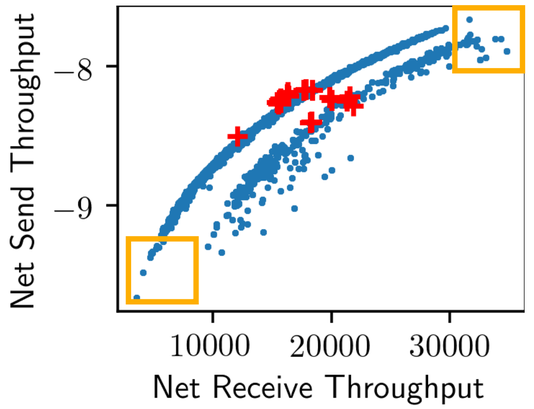

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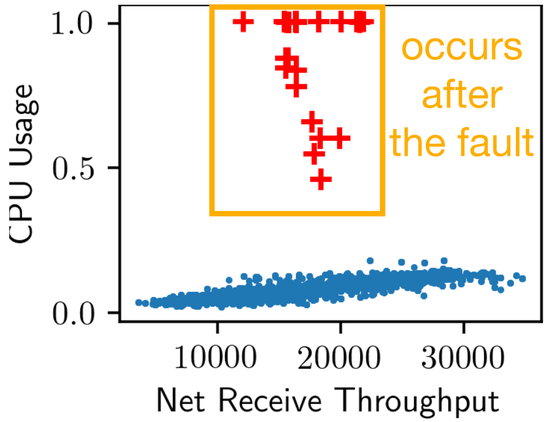

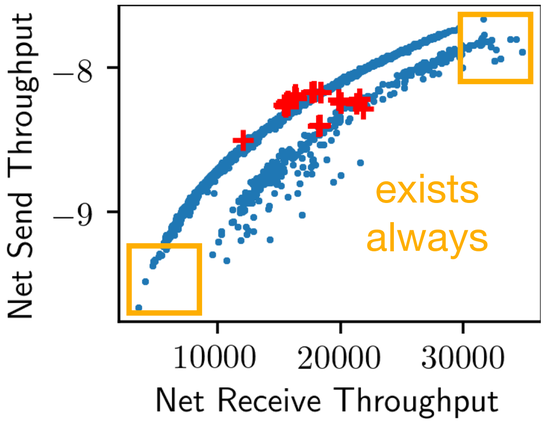

The number of anomalies with respect to useful features and irrelevant features are different

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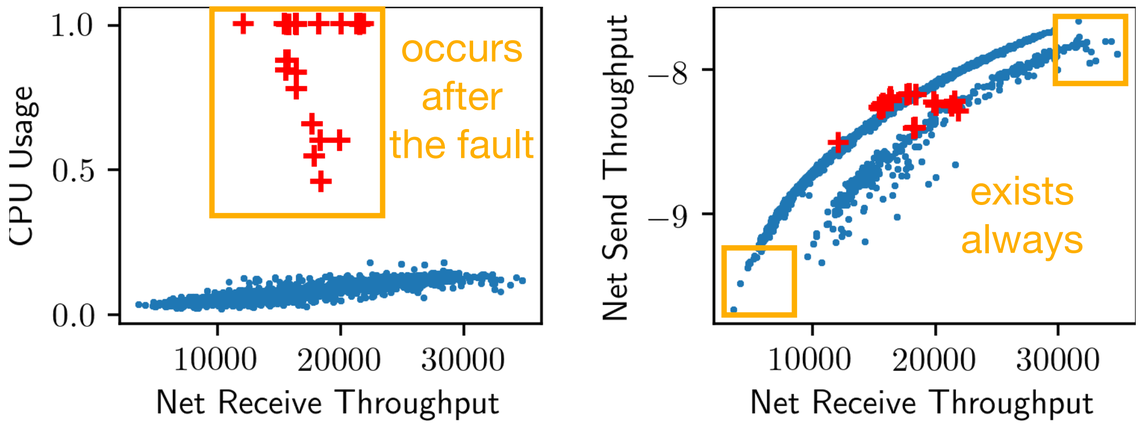
1. Multi-Feature Anomaly Detection



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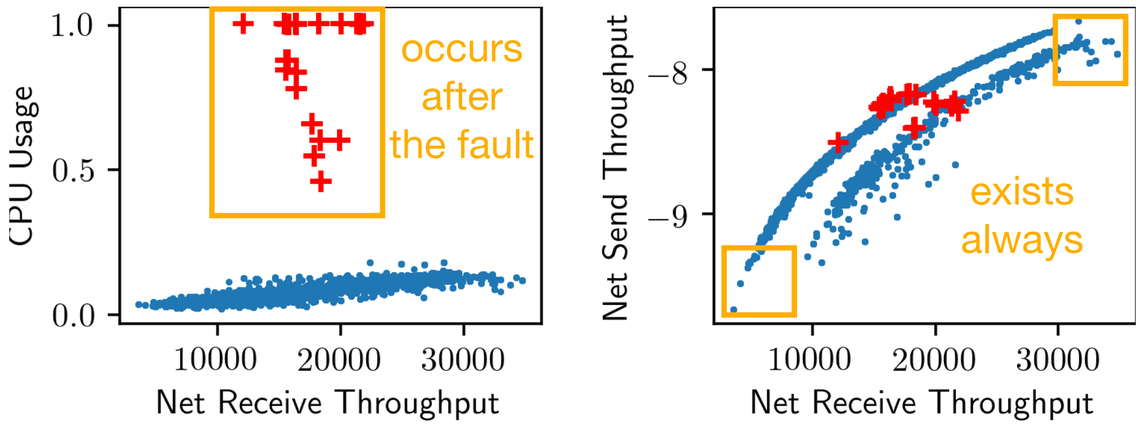

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Normal	99%	90%
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✅ Useful feature

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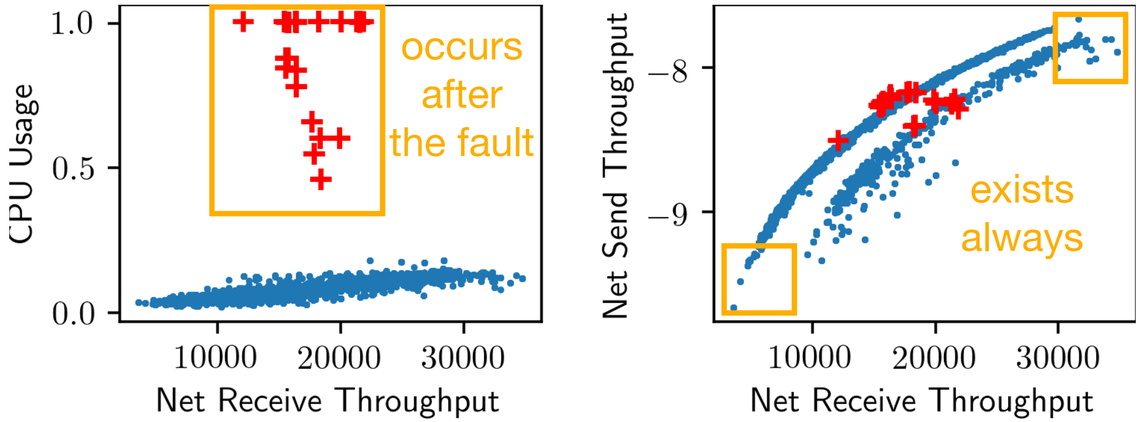

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CPU usage	Before	After
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✅ Useful feature

Throughput	Before	After
Normal	98%	98%
Abnormal	2%	2%

❌ Irrelevant feature

Core Idea

2. Mining Microservice Sets

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Highlight 2: (Extending Our Insight)
*We mine **microservice sets** with high supports and confidences*
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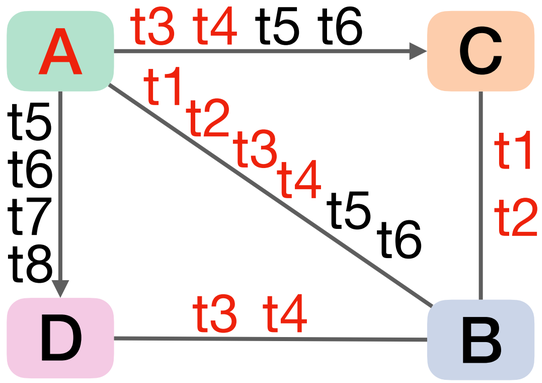

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Only those traces following pattern A->B->* are abnormal.

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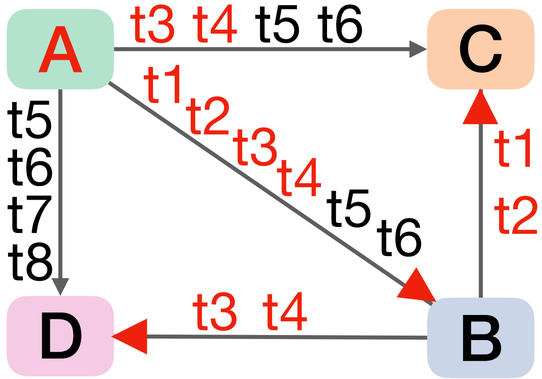

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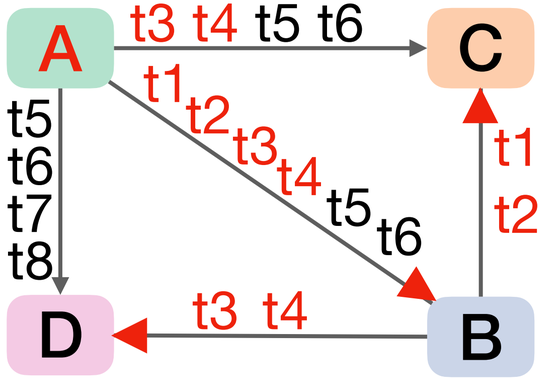

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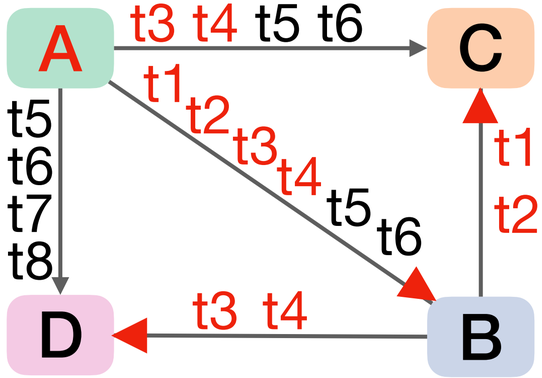

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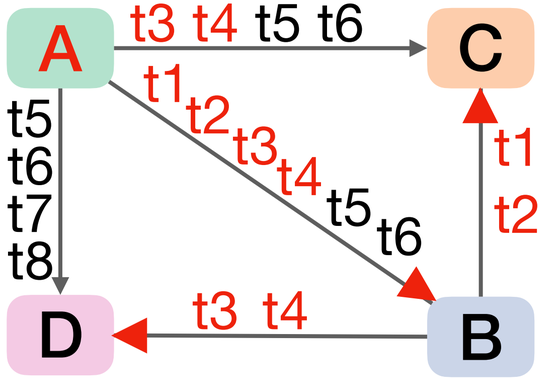

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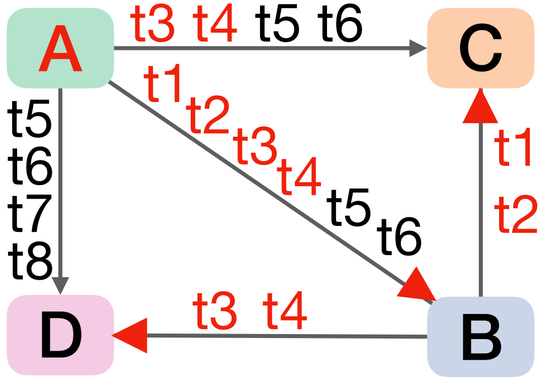

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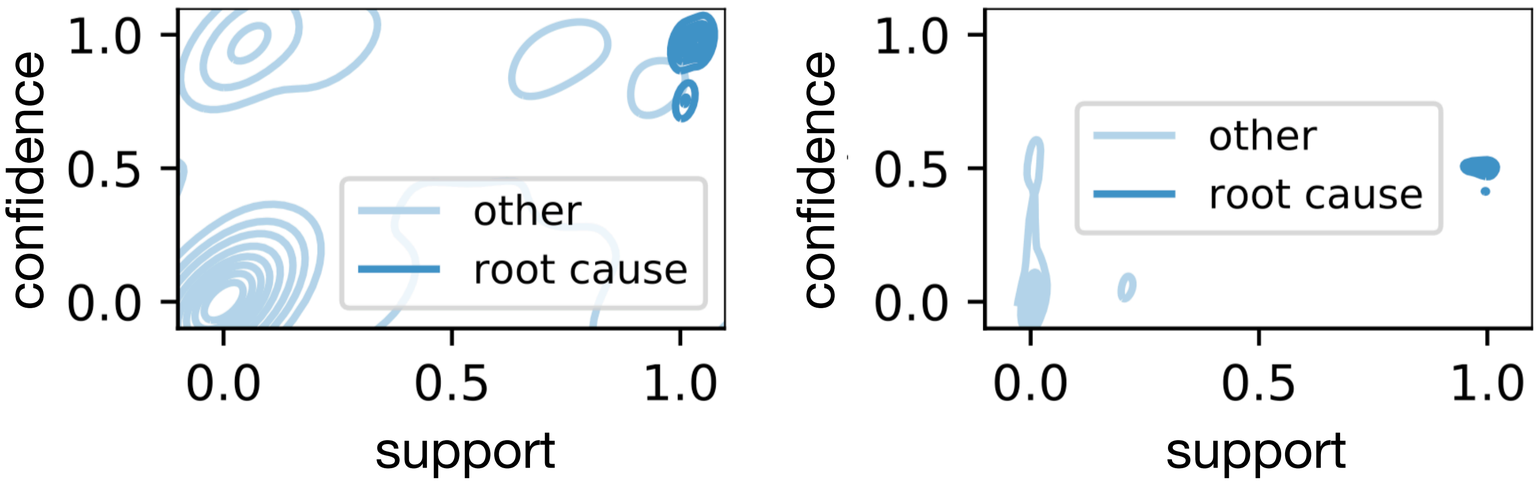

(a) Google Online Boutique (b) Production System $\mathcal{B}$

Fig. 4: The distribution of support and confidence

Our insight and the two key metrics are validated on the two systems

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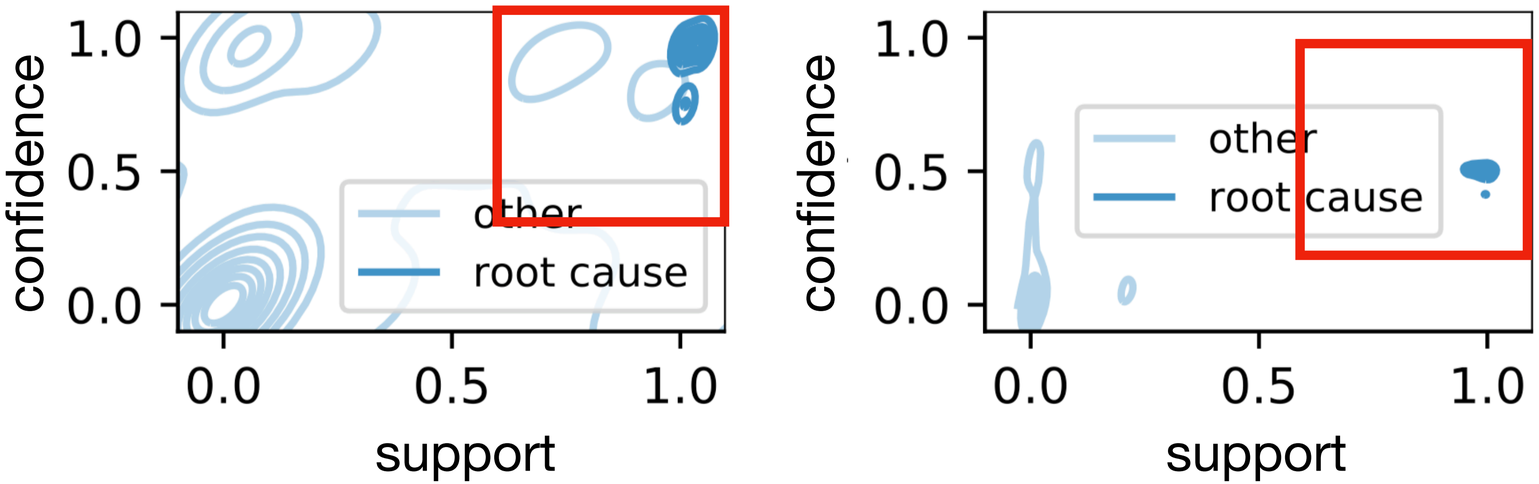

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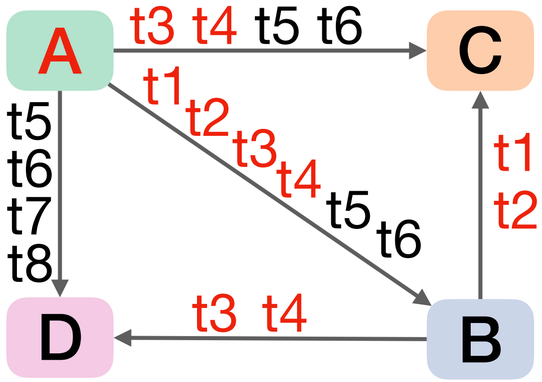

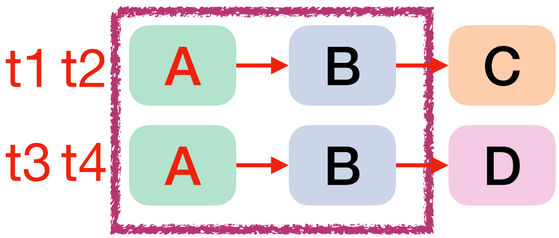

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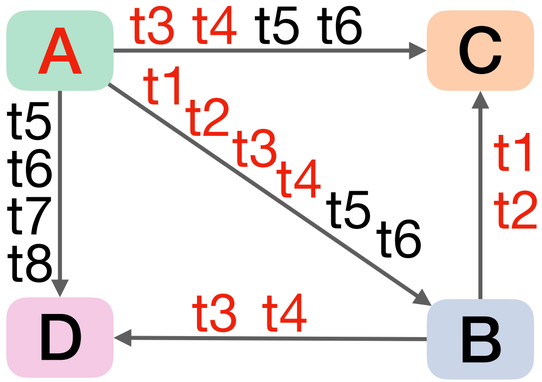

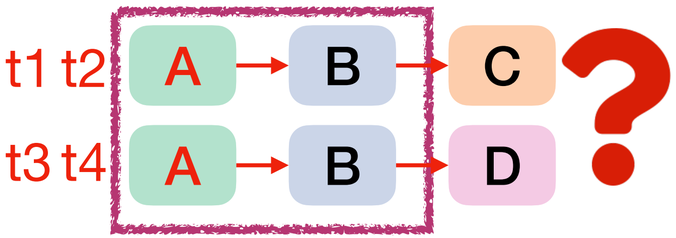

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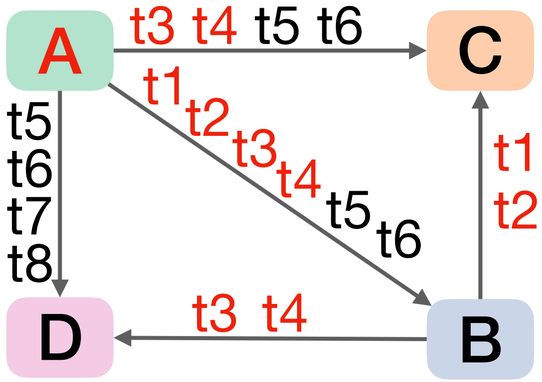

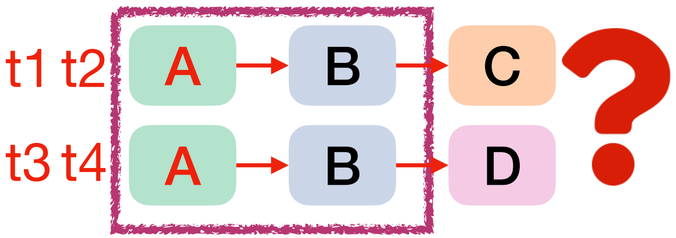

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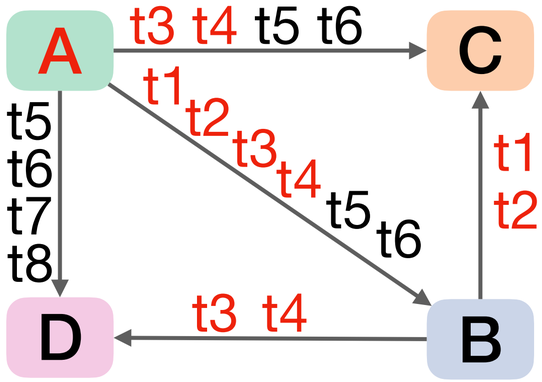

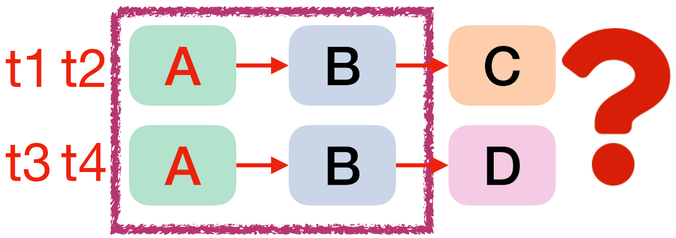

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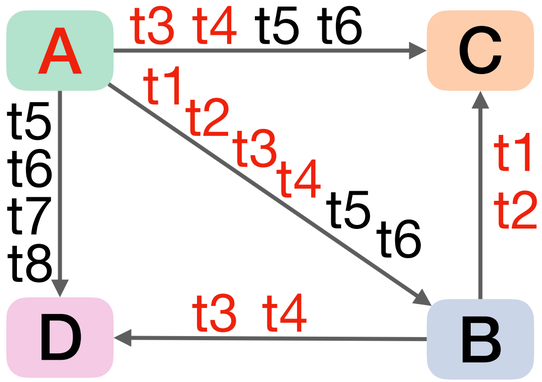

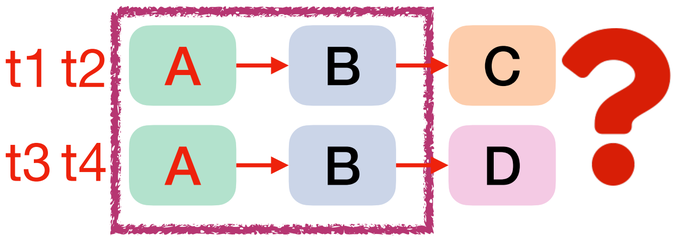

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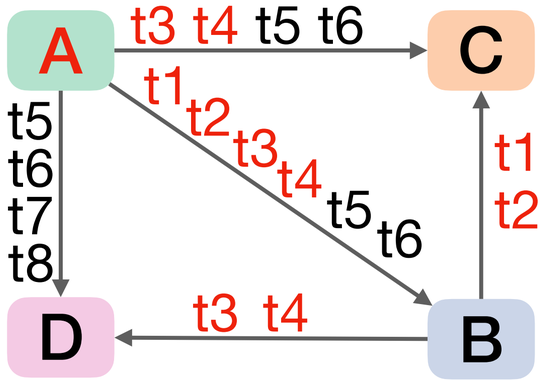

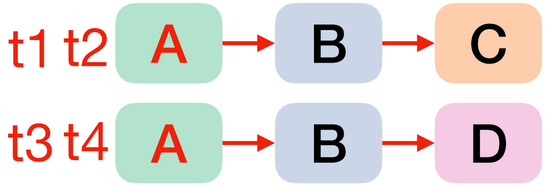

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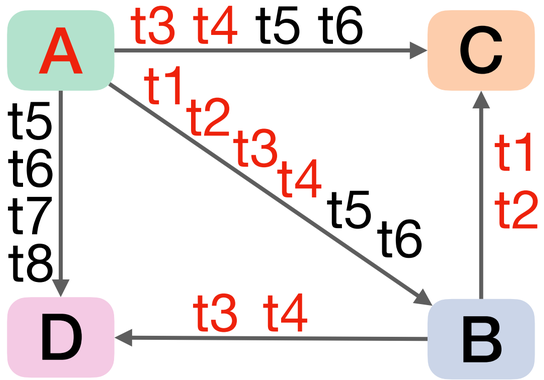

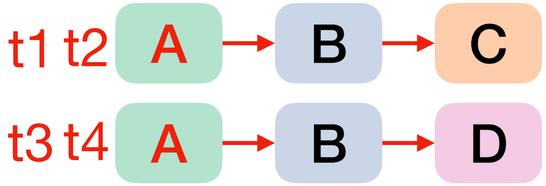

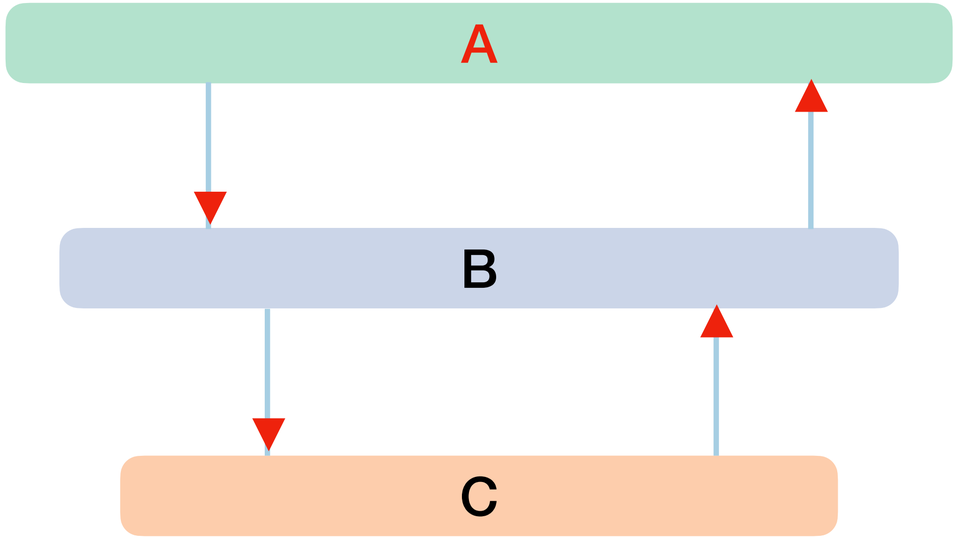

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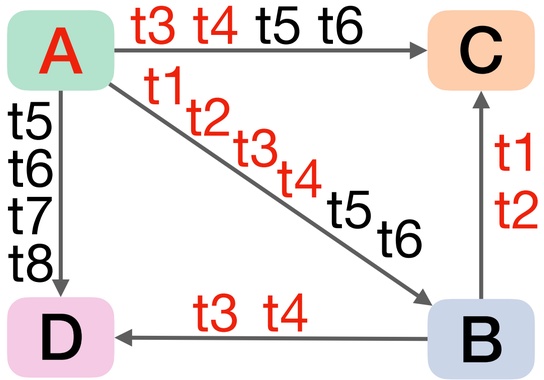

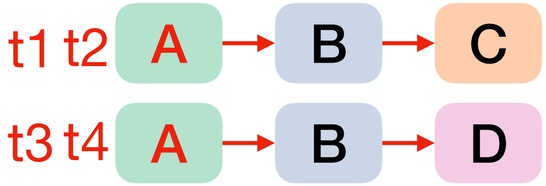

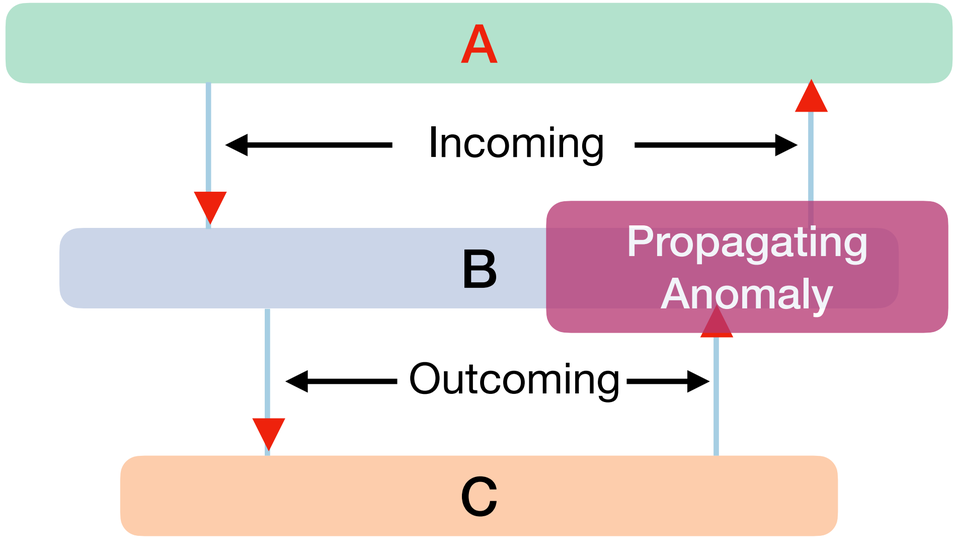

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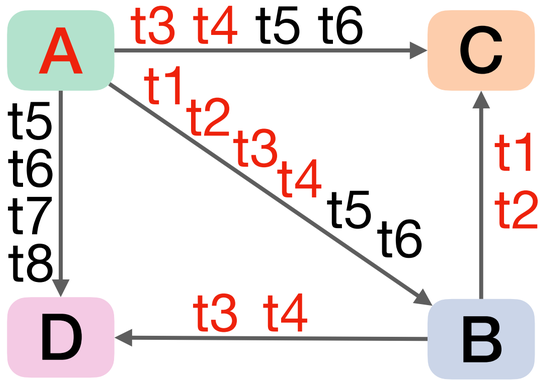

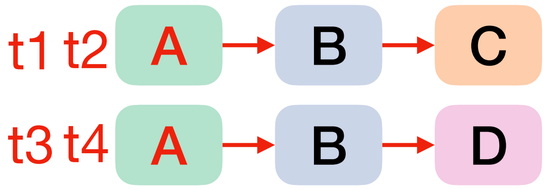

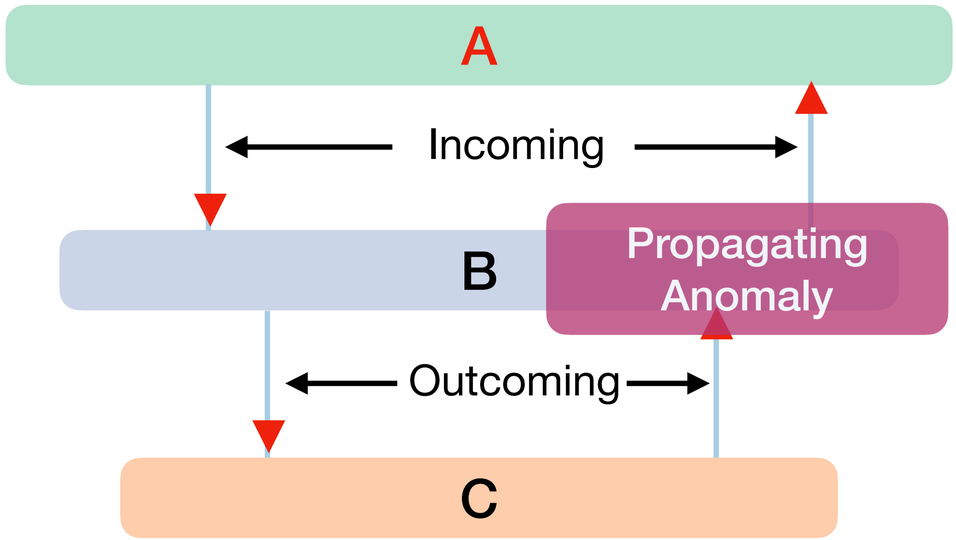

We rank the services inside one suspicious microservice set
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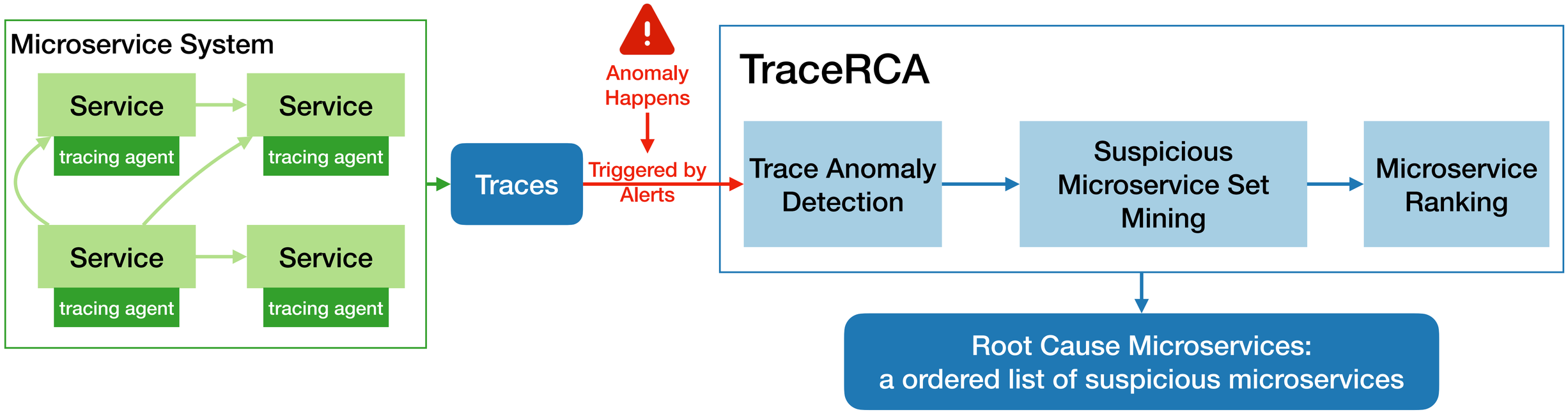

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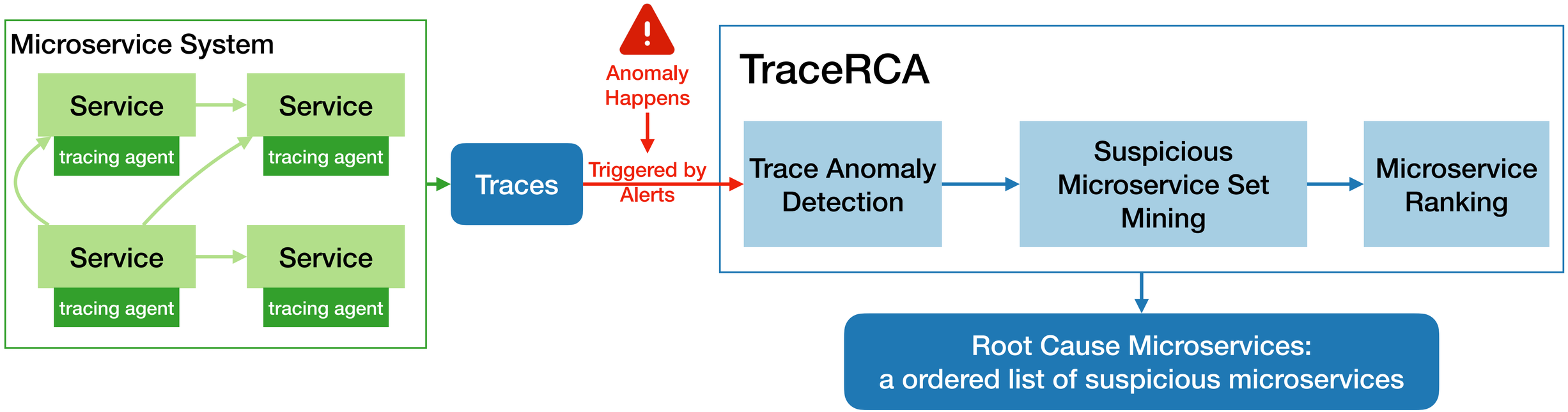

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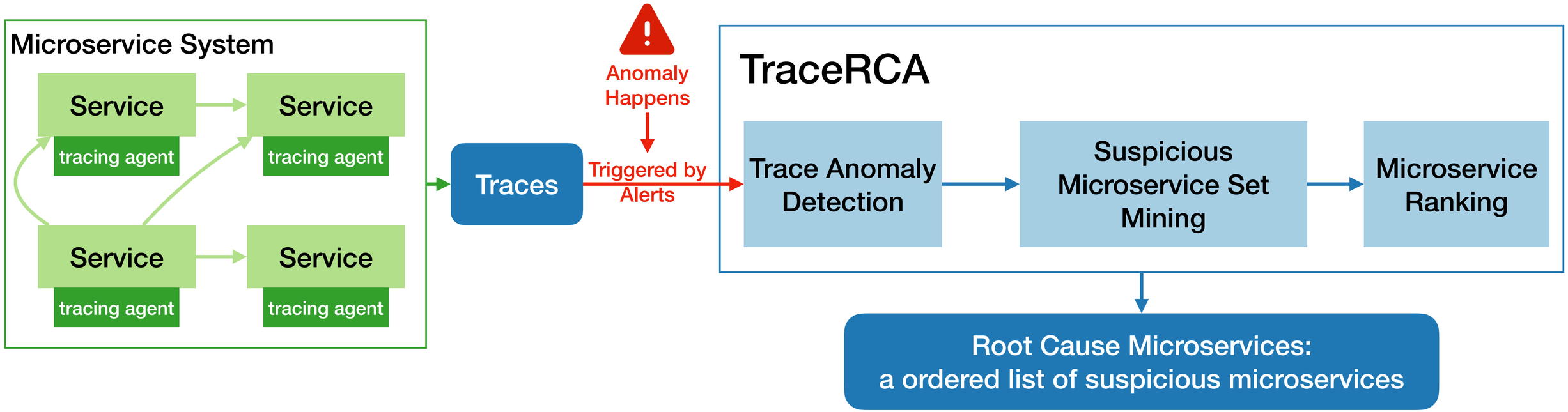

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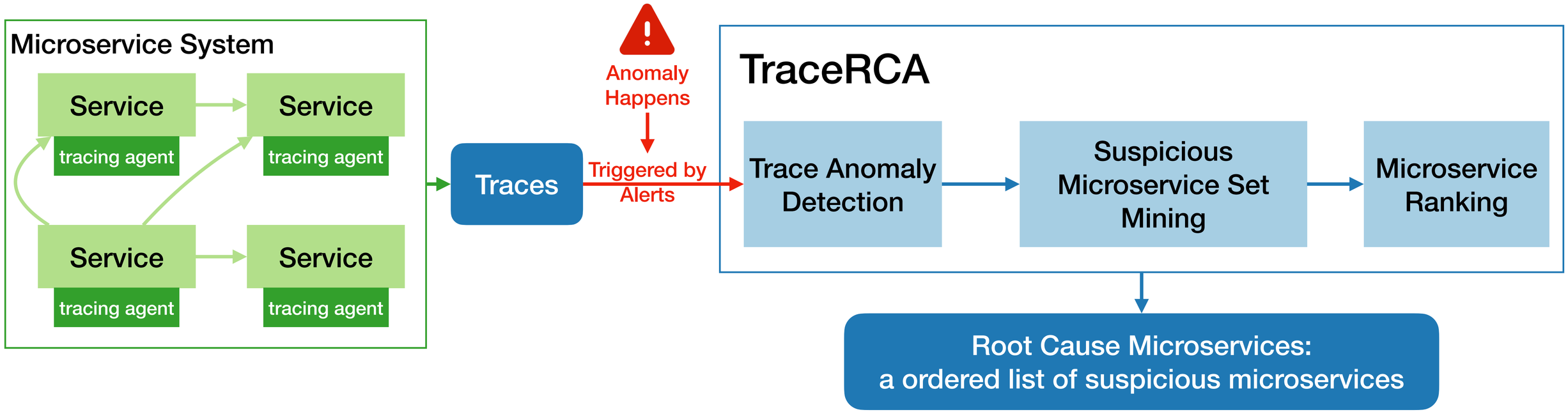

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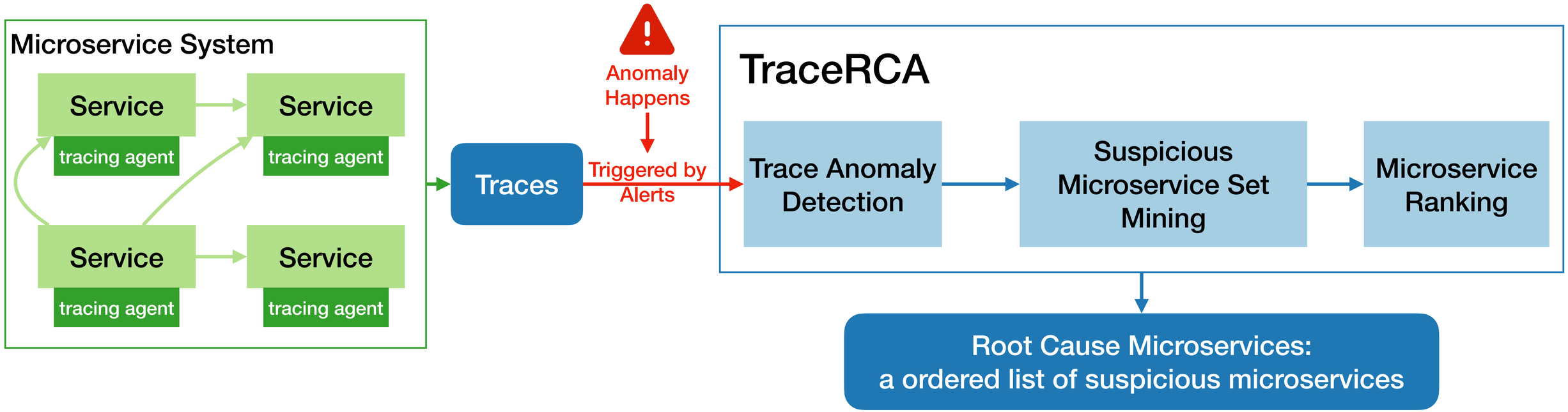

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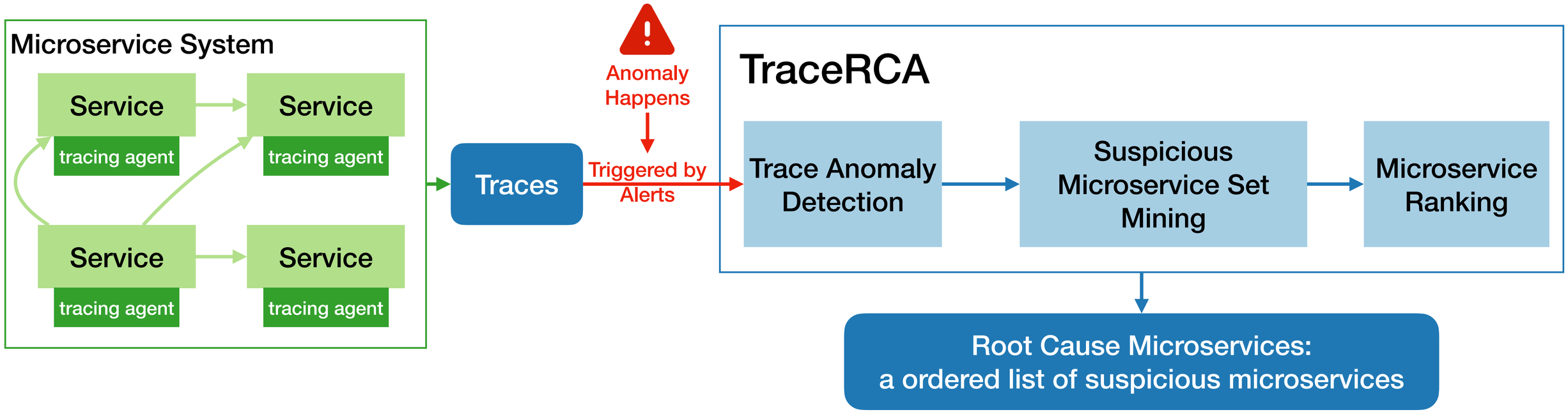

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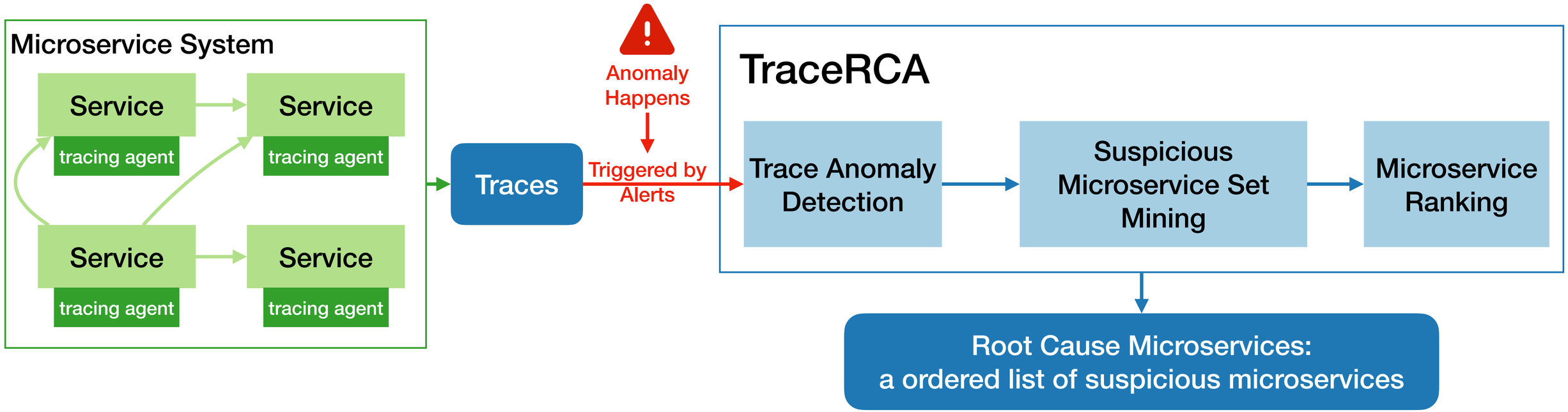

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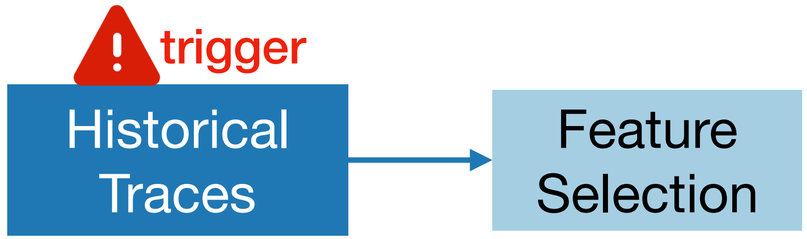

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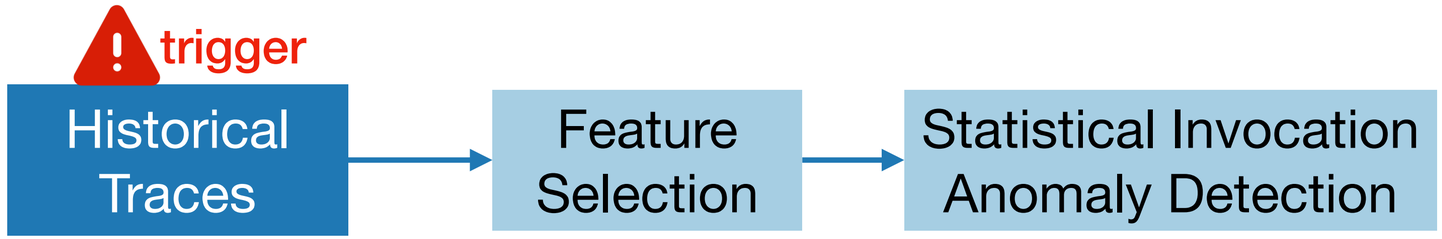

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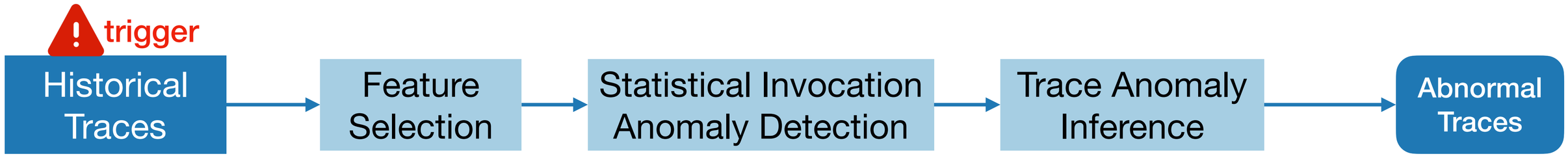

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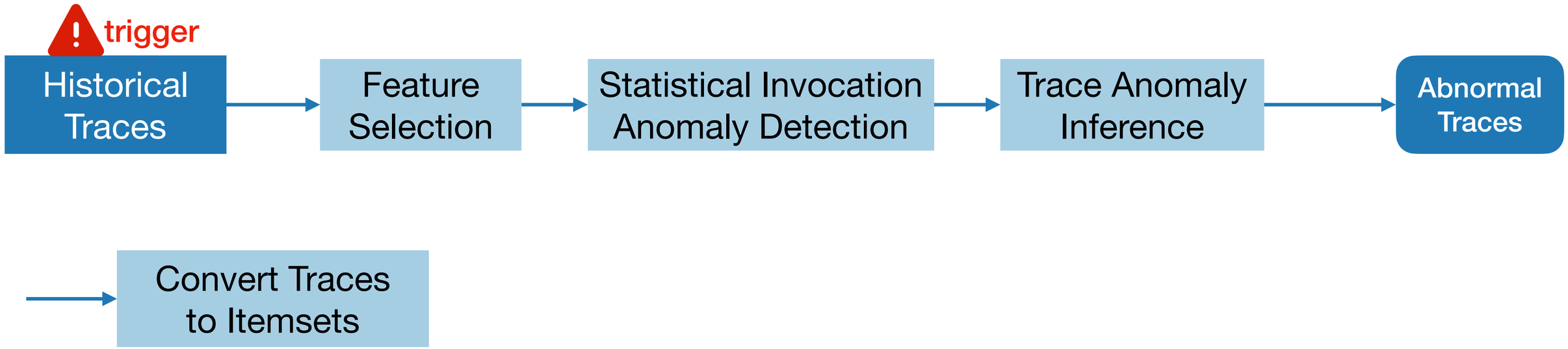

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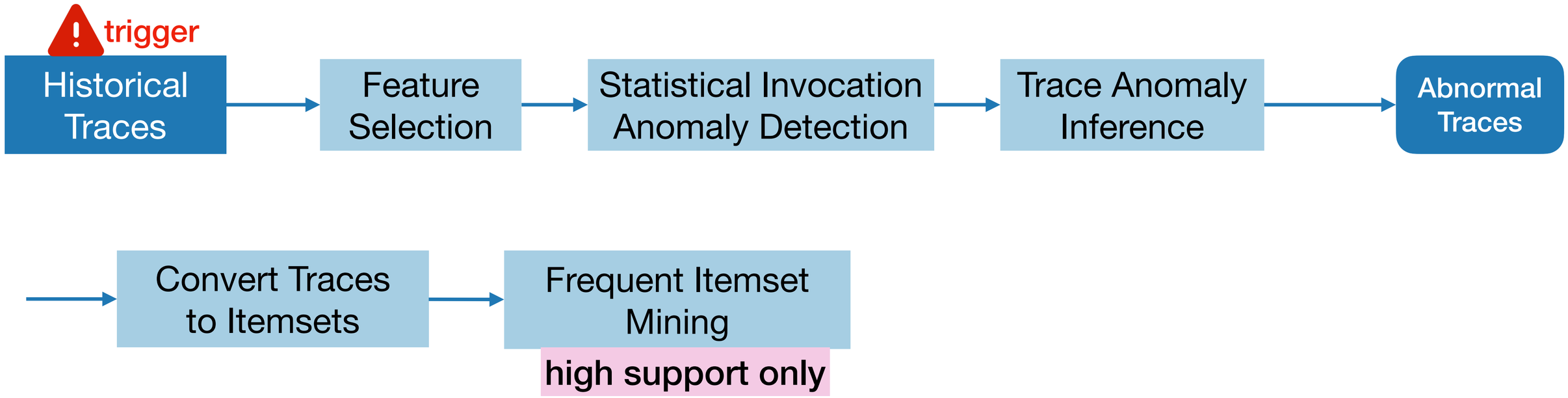

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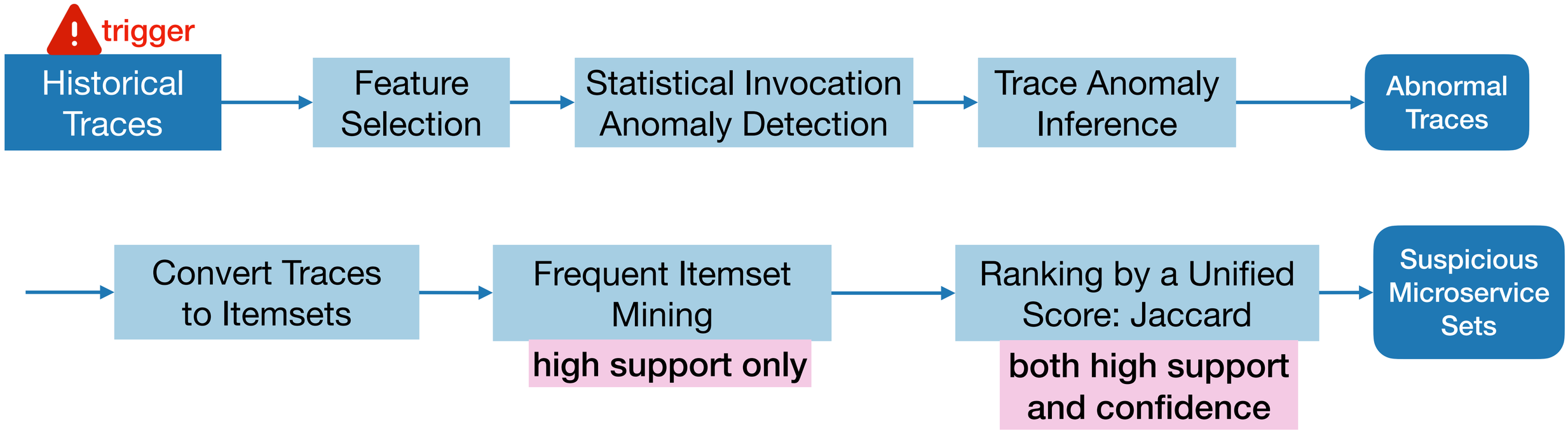

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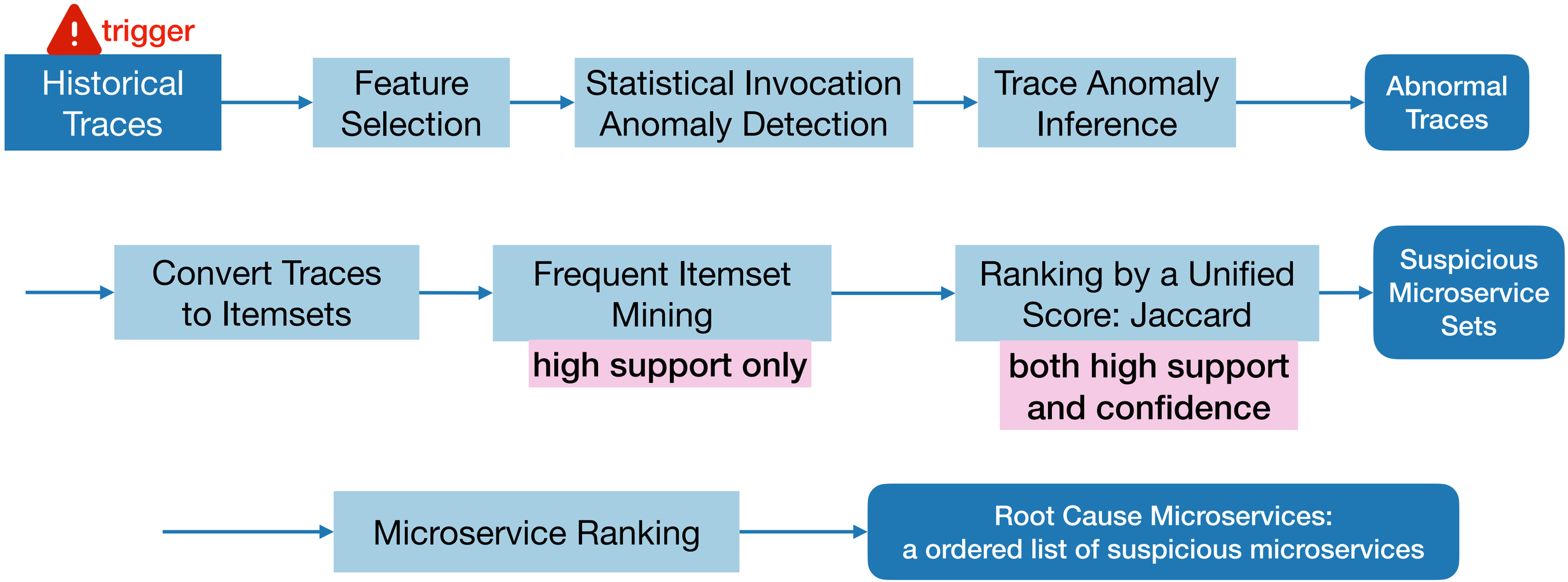

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Datasets

Dataset	Microservice Benchmark	Fault Type	Root-Cause Component Level	# Faults
A	Train-Ticket [TSE'18]	Application Bug	Microservice	58
		CPU exhausted	Microservice	59
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2. Our dataset is now public at https://github.com/netmanaiops/tracerca

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Overall Performance

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TABLE III: Comparison of root cause localization on faults of different levels on $\mathcal{A}$

Subject	Algorithm	A@1	⇑A@1	A@2	⇑A@2	A@3	⇑A@3	MAR	⇑MAR	MFR	⇑MFR
Microservice	TraceRCA	0.83	—	0.93	—	0.97	—	1.39	—	1.34	—
	MicroScope	0.56	**46.67%**	0.62	**49.49%**	0.70	**37.33%**	3.64	**61.77%**	3.47	**61.26%**
	MEPFL (RF)	0.94	-12.00%	0.97	-4.82%	0.97	-0.64%	1.42	**1.98%**	1.38	**2.71%**
	Random Walk	0.51	**61.96%**	0.86	**7.25%**	0.94	**3.00%**	1.97	**29.37%**	1.91	**29.51%**
	RCSF	0.52	**60.00%**	0.86	**7.64%**	0.93	**3.69%**	1.68	**16.98%**	1.60	**16.02%**
	TraceAnomaly	0.49	**70.85%**	0.59	**58.14%**	0.63	**53.11%**	4.42	**68.54%**	4.34	**69.13%**
Container	TraceRCA	0.80	—	0.80	—	0.80	—	3.80	0%	3.80	—
	MicroScope	0.20	**300.00%**	0.40	**100.00%**	0.40	**100.00%**	7.20	**47.22%**	7.20	**47.22%**
	MEPFL (RF)	0.80	0.00%	0.80	0.00%	1.00	-20.00%	1.40	-171.43%	1.40	-171.43%
	Random Walk	0.40	**100.00%**	0.60	**33.33%**	0.60	**33.33%**	8.40	**54.76%**	8.40	**54.76%**
	RCSF	0.40	**100.00%**	0.60	**33.33%**	0.60	**33.33%**	3.60	-5.56%	3.60	-5.56%
	TraceAnomaly	0.20	**300.00%**	0.30	**166.67%**	0.30	**166.67%**	7.10	**46.48%**	7.10	**46.48%**
API	TraceRCA	0.83	—	0.83	—	0.83	—	1.75	—	1.75	—
	MicroScope	0.58	**42.86%**	0.67	**64.29%**	0.92	-9.09%	2.00	**12.50%**	2.00	**12.50%**
	MEPFL (RF)	0.83	0.00%	1.00	-16.67%	1.00	-16.67%	1.17	-50.00%	1.17	-50.00%
	Random Walk	0.58	**42.86%**	0.75	**11.11%**	0.64	**29.63%**	2.33	**25.00%**	2.33	**25.00%**
	RCSF	0.42	**100.00%**	0.58	**42.86%**	0.67	**25.00%**	2.58	**32.26%**	2.58	**32.26%**
	TraceAnomaly	0.21	**287.33%**	0.36	**132.40%**	0.50	**66.00%**	5.86	**70.12%**	5.86	**70.12%**

TABLE IV: Comparison of root cause localization on multi-root-cause faults of $\mathcal{A}$

Subject	Algorithm	A@1	⇑A@1	A@2	⇑A@2	A@3	⇑A@3	MAR	⇑MAR	MFR	⇑MFR
multi-root-cause cases on $\mathcal{A}$	TraceRCA	0.45	—	0.82	—	0.95	—	1.77	—	1.09	—
	MicroScope	0.27	**66.67%**	0.27	**200.00%**	0.41	**133.33%**	5.18	**65.79%**	2.73	**60.00%**
	MEPFL (RF)	0.45	0.00%	0.95	-14.29%	0.95	0.00%	1.64	-8.33%	1.09	0.00%
	Random Walk	0.41	**11.11%**	0.64	**28.57%**	0.82	**16.67%**	2.27	**22.00%**	1.36	**20.00%**
	RCSF	0.23	**100.00%**	0.50	**63.64%**	0.73	**31.25%**	2.82	**37.10%**	1.73	**36.84%**
	TraceAnomaly	0.50	**-10.00%**	0.73	**12.75%**	0.82	**16.11%**	2.50	**29.20%**	1.00	**-9.00%**

Evaluation

Overall Performance

TABLE III: Comparison of root cause localization on faults of different levels on $\mathcal{A}$

Subject	Algorithm	A@1	⇑A@1	A@2	⇑A@2	A@3	⇑A@3	MAR	⇑MAR	MFR	⇑MFR
Microservice	TraceRCA	0.83	—	0.93	—	0.97	—	1.39	—	1.34	—
	MicroScope	0.56	**46.67%**	0.62	**49.49%**	0.70	**37.33%**	3.64	**61.77%**	3.47	**61.26%**
	MEPFL (RF)	0.94	-12.00%	0.97	-4.82%	0.97	-0.64%	1.42	**1.98%**	1.38	**2.71%**
	Random Walk	0.51	**61.96%**	0.86	**7.25%**	0.94	**3.00%**	1.97	**29.37%**	1.91	**29.51%**
	RCSF	0.52	**60.00%**	0.86	**7.64%**	0.93	**3.69%**	1.68	**16.98%**	1.60	**16.02%**
	TraceAnomaly	0.49	**70.85%**	0.59	**58.14%**	0.63	**53.11%**	4.42	**68.54%**	4.34	**69.13%**
Container	TraceRCA	0.80	—	0.80	—	0.80	—	3.80	0%	3.80	—
	MicroScope	0.20	**300.00%**	0.40	**100.00%**	0.40	**100.00%**	7.20	**47.22%**	7.20	**47.22%**
	MEPFL (RF)	0.80	0.00%	0.80	0.00%	1.00	-20.00%	1.40	-171.43%	1.40	-171.43%
	Random Walk	0.40	**100.00%**	0.60	**33.33%**	0.60	**33.33%**	8.40	**54.76%**	8.40	**54.76%**
	RCSF	0.40	**100.00%**	0.60	**33.33%**	0.60	**33.33%**	3.60	-5.56%	3.60	-5.56%
	TraceAnomaly	0.20	**300.00%**	0.30	**166.67%**	0.30	**166.67%**	7.10	**46.48%**	7.10	**46.48%**
API	TraceRCA	0.83	—	0.83	—	0.83	—	1.75	—	1.75	—
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	Random Walk	0.58	**42.86%**	0.75	**11.11%**	0.64	**29.63%**	2.33	**25.00%**	2.33	**25.00%**
	RCSF	0.42	**100.00%**	0.58	**42.86%**	0.67	**25.00%**	2.58	**32.26%**	2.58	**32.26%**
	TraceAnomaly	0.21	**287.33%**	0.36	**132.40%**	0.50	**66.00%**	5.86	**70.12%**	5.86	**70.12%**

TABLE IV: Comparison of root cause localization on multi-root-cause faults of $\mathcal{A}$

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	MEPFL (RF)	0.45	0.00%	0.95	-14.29%	0.95	0.00%	1.64	-8.33%	1.09	0.00%
	Random Walk	0.41	**11.11%**	0.64	**28.57%**	0.82	**16.67%**	2.27	**22.00%**	1.36	**20.00%**
	RCSF	0.23	**100.00%**	0.50	**63.64%**	0.73	**31.25%**	2.82	**37.10%**	1.73	**36.84%**
	TraceAnomaly	0.50	**-10.00%**	0.73	**12.75%**	0.82	**16.11%**	2.50	**29.20%**	1.00	**-9.00%**

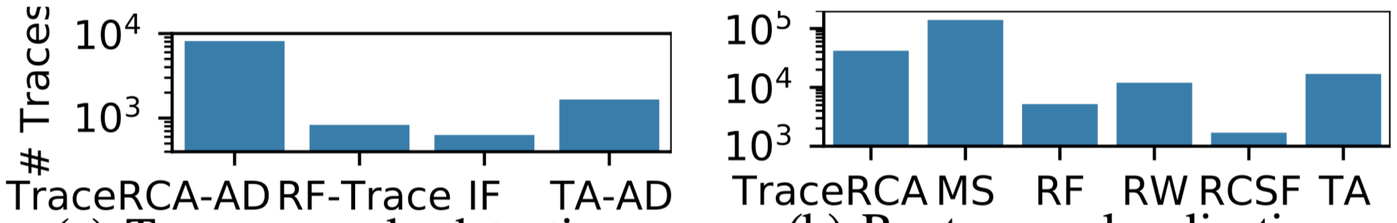
TraceRCA outperforms ***unsupervised*** baselines and perform as well as ***supervised*** approaches under different situations

Evaluation

Scalability

Evaluation

Scalability



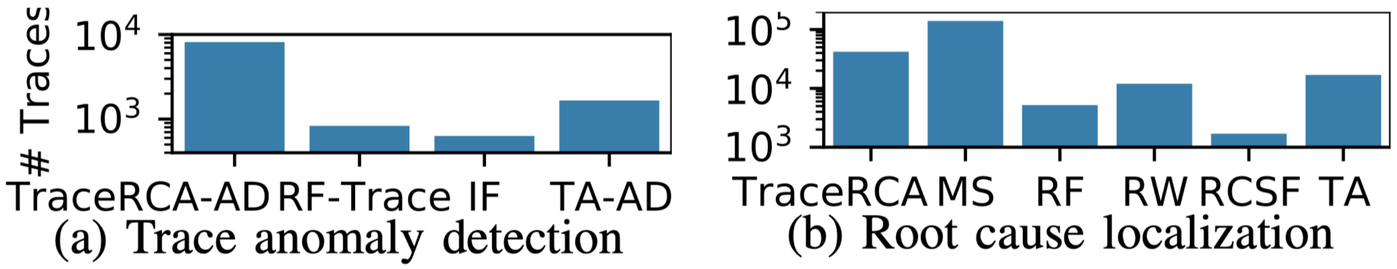
(a) Trace anomaly detection (b) Root cause localization

Fig. 13: Comparison of efficiency

TraceRCA handles 10,000 traces per second per core.

Evaluation

Scalability



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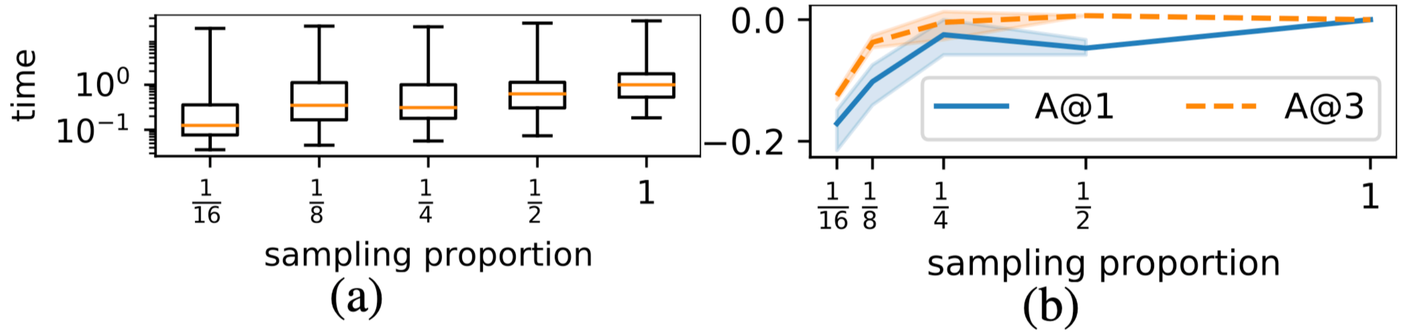
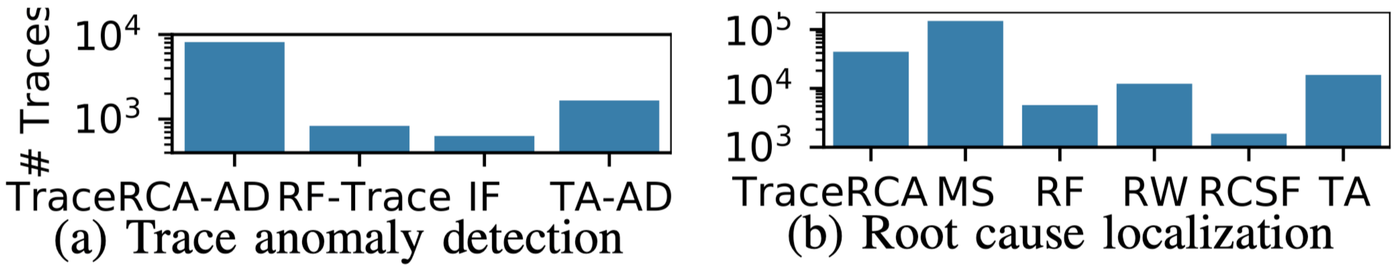


Fig. 14: Efficiency improvement and performance degradation of *TraceRCA* with trace sampling.

Evaluation

Scalability



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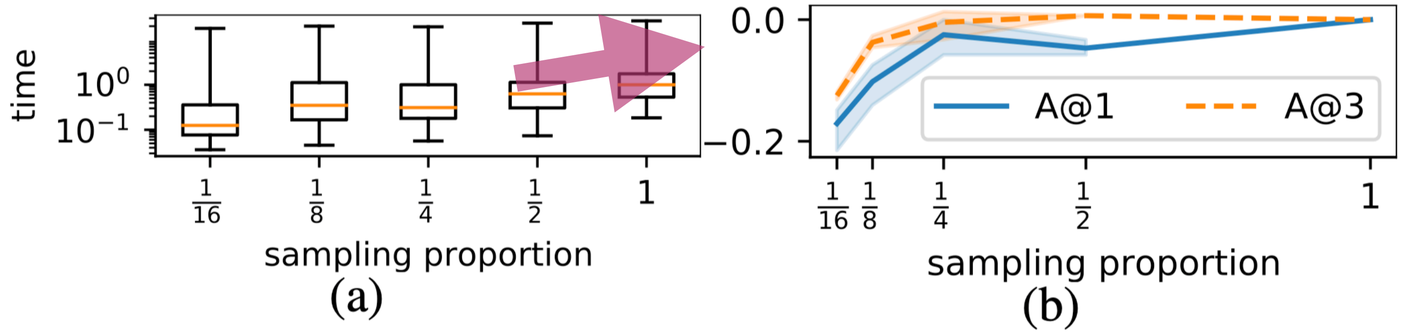

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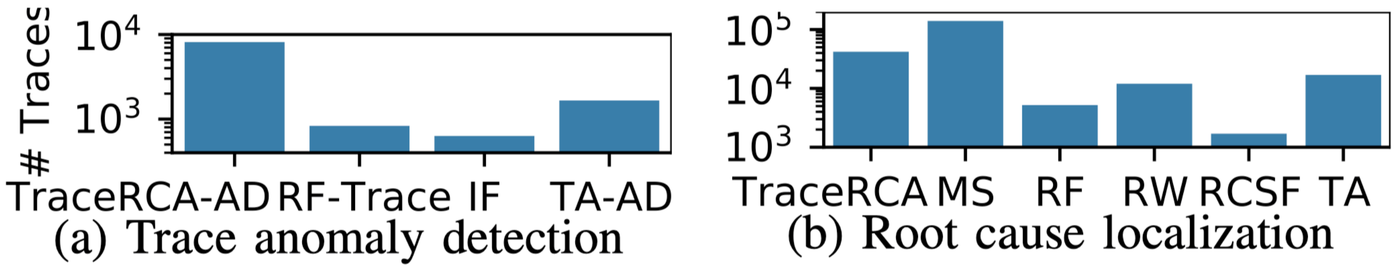
The running time of TraceRCA is linear to #traces.

Evaluation

Scalability



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TraceRCA handles 10,000 traces per second per core.

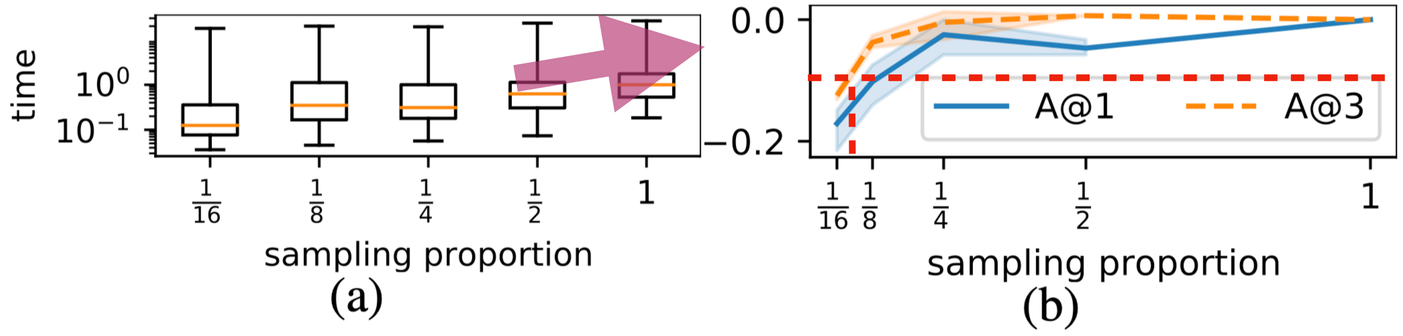

Fig. 14: Efficiency improvement and performance degradation of *TraceRCA* with trace sampling.

The running time of TraceRCA is linear to #traces.

TraceRCA achieves relative good performance with only 1/10 sampled traces.

Summary

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Motivation: Trace-based root-cause service localization; our insight and two key metrics

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Solution: TraceRCA, containing trace anomaly detection, microservice set mining, suspicious microservice ranking

Evaluation: Experiments based on an open-source benchmark and a production system

Thank You!
Q&A