



中山大學
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Nezha: Interpretable Fine-Grained Root Causes Analysis for Microservices on Multi-Modal Observability Data



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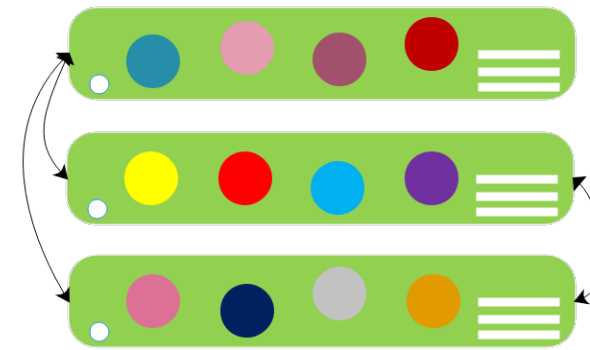
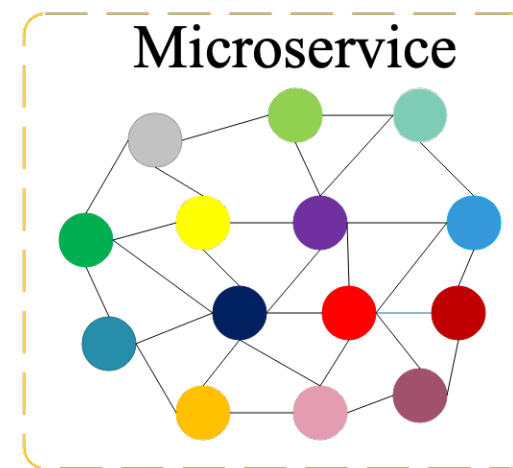
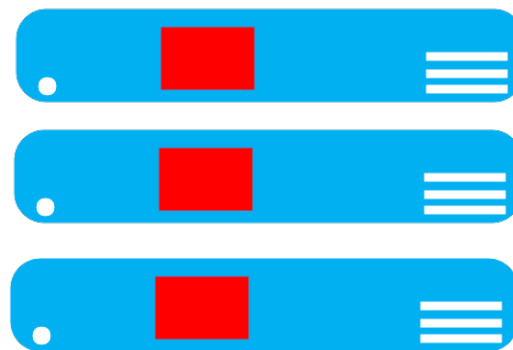
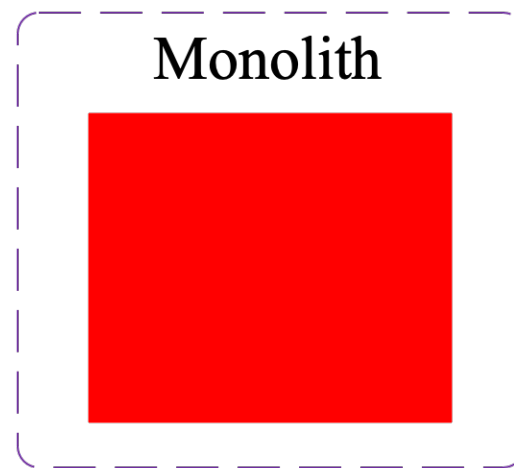
Xiaoyun Li



Zibin Zheng

Sun Yat-sen University, Guangzhou, China

- Microservice application consists of **many single-concerned, loosely-coupled** services
- ◆ Fast development & deployment
 - ◆ On-demand provisioning, elasticity
 - ◆ Language/framework heterogeneity



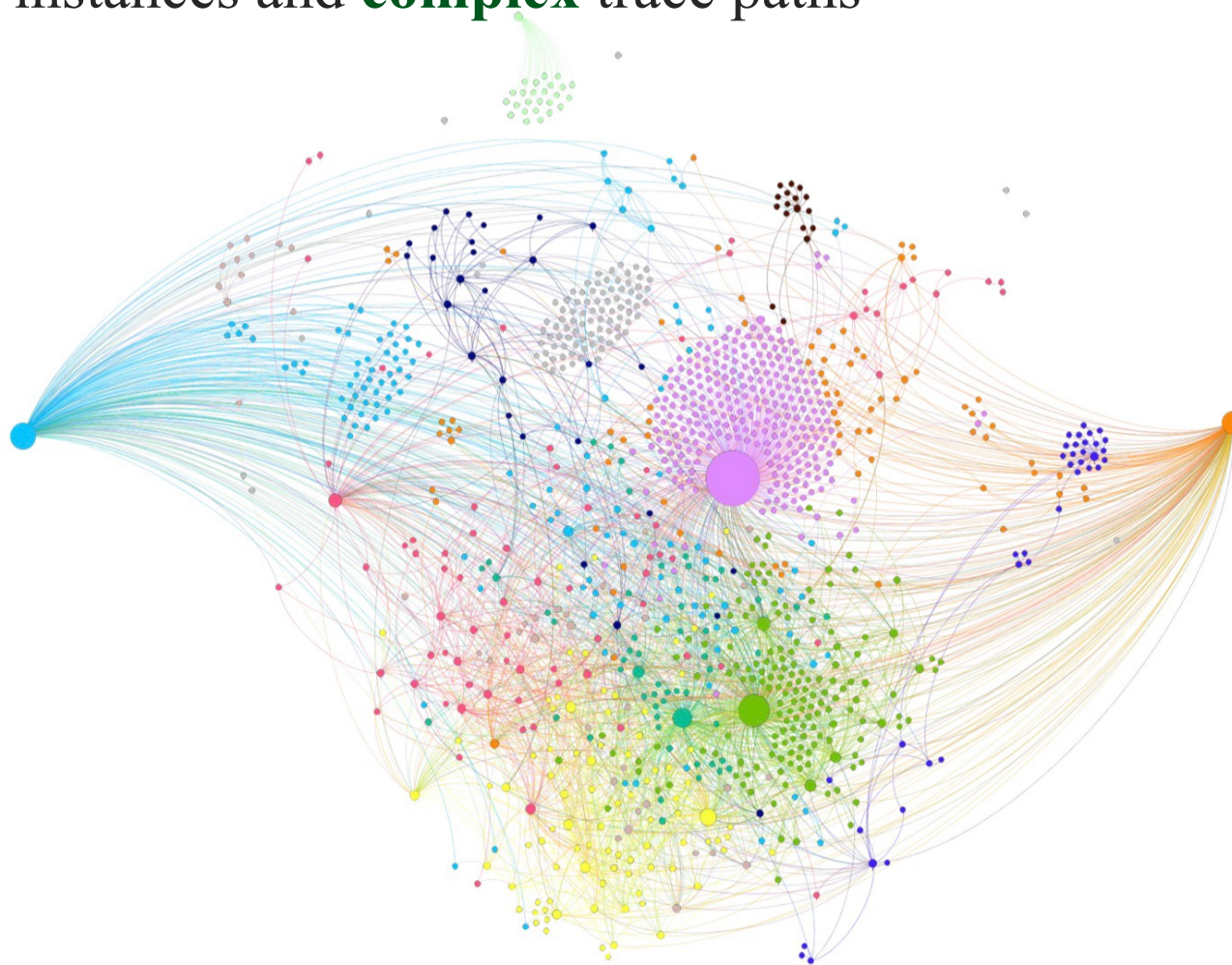
Introduction



- Failure is common in microservice systems



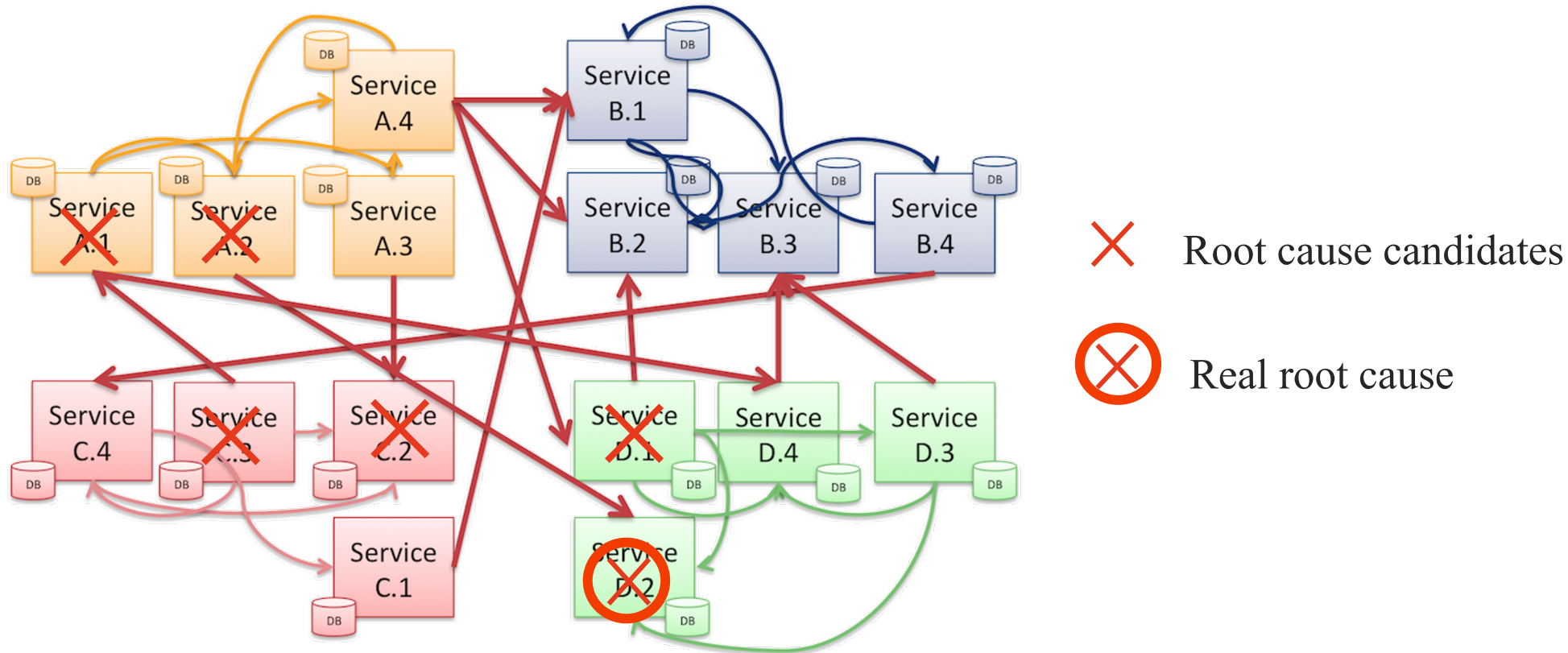
- Troubleshoot root causes in microservice application is time-consuming and error-prone
 - ◆ **Multiple** instances and **complex** trace paths



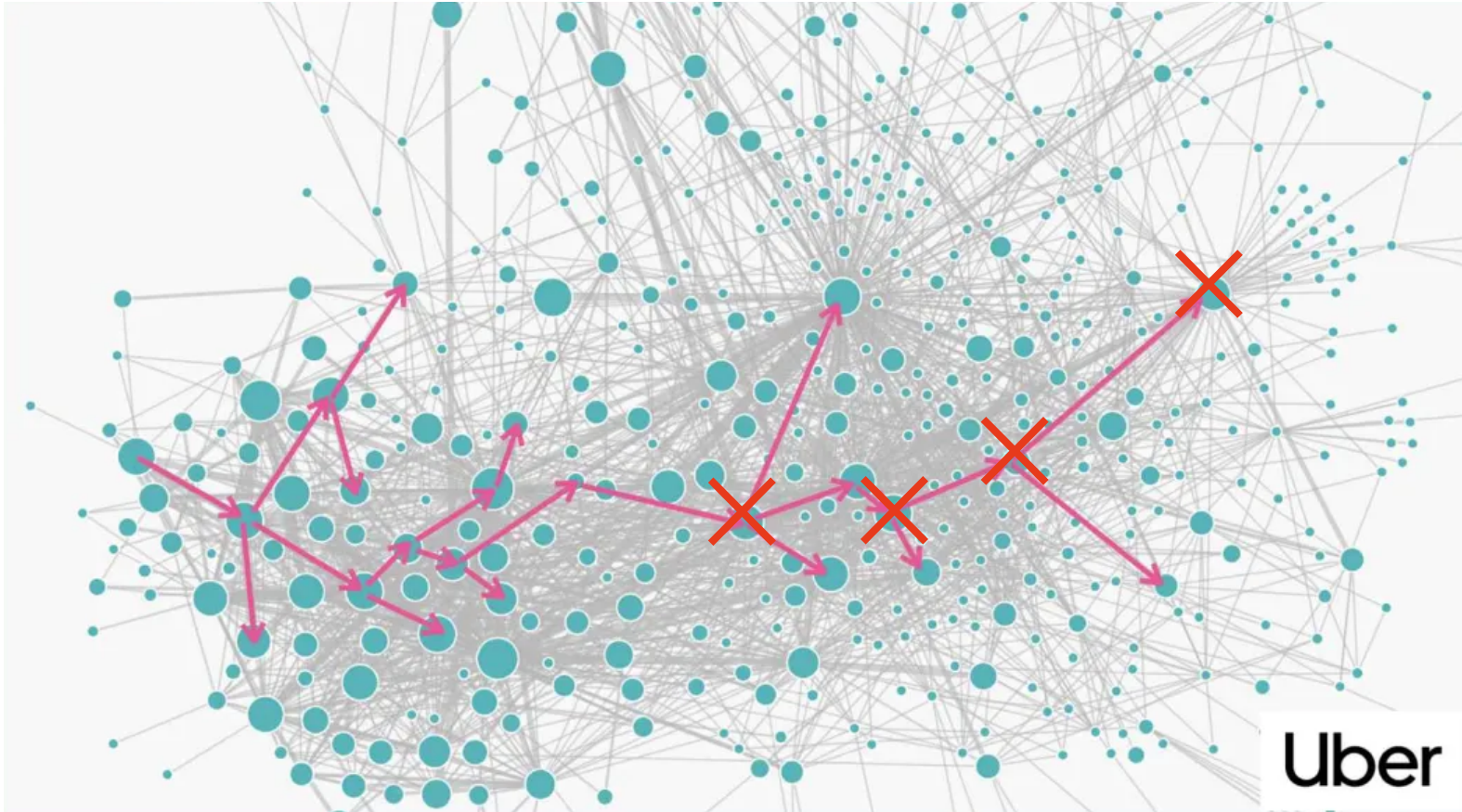
Dependency graph in Uber

➤ Root Cause Analysis in Microservice

- ◆ Multiple instances and complex trace paths
- ◆ Multiple root cause candidates caused by **anomaly propagation**



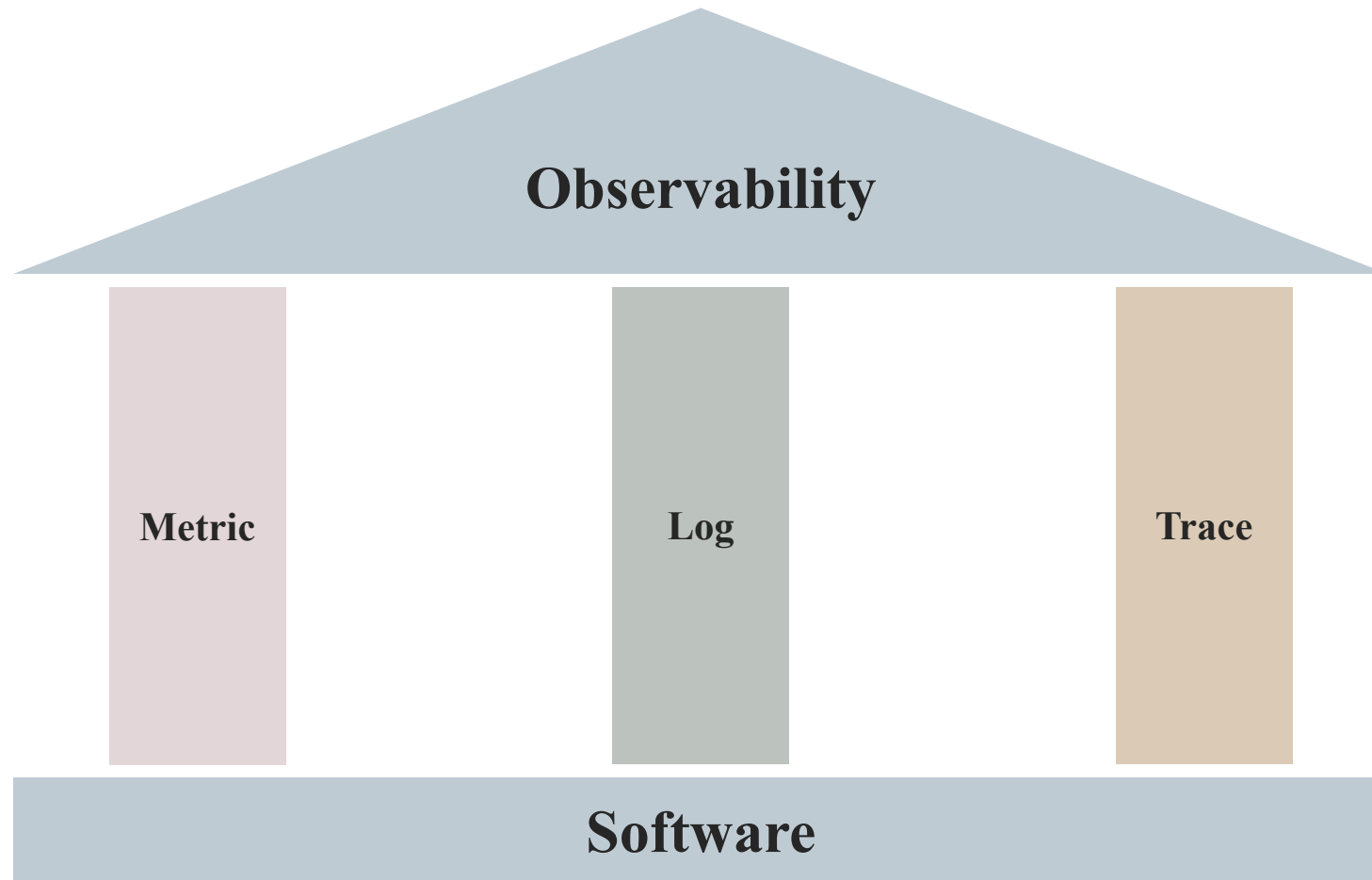
- Observability is crucial to localize root causes of microservice applications



What failed?
How should I fix them?



- 3 pillars of observability: **logs, metrics and traces**

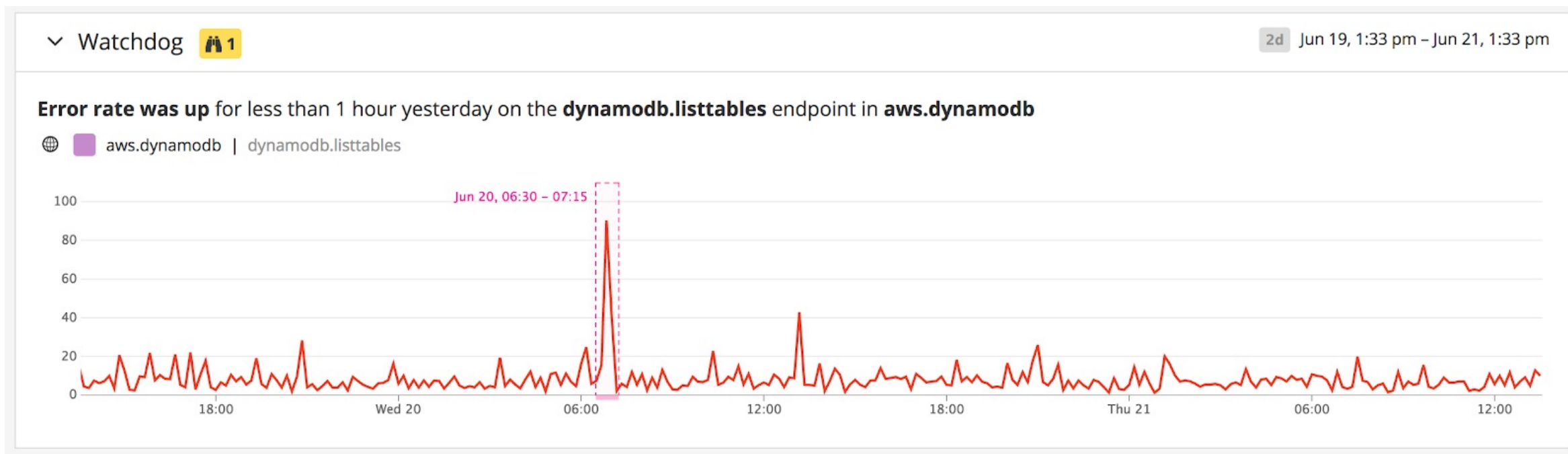


- Metric are **aggregations** over a period of time of **numeric** data about infrastructure or application

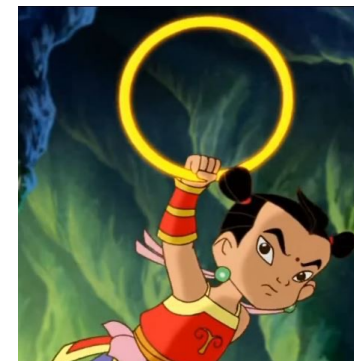
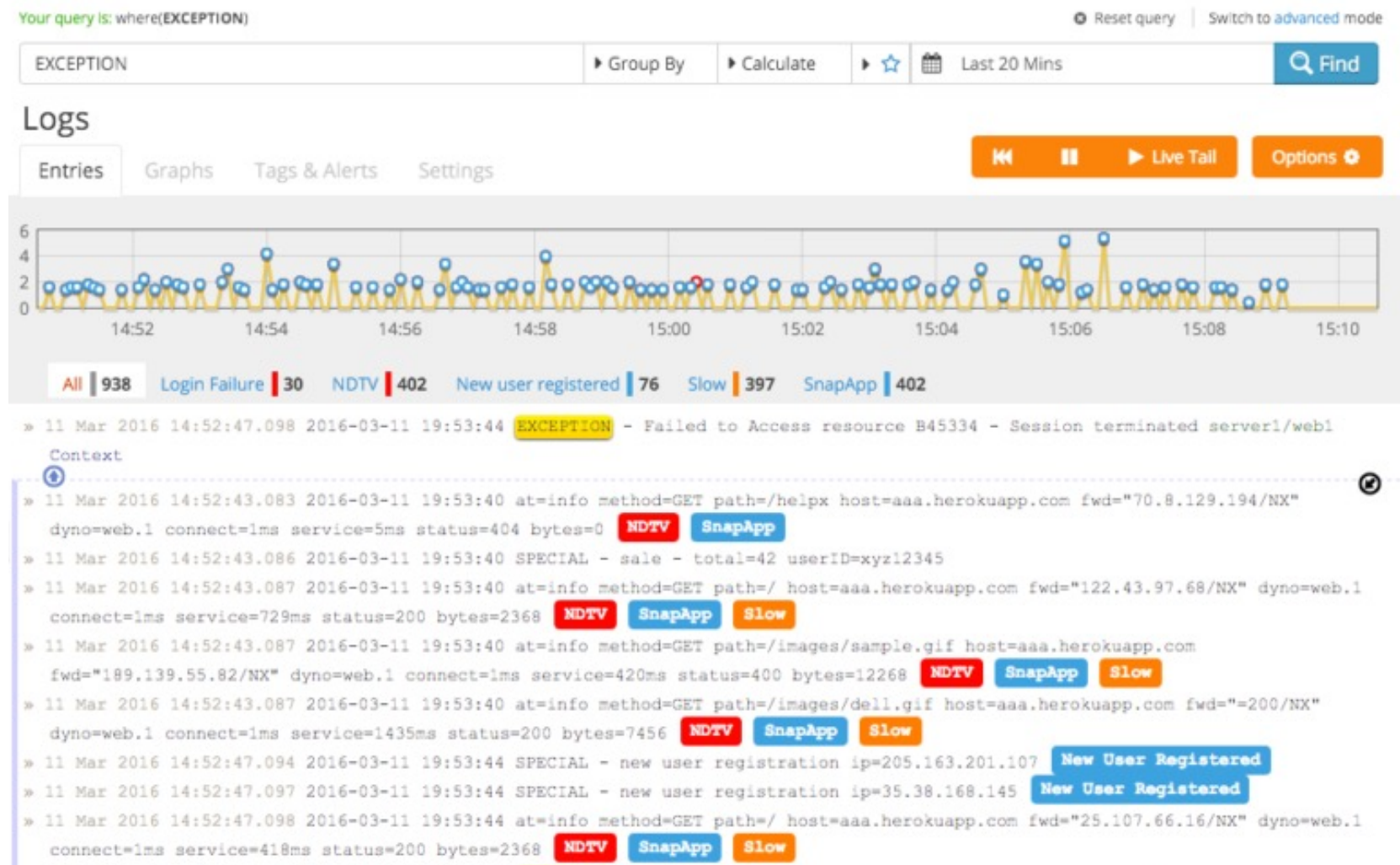


Nezha with
Feng Huo Lun

Metrics : Error Rate of Request



- Logs are **timestamped messages** emitted by services or other components

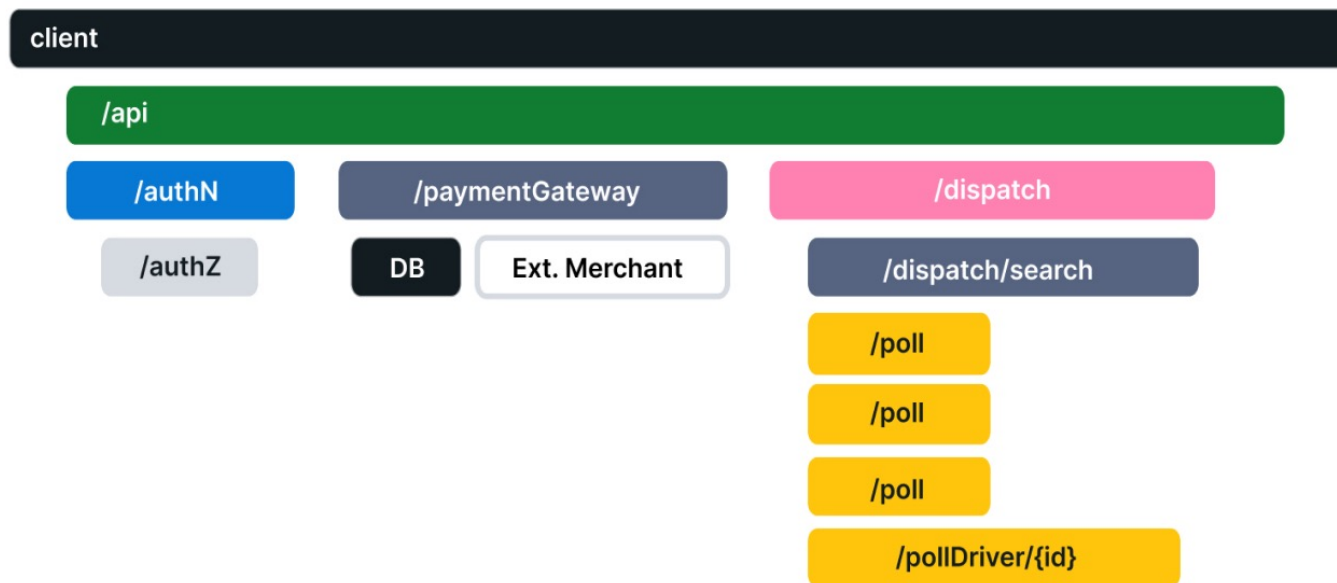


Nezha with
Qian Kun Quan

- Trace records the **paths** taken by requests as they **propagate** through multi-service
 - ◆ A trace is made of one or more spans
 - ◆ A span represents a unit of work or operation

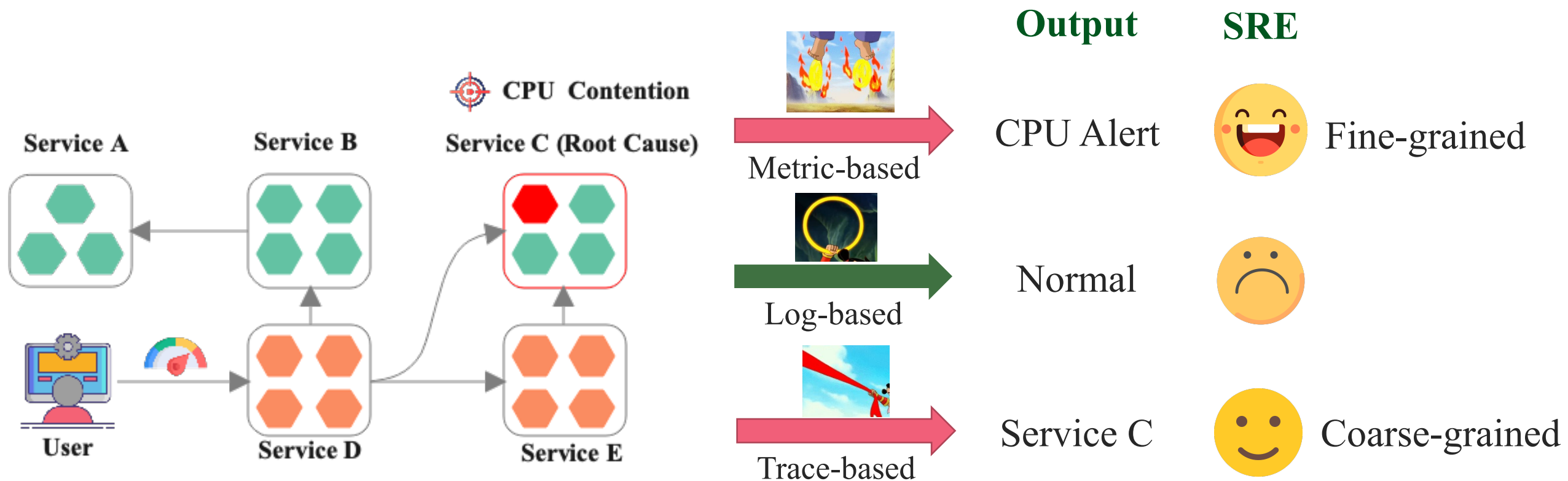


Nezha with
Hun Tian Ling



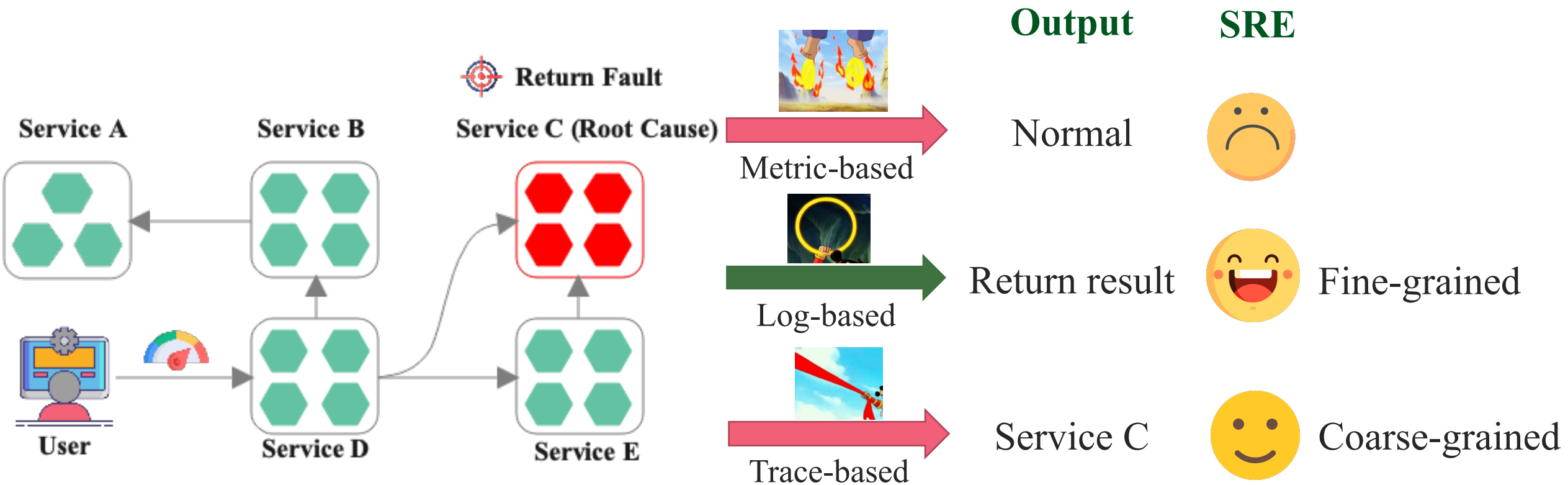
Motivation

- Certain anomalies may not be apparent in some data sources
 - ◆ **CPU contention** is not obvious in **logs**



➤ Certain anomalies may not be apparent in some data sources

◆ **Return fault** is not obvious in **metrics**

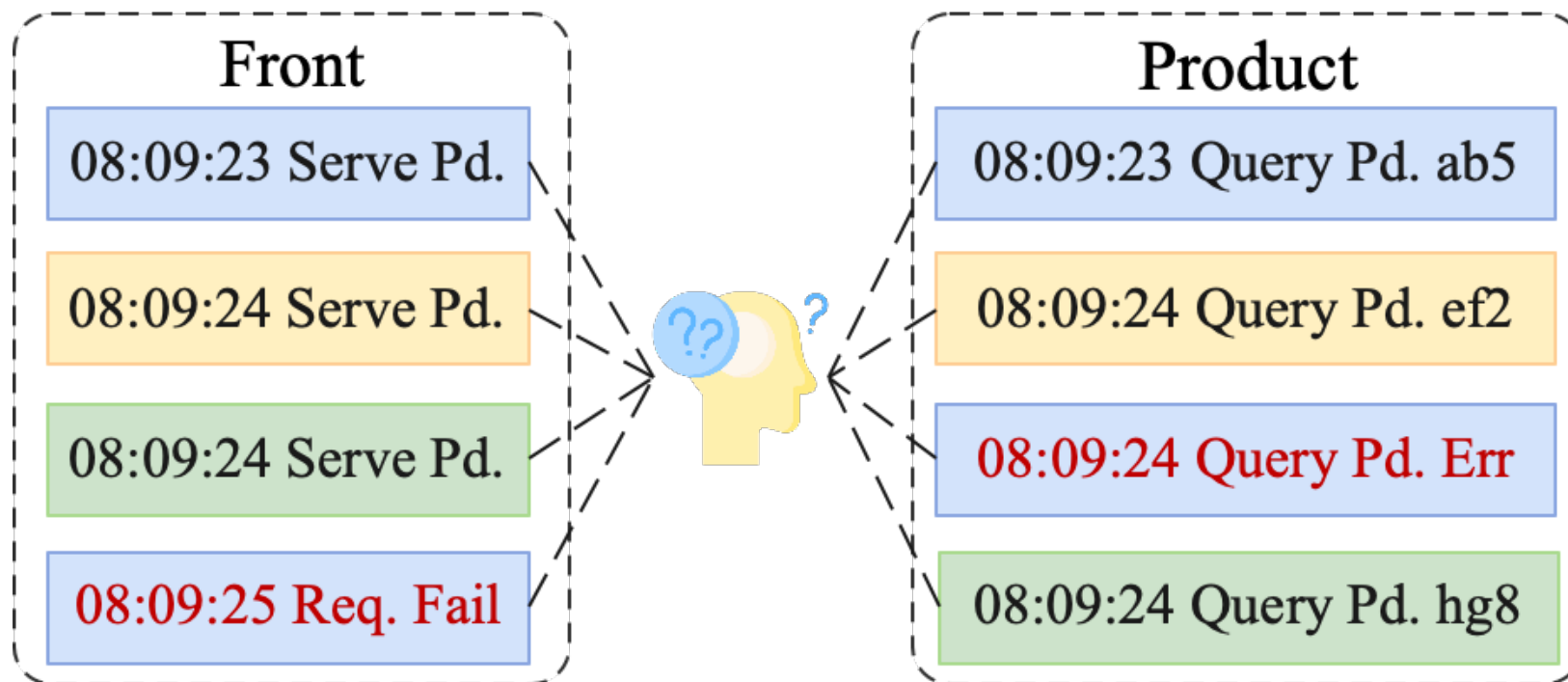


- Certain anomalies may not be apparent in some data sources
 - ◆ CPU Contention is not obvious in logs
 - ◆ Return fault is not obvious in metrics



✓ **Motivation1: Enhancing RCA through the Integration of Metrics, Logs, and Traces**

- Logs generated by a microservice can **interleave**, as it concurrently serves multiple requests

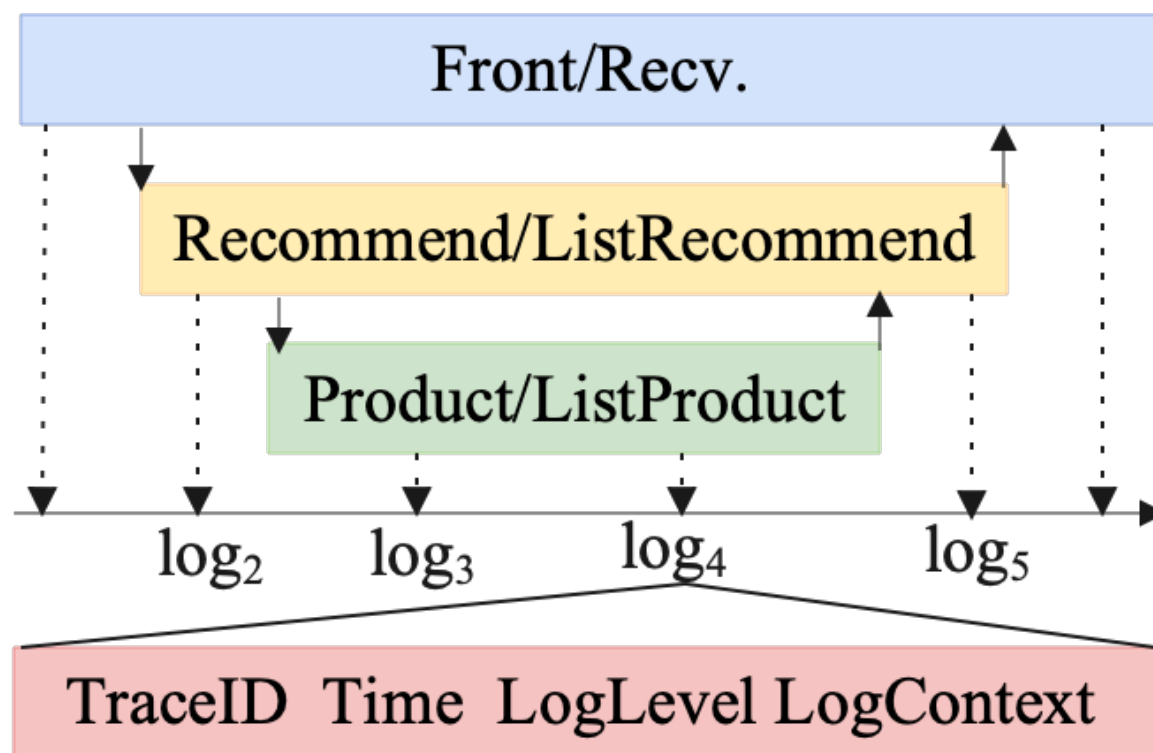


(a) Before integrating logs and traces

Which logs across multiple services are associated with the failed request?

Motivation

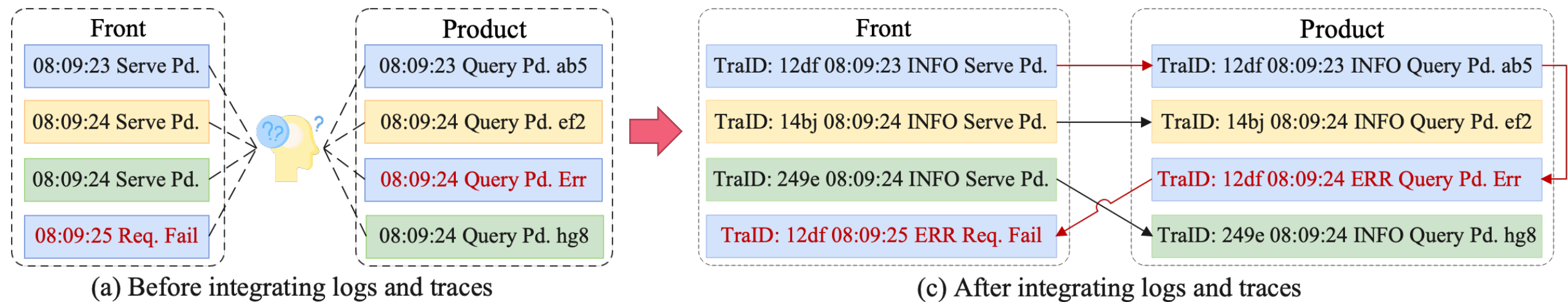
- Logs generated by a microservice can interleave, as it concurrently serves multiple requests
- **Inserting trace IDs** to logs to track the request-level information



(b) Integrating logs and traces

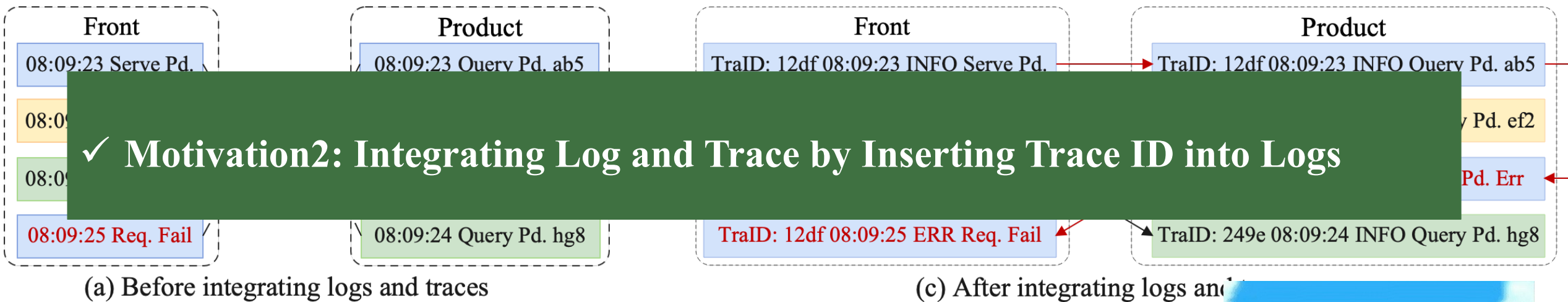
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- Logs generated by a microservice can interleave, as it concurrently serves multiple requests
- **Inserting trace IDs** to track the request-level descriptive information (e.g., logs)



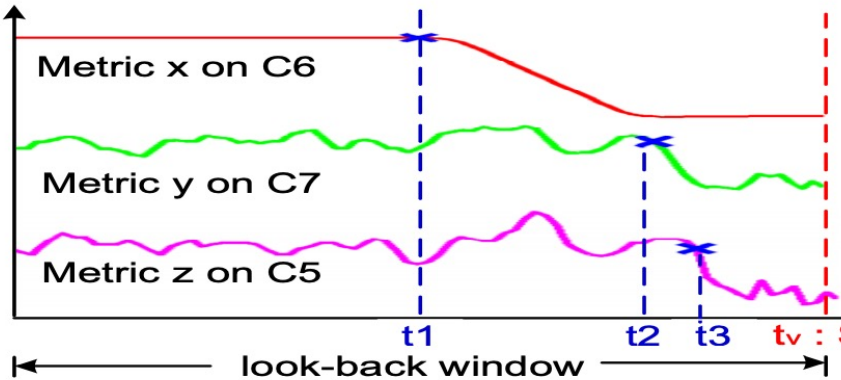
- Logs generated by a microservice can interleave, as it concurrently serves multiple requests
- Inserting trace IDs to track the request-level descriptive information (e.g., logs)

✓ Motivation2: Integrating Log and Trace by Inserting Trace ID into Logs



➤ Metrics, Log, Trace are **heterogeneous observability data**

Metrics



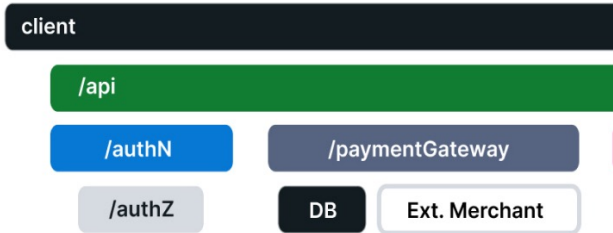
Numerical values

Log

```
09:59:38 INFO Receiving block from ip
09:59:38 INFO Allocate block
09:59:39 INFO Receiving block from ip
09:59:39 INFO Receiving block from ip
...
10:00:02 INFO AddStoredBlock
```

Text

Trace



Semi-structured text

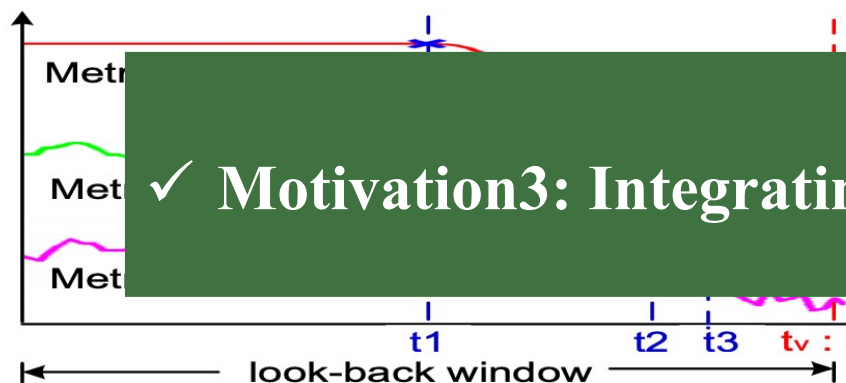
Motivation

- Metrics, Log, Trace are heterogeneous observability data

Metrics

Log

Trace



✓ Motivation3: Integrating Multi-modal Data in a Unified Representation

10:00:02 INFO AddStoredBlock

Numerical values

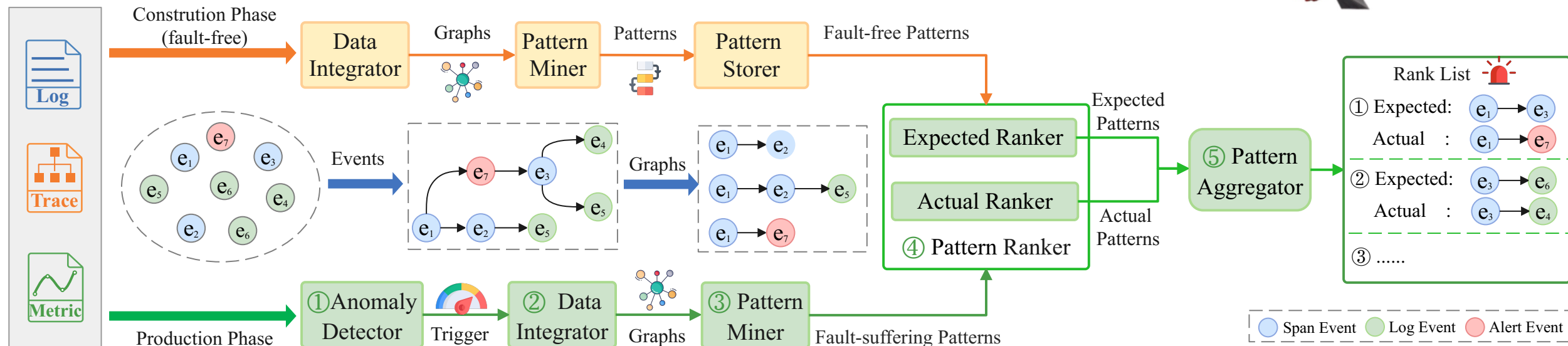
Textual records

Semi-structured text

➤ Nezha: an **unsupervised fine-grained** RCA approach by incorporative analysis of multi-modal data **in an interpretable manner**

① Trigger by existing anomaly detection approaches

Fault-free Construction Phase

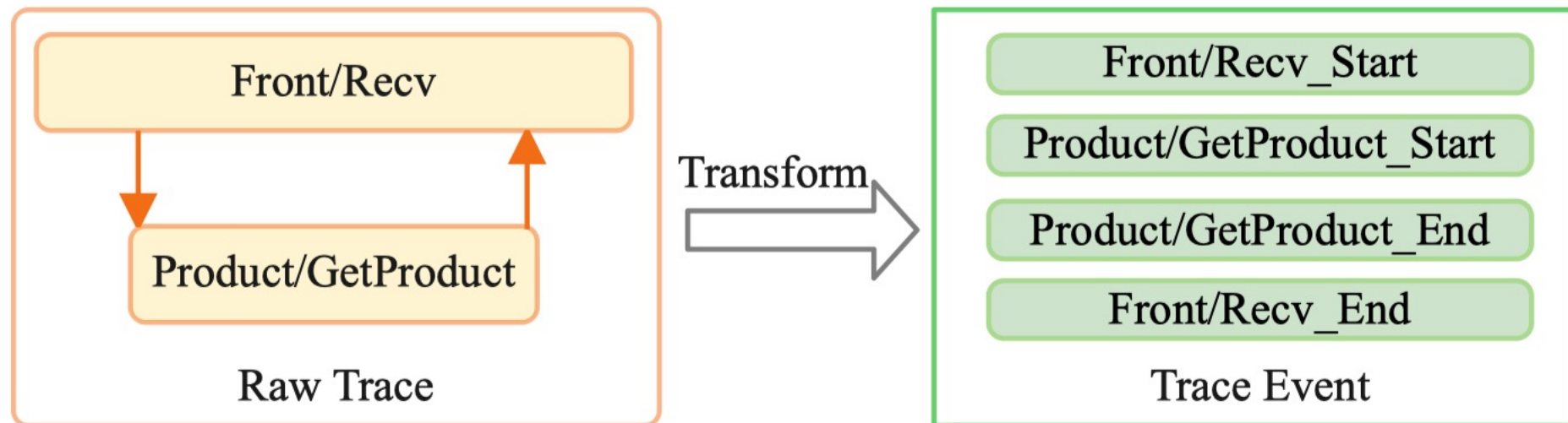


Fault-suffering Production Phase

➤ Nezha: an unsupervised fine-grained RCA approach with multi-modal data

② Integrate multi-modal data into **event graph**

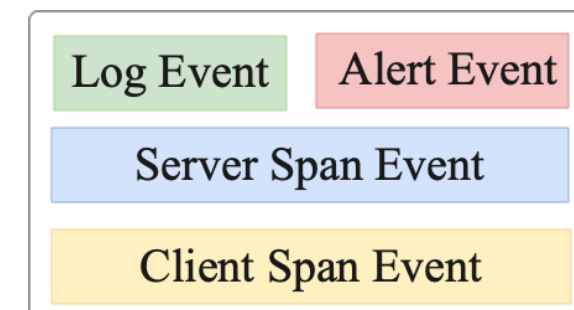
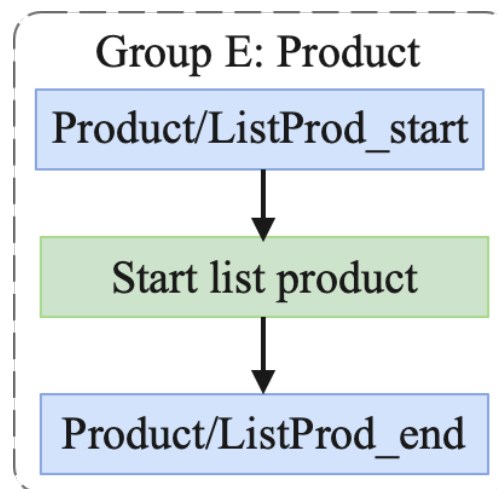
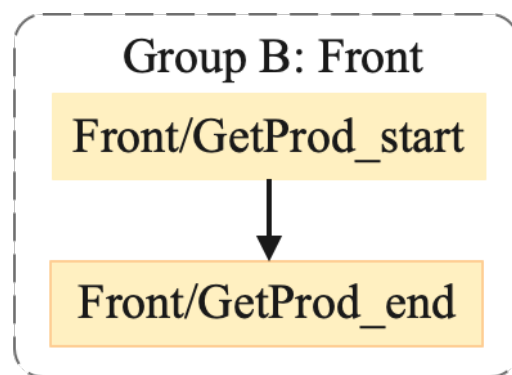
- I. Transform metrics as **metric alert events** by anomaly detection
- II. Transform logs as **log events** by log parsing
- III. Transform traces as **traces events**



➤ Nezha: an unsupervised fine-grained RCA approach with multi-modal data

② Integrate multi-modal data into event graph based on timestamps and trace ID

IV. Order events in the **same span** based on **timestamps**

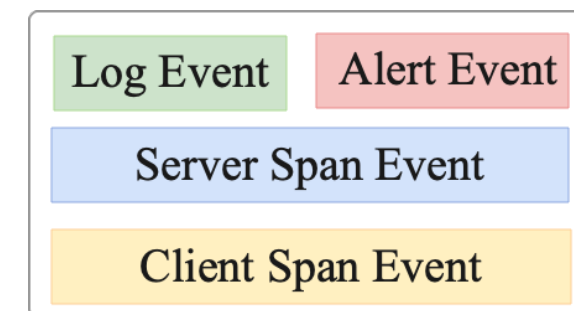
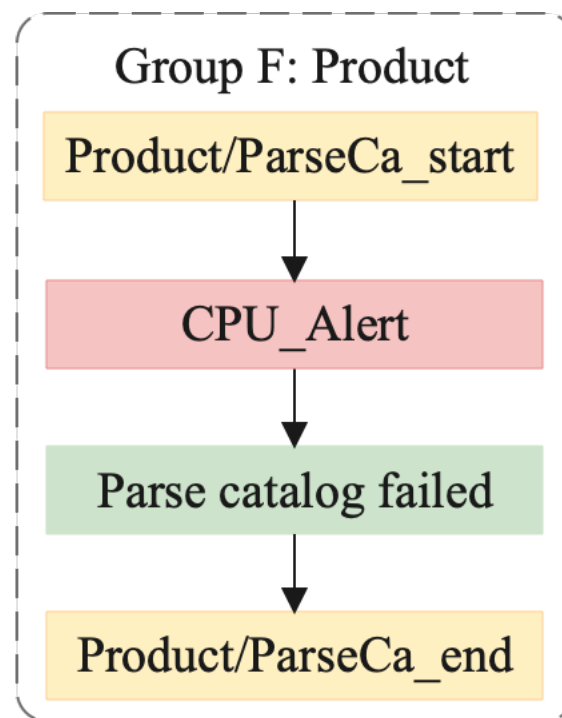
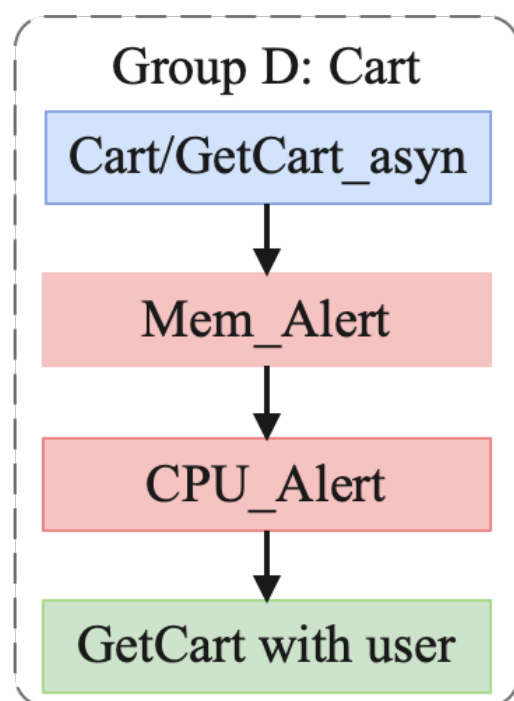


➤ Nezha: an unsupervised fine-grained RCA approach with multi-modal data

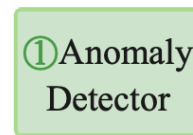
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IV. Order events in the same span based on timestamps

V. **Insert metric events** to event groups



Nezha Approach



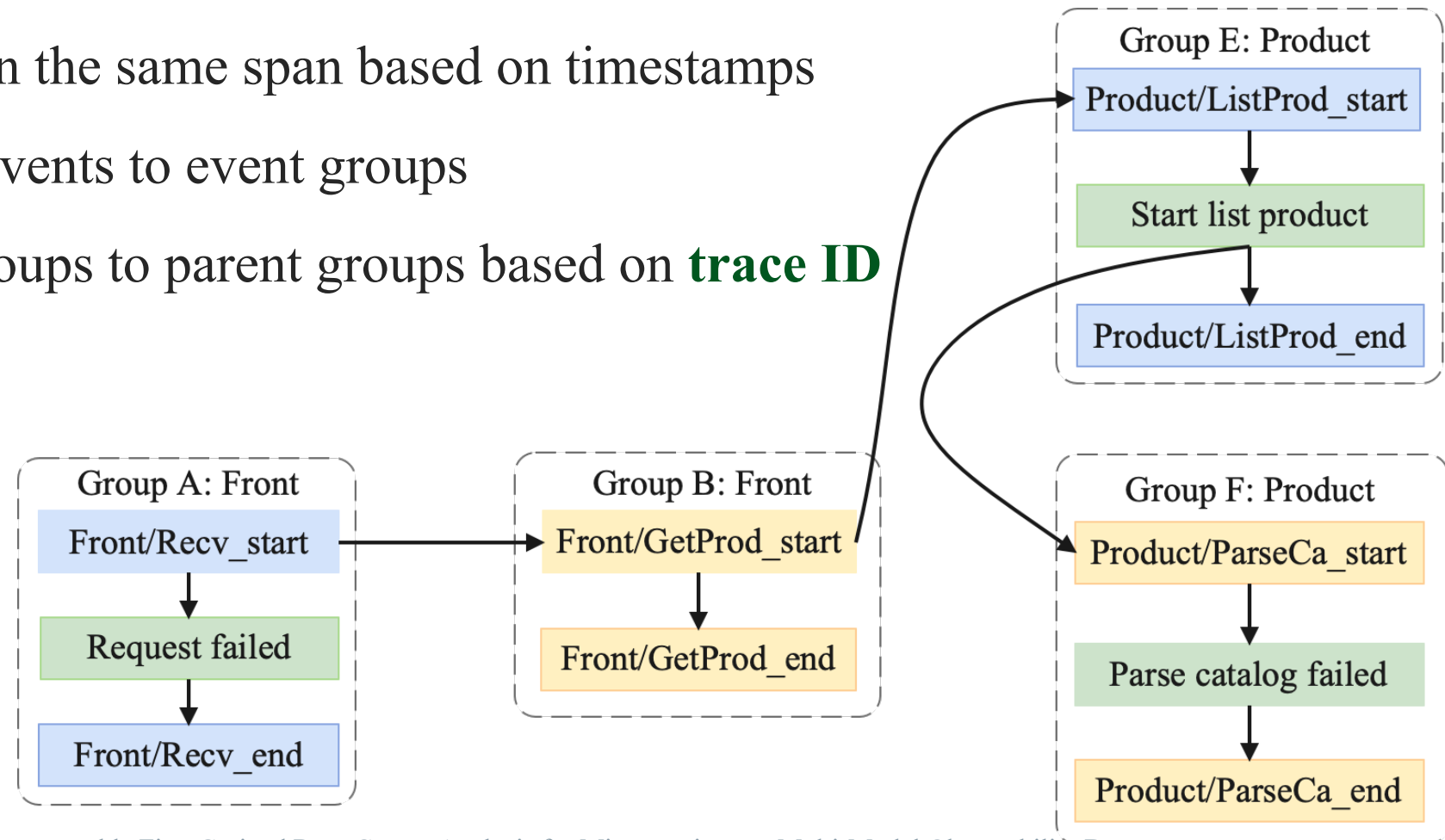
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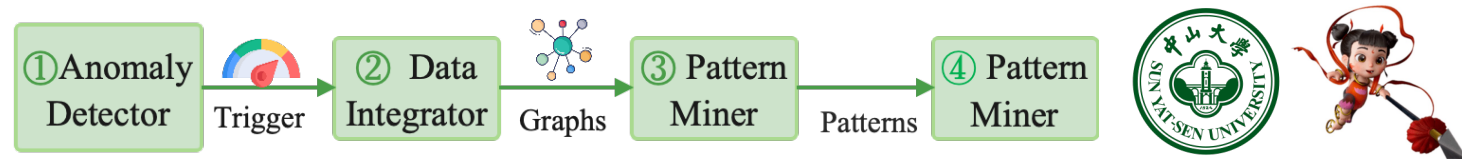
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IV. Order events in the same span based on timestamps

V. Insert metric events to event groups

VI. Insert child groups to parent groups based on **trace ID**

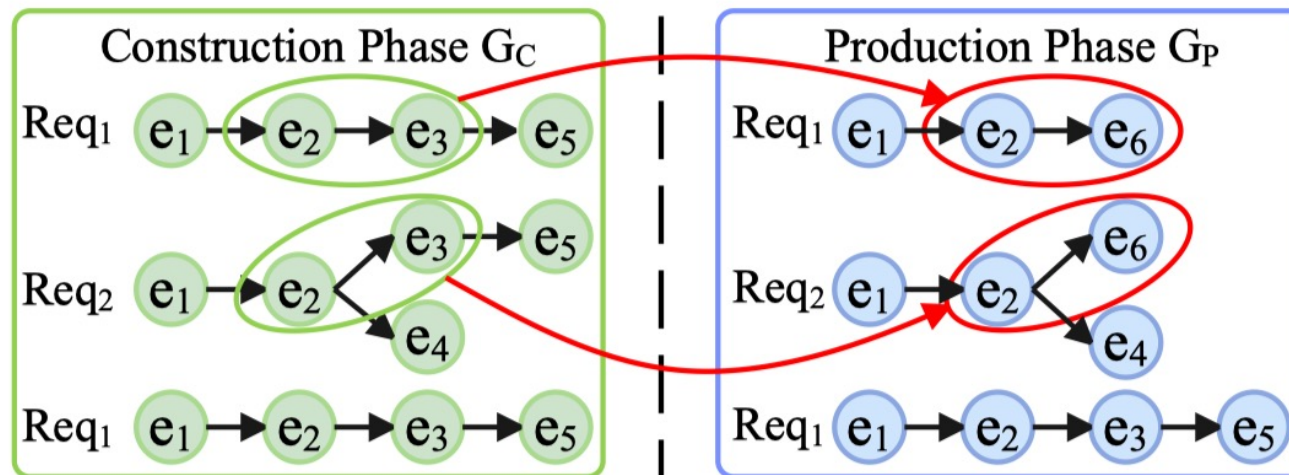




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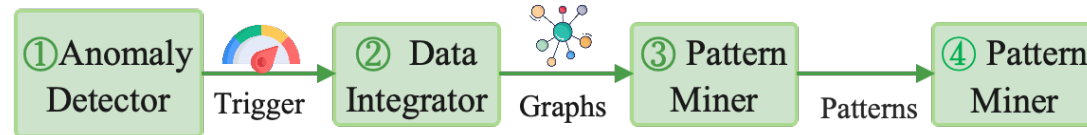
③ Mine frequent patterns from event graphs

I. Count the **occurrences** of each pattern to calculate the support of each pattern



Pattern	Support	
	S_C	S_P
$e_1 \rightarrow e_2$	3	3
$e_2 \rightarrow e_3$	3	1
$e_2 \rightarrow e_4$	1	1
$e_3 \rightarrow e_5$	3	1
$e_2 \rightarrow e_6$	0	2

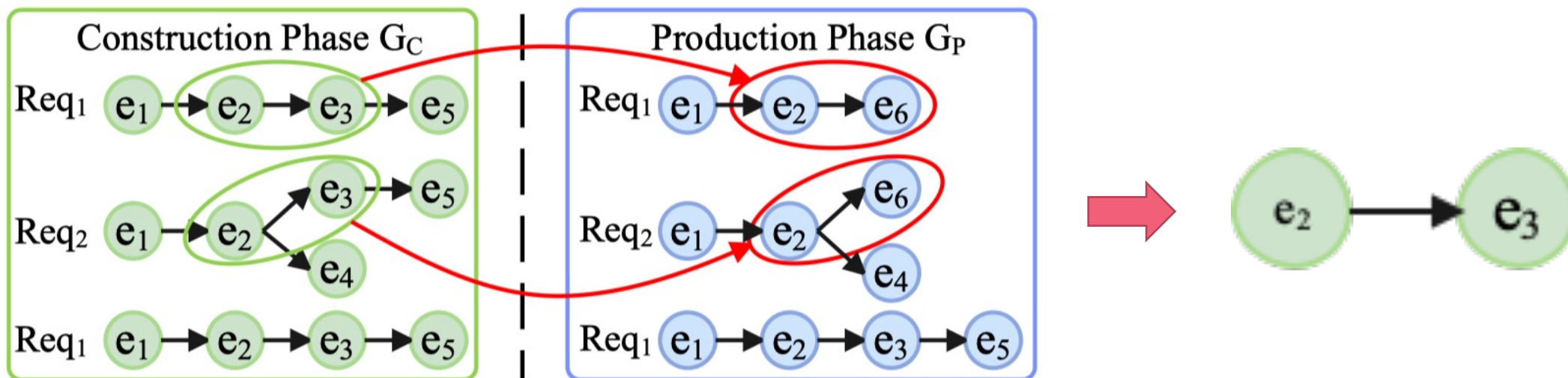
Nezha Approach



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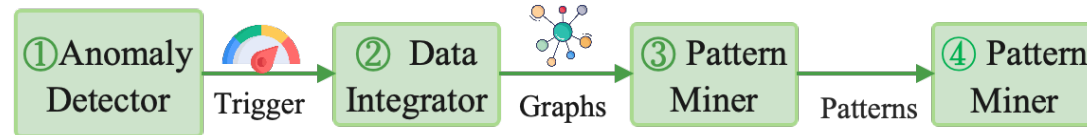
④ Rank suspicious patterns by comparing patterns between fault-free and fault-suffering

I. Expected Pattern: identify which patterns **do not follow expected execution** paths



✓ **Core Idea:** Rank event patterns that occur multiple times in the fault-free phase but rarely in the fault-suffering phase above other event patterns

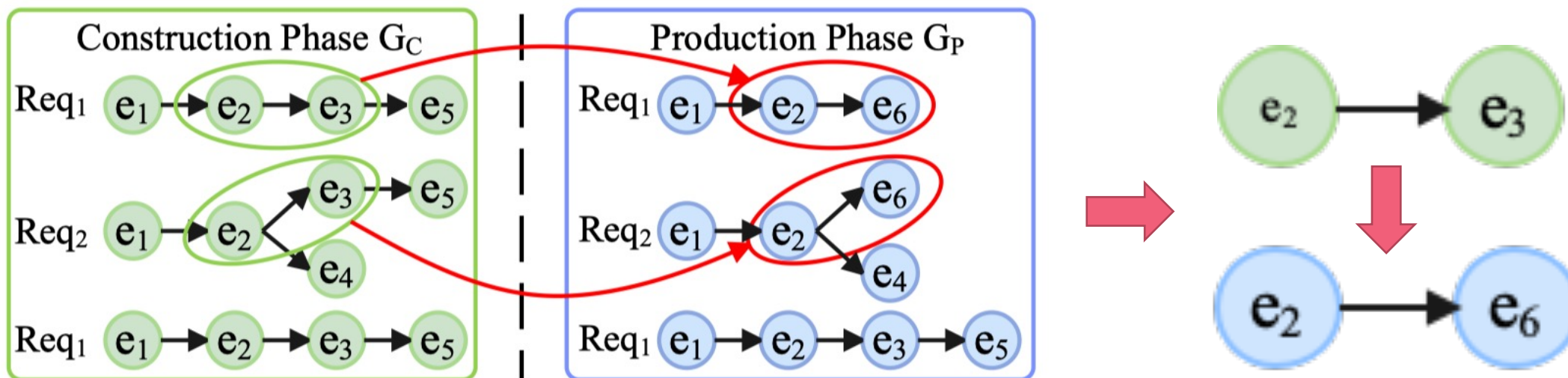
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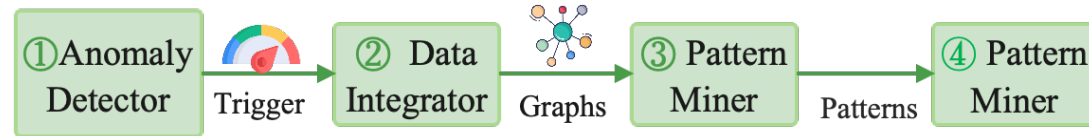
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④ Rank suspicious patterns by comparing patterns between fault-free and fault-suffering

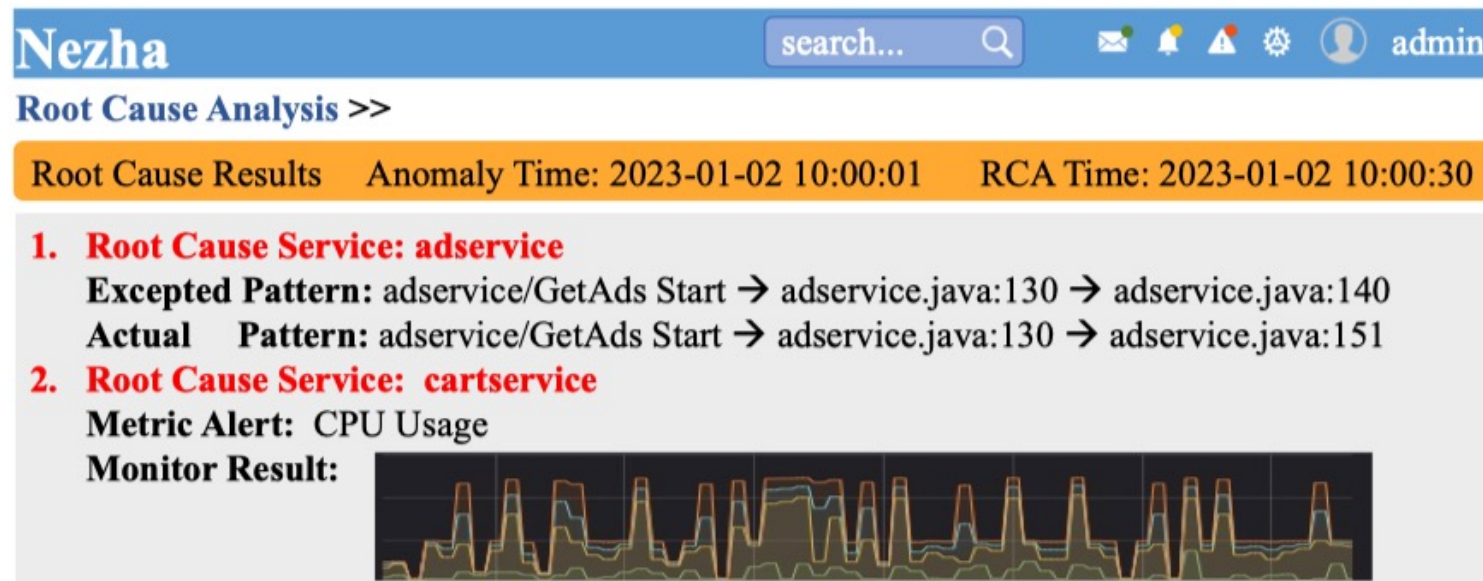
II. Actual Pattern: **how expected patterns change** in the actual fault-suffering phase



✓ **Core Idea:** Rank event patterns that occur multiple times in the fault-suffering phase but rarely in the fault-free phase above other event patterns.



- Nezha: an unsupervised fine-grained RCA approach with multi-modal data
 - ④ Rank suspicious patterns by comparing patterns between fault-free and fault-suffering
 - I. Expected Pattern: identify which patterns do not follow expected execution paths
 - II. Actual Pattern: how expected patterns change in the actual fault-suffering phase
 - III. Correlate expected patterns with actual patterns to provide the complete fault scene



➤ Benchmark

- ◆ OnlineBoutique¹
- ◆ TrainTicket²

```
log.error('Req Failed')
```

[Source Code](#)



```
trace_id = '{trace:032x}'.format(trace=ctx.trace_id)
span_id = '{span:016x}'.format(span=ctx.span_id)
log.error('Trace_id=%s Span_id=%s Req Failed', trace_id, span_id)
```

[Modified Code](#)

Insert trace ID into logs

➤ Fault

- ◆ CPU contention
- ◆ Network jam
- ◆ Error return
- ◆ Exception code

	OnlineBoutique	TrainTicket
CPU Contention	20	10
Network jam	22	10
Error return	8	13
Exception code	6	12
Total	56	45

1. <https://github.com/IntelligentDDS/Augmented-OnlineBoutique>

2. <https://github.com/IntelligentDDS/Augmented-TrainTicket>

➤ Root cause results at service level

Table 3: Comparison of baselines at service level.

Approach	OnlineBoutique			TrainTicket		
	AS@1	AS@3	AS@5	AS@1	AS@3	AS@5
MicroScope	12.5	41.07	55.35	17.78	26.67	35.56
MicroRCA	16.07	62.5	92.75	20.00	31.11	44.44
SBLD	19.64	23.21	25.00	15.56	22.22	24.44
LogFaultFlagger	19.64	21.42	23.21	17.78	24.44	24.44
MicroRank	41.07	48.21	62.5	15.56	24.44	35.56
TraceAnomaly	30.35	33.92	48.21	13.33	28.89	33.33
PDiagnose	41.07	73.21	82.14	8.89	13.33	22.22
Nezha w/o $\mathcal{ML}$	14.28	17.85	17.85	6.67	8.89	11.11
Nezha w/o $\mathcal{M}$	26.78	33.92	35.71	55.56	62.22	68.89
Nezha w/o $\mathcal{L}$	64.28	64.28	64.28	42.22	44.44	44.44
Nezha	92.86	96.43	96.43	86.67	97.78	97.78

- ✓ Nezha achieves high accuracy in $AS@1$ (90%), $AS@3$ (97%)
- ✓ Nezha outperforms all the baseline approaches
- ✓ Each data source contributes to the effectiveness of Nezha

- Root cause result at inner-service level
 - ◆ Resource Type or Code Block

Table 4: Comparison of baselines at inner-service level

Approach	OnlineBoutique			TrainTicket		
	AIS@1	AIS@3	AIS@5	AIS@1	AIS@3	AIS@5
SBLD	14.28	17.85	17.85	15.56	22.22	24.44
LogFaultFlagger	19.64	21.42	21.42	15.56	24.44	24.44
PDiagnose	35.71	53.57	71.42	8.89	13.33	15.56
Nezha w/o $\mathcal{M}$	26.78	33.92	35.71	55.56	62.22	68.89
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Nezha	92.86	96.43	96.43	86.67	97.78	97.78

- ✓ Nezha achieves high accuracy in AIS@1 (87%), AS@3 (97%)
- ✓ Nezha outperforms all the baseline approaches
- ✓ Each data source contributes to the effectiveness of Nezha

➤ Efficiency of Nezha

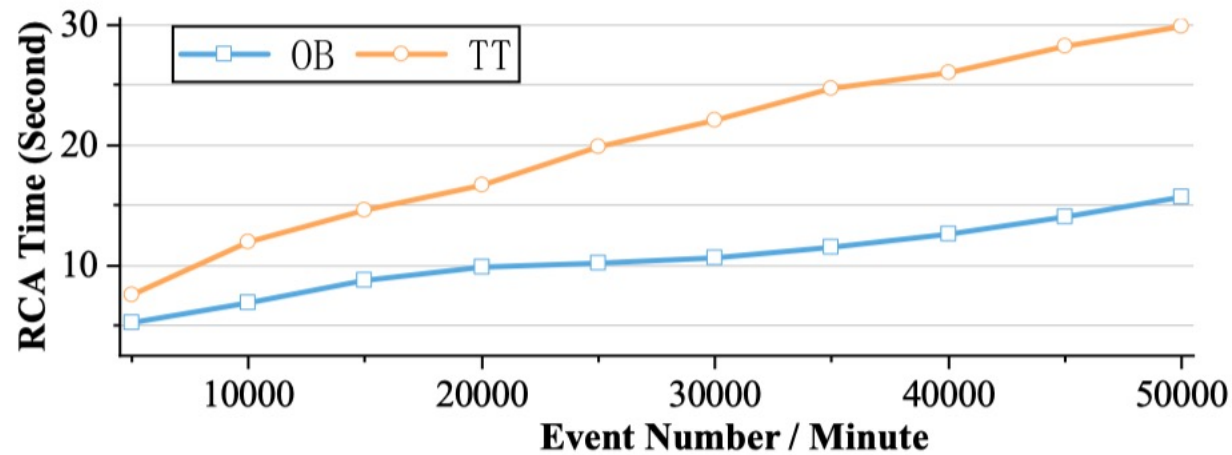
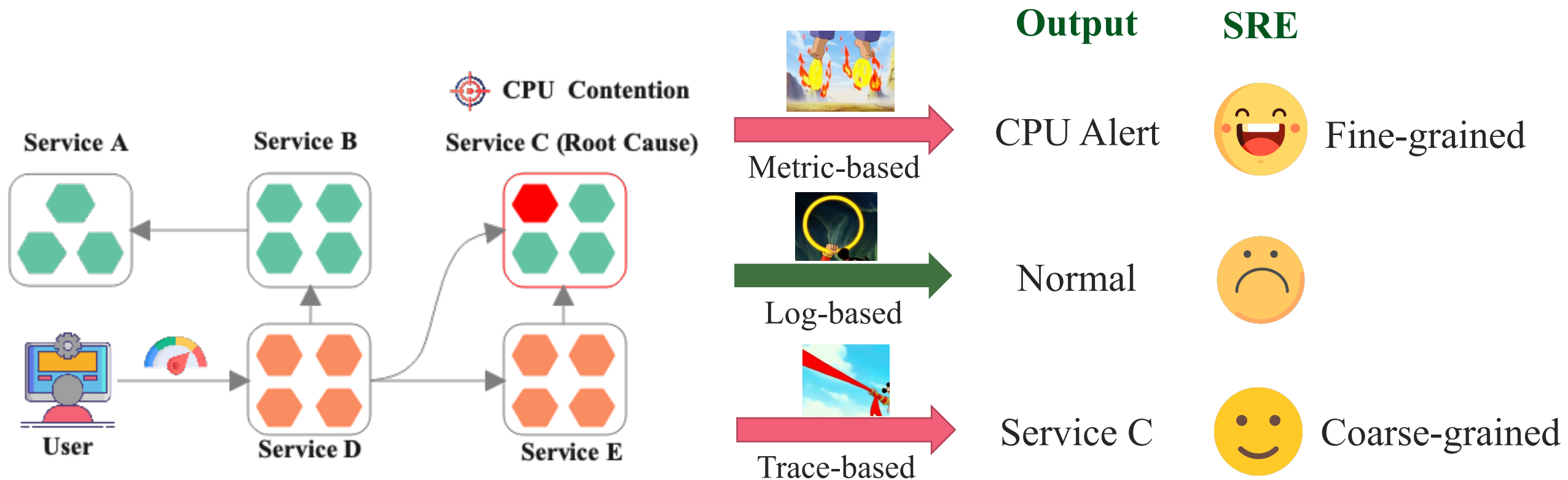


Figure 11: Change of diagnosis time with event number.

- ✓ Diagnosis time of Nezha increases linearly with the number of events
- ✓ Nezha takes 16 seconds to determine root causes in a time window of 50,000 events

- Certain anomalies may not be apparent in some data sources
 - ◆ CPU contention is not obvious in logs

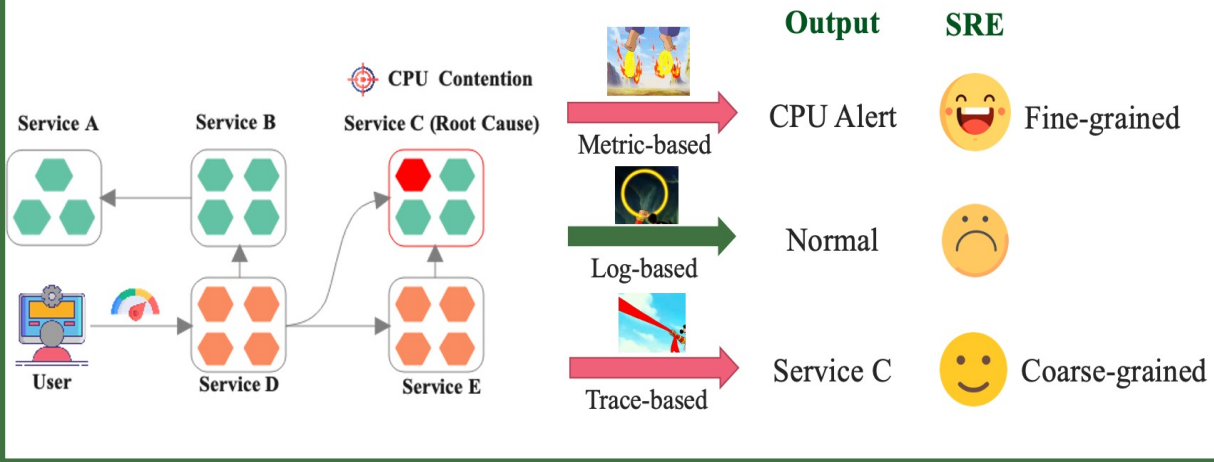


Conclusion



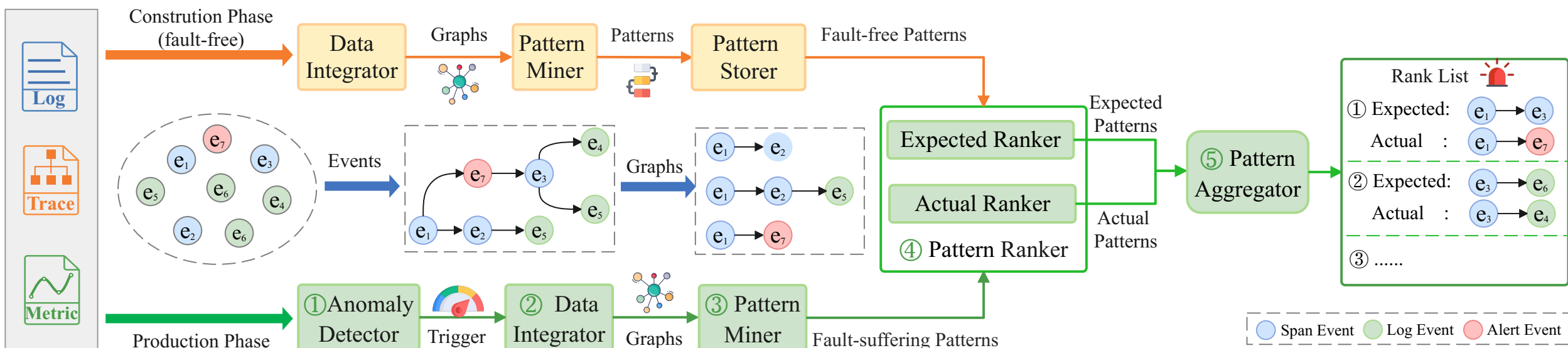
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- Nezha: an unsupervised fine-grained RCA approach by incorporative analysis of multi-modal data in an interpretable manner

Fault-free Construction Phase



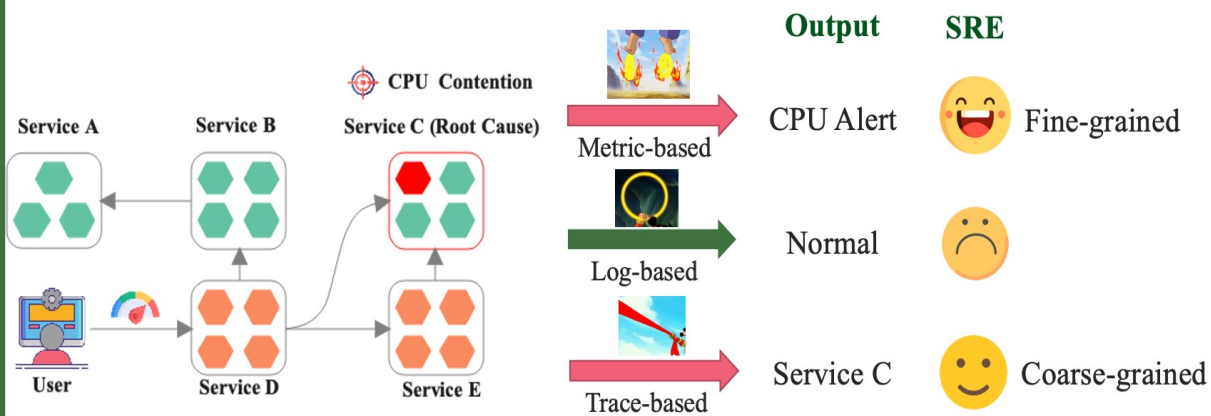
Fault-suffering Production Phase

Conclusion



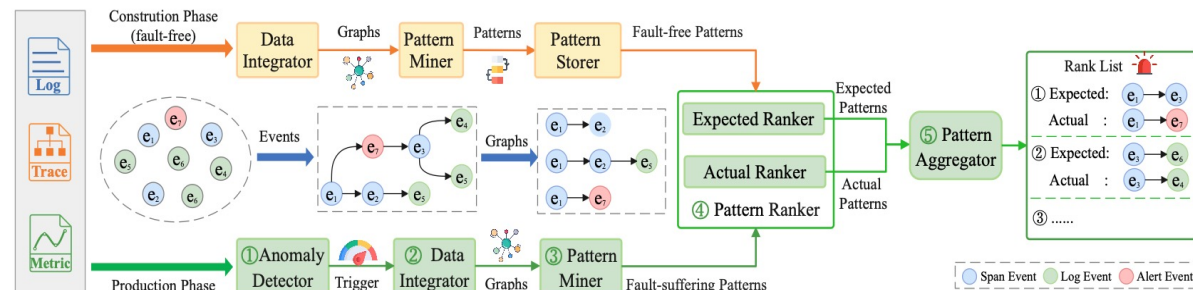
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Fault-suffering Production Phase

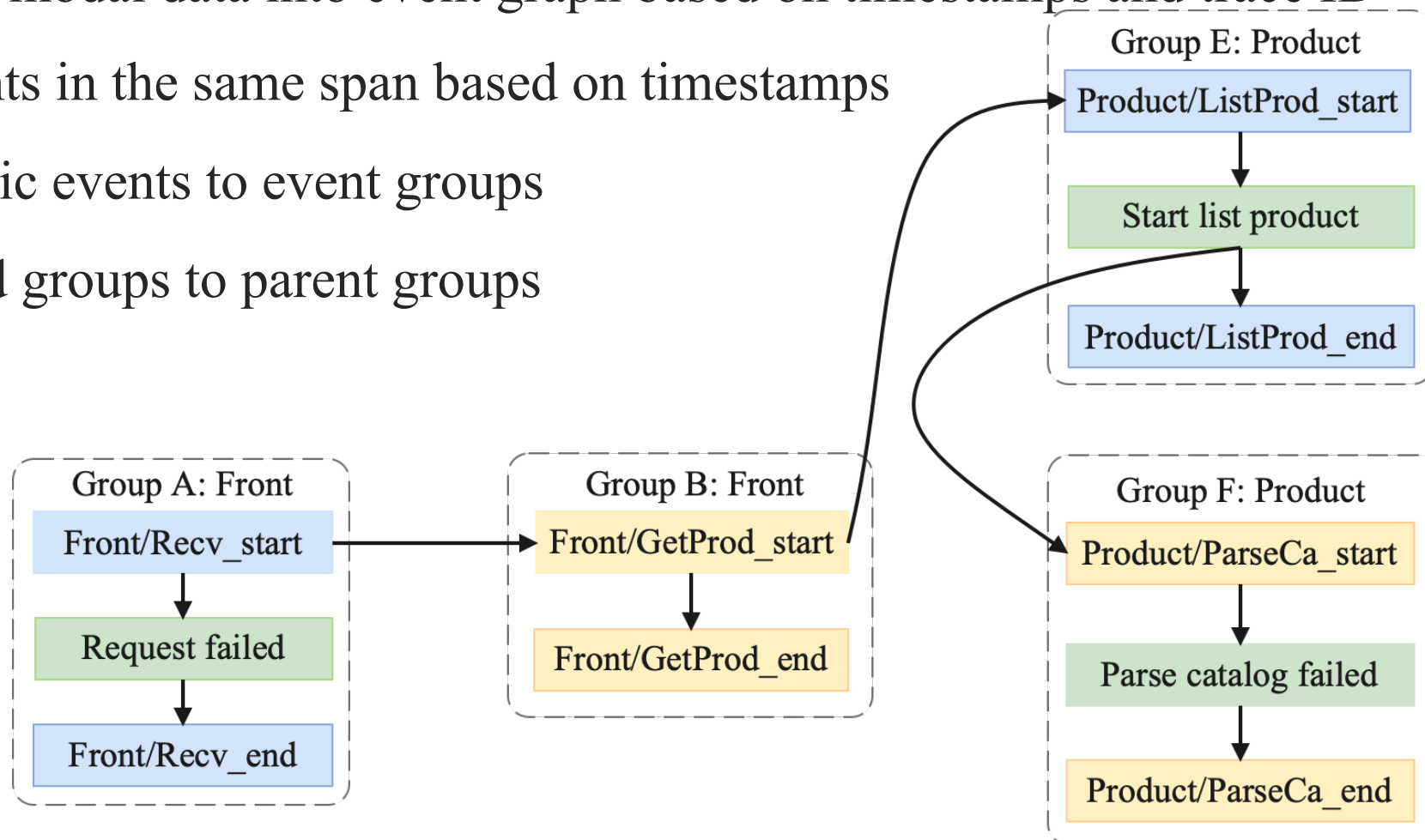
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② Integrate multi-modal data into event graph based on timestamps and trace ID

IV. Order events in the same span based on timestamps

V. Insert metric events to event groups

VI. Insert child groups to parent groups

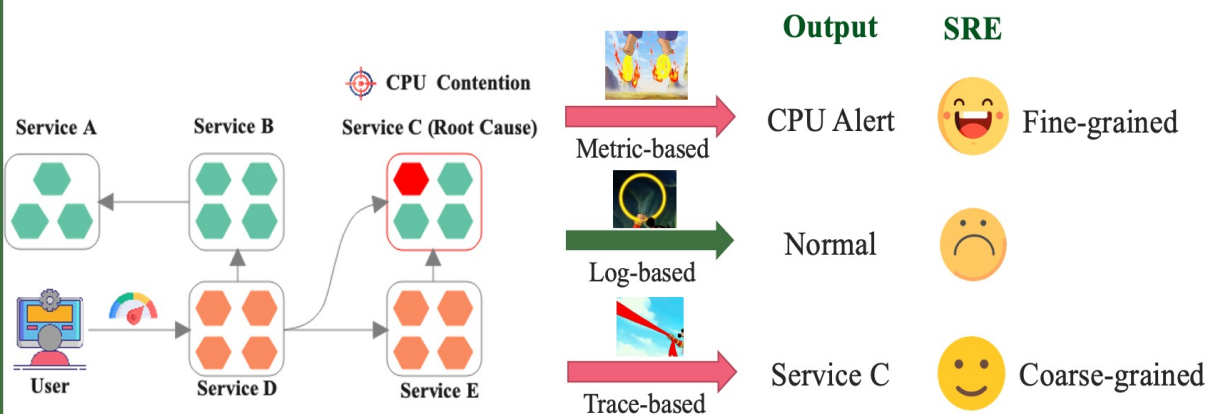


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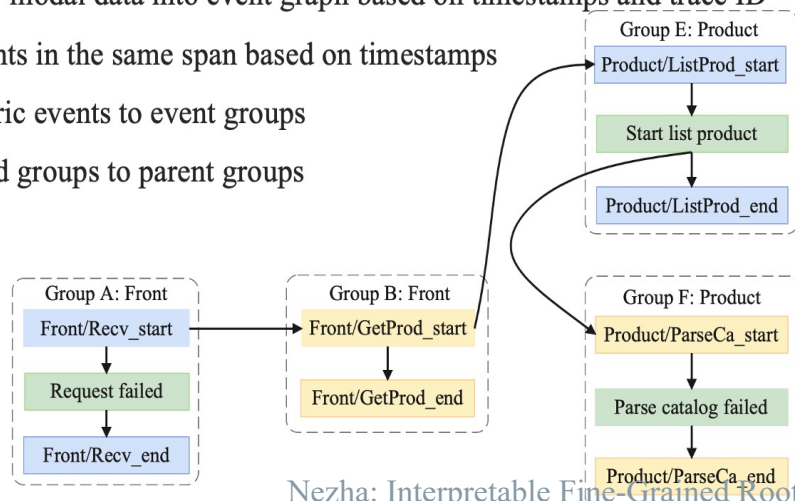
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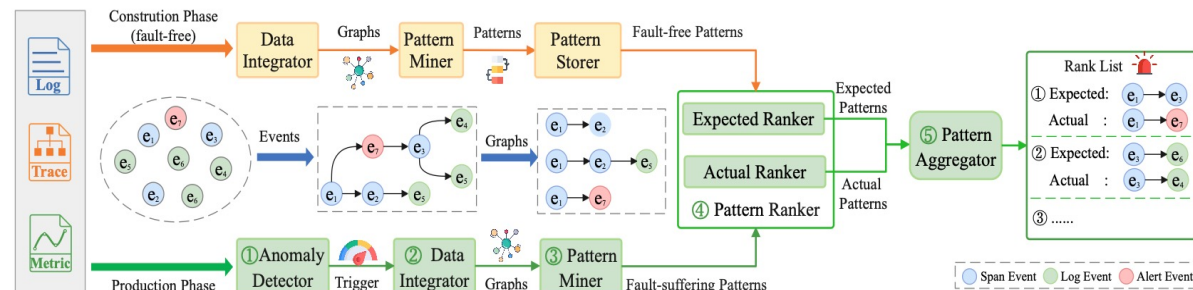
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Nezha: Interpretable Fine-Grained Root Causes Analysis for Microservices on Multi-Modal Observability Data.

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Fault-free Construction Phase



Fault-suffering Production Phase

➤ Root cause result at service level

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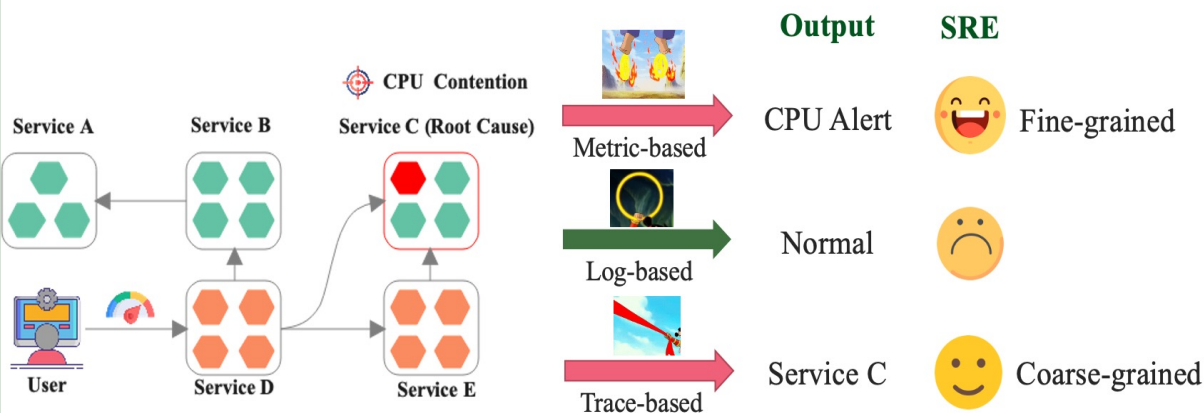
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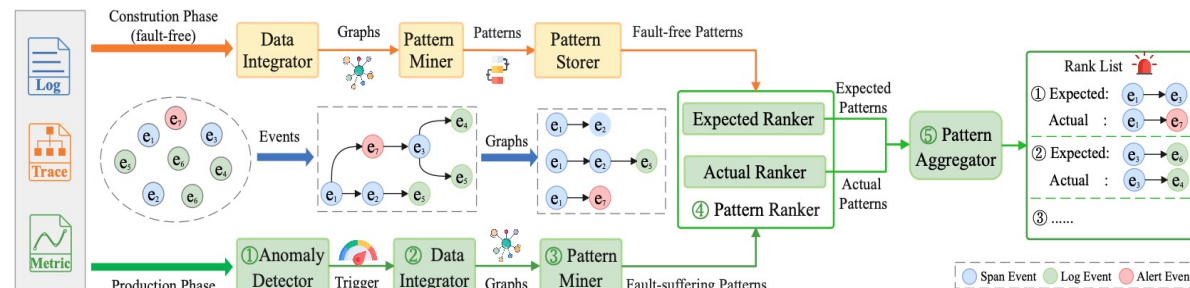
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Fault-free Construction Phase



Fault-suffering Production Phase

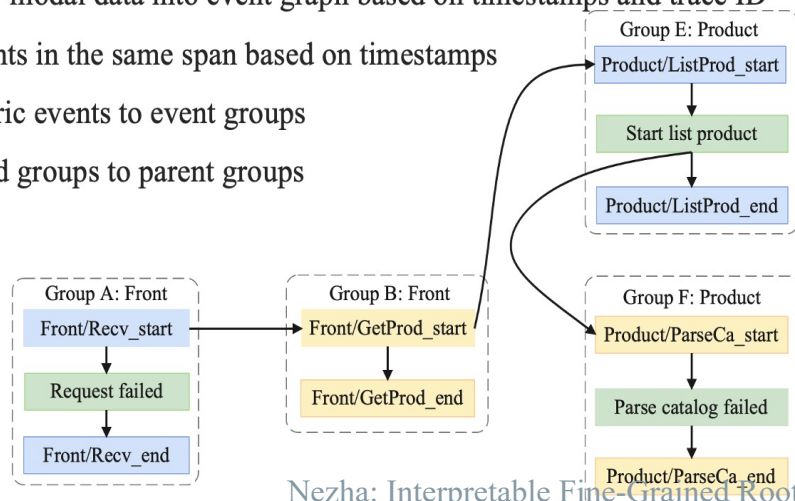
➤ Nezha: an unsupervised fine-grained RCA approach with multi-modal data

② Integrate multi-modal data into event graph based on timestamps and trace ID

IV. Order events in the same span based on timestamps

V. Insert metric events to event groups

VI. Insert child groups to parent groups



Nezha: Interpretable Fine-Grained Root Causes Analysis for Microservices on Multi-Modal Observability Data.

➤ Root cause result at service level

Table 3: Comparison of baselines at service level.

Approach	OnlineBoutique			TrainTicket		
	AS@1	AS@3	AS@5	AS@1	AS@3	AS@5
MicroScope	12.5	41.07	55.35	17.78	26.67	35.56
MicroRCA	16.07	62.5	92.75	20.00	31.11	44.44
SBLD	19.64	23.21	25.00	15.56	22.22	24.44
LogFaultFlagger	19.64	21.42	23.21	17.78	24.44	24.44
MicroRank	41.07	48.21	62.5	15.56	24.44	35.56
TraceAnomaly	30.35	33.92	48.21	13.33	28.89	33.33
PDiagnose	41.07	73.21	82.14	8.89	13.33	22.22
Nezha w/o $M\mathcal{L}$	14.28	17.85	17.85	6.67	8.89	11.11
Nezha w/o M	26.78	33.92	35.71	55.56	62.22	68.89
Nezha w/o $\mathcal{L}$	64.28	64.28	64.28	42.22	44.44	44.44
Nezha	92.86	96.43	96.43	86.67	97.78	97.78

✓ Nezha achieves high accuracy in AS@1 (90%), AS@3 (97%)

✓ Nezha outperforms all the baseline approaches

✓ Each data source contributes to the effectiveness of Nezha



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Thank you !

Q & A

I am looking for post-doc opportunities

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<https://github.com/IntelligentDDS/Nezha>