

Eadro: An End-to-End Troubleshooting Framework for Microservices on Multi-Source Data

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May, 2023



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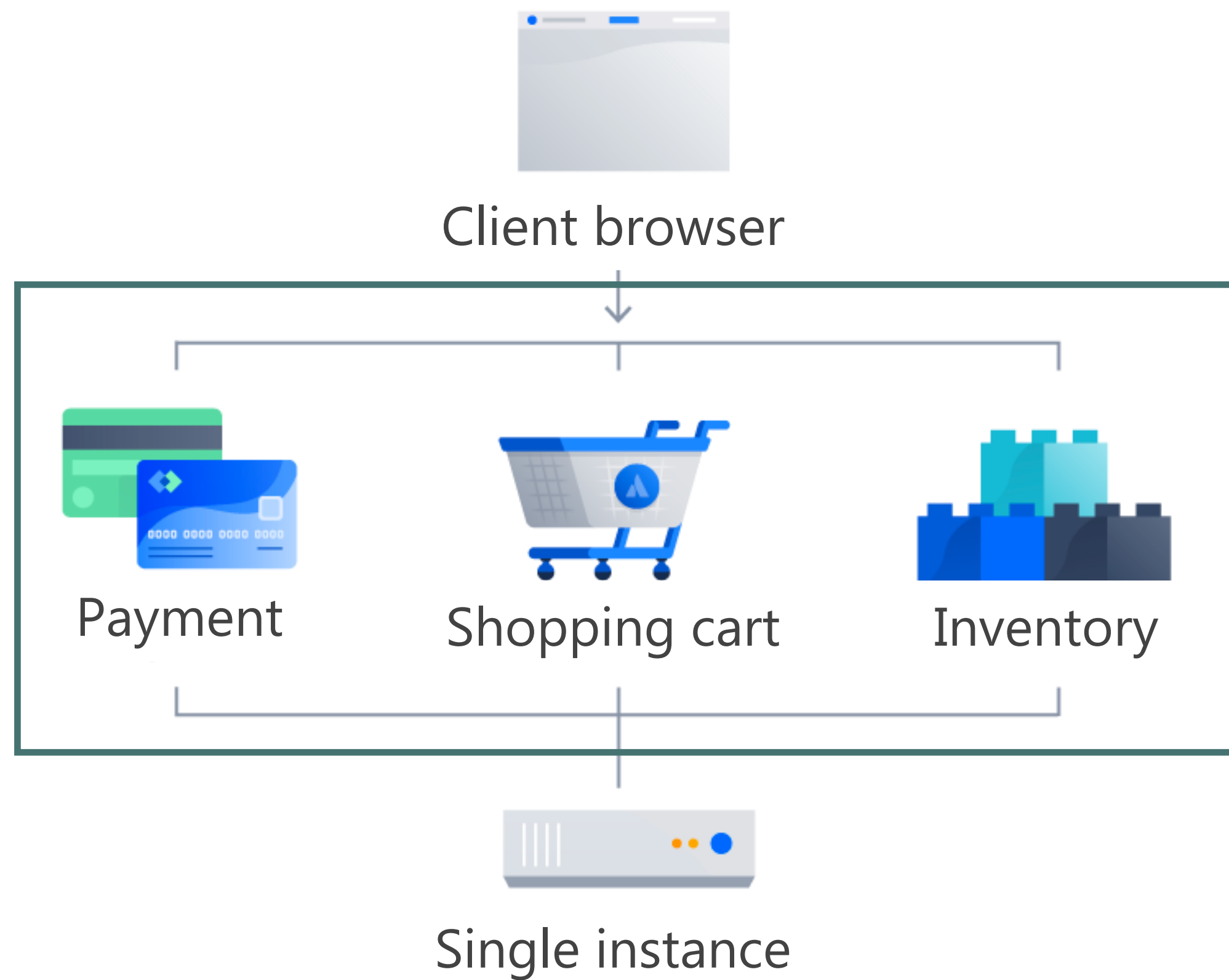
EVALUATION



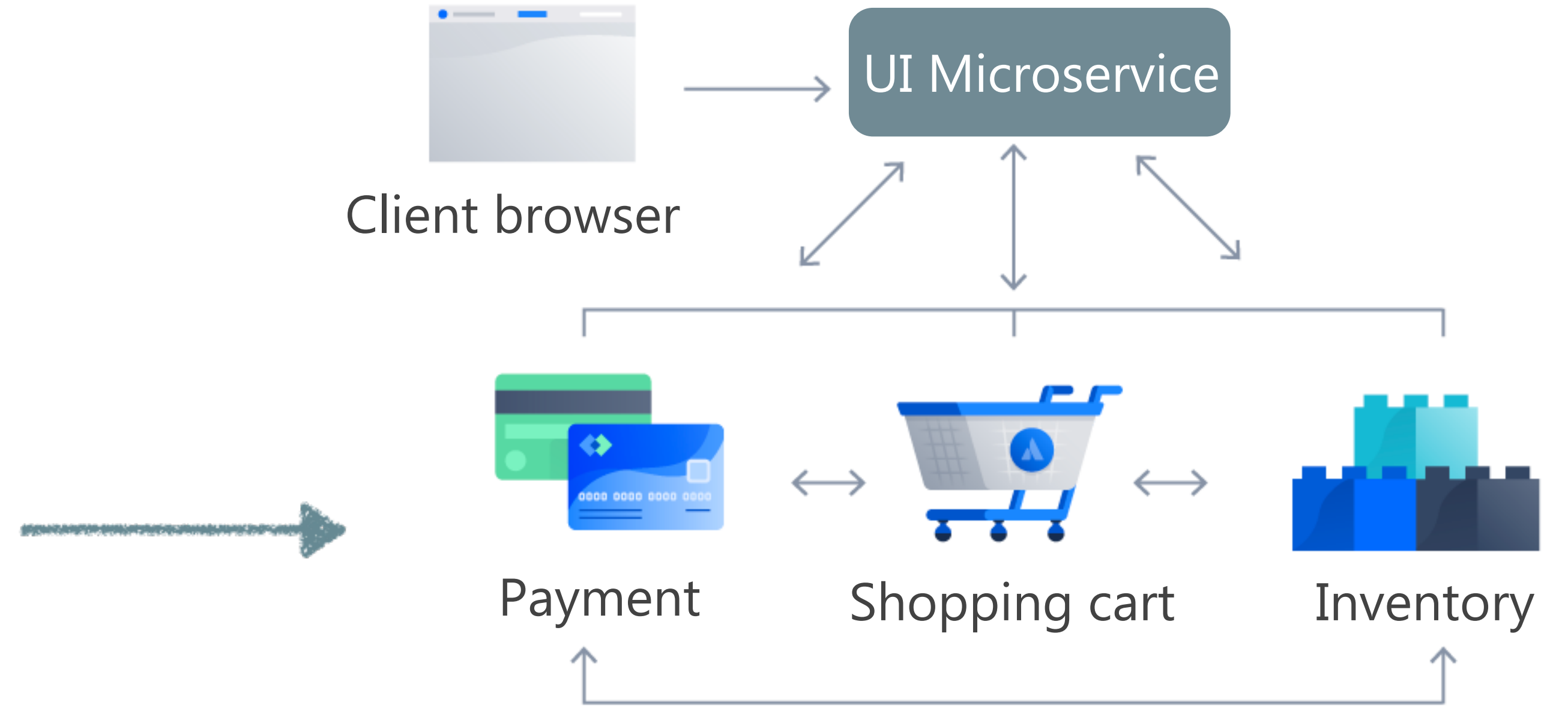
01 INTRODUCTION

Background

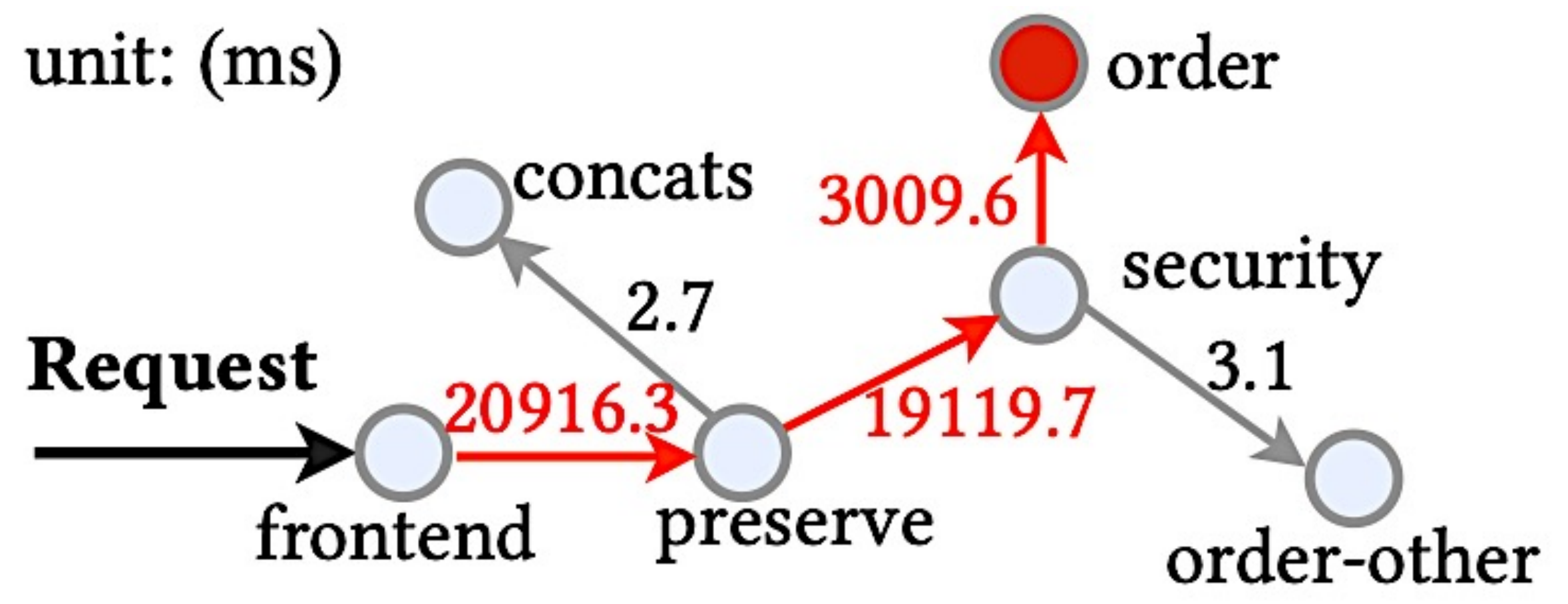
Monolithic



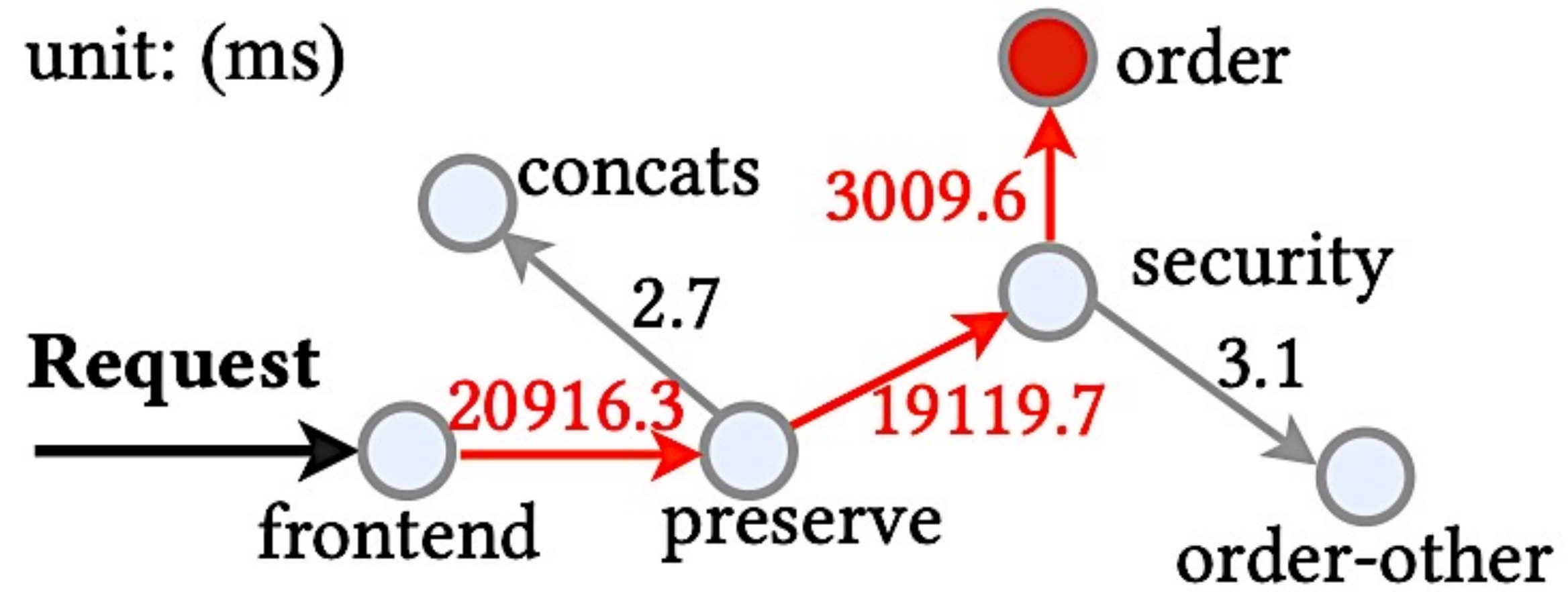
Microservice



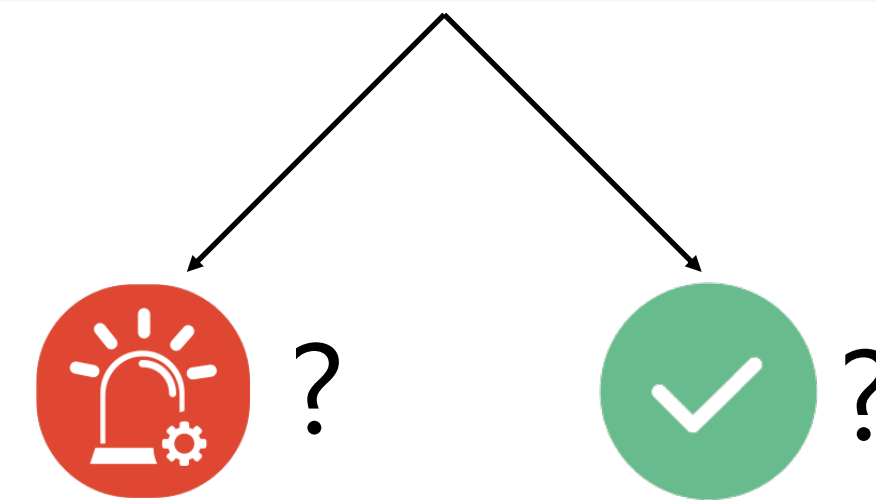
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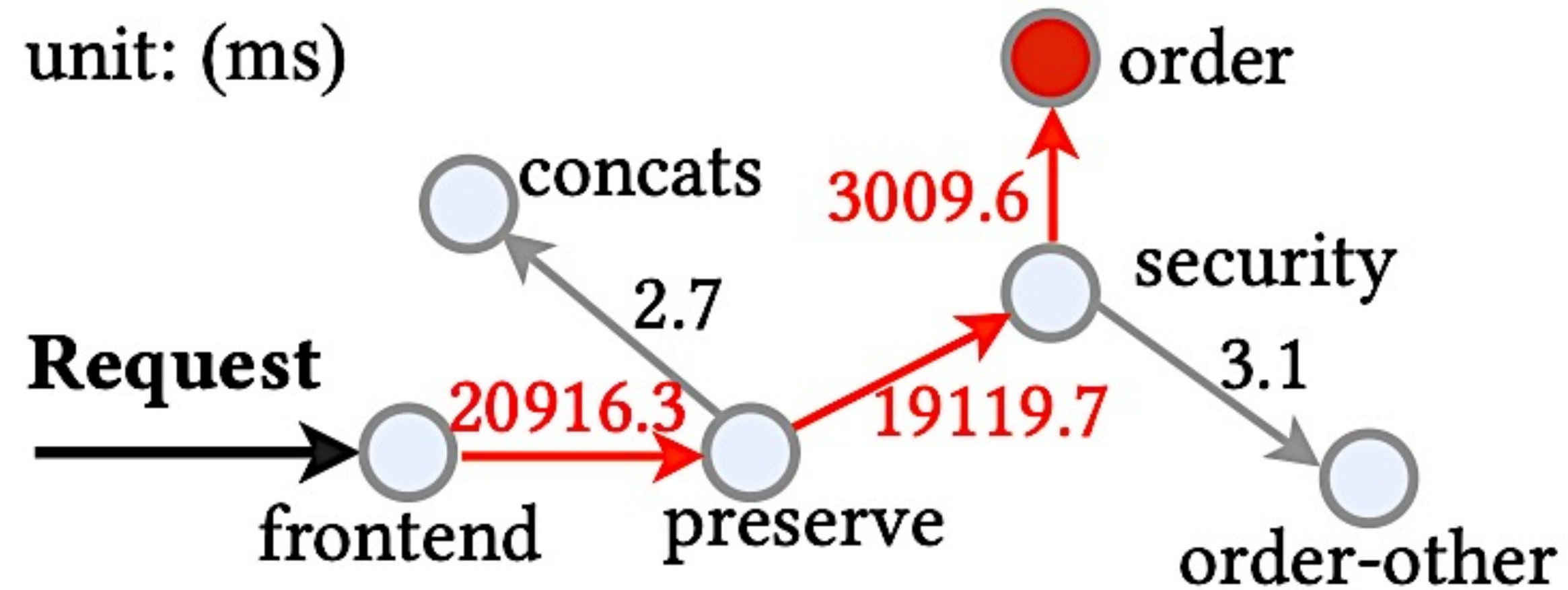
Background



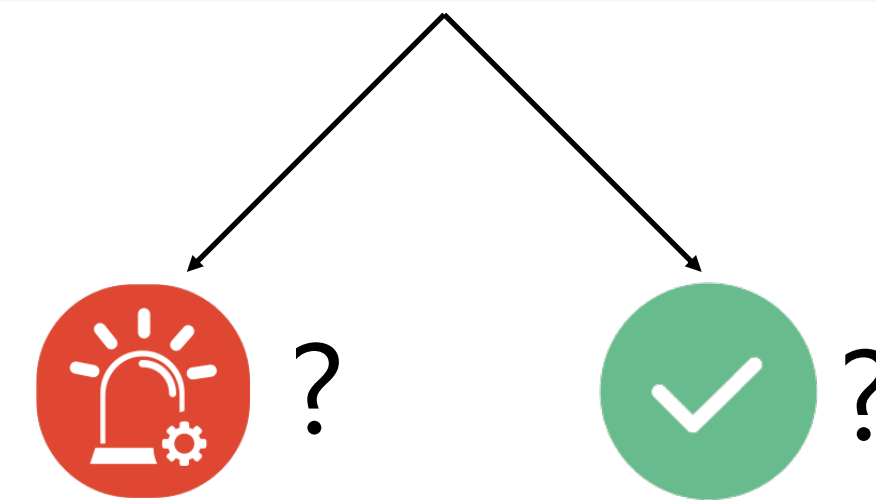
Anomaly detection (AD) identifies the existence of an anomaly.



Background

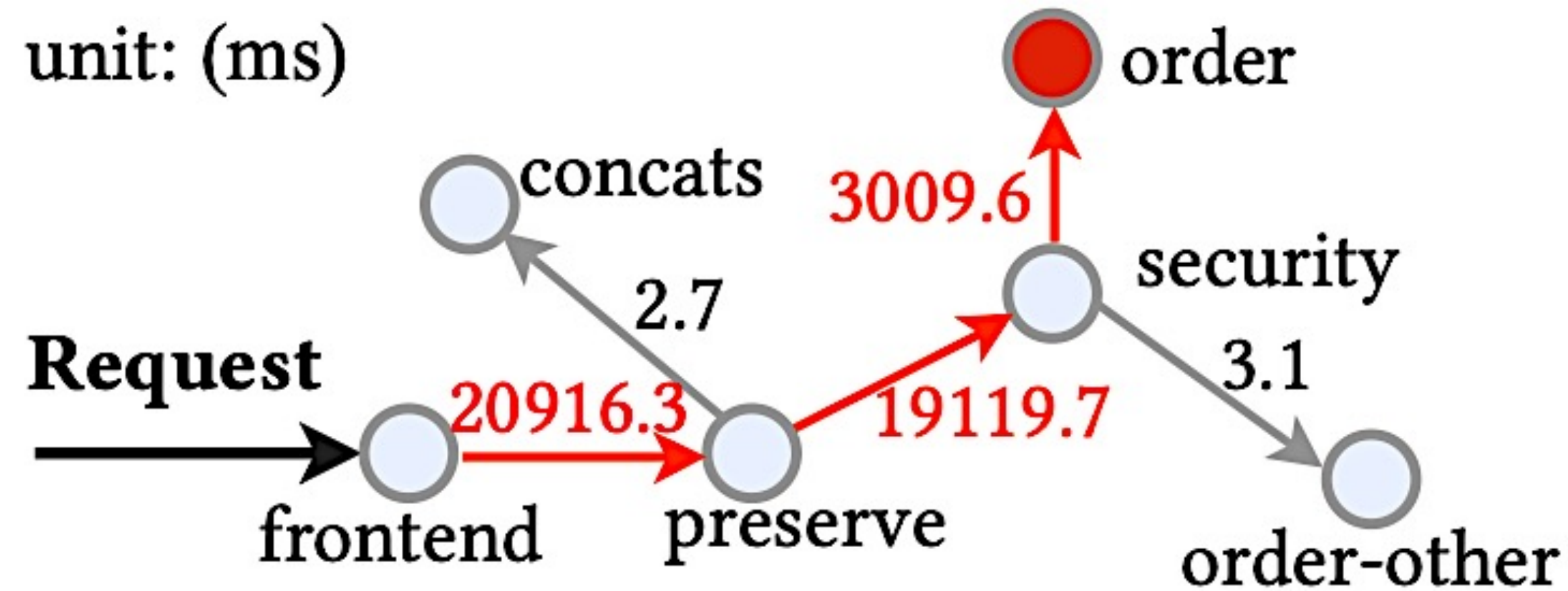


Anomaly detection (AD) identifies the existence of an anomaly.

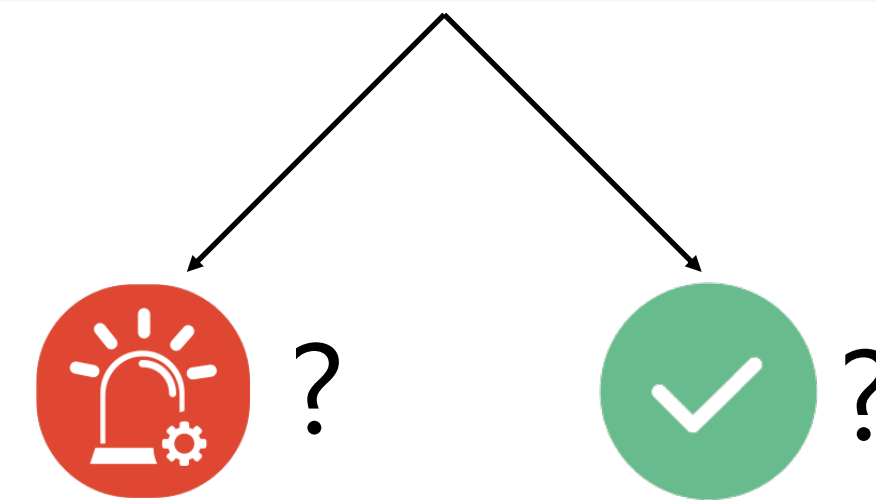


But we need finer-grained information...

Background

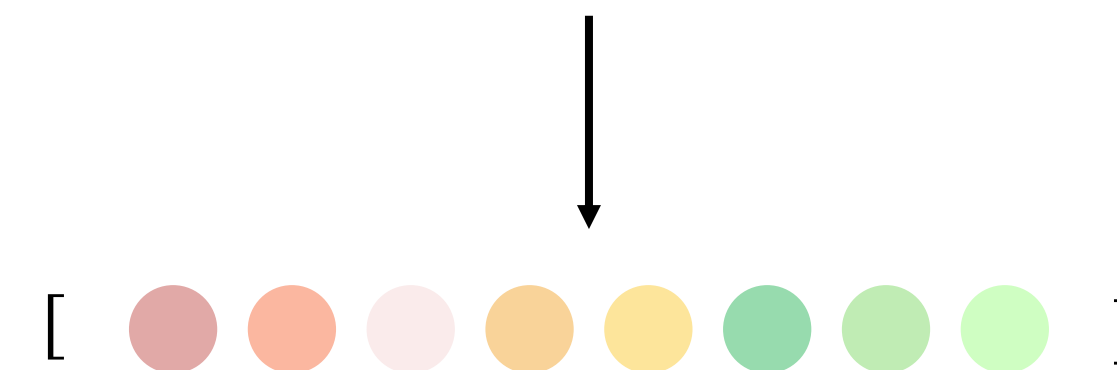


Anomaly detection (AD) identifies the existence of an anomaly.

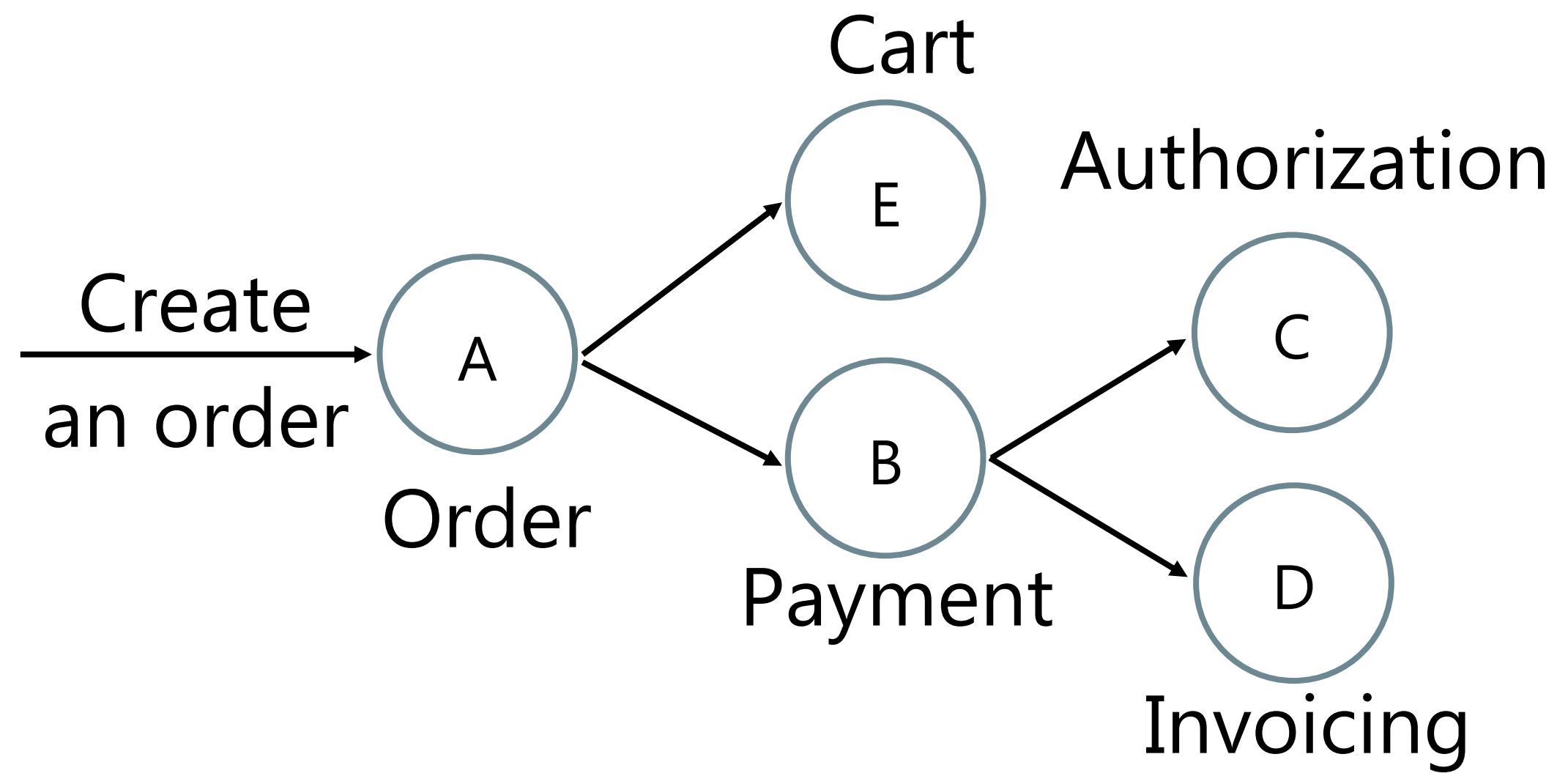


But we need finer-grained information...

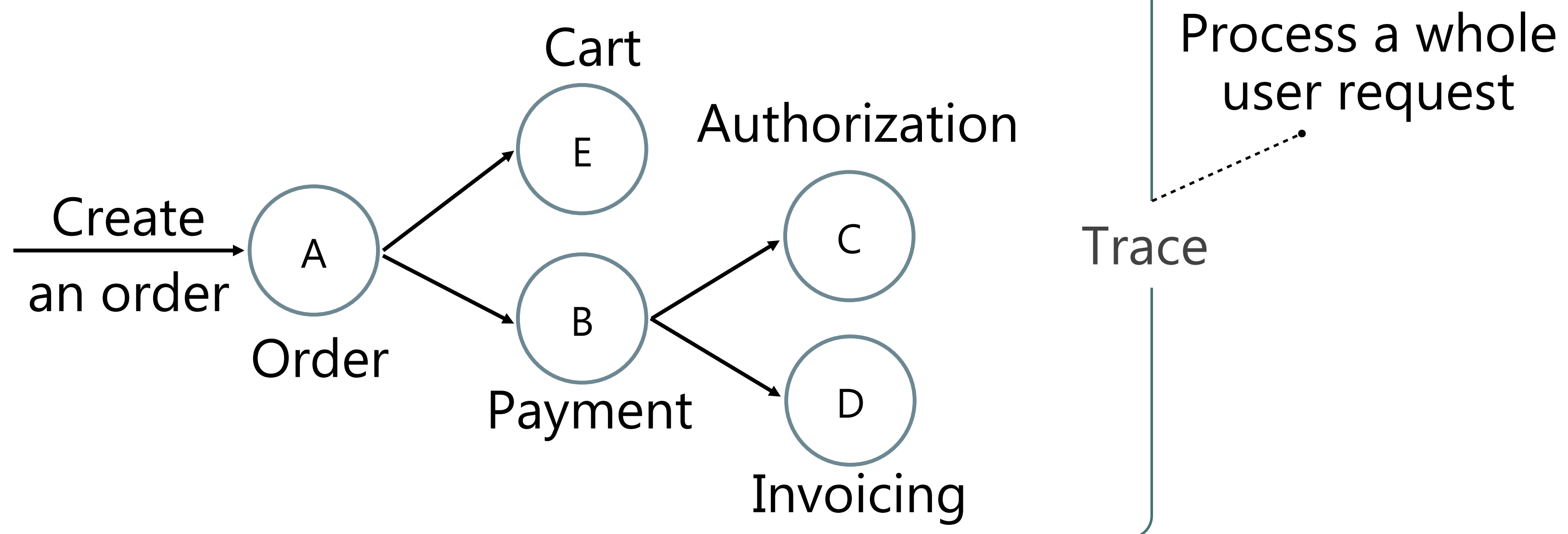
Root cause localization (RCL) answers the probability of each microservice being the culprit.



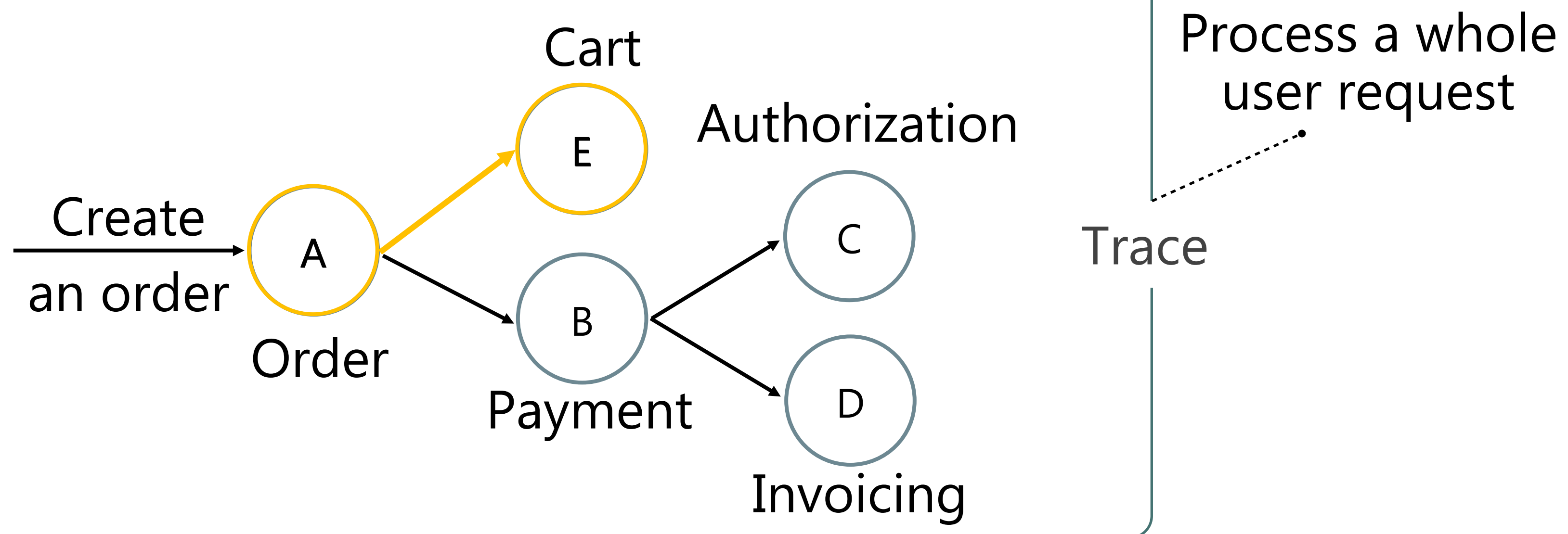
Terminologies



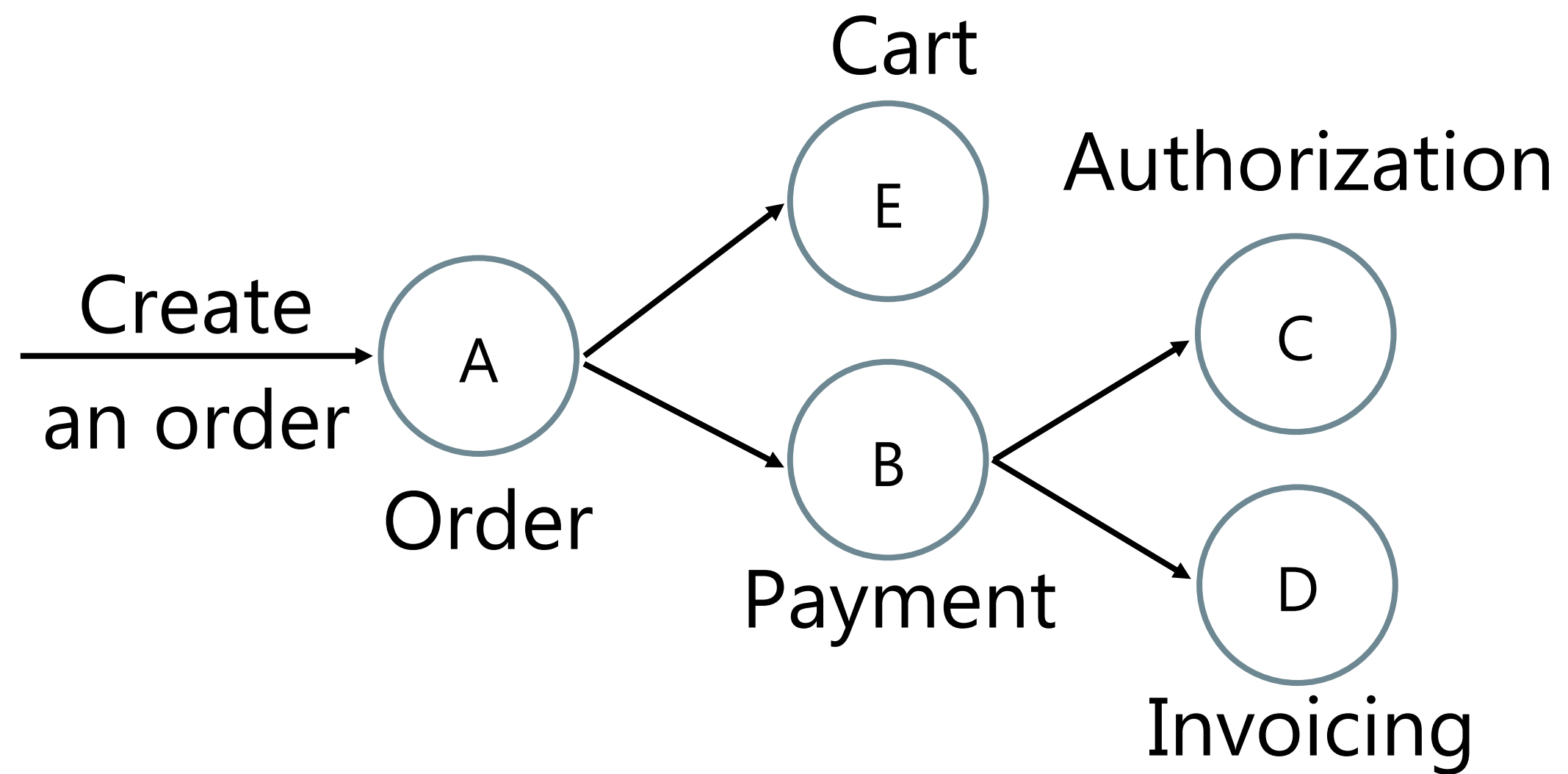
Terminologies



Terminologies

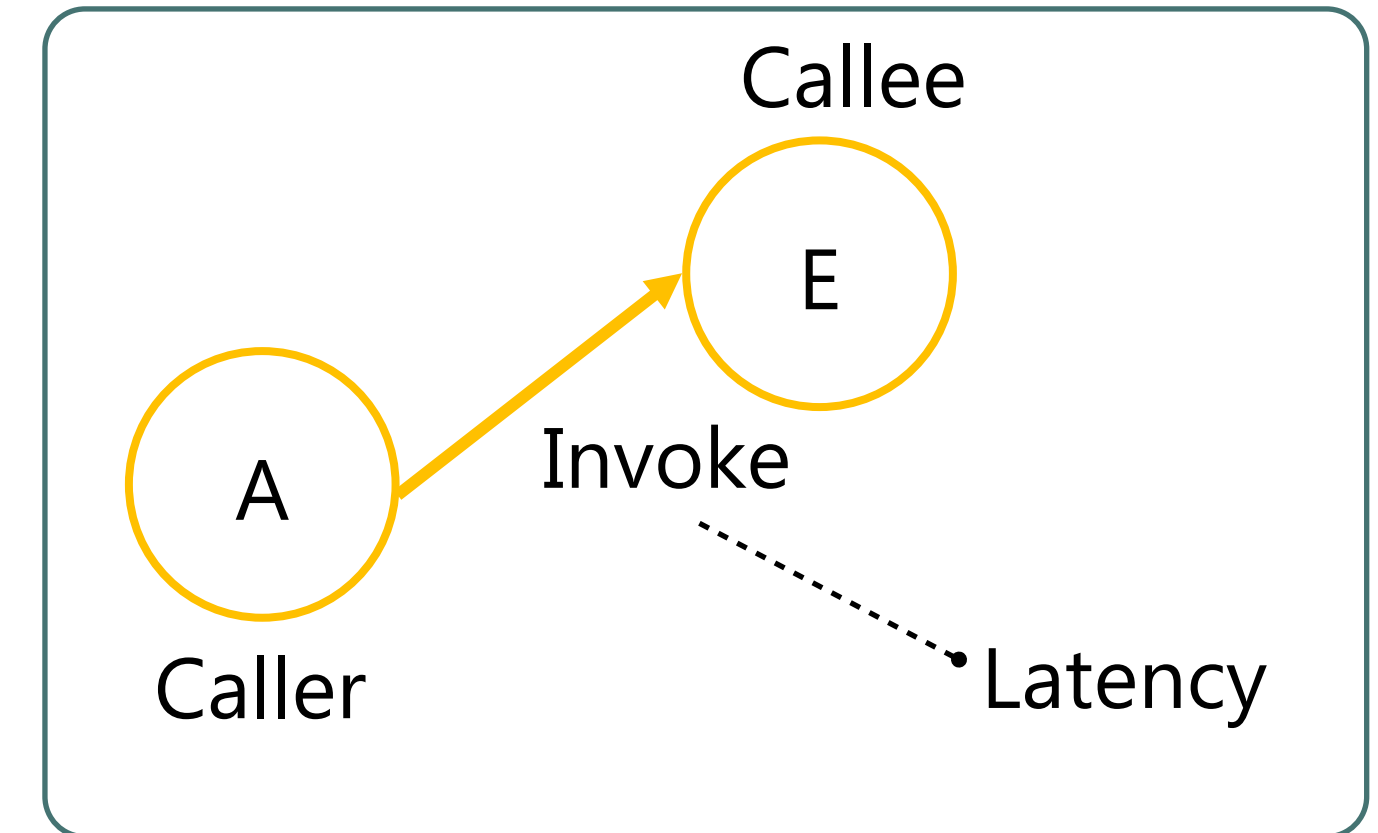


Terminologies

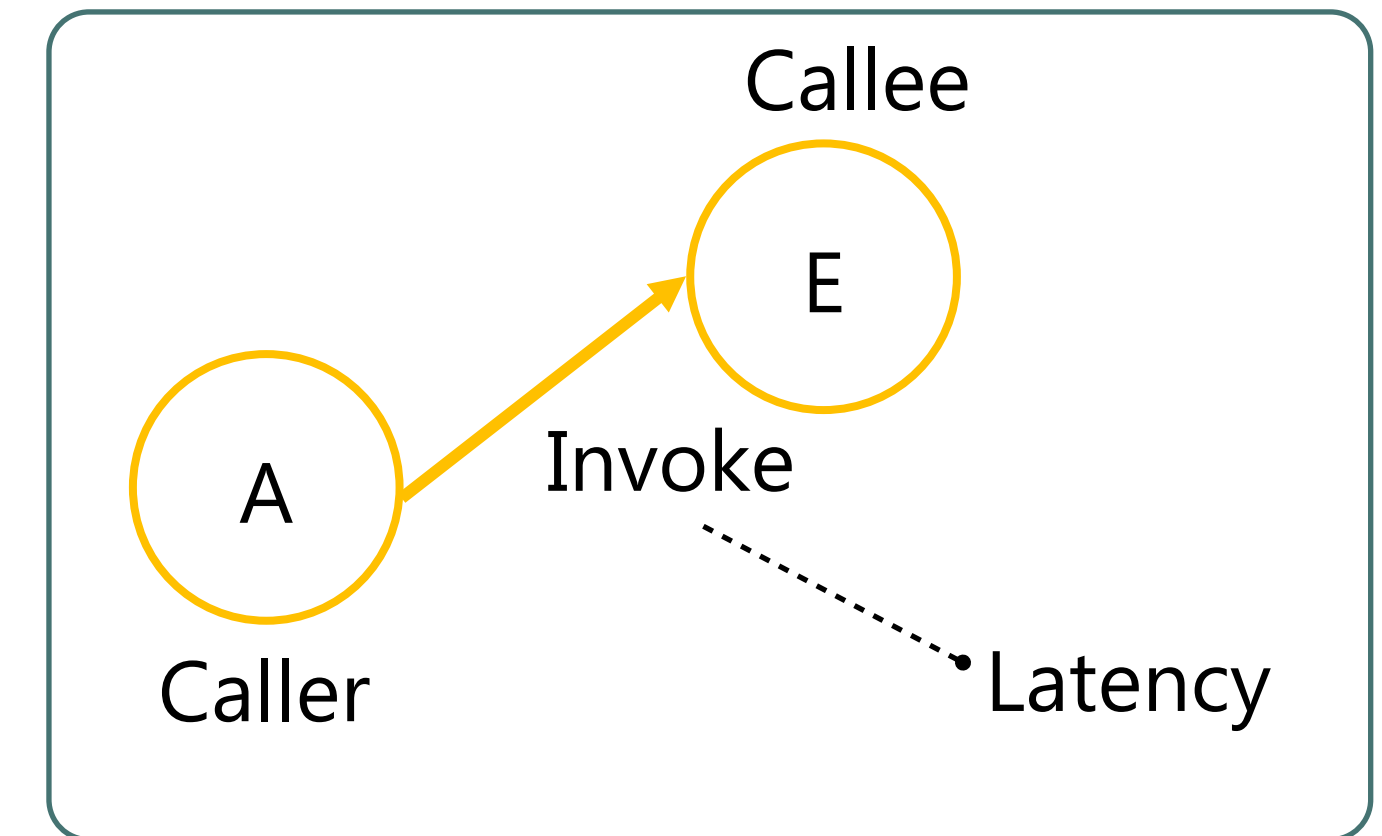
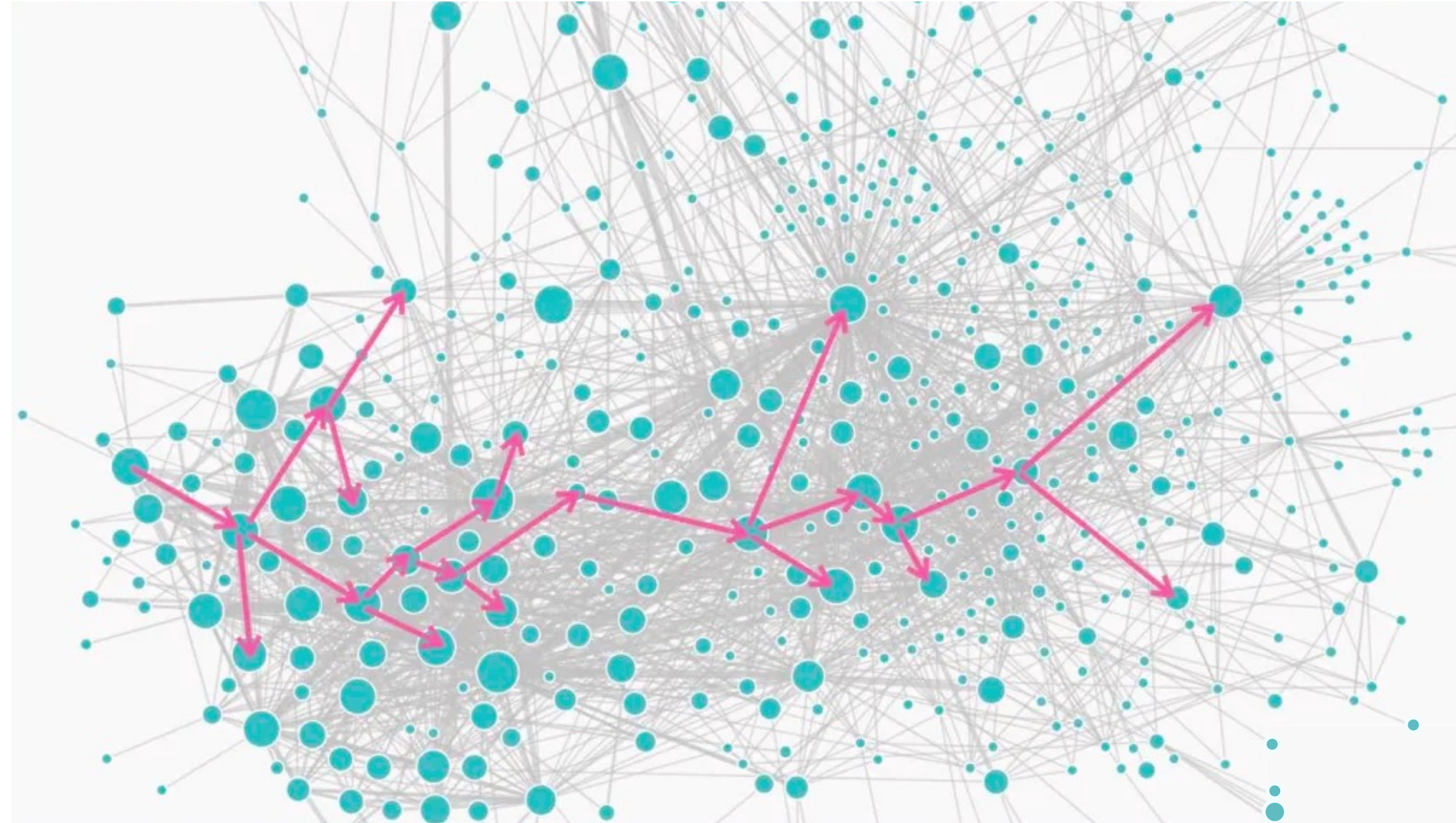


Process a whole user request

Trace



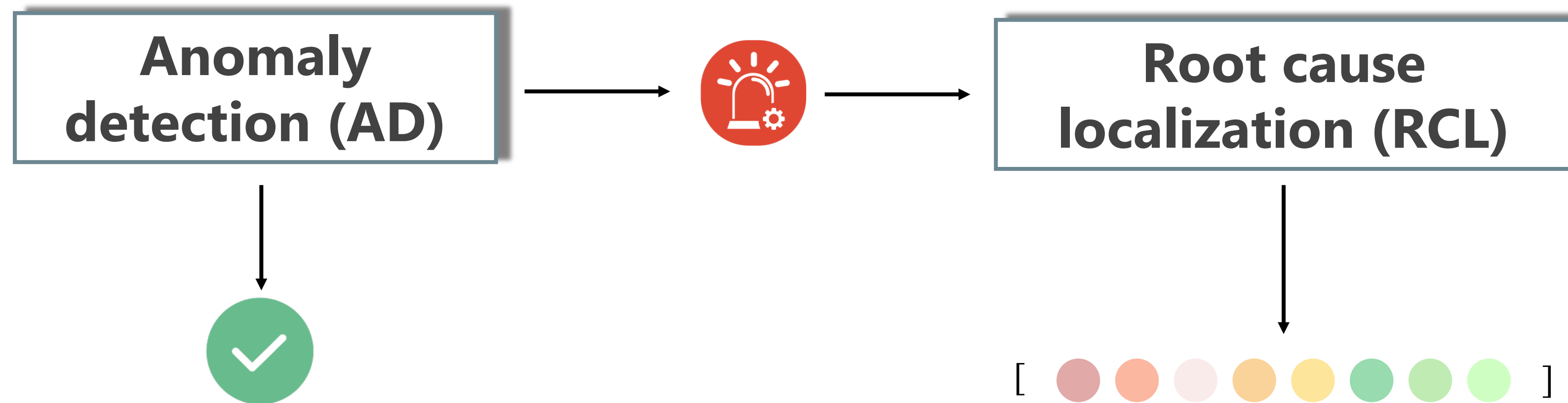
Terminologies



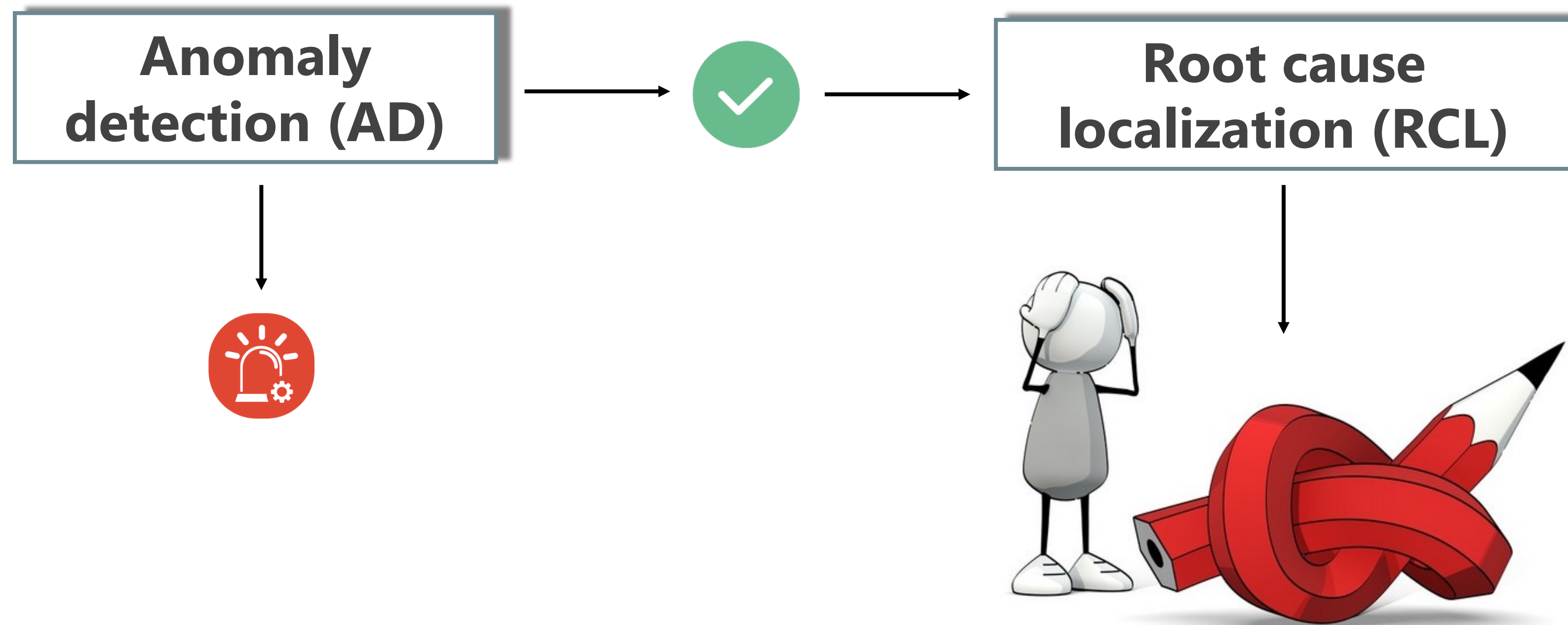
An aerial view of a dense city skyline at dusk, featuring numerous skyscrapers and residential buildings. The city is surrounded by lush green hills. A white semi-circular graphic is overlaid on the center of the image, containing the text "02 MOTIVATION".

02 MOTIVATION

Inaccurate AD Results Limits RCL's Accuracy



Inaccurate AD Results Limits RCL's Accuracy



Inaccurate AD Results Limits RCL's Accuracy

Current detectors attached with localizers cannot deliver satisfying accuracy.

Three main kinds of **RCL-oriented** anomaly detectors:

- ▶ Statistical tools (e.g., N-sigma)
- ▶ Feature engineering + Machine Learning (e.g., OC-SVM)
- ▶ SPOT (based on Extreme Value Theory)

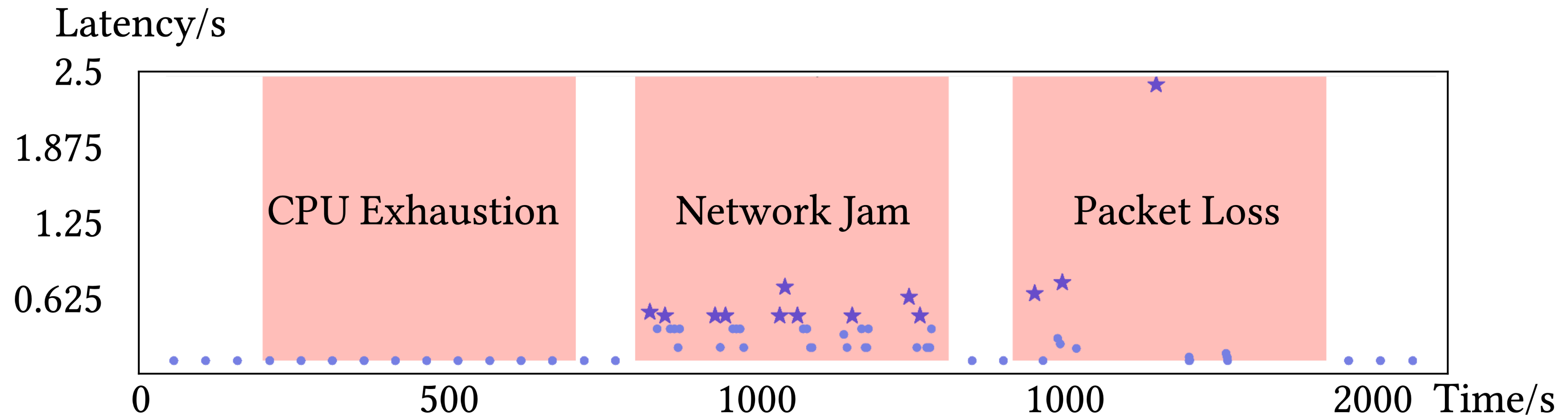
COMPARISON OF COMMON ANOMALY DETECTORS

	N-sigma	FE+ML	SPOT
FOR	0.632	0.830	0.638
FDR	0.418	0.095	0
#Infer/ms	0.207	1.361	549.169

$$FOR = \frac{FN}{FN+TN}, FDR = \frac{FP}{FP+TN}$$

Consider data besides traces

Traces are insufficient to reveal all potential faults despite their wide usage.



For example, network-related faults incur obvious anomalies in latency of "travel", but the CPU exhaustion fault does not.

An aerial photograph of a dense urban skyline, likely Hong Kong, taken at dusk. The city is filled with numerous high-rise buildings, many of which are illuminated with warm lights. The sky is a deep blue, and the water in the background is visible. A large white semi-circular graphic is overlaid on the center of the image, framing the text.

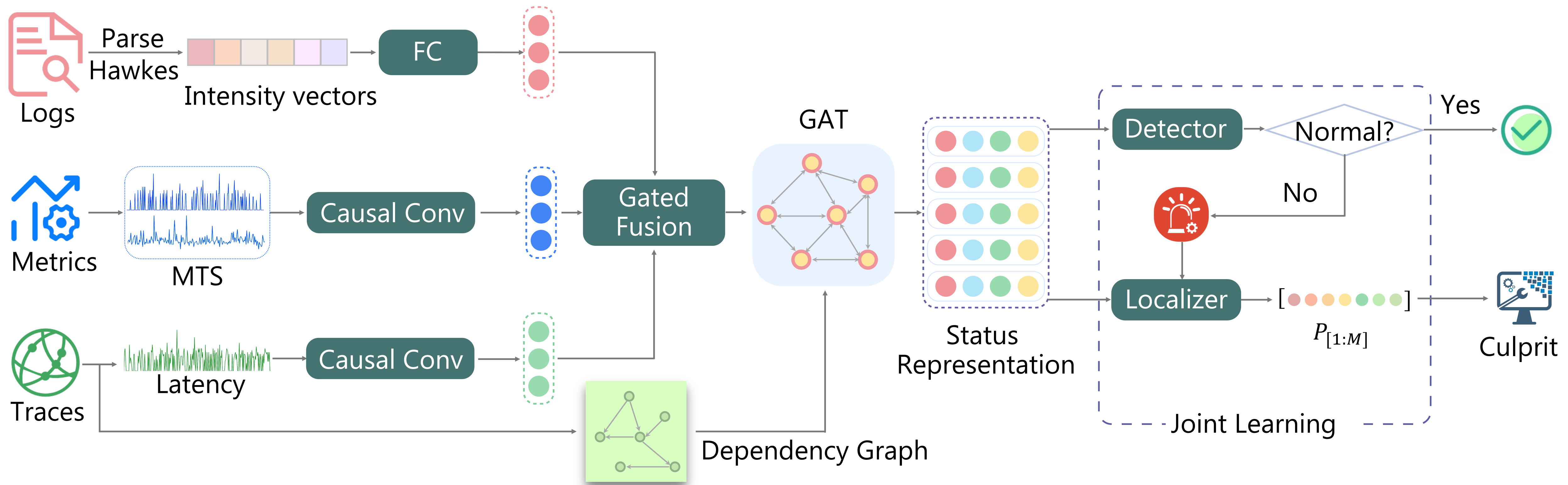
03 METHODOLOGY

Overview

1 Modal-wise Learning

2 Dependency-aware Status Learning

3 Detection & Localization



1 Modal-wise Learning

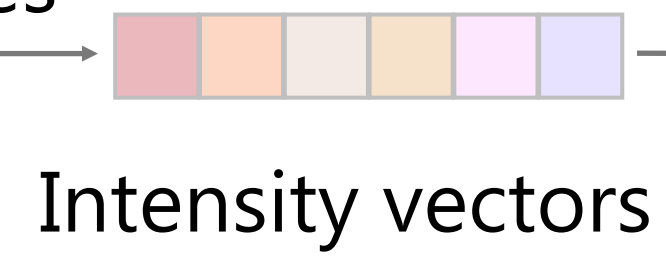
Log Modeling



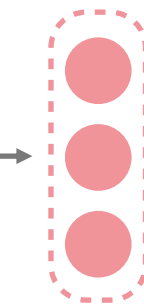
Parse
Drain

ZADD: no key specified
Failed to write home timeline to home-timeline-service
Failed to get reply: Connection reset by peer
User jack already existed.
User aaa already existed.

Hawkes



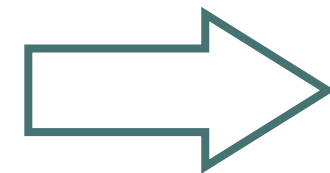
FC



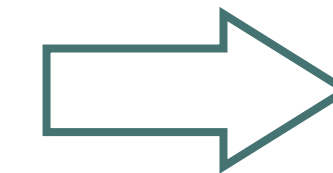
Log representation

The infinitesimal probability of an arrival during $[t, t + dt)$ is: $\lambda_l(t) = \left(\mu_l(t) + \sum_{t_i: t_i < t} \phi(t - t_i) \right)$

Parsing



Estimating



Embedding

1 Modal-wise Learning

The infinitesimal probability of an arrival during $[t, t + dt)$ is: $\lambda_l(t) = \left(\mu_l(t) + \sum_{t_i: t_i < t} \phi(t - t_i) \right)$

Log Modeling



Parse
Drain

ZADD: no key specified
Failed to write home timeline to home-timeline-service
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User jack already existed.
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Hawkes

Intensity vectors

FC

Log representation

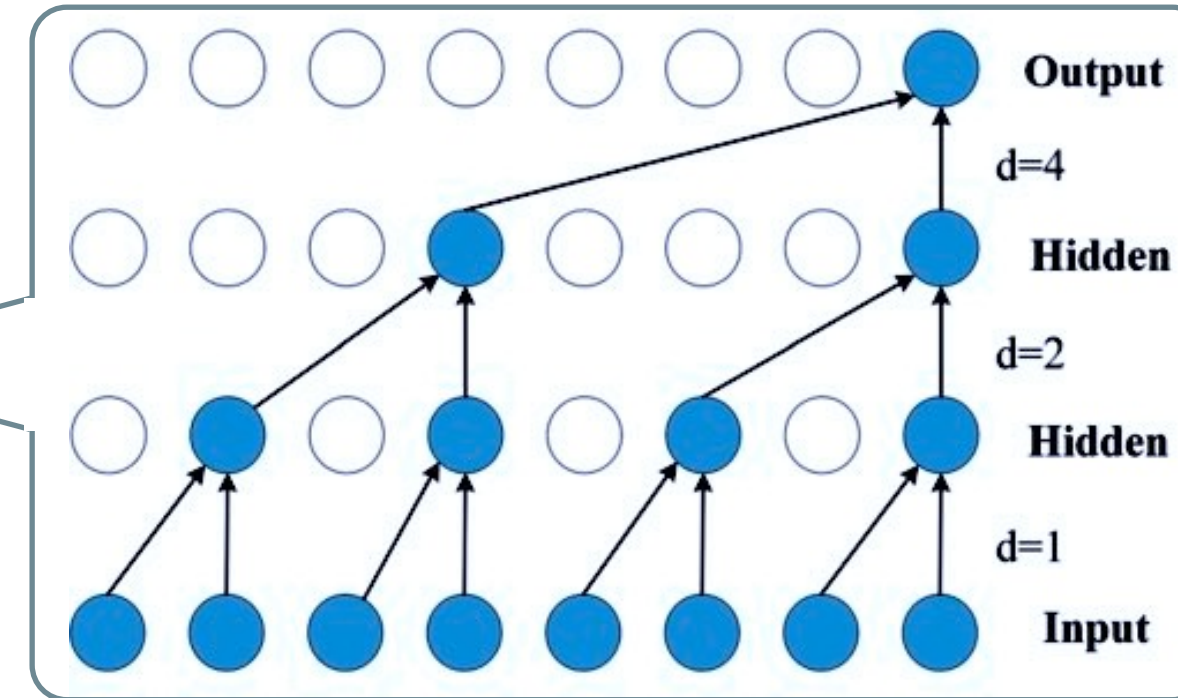
Metric Modeling



Metrics

MTS

Causal Conv
Self-Attn

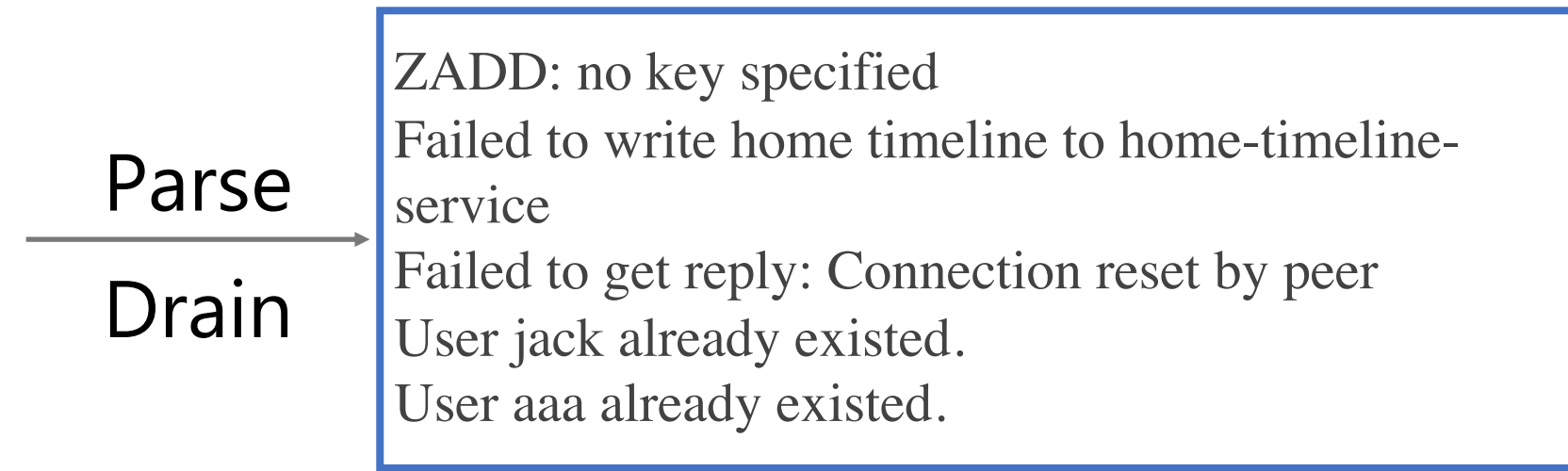


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1 Modal-wise Learning

The infinitesimal probability of an arrival during $[t, t + dt)$ is: $\lambda_l(t) = \left(\mu_l(t) + \sum_{t_i: t_i < t} \phi(t - t_i) \right)$

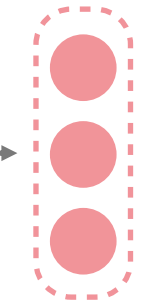
Log Modeling



Hawkes

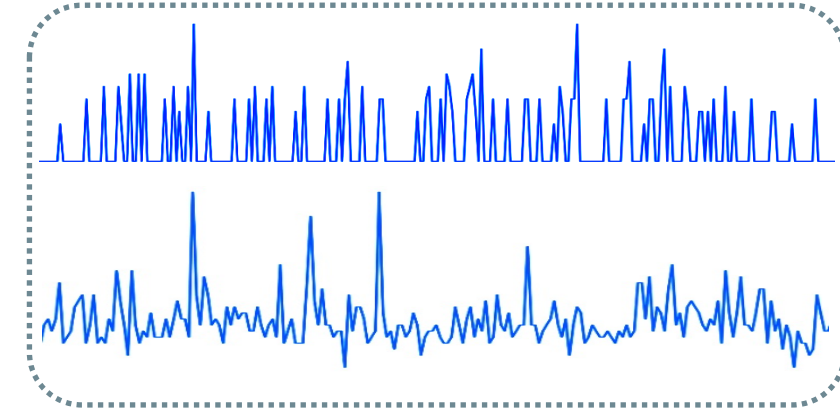


FC

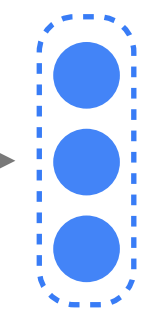
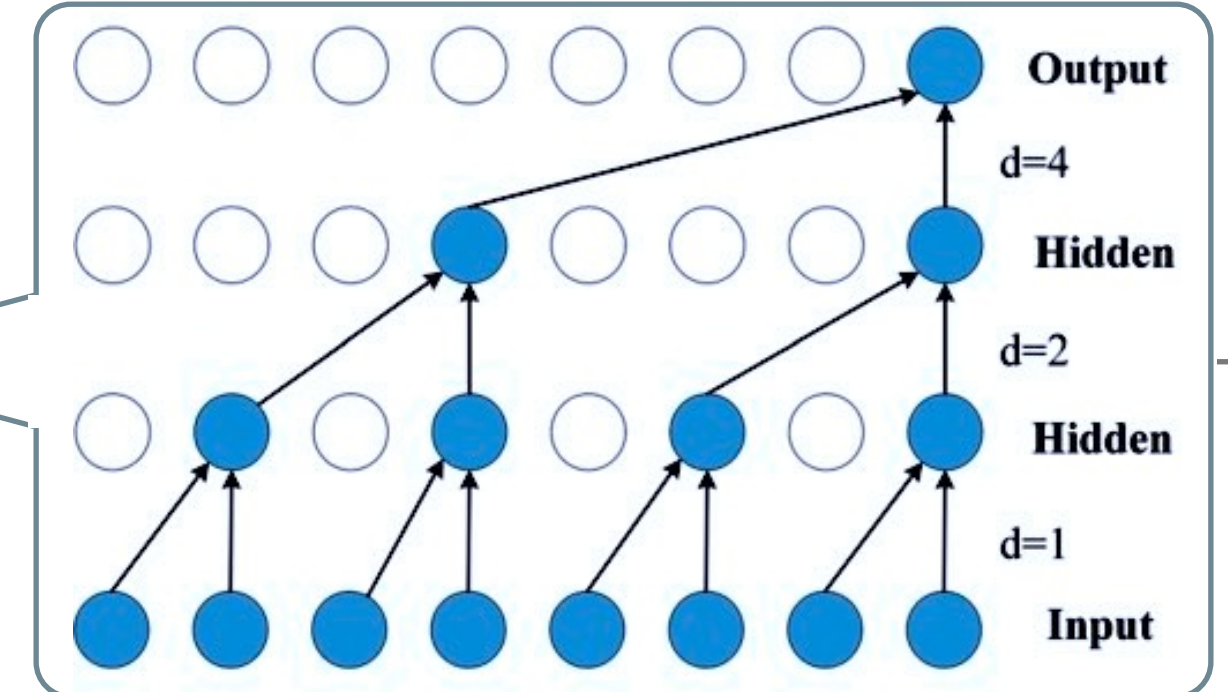


Log representation

Metric Modeling

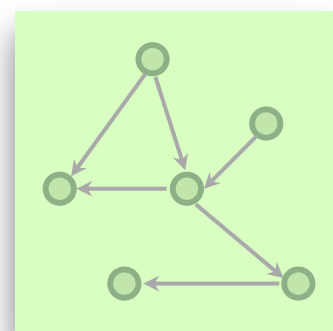
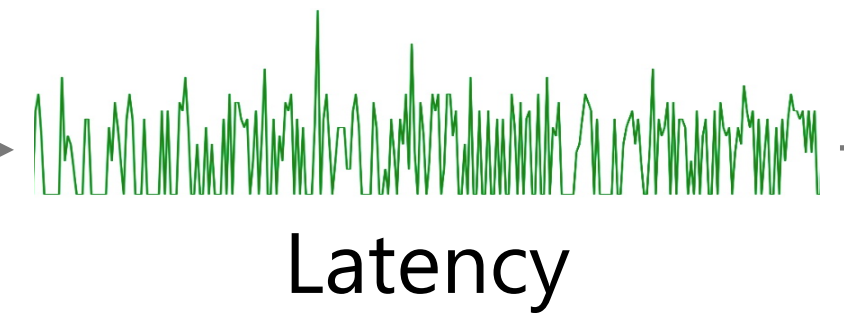
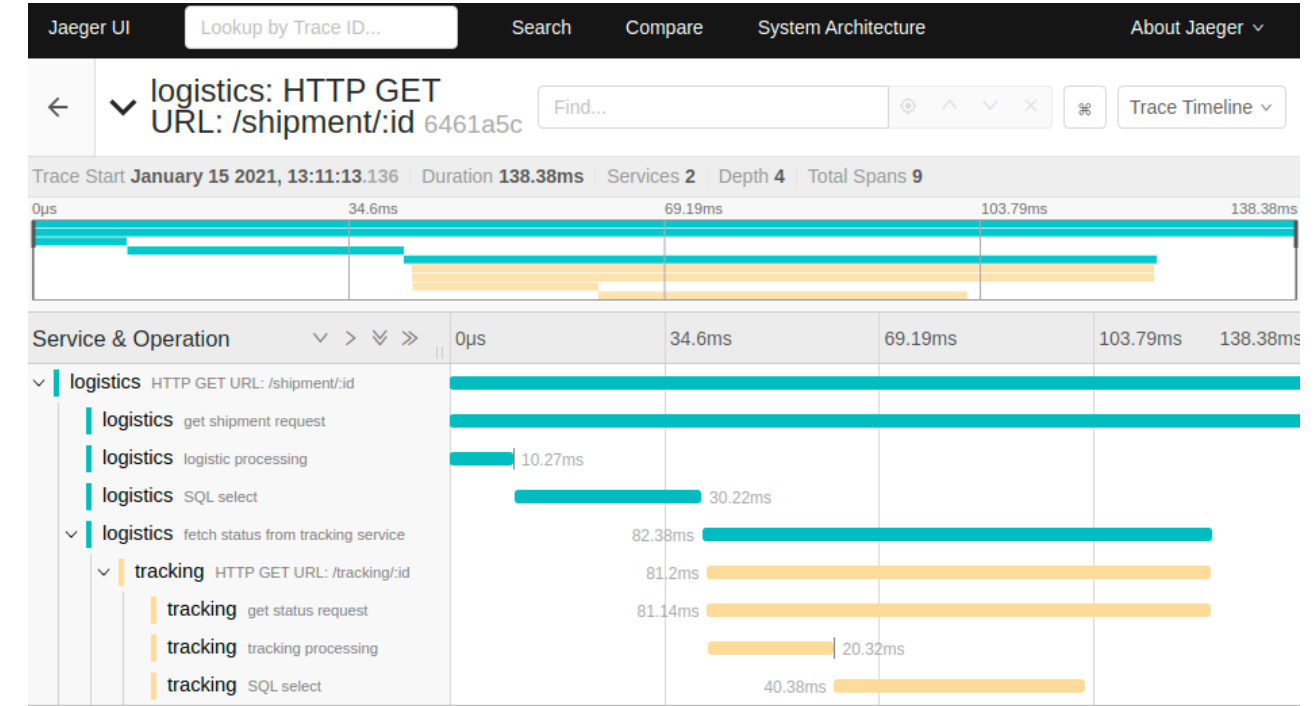


Causal Conv
Self-Attn

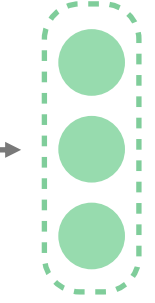


Metric representation

Latency Modeling (of traces)

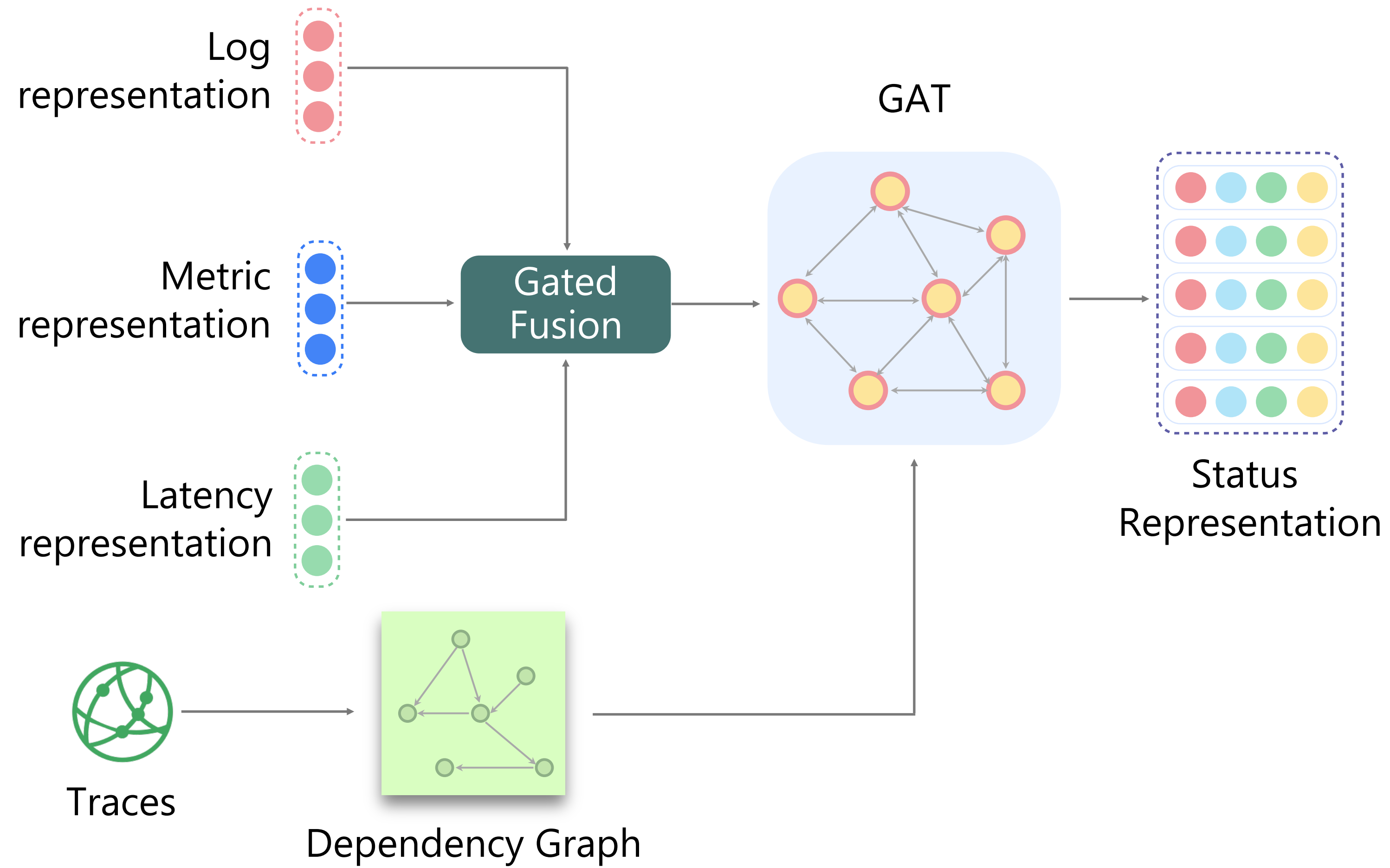


Causal Conv
Self-Attn

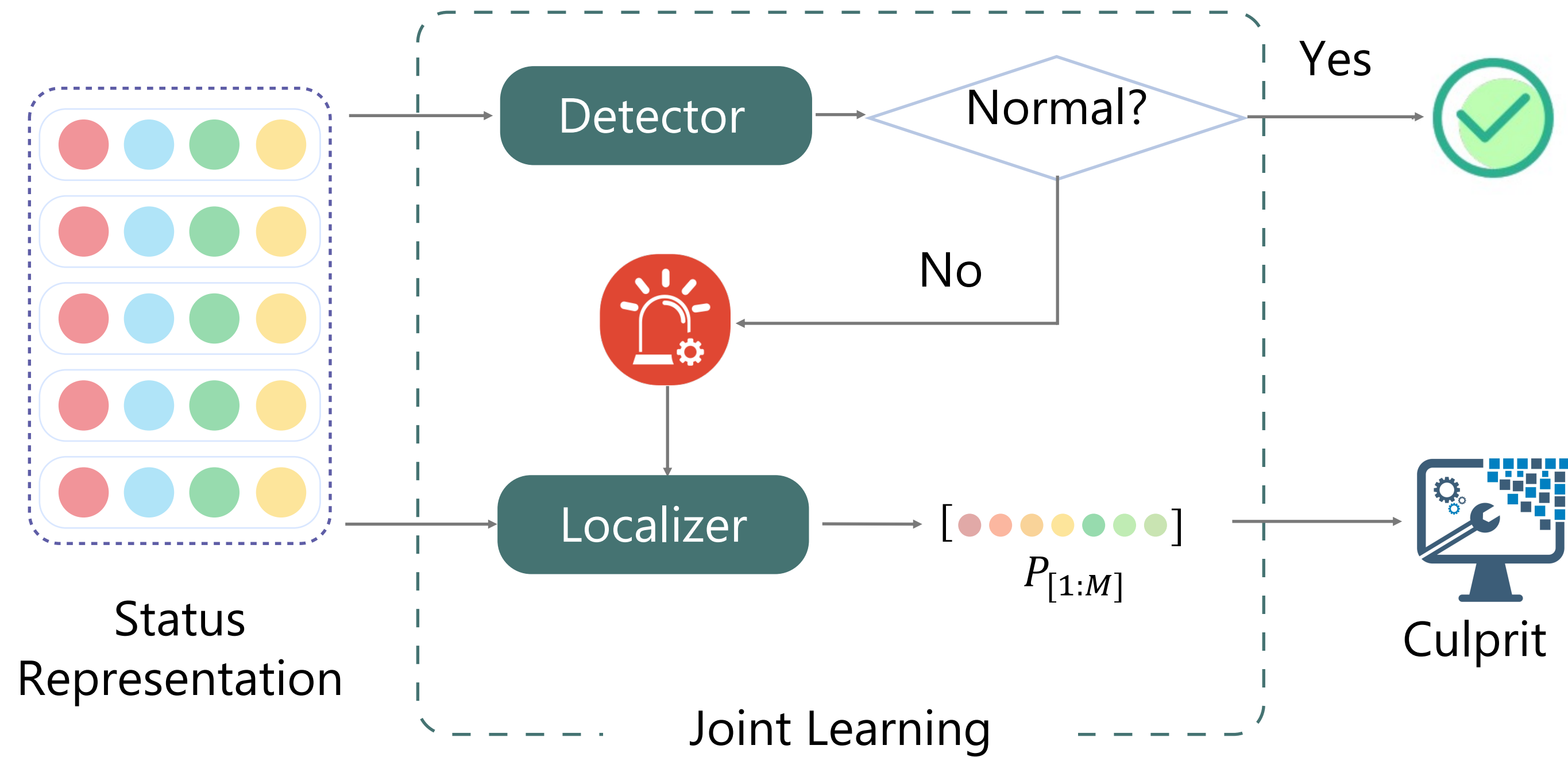


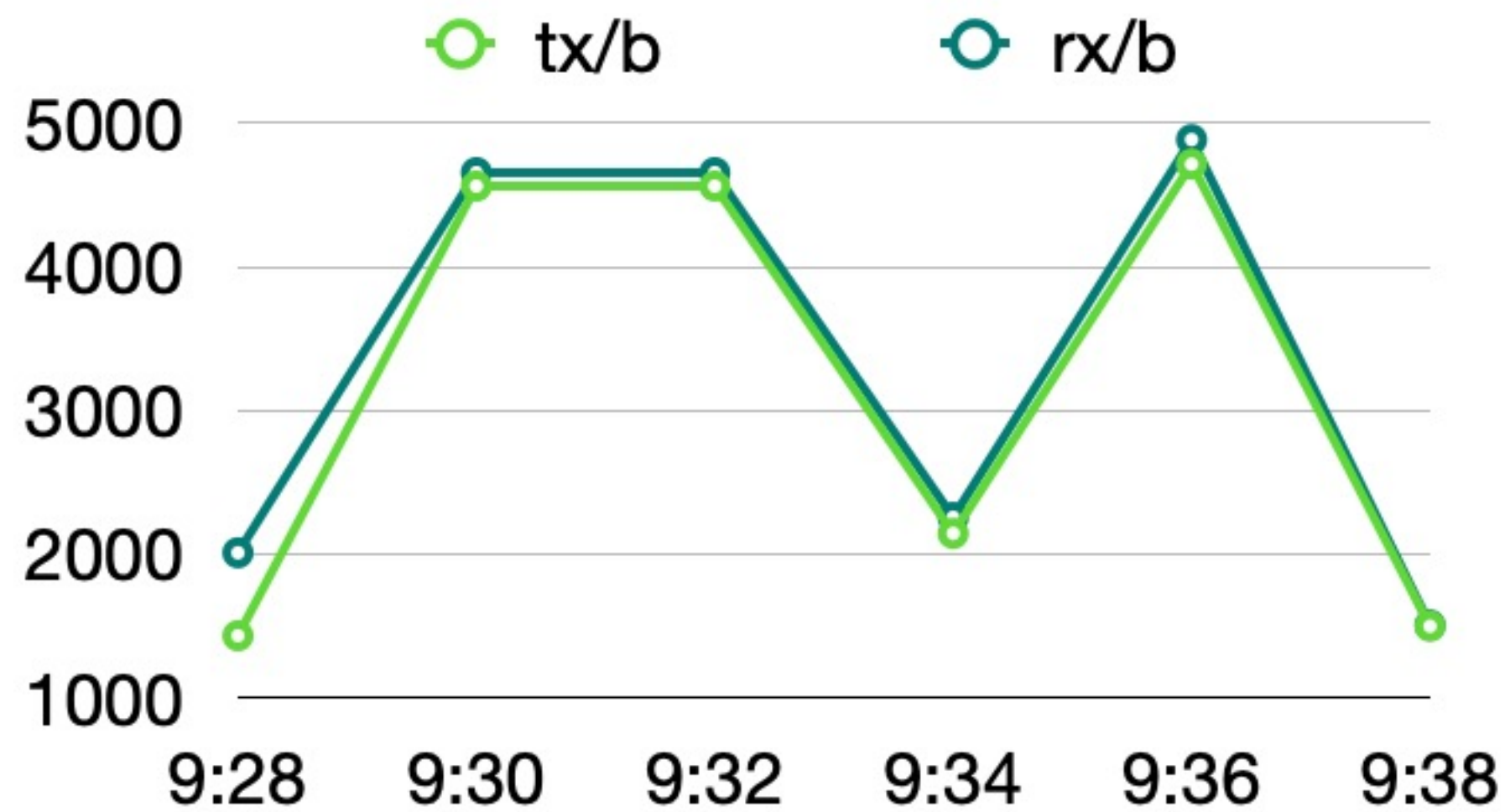
Latency representation

2 Dependency-aware Status Learning




3 Detection & Localization

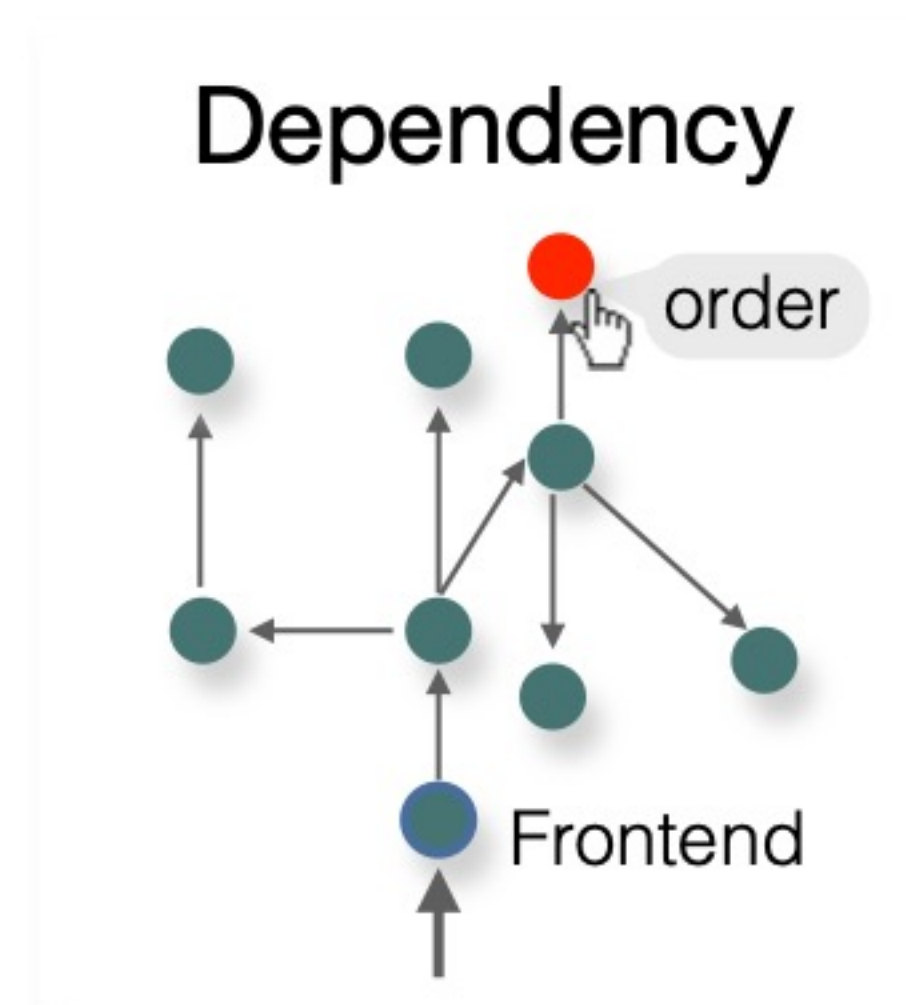




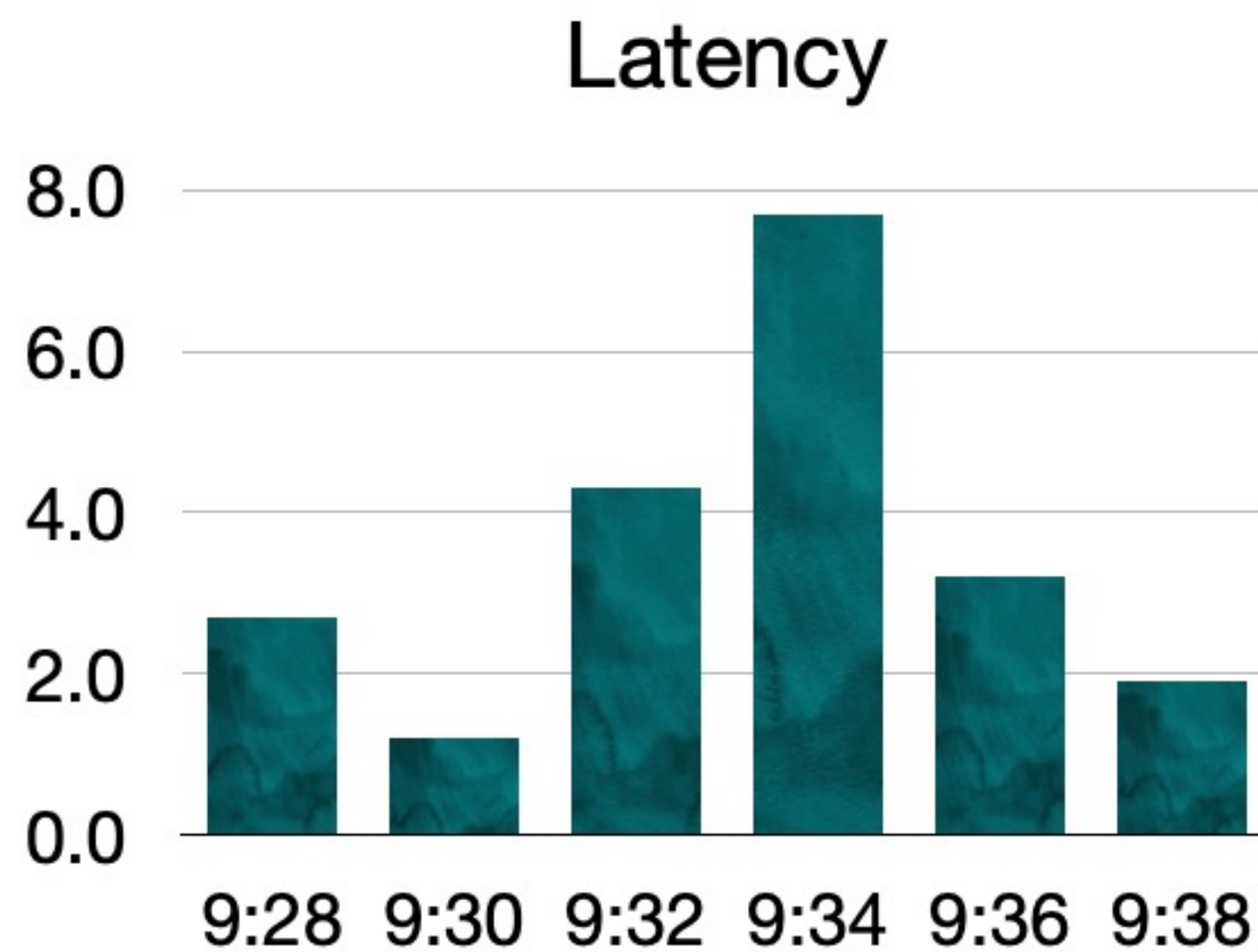
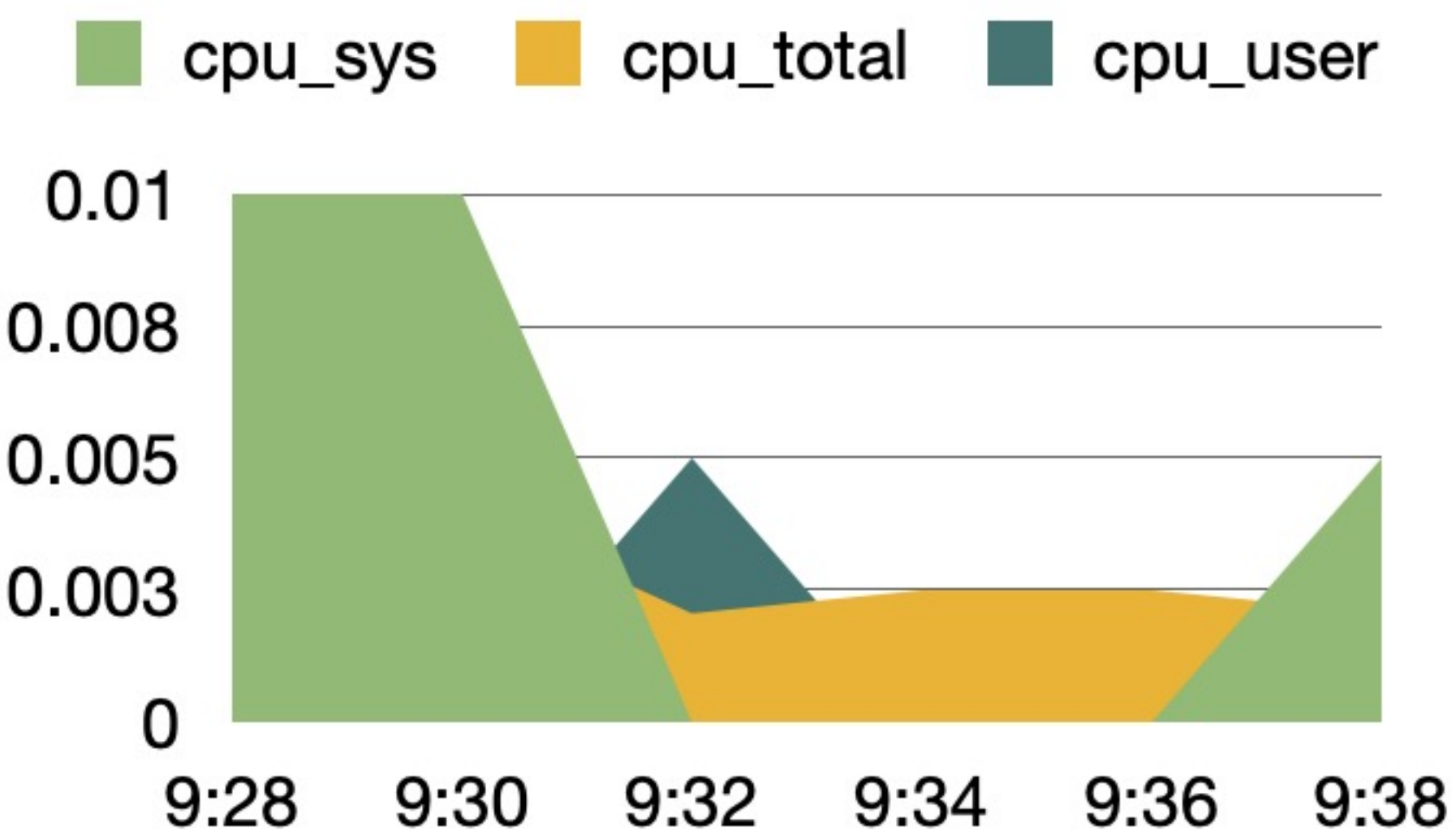
Frequency: 2T



ts-order-service




Log File Download



Root Cause List

Service	Probability
order	0.972
preserve	0.087
security	0.011
frontend	0.010



Trace File Download

An aerial photograph of a dense urban skyline, likely Hong Kong, during the 'blue hour'. The sky is a deep, hazy blue, and the city lights are beginning to glow. In the foreground, a lush green forested hillside rises up to the base of the buildings. The middle ground is filled with a variety of high-rise structures, including residential towers and commercial skyscrapers. Some buildings have distinctive architectural features, like a tall, thin tower with a blue facade and another with a white 'X' pattern. The background shows a wide body of water, possibly a harbor, with more distant city lights and structures visible across the water. A large, white, semi-circular graphic element is superimposed over the center of the image, framing the text.

04 EVALUATION



RQ1: How effective is Eadro in anomaly detection?



RQ2: How effective is Eadro in root cause localization?



RQ3: How much does each data source contribute?

RQ1: Effectiveness in AD

Eadro improves F1-score by 53.82%~92.68% compared to baselines and 3.13%~25.32% compared to derived methods.

PERFORMANCE COMPARISON FOR ANOMALY DETECTION

Approaches	$\mathcal{T}\mathcal{T}$			$\mathcal{S}\mathcal{N}$		
	$F1$	Rec	Pre	$F1$	Rec	Pre
TraceAnomaly	0.486	0.414	0.589	0.539	0.468	0.636
MultimodalTrace	0.608	0.576	0.644	0.676	0.632	0.726
MS-RF-AD	0.817	0.705	0.971	0.773	0.866	0.700
MS-SVM-AD	0.787	0.678	0.938	0.789	0.770	0.808
MS-LSTM	0.967	0.997	0.940	0.948	0.959	0.937
MS-DCC	0.965	0.993	0.938	0.948	0.962	0.934
Eadro	0.989	0.995	0.984	0.986	0.996	0.977

RQ2: Effectiveness in RCL

Eadro increases Top-1 Hit Rate by 290%~5068% than baselines and 26.93%~66.16% than the derived methods.

PERFORMANCE COMPARISON FOR ROOT CAUSE LOCALIZATION

Approaches	$\mathcal{T}\mathcal{T}$					$\mathcal{S}\mathcal{N}$				
	$HR@1$	$HR@3$	$HR@5$	$NDCG@3$	$NDCG@5$	$HR@1$	$HR@3$	$HR@5$	$NDCG@3$	$NDCG@5$
TBAC	0.037	0.111	0.185	0.079	0.109	0.001	0.085	0.181	0.048	0.087
NetMedic	0.094	0.257	0.425	0.195	0.209	0.069	0.187	0.373	0.146	0.218
MonitorRank	0.086	0.199	0.331	0.142	0.196	0.068	0.118	0.221	0.095	0.137
CloudRanger	0.101	0.306	0.509	0.218	0.301	0.122	0.382	0.629	0.269	0.370
DyCause	0.231	0.615	0.808	0.448	0.607	0.273	0.636	0.727	0.301	0.353
MS-RF-RCL	0.637	0.922	0.970	0.807	0.827	0.704	0.908	0.970	0.825	0.851
MS-SVM-RCL	0.541	0.908	0.944	0.814	0.820	0.614	0.838	0.955	0.741	0.790
MS-LSTM	0.756	0.930	0.969	0.859	0.877	0.757	0.884	0.907	0.834	0.844
MS-DCC	0.767	0.938	0.972	0.870	0.882	0.789	0.968	0.985	0.898	0.905
Eadro	0.990	0.992	0.993	0.994	0.994	0.974	0.988	0.991	0.982	0.983

RQ3: Usefulness of Each Data Source



All of the involved data sources can all contribute to Eadro, and traces contribute the most.

EXPERIMENTAL RESULTS OF THE ABLATION STUDY

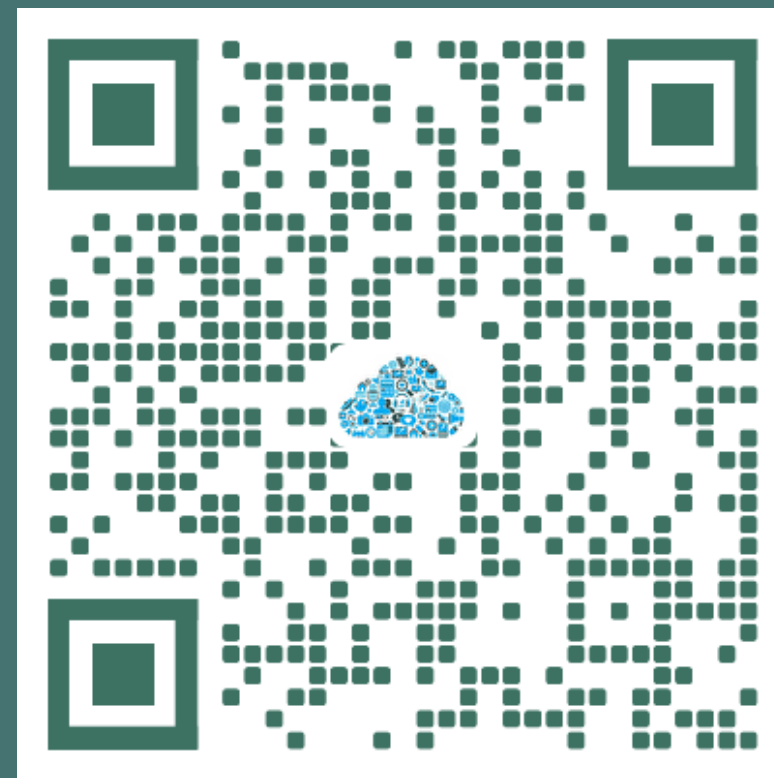
Variants	$\mathcal{T}\mathcal{T}$			$\mathcal{S}\mathcal{N}$		
	$HR@1$	$HR@5$	$F1$	$HR@1$	$HR@5$	$F1$
Eadro	0.990	0.993	0.989	0.974	0.991	0.986
Eadro w/o \mathcal{L}	0.926	0.993	0.964	0.902	0.954	0.972
Eadro w/o \mathcal{M}	0.776	0.962	0.960	0.684	0.947	0.974
Eadro w/o \mathcal{T}	0.785	0.930	0.945	0.627	0.930	0.957
Eadro w/o \mathcal{G}	0.803	0.982	0.970	0.791	0.960	0.946

THANKS

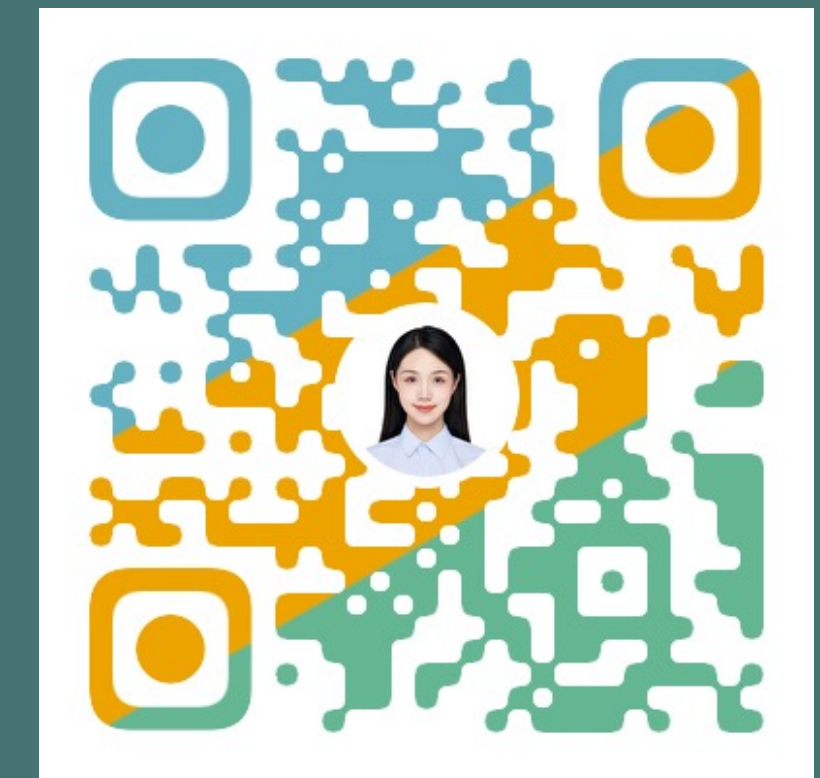
Presenter: Cheryl LEE



Arise Lab



Full Paper



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