Cornell University
Computer Systems Laboratory

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SAGE: PRACTICAL AND SCALABLE ML-DRIVEN PERFORMANCE DEBUGGING IN MICROSERVICES

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ASPLOS 2021 - Session 4: Microservices
@ 4:30 – 4:45 PM PDT, April 19th, 2021

Executive Summary

- **Motivation**
  - Microservices become increasingly popular in cloud systems
  - Service-level objectives (SLOs) govern interactive microservices
- **Challenges in microservice performance debugging**
  - ML outperforms traditional heuristics
- **Sage: Root cause analysis system using unsupervised learning**
  - Use Causal Bayesian Networks for causal relationships among microservices
  - Use counterfactuals to detect root causes (services and resources) of SLO violations

BACKGROUND: MICROSERVICES

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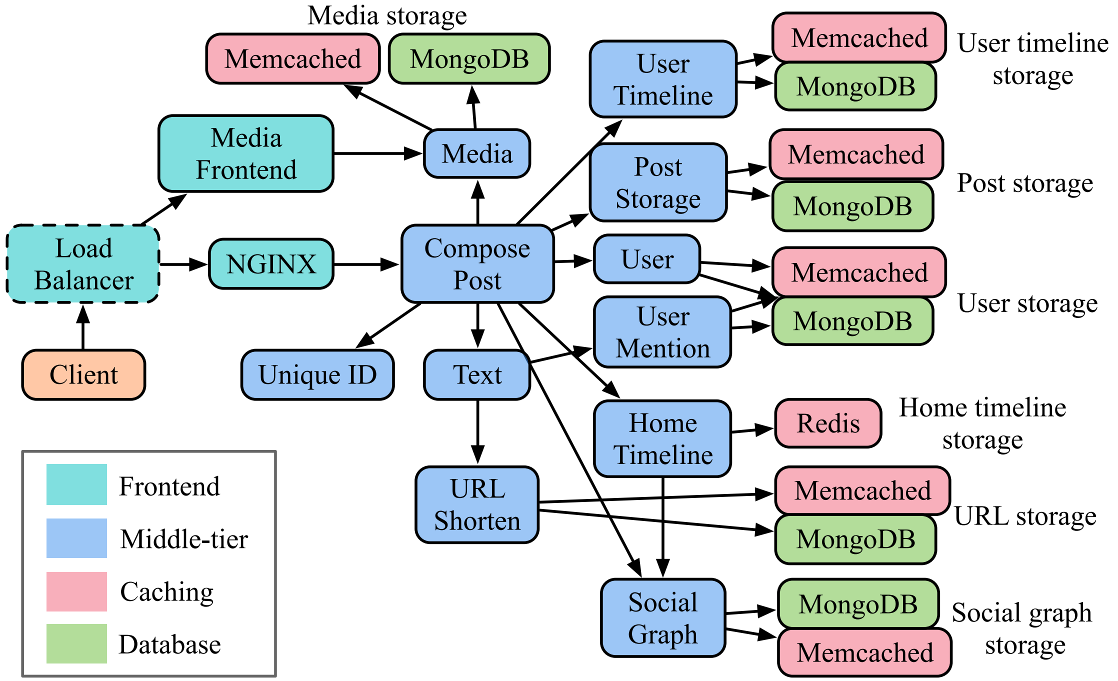
- **Microservices**
  - Fine-grained, loosely-coupled, and single-concerned
  - Communicate with RPCs or RESTful APIs
  - SLOs: tail latency, availability, …
- **Pros**
  - Agile development
  - Better modularity & elasticity
  - Testing and debugging in isolation
- **Cons**
  - Different hardware & software constraints
  - Dependencies → complicate cluster management



Social Network

[1] Yu Gan et al. "An Open-Source Benchmark Suite for Microservices and Their Hardware-Software Implications for Cloud and Edge Systems", *ASPLOS 2019*

BACKGROUND: MICROSERVICES

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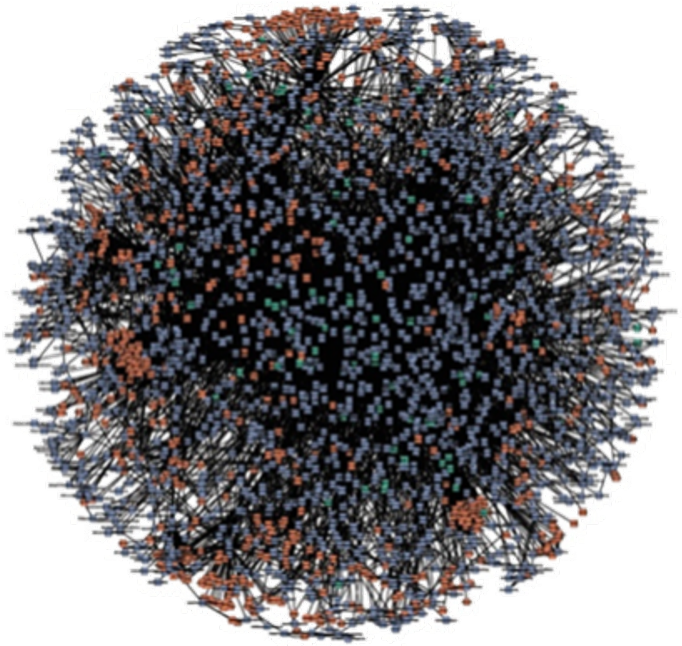

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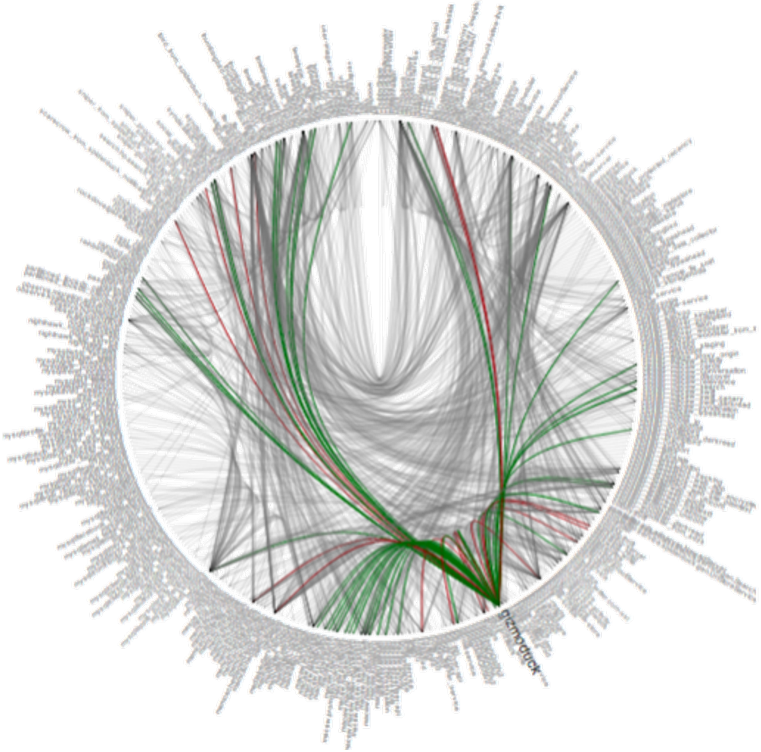

Challenges of Microservice Perf Debugging

- **Microservices are more sensitive to performance unpredictability[1]**
- **Complex network dependencies[1]**
  - Hotspots can propagate
  - Difficulty in locating the root cause
- **Complex tracing and monitoring**
  - Requires end-to-end tracing and aggregation
  - Millions of timeseries over a long period of time
  - Complicates performance debugging, but makes data-driven methods possible

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PREVIOUS STUDIES

- **Previous work**
  - CauseInfer[1] [INFOCOM'14]
  - Microscope[2] [ICSOC'18]

  Detect root cause with PC-algorithm
  - Seer[3] [ASPLOS'19]: Proactive root cause detection system

- **Limitations:**
  - PC-algorithm: Poor scalability, prone to statistical errors
  - Seer: Requires data labeling, high-precision time series & kernel-level tracing

[1] P. Chen, Y. Qi, P. Zheng, and D. Hou, "Causeinfer: Automatic and distributed performance diagnosis with hierarchical causality graph in large distributed systems," INFOCOM 2014
[2] J. Lin, P. Chen, and Z. Zheng, "Microscope: Pinpoint performance issues with causal graphs in micro-service environments," *ICSOC 2019*
[3] Y. Gan, Y. Zhang, K. Hu, Y. He, M. Pancholi, D. Cheng, and C. Delimitrou, "Seer: Leveraging Big Data to Navigate the Complexity of Performance Debugging in Cloud Microservices," *ASPLOS 2019*

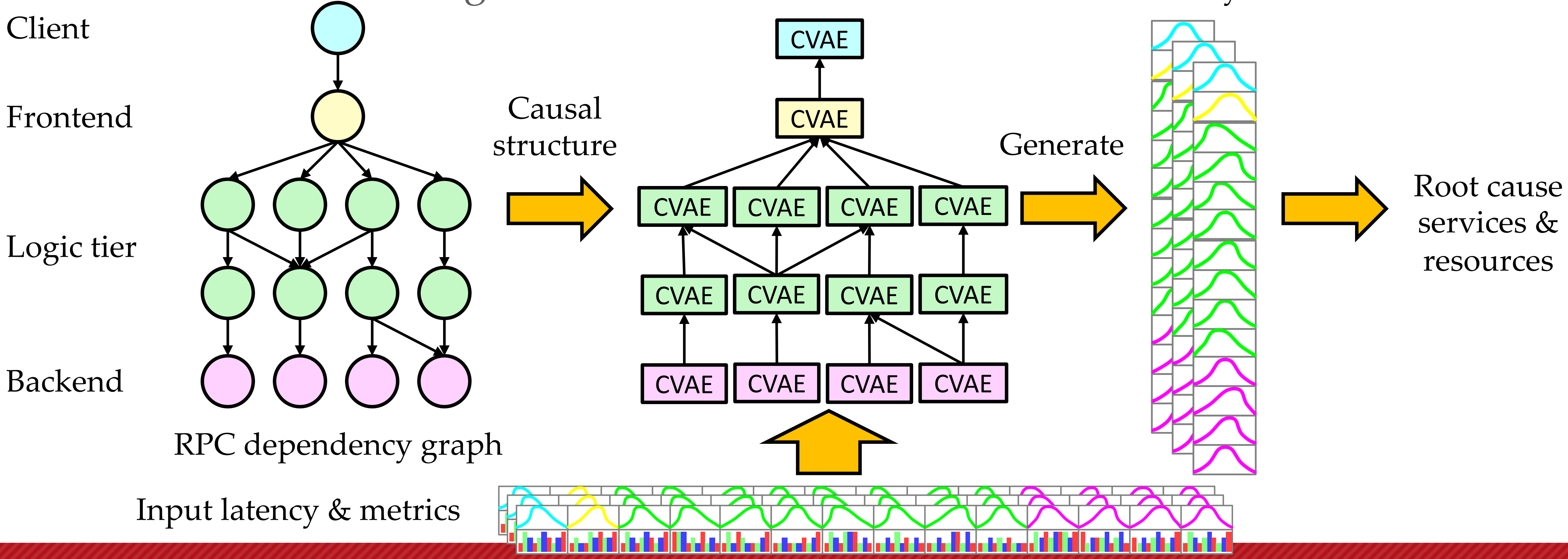
Design Principles of Sage

- **No need to label data**
  - Challenge: correlation does not imply causation
  - Requires a causal model
- **Robust to sampling frequency**
  - Suitable for instrumentation in production
  - Not using temporal patterns for inference
- **No need for kernel-level tracing**
- **Practical adjustment to service updates**

- **Focuses on resource provisioning-related performance issues**

Overview of Techniques

- **Approach:**
  - Causal Bayesian network (CBN) modeling
  - Causal inference with generated counterfactuals



Causal Bayesian Network Modeling

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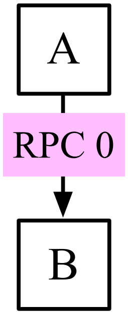
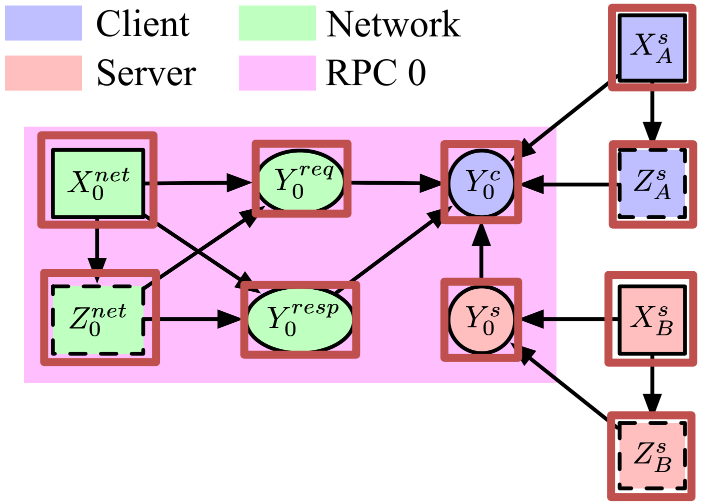
- **Causal Bayesian Network (CBN)**
  - A probabilistic graphical model where edges indicate causal relationships
- **Reason for using CBN modeling**
  - A tool for structural causal inference
  - Interpretable and explainable

Nodes in the CBN

- **Service, node and network metrics (*X* nodes)**
  - Service and node metrics: CPU, memory, disk
  - Network metrics
- **RPC and network latency (*Y* nodes)**
  - Client- & server-side latency, request and response network delay
- **Latent variables (*Z* nodes)**
  - Unobservable or immeasurable
  - Assumed multivariate Gaussian distribution

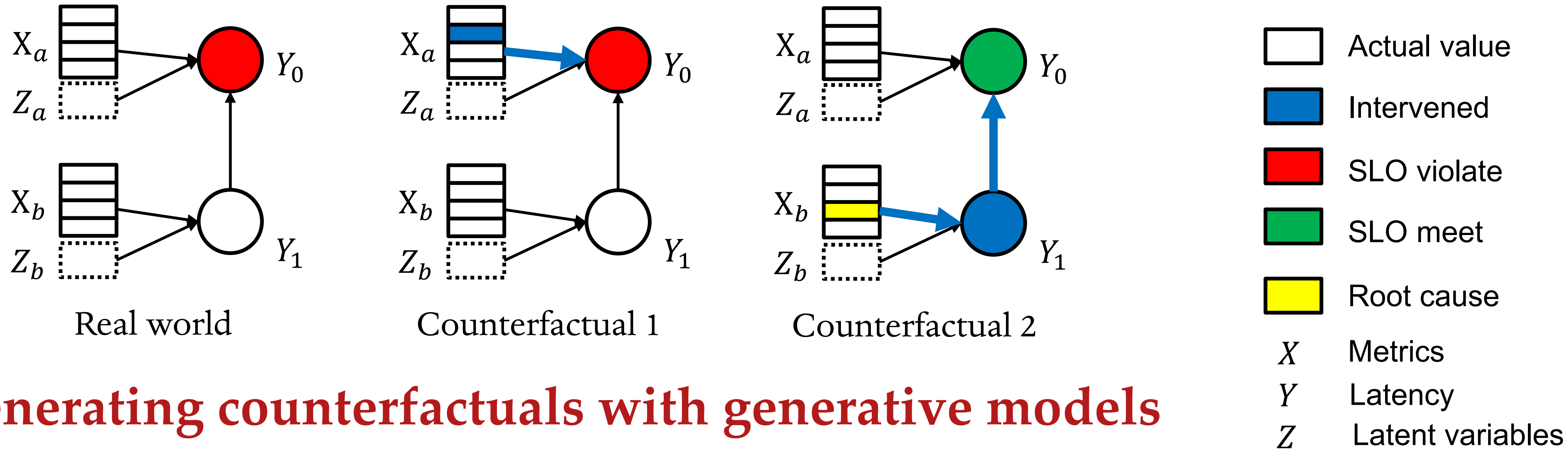




CBN of two services

Causal Inference with Counterfactuals

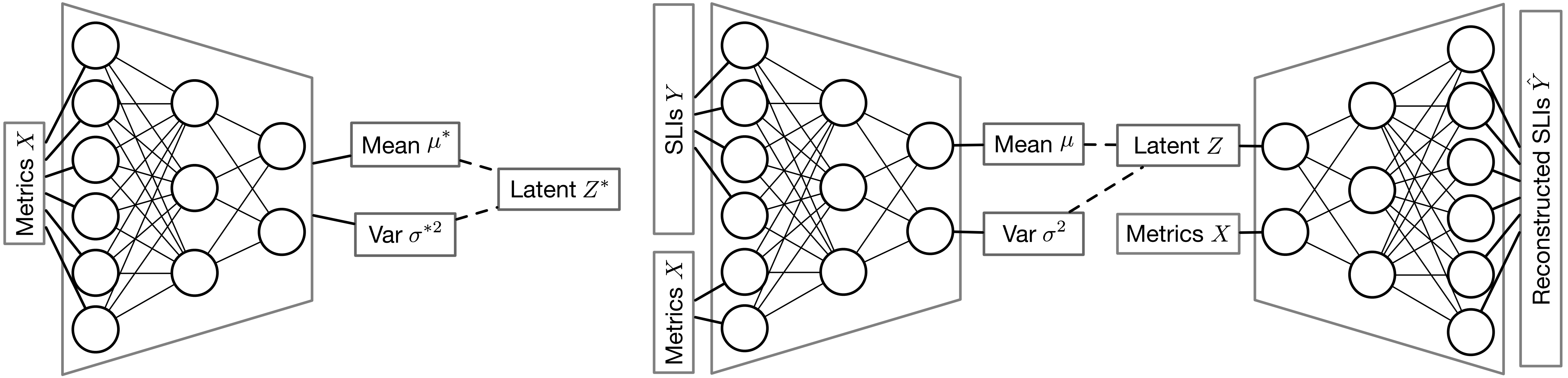
- **Counterfactual queries**
  - Queries of hypothetical end-to-end latency if some metrics had been "normal"
  - Root causes: metrics that hypothetically solve the end-to-end performance issue



- **Generating counterfactuals with generative models**

Conditional Variational Autoencoder (CVAE)

- **Prior network:** Learn prior distribution $p_\psi(Z \mid X)$
- **Encoder:** Learn posterior distribution $q_\theta(Z \mid X, Y)$
- **Decoder:** Reconstruct input SLI data by $p_\varphi(Y \mid X, Z)$ with Z sampled from posterior distribution
- **Loss function:** $L_{CVAE} = \underbrace{-\mathbb{E}_{Z \sim q_\theta(Z|X,Y)}\left[\log p_\varphi(Y \mid X, Z)\right]}_{\text{Reconstruction loss}} + \underbrace{\beta \cdot D_{KL}[q_\theta(Z \mid X, Y) \parallel p_\psi(Z \mid X)]}_{\text{KL divergence regularization}}$



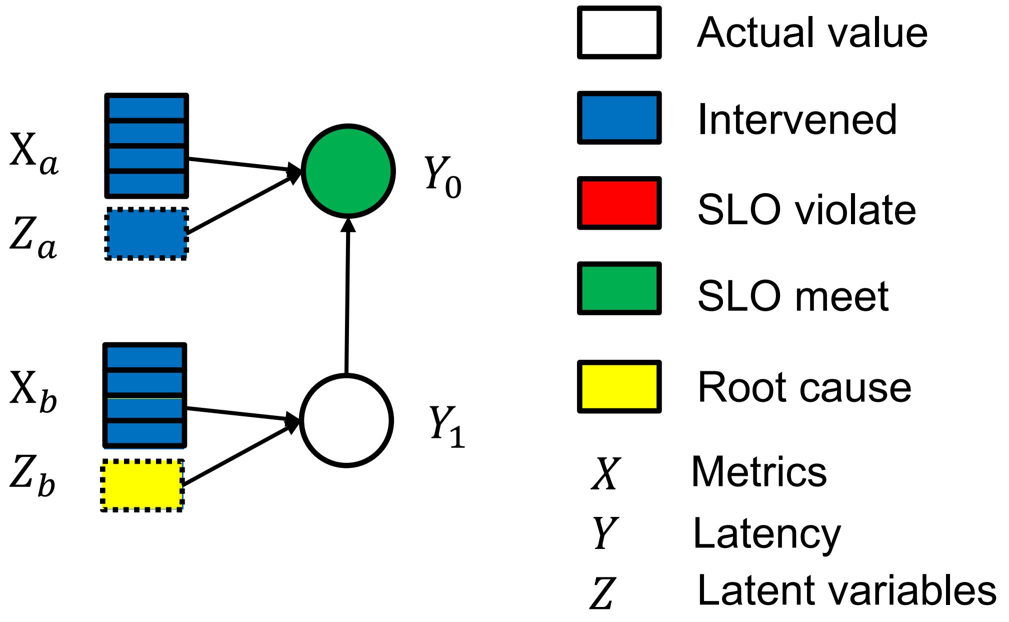
Prior network $p_\psi(Z \mid X)$ Encoder $q_\theta(Z \mid X, Y)$ Decoder $p_\varphi(Y \mid X, Z)$

Graphical Variational Autoencoder (GVAE)

- **GVAE - factorizing CVAE according to the CBN model**
  - Factorization of the loss function: $L_{GVAE} = \sum L_{CVAE}$
  - One encoder and prior network for each service & network channel
  - One decoder for each RPC
  - Decoder connections are determined by the **information flow** in the CBN
- **Benefits of using GVAE**
  - Connection pruning to enforce the network to follow the causal model
  - Better interpretability
  - Faster retraining upon microservice updates

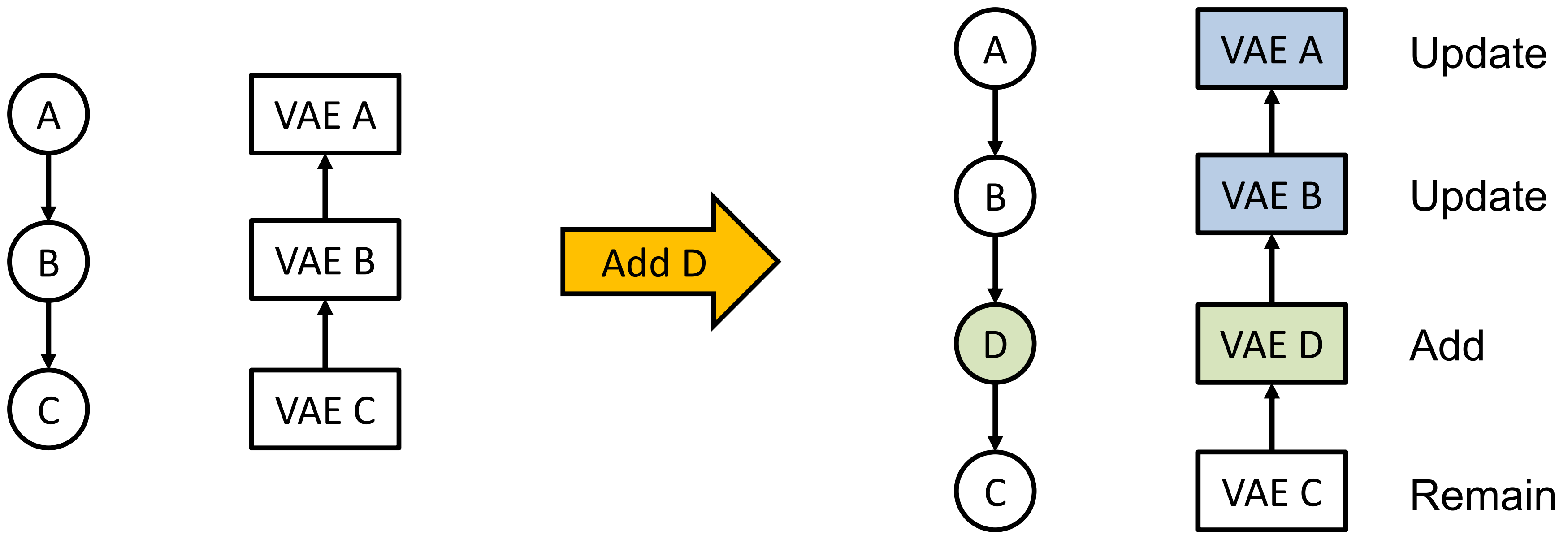
Root Cause Detection with GVAE

- **Learn the latent variables (Z) from the encoder**
- **Calculate "normal" values of metrics and latent variables**
  - Median value among normal traces
- **Two-level intervention for root cause detection**
  - Locate culprit services
  - Locate culprit resource



Incremental & Partial Retraining

- **Microservices updated frequently**
  - Services added, removed & updated
- **Incremental & partial retraining**
  - Only retrain upstreaming services affected by the updates



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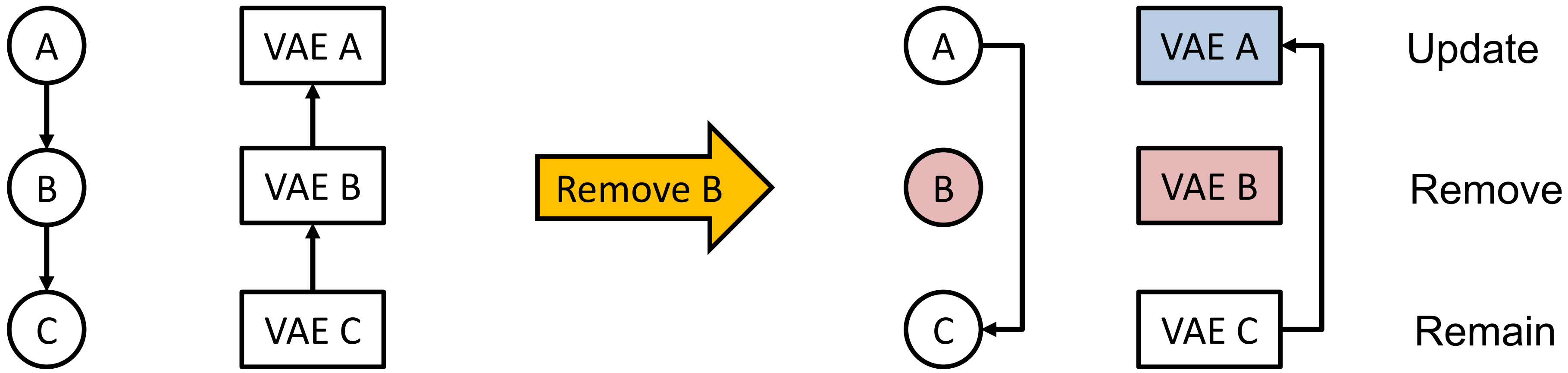

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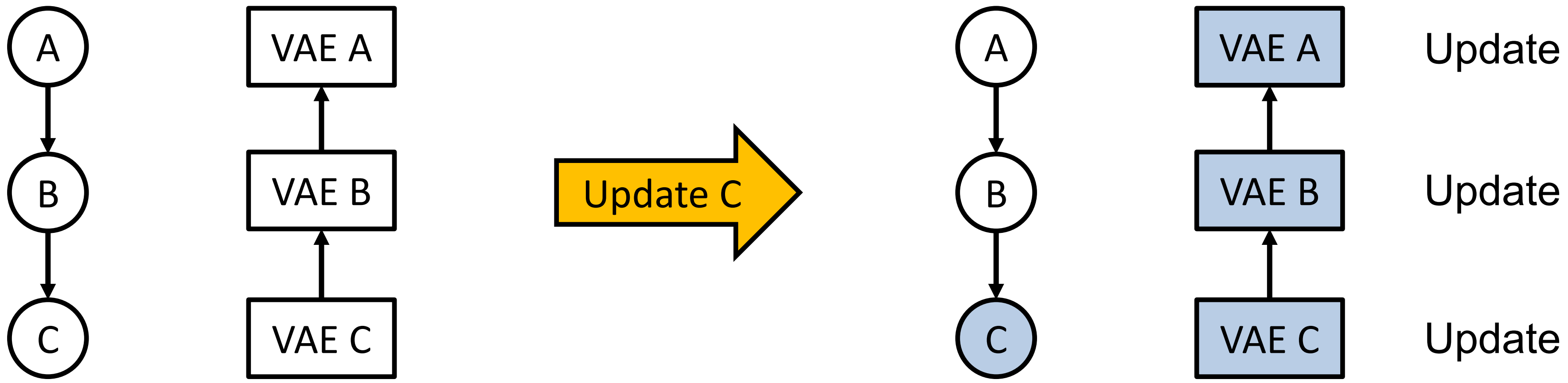
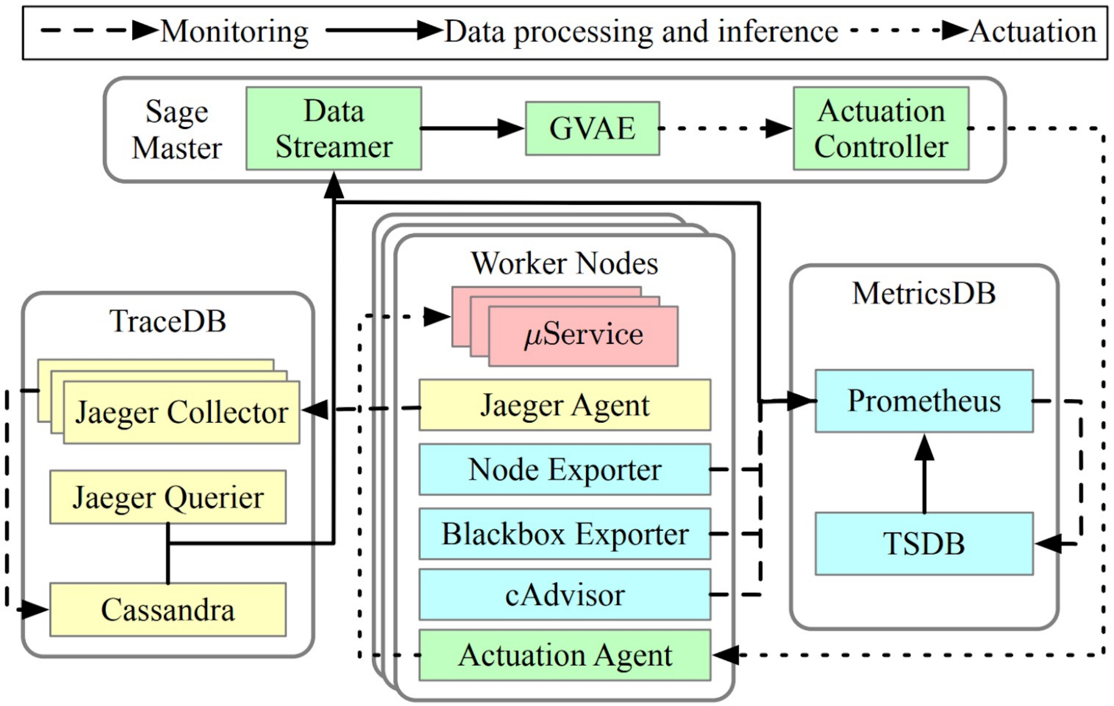


System Design

- **Monitoring**
  - Jaeger and Prometheus for collecting traces & performance metrics
- **Data collection**
  - Preprocessing, normalization
- **GVAE model**
  - Implemented with PyTorch
- **Actuation**
  - Scale up/out, CAT, network BW partitioning



System overview

EVALUATION

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- **Methodology**
  - Applications
    - » Synthetic Thrift chain and fanout services
    - » DeathstarBench[1]
  - Systems
    - » Local cluster: 2-socket 40-core servers with 128GB RAM and 2-socket 88-core servers with 188GB RAM each
    - » Google Compute Engine: 84 nodes with 4-64 cores, 4-64GB RAM and 20-128GB SSD
  - Baselines and prior work
    - » Autoscaling and Offline Oracle
    - » CauseInfer[2] and Microscope[3]
    - » Seer[4]

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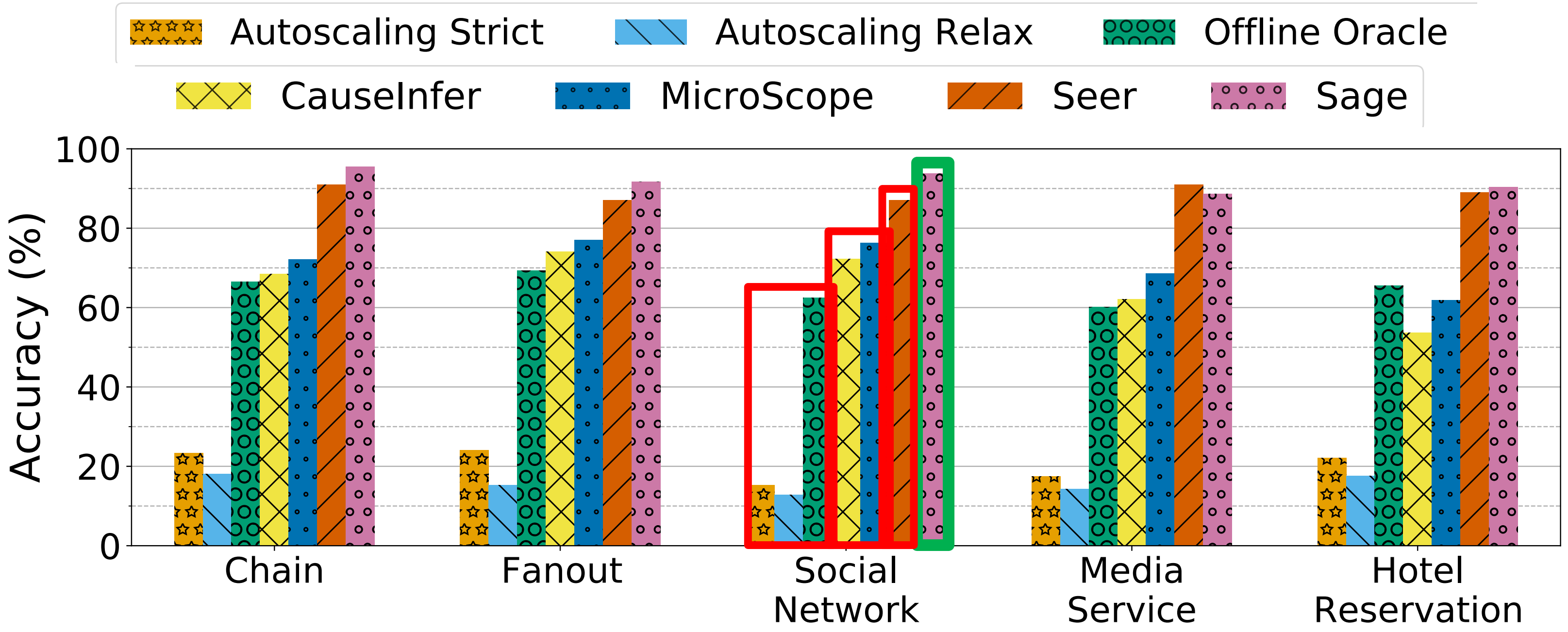
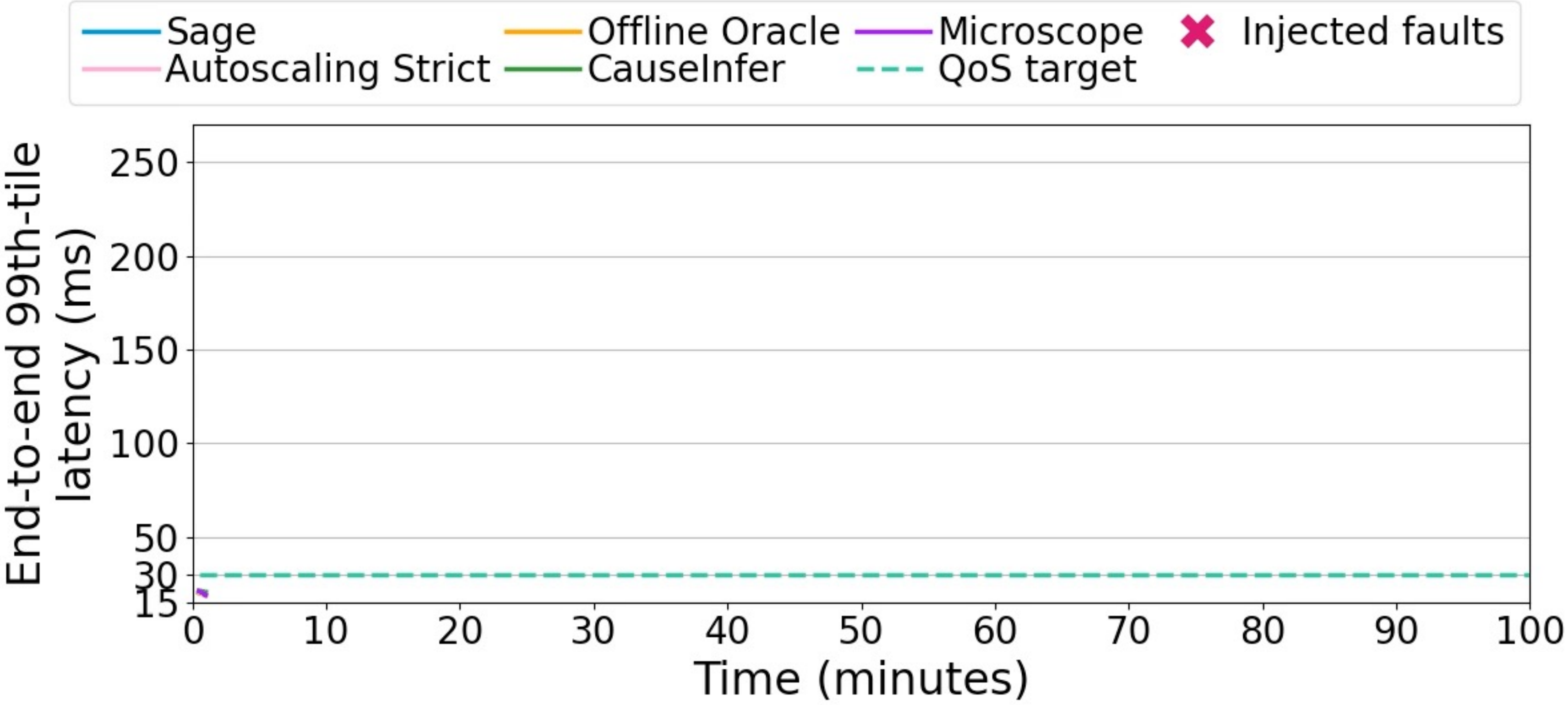
Evaluation

- **Accuracy of detecting root cause**
  - Sage has 88%-95% accuracy across five applications
  - CauseInfer and Microscope have low accuracy due to errors in finding causal relationships with PC-algorithm
  - Seer has similar accuracy, but Sage needs less information

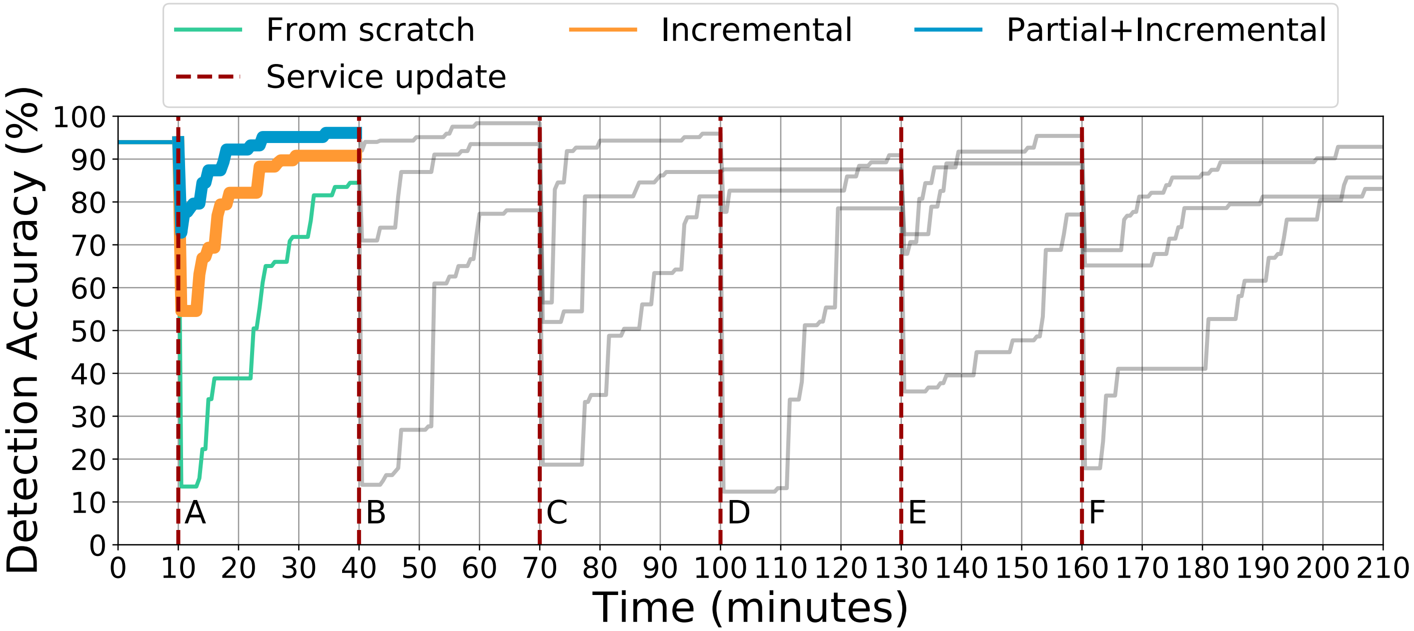


- **Actuation**
  - Sage resolves SLO violations fast
  - Because of false negatives, other methods cannot always resolve the issue



EVALUATION

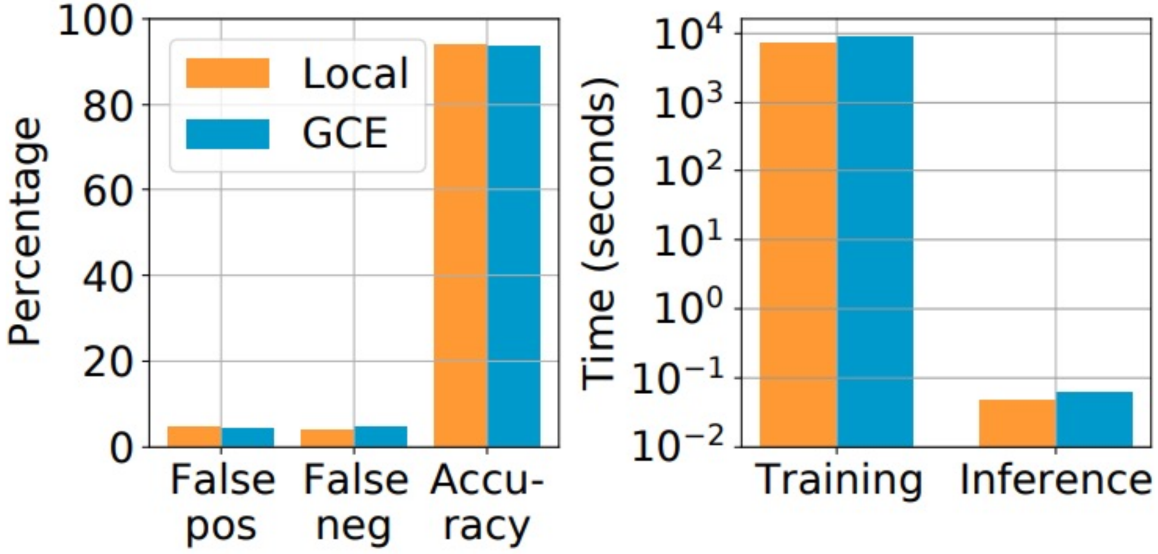
- **Incremental & partial retraining**
  - Less accuracy drop & faster convergence
  - Incremental retraining: reusing neural network parameters
  - Partial retraining: updating subset of neurons



A: One service added at frontend
B: One service updated
C: One service removed
D: One service added at backend
E: Multiple services added, updated, and removed
F: More services added, updated, and removed

EVALUATION

- **Scalability on GCE**
  - 84 nodes with 4-64 cores, 4-64GB RAM and 20-128GB SSD
  - 6.7x more containers
  - Comparable accuracy with local runs
  - 19.4% increase in training time and 26.5% increase in inference time
    - » Collecting distributional data across replicas



Conclusions

- **Performance debugging for microservice is challenging**
- **Sage: Root cause detection system based on unsupervised learning**
  - Causal Bayesian network for modeling causal relationships
  - Counterfactual queries for root cause detection
- **Evaluation with representative microservices**
  - Accurate detection and fast actuation
  - Fast convergence upon service updates
  - Scales well to large clusters on GCE
- **Future work**
  - More types of issues: design bugs, security issues, …

Thank you!

Questions are welcome at Session 4 Q&A Panel

@ 4:45 – 5:00 PM PDT, April 19th, 2021