FIRM: An Intelligent Fine-grained Resource Management Framework for SLO-oriented Microservices

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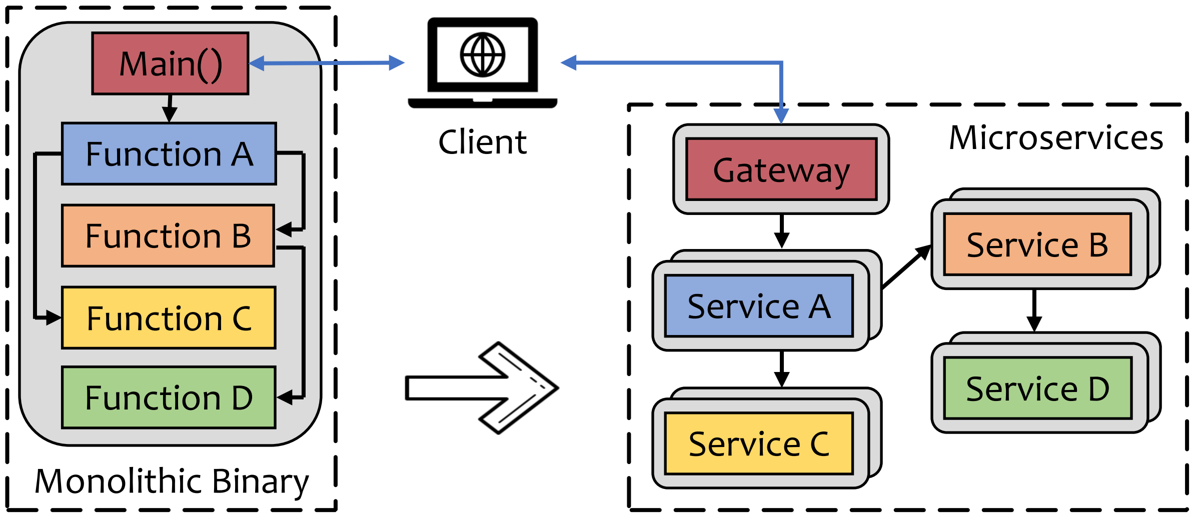
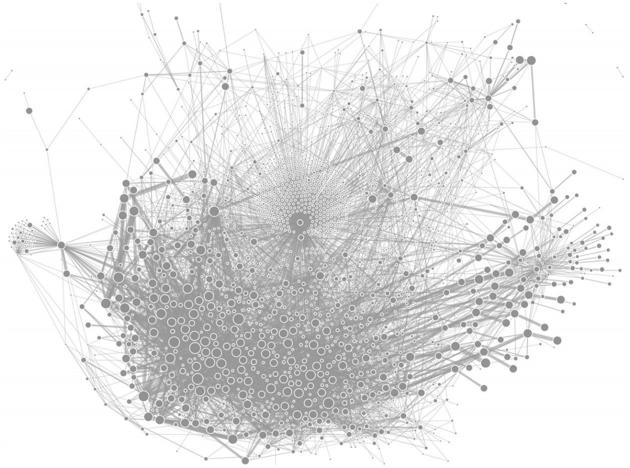
From Monolithic to Microservices

- Microservice architecture growing in popularity
- A set of loosely-coupled, self-concerned "micro" services
  - Scalability, fault isolation, flexibility, etc.
- Scale and complexity are increasing
  - Increasing in scale, e.g. 700+ (Netflix in '17), 1000+ (Uber in '19)
- Performance guarded by service level objectives (SLOs)
  - Violation leads to financial loss (100ms increase converted to $0.7 billion loss in Amazon sales (Q4 '18)





Uber in 2019

Performance Predictability in Microservices is Hard

Challenge #1: Difficulty in isolating root causes of SLO violations

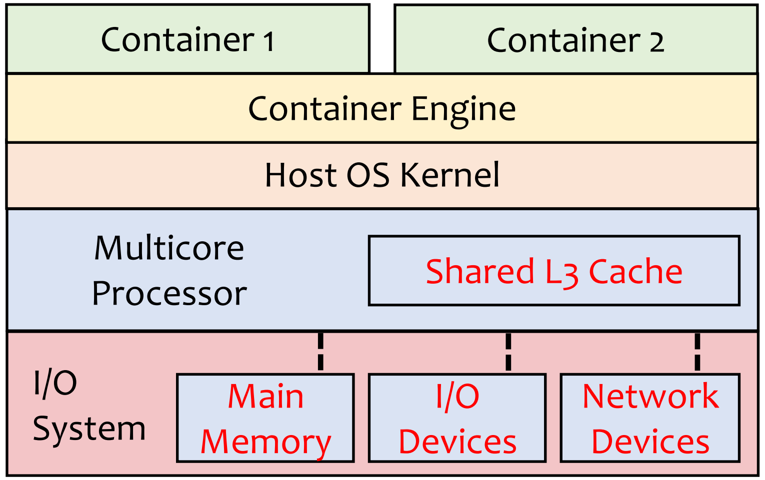
- Complex inter-microservice dependencies cascading SLO violations

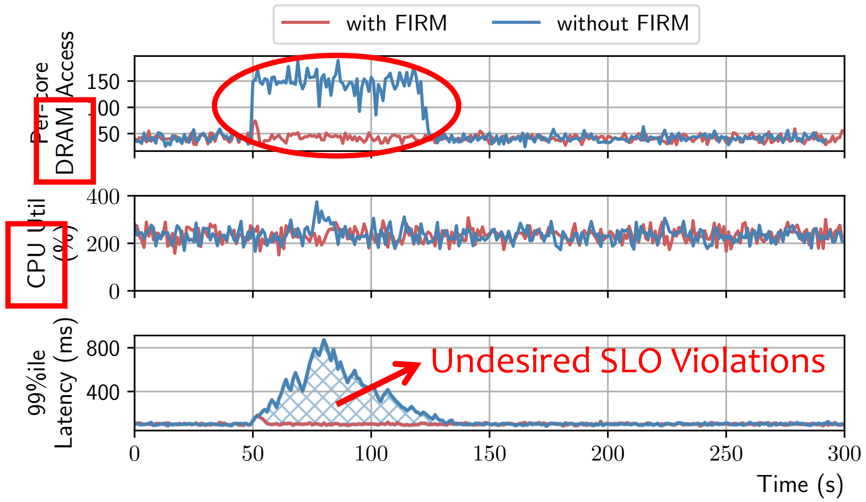
Challenge #2: Inability in capturing shared-resource contention at a lower-level

- Interference over shared resources (e.g. LLC, memory bandwidth, network devices)

Challenge #3: Difficulty in taking the right action to mitigate SLO violations

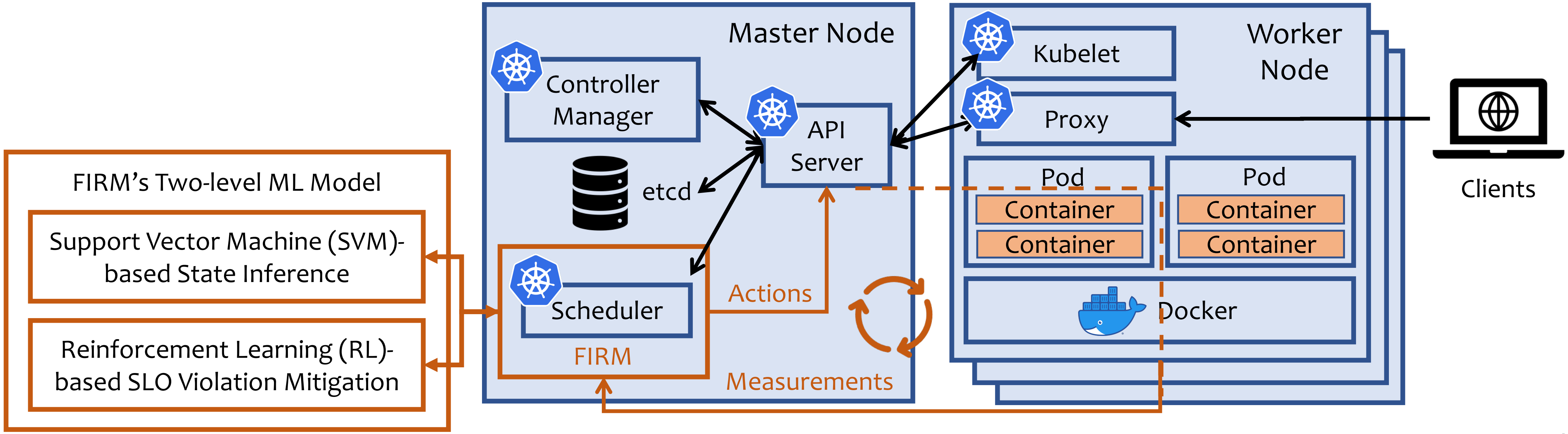
- High fidelity performance models/scheduling heuristics -> significant human-effort and training
- Frequent service updates/migrations -> recurring effort for model reconstruction and re-training





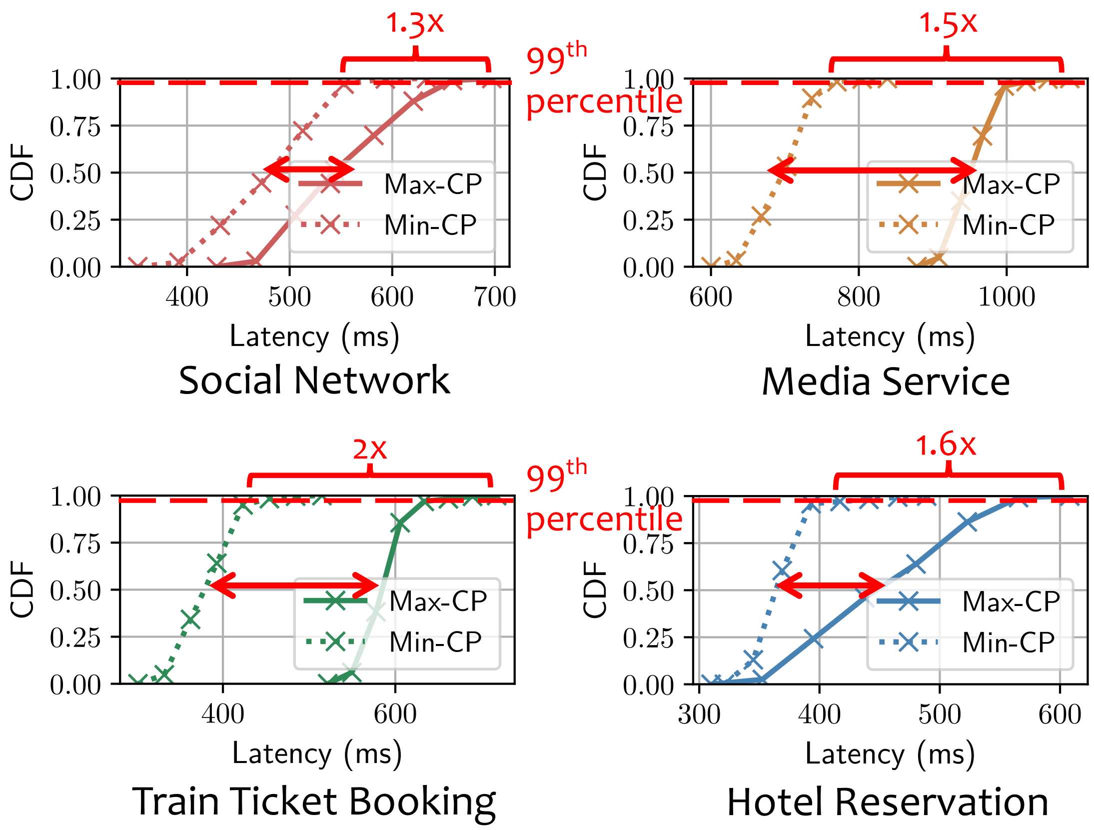
FIRM As The Cure

- Two-level machine learning based SLO violation mitigation framework
  - *Challenge #1* – Detection and localization of SLO violations to individual microservices
  - *Challenge #2 & #3* – Estimation of resources in contention and dynamic resource reprovision
  - Benefits: Improved interpretability and less training time
- Designed, developed, and deployed in a 15-node Kubernetes cluster
- Outperforms Kubernetes autoscaling by up to 16x in reducing SLO violations



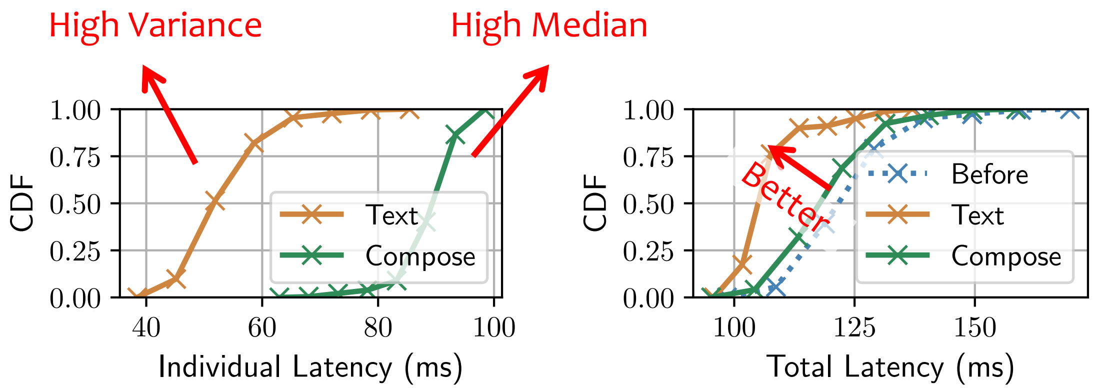
Insight 1: Dynamic Behavior of Critical Paths

- Critical path defines the longest path in execution
- Detection of critical paths helps reveal the bottleneck of performance
- Critical path is not static, but dynamically changing based on the performance of individual service instances
  - Different type of underlying shared-resource contention
  - Different degree of sensitivity to the same type of interference
- It's important to capture the changes at runtime, and make runtime decision



Insight 2: Significance of Latency Variability

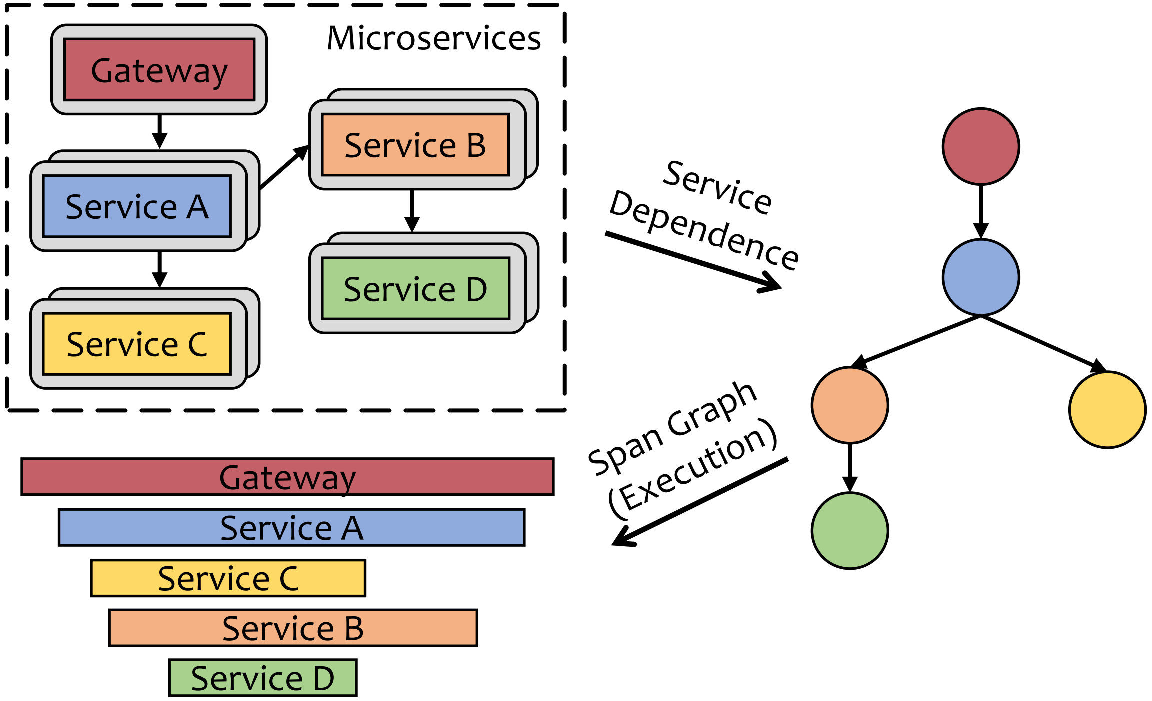
- Microservices with larger latency are not necessarily the root causes of SLO violations
- Processing time with higher variance makes it harder to obtain low tail latency
- Variability represents opportunities for reducing latency

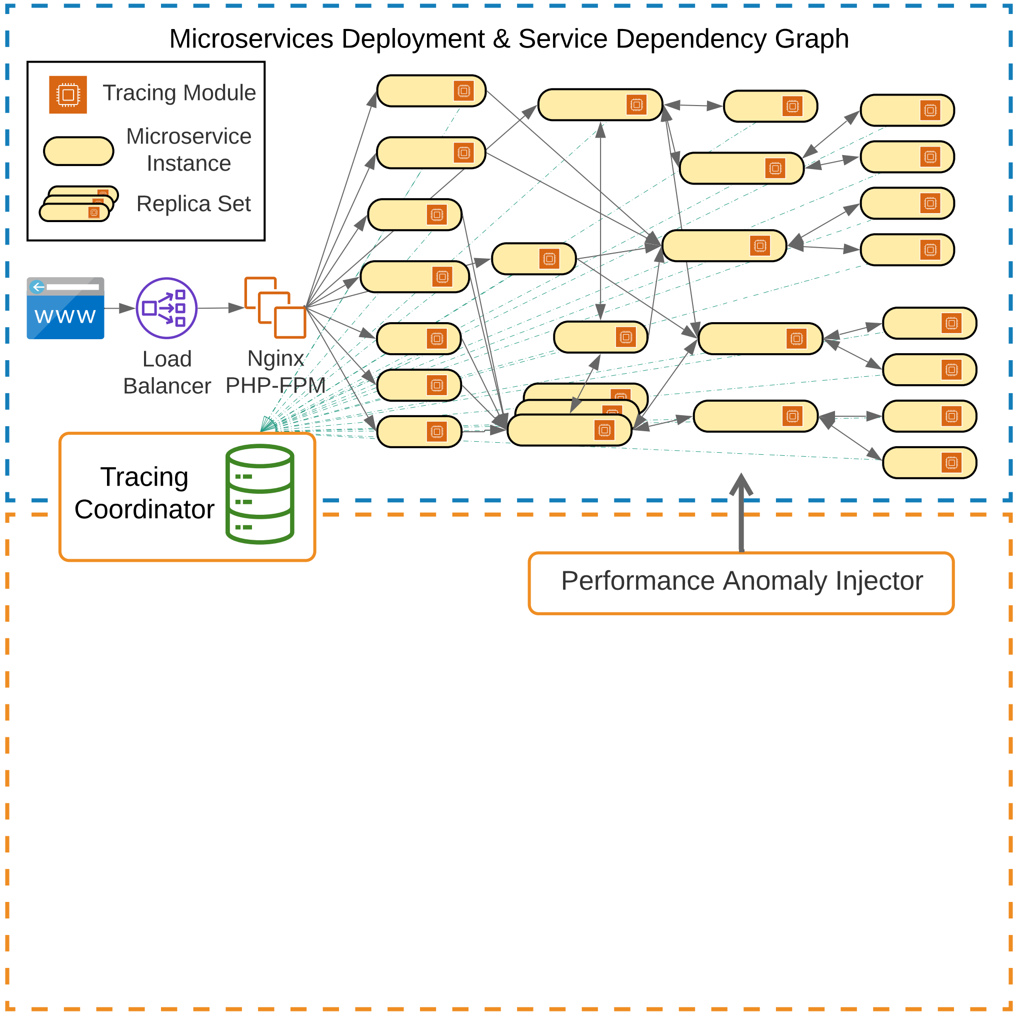


Social Network – Composing Post Request

State Inference (1)

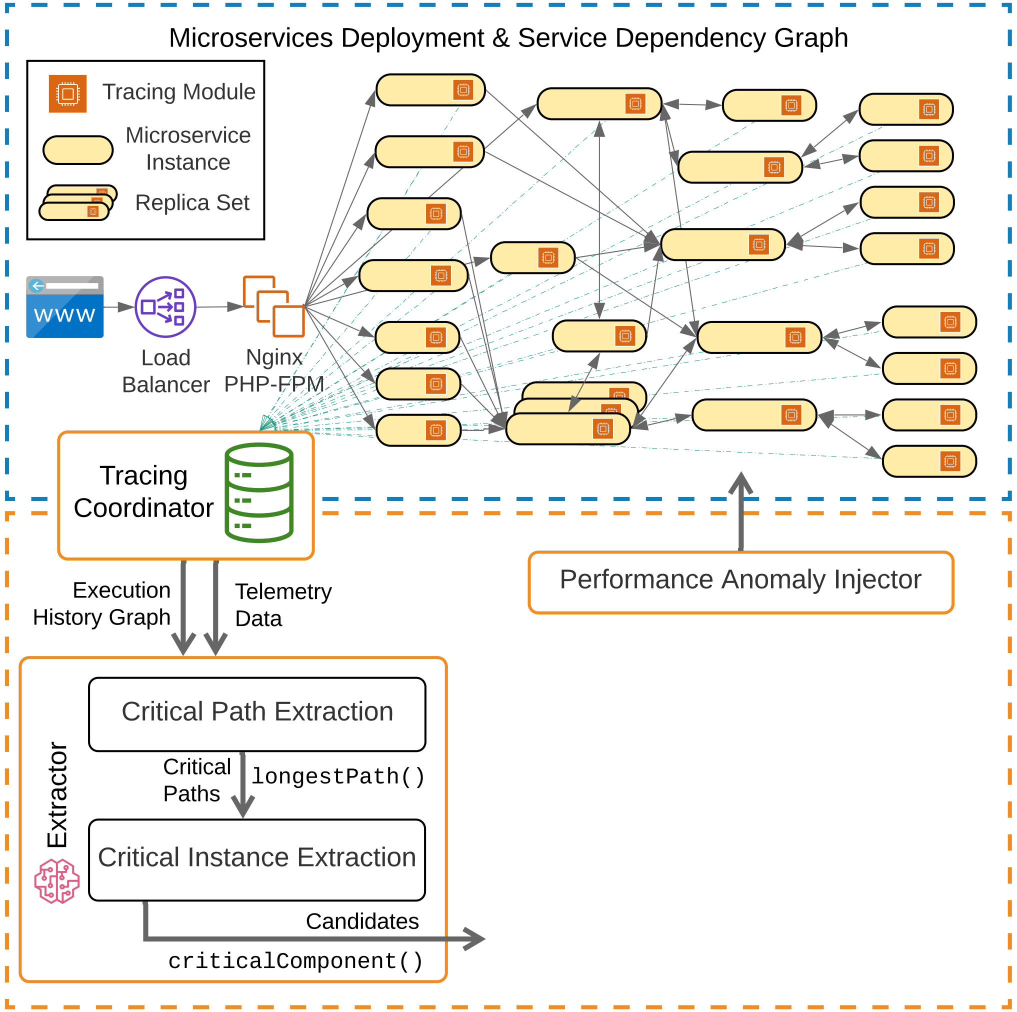
- Real-time observability on request execution provided by end-to-end distributed tracing
- Auto-labeled training data driven by the performance anomaly injection





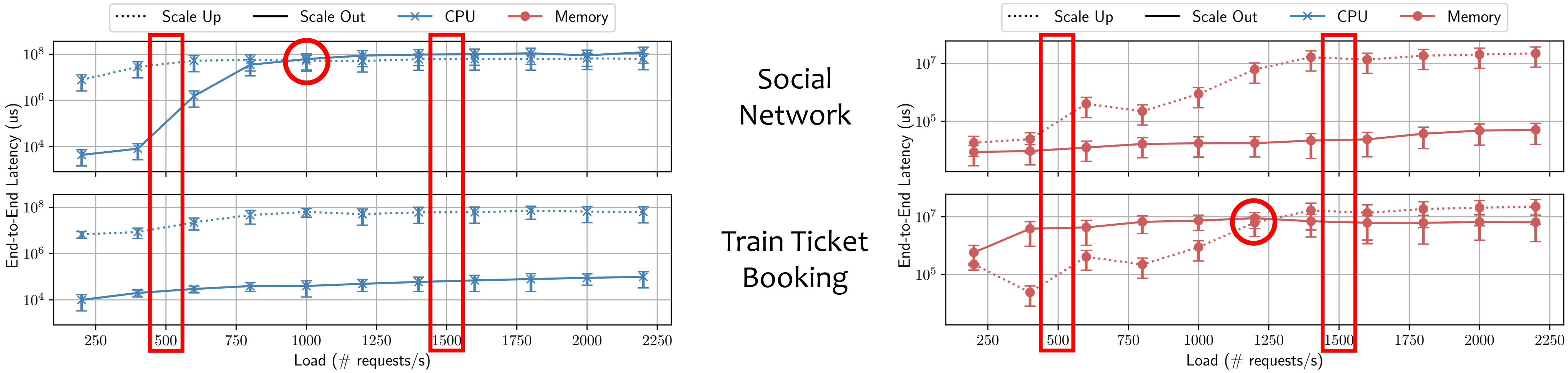
State Inference (3)

- Real-time observability on request execution provided by end-to-end distributed tracing
- Auto-labeled training data driven by the performance anomaly injection
- SLO violation detection and narrow down via critical path analysis
- SVM-based critical component localization
  - Given individual latency vector T_i, and end-to-end latency vector T_{CP}
  - Relative importance defined as the Pearson correlation coefficient between T_i and T_{CP}
  - Congestion intensity defined as 99-th percentile value divided by median value of T_i



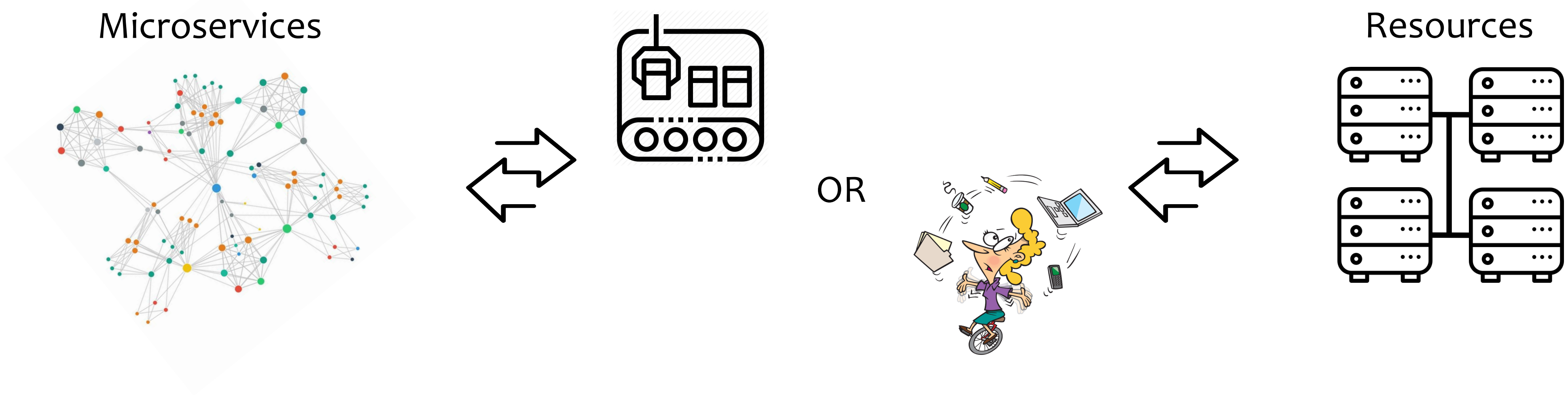
Insight 3: No Common Mitigation Policy for All

- SLO violation mitigation policies vary with applications, user loads, and the types of resource in contention
- Designing optimal resource provisioning strategy is intractable, just like scheduling problems
  - Modeling complexity: *Tetris [SIGCOMM '14], Jokey [EuroSys '12]*
  - Placement constraints: *TetriSched [EuroSys '16], device placement [NIPS '17]*
  - Data locality: *Delayed scheduling [EuroSys '10], SWAG [SoCC '15]*
  - …



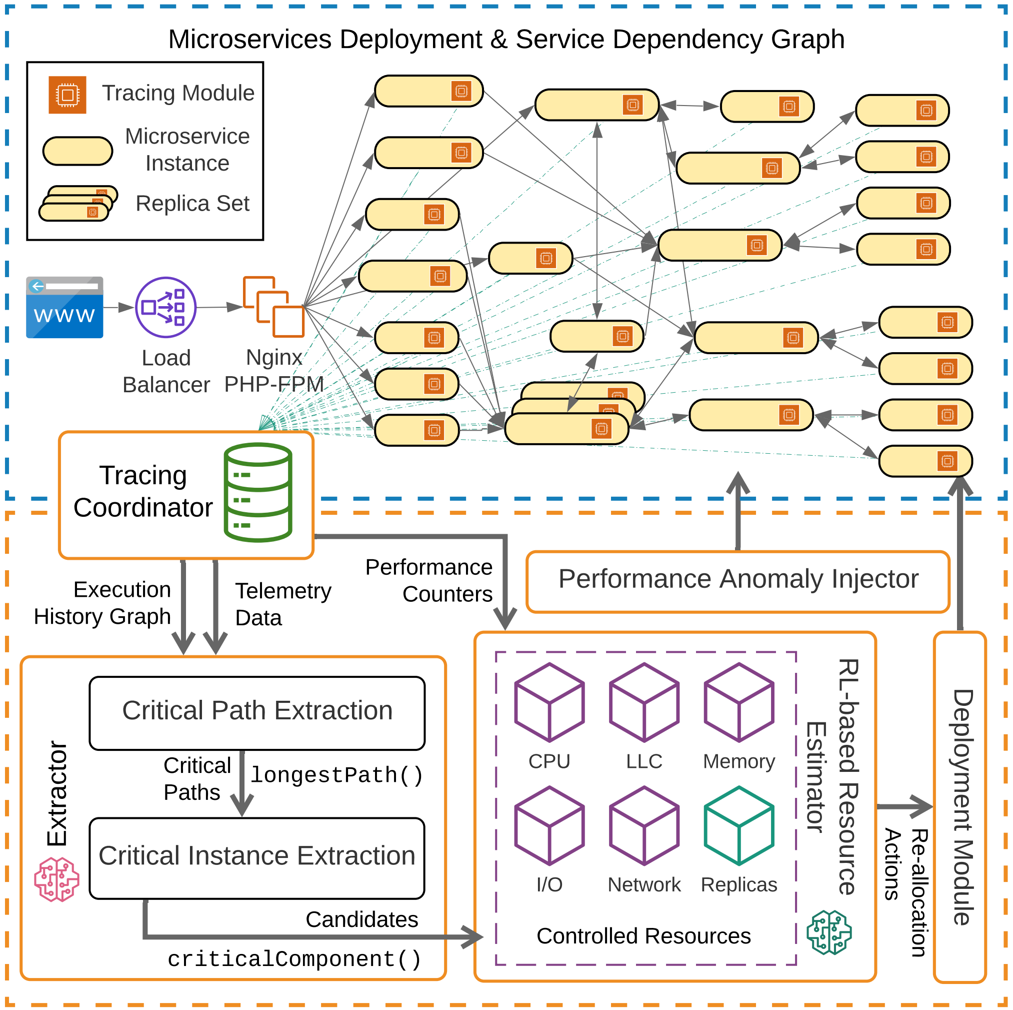
Why not human-driven performance engineering?

- No "one-size-fits-all" solution for the online decision problem
  - Best algorithm depends on specific workload and system
- Human-driven performance engineering
  - Assume a simple system model
  - Produce some clever heuristics
  - Painstakingly test & tune the heuristics in practice
  - Redo the above steps ↺
- RL-based SLO violation mitigation
  - Assume a random scheduling policy
  - Perceive states and receive rewards
  - Optimize the policy based on the rewards
  - Loop continues until convergence ↺
- Is there a way to work around human-generated heuristics? Yes



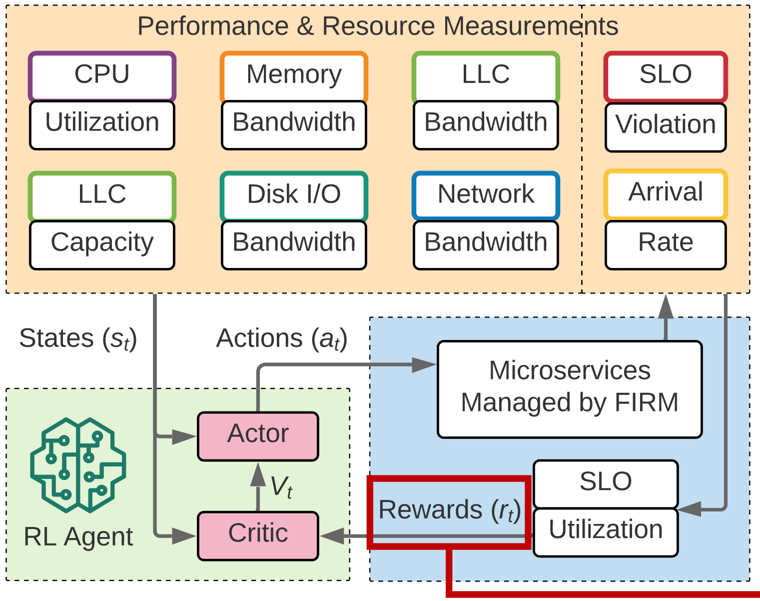
SLO Violation Mitigation (1)

- Observability improved through online distributed tracing
- Auto-labeled training data and RL online learning driven by the performance anomaly injector
- SLO violation detection and localization via critical path analysis
- SVM-based critical component extraction
- SLO violation mitigation based on reinforcement learning
  - Identifies low-level resource contention
  - Estimates the right amount to reprovision



SLO Violation Mitigation (2)

- An RL-based resource estimation agent that learns to make provisioning decisions directly from experience
- Optimizes objectives end-to-end:
  - Minimize SLO violation
  - Maximize resource utilization efficiency



Mitigate SLO Violation Fast

Avoid Over-provisioning

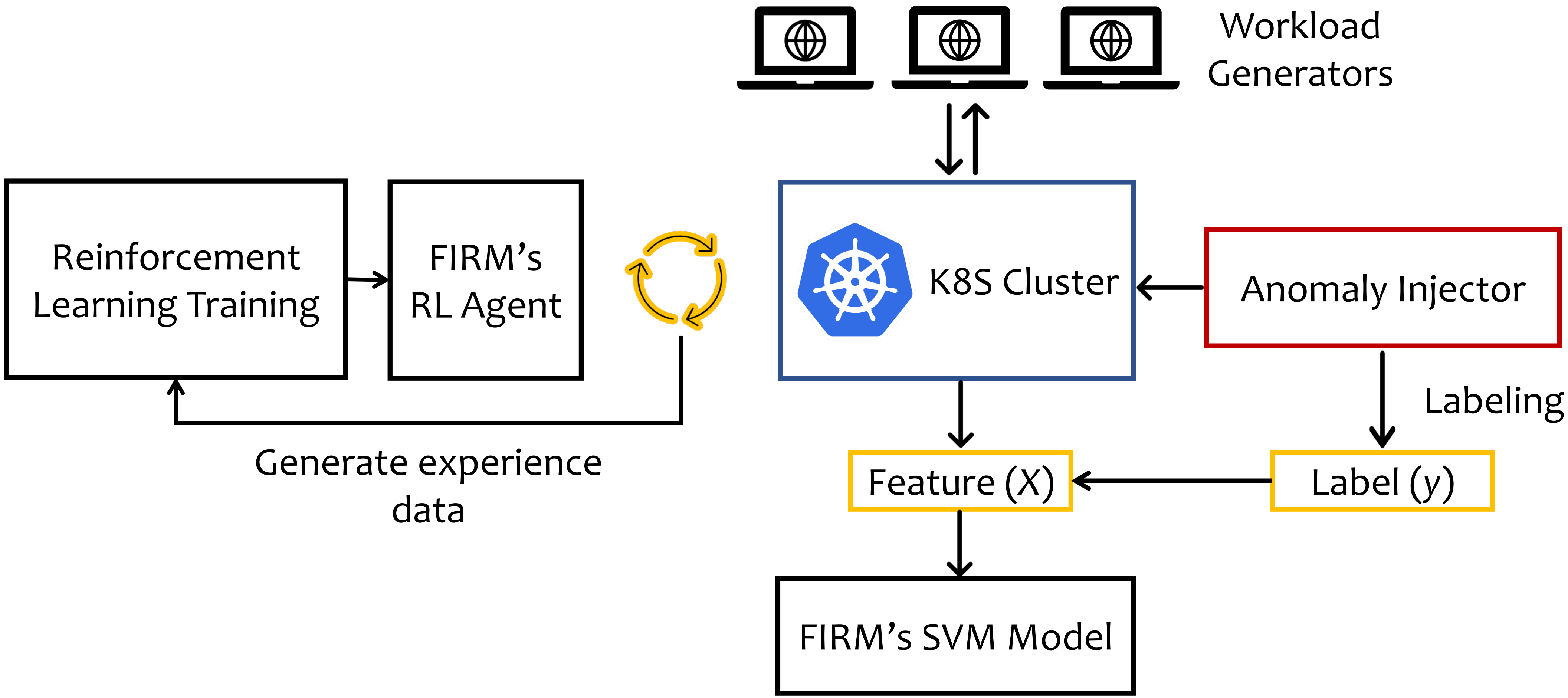
$$r(t) = \alpha \cdot SM_t \cdot |\mathcal{R}| + (1-\alpha) \cdot \sum_i^{|\mathcal{R}|} RU_t^i / RL_t^i$$

$$SM_t = \frac{Latency_{SLO}}{Latency_t}$$ (SLO maintenance)

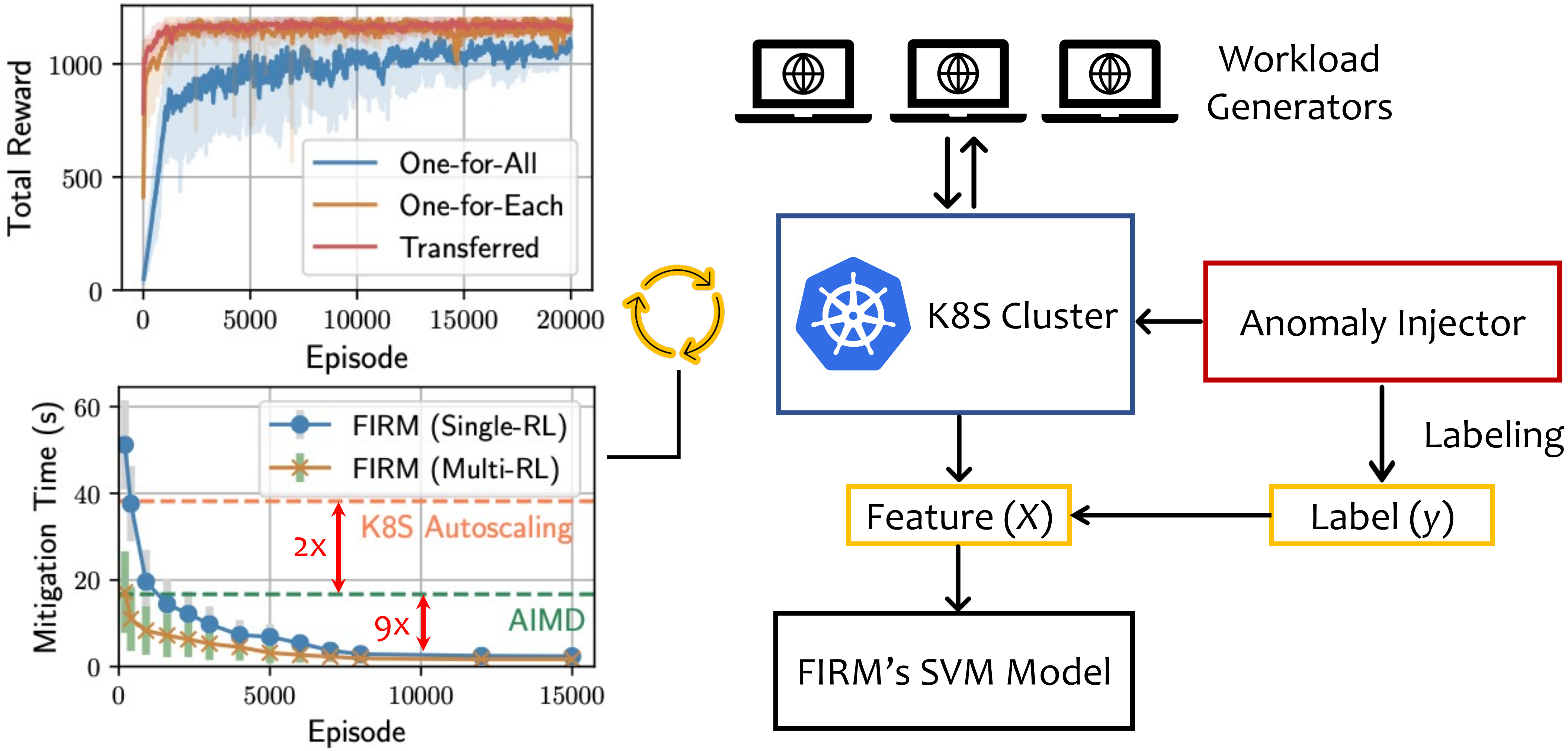
Resource utilization of i at time t

Resource limit of i at time t

Multilevel ML Training



Multilevel ML Training



Evaluation

- Implemented and deployed FIRM on a Kubernetes cluster of 15 physical nodes
- Running microservices benchmarks from DeathStarBench [1] and TrainTickets [2] driven by open-loop workload generators
- Training and experiments driven by performance anomaly injection
- Comparison targets include Kubernetes autoscaling [3] and an additive increase multiplicative decrease (AIMD)-based method [4]

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[1] Yu Gan, Yanqi Zhang, Dailun Cheng, Ankitha Shetty, Priyal Rathi, Nayan Katarki, Ariana Bruno, Justin Hu, Brian Ritchken, Brendon Jackson, et al. An opensource benchmark suite for microservices and their hardware-software implications for cloud & edge systems. In Proceedings of the Twenty-Fourth International Conference on Architectural Support for Programming Languages and Operating Systems, pages 3–18, 2019.

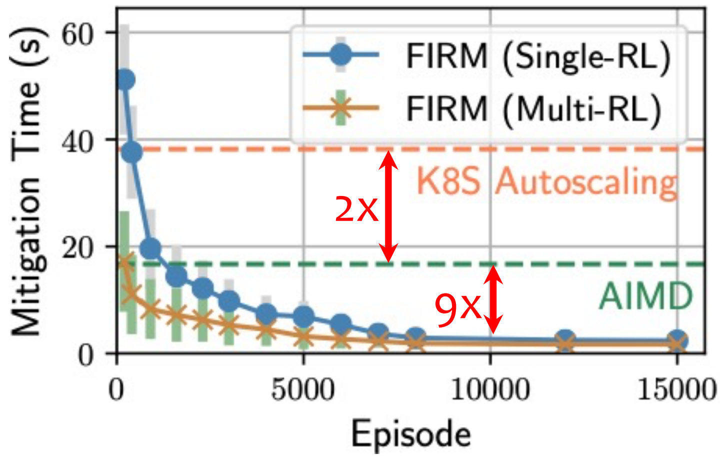
[2] Train Ticket - A train-ticket booking system based on microservice architecture. https://github.com/ FudanSELab/train-ticket.

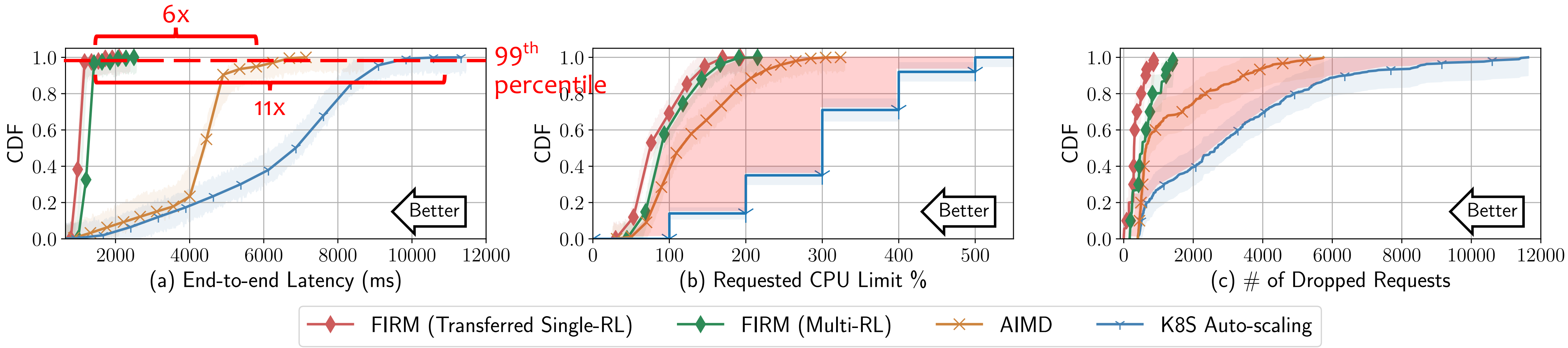
[3] Autoscaling in Kubernetes. https:// kubernetes.io/blog/2016/07/autoscalingin-kubernetes/

[4] Sonja Stüdli, M. Corless, Richard H. Middleton, and Robert Shorten. On the modified AIMD algorithm for distributed resource management with saturation of each user’s share. In Proceedings of 2015 54th IEEE Conference on Decision and Control (CDC), pages 1631–1636. IEEE, 2015.

Results

- Reduces the SLO violation mitigation time by up to 9× compared with AIMD
- Reduces the average tail latencies by up to 6-11×
- Reduces the overall average requested CPU limit by 29-62%
- Reduces the number of dropped/timed out requests by up to 8x





Conclusion

- FIRM uses SVM-based critical component extraction to localize at runtime root cause microservice instances for SLO violations
- FIRM uses RL to generate workload-specific mitigation policies, optimized to estimate resources in contention and provide re-provision actions
- FIRM leverages the two-level ML model structure to improve interpretability and save training time
- FIRM outperforms Kubernetes auto-scalers and AIMD-based methods

Thank you!

Check out the full paper for more details!

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