Multi-dimensional Autoscaling: A Comparison of Agent-based Methods

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Víctor Casamayor Pujol, and Schahram Dustdar

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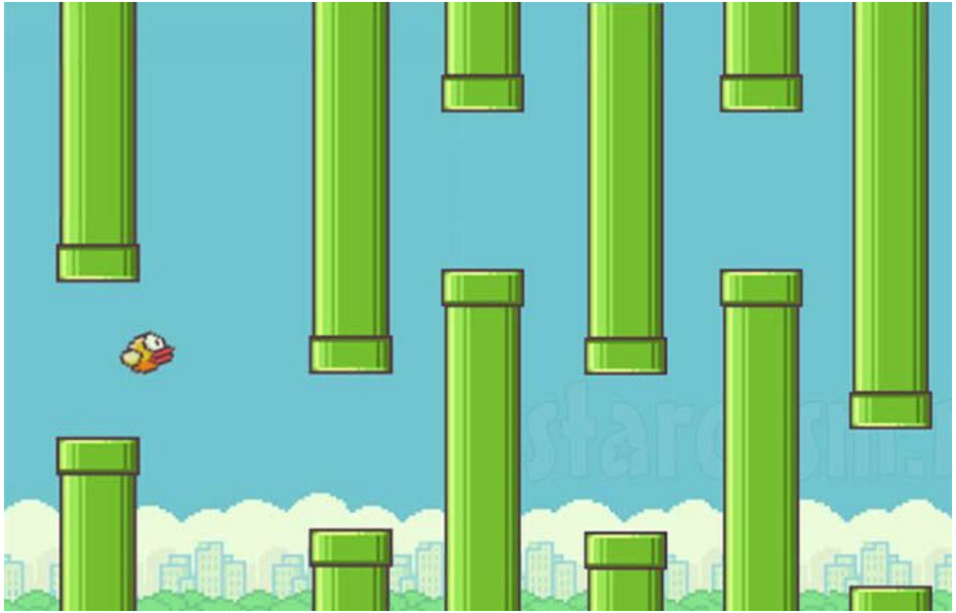

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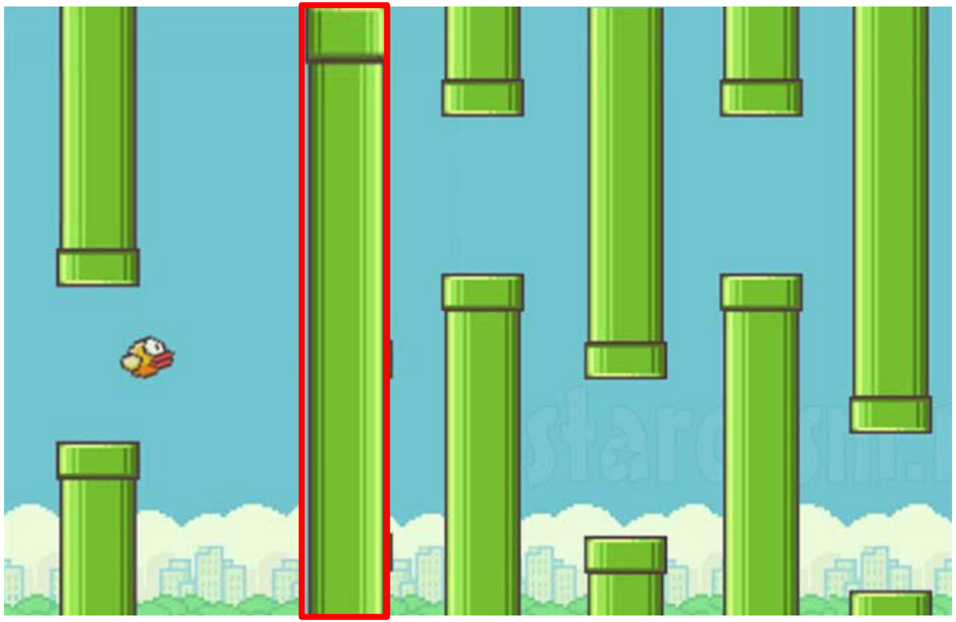

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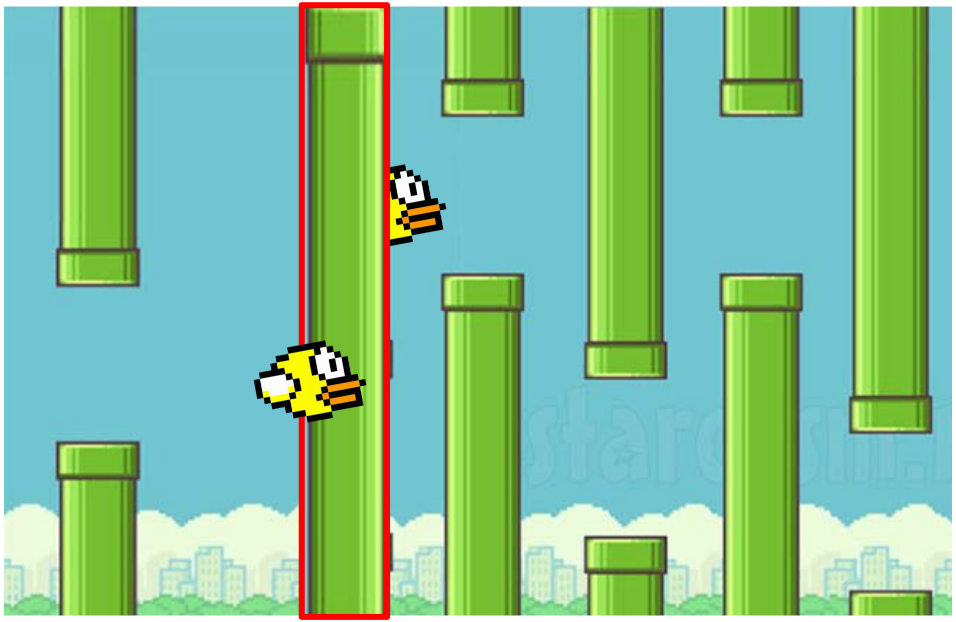

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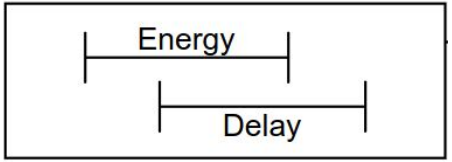
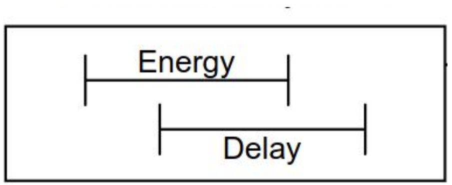
Can't pass obstacle?

Use another dimension to improve flexibility of agent (i.e., action space)



want to ensure **requirements** (= goals)
of systems, e.g., latency of OpenReview



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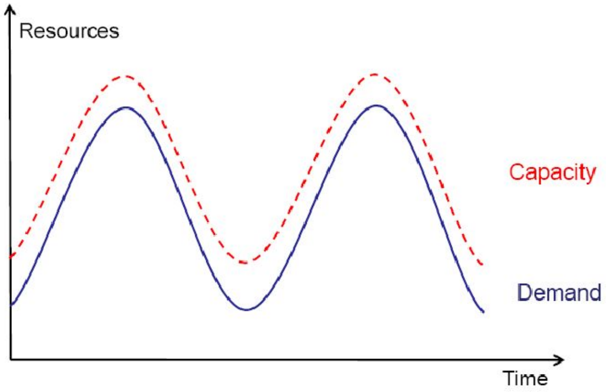
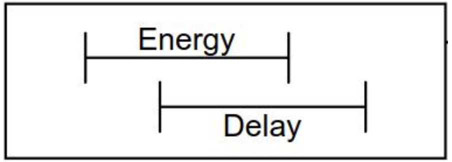


dynamic resource allocation according to current **demand**, e.g., submission time



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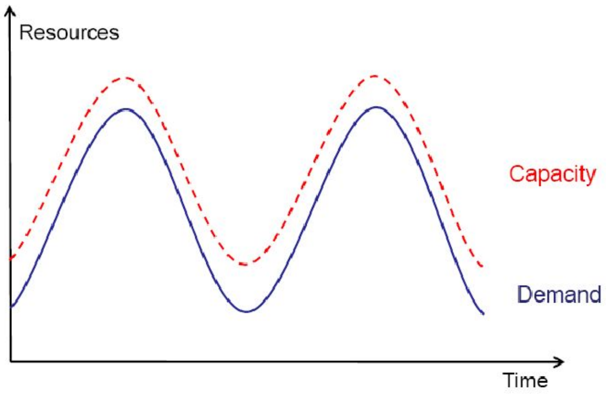
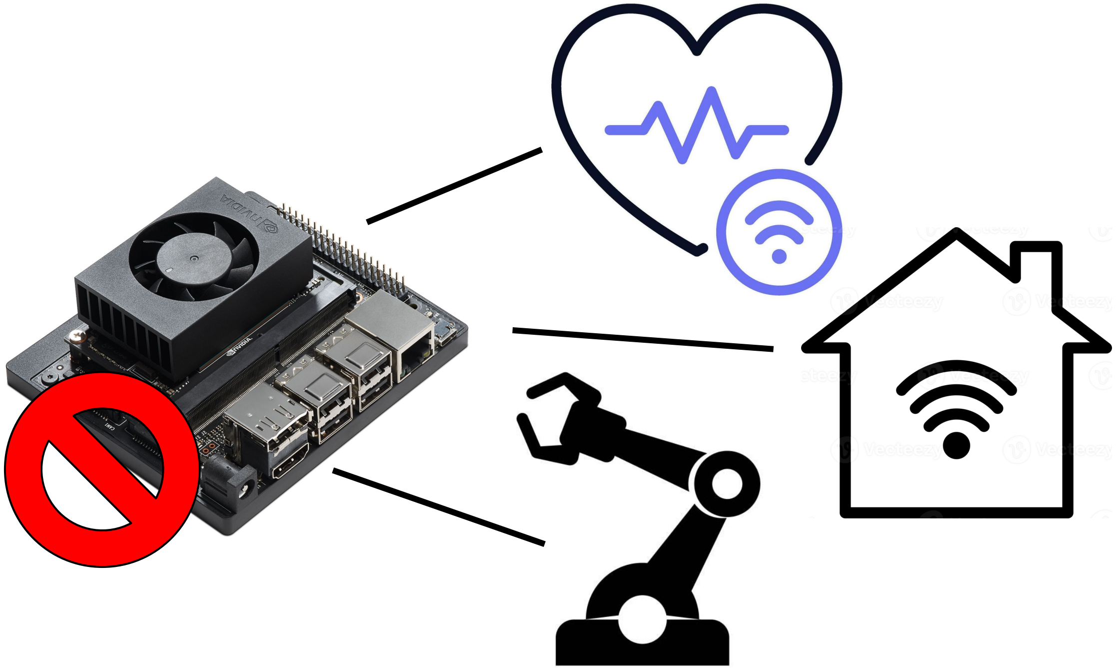
works well with infinite resources

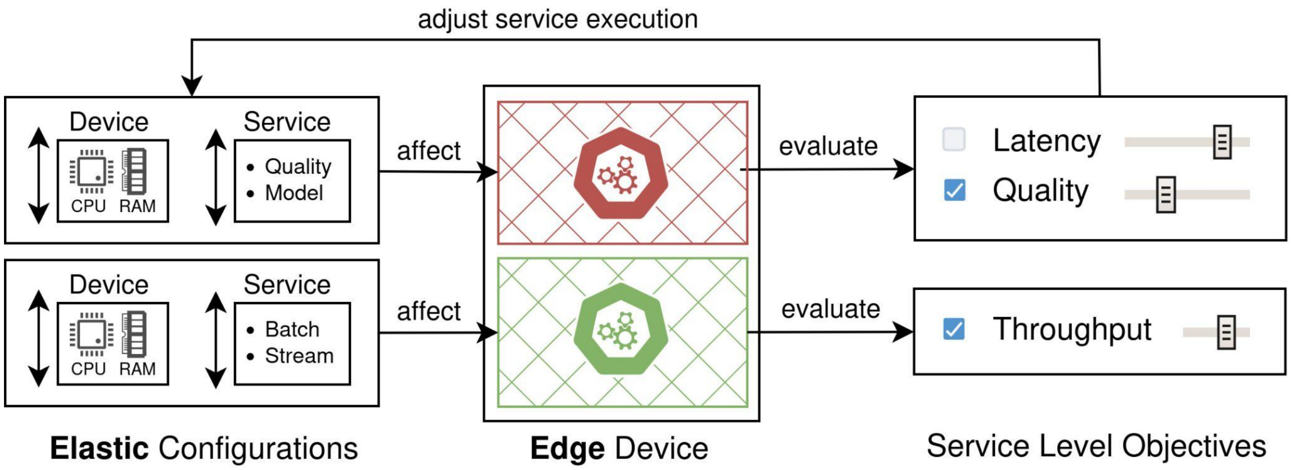


dynamic resource allocation according to current **demand**, e.g., submission time

doesn’t work under resource limits



Multi-Dimensional Elasticity: Systems Perspective



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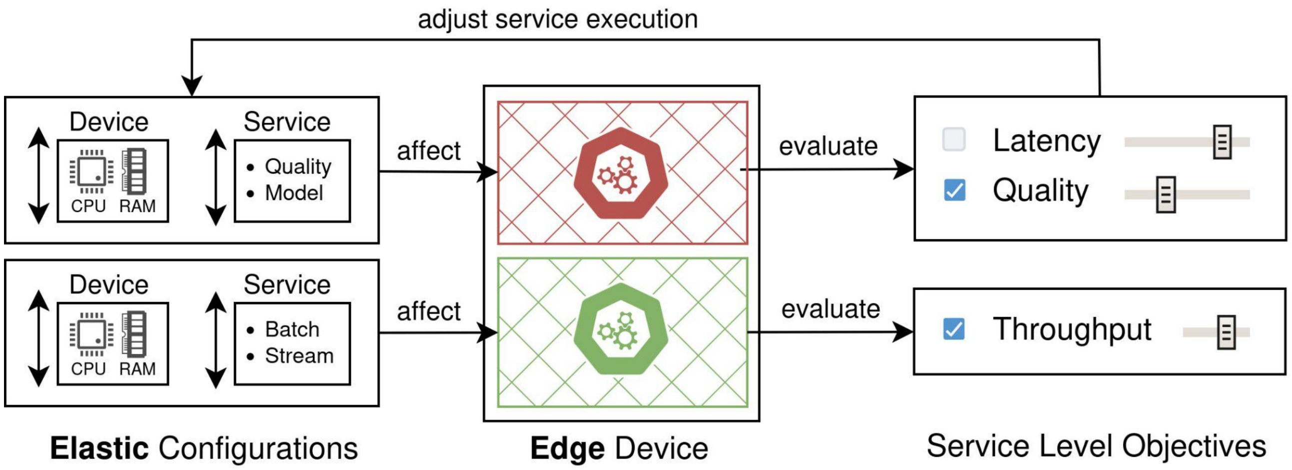

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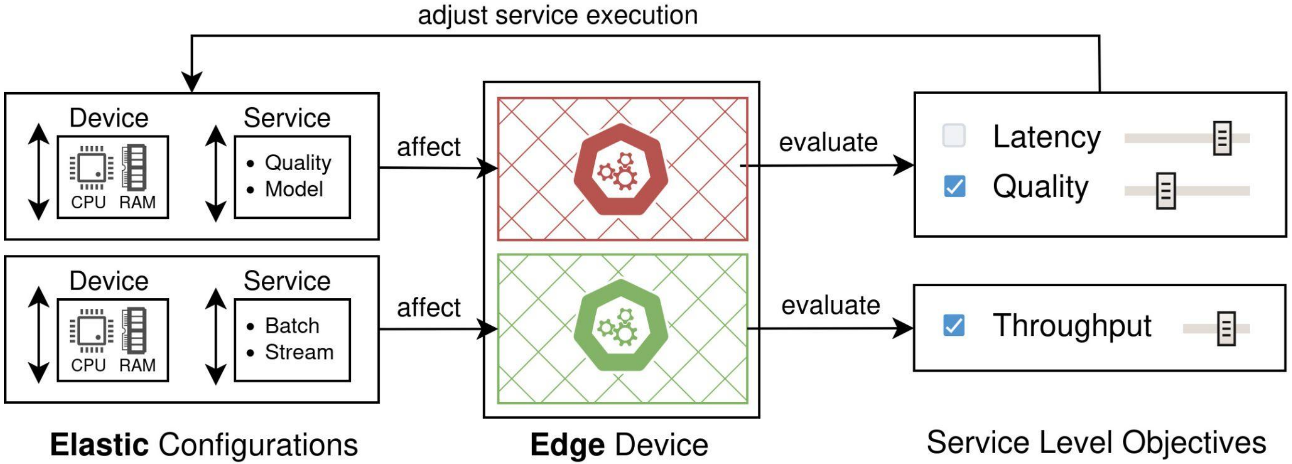

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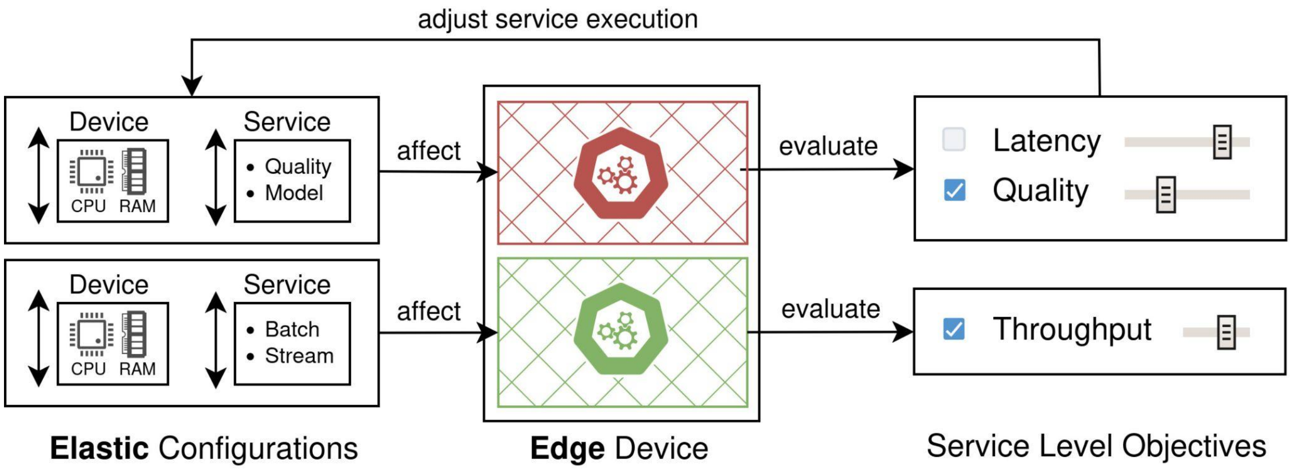

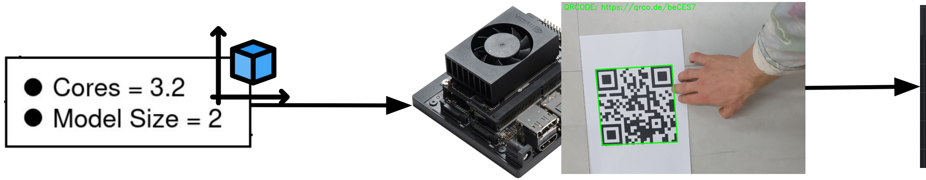

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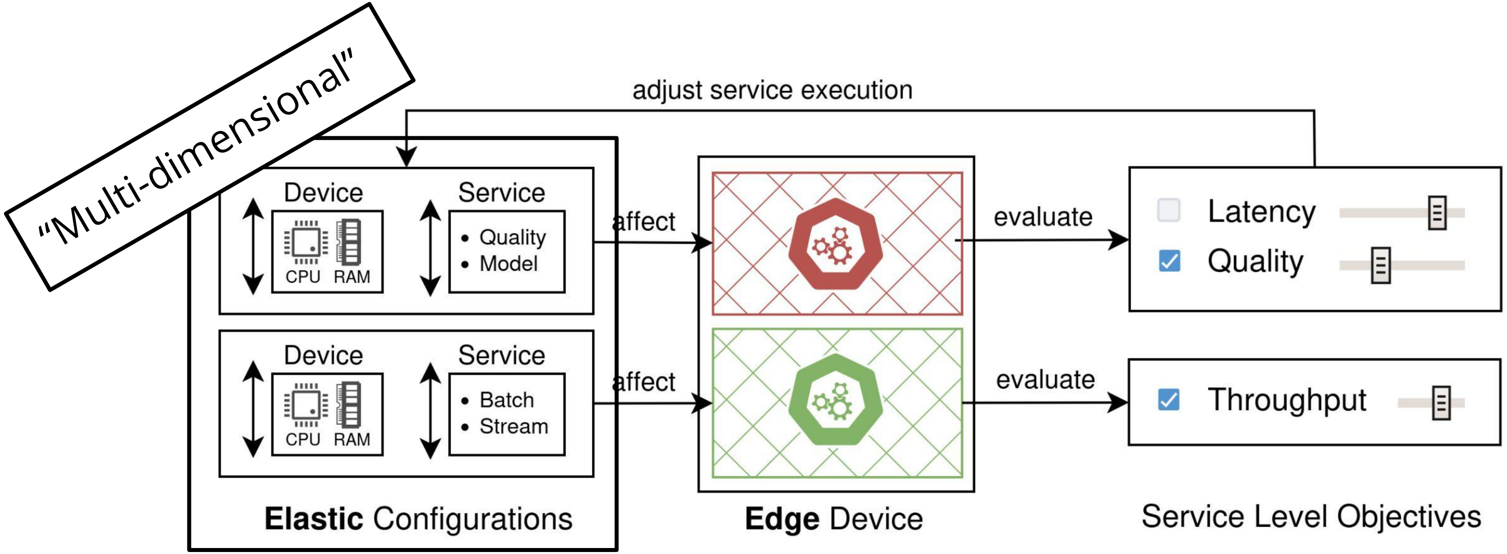

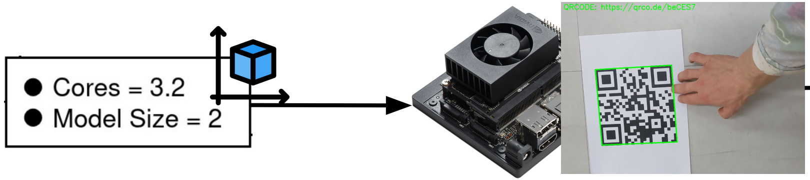

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Reformulated in AIF Terms: Mapping

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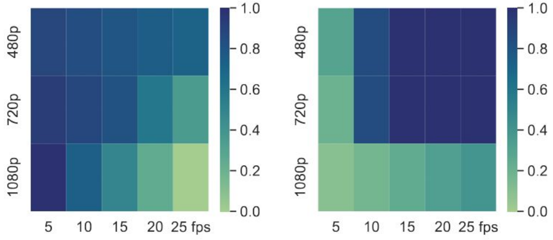

(b) Pragmatic value (c) Information gain

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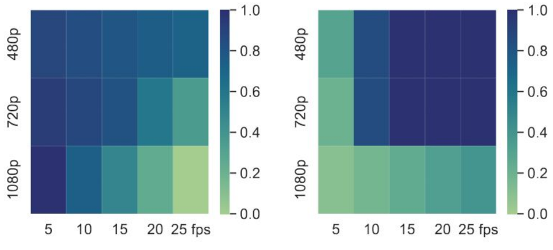

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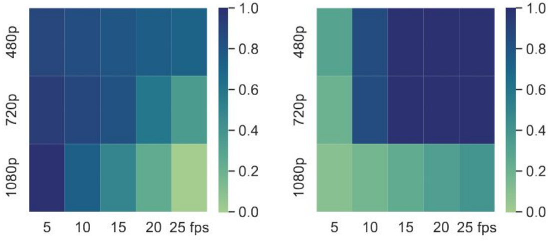

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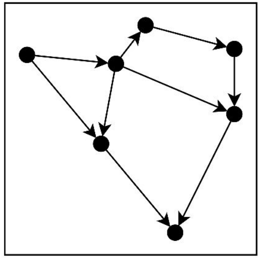

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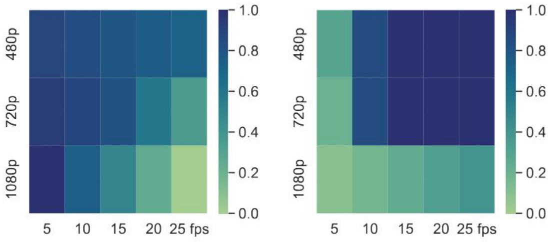
→ Formulate as POMDP, create interfaces for agents to **sense** the environment and **act** on services/devices; playground to compare performance of agent types



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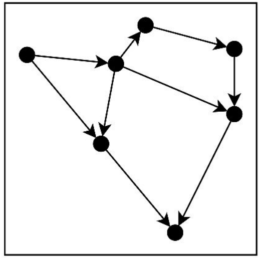
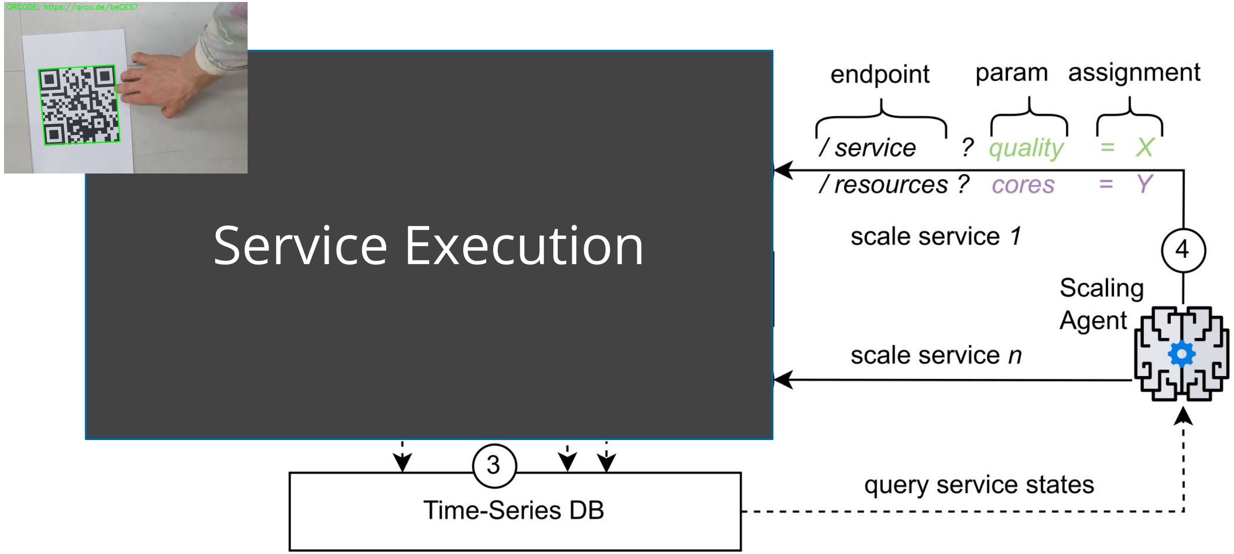


Experimental Setup: Environment



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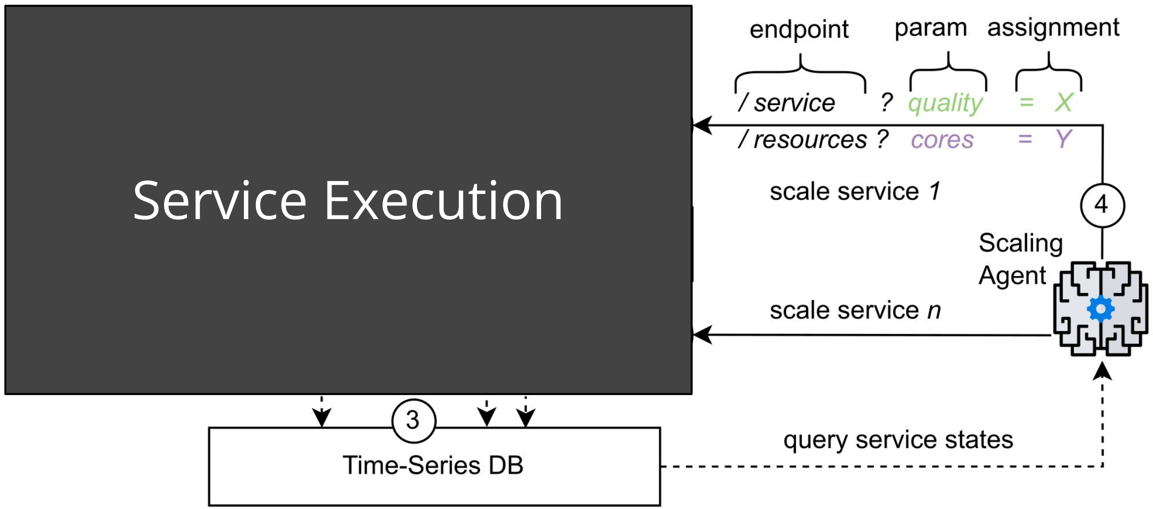

Action frequency **limited** by domain's temporal dynamics

"cool down period"

Choose autoscaling interval of 5s for picking new action

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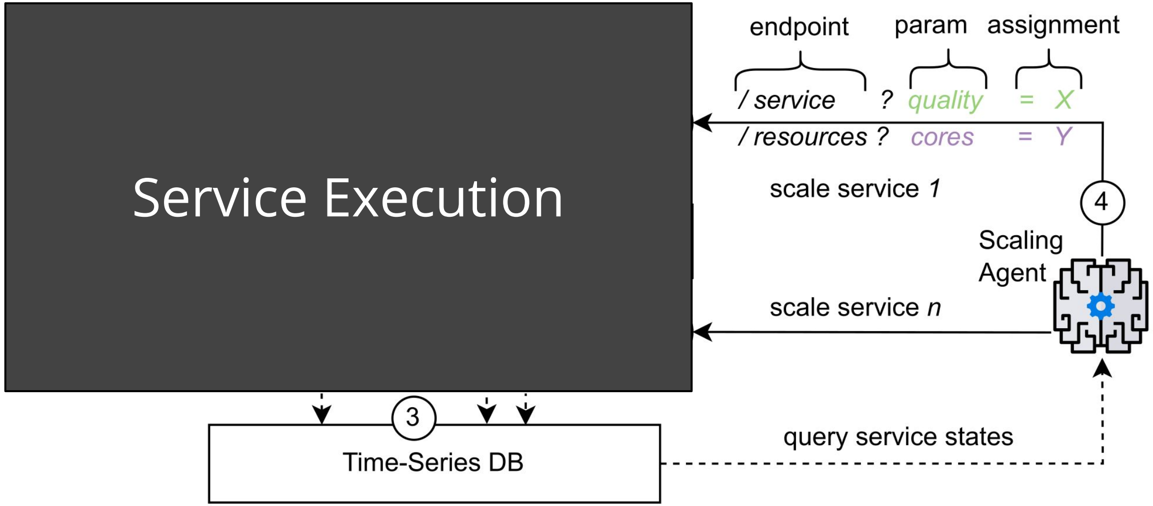

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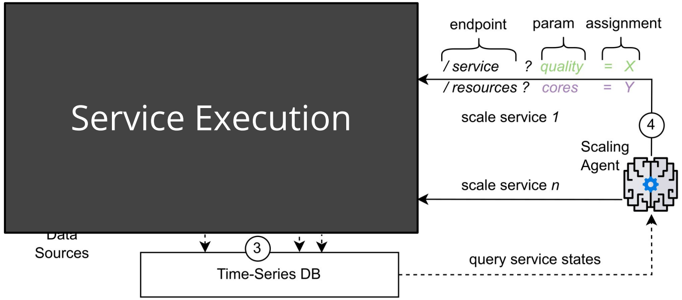
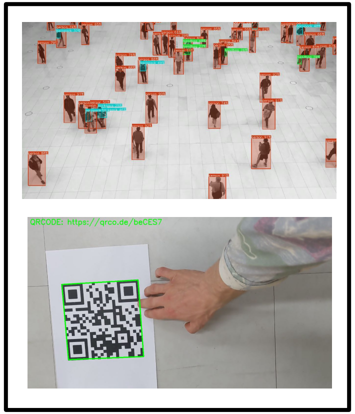
Must be **sample-efficient**; conflicts with **common** RL

Experimental Setup: Environment (2)





Find **scaling policy** that optimizes performance

Problem instance:
2 services (QR, CV)

3 **interventional** parameters (quality, model size, resource allocation between services)

1 **dependent** parameter (service throughput / rps)

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\+ **preferred** observations (high quality and throughput)

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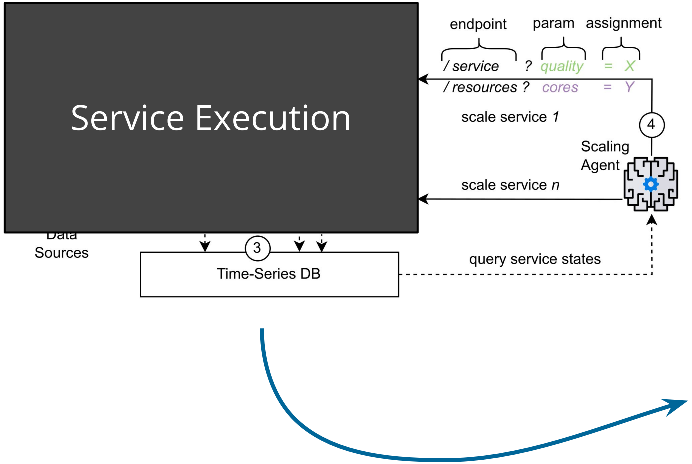

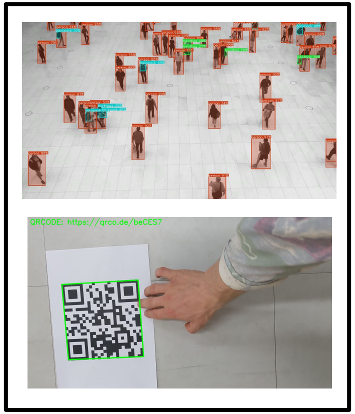

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→ **Optimize** the requirements fulfillment through 4 different agents (DQN, 2x AIF, Regression)

Experimental Setup: Agents

DQN agent work on heavily discretized space; requires offline pretraining in custom gymnasium environment

AIF agent uses pymdp [1] with equally discretized space; 35 policy options and 300k different state combination

DACI agent uses MCTS [2] methods for mapping high-dimensional observations into compressed latent space

RASK agent explores dependencies in the processing environment through continuous regression functions; uses numerical solver for finding optimal policy

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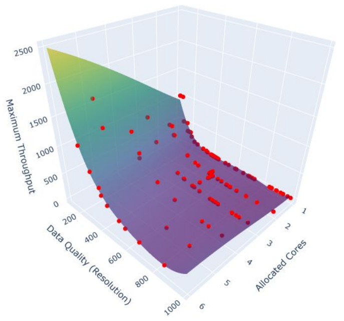

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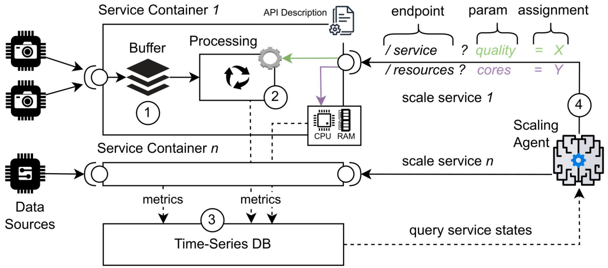
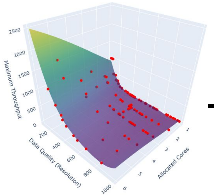
Experimental Setup: Scenarios

Start processing services and one of the scaling agents; let agent operate for **250s** (i.e., sense and act in env.)

Capture **reward** (i.e., requirements fulfillment) and the **time** that agents require to infer a scaling policy





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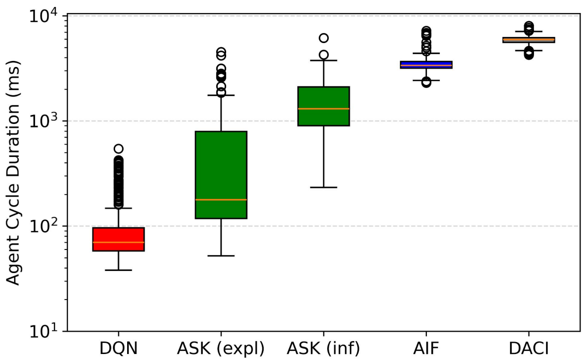
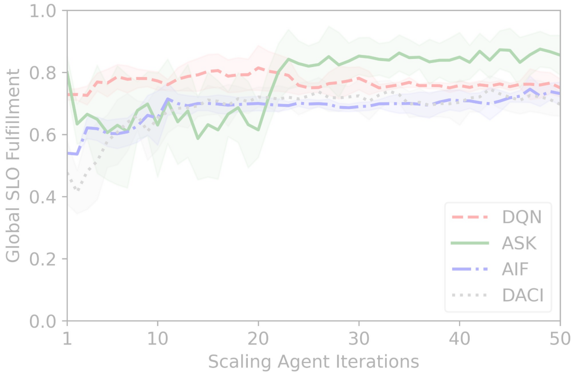
Experimental Results

Runtime: DQN performs best with runtimes < 100ms; highly optimized on hardware; AIF and DACI most computations



Reward: ASK superior, other agents similar. ASK operates in **continuous** space and makes fine-grained scaling actions



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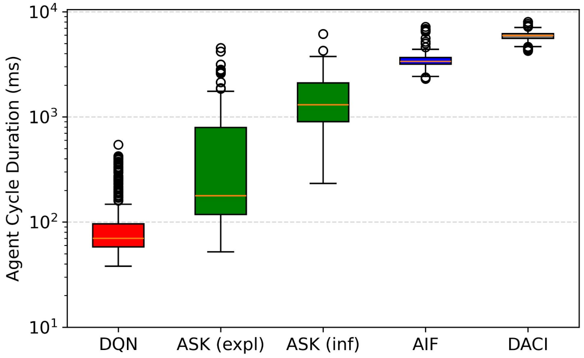

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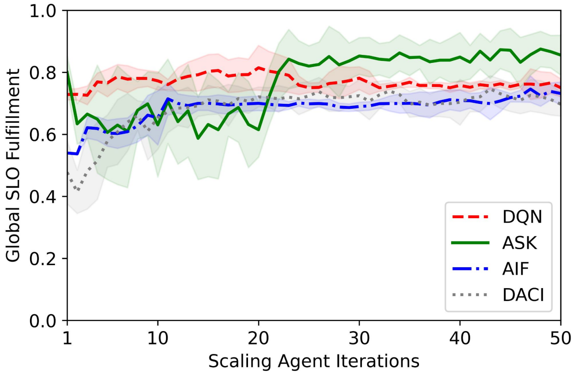

Conclusion

Motivation: Large-scale computing systems pose infinity of optimization problems; must explore behavior during runtime due changing variable distributions.

Solution: Model processing environment through POMDP and train state transition models; compare four agents.

Benefit: Create stable autoscaling policies; embed AIF agents into common use cases and allow comparison with contemporary ML approaches (e.g., DQN).

Future work: sophisticated exploration schemes for continuous variables built on Gaussian processes.