Metis: Learning to Schedule Long-Running Applications in Shared Container Clusters at Scale

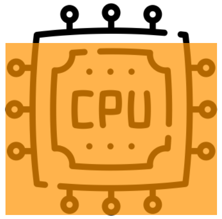
Luping Wang*, Qizhen Weng*, Wei Wang, Chen Chen, Bo Li
Hong Kong University of Science and Technology

Long-Running Applications (LRAs) are critical in modern datacenters

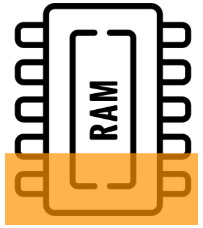
- Also known as *latency-critic (LC) services*, which are of commercial value, e.g.,
  - Stream processing
    - Interactive data analytics
      - Caching/Storage services …

- LRAs usually run for hours to months and occupy substantial resources.

Alibaba:

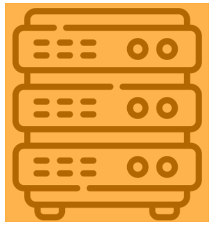


94%



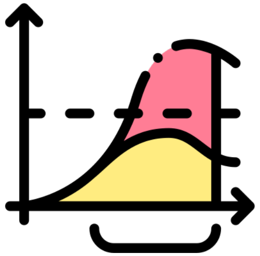
37%

Microsoft:



LRA-dedicated machine/clusters

Google:



High proportion of long production Jobs.

Reiss, Charles, et al. "Heterogeneity and dynamicity of clouds at scale: Google trace analysis." Proceedings of the Third ACM Symposium on Cloud Computing. 2012.
Garefalakis, Panagiotis, et al. "Medea: scheduling of long running applications in shared production clusters." Proceedings of the Thirteenth EuroSys Conference. 2018.
“Alibaba production cluster data,” https://github.com/alibaba/clusterdata.

LRAs are non-trivial to schedule

- LRAs have stringent SLO (Service-Level Objective) requirements.
- LRAs have sophisticated performance interactions among themselves.
    - I/O dependencies — *affinity*: better co-located

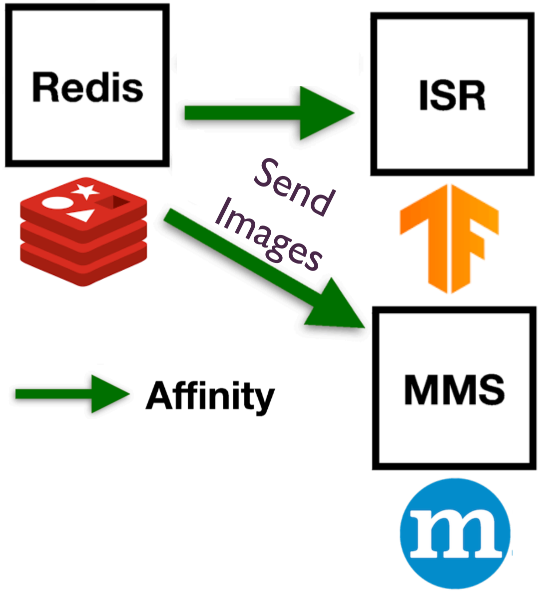
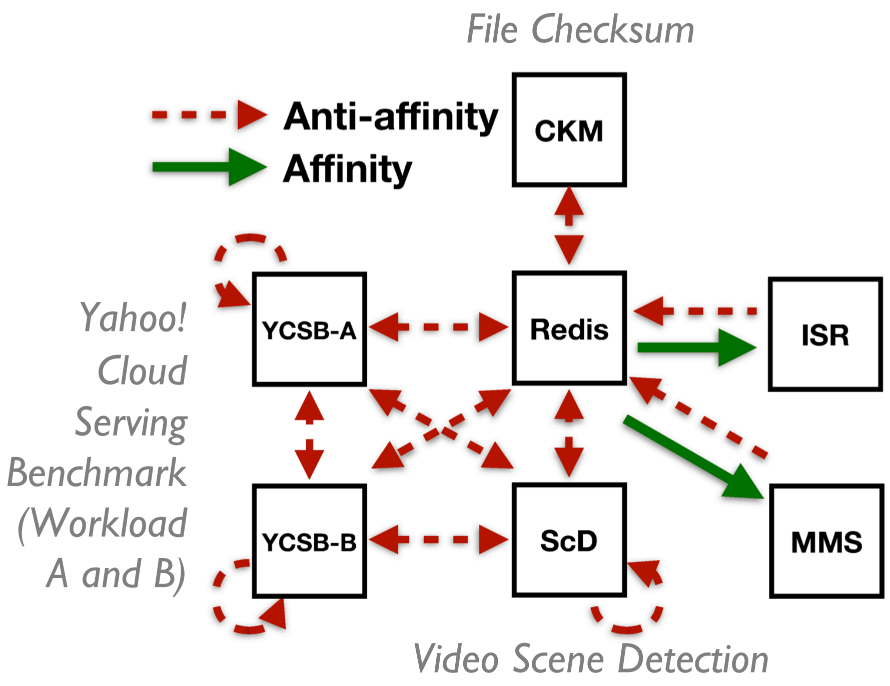


Image Super Resolution with TensorFlow.

MXNet Model Server, classifying images.

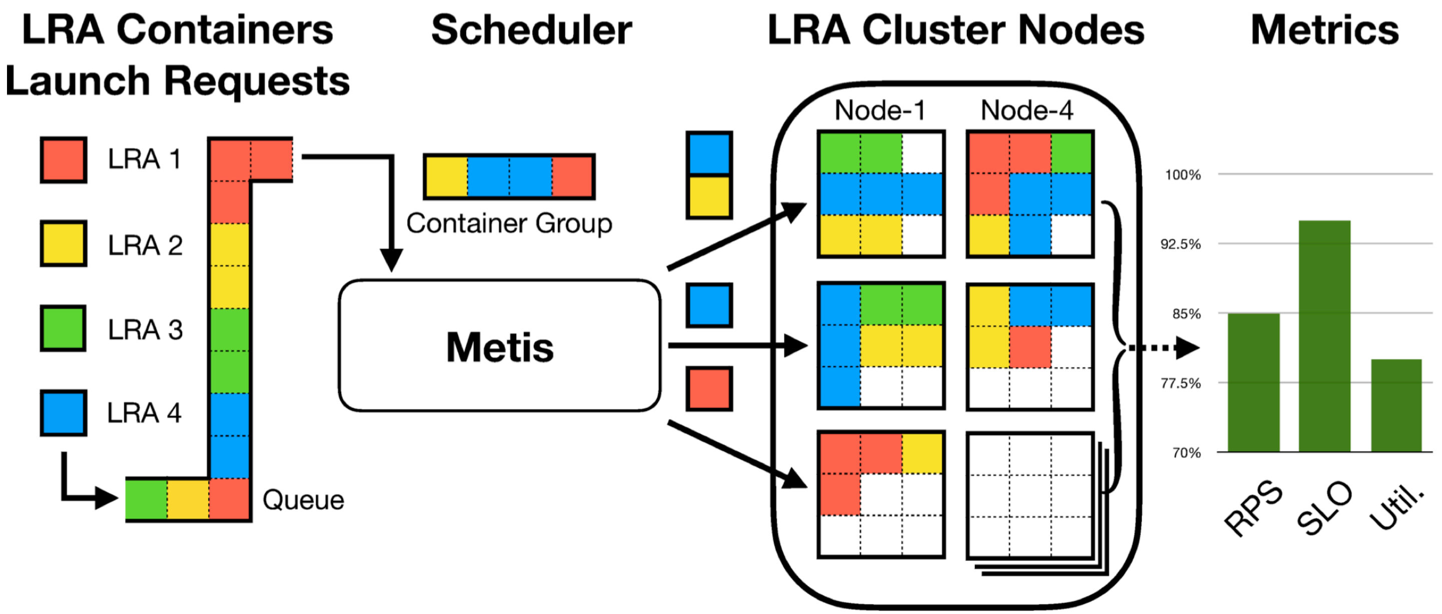
LRAs are non-trivial to schedule

- LRAs have stringent SLO (Service-Level Objective) requirements.
- LRAs have sophisticated performance interactions among themselves.
  - I/O dependencies — *affinity*: better co-located
  - Shared resources contention — *anti-affinity*: better scattered
    - CPU last-level cache
    - Memory bandwidth
    - Network and disk I/O …



Metis: Learning-based LRA scheduler

- Pursue LRAs' best end-to-end performance of *various metrics.*
- Directly learn LRAs' interactions from *traces, instead of prior knowledge.*
- Scale to thousands of nodes *within moderate latency.*



SC20

Outline

- Introduction
- Prior Arts and Metis' Approach
- Hierarchical Reinforcement Learning
- Evaluation

Prior Arts: Constraint-Based Schedulers

Medea scheduler workflow:

(0. Cluster operators identify interactions.)

1. Manually set placement constraints.
2. Solve Integer linear program (ILP).
3. Executes ILP solution.

$$\text{maximize} \quad \frac{w_1}{k}\sum_{i=1}^{k} S_i + \frac{w_2}{m}\sum_{l=1}^{m} v_c^l + \frac{w_3}{N}\sum_{n=1}^{N} z_n$$

subject to:

$$\forall i, j : \sum_{n=1}^{N} X_{ijn} \leq 1$$

$$\forall n : \sum_{i=1}^{k}\sum_{j=1}^{T_i} r_{ij} \cdot X_{ijn} \leq R_n^f$$

$$\forall i : \sum_{n=1}^{N}\sum_{j=1}^{T_i} X_{ijn} - T_i S_i = 0$$

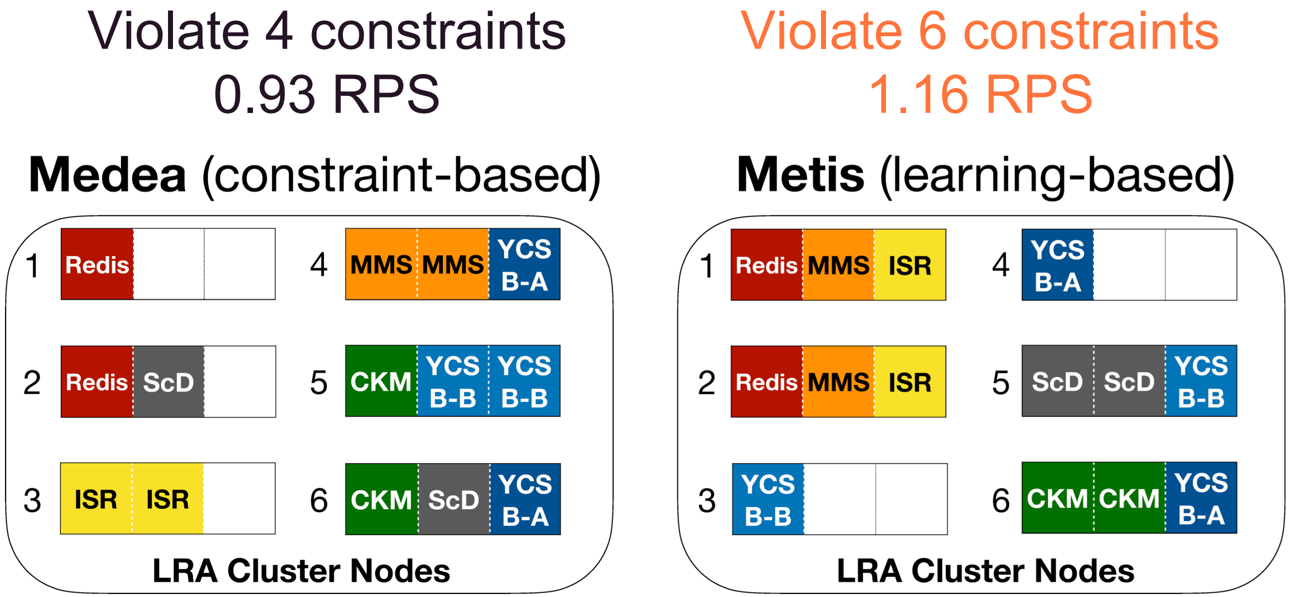
$$\forall n : \sum_{i=1}^{k}\sum_{j=1}^{T_i} r_{ij} \cdot X_{ijn} - B_n(1 - z_n) \leq R_n^f - r_{min}$$

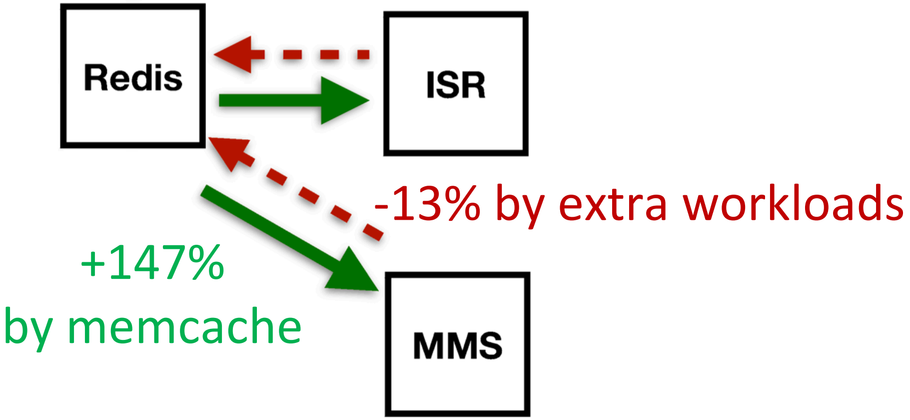
Garefalakis, Panagiotis, et al. "Medea: scheduling of long running applications in shared production clusters." Proceedings of the Thirteenth EuroSys Conference. 2018.

Prior Arts: Constraint-Based Schedulers

Problems:

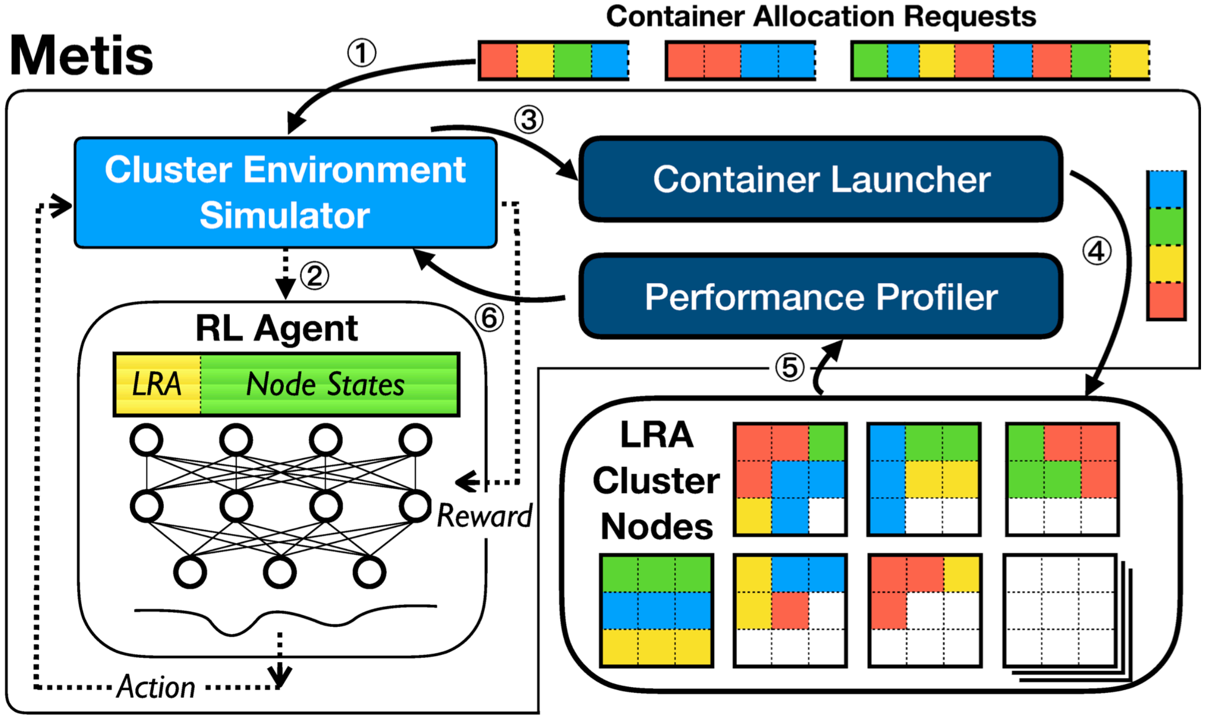
1. Expensive to get constraints.
2. Inefficient at scale (>10 hours to place 3,000 containers to 700 machines).
3. Suboptimal. Constraints are *qualitative*, but not *quantitative*. Esp. given *conflicting constraints*.





Metis: Make end-to-end scheduling by *Reinforcement Learning*

1. Group container requests.
2. Train an RL agent *for each group*.
3. Collect placement decisions.
4. Launch containers in cluster.
5. Profile containers' performance.
6. Improve RL env. simulator.



Implementation

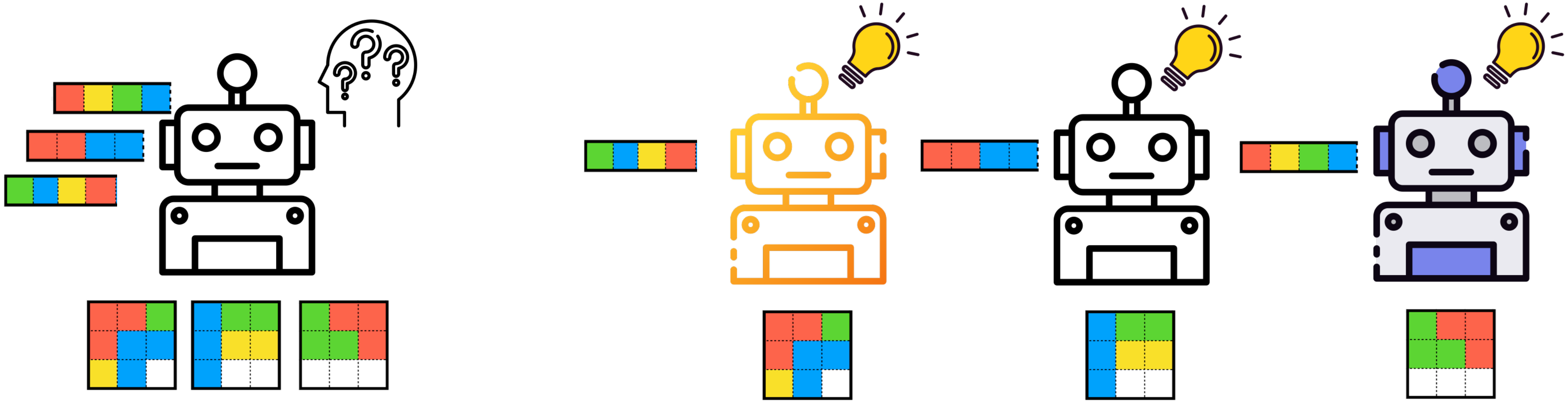
- Algorithms, baselines, and benchmarks (in Docker) are available at https://github.com/Metis-RL-based-container-sche/Metis

Metis: Training dedicated RL agents *on the spot*

Trades computation and latency for better performance.

Offline-trained agent performs badly, because the input are highly variant:

- Cluster state changes after each deployment.
- Input container group can have *millions* of combinations, e.g.,
  Picking 30 containers from 7 apps (with repetition) gives ~2 million outcomes.

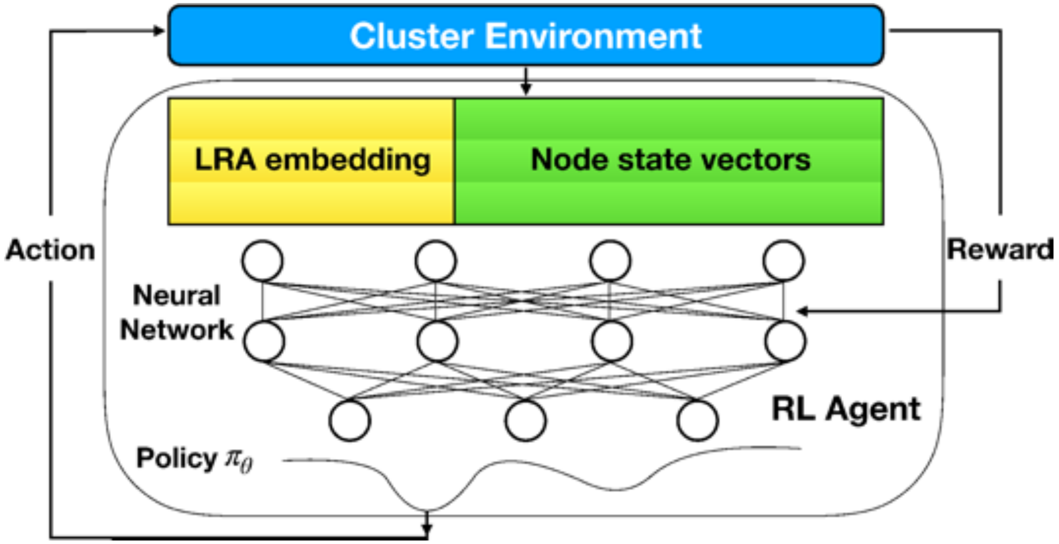


Outline

- Introduction
- Prior Arts and Metis' Approach
- Hierarchical Reinforcement Learning
- Evaluation

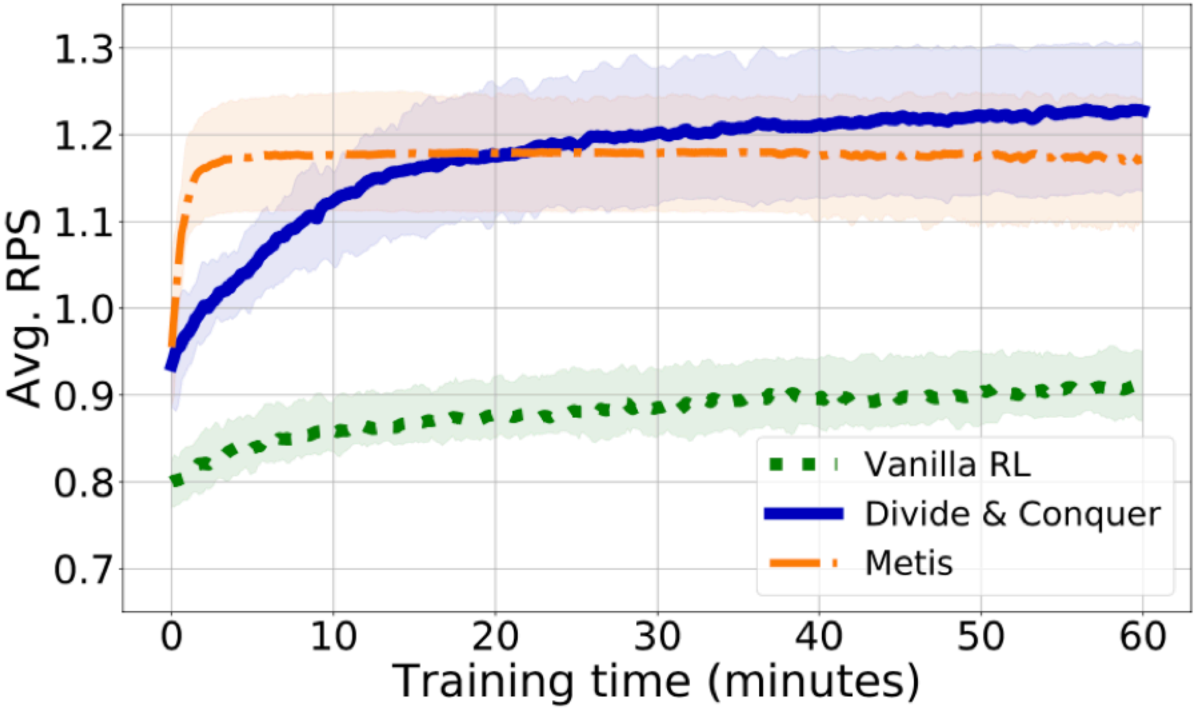
Hierarchical Reinforcement Learning

- Co-locating containers using Reinforcement Learning
  - End-to-end scheduling process
  - Intelligent interference-capture method: try-trail
  - Generally support various scheduling objectives
  - Scalable



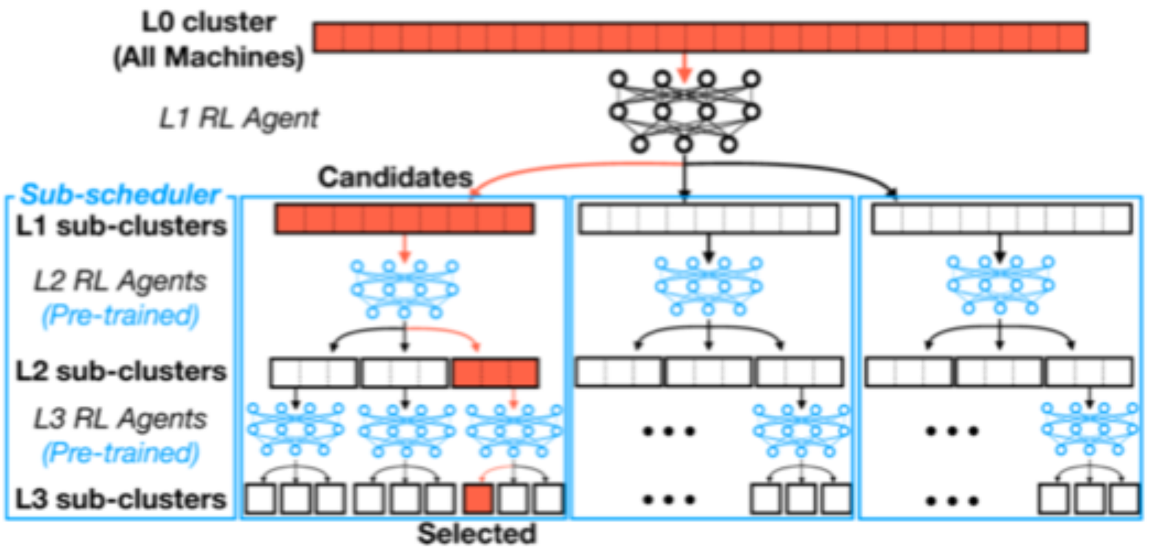
Hierarchical Reinforcement Learning

- Novelty: Hierarchical Reinforcement Learning for Scalability
  - Cluster scale: thousands of machines
  - Large action and state space: poor performance



Hierarchical Reinforcement Learning

- Novelty: Hierarchical Reinforcement Learning for Scalability
  - Select a hosting machine: select a sub-cluster first
  - Reduced state and action space
  - Reusable building blocks (Spatial)
  - Offline vs Online



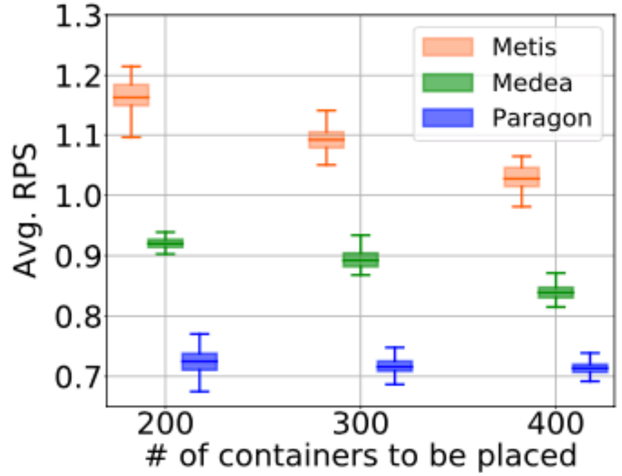
Outline

- Introduction
- Prior Arts and Metis' Approach
- Hierarchical Reinforcement Learning
- Evaluation

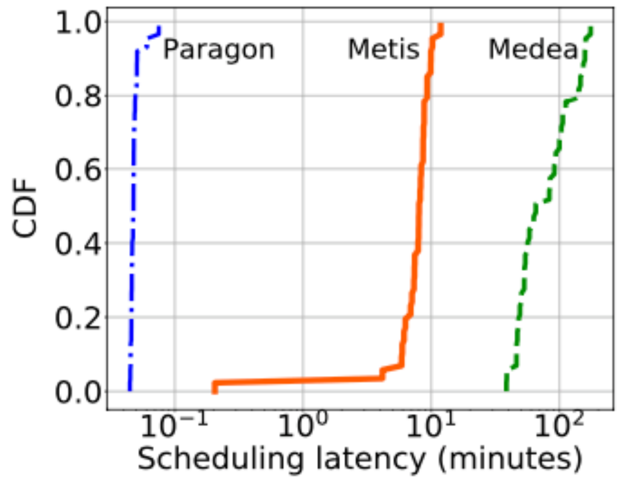
Evaluation: Setup

- Prototype deployment on a EC2 clusters
  - Scale: a medium one with 81 nodes and a large one with 729 nodes.
  - Each node: m5.4xlarge instance with 16 vCPUs, 64 GB memory
  - Docker containers: each with 2 vCPUs and 8 GB memory.
- Metrics
  - Container performance: RPS
  - Cluster resource fragmentation: % of empty nodes
- Baselines
  - Medea
  - Paragon

Evaluation: *Scheduling Performance*



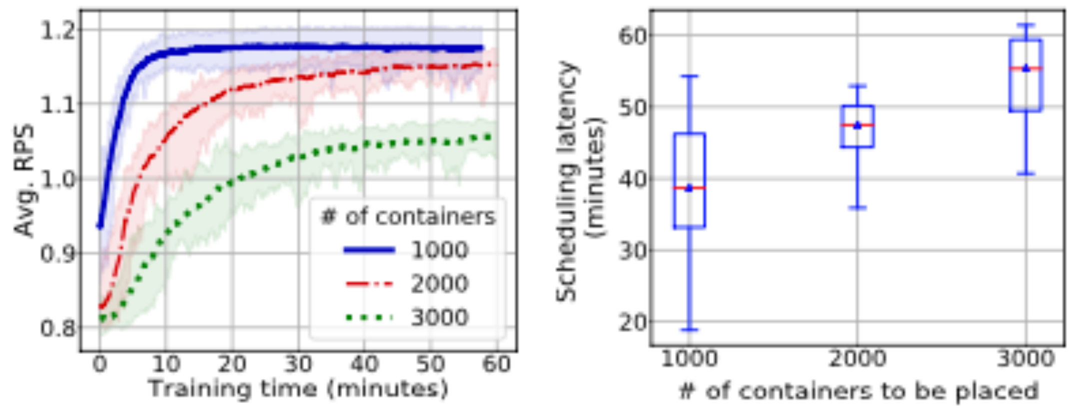
(a) Average RPS with various container group sizes.



(b) Distribution of scheduling latency in all container groups.

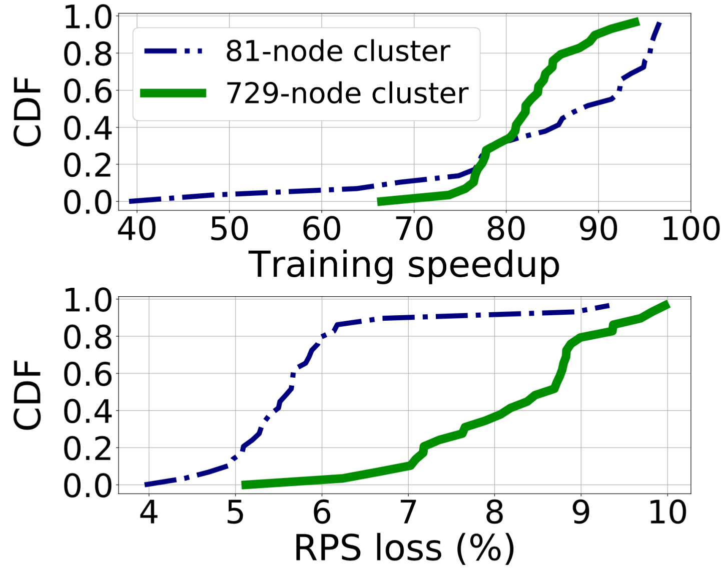
- 81-node cluster
- 200-400 containers
- 25% and 61% higher RPS than Medea and Paragon
- Modest scheduling latency within 10 min

Evaluation: *Scheduling Scalability*



(a) Learning curve of the RL Agent.

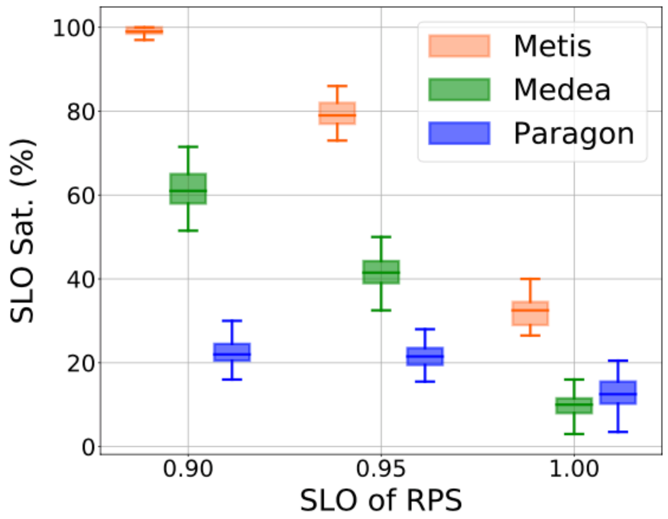
(b) Scheduling latency.



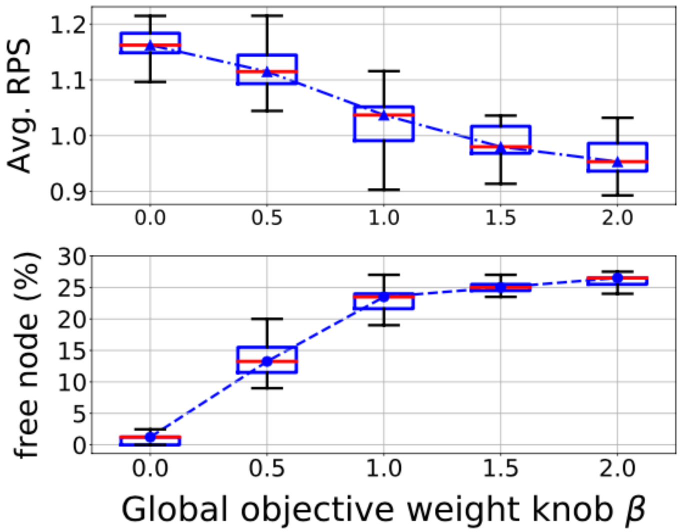
- Large-scale experiments
  - 729-node, 1k-3k containers
  - Comparable performance to that in previous 81-node clusters
  - Timely scheduling within 1 hour

- Sub-scheduler design
  - Accelerates RL convergence by 40×–95×
  - less than 10% loss of RPS

Evaluation: *Support of Various Scheduling Objectives*



- Maximizing SLO Satisfactions
  - Outperforming Medea and Paragon by 1.6× and 4.4× on average



- Minimizing Resource Fragmentation
  - Reward: weighted sum of RPS and vacant machines
  - Smooth trade-off between the two objectives