CAPES: Unsupervised System Performance Tuning Using Neural Network-Based Deep Reinforcement Learning

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The problems

- Large-scale high-performance computer storage systems play an important role in modern computing technologies:
  - Data centers
  - High-Performance Computers
  - Storage for enterprise computing
- Their performance can degrade dramatically during peak hours.
- Traditional tuning methods are costly because they require:
  - Human experts
  - Lengthy tune-benchmark-tune cycles
  - Fine tuning for each workload

Deep Q-Learning (DQL)

- Reinforcement learning concerns with how an agent ought to take actions in an environment in order to maximize a cumulative reward.
- DQL is reinforcement learning that uses Q-function to calculate reward and deep neural networks as value function.
- Q-function: the maximum discounted future reward when performs perfectly.

$$Q(s_t, a_t) = \sum_{i=t}^{n} \gamma^{i-t} r_t$$

(s_t is system state at time t, a_t is action at time t, r_t is reward at time t, γ is reward discount.)

- Q can be solved iteratively (Bellman's equation), which indicates that Q-learning can converge:

$$Q(s,a) = r + \gamma \max_{a'} Q(s', a')$$

Advantages

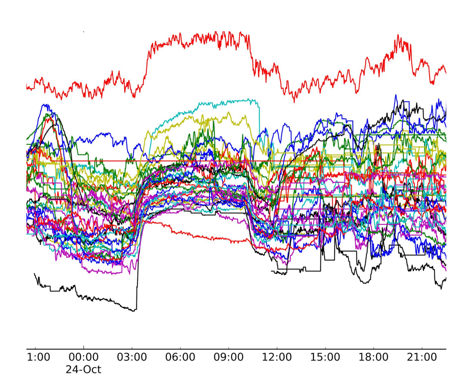
End-to-end coverage:
- Controls congestion at client, network, servers, and drives.

Improve throughput or fairness during congestion:
or both at the same time!

Fully automatic and requires little human effort:
- Online training and real-time online tuning, good at tuning dynamic and changing workloads.
- Faster than human tuning cycles.
- Works with any parameters of any systems in theory.

Our solution: Deep Q-Learning for traffic control

- Uses *congestion window size* and *rate limit* to control storage traffic.
- Uses fully automatic, unsupervised, Deep Neural Network-based reinforcement learning to turn parameter values.



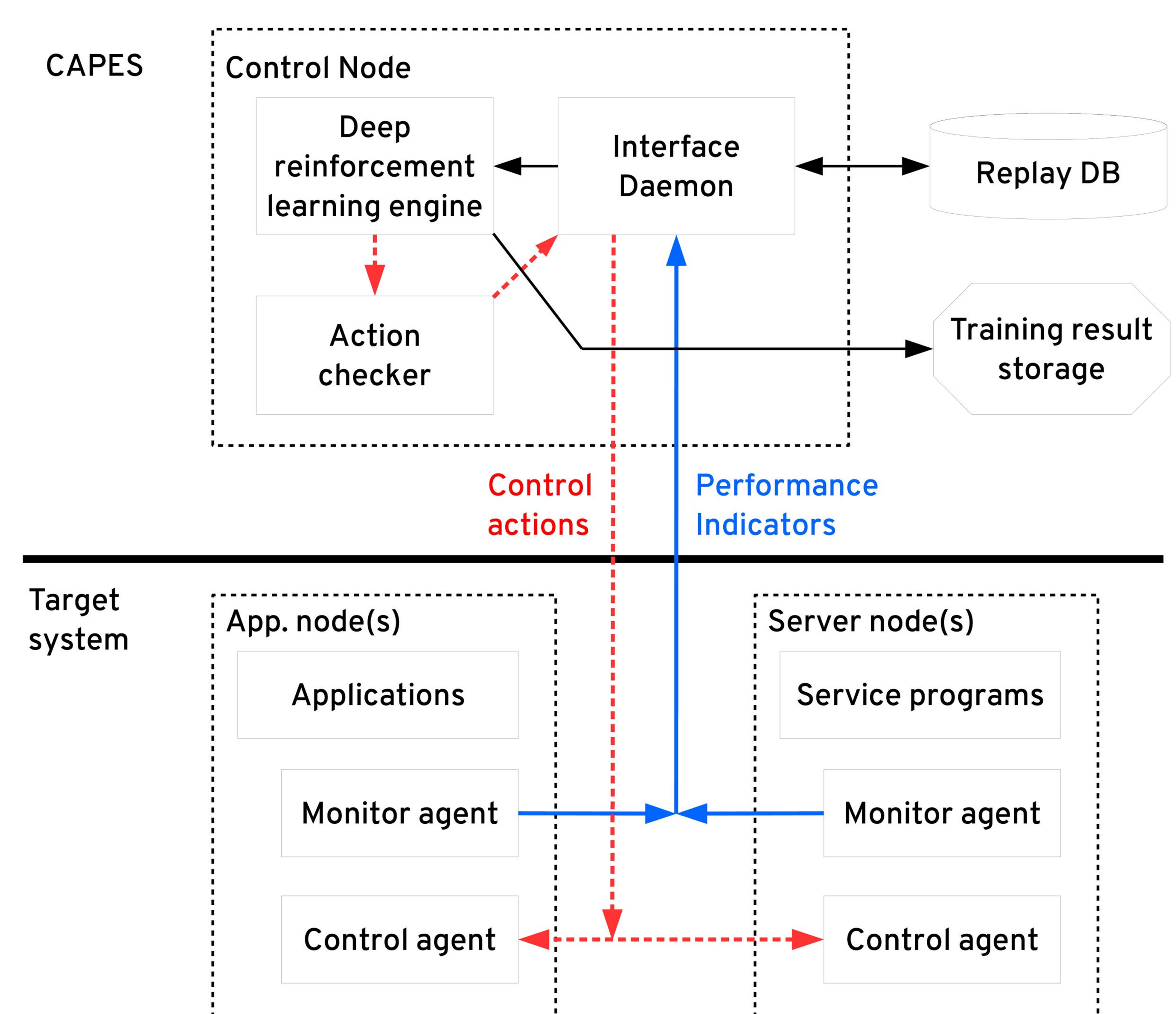
Unfiltered raw performance indicators (system state) → Value function →

Candidate action	Predicted reward
Action 0: Do nothing	0.382
Action 1: Increase Parameter A	0.741
Action 2: Decrease Parameter A	0.127
Action 3: Increase Parameter B	0.547
Action 4: Decrease Parameter B	0.123
Action 5: Increase Parameter C	0.372
Action 6: Decrease Parameter C	0.457

Action table (possible actions)

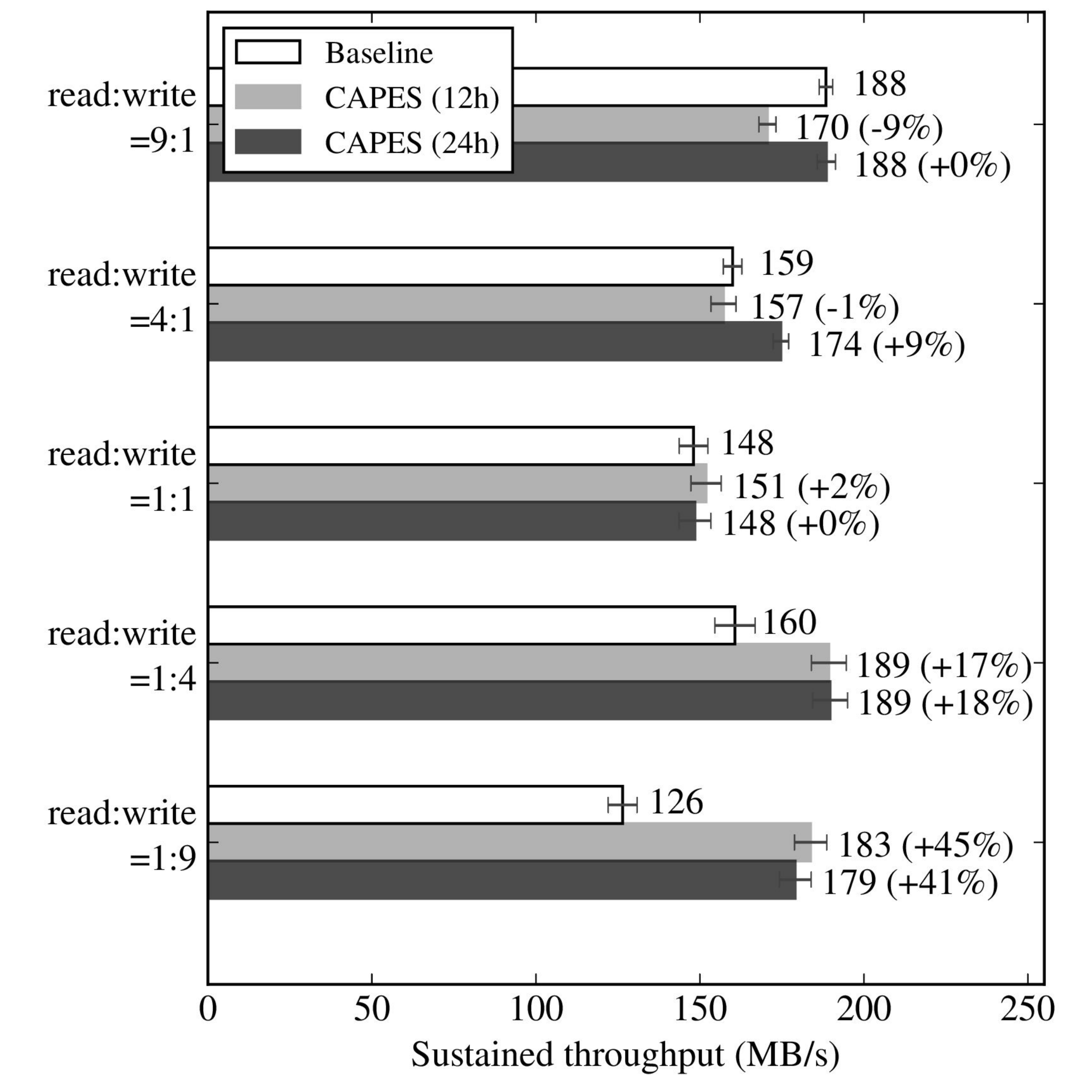
- Deep Q-Learning is an online reinforcement learning method, in which the system automatically explores tuning actions, collect rewards, and uses DNN to extrapolate to unseen situations.
- Input to the system is *Performance Indicators*, which include all measurement data of the target system.
- A set of predesignated *actions* decide how to tweak parameters.
- In each tick, the Value function (DNN) calculates which action has the highest anticipated *reward* and performs that action.

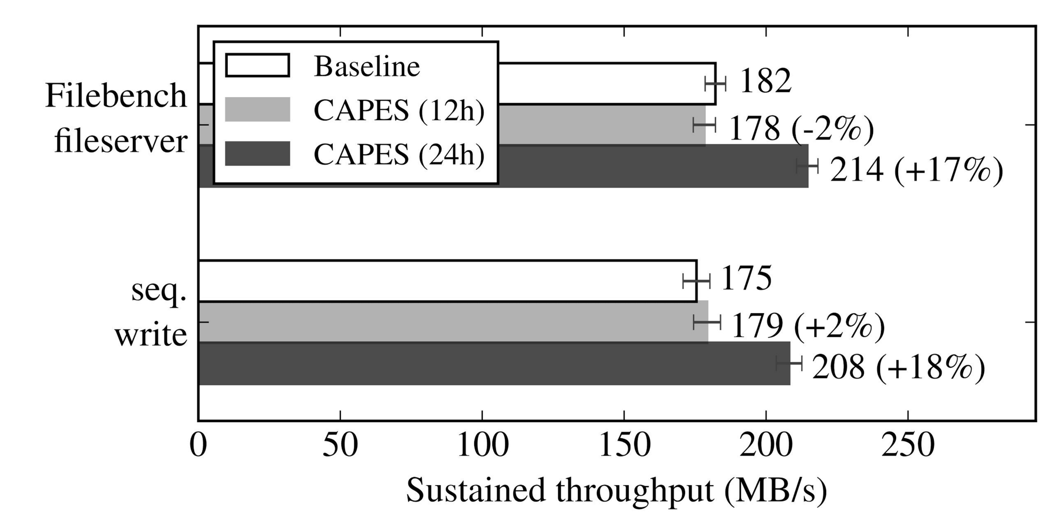
CAPES Design



Performance indicators	Definition
write throughput	the write throughput of the past second
read throughput	the read throughput of the past second
ack_ewma	exponentially weighted moving average (EWMA) of gaps between RPC acks
send_ewma	EWMA of gaps between sender timestamp embedded in RPC acks
pt	the time needed for server to finish reading/writing 1 MB data request
pt_ratio	current pt / min(pt) seen so far
dirty bytes in write cache	the dirty bytes on the client write cache

Prototype and Evaluation on Lustre





- Implemented using TensorFlow running on GPU.
- DNN has 2 hidden layers and uses Adam optimizer.
- Exploration period is 2 h.
- 4 servers + 5 cilents with multiple threads to saturate the bandwidth.
- CAPES control server uses GPU
- Graph shows throughputs at saturation point.
- Tuning congestion window size has a larger effect on write-heavy workloads.
- 12 h training time is enough for simple workloads (1st fig), and 24 h is needed for complex workloads (2nd fig).

Conclusion and Future Work

- Minimally intrusive, can be deployed to production system.
- Fully unsupervised, model-less tuning.
- Online training and responsive to changing workloads.
- Effect on a wide range of workloads, especially write heavy workloads.
- Suitable for any deployment before hitting the scale-out bottleneck.
- For details of CAPES, such as full algorithm, overfitting test, and prediction error over time, refer to paper "CAPES: Unsupervised Storage Performance Tuning Using Neural Network-Based Deep Reinforcement Learning." SC'17.
- Source code will be available at: https://github.com/mlogic/capes-oss

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