Adaptive Request Scheduling for the I/O Forwarding Layer

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Motivation

- **Parallel I/O** is a challenge for HPC
- Decades of research into optimization techniques
  - MPI collective I/O, reordering aggregation techniques, alignment to stripe locks, I/O scheduling, …
- **Results depend** on the workload
  - They are hard to replicate
  - We may lose performance if we use the techniques for inadequate situations
  - Success also depends on the **right values for parameters**
- **This work:** apply a reinforcement learning technique to adapt

Summary

~~Motivation~~

The TWINS scheduling algorithm

Adaptive request scheduling

Results

Final remarks

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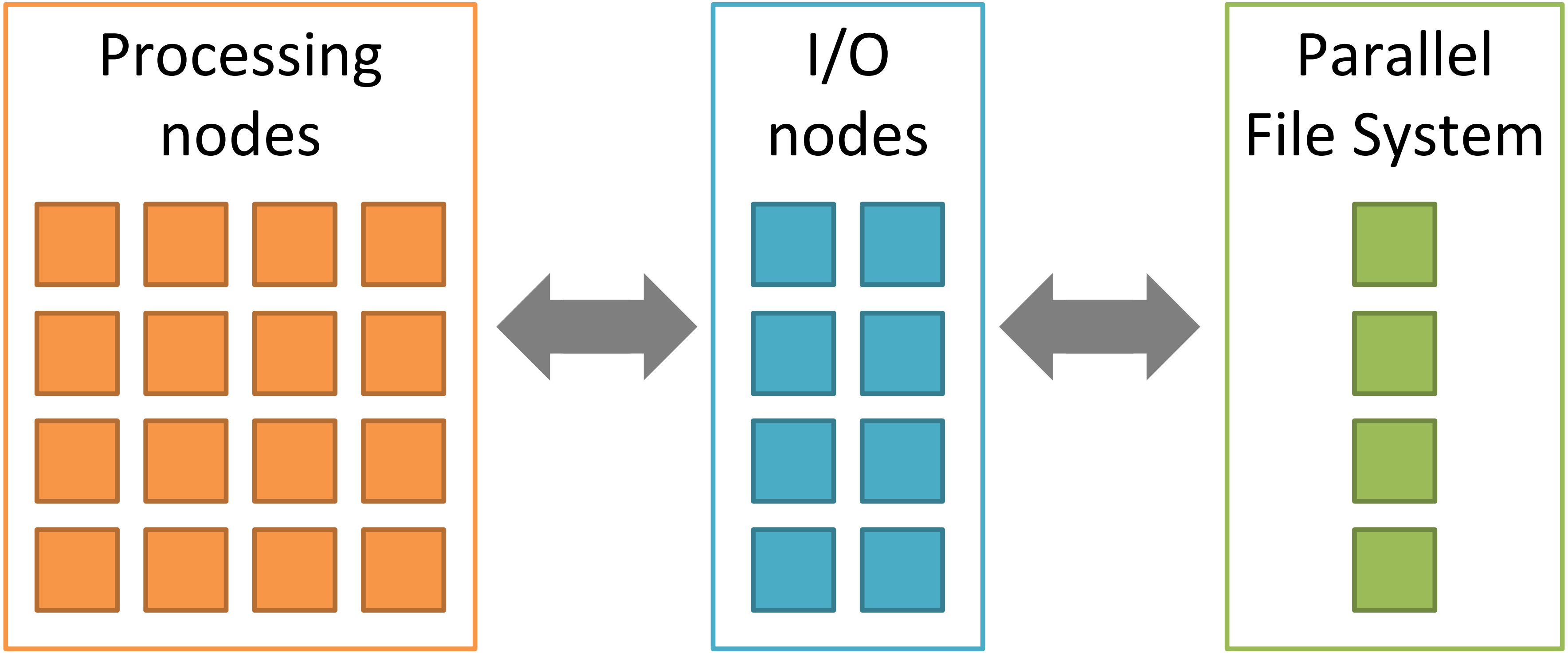

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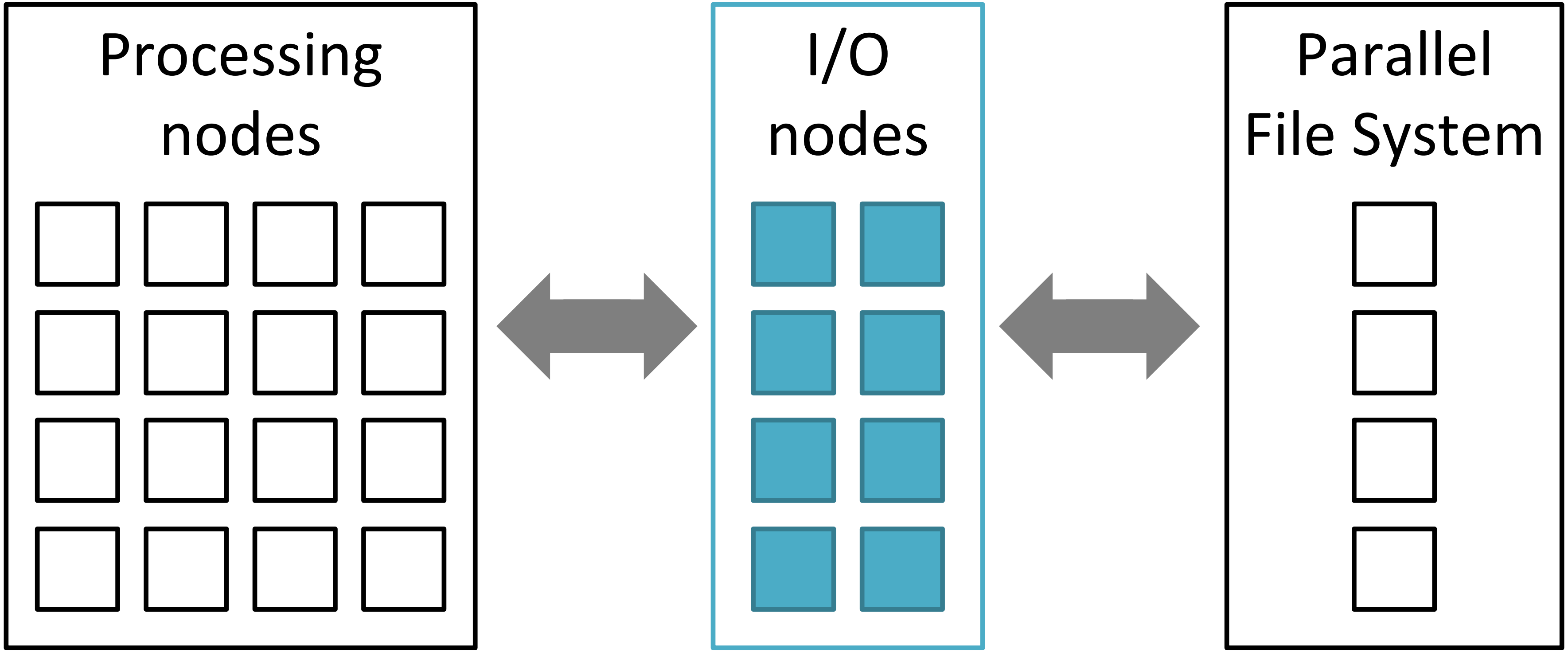
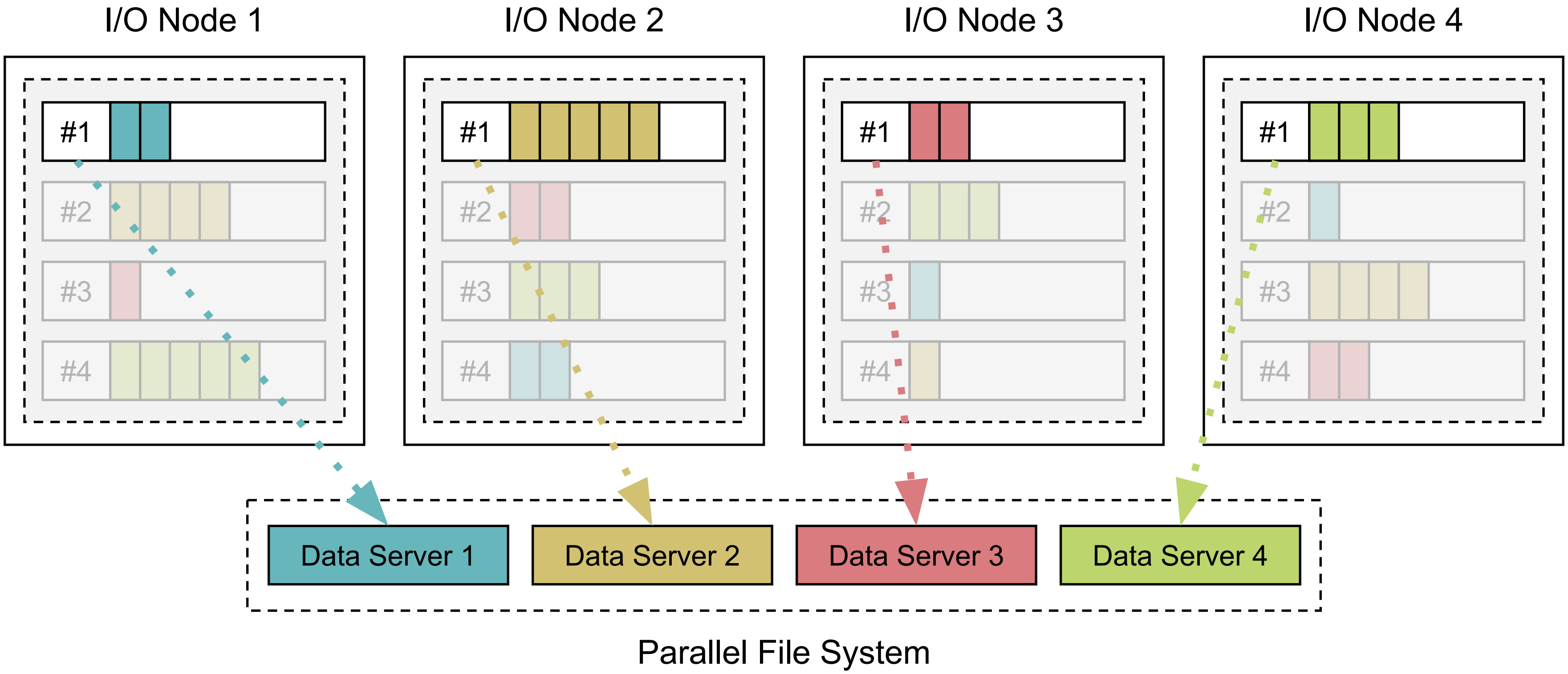

Processing nodes
I/O nodes
Parallel File System

The TWINS scheduler

- One request queue per data server
- The I/O node only accesses one of the servers during each time window
- Different I/O nodes access the servers in different orders

J.Bez, F.Z.Boito et al., 2017, "TWINS: server access coordination in the I/O forwarding layer"



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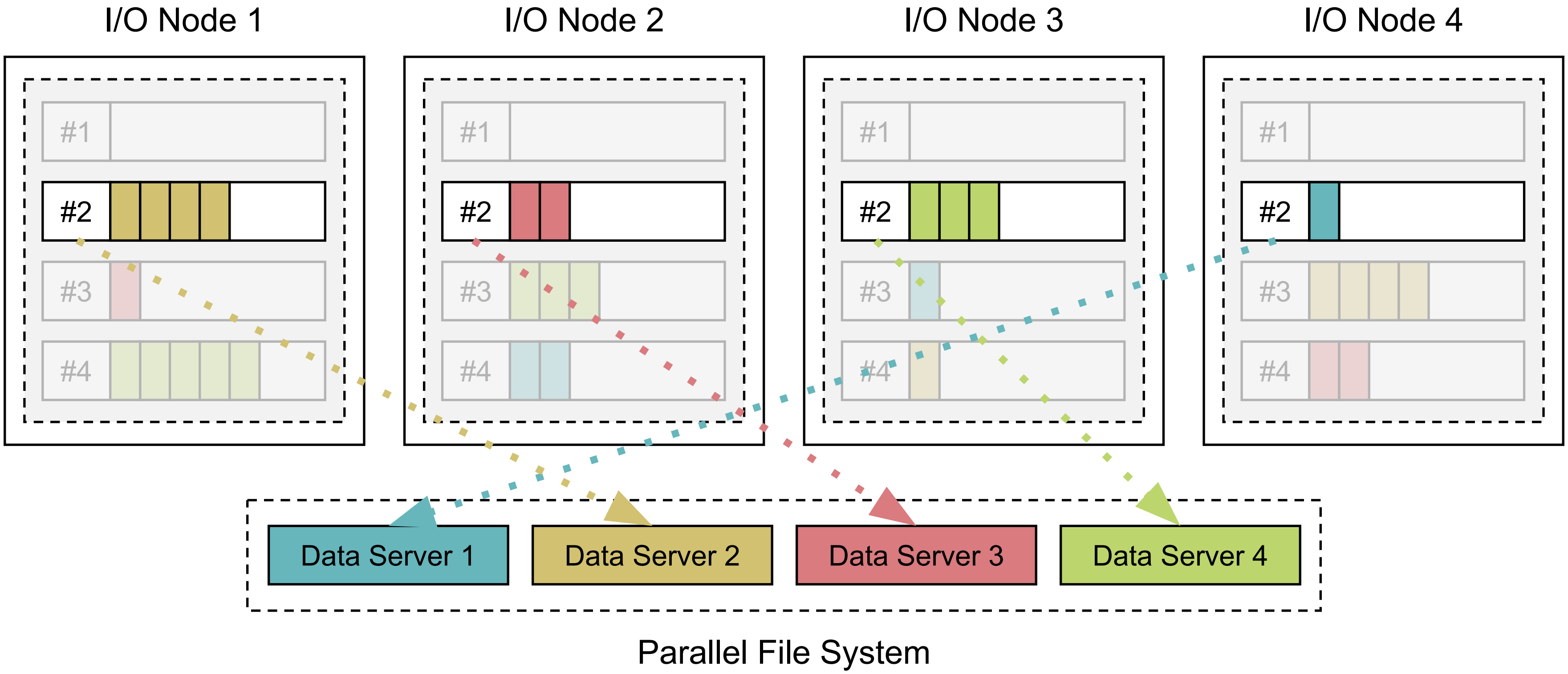

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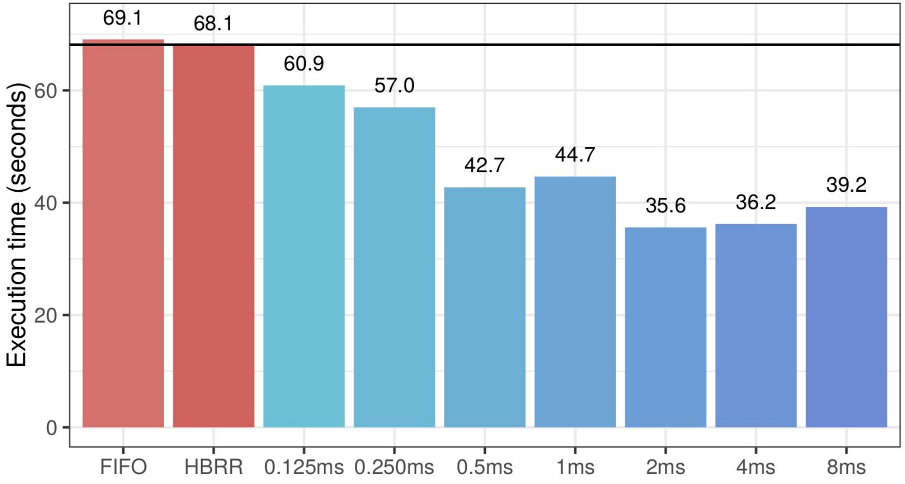
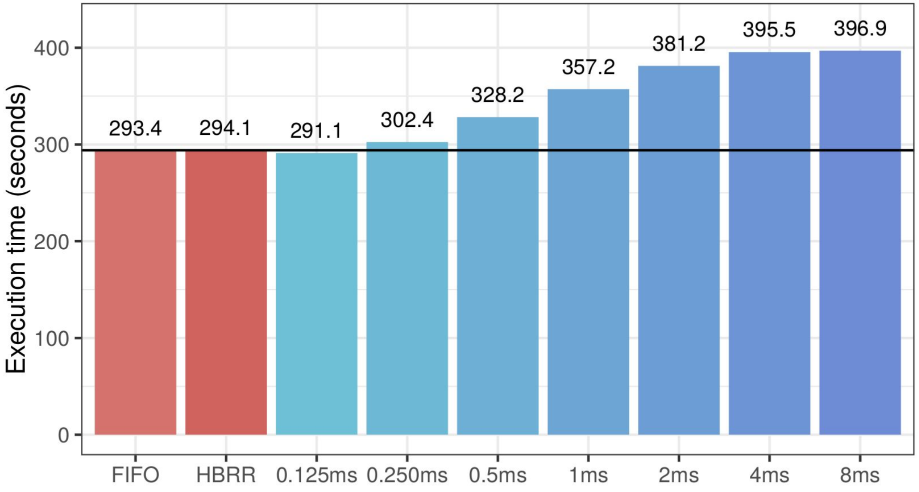
TWINS results



1D-strided read through 8 I/O nodes



Contiguous write through 2 I/O nodes

128 processes, IOFSL forwarding, 4 PVFS servers, 4GB shared file, 32KB requests

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Reinforcement Learning approach

- We want to learn, but **without a long training phase**
- Approach: k-armed bandit problem
  - K possible actions, no prior information
  - take one action at each step, observe reward and update value estimates
- We need to learn one policy per access pattern (what is the best value)
  - **Contextual bandit** (associative search task)

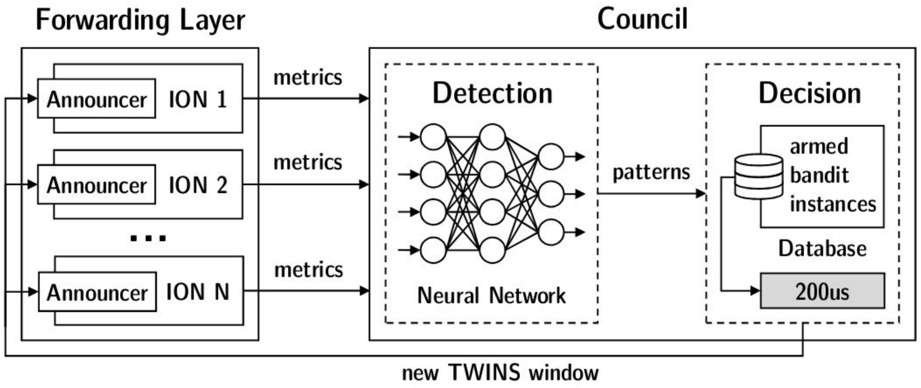
Approach

- Each armed bandit "instance": **ε-greedy algorithm**
- Value estimates are incrementally computed sample averages (reward is bandwidth)

$$Q_{t+1}(a) = Q_t(a) + \frac{1}{N(a)}[R - Q_t(a)]$$

- **Global decisions made by a council**
- Chose the value that is the best

  for most I/O nodes



Access pattern classification

- Context is defined by
  - Operation (read or write)
  - Number of files per process (N-to-1 or N-to-N)
  - Average request size
  - Spatiality (contiguous or strided) <- not readily available
- Use a neural network to detect **spatiality** from observed metrics
  - It has to be trained but with less experiments than for the whole thing

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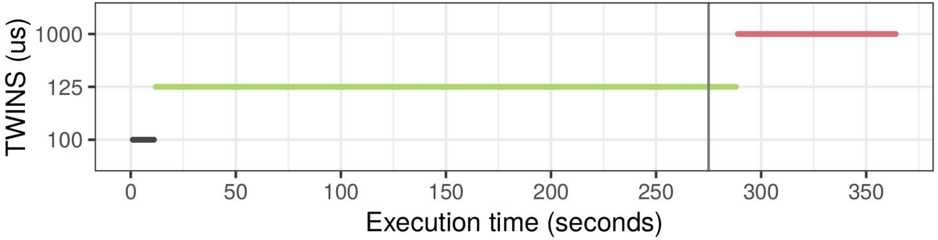
1 - Evaluate the access pattern detection

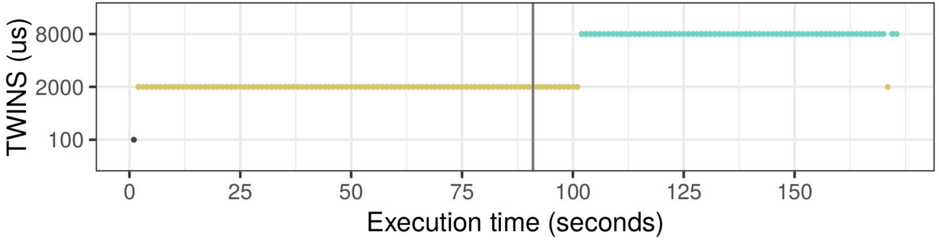
- Assume right context -> right decision
- Offline evaluation (with traces) - precision (%)

	Min	**Mean**	**Median**	**Max**
Read	98	99	100	100
Write	53	97	100	100

- Execution (the council is previously told what is the best window size)



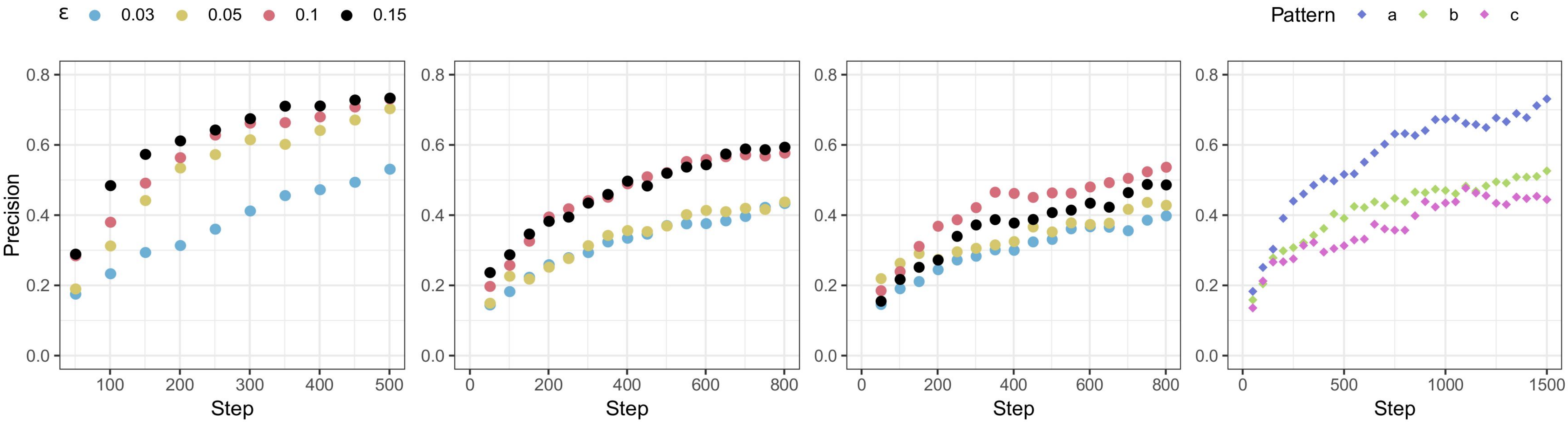
1 I/O node, file per process, contiguous 256KB requests



8 I/O nodes, shared file, contiguous, 256KB requests

2- Evaluate the learning

- Assume perfect access pattern detection
- Offline evaluation (with traces)



Pattern a - 128 procs, read, shared file, 8 I/O nodes, 32KB reqs, 1D-strided

Pattern b - 128 procs, write, shared file, 2 I/O nodes, 32KB reqs, contiguous

Pattern c - 512 procs, read, shared file, 8 I/O nodes, 32KB reqs, contiguous

ε=0.15

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Final Remarks

- Tuning optimization techniques and parameters is difficult (But important!)
- We used a reinforcement learning technique to **learn the best choices**
  - Tune the window size of the TWINS scheduler
  - Got to 0.98 of the best performance, ~70% of precision
- **This system has a long life!**
- Some caveats
  - Need to select a few good values for the parameter
    - Maybe we don't know the optimal, but we already have some improvement
    - Too many choices = slow learning
  - Need to know what are the parameters that define the context
  - Bandwidth as reward
- Now: investigating the trade-off between centralized decision and scalability

Final Remarks

This paper was submitted and is being reviewed

Available at https://hal.inria.fr/hal-01994677