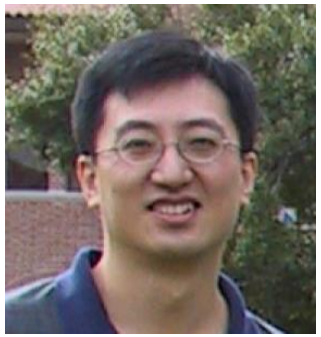
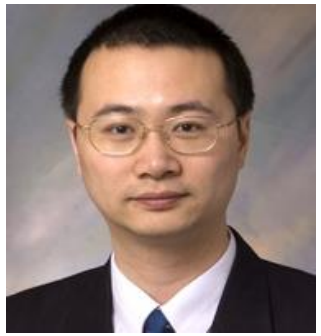
SLearn: A Case for Task Sampling based Learning for Cluster Job Scheduling

Akshay Jajoo*



Y. Charlie Hu



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Challenges in Cluster Scheduling

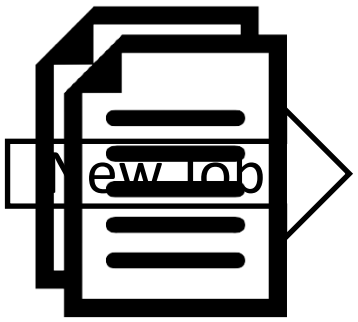
- **Online**: Jobs arrive online
  - They compete for shared resources
- **Diverse SLOs**: Different jobs have different SLOs
  - Deadline, fast completion, least network usage, etc.
- **Non-clairvoyant**: Runtime properties of these jobs are unknown
  - Resource needs are diverse

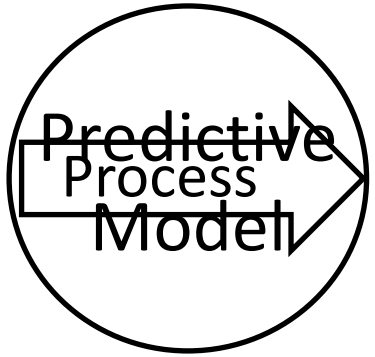
An Effective Approach for Cluster Scheduling

Learn runtime characteristics of pending jobs

Widely Used Approach for Learning

History-based learning:
Learning from past execution history
(Learning in Time)





Previous Work on History-based Learning

- **3Sigma (Eurosys 2018)**
- **Don’t Cry Over Sp…. (ATC 2017)**
- **Morpheus (OSDI 2016)**
- **Perforator (SoCC 2016)**
- **JamiasVu (Techreport, 2016)**
- **Corral (Sigcomm 2015)**
- **Rayon (SoCC 2014)**
- **Jockey (EuroSys 2012)**

Learning offline models for recurring jobs

Periodically updating the offline learned models

Learning for new jobs

History based Learning – Assumptions and Reality

Assumption 1: Most of the jobs are recurring ✗

- ✓ Corral [43] and Jockey [30] → only 40% recurring jobs
- ✓ Morpheus [44] → 60% are recurring

Assumption 2: Same or similar jobs will perform consistently over time ✗

- ✓ In a Microsoft cluster, within a year ratio for two types of machines changed from 80/20 to 55/45 [44]
  - Same job's performance varies by 40% on the two machines
- ✓ 50% of applications were updated every month [44]

[43]: Corral, Sigcomm'2015 [30]: Jockey, Eurosys' 2012 [44]: Morpheus, OSDI'2016

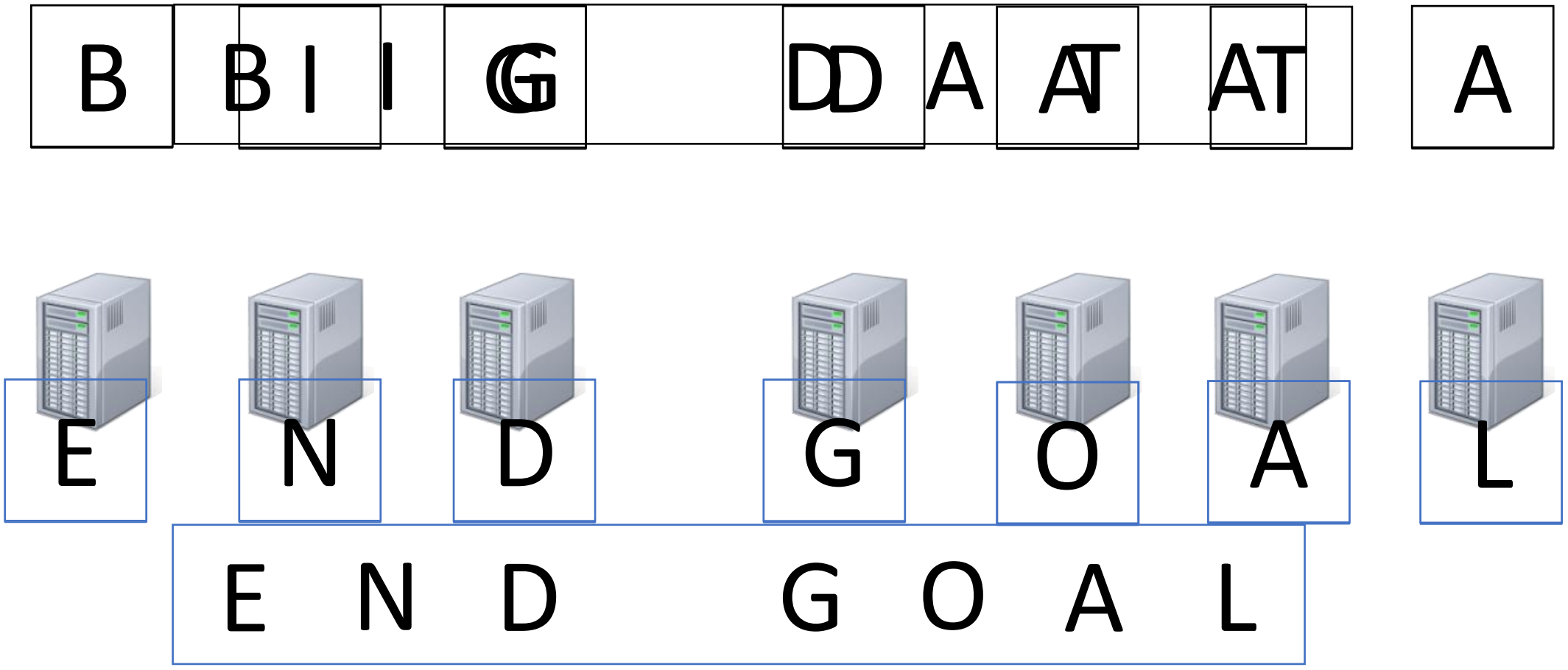
Poor Prediction Accuracy of History-based Learning

- State-of-the-art history-based predictor, 3Sigma [47],
  - Predicts with more than 100% error for 23% of jobs
  - For a significant fraction of jobs, it's error is more than 1000%

[47]: 3Sigma, Eurosys 2018

An alternate approach for learning:

SLearn - Learning in space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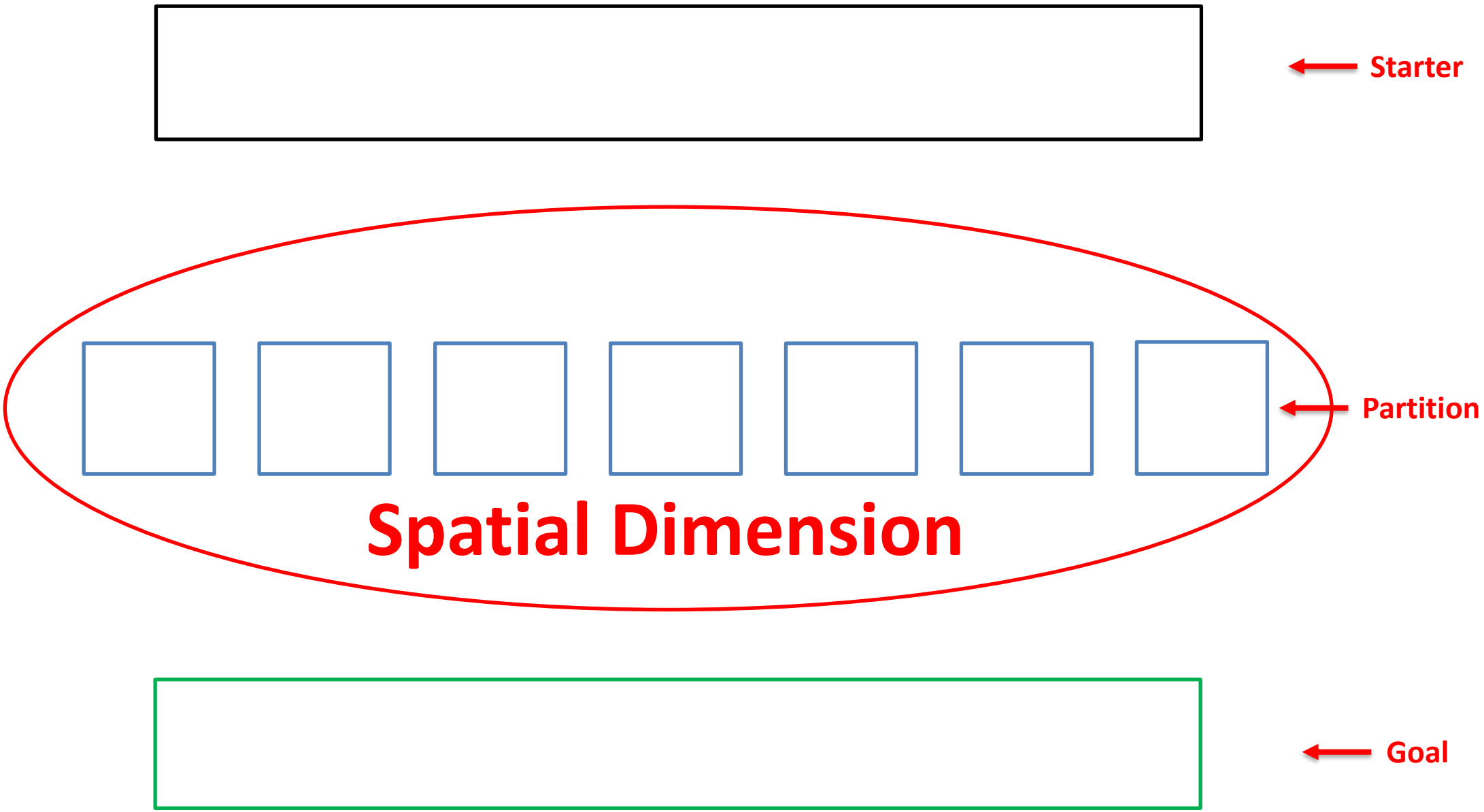
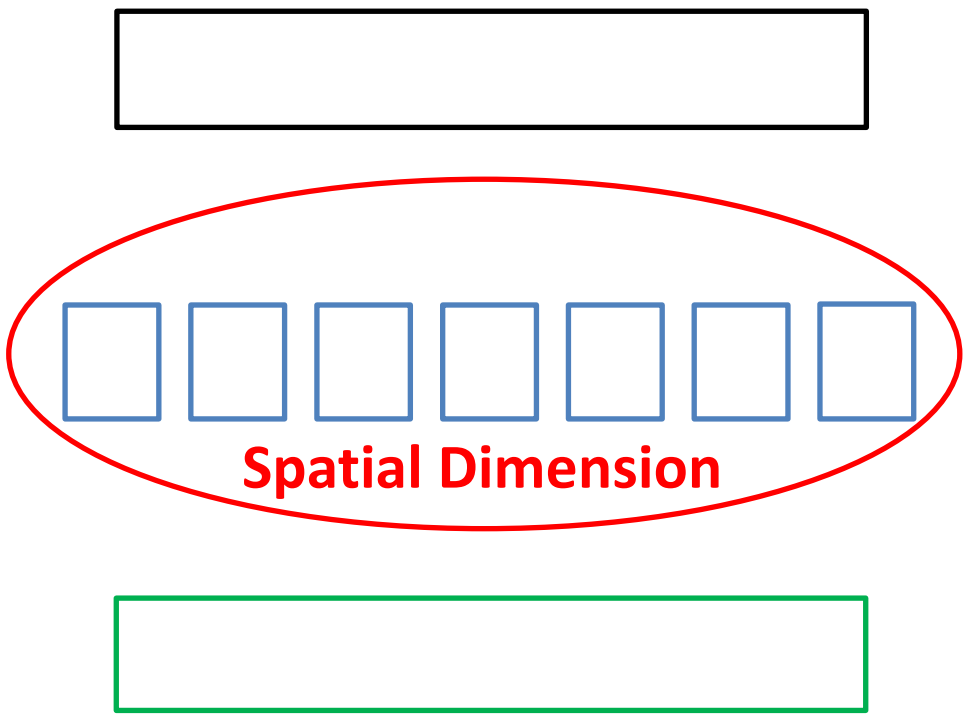
Key Insight: Spatial Dimension



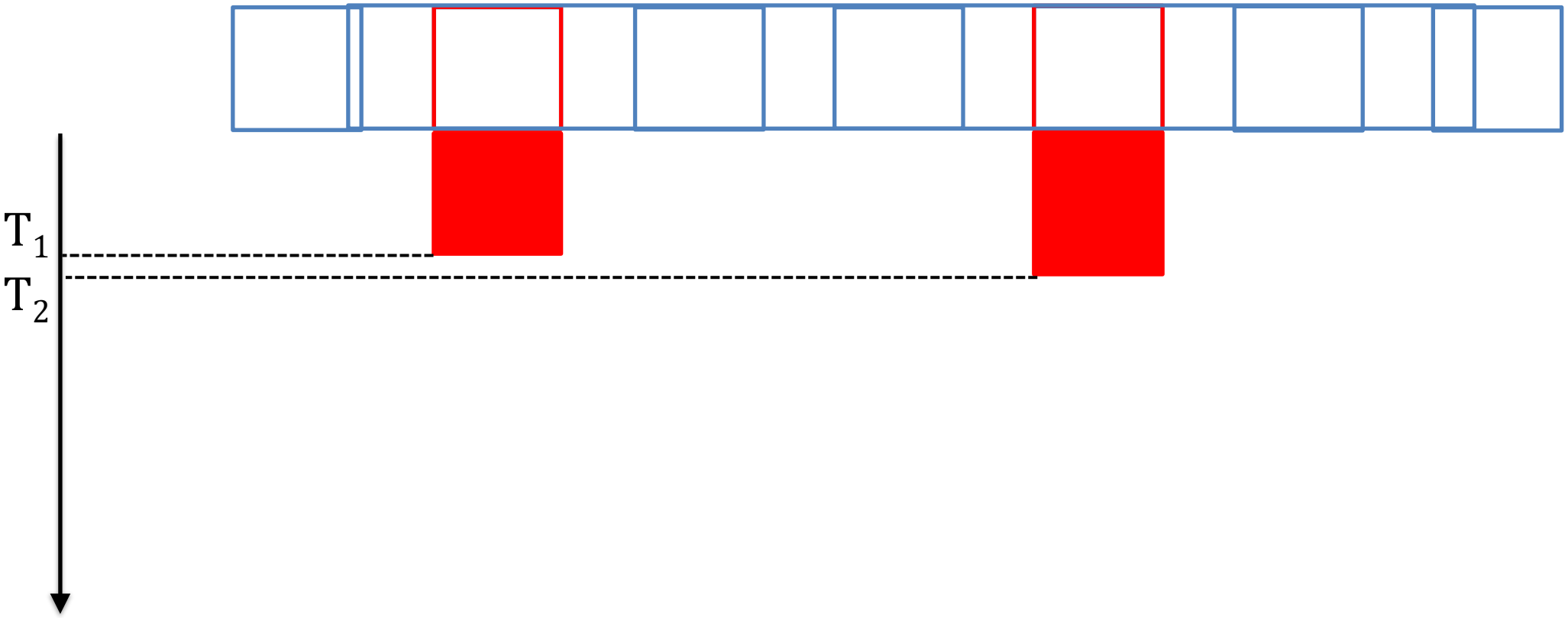
SLearn – Key Idea



Can this spatial dimension be exploited to learn job properties?

Sampling the population is an effective way to learn its properties.

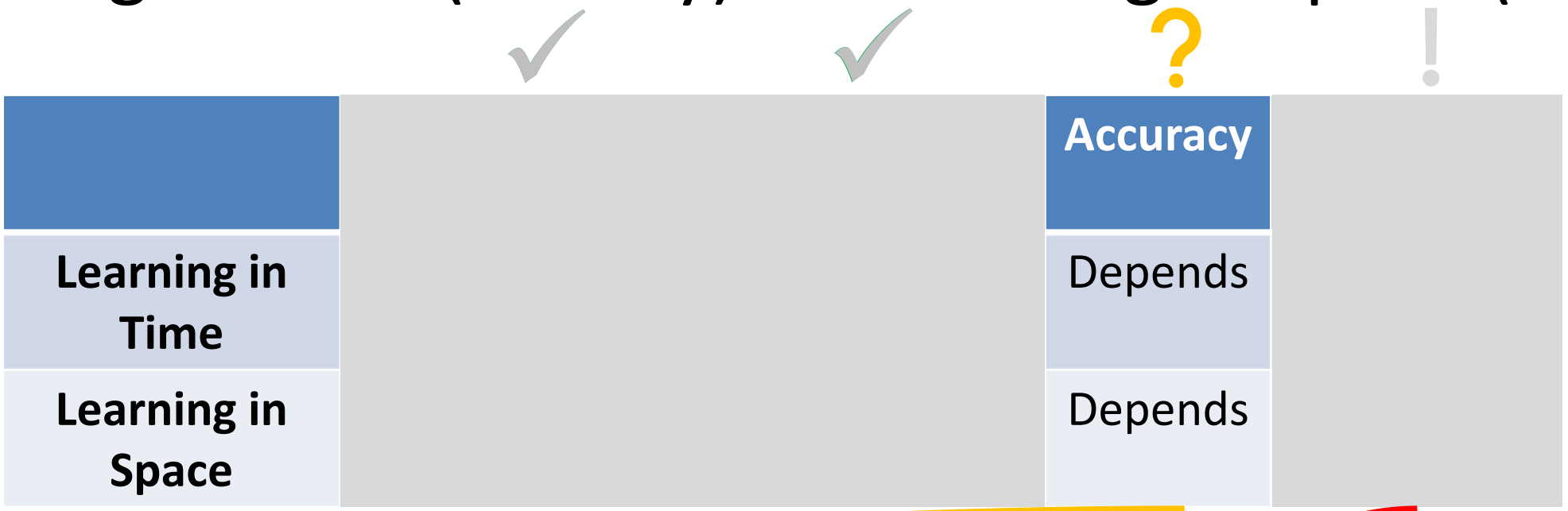
SLearn: Online Learning by Sampling the Spatial Dimension



$$T = \frac{T_1 + T_2}{2}$$

$$\text{Total Size} = 7 * T$$

Learning in Time (History) vs. Learning in Space (SLearn)



	Accuracy
Learning in Time	Depends
Learning in Space	Depends

1. Will learning in space be more accurate than in time?

2. If so, will the better accuracy be able to compensate for the delay due to sampling?

Trace based Variability Analysis

Variation Across Time vs Variation Across Space

Traces Properties	2Sigma [1]	Google 2011 [8]	Google 2019 [11]
Duration	7 Months (Jan-July'16)	29 Days, May 2011	31 Days, May 2011
Machines	872 (441 + 431)	~12.5K	~8*12.5K
Number of Jobs	~0.4 Million	~0.7 Million	~30 Million

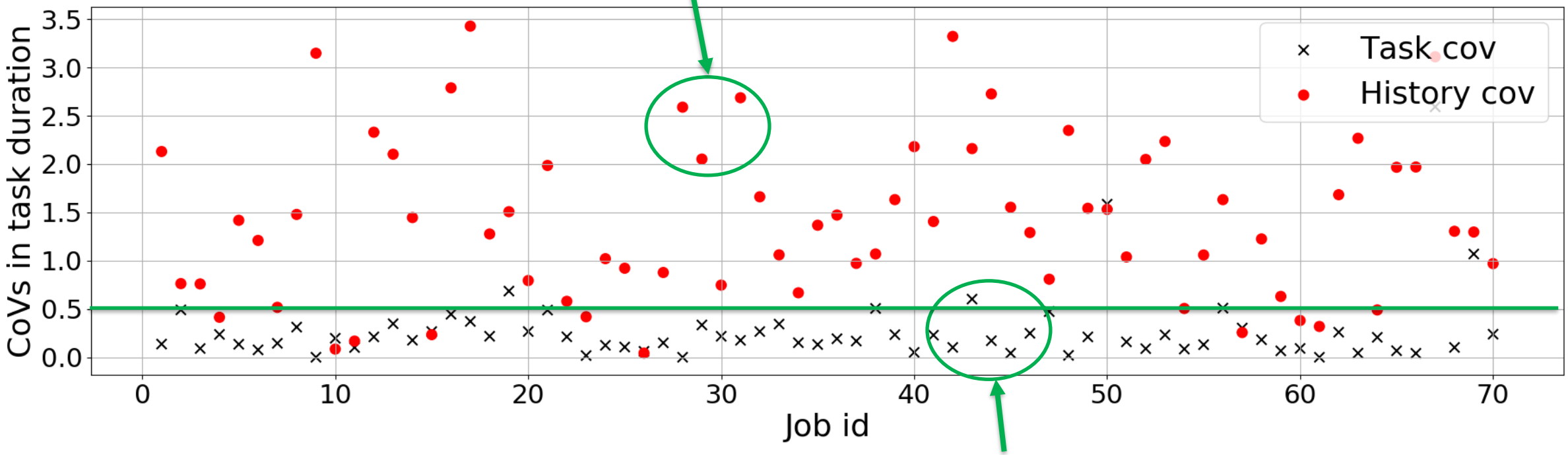
[1] : 2Sigma hedge fund: www.twosigma.com

[8] : Google Cluster Trace 2011 https://github.com/cluster-data

[11]: Google Cluster Trace 2019 https://research.google/tools/datasets/google-cluster-workload-traces-2019/

CoVs of the Estimated Job Size: Space vs. Time

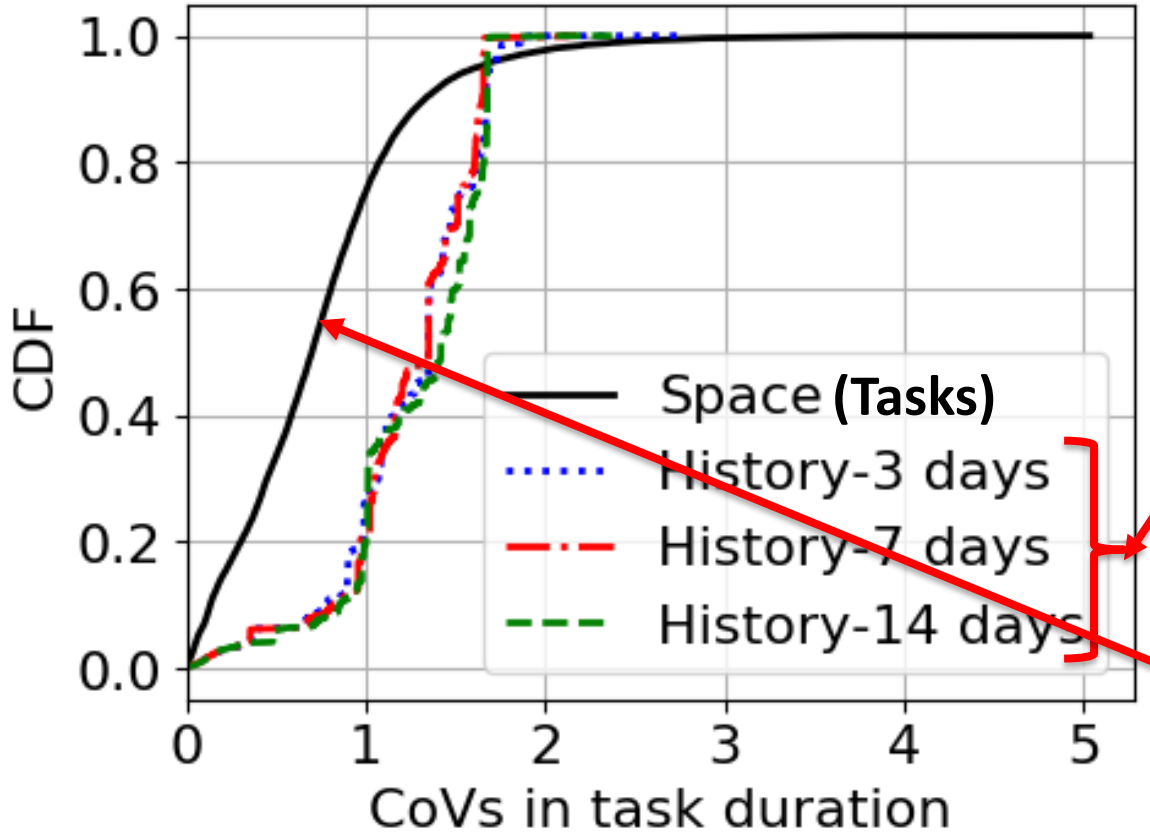
History (Time) = CoV in average task lengths of similar jobs



$$\text{Tasks (Space)} = \frac{CoV\ of\ lengths\ of\ sampled\ tasks}{\sqrt{Number\ of\ tasks\ sampled}}$$

Figure shows analysis results for 70 jobs selected at random from the 2Sigma trace

Varying the History Length in Estimation across Time

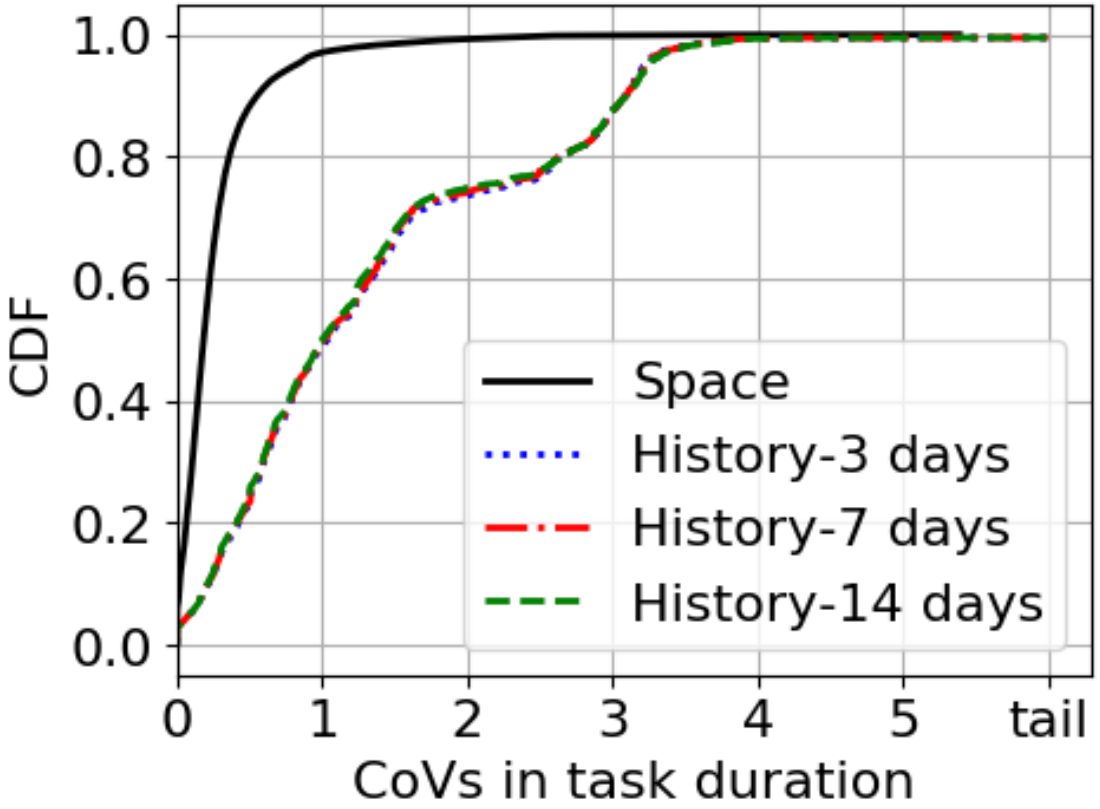


Google 2019

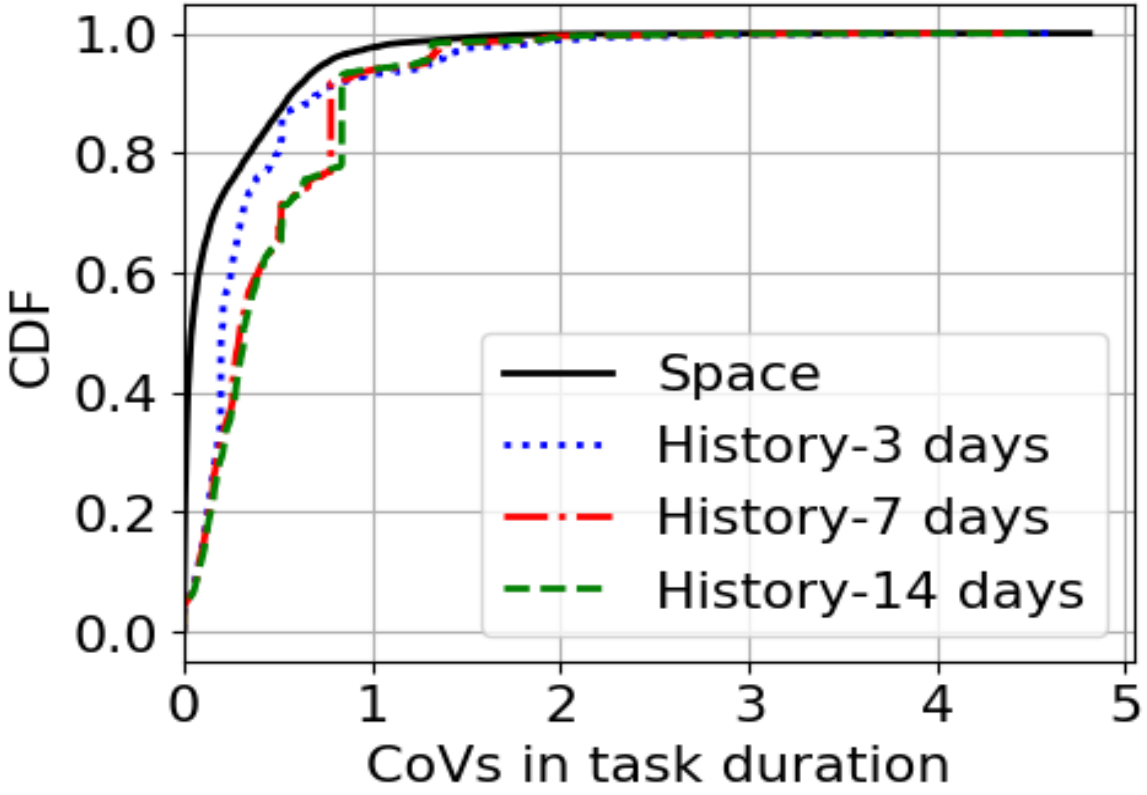
CDFs of CoVs of estimated job size across history with varying history duration

Variation across tasks (Space) is lower than variation across history (time) for all history lengths

Varying the History Length in Estimation across Time

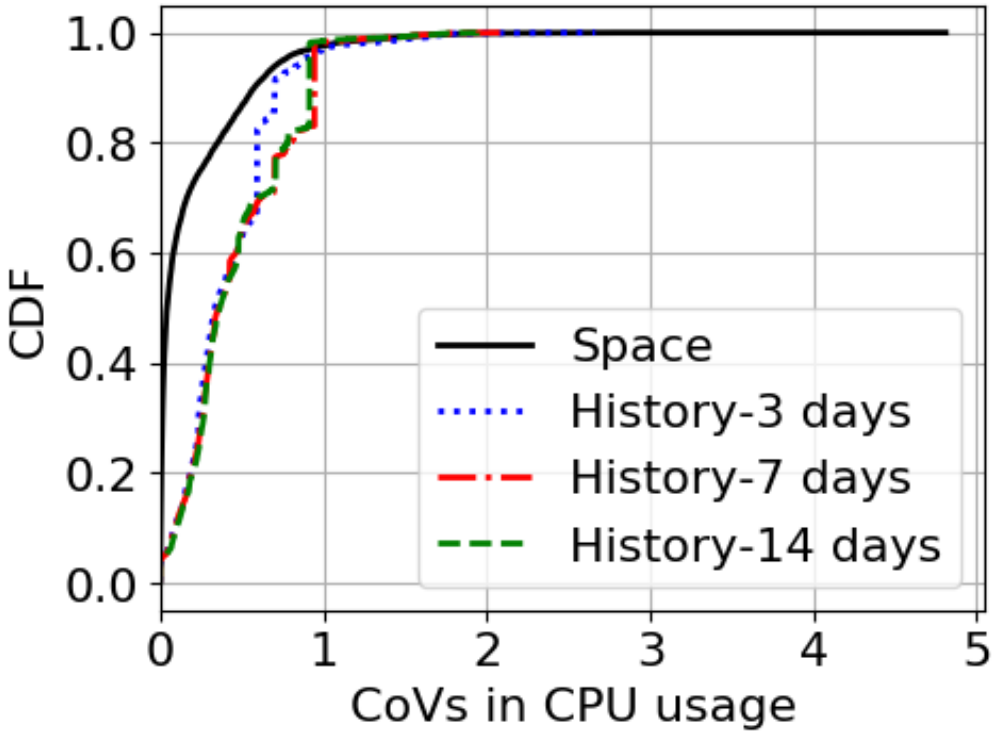


2Sigma

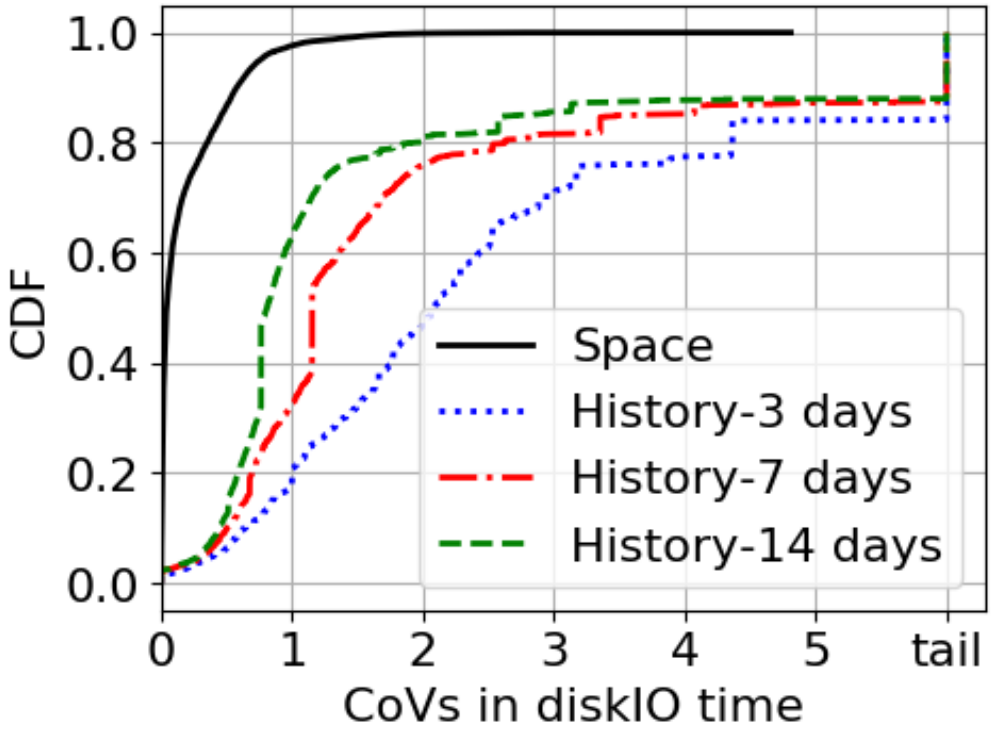


Google 2011

Varying the History Length in Estimation across Time Other Properties



Google 2011



Google 2011

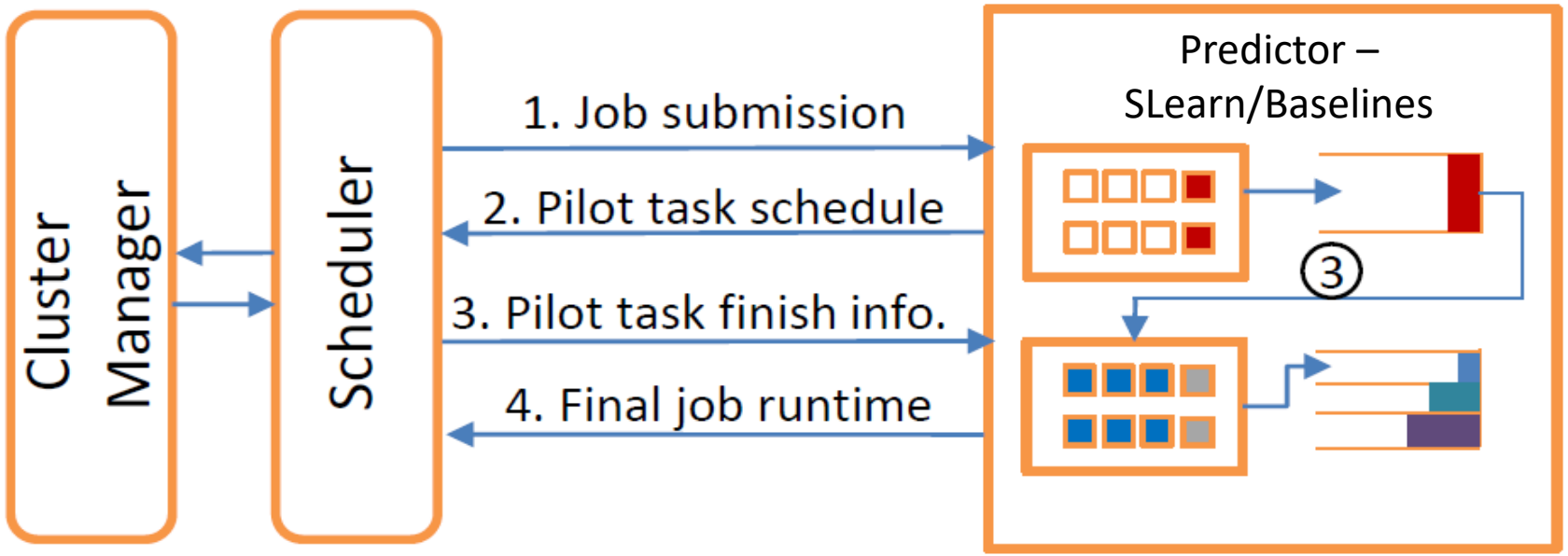
Learning in Time (History) vs. Learning in Space

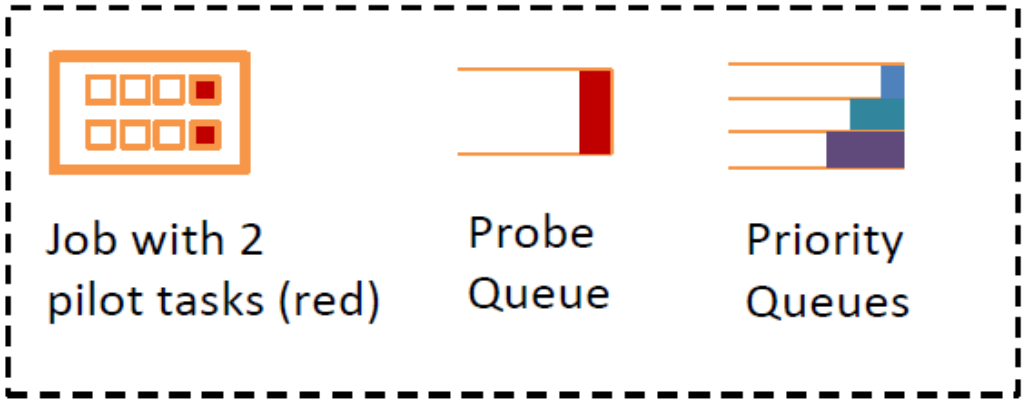
	Prediction Overhead
Learning in Time	No
Learning in Space	Yes

1. Will learning in space be more accurate than in time?

2. If so, will the better accuracy be able to compensate for the delay due to sampling?

Generic Scheduler (GS)





SLearn Predictor – Design Overview

- Samples a small fraction of tasks for each job
- Schedules at a high priority till completion
- Uses their runtime to estimate job runtime

SLearn Predictor – Implementation Challenges

- How to ensure high priority for sampling tasks?
  - Sampling jobs are given 2nd highest priority
- Won't sampling delay be too hard on jobs with very few tasks?
  - Jobs under certain width are bypassed from sampling and given the highest priority
- How to determine sample tasks?
  - Sample size
    - Decided by an adaptive algorithm
  - Picking the sampling tasks
    - Random

Baseline Predictors and Policies

1. 3Sigma (Eurosys 2018) – State-of-the-art history-based predictor
2. 3SigmaTL – 3Sigma + thin bypass like SLearn
3. Point Median – Like 3Sigma, predicts median runtime
4. LAS (SoCC 2018) – Online approximation of SJF, *e.g.,* Kairos
5. FIFO – Basic Yarn scheduler
6. Oracle – 100% accurate prediction

Experiment Details

Workload – Extracted from larger traces

Source	2Sigma [1]	Google 2011 [8]	Google 2019 [11]
New Name	2STrace	GTrace11	GTrace19
Number of jobs	1253	1251	1255

Experiments

JCT improvement
Working of adaptive sampling

Runtime error prediction
Real 150 node testbed

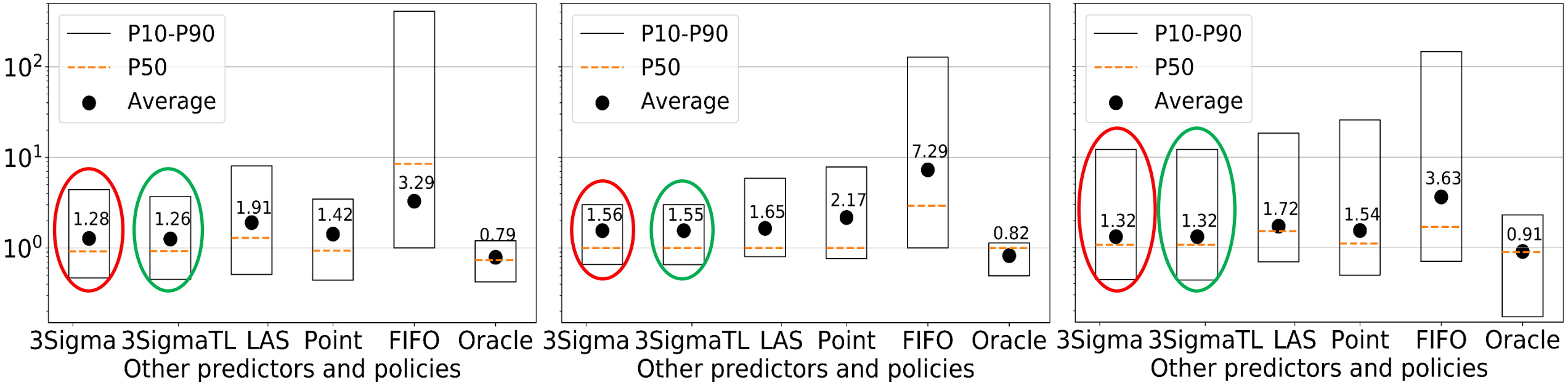
[1] : 2Sigma hedge fund: www.twosigma.com

[8] : Google Cluster Trace 2011 https://github.com/cluster-data

[11]: Google Cluster Trace 2019 https://research.google/tools/datasets/google-cluster-workload-traces-2019/

Job Completion Time (JCT) Speedup

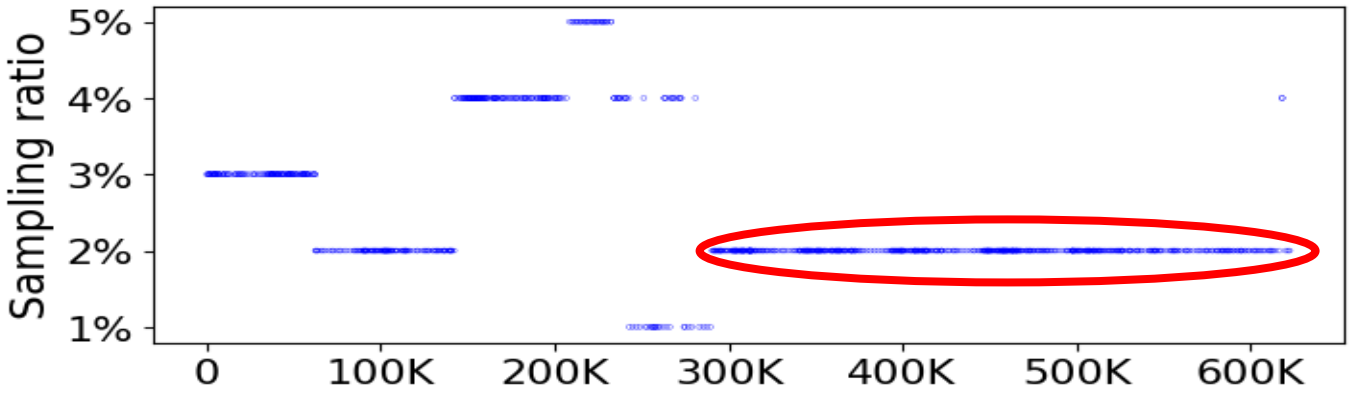
Speedup = (JCT with baseline) / (JCT with SLearn)
Higher the speedup better is SLearn



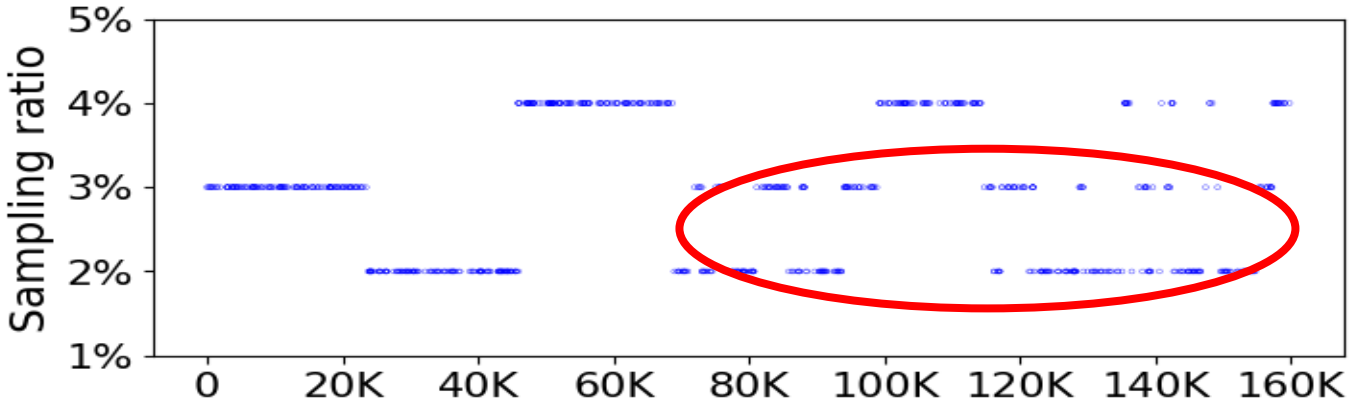
2STrace **GTrace11** **GTrace19**

Adaptive Sampling Algorithm in Action

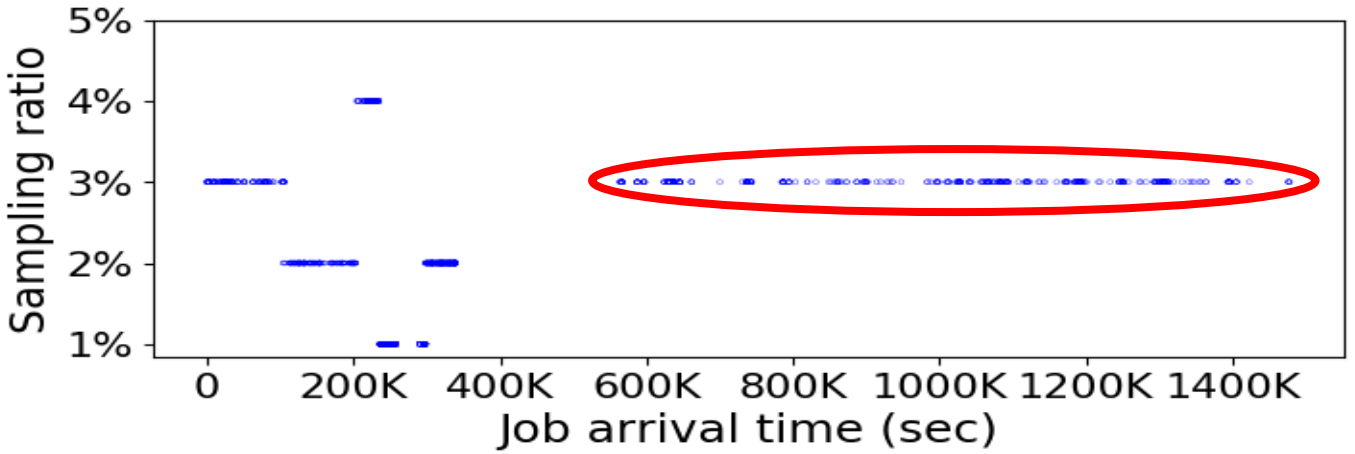
2STrace



GTrace11



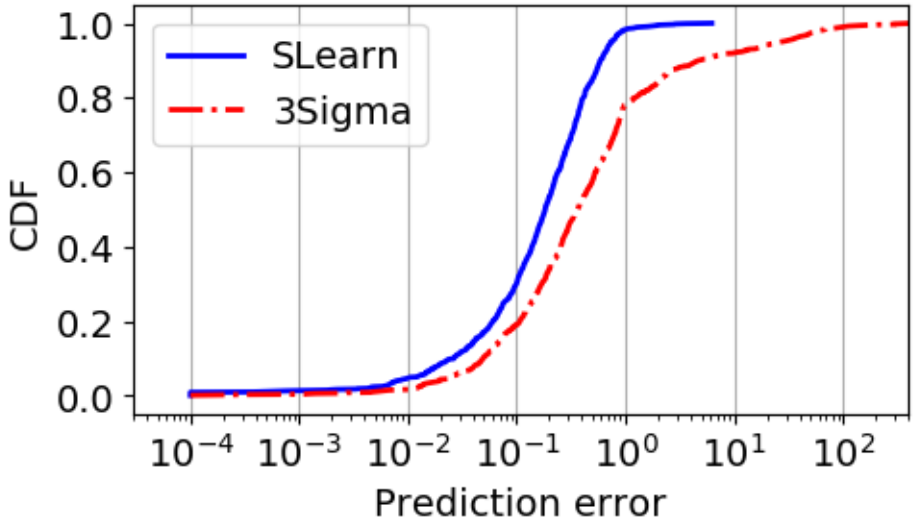
GTrace19



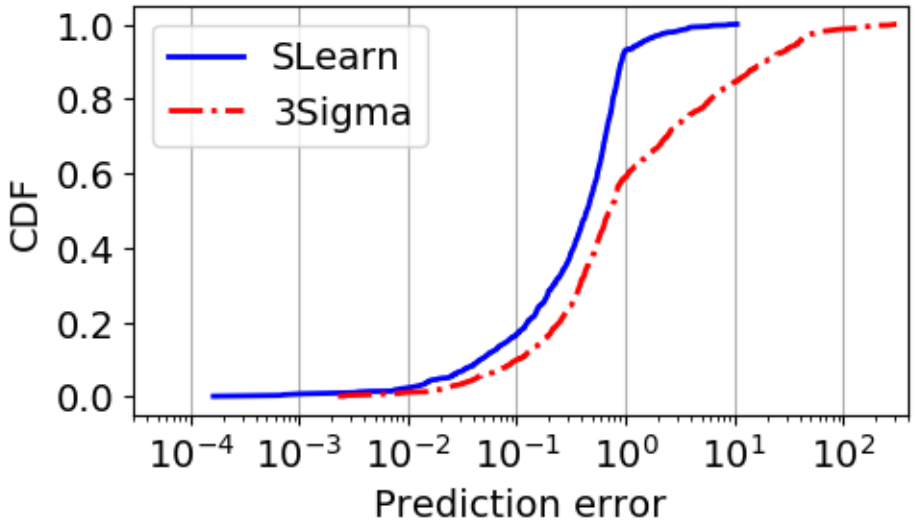
The adaptive sampling algorithm effectively balances the trade-off between prediction accuracy and sampling overhead.

Learning Accuracy

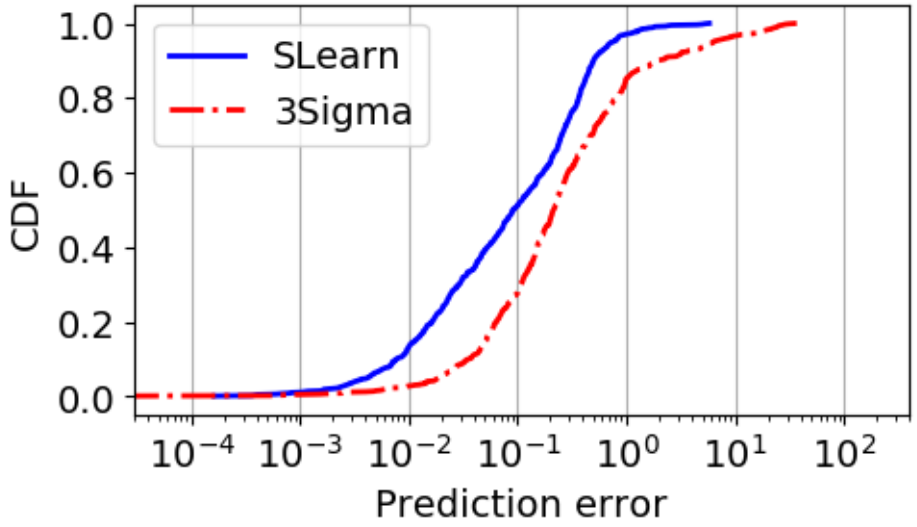
2STrace



GTrace19

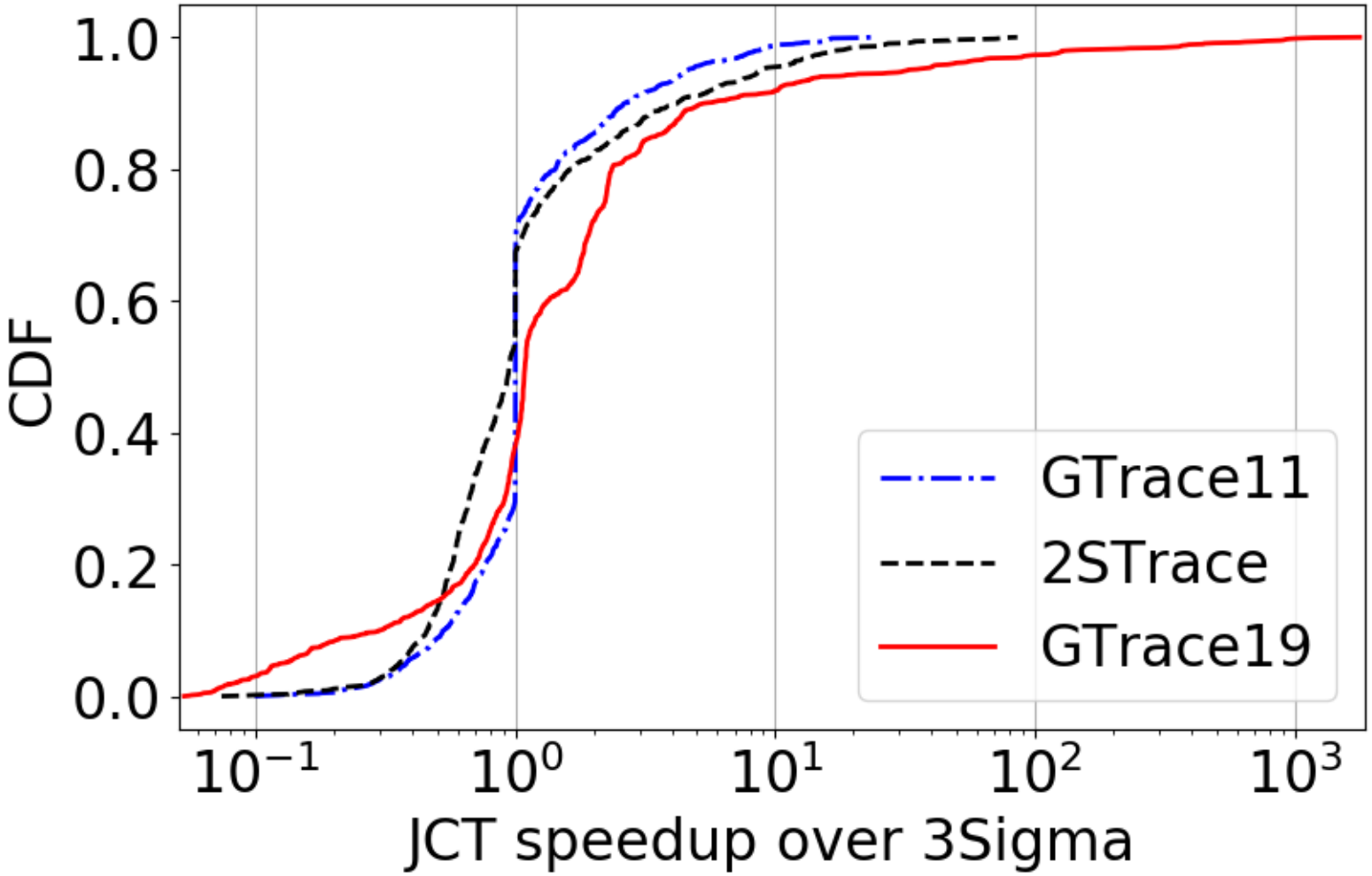


GTrace11



JCT Speedup on Testbed

150 Node Azure Cluster

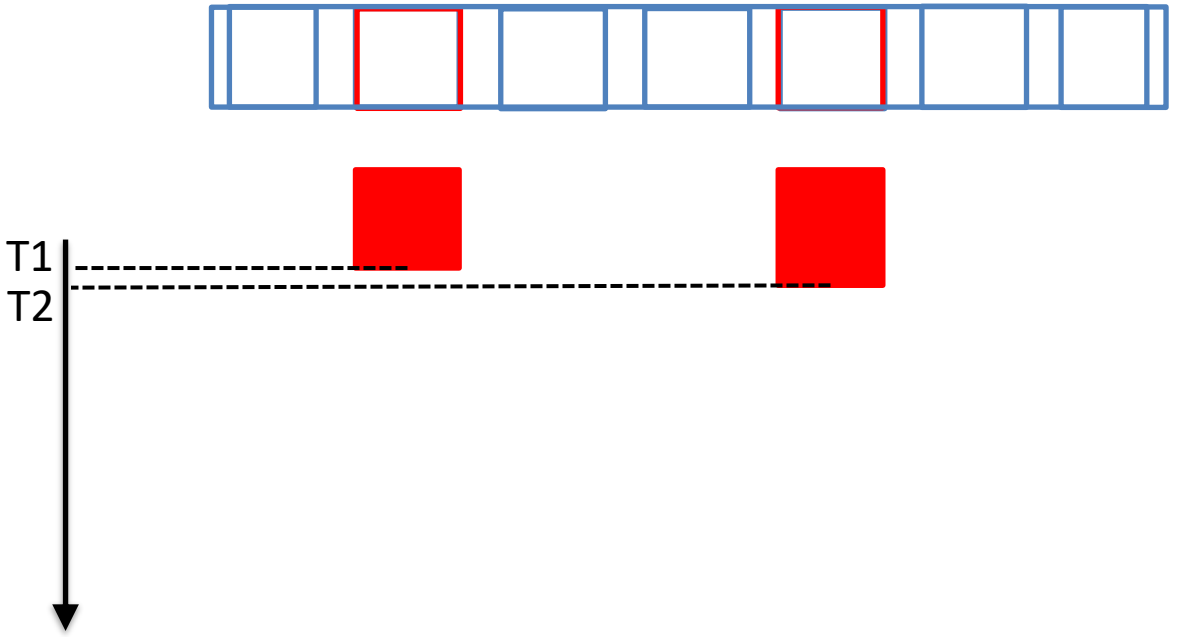


Additional Results and Future Work

- Additional Results: SLearn for DAG
  - 1.26 x over 3Sigma-DAG
- Future work:
  - Combining history and sampling
  - Dynamic adjustment of ThinLimit
  - Sampling in heterogeneous clusters

SLearn - Summary

- History-based learning suffers from an outdated history
- We propose and show the effectiveness of a new task-sampling based method to learn runtime properties of distributed jobs online
- We have performed large-scale trace analysis, simulation and testbed experiments



SLearn improves average job completion time over state-of-the-art history-based system, 3Sigma, by

1.56 ✖