TEXAS TECH UNIVERSITY SYSTEM

Data Centers Job Scheduling with Deep Reinforcement Learning

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Background

- The HPC job scheduler is a global queuing system
- Jobs are submitted to a centralized job queue
- Jobs are ordered in the queue based on their priorities
- Scheduler picks jobs to run based on available resources
- Re-claim resources once a job finishes

Background

- Conventional HPC Job Scheduling Policies
  - FCFS
  - Backfiling
  - Preemption (w/o resumption)
  - List scheduling
  - Fairness Sharing
- Real world HPC job schedulers
  - Slurm
  - SGE(UGE)
  - PBS

Motivation

- Design a method to learn the policy automatically
- Adaptive to the workload or optimization objects
- Save time and effort for system administrators
- No job profile information is needed

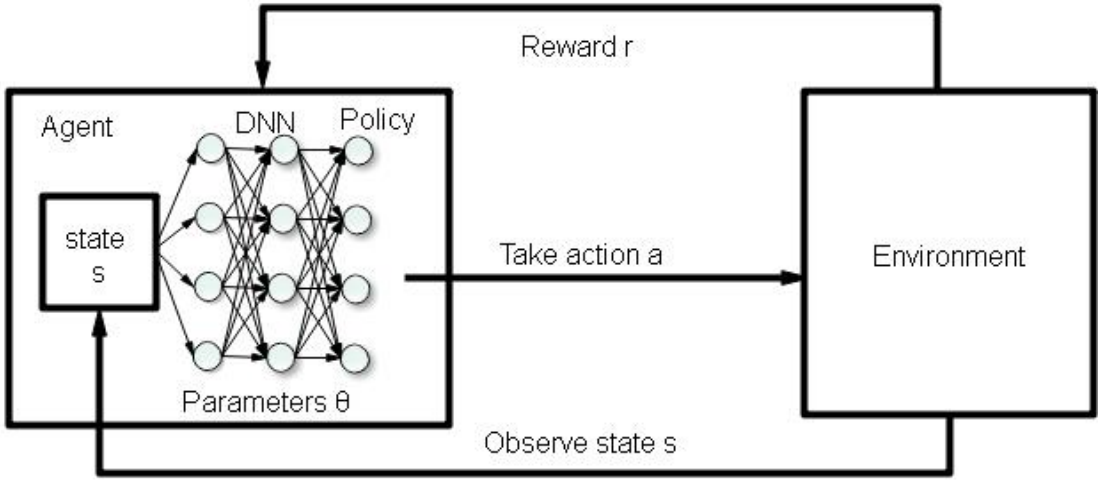
Reinforcement Learning

- Make sequential decisions
- Learn by interacting with the environment

[2] Silver, David, et al. "Mastering the game of Go with deep neural networks and tree search." *nature* 529.7587 (2016): 484.

Reinforcement Learning

- Deep Reinforcement Learning with Policy gradient method



[1] H. Mao, M. Alizadeh, I. Menache, and S. Kandula, “Resource Management with Deep Reinforcement Learning,” in *Proceedings of the 15th ACM Workshop on Hot Topics in Networks - HotNets ’16*, Atlanta, GA, USA, 2016, pp. 50–56.

Proposed A2C Job Scheduling framework

- Job scheduling with Deep reinforcement Learning

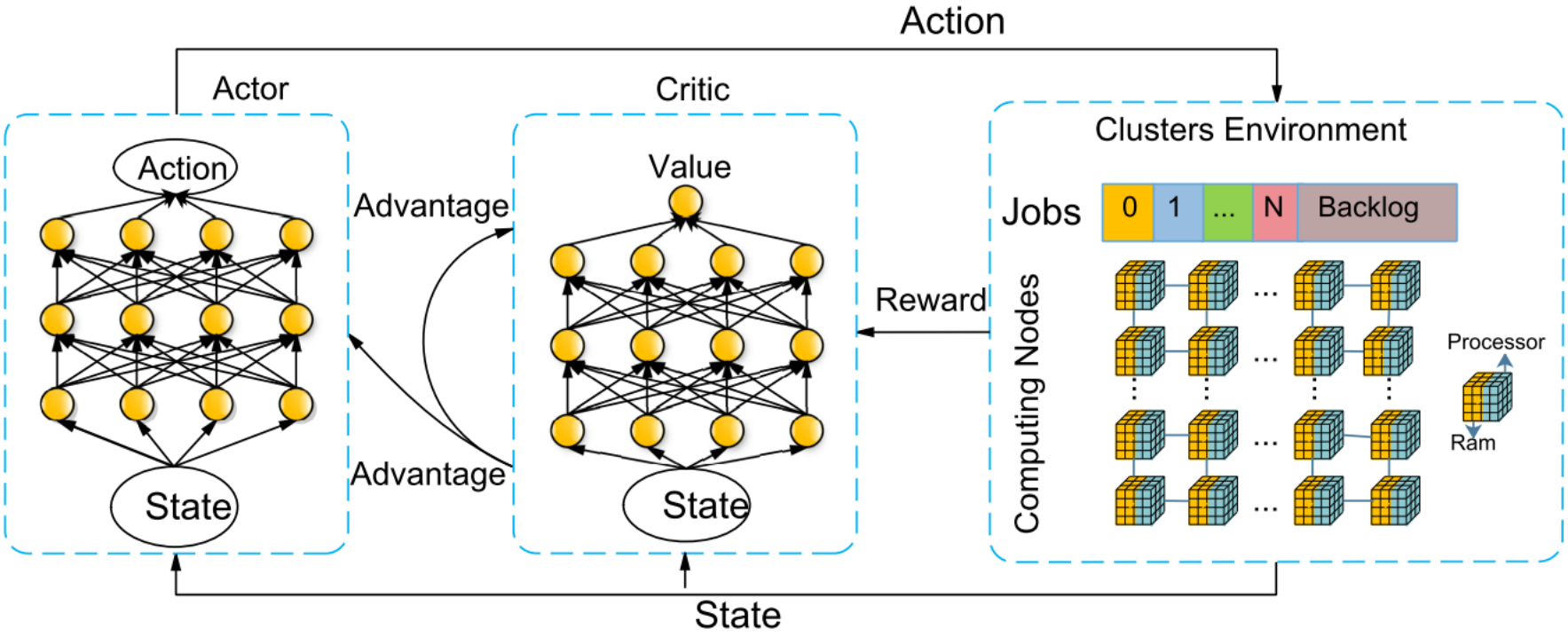


Figure 2: **A2C job scheduling framework.**

A2C Problem Statement

- Agents
- Actor: generate actions, to choose jobs from the queue
- Critic: to evaluate actions of the actor
- Agent Action space: $\{0, 1, 2, \ldots N\}$, $a = j$ means j-th job in queue will be allocated; $a = 0$, void action

A2C Problem Statement

- Reward Function
- Individual reward for *the actor*: $r_t = -\frac{1}{T_j}$
- Expected discount reward: $E[\sum_{k=0}^{\infty} \gamma^k r_{t+k}]$
- The actor attempts to maximize its expected discounted reward.

Experiment Settings

- Hardware:

  48 GB ram and

  two Nvidia RTX-2080 GPUs, 2944 cuda cores

- Software:

  Tensorflow

- Parameters

  Learning rates: actor 0.0001, critic 0.001

  Actor : 2 layers of CNN, 1 flatten layer, 1 dense layer

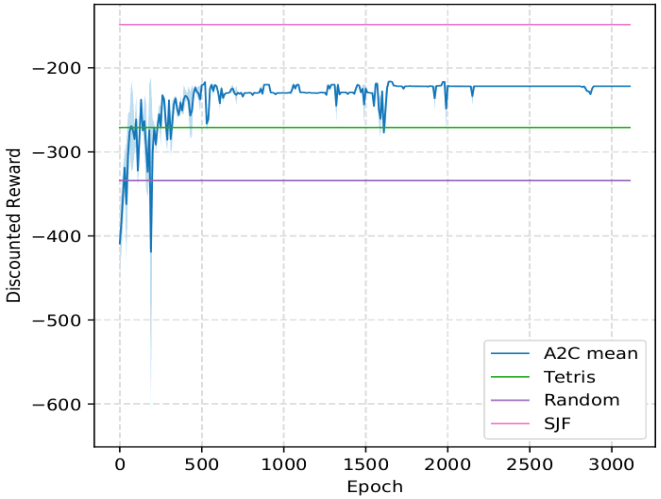
  Critic : 2 layers of CNN, 1 flatten layer, 1 dense layer

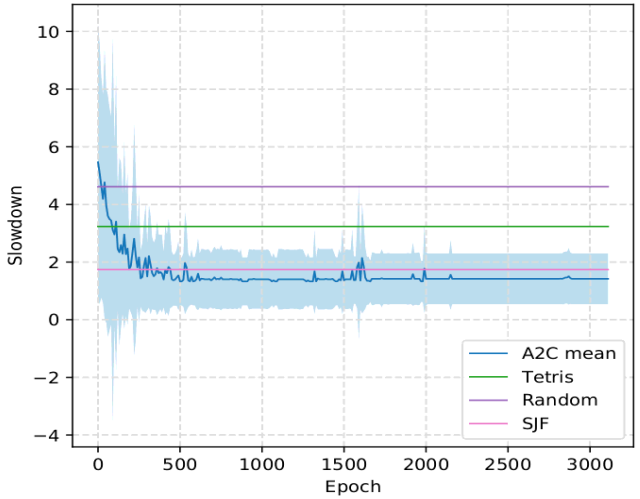
Simulation Results

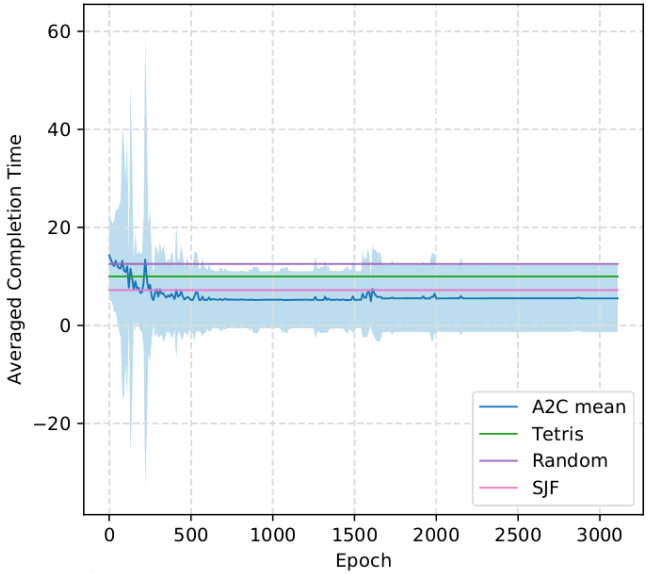
- Simulated workloads

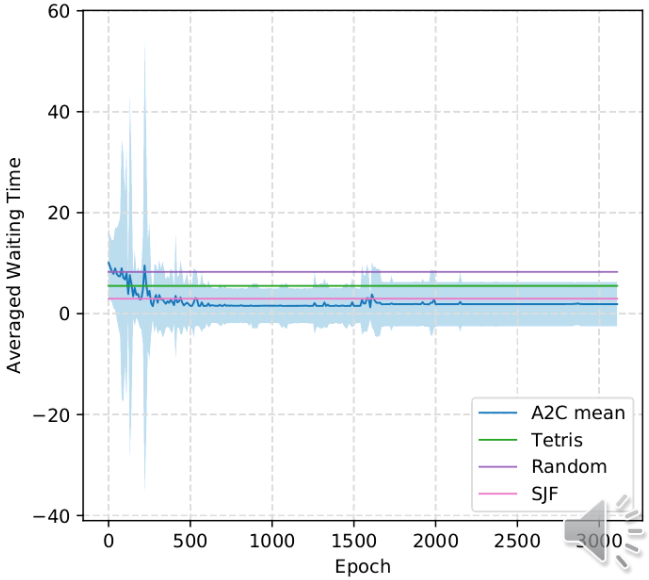
Metrics

- Slowdown:
- Turnaround time:
- Waiting time:

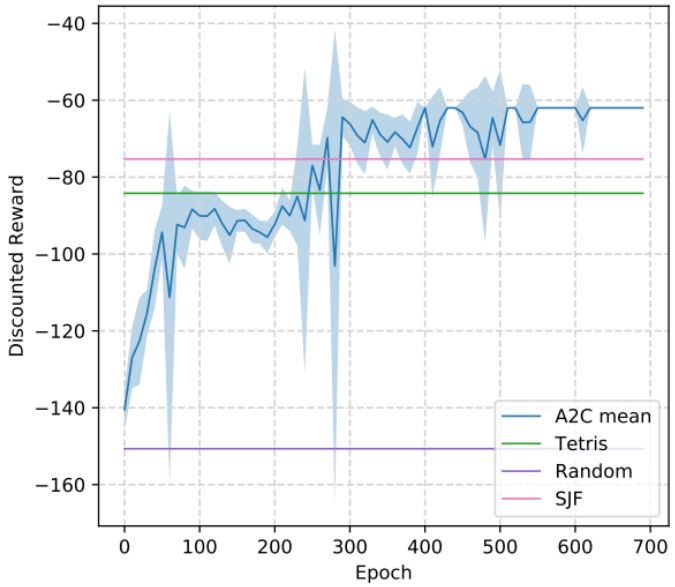


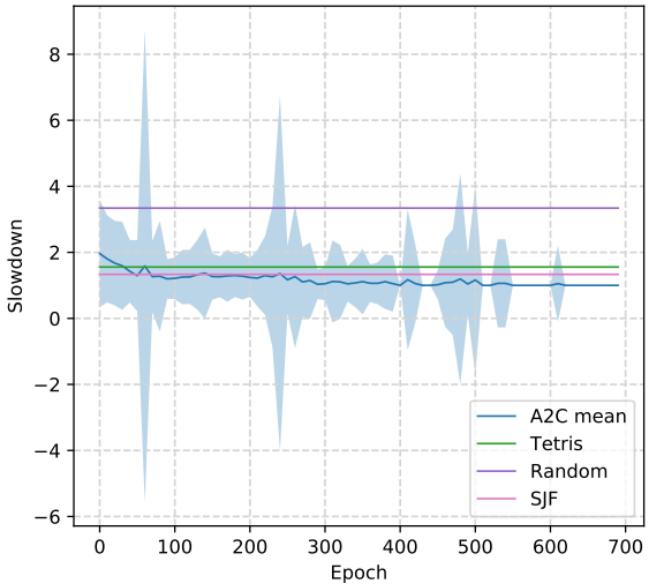


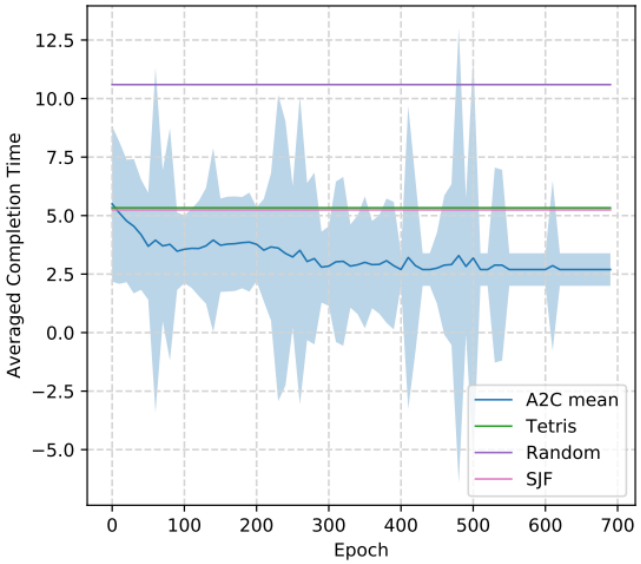


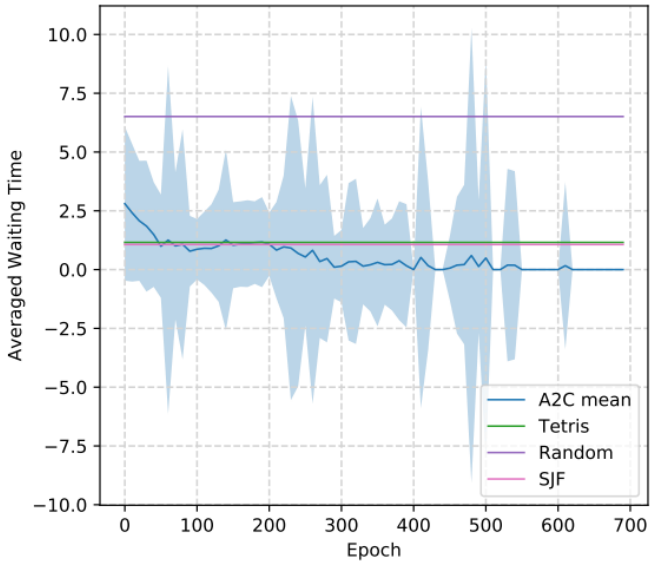


Simulation Results from Job Traces Data









Simulation Results from Job Traces Data

Table 4: **Results of Job Traces**

Type	Random	Tetris	SJF	A2C
Slowdown	3.52±0.00	1.82±0.00	1.61±0.00	**1.01±0.02**
CT^*	10.2±0.00	5.55±0.00	5.51±0.00	**2.58±0.01**
WT^*	6.32±0.00	1.25±0.00	1.21±0.00	**0.01±0.02**

Conclusion

- A2C scheduler could find the effective scheduling policy automatically
- Can save time and effort of the system administrators.
- Our experiments on both simulated data and real jobs traces of HPC systems show that this proposed method performs better than the widely used heuristics.

Thank you !

Q & A