



UNIVERSITÄT
PADERBORN

CN-UPB/PG : ARTIFICIAL INTELLIGENCE FOR
COMPUTER NETWORKS

SEMINAR PAPER:

RESOURCE MANAGEMENT WITH DEEP REINFORCEMENT LEARNING

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Resource Management Challenges and Scopes of Reinforcement Learning

Online decision making under massive workload

Interdependency between tasks

Dynamic and
complex models

Alternative
to general
heuristics

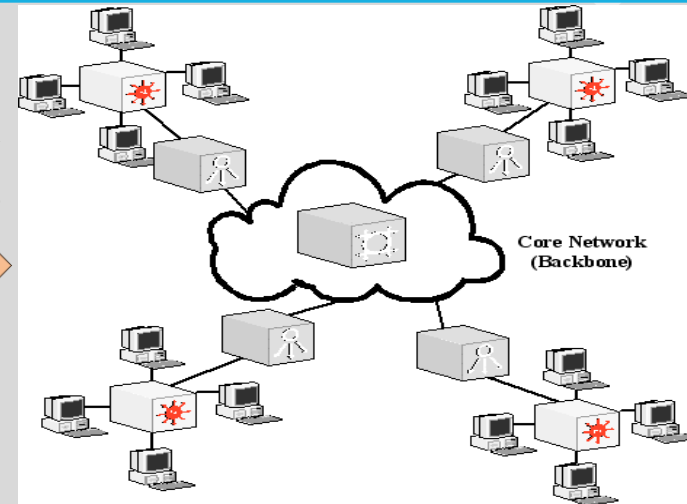


Figure 1 : Cluster computing [1]

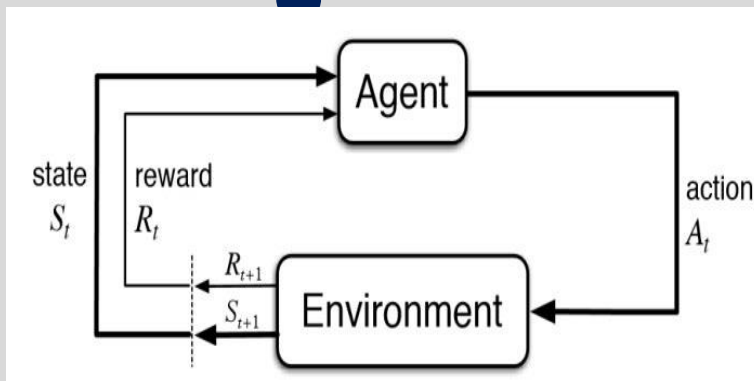


Figure 2 : Reinforcement Learning model [2]

Repetitive decisions provide abundant training data

Deep NN to model complex systems

RL agent can be trained to optimize system objectives

Proposed Model: DeepRM

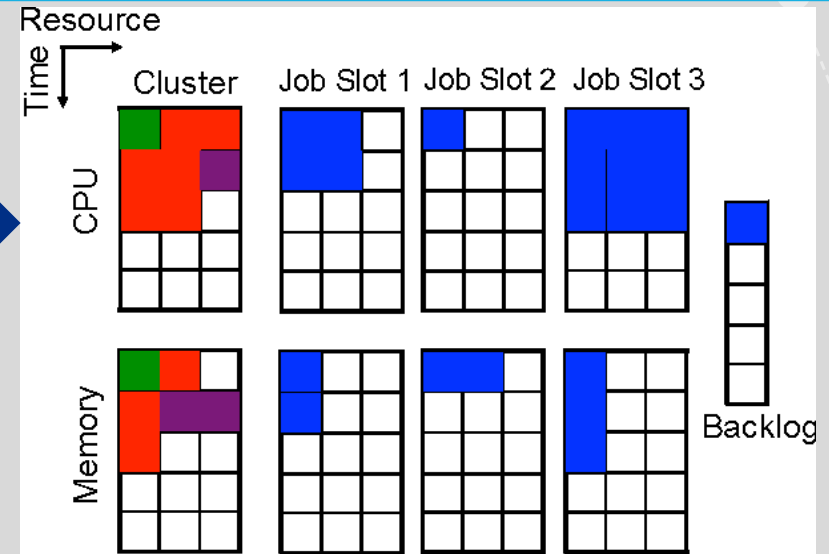
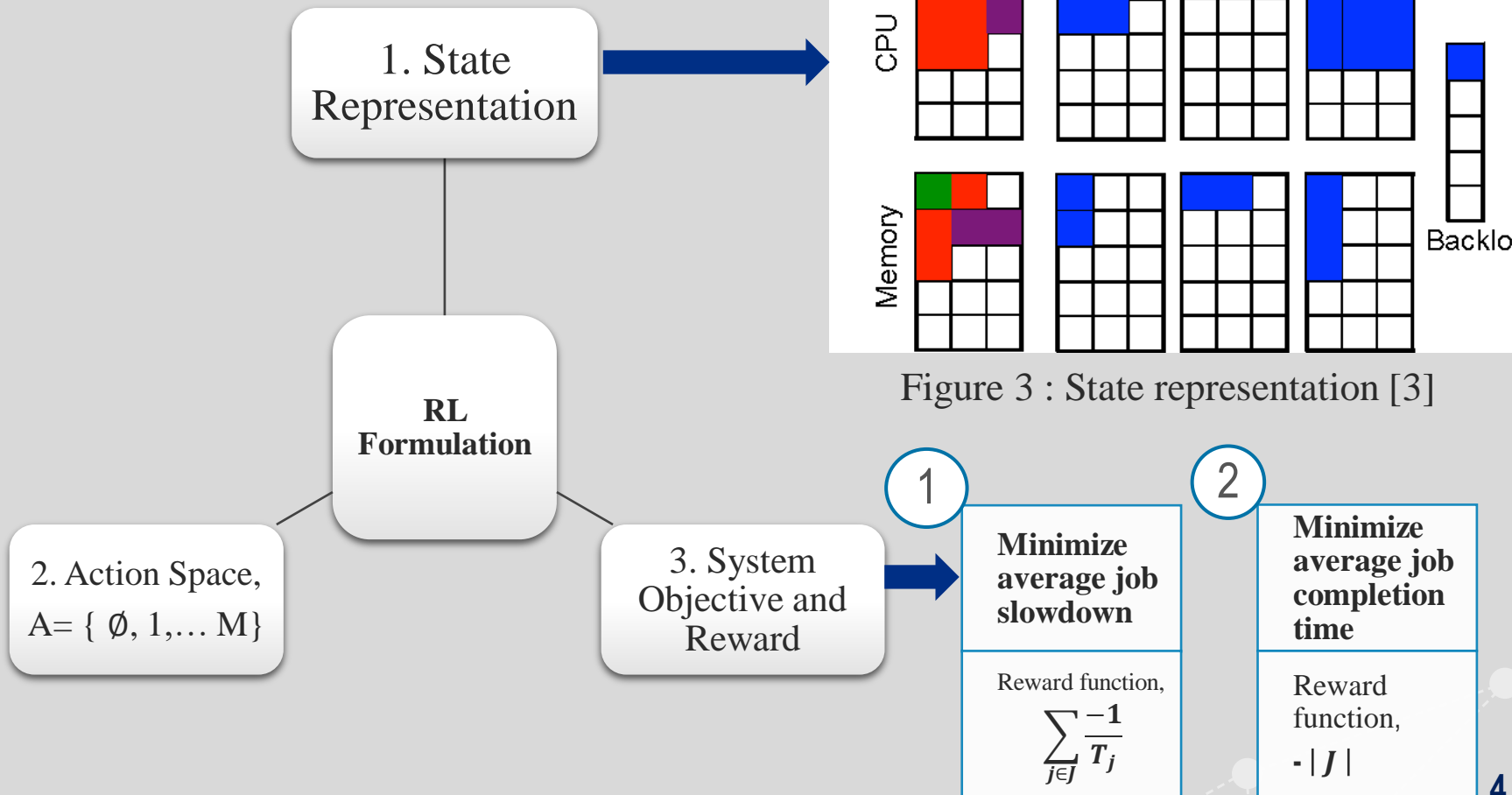


Figure 3 : State representation [3]



Training Algorithm

Notation Table

Variable	Description
r_j	Resource requirements of a job, j
T_j	Duration (ideal) of the job
C_j	Completion time of job
J	Set of jobs (scheduled and waiting) currently in the system
γ	Discount factor
v_t	Discounted cumulative reward
b_t	Baseline value
t	timestep
M	subset of jobs
N	No. of episodes

```

for each iteration:
     $\Delta\theta \leftarrow 0$ 
    for each jobset:
        run episode  $i = 1, \dots, N$ :
             $\{s_1^i, a_1^i, r_1^i, \dots, s_{L_i}^i, a_{L_i}^i, r_{L_i}^i\} \sim \pi_\theta$ 
            compute returns:  $v_t^i = \sum_{s=t}^{L_i} \gamma^{s-t} r_s^i$ 
            for  $t = 1$  to  $L$ :
                compute baseline:  $b_t = \frac{1}{N} \sum_{i=1}^N v_t^i$ 
                for  $i = 1$  to  $N$ :
                     $\Delta\theta \leftarrow \Delta\theta + \alpha \nabla_\theta \log \pi_\theta(s_t^i, a_t^i) (v_t^i - b_t^i)$ 
                end
            end
        end
    end
     $\theta \leftarrow \theta + \Delta\theta$  % batch parameter update
end

```

Figure 4 : Policy training algorithm [3]

Comparison

Comparables :

- a DeepRM agent
- a Shortest Job First agent
- a Packer agent
- A Tetris agent [4]

DeepRM is customizable
for different objectives!

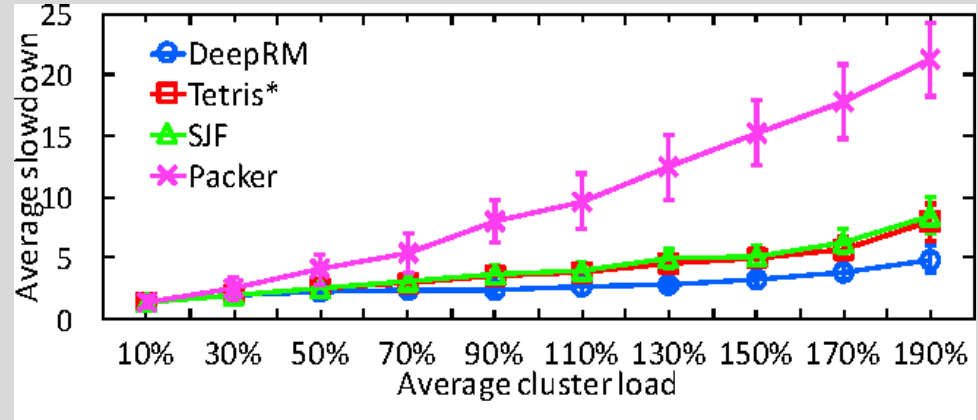


Figure 5 : Average job slowdown at different levels [3]

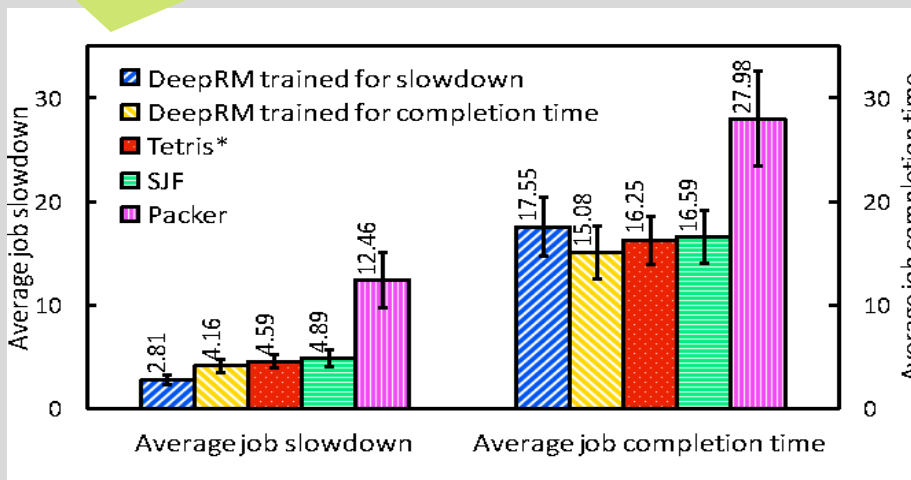


Figure 6 : Performance for different objectives [3]

Experimental parameters

$M = 10$

$N = 20$

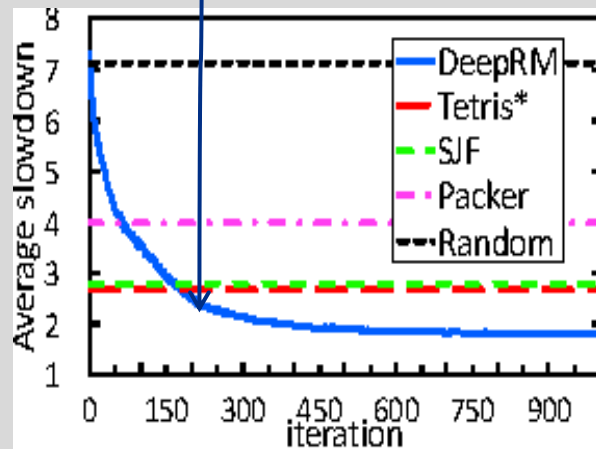
Training iterations = 1000

Learning rate = .001

$\gamma = 1$

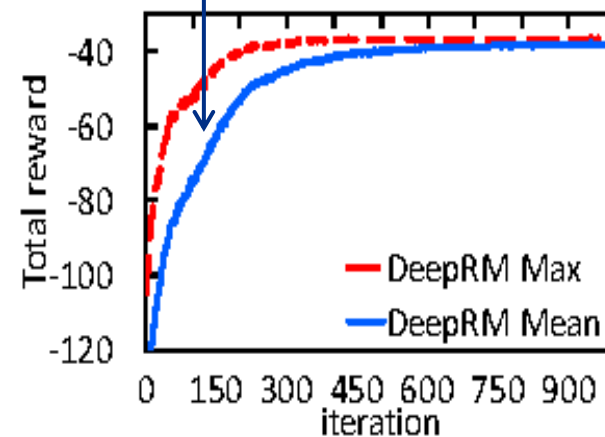
Convergence of DeepRM

After 200 iteration, DeepRM beats Tetris



(a) average slowdown

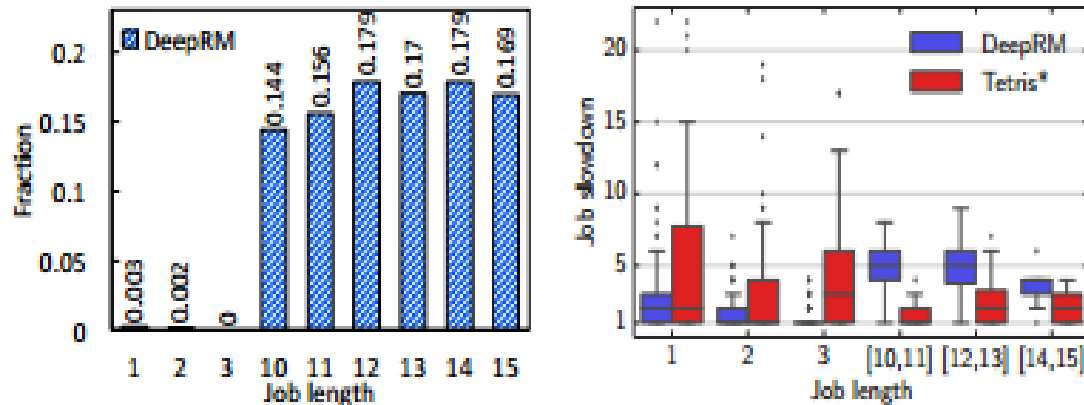
Large gap between max and average value indicates the need for further learning



(b) total reward

Figure 7 : Learning curve showing the slowdown and the total reward performance [3]

Performance Gain



(a) length of withheld jobs

(b) slowdown vs. job length

Figure 8 : Performance gain of DeepRM by withholding large jobs [3]

- ✓ DeepRM learns to withhold large jobs
- ✓ Slowdown for small jobs is significantly smaller with DeepRM than Tetris

Limitation

- Overlooking machine boundaries and resource fragmentation
- Data local allocations
- Inter task dependency matters in real world
- Bounded time horizon to compute the baseline value

$$b_t = \frac{1}{N} \sum_{i=1}^N v_t$$

Future Work

- Guiding the agent towards data local allocations with appropriate reward function
- Use of value network to compute the baseline

References

- [1] Yu, Lean & Wang, Shouyang & Lai, Kin Keung & Wu, Yue. (2005). A framework of Web-based text mining on the grid. 2005. 6 pp.-. 10.1109/NWESP.2005.3.
- [2] <https://www.kdnuggets.com/2018/03/5-things-reinforcement-learning.html>
- [3] H. Mao, M. Alizadeh, I. Menache, and S. Kandula, “Resource Management with Deep Reinforcement Learning,” *Proceedings of the 15th ACM Workshop on Hot Topics in Networks*, pp. 50–56, 2016.
- [4] R. Grandl, G. Ananthanarayanan, S. Kandula, S. Rao, and A. Akella. "Multi-resource Packing for cluster schedulers," *Proceedings of the 2014 ACM Conference on SIGCOMM*, pp. 455–466, 2014.

Thank You !