



Implementing an Artificial Intelligence with the kernel of an Operating System

Introduction

What: Modifying **Linux kernel** to implement an **Artificial Intelligence**
Why: Learning how to **distribute the resources** (CPU, memory)
How: Designing artificial agents
Where: Process scheduling – Process migration – Page reclaiming

Learning

Environment: Partially observable Stochastic Dynamic Episodic
 Discrete Multi-agent Unknown

- The type of processes running is unknown
- The memory needed is unknown
- The number of CPU available is unknown
- The number of processes running not constant

Approach: Reinforcement Learning – *Markov Decision Process*
 Q-Learning $Q(s, a)$ – How good is it to do action a in state s ?
 Value Function Approx. – Q based on weighted w features x

$$\hat{Q}(s, a) = x(s)^T w \quad w \leftarrow w - \alpha [R(s, a) + \gamma \max_{a'} Q(s', a') - \hat{Q}(s, a)] \frac{d\hat{Q}(s, a)}{dw}$$

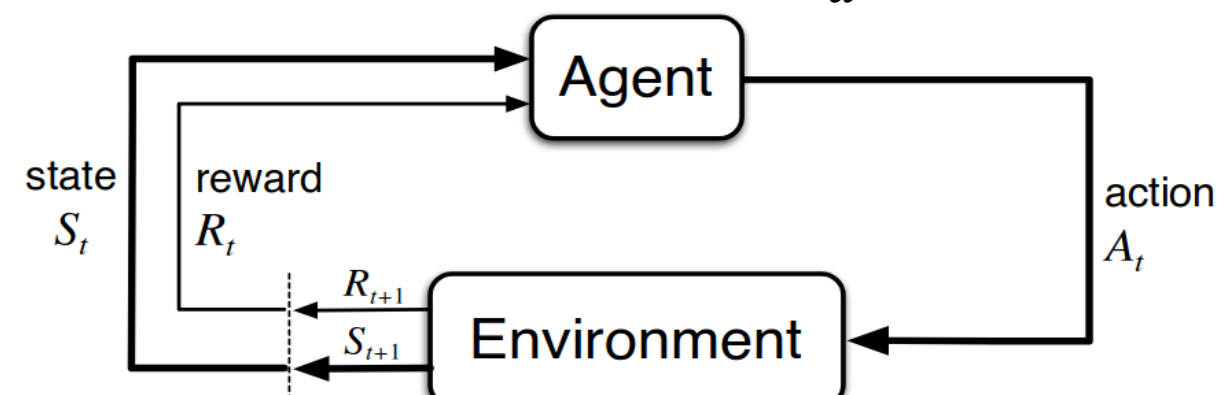


Figure 1: the agent-environment in MDP.[1]

Design

Smartly Fair Scheduler – SFS

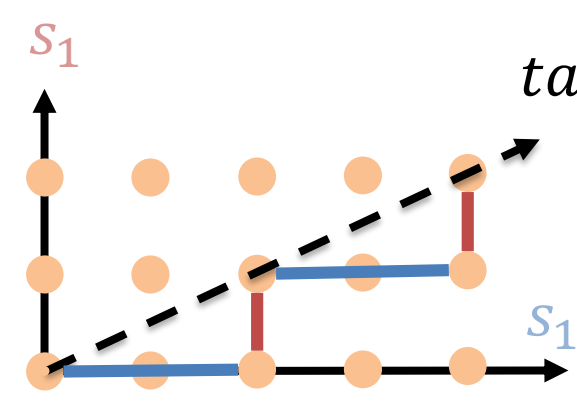
Inspired by: Real-time Scheduler with Reinforcement Learning [2]
Idea: Learn an **Utilization Target (ta)** – means perfect fairness

Features t_i to estimate ta :

- processes' priority
- avg. nbr. of locks acquired
- avg. nbr. if times blocked
- avg. nbr. of times sleeping

Process	State	Priority
P1	s1	2
P2	s2	1

● timeslice



State: i th process's runtime s_i with $s = \sum_i s_i$

Q: $\hat{Q}(s, a_i) = |s_i - ta_i \cdot s| - |s'_i - ta_i \cdot s'|$ with $ta_i = \frac{t_i^T w}{\sum_j t_j^T w}$

Action: $a = \arg\max_{a_i} \hat{Q}(s, a_i)$ that schedules the i th process

Reward: $R(s, a_i) = \sum_{j \neq i} |s_i p_j - s_j p_i| - \sum_{j \neq i} |s'_i p_j - s'_j p_i|$ with p the priority

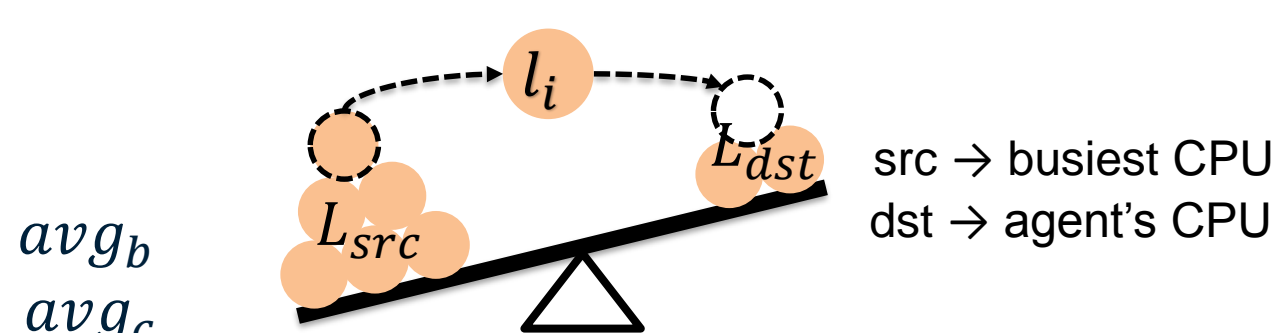
Smart Balance – SB

Inspired by: Operating System scheduling on Heterogeneous Core systems [3]

Idea: Learn how to estimate the **Load (L)** of a CPU

Features t_i to estimate L :

- avg. delta execution
- avg. nbr. of times scheduled
- avg. nbr. of times blocked
- avg. nbr. of completion



State: state of i th process t_i and y th CPU $c_y = \sum_i t_i$ with $s = \{c_1, \dots, c_k\}$

Q: $\hat{Q}(s, a_i) = \begin{cases} L_{dst} & \text{keep it} \\ L_{src} + l_i & \text{move it} \end{cases}$ with $l_i = t_i^T w$ and $L_y = \sum_i l_i$

Action: $a = \arg\max_{a_i} \hat{Q}(s, a_i)$ that keeps the i th process or moves it

Reward: $R(s, a_i) = (avg'_c - avg'_b) - (avg_c - avg_b)$

Smart Page Frame Reclaiming Algorithm – SPFRA

Idea: learn how to estimate the **utility** of a page

Features to estimate page's **utility**:

- nbr. of pages to reclaim
- time since the last access
- avg. time between each access to a page avg_t

} for page queue q
 } for page p_i

State: state of i th page p_i and queue q with $p = \sum_i p_i$ and $s = \{p, q\}$

Q: $\hat{Q}(s, a_i) = \begin{cases} p^T w_p - q^T w_q & \text{keep it} \\ (p - p_i)^T w_p - q^T w_q & \text{swap it out} \end{cases}$

Action: $a = \arg\max_{a_i} \hat{Q}(s, a_i)$ that swaps the i th page out or keeps it

Reward: $R(s, a_i) = \begin{cases} avg_t - t & \text{keep it} \\ -(avg_t - t) & \text{swap it out} \end{cases}$ with t time since reclaiming

Tests and Results

Focus: Behavior of the agents – Can they learn ?

OS: Debian (generated with Debootstrap)

Virtualizer: Qemu

Test cases: - CPU-Bound processes
 - I/O-Bound processes
 - Processes blocking each others

Only the process scheduler and process migration are tested.

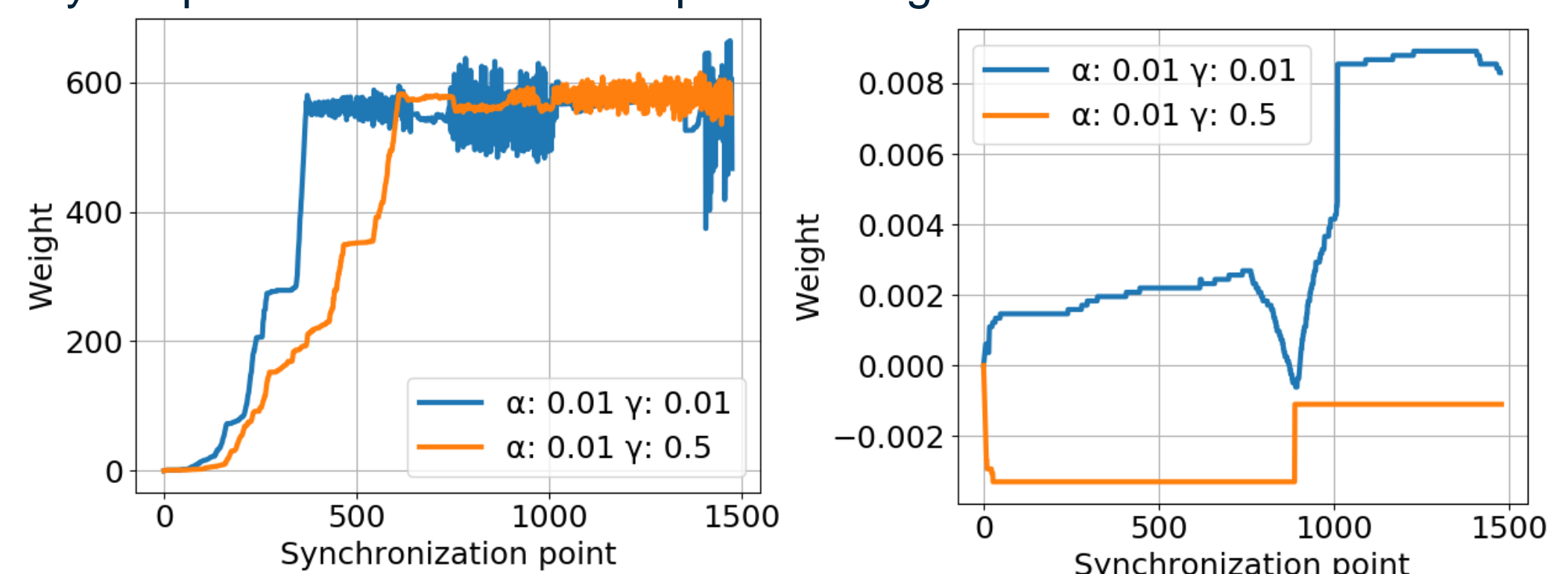


Figure 2: SFS with CPU-Bound processes, priority and avg. nbr. of times sleeping weights

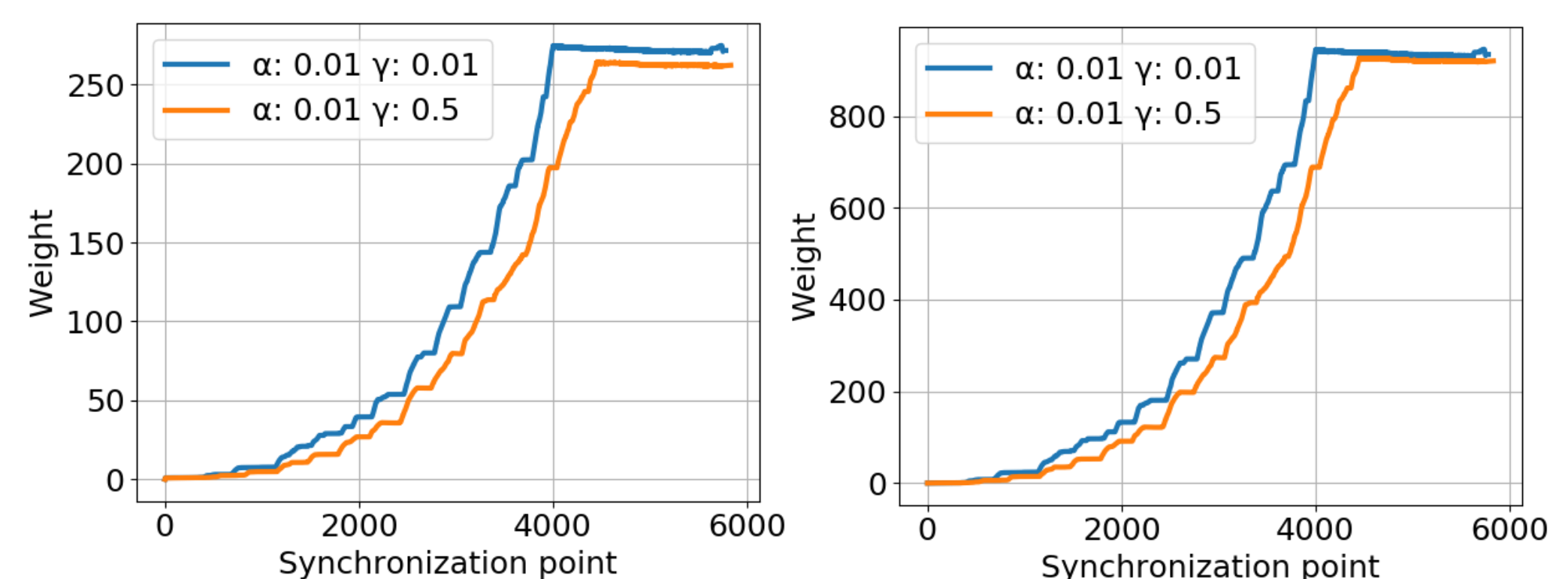


Figure 3: SFS with I/O-Bound processes, priority and avg. nbr. of times sleeping weights

Conclusion

Results: - The agents can learn regarding the different test cases
 - Some difficulties in choosing learning and discount factors

Further work: - Testing SPFRA
 - Evaluating the performances
 - Optimizing the code
 - Designing agents for other parts of a kernel

The **final idea** on which is based this project is to **create a complete adaptable operating system** regarding its environment where **each part is implemented with an agent** that work together with the others.

References

- [1] Richard S. Sutton and Andrew G. Barto. Reinforcement Learning: An Introduction. 2nd Edition. MIT Press, 2017
- [2] Christopher Gill Robert Glaubius Terry Tidwell and William D. Smart. "Real-Time Scheduling via Reinforcement Learning".
- [3] David Vengerov Alexandra Fedorova and Daniel Doucette. "Operating system scheduling on heterogeneous core systems".