Improving Fairness in Memory Scheduling

Using a Team of Learning Automata

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Outline

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- harmonic speedup $= \frac{N}{\sum_i \frac{IPC_i^{alone}}{IPC_i^{shared}}}$
- Provides a good balance between fairness and system performance

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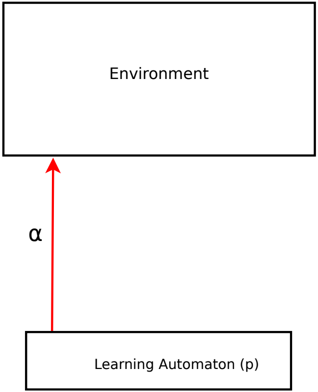
Higher the probability value for a thread, higher is its priority for DRAM scheduling.

Operation of a Single FALA



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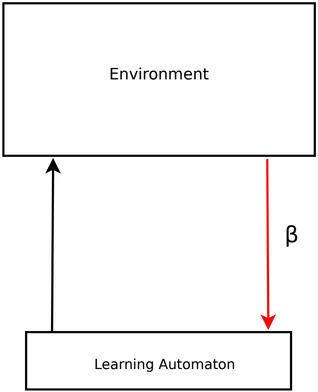

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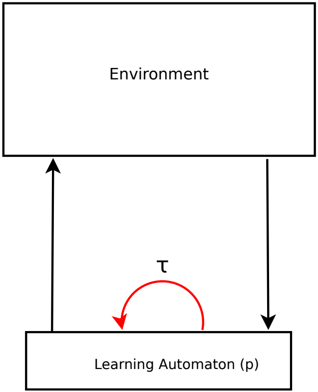

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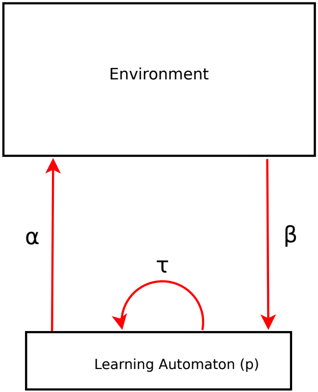

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- This cycle repeats forever

The Learning Algorithm τ

Linear Reward-Inaction (L_{R-I}) [7] is one learning algorithm:

$$p_i = p_i + \lambda \cdot \beta \cdot (1 - p_i)$$
$$p_j = p_j - \lambda \cdot \beta \cdot p_j, \quad \forall j \neq i$$

The above 2 equations can be combined using vector notation:

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The automata implicitly cooperate to perform a stochastic search over the space of rewards [7] : coordination among multiple memory controllers.

Scheduling

Algorithm 1 Request prioritization in each memory controller

1. **Sampled action first:** Select a request according to the action probability vector.
2. **Row hit first:** Select a request which hits the row-buffer.
3. **Oldest first:** Select the oldest request.

Algorithm 2 Sampling an action

```
cum_prob[0] = p[0]
for count ← 1, (numThreads − 1) do
    if rnd < cum_prob[count − 1] then
        break
    else
        cum_prob[count] = cum_prob[count − 1] + p[count]
    end if
end for
action ← count − 1
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Results

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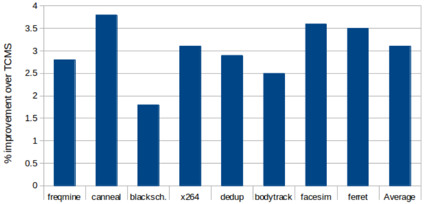

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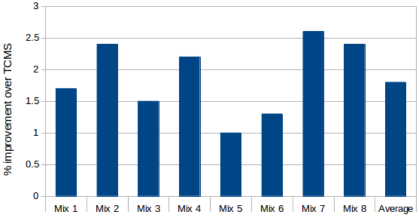
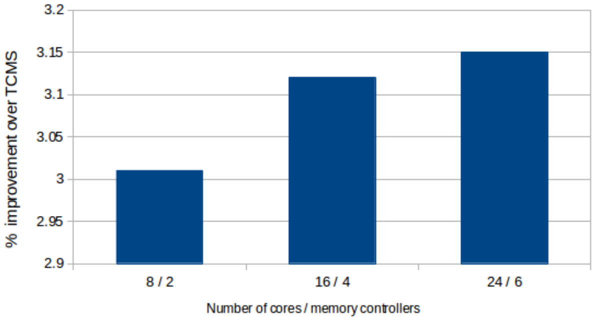


Scalability



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Questions ?

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