Pythia

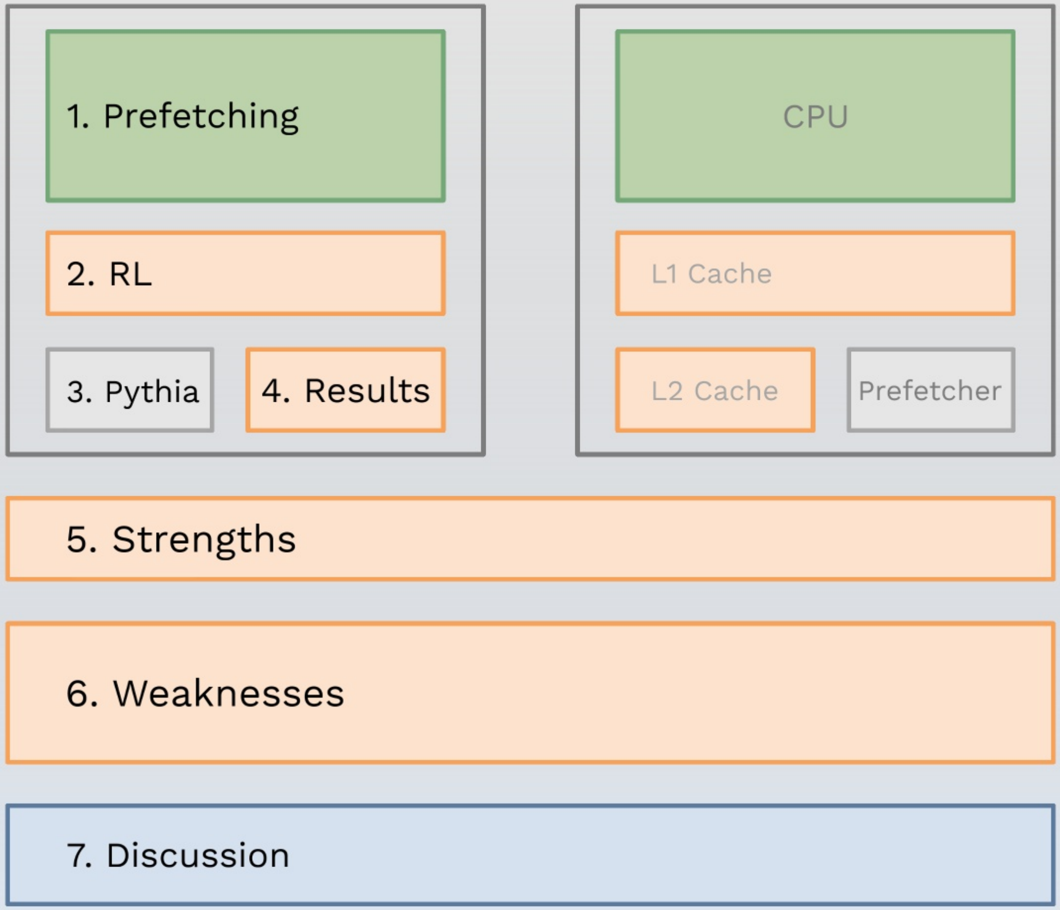
A Customizable
Hardware Prefetching Framework
Using Online Reinforcement Learning

Presented by
Cedric Caspar

Rahul Bera, Konstantinos Kanellopoulos, Anant V.Nori, Taha Shahroodi, Sreenivas Subramoney, Onur Mutlu

ETH Zürich, Processor Architectur Research Labs, Intel Labs, TU Delft

Overview


1. Prefetching
2. RL
3. Pythia
4. Results
CPU
L1 Cache
L2 Cache
Prefetcher
5. Strengths
6. Weaknesses
7. Discussion

Executive Summary

Background: Prefetchers predict address of future memory requests by finding access patterns from program context / feature

Problem: Three key shortcomings of prior prefetchers:

- Using only single program feature
- Lack of system awareness / feedback
- Lack of in-silicon customizability

Goal: Design adaptive and multi-feature prefetching framework

Contribution: Pythia, formulating prefetching as a reinforcement learning problem

Results:

- Evaluated using wide range of workloads
- Outperforms current best prefetchers by 3.4%, 7.7% & 17% in 1/4/bw-constrained cores

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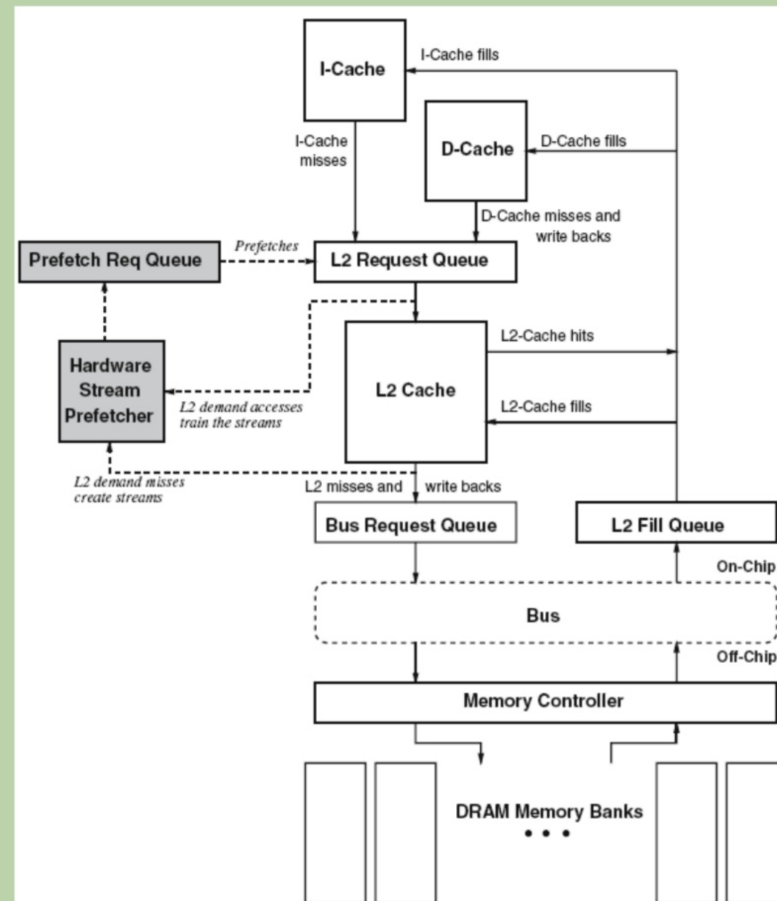
- **Solutions**:
  - Reduce latency
  - Tolerate latency via multithreading
  - Hide latency via caching/prefetching



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Key Ideas for Pythia:
- **Adaptive** to access pattern switch
- Memory **bandwidth consideration**
- **Parametric** variability for the prefetcher

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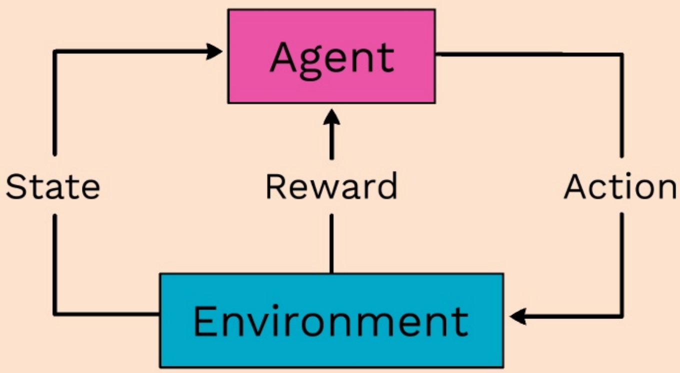

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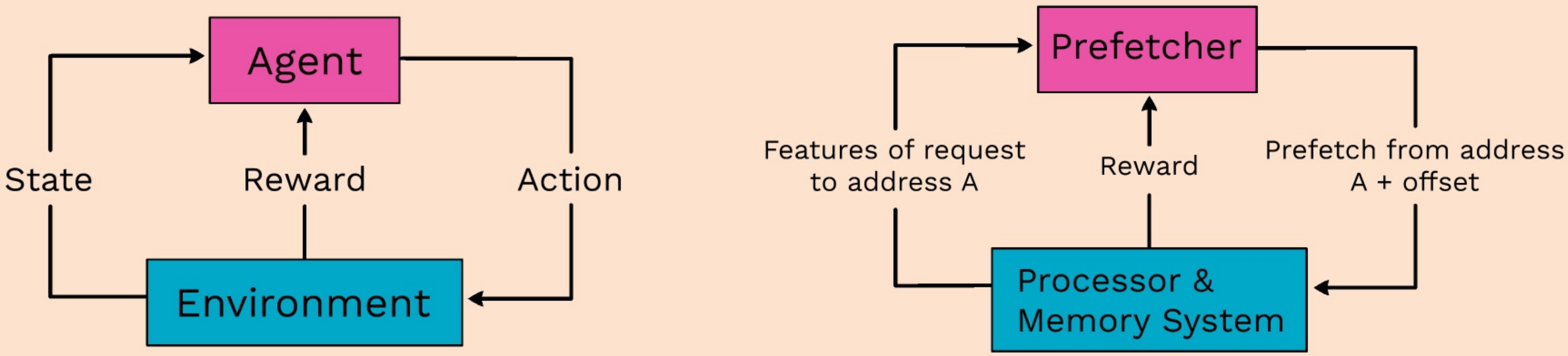

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What is State?

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k-dimensional feature vector

feature = **control flow** component + **data flow** component

	control flow component	data flow component
e.g.	- PC	- Cacheline Address
	- Branch PC	- Physical Page Number
	- Last 3 PCs, ...	- last 4 deltas, ...

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What is State?

k-dimensional feature vector

feature	=	**control flow** component	+	**data flow** component
e.g.		- PC - Branch PC - Last 3 PCs, ...		- Cacheline Address - Physical Page Number - last 4 deltas, ...

What is Action?

Given a demand address A **select prefetch offset O**

Action range: [-63,63], will be pruned for efficiency

If **zero-offset** selected, **no prefetch** is generated

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Defines the **objective** of Pythia encapsulating two metrics:

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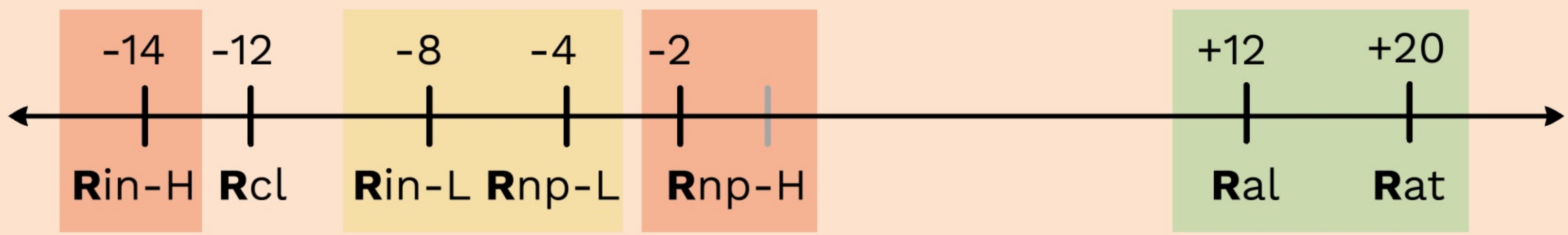

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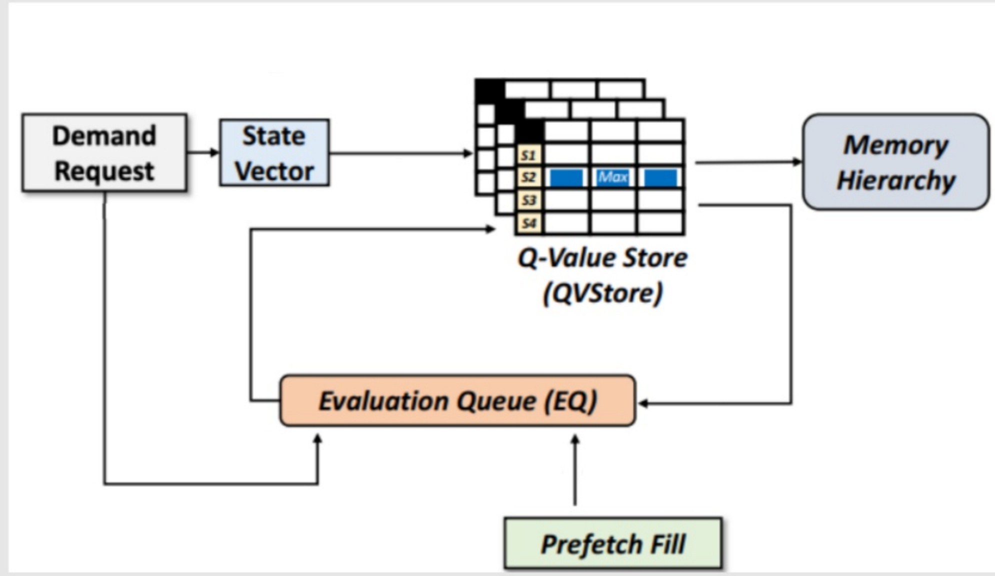
3. Pythia Design

Two major components:

- **Q-Value store**
- **Evaluation Queue**



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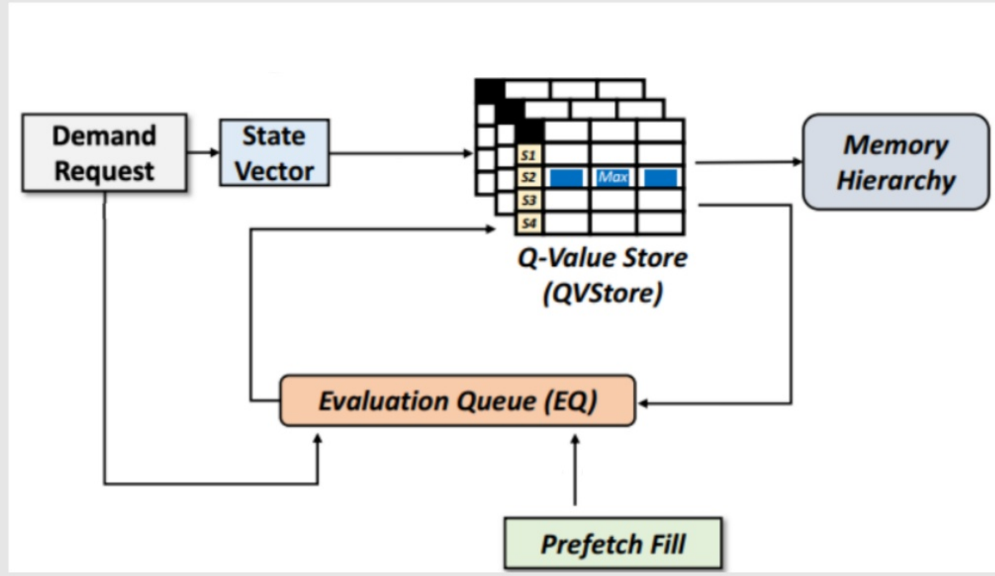
Prefetch sequence



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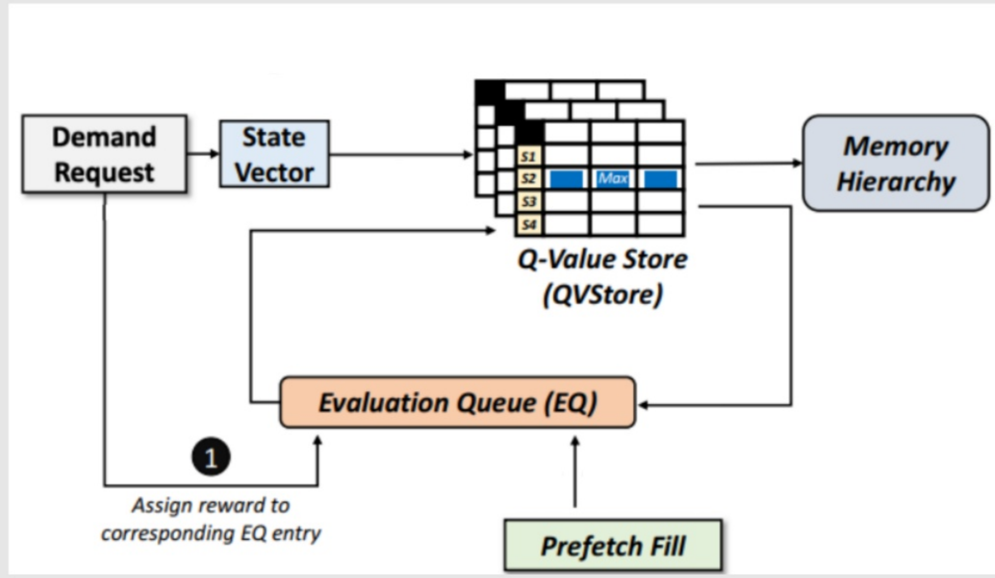
Prefetch sequence

1. **Search EQ** for every new demand and assign rewards



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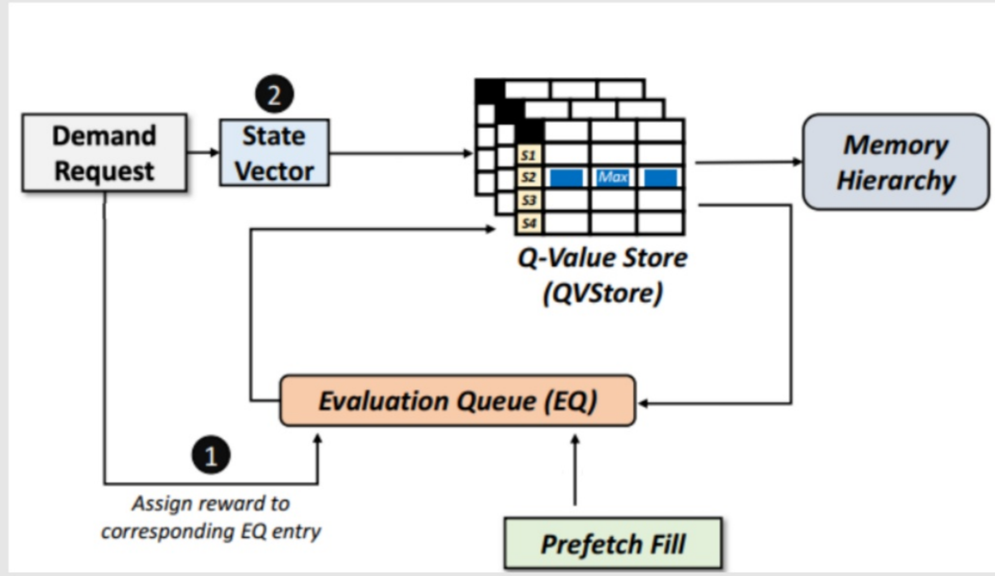

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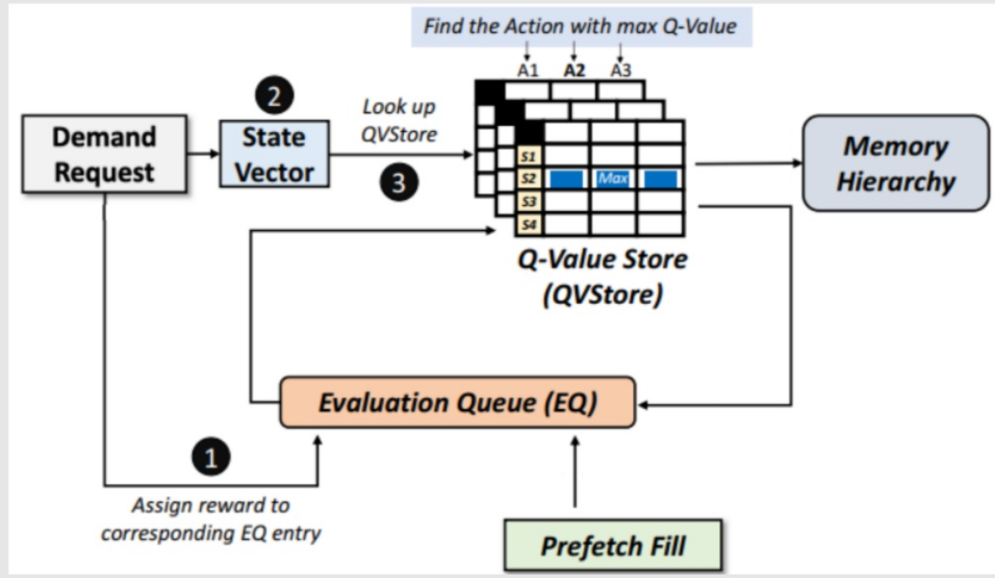

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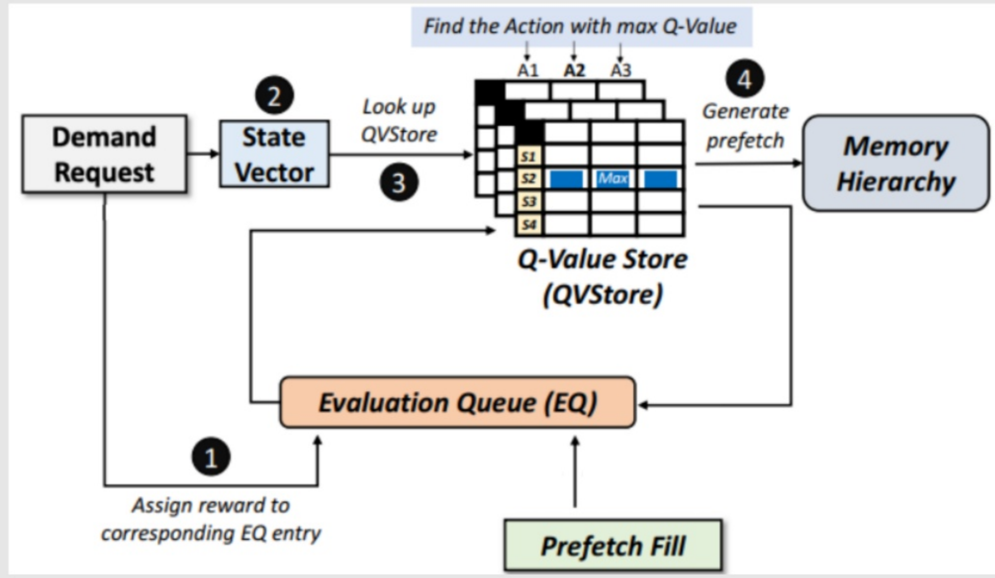

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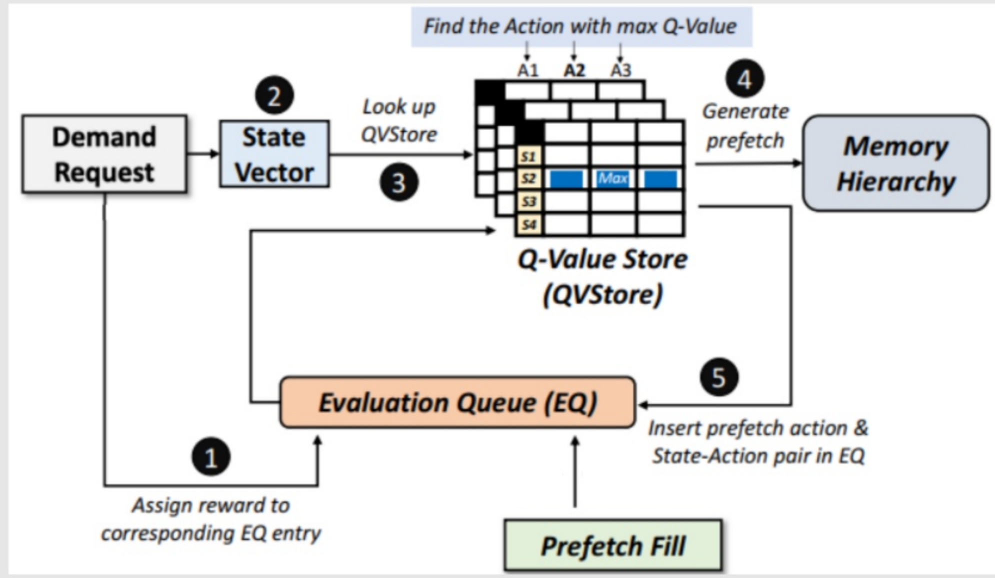

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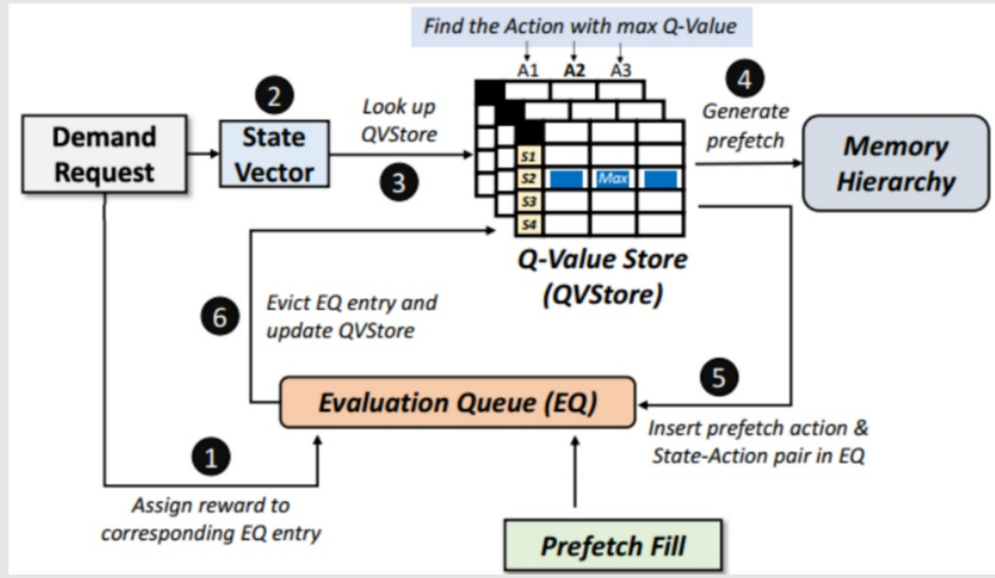

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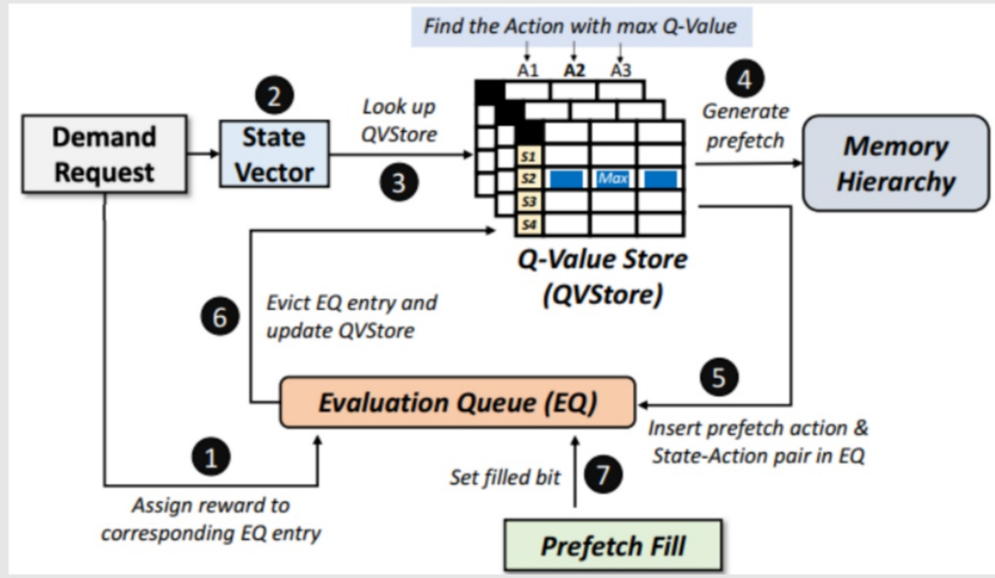
7. When memory loads the value set **filled bit** in corresponding EQ entry



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Organisation of QVStore

The **heart of Pythia** is the **Q-Value** store which
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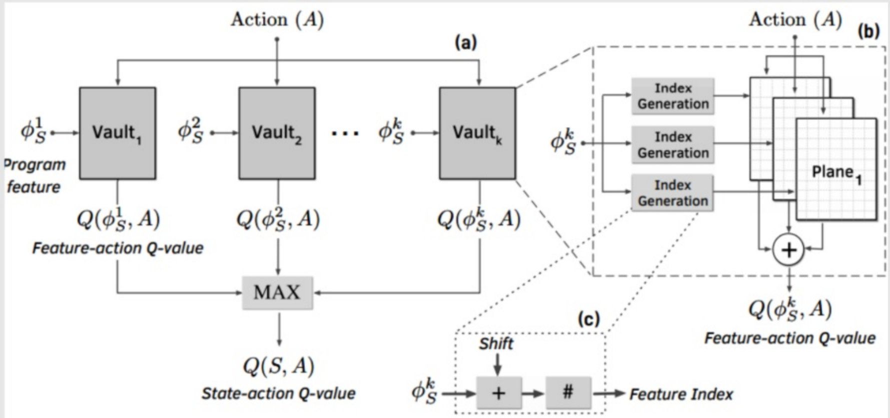
Problem:

- Table size k features, hashing
- Fast search pipelining



Feature-action pairs stored in **vaults**

Multiple overlapping hash-functions implementing tile encoding

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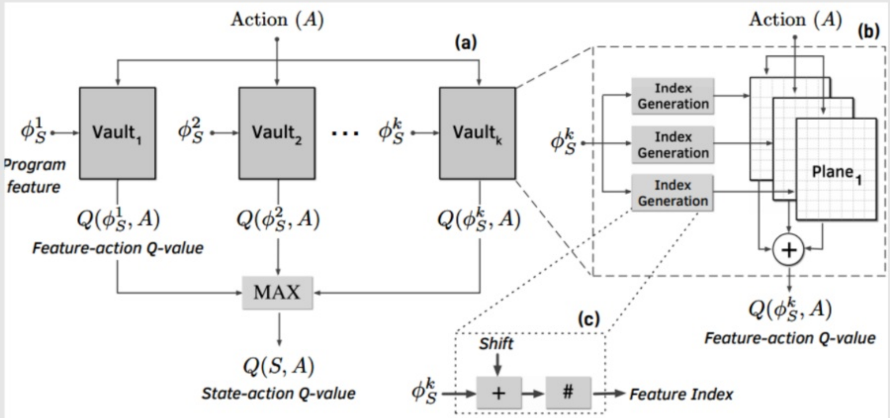

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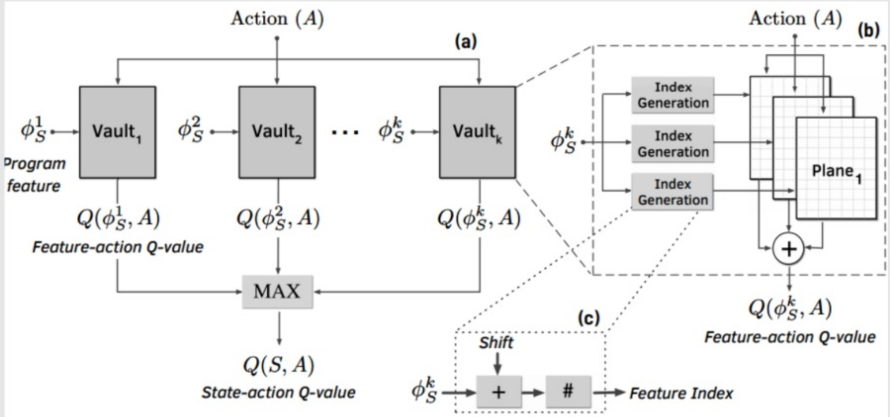

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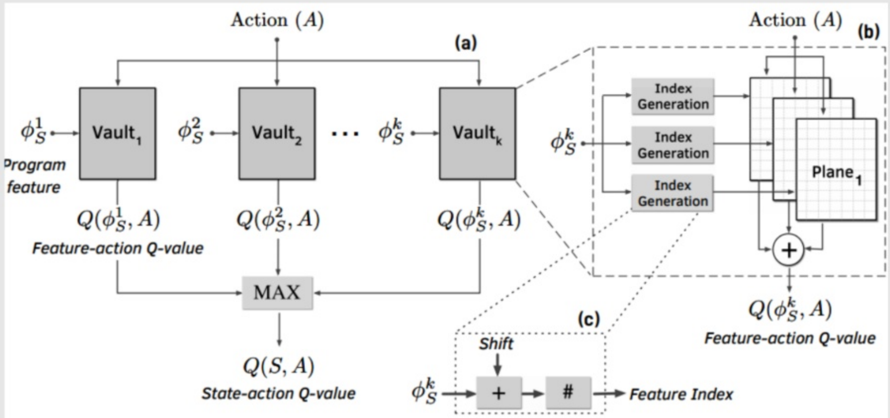

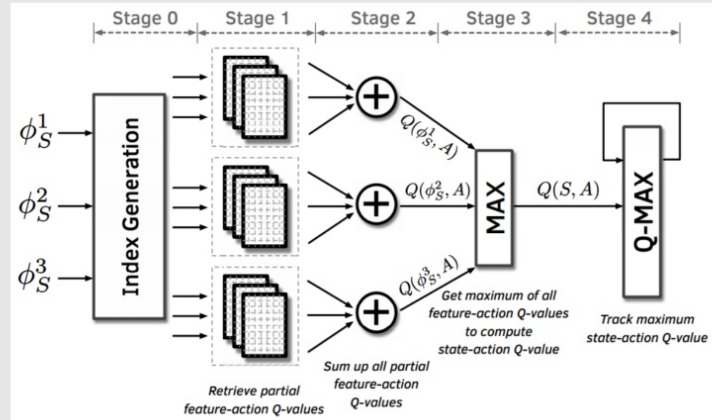

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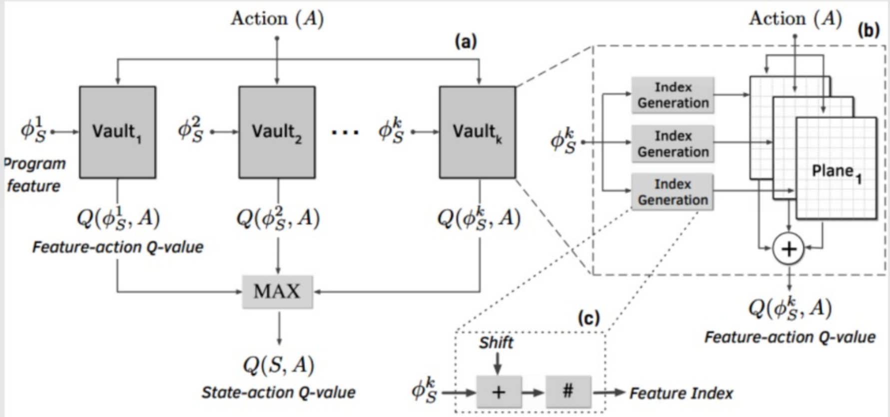

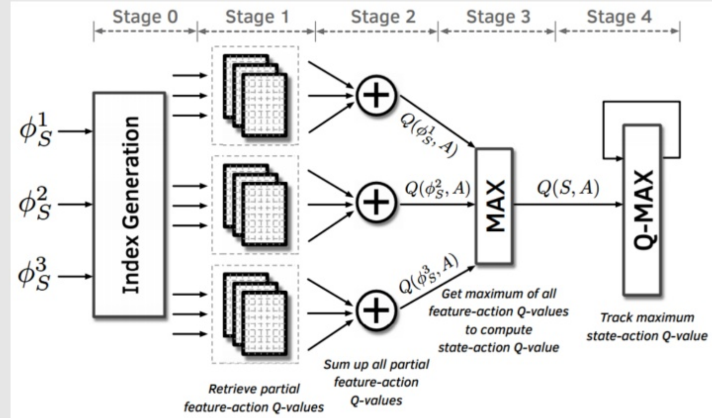

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=> **drastic decrease** of critical path

=> area **overhead** stays **minimal**

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Lots of hyperparameters

State space exploration (aka. brute forcing)

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Features	`PC+Delta`, `Sequence of last-4 deltas`
Prefetch Action List	{-6,-3,-1,0,1,3,4,5,10,11,12,16,22,23,30,32}
Reward Level Values	$\mathcal{R}_{AT}$=20, $\mathcal{R}_{AL}$=12, $\mathcal{R}_{CL}$=−12, $\mathcal{R}^{H}_{IN}$=−14, $\mathcal{R}^{L}_{IN}$=−8, $\mathcal{R}^{H}_{NP}$=−2, $\mathcal{R}^{L}_{NP}$=−4
Hyperparameters	$\alpha = 0.0065$, $\gamma = 0.556$, $\epsilon = 0.002$

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4. Performance Analysis

State of the art **prefetcher competition**:

• **SPP**	Path Confidence Lookahead	**6.2 KB**
• **Bingo**	Spatial Data Pattern	**46 KB**
• **MLOP**	Multi-Lookahead Offset	**8 KB**
• **DSPatch**	Dual Spatial Pattern	**3.6 KB**
• **PPF**	Perceptron-based Filtering	**39.3 KB**
• **Pythia**	Reinforcement Learning	**25.5 KB**

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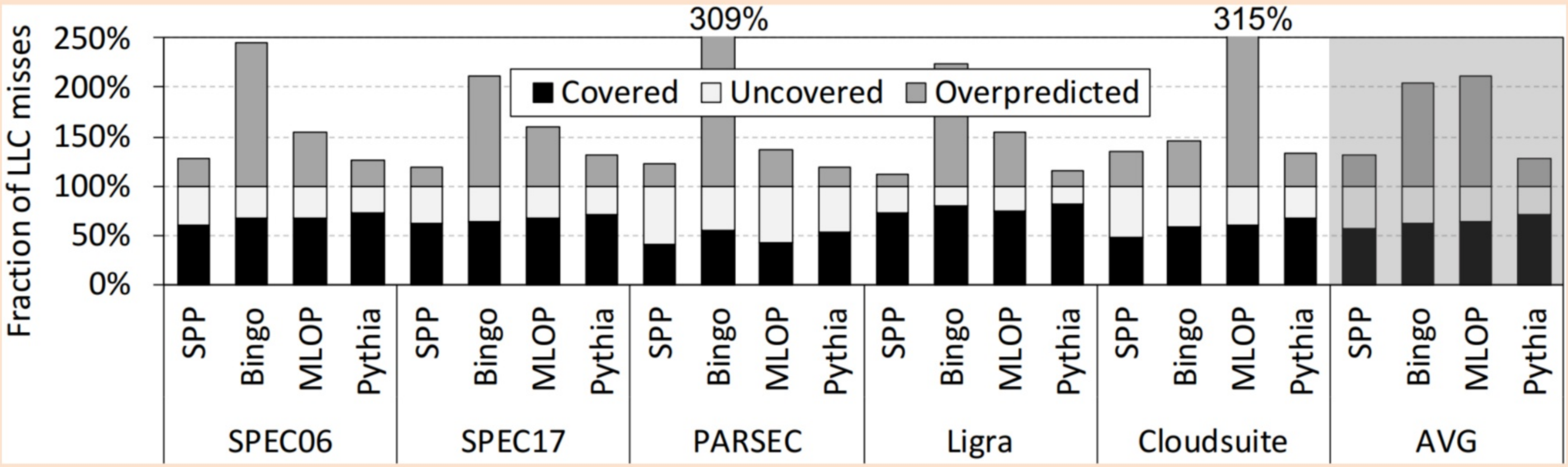
Coverage & Overprediction



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Coverage & Overprediction

Pythia consistently brings the highest coverage while having lowest overpredictions

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Workload Speedup

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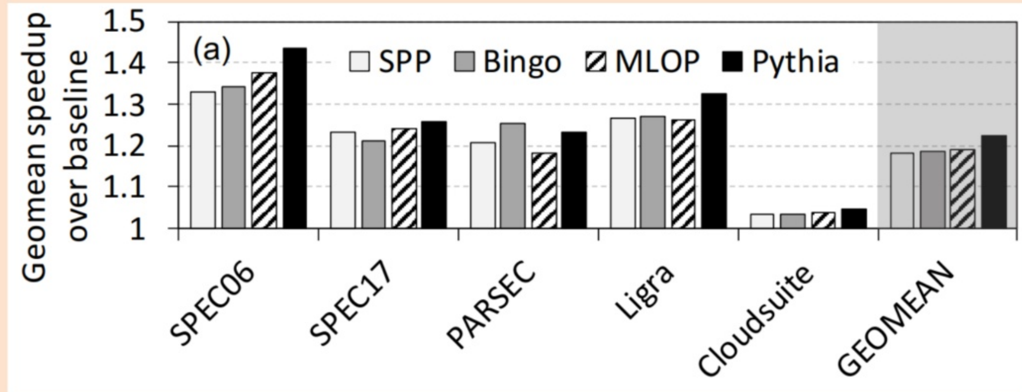
Workload Speedup

Single Core System



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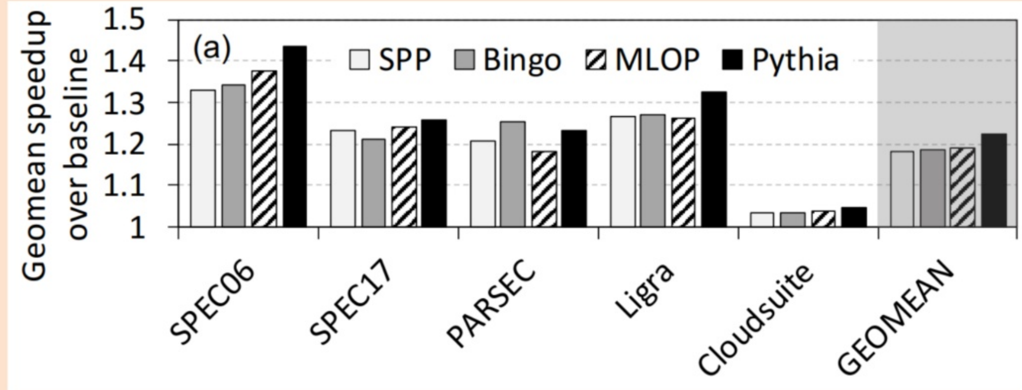
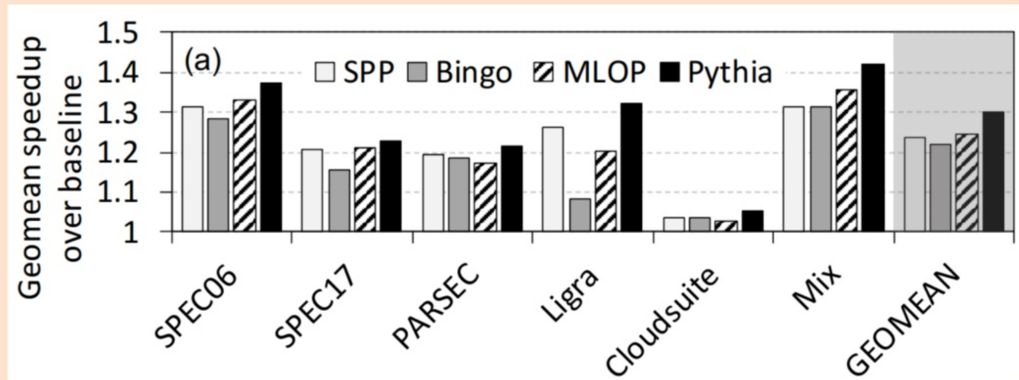


Four Core System



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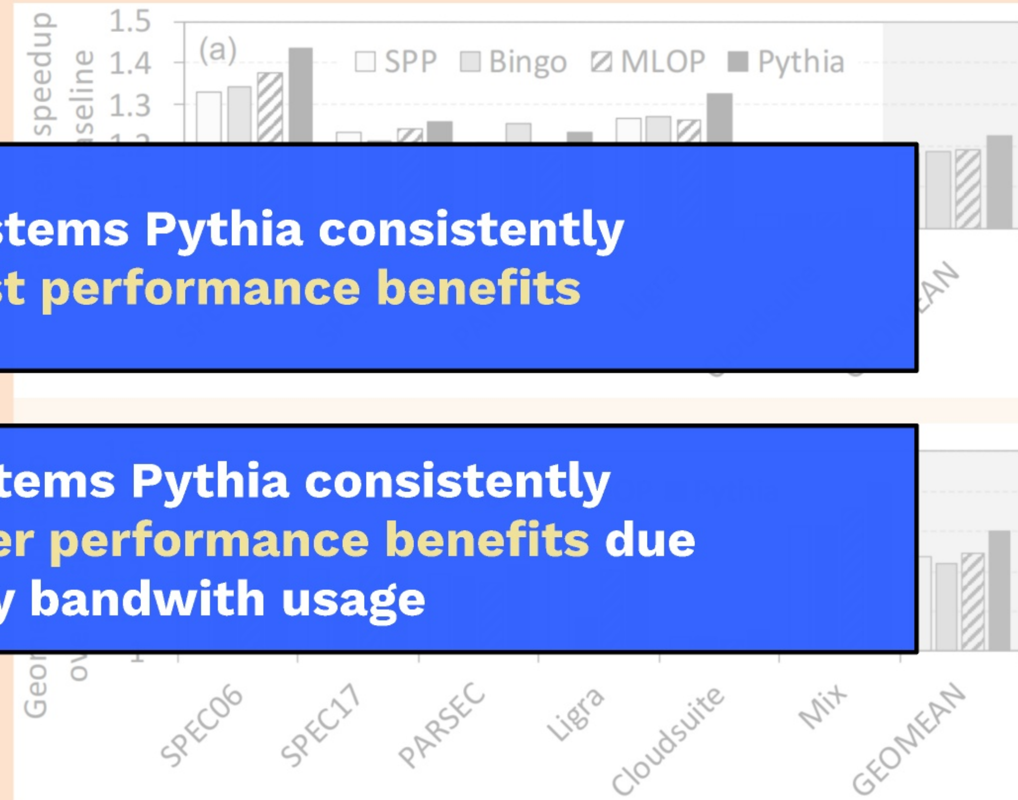
Workload Speedup

Single Core System

In single core systems Pythia consistently brings the highest performance benefits



In multi core systems Pythia consistently brings even higher performance benefits due to better memory bandwith usage

Four Core System

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Strengths of the Paper

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Strengths of the Paper

- **Simple** idea, great execution
- Multiple **levels of detail** presented
- **Intuitive** illustrations
- Good amount of self **analysis**, **reflection** conceptually and **testing**
- **Example** usage & installation

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Weaknesses of the Paper

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Weaknesses of the Paper

- A **lot of repetition** in the beginning
- Typical ML problem: **Only knows it works, not how!**
- **Brute forcing** its way through and no report of struggle
- Paper only states Pythia is better than everybody
  but what is the **theoretical limit** or **future improvements?**

Discussion

Are there security vulnerabilities with Prefetching as RL?

Are Prefetchers still needed with the rise of Near/In Memory Processing?

Could this Prefetcher be used in the Industry soon?
Is the simple adaption worth the benefith and overcome the "lazyness" of the industry?

Innovation instead of exploration?

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