

CHROME: Concurrency-Aware Holistic Cache Management Framework with Online Reinforcement Learning

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ILLINOIS TECH



Cache Management

Cache Management: Essential for bridging the performance gap between fast CPU and slower main memory

Cache Replacement

- Determines which cache blocks to evict when new data needs to be loaded

Cache Bypassing

- Decides whether incoming data should be stored in the cache

Prefetching

- Predictively loads data into the cache before it is actually requested by the CPU

Limitations of Current Cache Management Schemes

We observe there are **two common limitations** faced by traditional cache management techniques:

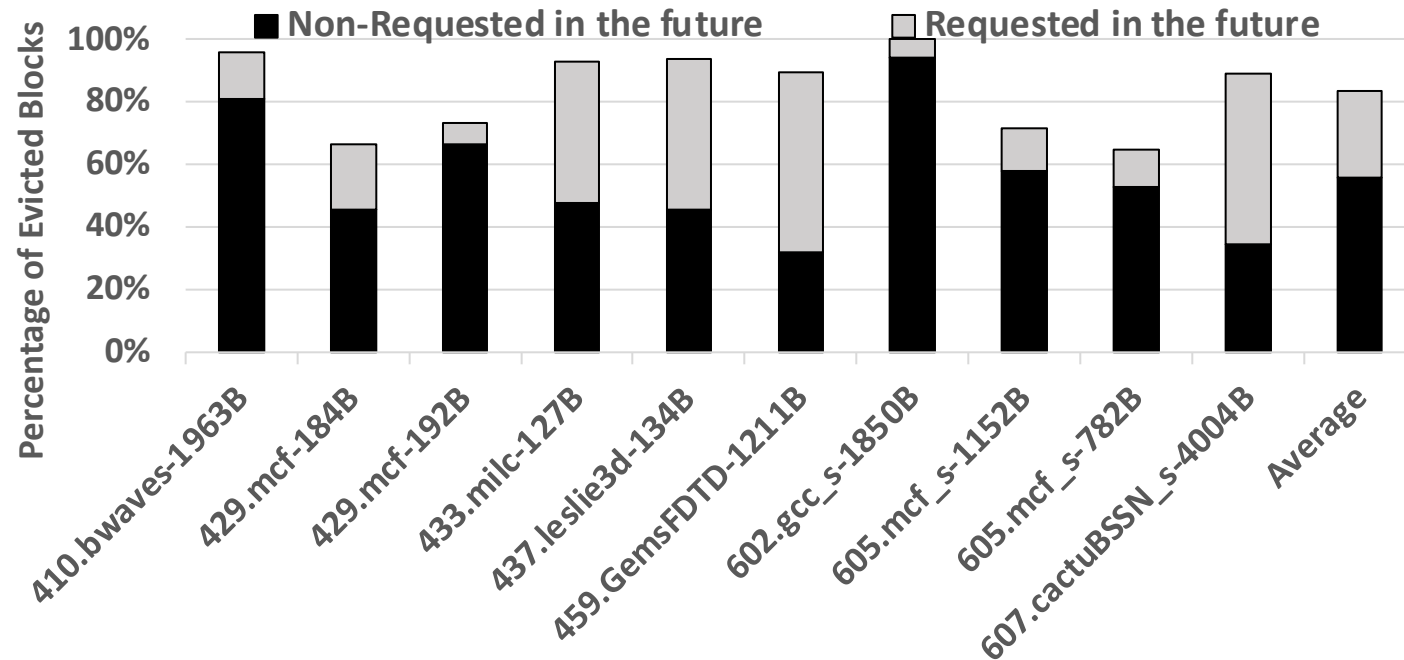
1 Lack of Holistic View

- Current schemes often examine cache replacement, bypassing, and prefetching in isolation, overlooking the potential benefits that could arise from a joint optimization strategy

2 Lack of Adaptability

- Current schemes often rely on fixed heuristics that don't account for the changing access patterns of modern applications and system configurations

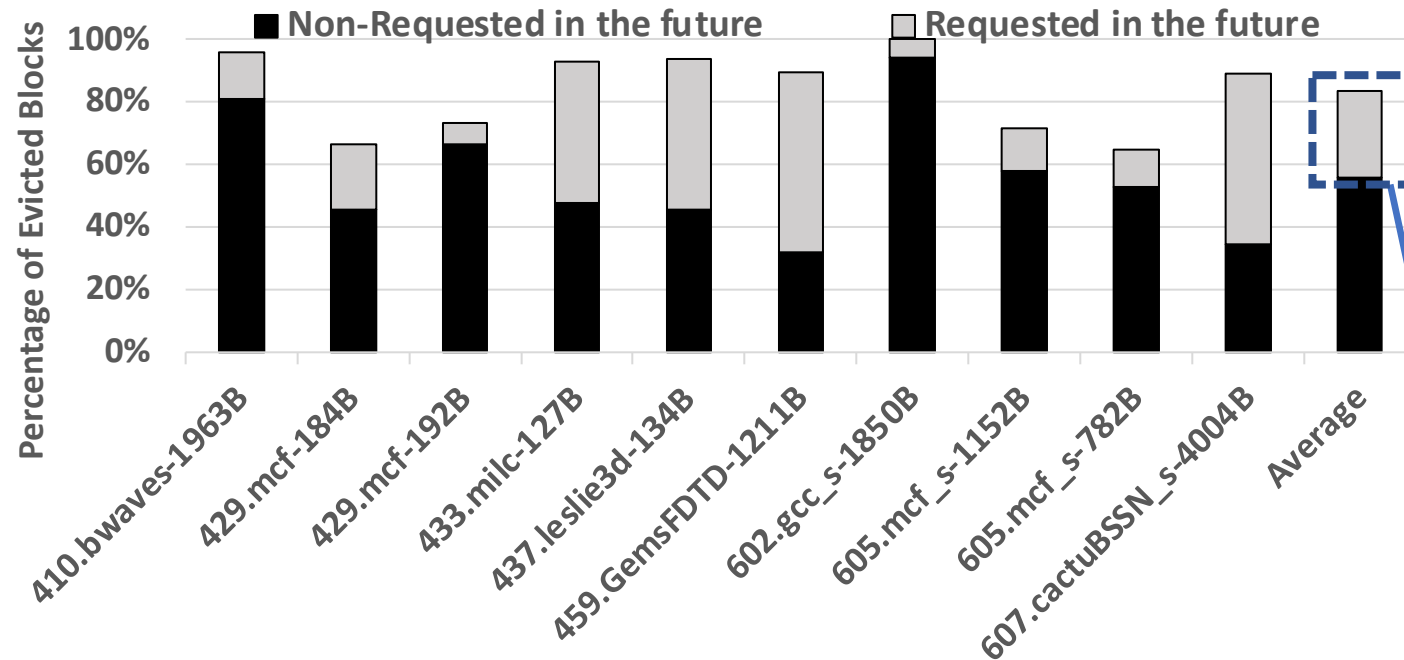
Lack of Holistic View



83.7% of evicted blocks in shared LLC are **not reused before eviction**;
70.0% of the blocks that are not reused before eviction are attributed to **prefetching**

Inspecting Unresued Blocks in LLC with Gilder management scheme [MICRO'19]. Next-line prefetcher is used at L1 and stride prefetcher is used at L2.

Lack of Holistic View

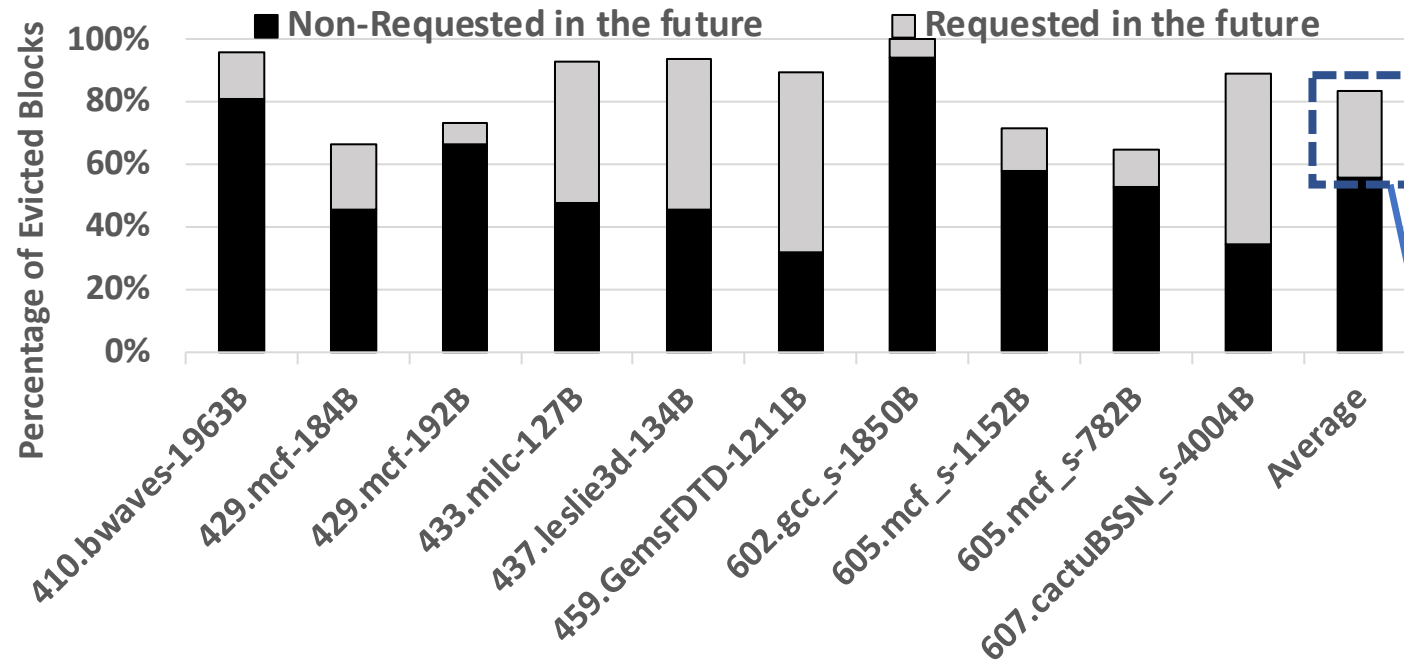


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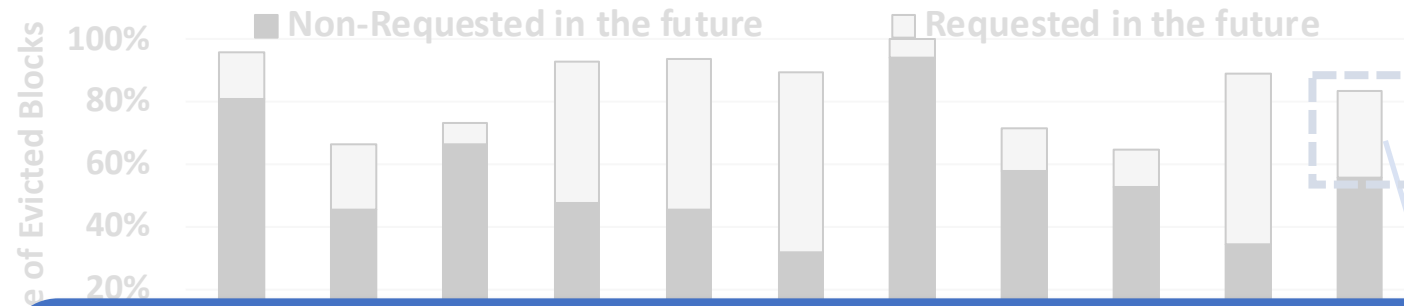
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Possible enhancement: integrates cache bypassing and replacement policies with pattern-based prefetching

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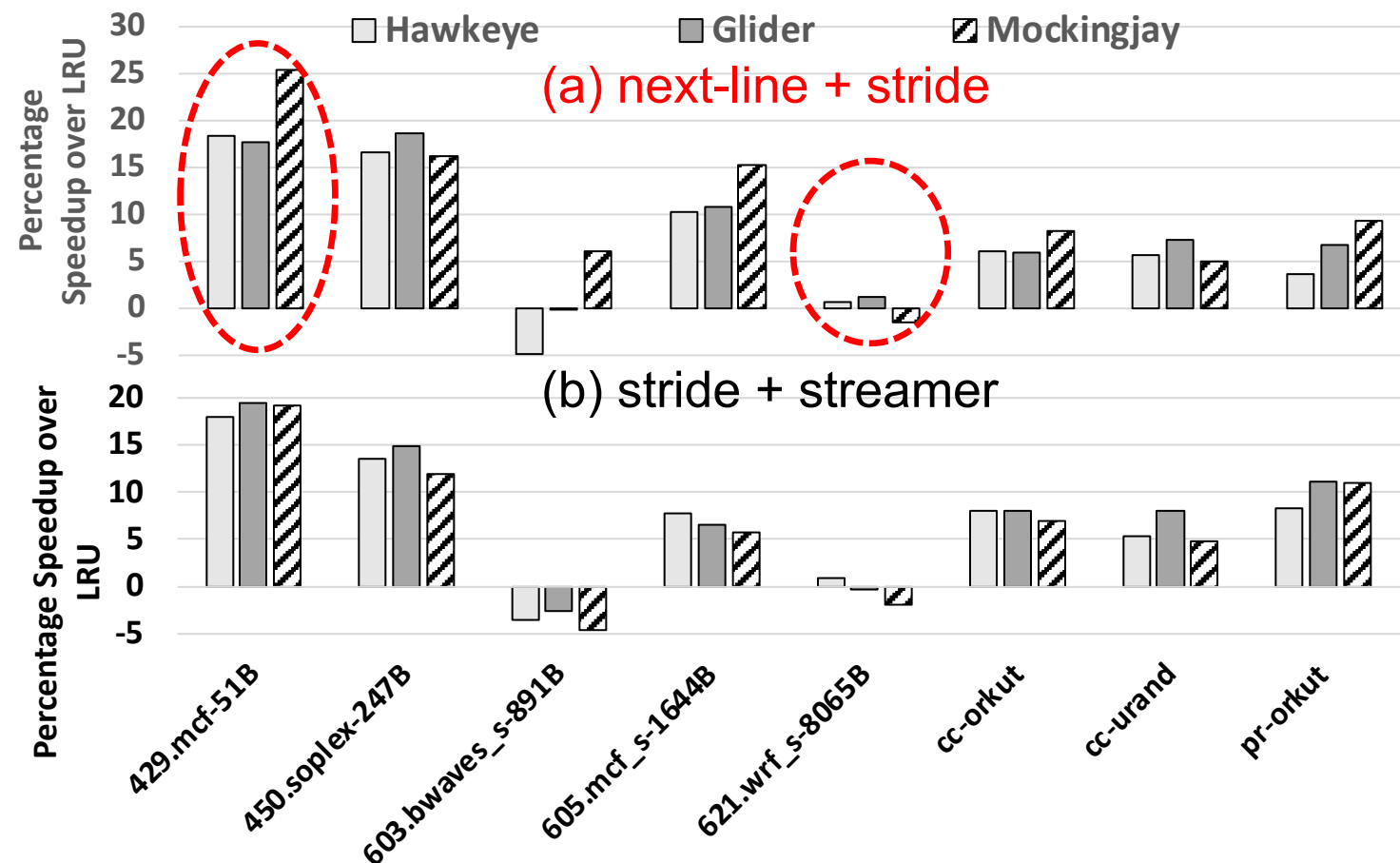


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A holistic cache management scheme is needed:

- **Cache bypassing** needs to be utilized to identify the blocks accessed only once
- **Cache replacement** needs to be aware of **prefetching**, to avoid the eviction of vital data

Lack of Adaptivity



Three state-of-the-art cache management schemes:

Hawkeye [ISCA'16]

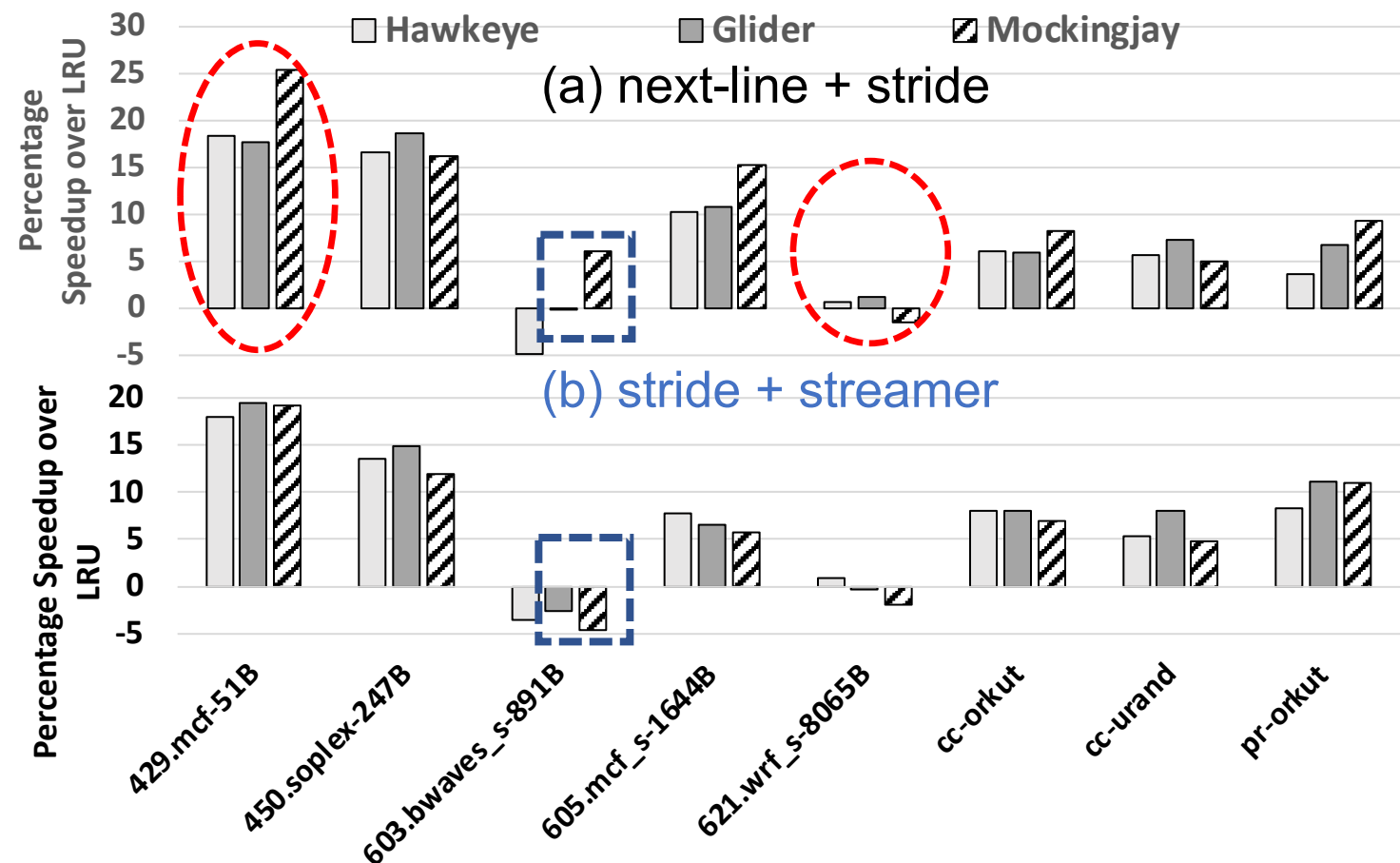
Glider [MICRO'19]

Mockingjay [HPCA'22]

**Inconsistent performance
across different workloads**

Comparing speedup over LRU on a 4-core system between: (a) using next-line prefetcher at L1 and stride prefetcher at L2, and (b) using stride prefetcher at L1 and streamer prefetcher at L2.

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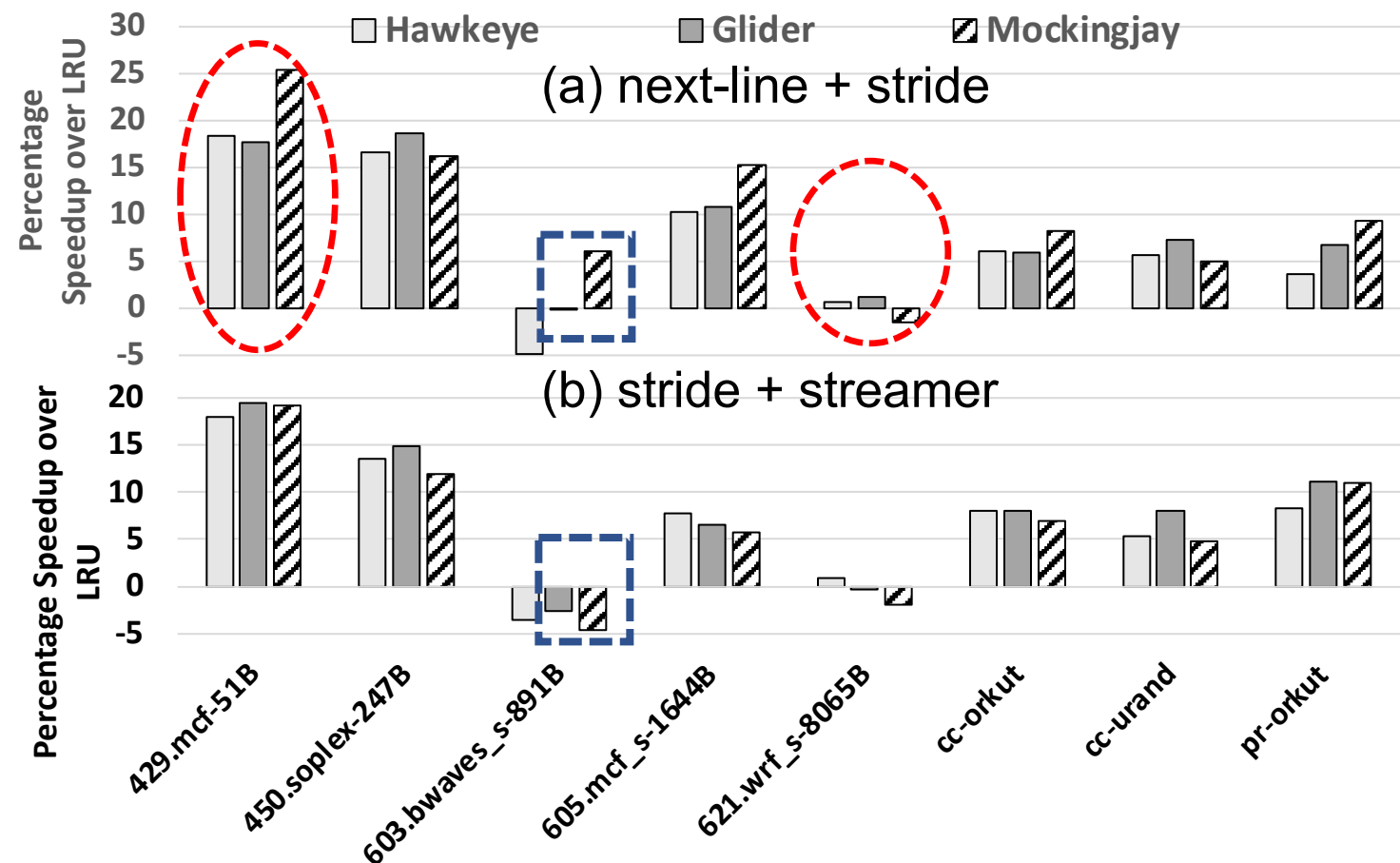
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Inconsistent performance across different workloads

Performance varies among diverse system configurations

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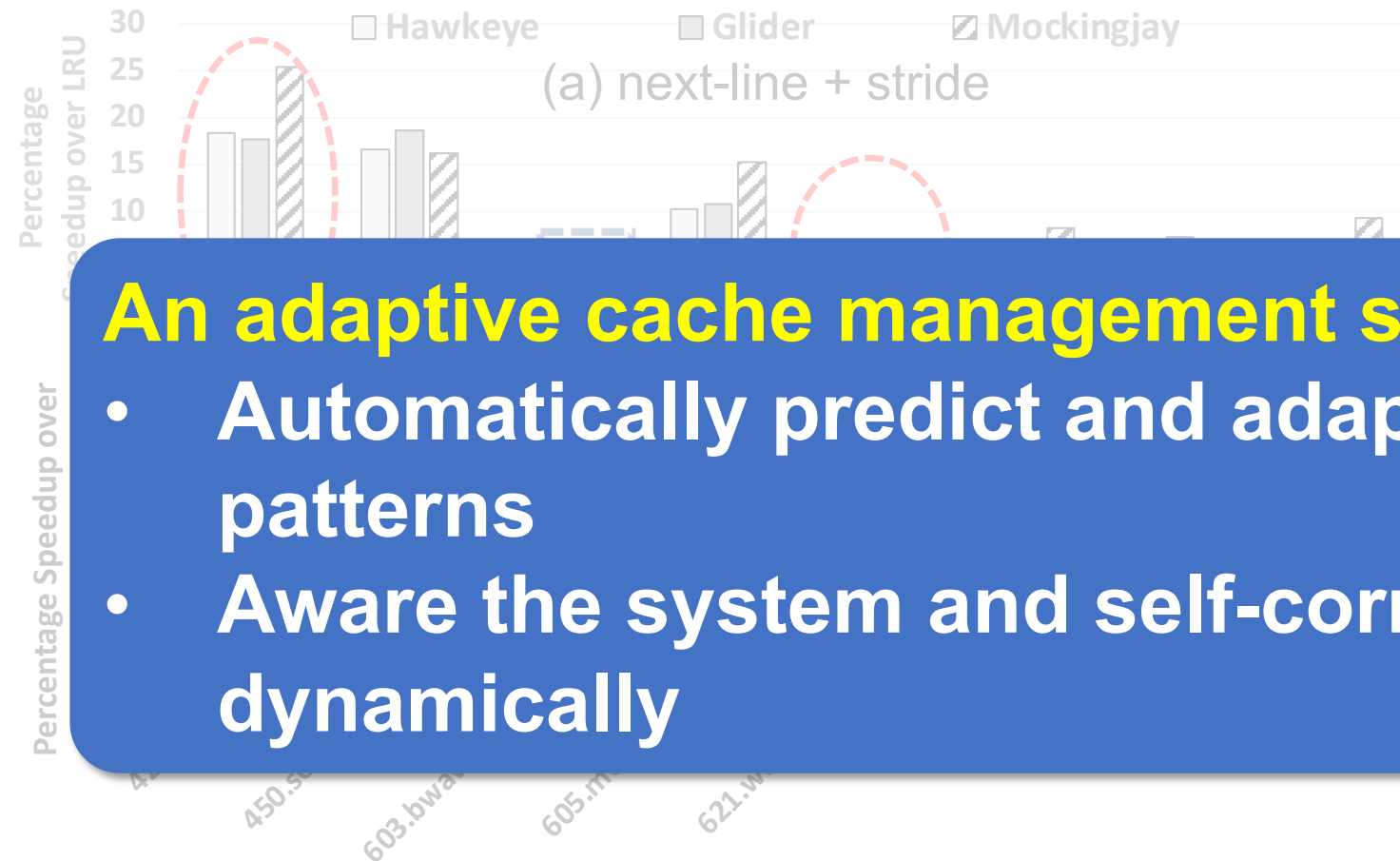
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Inconsistent performance across different workloads

Performance varies among diverse system configurations

Possible enhancement:
adaptive framework to handle diverse workloads and system configurations

Lack of Adaptivity



Inconsistent performance
across different workloads

An adaptive cache management scheme is needed:

- Automatically predict and adapt to various access patterns
- Aware the system and self-correct decisions dynamically

and system configurations

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Our Solution

A **holistic** cache management framework that **dynamically adapts** to various workloads and system configurations

Key Contributions: CHROME

Holistic Integration: Integrate cache bypassing and replacement with pattern-based prefetching

Dynamic Online Learning: Utilizes online reinforcement learning to adapt cache management to varying workloads and system configurations

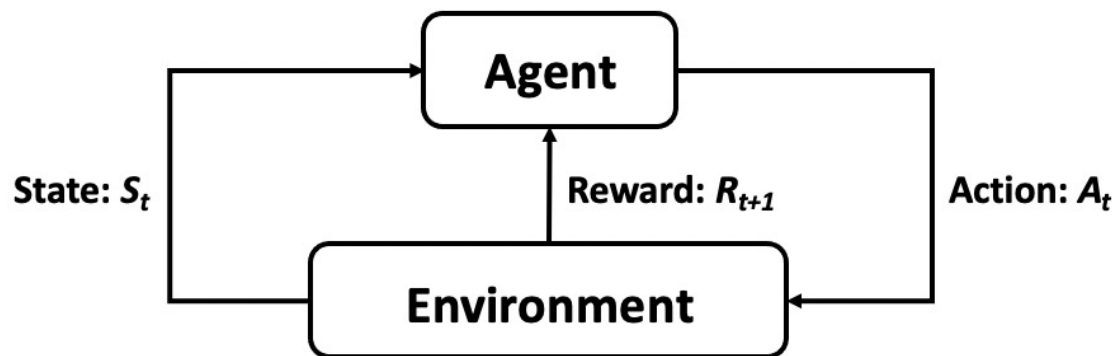
Multiple Program Features: Employs multiple program features to achieve a thorough understanding of memory access patterns

Concurrency-Aware Rewards: Implements a reward system that is aware of concurrent accesses, factoring in system-level feedback for decision-evaluation

Efficient Design: Achieves a minimal hardware overhead

Reinforcement Learning (RL)

- **Autonomously** learn through **feedback** from actions and experiences in an **interactive** environment
- Algorithmic approach to learn to take an **action** in a given **situation** to **maximize** a numerical **reward**



- Agent stores **Q-values** for **every** state-action pair
 - **Expected return** for taking an action in a state
 - Given a state, selects action that provides **highest** Q-value

Why RL?

Adaptive online learning:

- Allows CHROME to continuously learn and adapt by receiving rewards from real-time interactions

Learning with multiple features

- Learning process is enriched by utilizing a wide range of program features

Environment-Derived Rewards

- Surpasses static, intuition-based methods by employing a dynamic reward system directly informed by environmental feedback

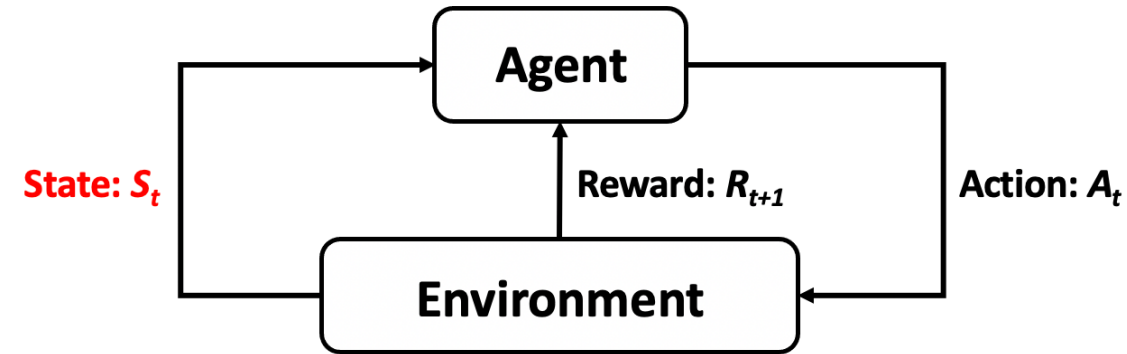
Acceptable overhead

- Does not require offline training and can be designed with smaller model size
- Q-values for state-action pairs can be stored in a lookup table

Formulating Cache Management as an RL Problem

What is State?

- A vector of features for each access
- Feature: **{control-flow, data access}**
- Control-flow of demands examples:
 - PC (Program Counter), sequence of last 4 PCs, ...
- Data-access examples:
 - memory address, page number, page offset, ...
- **$S = (\text{PC}, \text{page number})$**
- **Distinguish** between **demand accesses** and **prefetch accesses**



Formulating Cache Management as an RL Problem

What is Action?

- Eviction Priority Value (EPV)
 - Reflects the eviction priorities of the cache block
 - Three possible EPVs: low, moderate, high
- Cache miss (4 optional actions):
 - **Bypass** LLC
 - **Insert** the corresponding block in LLC with an **EPV of low, moderate, or high**
- Cache hit (3 optional actions):
 - **Update** the EPV of the corresponding block **to low, moderate, or high**

Formulating Cache Management as an RL Problem

What is Reward?

- The rewards of CHROME:
 - Reflect the accuracy of each action
 - Distinguish between actions triggered by demand or prefetching
 - Take into account system-level feedbacks
- **Eight** distinct reward levels:
 - **Accuracy**: Encourages CHROME to make precise decisions, reducing cache misses
 - **Prefetching Awareness**: Motivates CHROME to prioritize blocks likely to be requested next by demand accesses over those that might be requested by prefetch accesses
 - **Concurrency-Aware System Feedback**: Identifies cores causing LLC obstruction at runtime, promoting actions that mitigate the obstruction

CHROME Overview

The diagram illustrates the CHROME framework's architecture, divided into two main functional areas: **RL Decision** (top, yellow background) and **RL Training** (bottom, blue background).

RL Decision (Top Section):

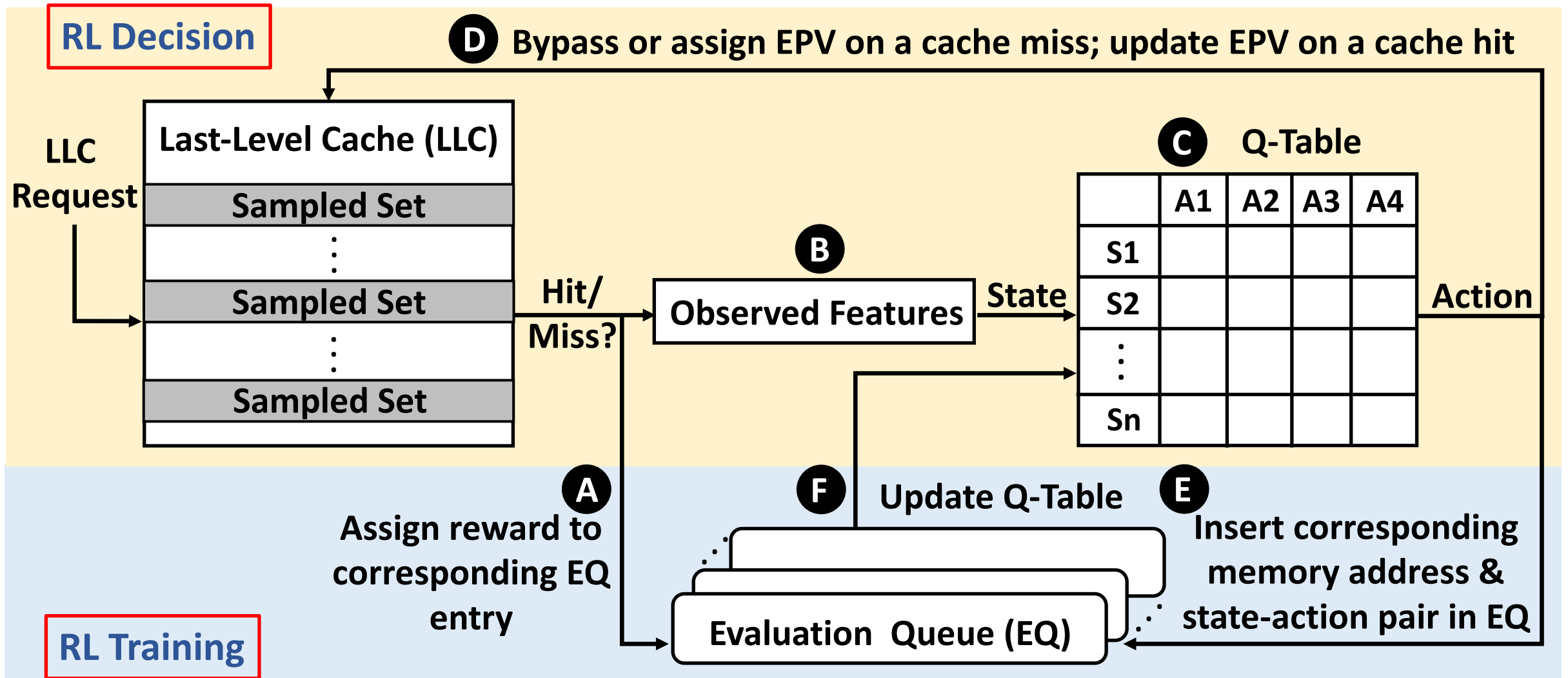
- An **LLC Request** enters the **Last-Level Cache (LLC)**, which contains multiple **Sampled Set** entries.
- Step **D**: **Bypass or assign EPV on a cache miss; update EPV on a cache hit**. This step is triggered by the LLC request and feeds into the **Observed Features** block.
- The **Observed Features** block outputs a **State** to the **Q-Table**.
- The **Q-Table** is a matrix with states (S1, S2, ..., Sn) on the rows and actions (A1, A2, A3, A4) on the columns.
- The **Q-Table** outputs an **Action**.

RL Training (Bottom Section):

- Step **A**: **Assign reward to corresponding EQ entry**. This step is triggered by the **Hit/Miss?** signal from the LLC and feeds into the **Evaluation Queue (EQ)**.
- The **Observed Features** block also feeds into the **Evaluation Queue (EQ)**.
- Step **E**: **Insert corresponding memory address & state-action pair in EQ**. This step is triggered by the **Action** from the Q-Table and feeds into the **Evaluation Queue (EQ)**.
- Step **F**: **Update Q-Table**. This step is triggered by the **Evaluation Queue (EQ)** and feeds back into the **Q-Table**.

Legend:

- LLC Request**: Indicated by a red arrow pointing to the Last-Level Cache.
- Hit/Miss?**: A signal from the Last-Level Cache to the Evaluation Queue.
- State**: A signal from Observed Features to the Q-Table.
- Action**: A signal from the Q-Table to the Evaluation Queue.



CHROME Design

Q-Table

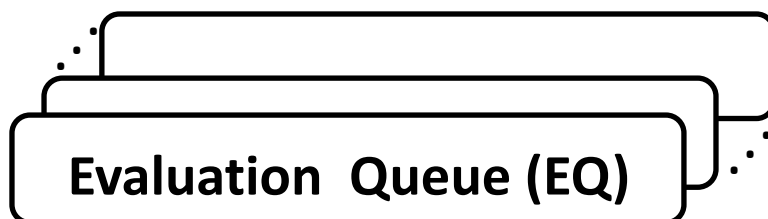
| | A1 | A2 | A3 | A4 |
|----------------|----|----|----|----|
| S1 | | | | |
| S2 | | | | |
| ⋮ | | | | |
| S _n | | | | |

Q-Table:

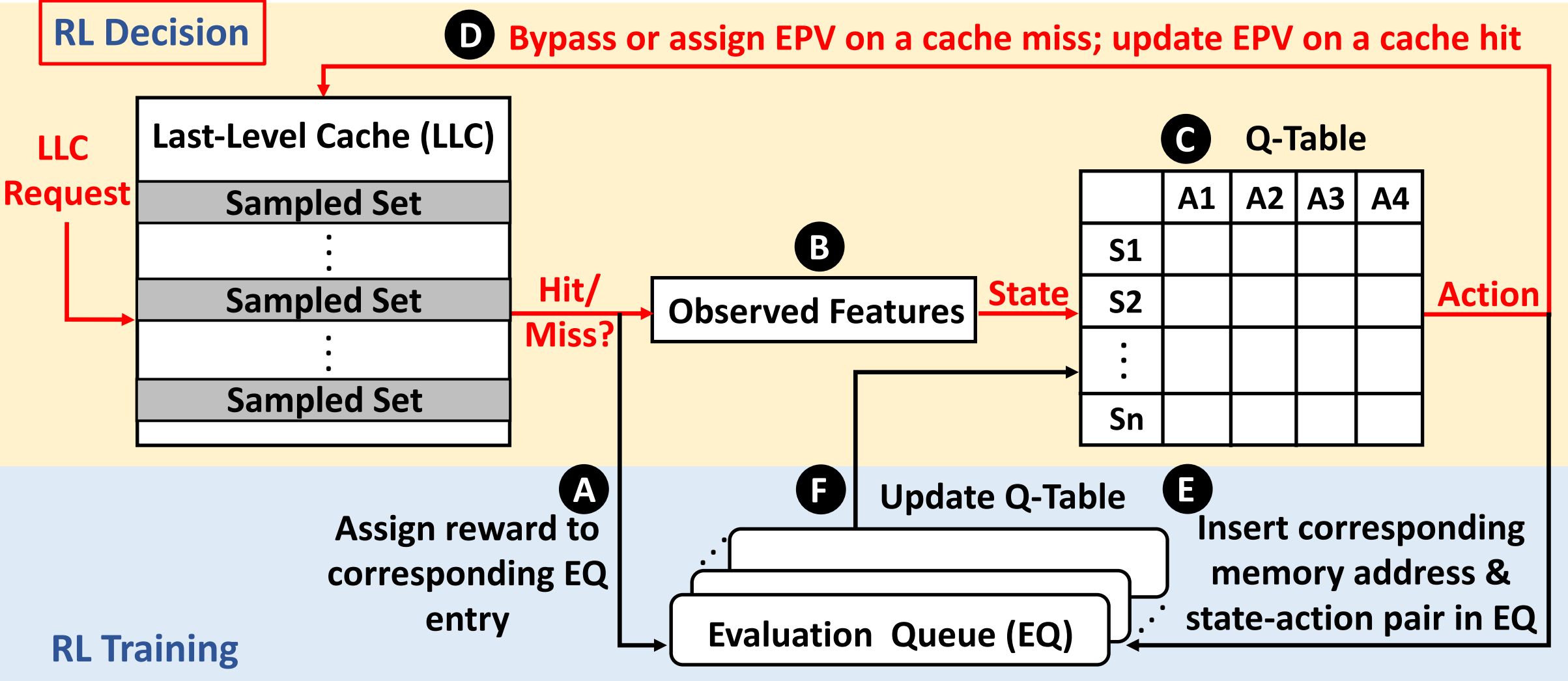
- Tracks the Q-values of all observed state-action pairs
- Given a state, CHROME picks a reasonable action based on the Q-Table

Evaluation Queue:

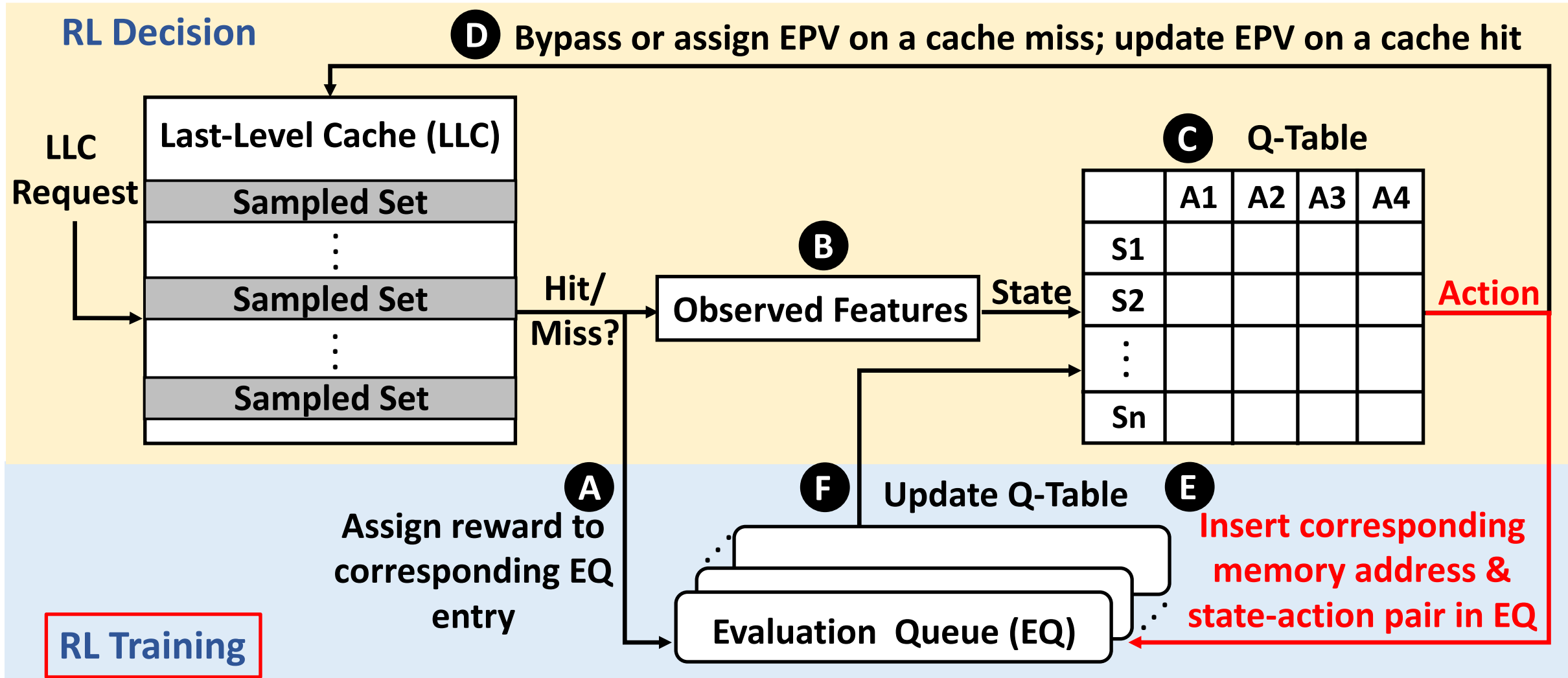
- Several first-in-first-out queues, each with a fixed capacity
- Records the actions of CHROME within a temporal window, which assists in rewarding



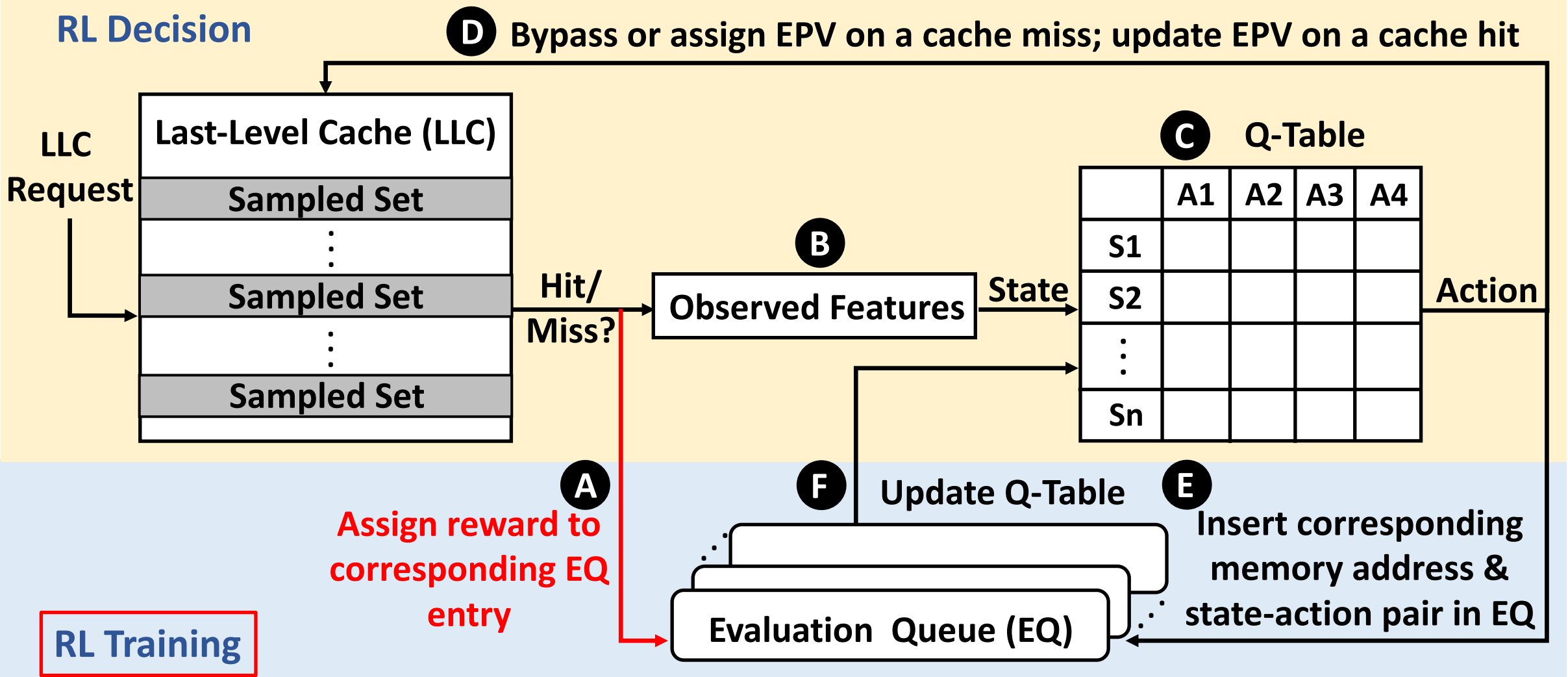
CHROME Workflow



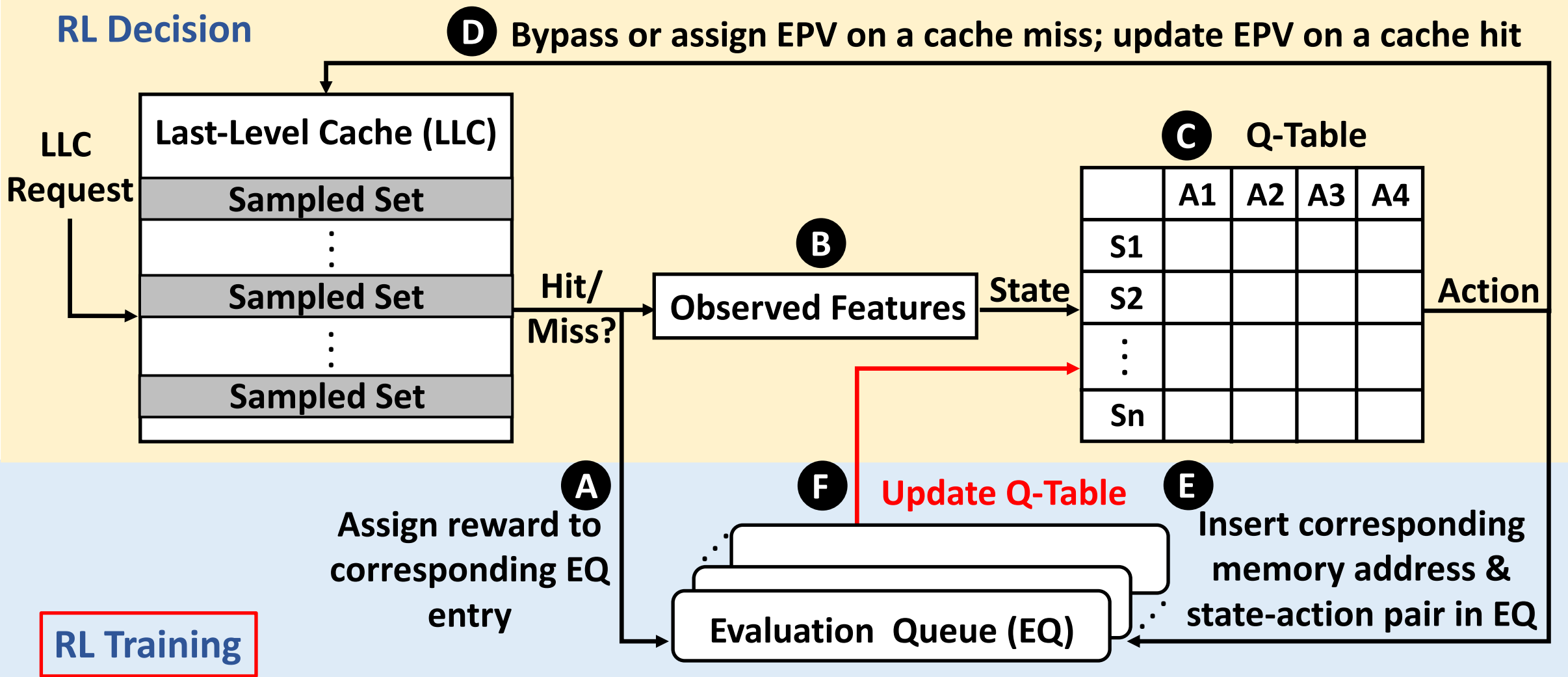
CHROME Workflow



CHROME Workflow



CHROME Workflow



More in the Paper

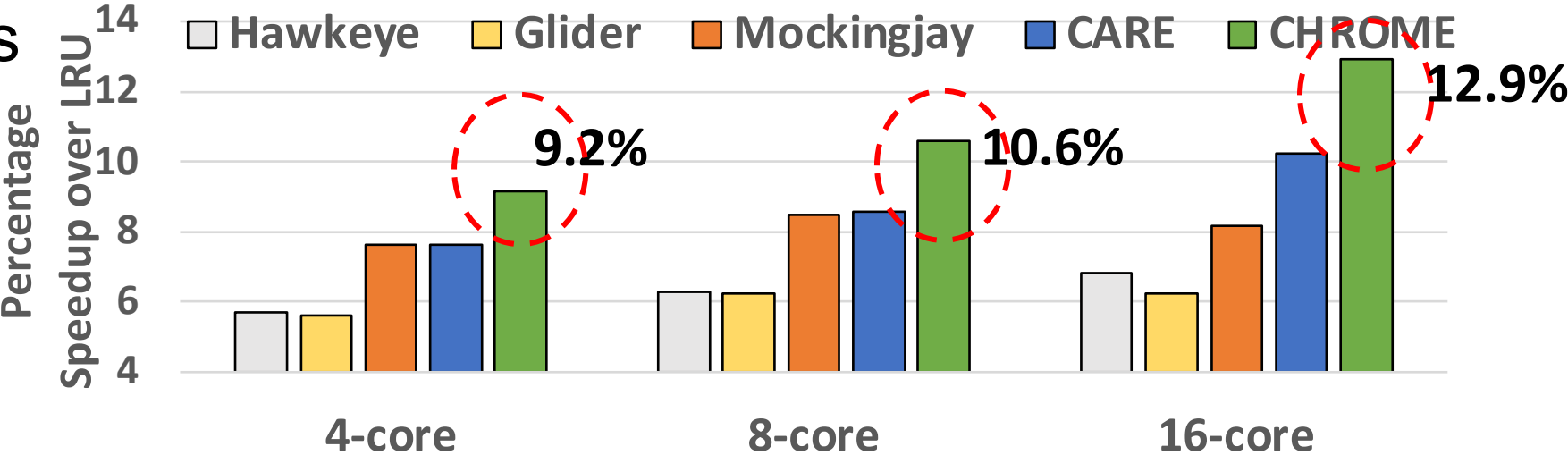
- Details on concurrency-aware system-level feedback
- Insights into the reward systems
- Pipelined organization of Q-Table
- EQ organization and Q-value update
- Tuning of the hyper-parameter
- Overhead analysis

Simulation Methodology

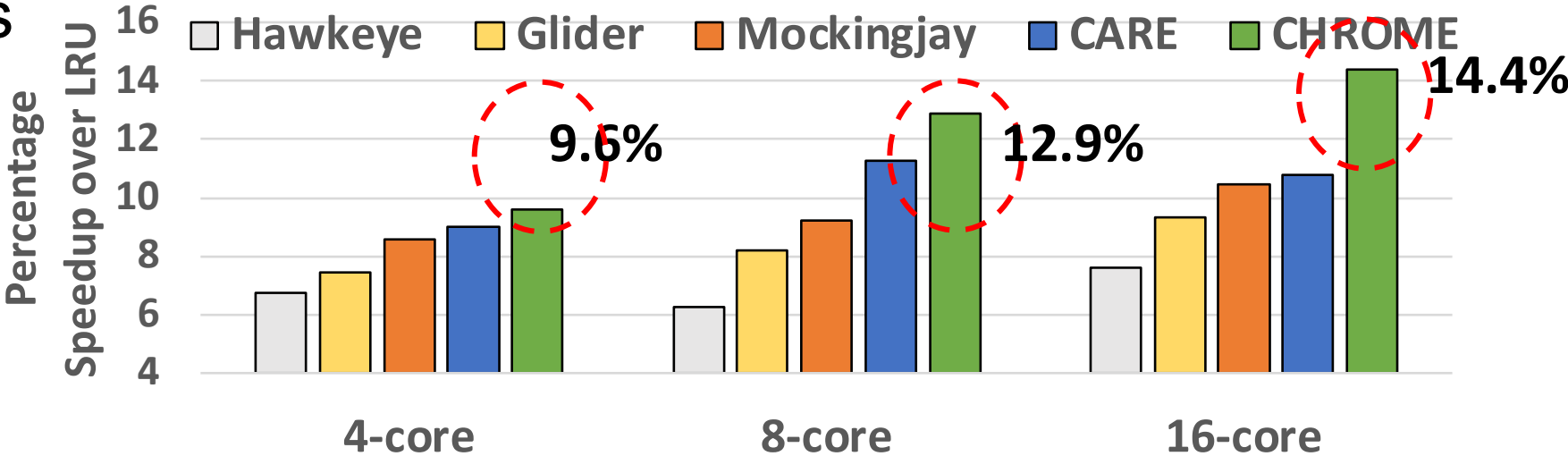
- **Champsim** trace-driven simulator
- **57** memory-intensive workload traces
 - SPEC CPU2006 and CPU2017
 - GAP
- **Homogeneous** and **heterogeneous** multi-core mixes
- **Prefetchers:**
 - L1D: Next-line prefetcher
 - L2: Stride prefetcher
- **Five** state-of-the-art LLC management schemes:
 - LRU
 - Hawkeye [ISCA'16]
 - Glider [MICRO'19]
 - Mockingjay [HPCA'22]
 - CARE [HPCA'23]

Performance with Varying Core Count

SPEC workloads
homogeneous



SPEC workloads
heterogeneous



Performance with Varying Core Count

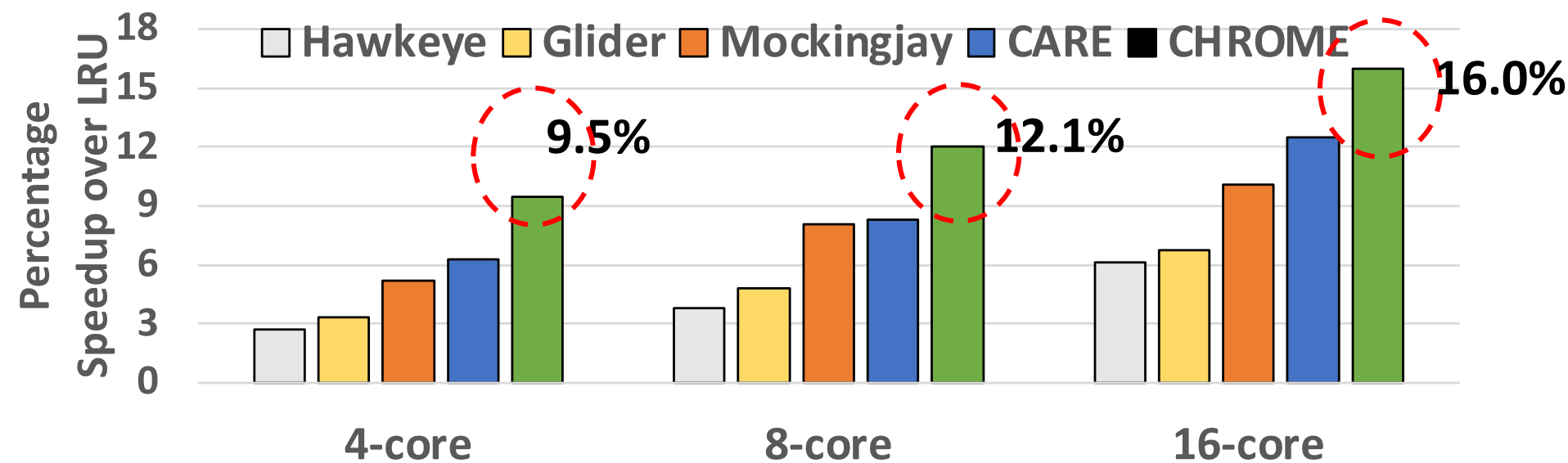
CHROME can accurately provide cache management for different workloads

CHROME outperforms all other schemes across all system configurations

Performance advantage of CHROME over others increases with more cores

Performance on Unseen Traces

GAP workloads



Performance on Unseen Traces

GAP workloads

The holistic view provides a performance guarantee

Online RL provides good adaptability and scalability

Summary

CHROME is a **holistic** cache management framework

CHROME continuously learns the policy by utilizing **online RL**

CHROME considers **multiple program features** and **concurrency-aware system-level feedback** information

CHROME **outperforms** state-of-the-art cache management schemes

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FAQs