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

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## **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

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## Examples of Cache Management Schemes

- Hawkeye [ISCA'16]
  - Cache replacement based on reuse prediction
  - Formulated as a binary classification problem (cache friendly or cache averse)
  - PC based predictor
- Glider [MICRO'19]
  - Cache replacement
  - Use LSTM for offline training and SVM for online decision making
- Mockingjay [HPCA'22]
  - Holistic approach encompassing cache replacement and bypassing, and support prefetching (with distinction between demand and prefetch accesses)
  - Extends Hawkeye -> multiclass reuse prediction
  - Policies are statically designed based on fixed assumptions
- CARE [HPCA'23]
  - Cache replacement considering both data locality and access concurrency

## **Limitations of Current Cache Management Schemes**

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

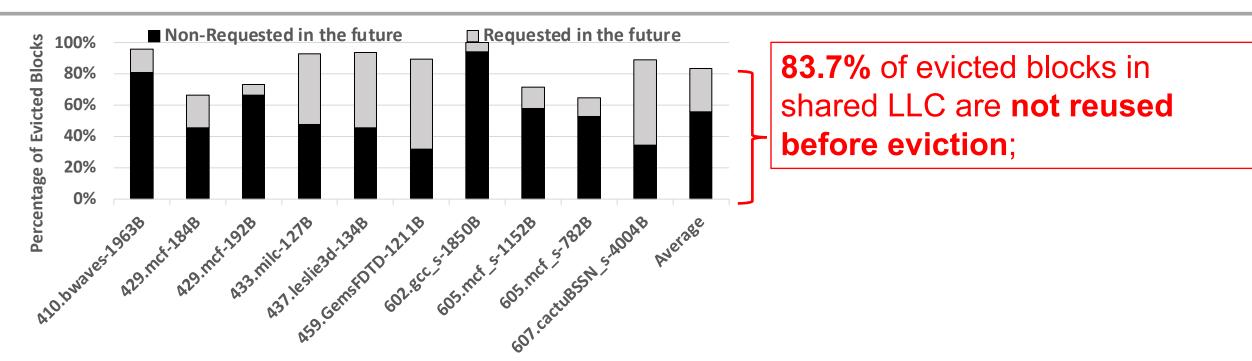
#### Lack of Holistic View

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

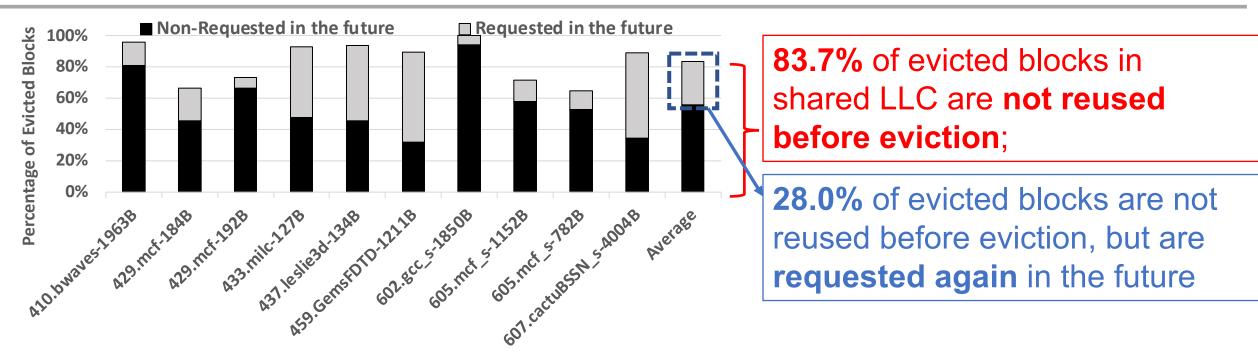
#### Lack of Adaptability

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

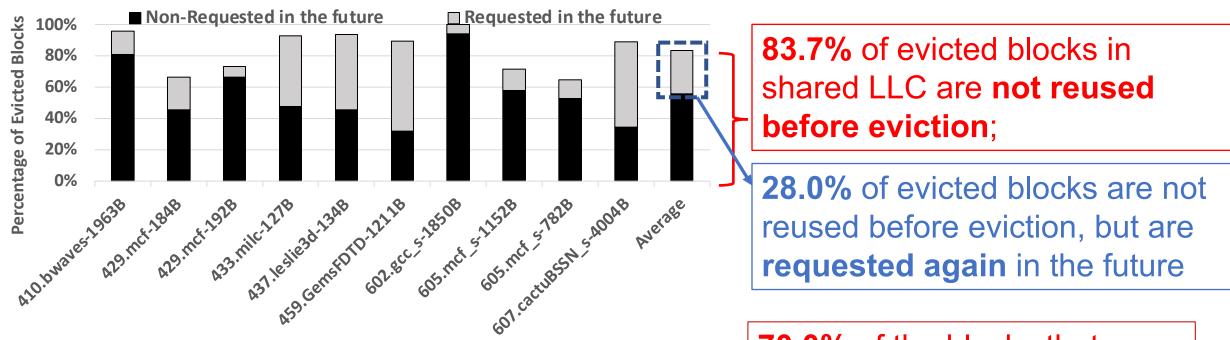
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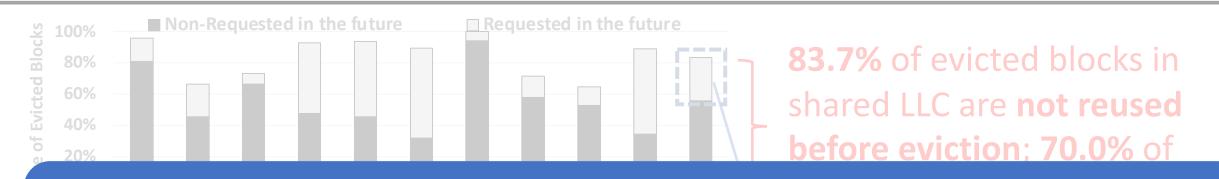
Inspecting Unresued Blocks in LLC with Gilder management scheme [MICRO'19]. Next-line prefetcher is used at L1 and stride prefetcher is used at L2.



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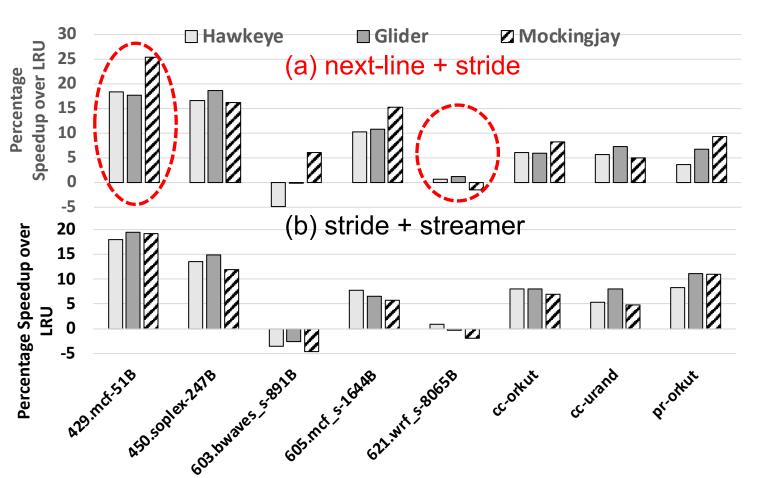
Inspecting Unresued Blocks in LLC with Gilder management scheme [MICRO'19]. Next-line prefetcher is used at L1 and stride prefetcher is used at L2. **70.0%** of the blocks that are not reused before eviction are attributed to **prefetching** 



A holistic cache management scheme is needed:

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

## Lack of Adaptivity



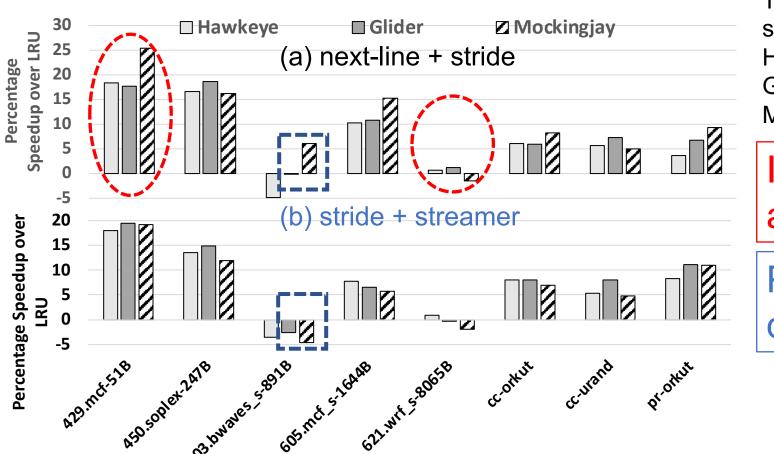
Three state-of-the-art cache management schemes: Hawkeye [ISCA'16] Glider [MICRO'19] Mockingjay [HPCA'22]

Inconsistent performance across different workloads

5

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.

## Lack of Adaptivity



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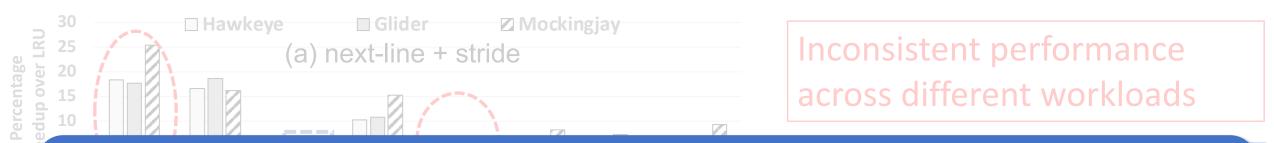
Inconsistent performance across different workloads

Performance varies among diverse system configurations

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## Lack of Adaptivity



# An adaptive cache management scheme is needed: Automatically predict and adapt to various access patterns

 Aware the system and self-correct decisions dynamically

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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#### and system configurations

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

## **Key Contributions: CHROME**

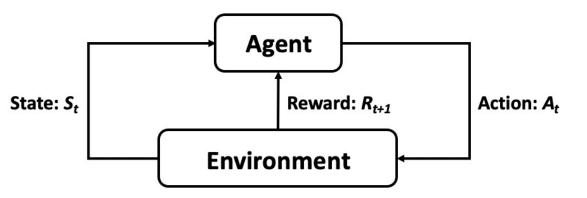
Holistic Integration: Integrate cache bypassing and replacement with pattern-based prefetching **Dynamic Online Learning:** Utilizes online reinforcement learning to adapt cache management to varying workloads and system configurations **Multiple Program Features:** Employs multiple program features to achieve a better 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

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## **Reinforcement Learning (RL)**

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



- To do that, 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

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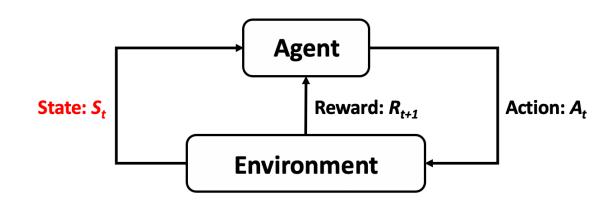
## Formulating Cache Management as an RL Problem

#### What is State?

- A vector of features for each access
- Feature selection is tradeoff between performance and overhead
- Feature: {control-flow, data access}
  - Control-flow of demands examples: PC, seq. of PCs, call stack, ...
  - Data-access examples: memory address, page number, page offset, delta, ...
  - S = (PC signature, page number)

#### • PC signature:

- Hashed PC and hit/miss information
- One bit to distinguish demand vs. prefetch access
- Incorporate core number (to differentiate behaviors among the cores)



## 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 possible actions):
  - Bypass LLC
  - Insert the corresponding block in LLC with an EPV of low, moderate, or high
- Cache hit (3 possible actions):
  - Update the EPV of the corresponding block to low, moderate, or high

## Formulating Cache Management as an RL Problem

#### What is Reward?

- CHROME provides 8 distinct rewards
- Accuracy: Reward hits and penalize misses; ALSO, for blocks not to be accessed in near future, incentivize bypass on misses or assign high EPV on hits
- Prefetching Awareness: 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 (LLC obstruction = if C-AMAT is greater than memory access time)

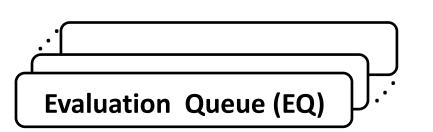
## CHROME Design

Q-Table

	A1	A2	<b>A3</b>	A4
<b>S1</b>				
<b>S2</b>				
•				
Sn				

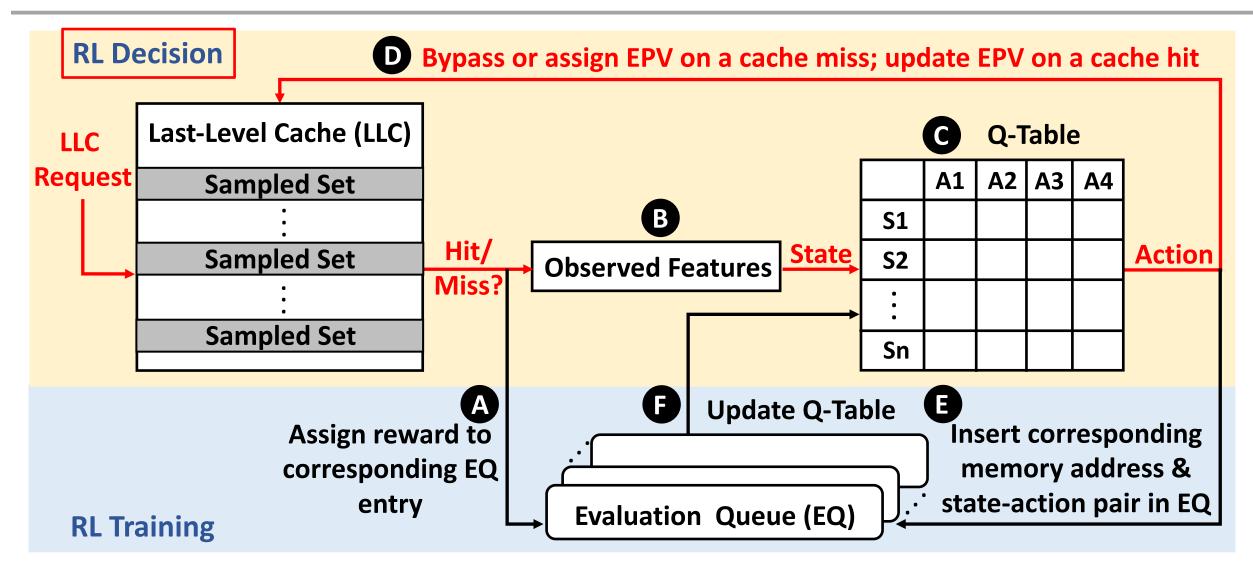
#### **Q-Table:**

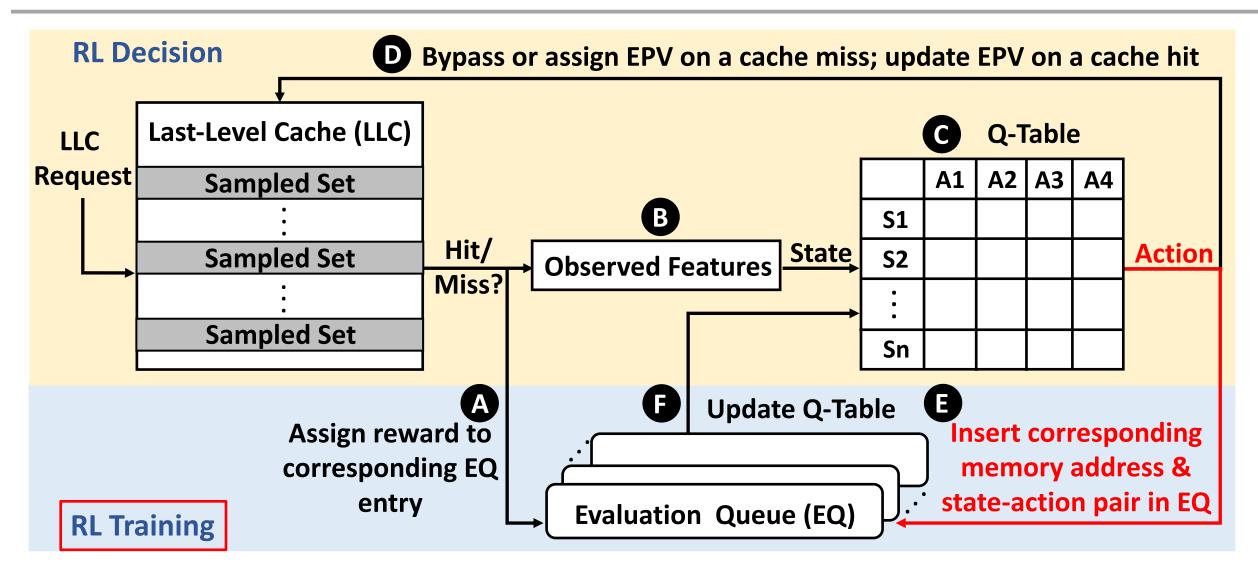
- Tracks the Q-values of all observed state-action pairs
- Given a state, CHROME picks a reasonable action based on the Q-Table

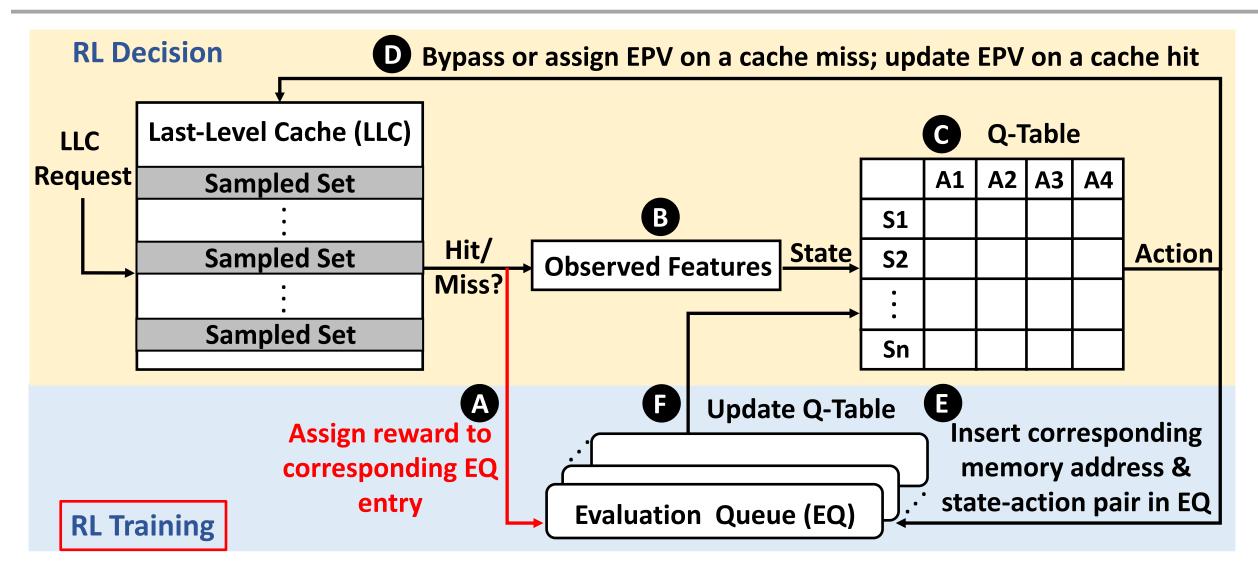


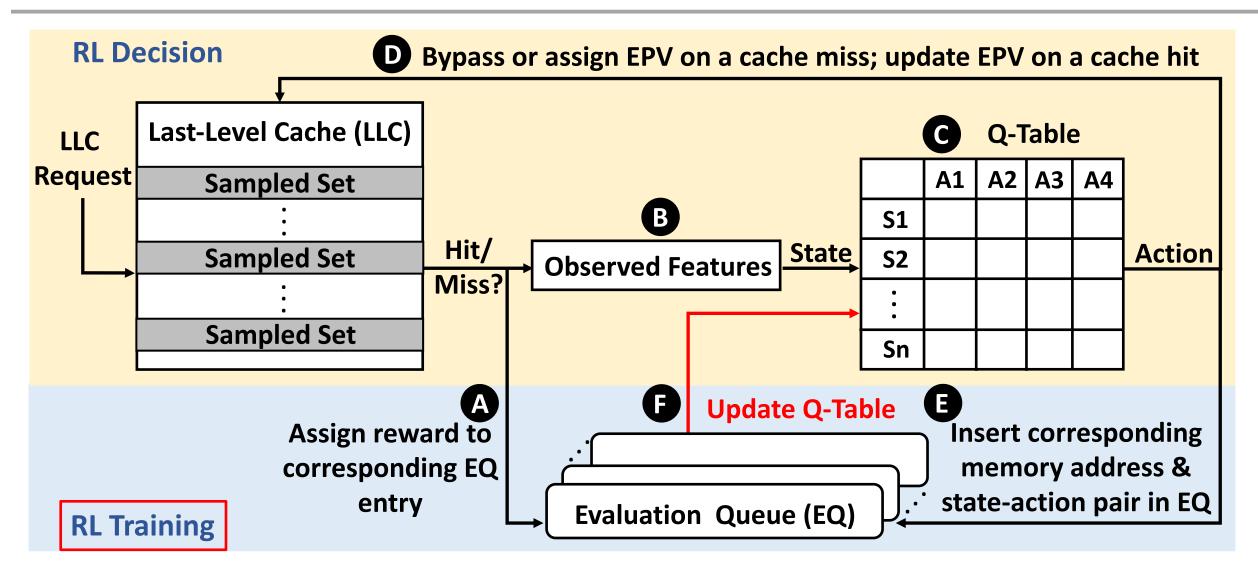
#### **Evaluation Queue:**

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









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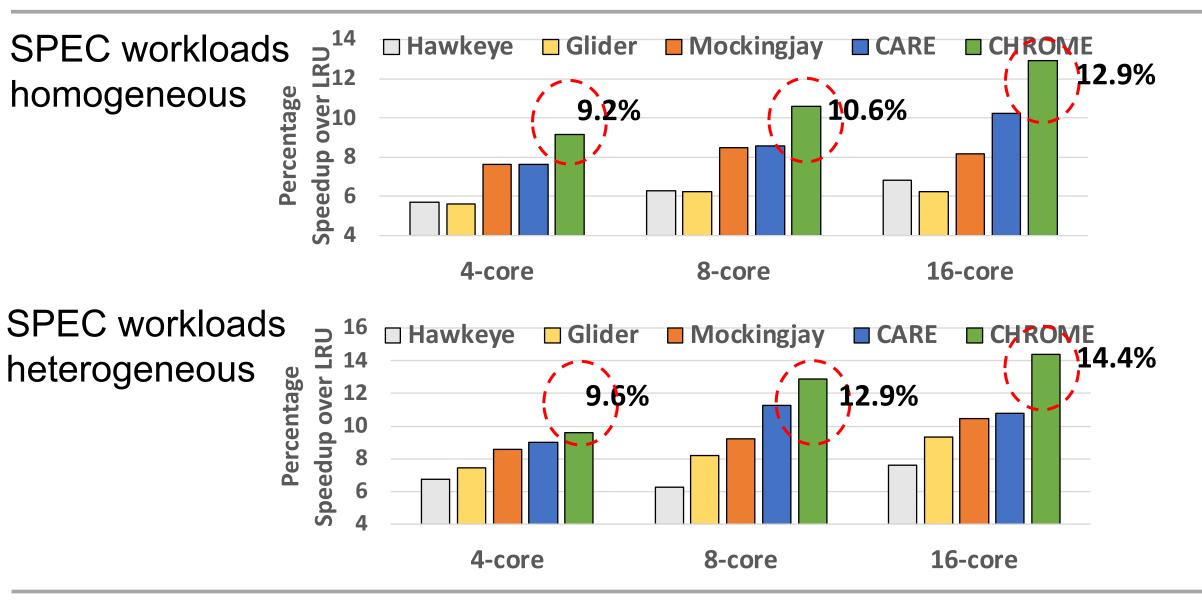
## More in the Paper

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

## **Simulation Methodology**

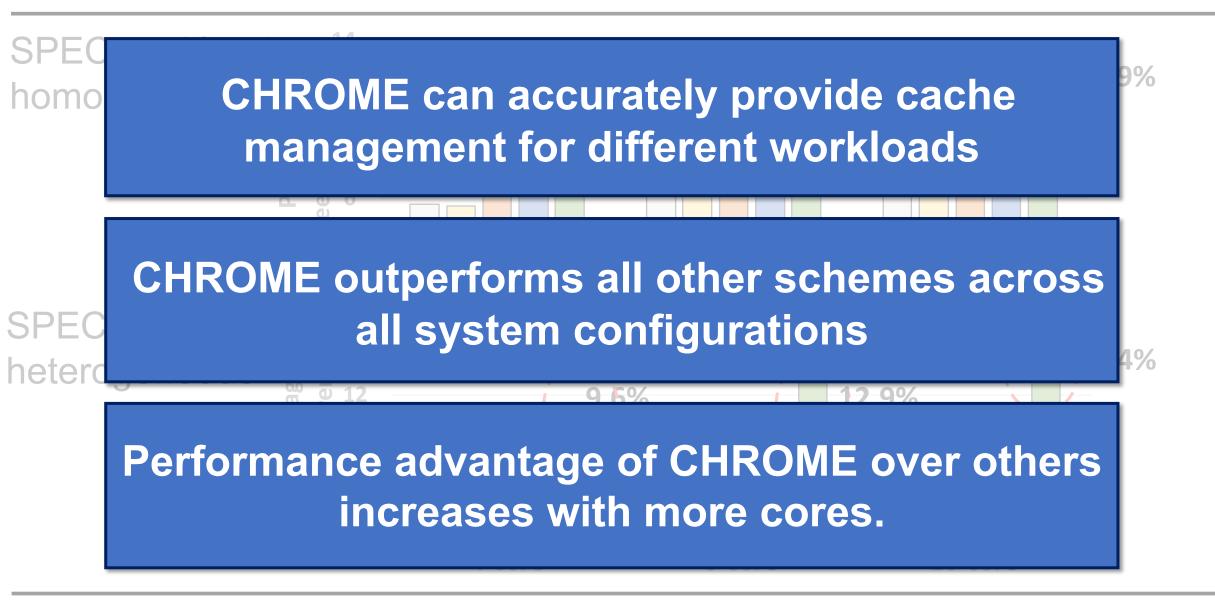
- Champsim trace-driven simulator
- 57 memory-intensive workload traces
  - SPEC CPU2006 and CPU2017
  - GAP
- Homogeneous and heterogeneous multi-core mixes
- Prefetchers:
  - L1D: Next-line prefetcher
  - L2: Stride prefetcher
- Five state-of-the-art LLC management schemes:
  - LRU
  - Hawkeye [ISCA'16]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

### **Performance with Varying Core Count**



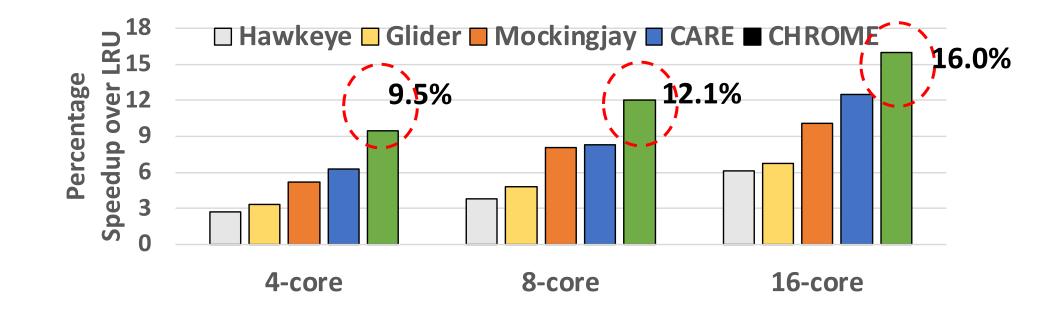
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#### **Performance with Varying Core Count**



#### **Performance on Unseen Traces**

GAP workloads



#### **Performance on Unseen Traces**

**GAP** workloads



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## Cost

TABLE III: Storage overhead of CHROME.

Component	Details	Overhead
Q-Table	2 features; 4 sub-tables/feature; 2048 entries/sub-table; 16 bits/entry	32KB
EQ	64 queues; 28 entries/queue; 58 bits/entry (state: 33 bits, action: 2 bits, reward: 6 bits, hashed address: 16 bits, trigger: 1 bit)	12.7KB
Metadata	EPV (2-bit/LLC block)	48KB
Total		92.7KB

TABLE IV: Storage overhead for different schemes (4-core configuration, 12-way 12MB LLC).

	Holistic	<b>Concurrency-aware</b>	Overhead
Hawkeye [21]	No	No	146KB
Glider [44]	No	No	254KB
Mockingjay [43]	Yes	No	170.6KB
CARE [43]	No	Yes	130.5KB
CHROME	Yes	Yes	92.7KB

- The complexity of the prediction path is similar to that of the other SOTA prediction-based schemes
- We used CACTI 7.0 to estimate the latency for the Q-Table lookups, also the area and power consumption:
  - Q-Table lookup latency is ~2 cycles
  - Q-Table operations are off the critical path -> no interference with cache controller
- The area and power consumption of CHROME is rather modest



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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