

Sibyl: Adaptive and Extensible Data Placement in Hybrid Storage Systems Using Online Reinforcement Learning

Gagandeep Singh, Rakesh Nadig, Jisung Park, Rahul Bera,
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Sander Stuijk, Henk Corporaal, Onur Mutlu

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Executive Summary

- **Background:** A hybrid storage system (HSS) uses multiple different storage devices to provide high and scalable storage capacity at high performance
- **Problem:** Two key shortcomings of prior data placement policies:
 - Lack of **adaptivity** to:
 - **Workload changes**
 - **Changes in device types and configurations**
 - Lack of **extensibility** to more devices
- **Goal:** Design a data placement technique that provides:
 - **Adaptivity**, by **continuously learning and adapting** to the **application and underlying device characteristics**
 - **Easy extensibility** to incorporate a wide range of hybrid storage configurations
- **Contribution:** Sibyl, the first reinforcement learning-based data placement technique in hybrid storage systems that:
 - Provides **adaptivity** to changing workload demands and underlying device characteristics
 - Can **easily extend** to any number of storage devices
 - Provides **ease of design and implementation** that requires only a small computation overhead
- **Key Results:** Evaluate on **real systems** using a wide range of workloads
 - Sibyl **improves performance by 21.6%** compared to the best previous data placement technique in dual-HSS configuration
 - In a tri-HSS configuration, Sibyl outperforms the state-of-the-art-policy policy by **48.2%**
 - Sibyl achieves **80% of the performance** of an oracle policy with storage overhead of only **124.4 KiB**

Talk Outline

Key Shortcomings of Prior Data Placement Techniques

Formulating Data Placement as Reinforcement Learning

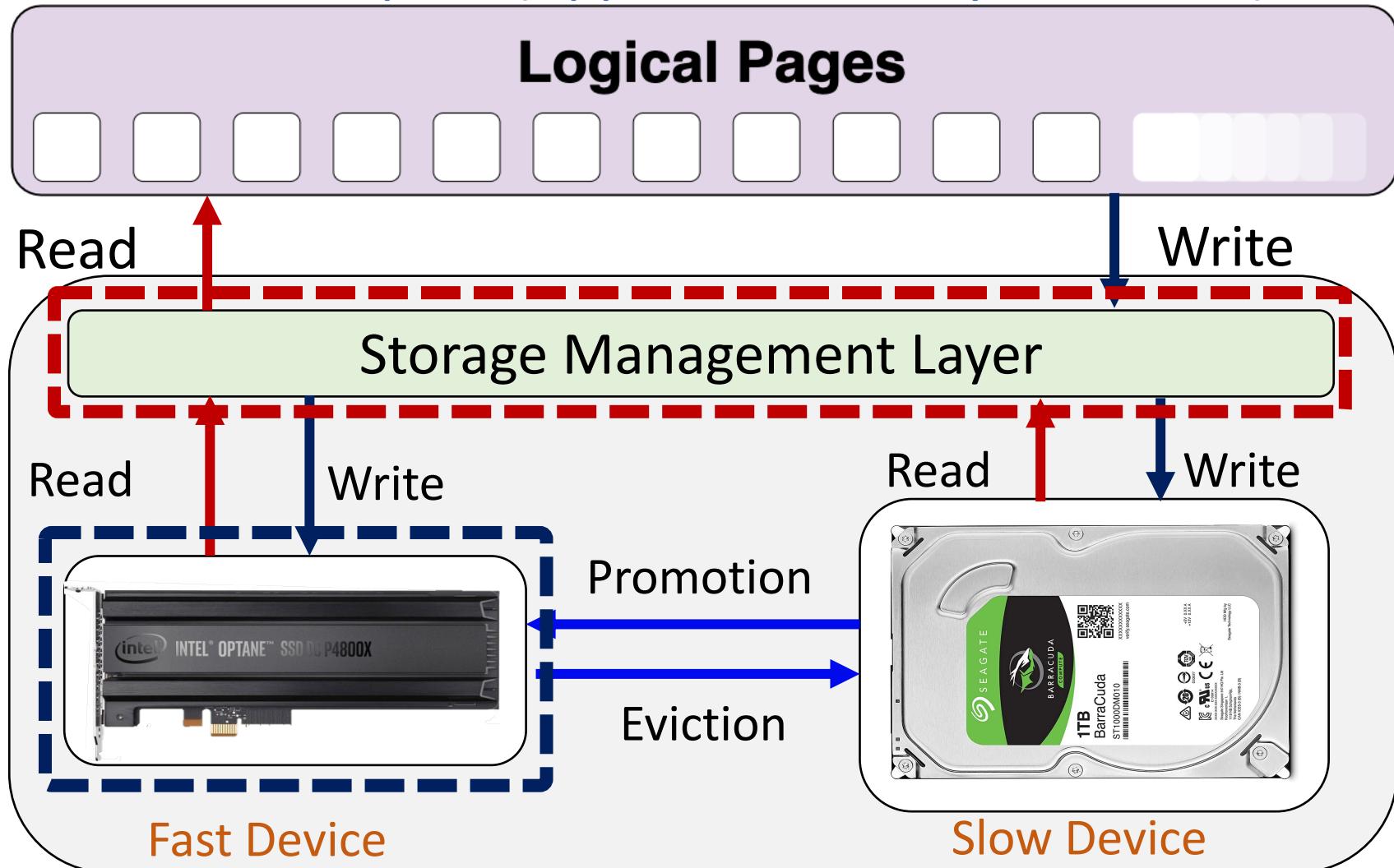
Sibyl: Overview

Evaluation of Sibyl and Key Results

Conclusion

Hybrid Storage System Basics

Address Space (Application/File System View)



Hybrid Storage System Basics

Logical Address Space (Application/File System View)

Logical Pages

Performance of a hybrid storage system
highly depends on the ability of the
storage management layer



Key Shortcomings in Prior Techniques

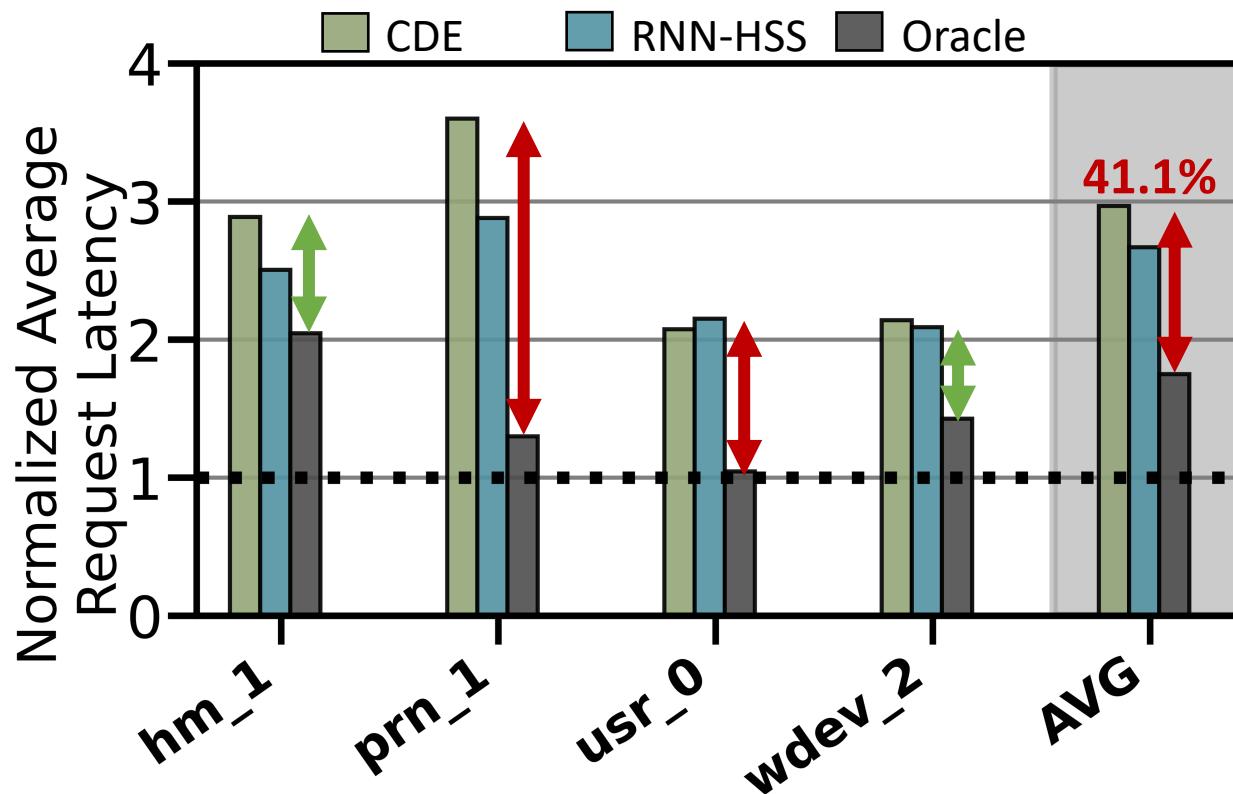
We observe **two key shortcomings** that significantly limit the performance benefits of prior techniques

1. Lack of **adaptivity to:**
 - a) Workload changes
 - b) Changes in device types and configuration
2. Lack of **extensibility** to more devices

Lack of Adaptivity

Workload Changes

Prior data placement techniques consider only a **few workload characteristics** that are **statically tuned**

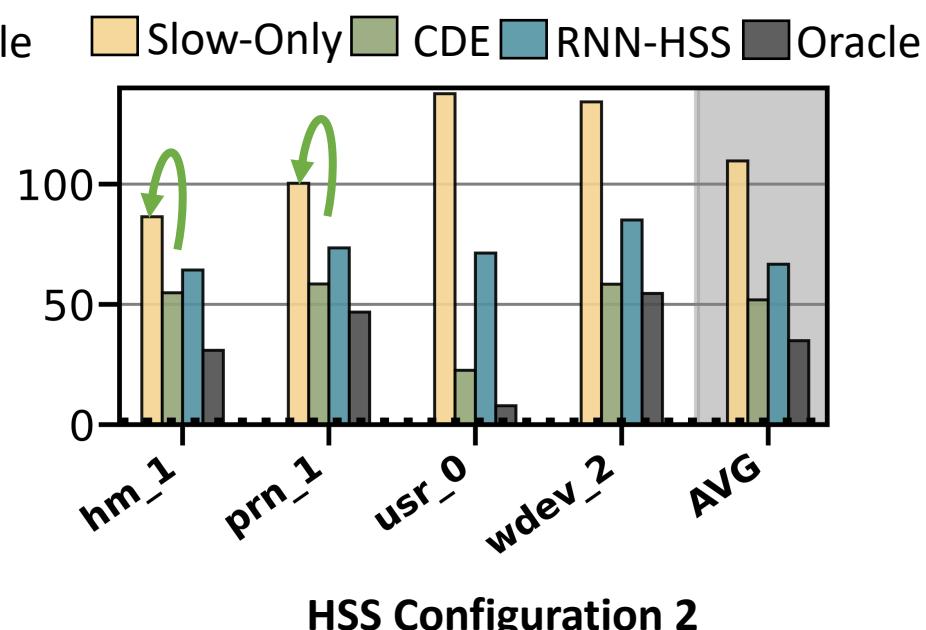
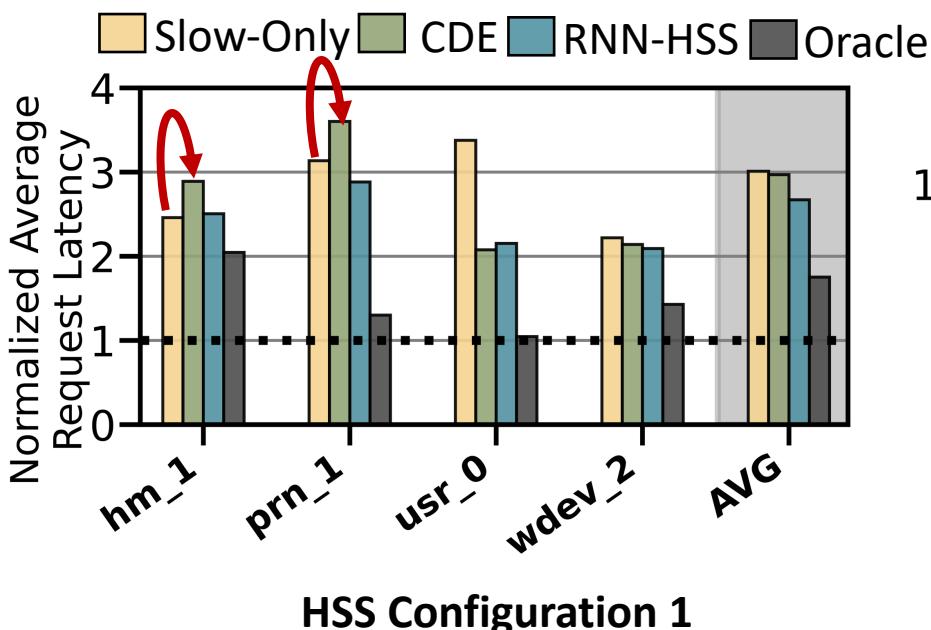


Lack of Adaptivity

Changes in Device Types and Configurations

Do not consider **underlying storage device**

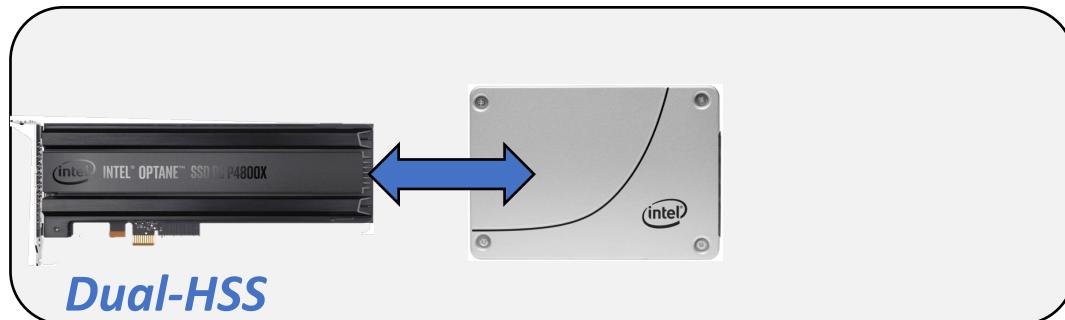
characteristics (e.g., changes in the level asymmetry in read/write latencies, garbage collection)



Lack of Extensibility

Rigid techniques that require significant effort to accommodate more than two devices

Change in storage configuration



Dual-HSS

SAFARI

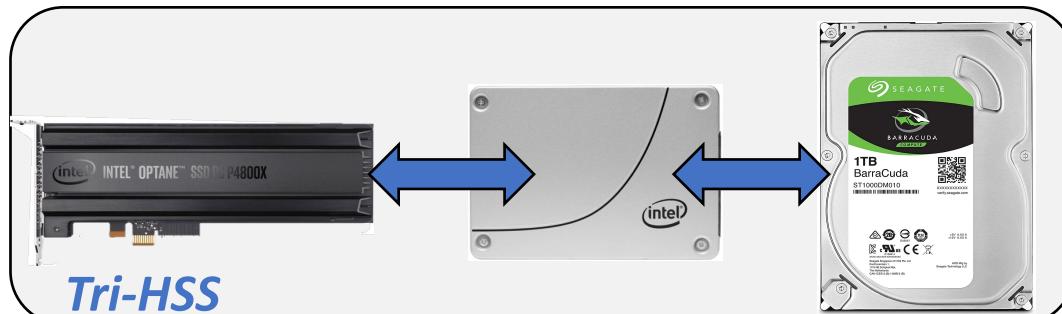
Lack of Extensibility

Rigid techniques that require significant effort to accommodate more than two devices

Change in storage configuration



Design a new policy



Tri-HSS

SAFARI

Our Goal

A **data-placement mechanism**
that can provide:

- 1. Adaptivity**, by **continuously learning** and **adapting** to the application and underlying device characteristics
- 2. Easy extensibility** to incorporate a wide range of hybrid storage configurations

Our Proposal



Sibyl

Formulates data placement in
hybrid storage systems as a
reinforcement learning problem

Sibyl is an oracle that makes accurate prophecies

<https://en.wikipedia.org/wiki/Sibyl>

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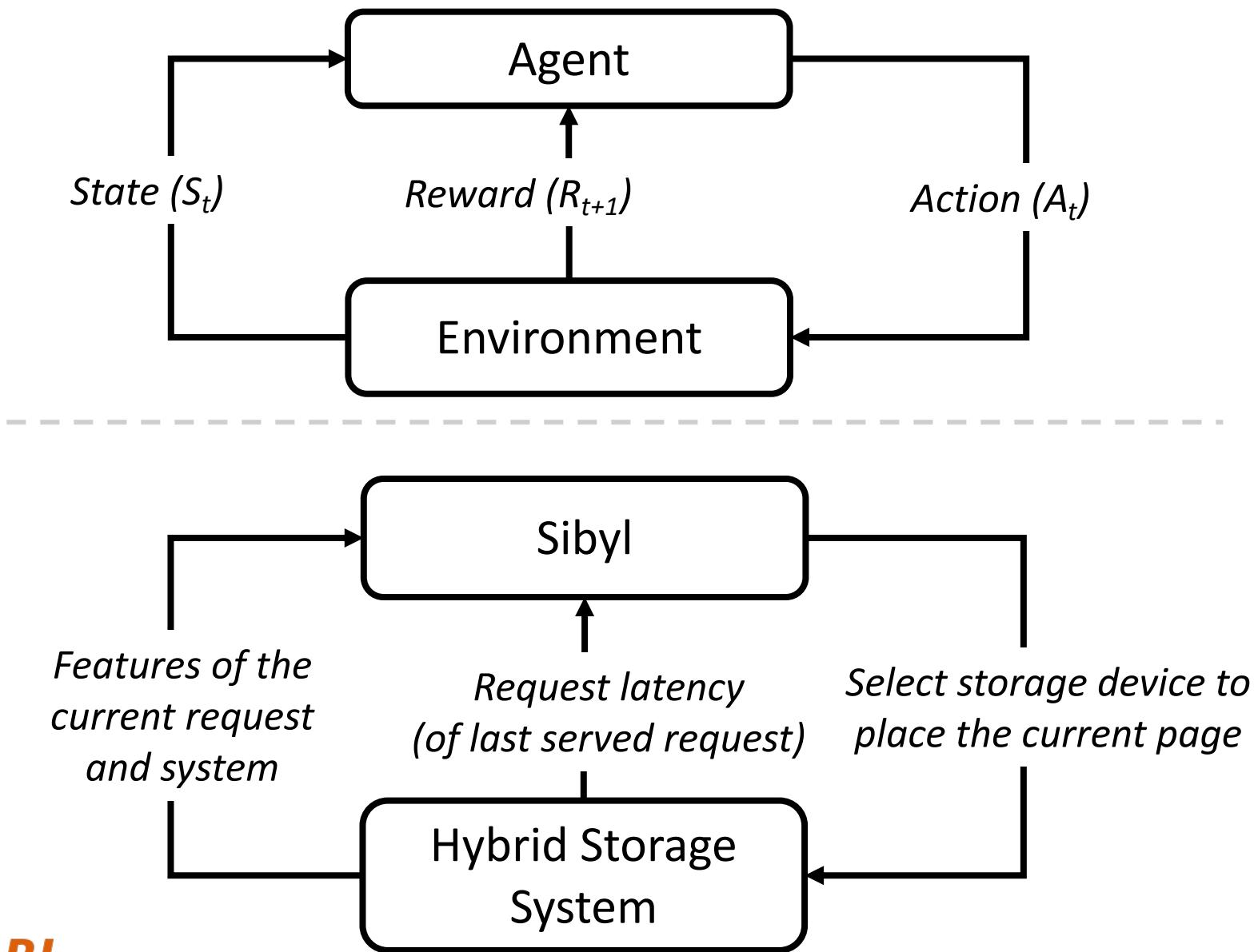
Basics of Reinforcement Learning (RL)

Agent

Environment

Agent learns to take an **action** in a given **state**
to maximize a numerical **reward**

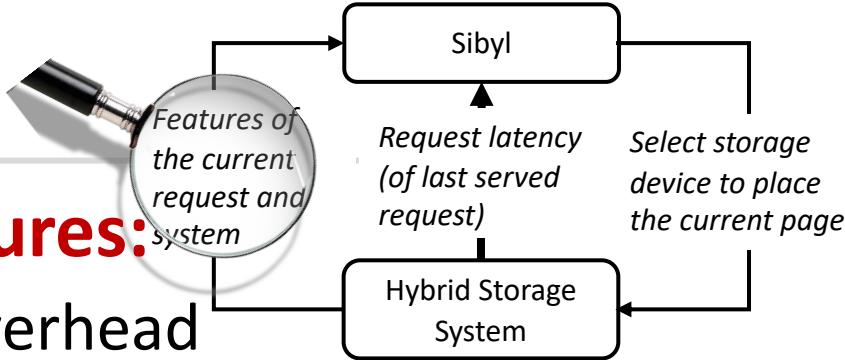
Formulating Data Placement as RL



What is State?

- **Limited number of state features:**

- Reduce the implementation overhead
- RL agent is more sensitive to reward



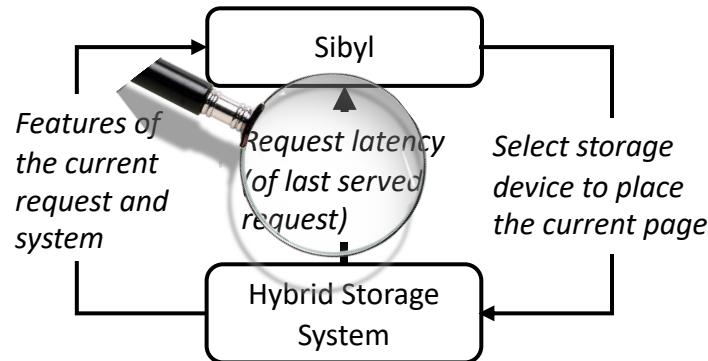
- **6-dimensional** vector of state features

$$O_t = (size_t, type_t, intr_t, cnt_t, cap_t, curr_t)$$

- We **quantize the state representation** into bins to reduce storage overhead

What is Reward?

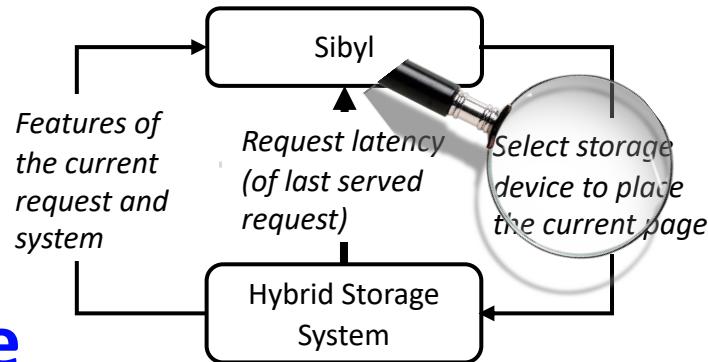
- Defines the **objective** of Sibyl



- We formulate the reward as a function of the **request latency**
- Encapsulates three key aspects:
 - **Internal state of the device** (e.g., read/write latencies, the latency of garbage collection, queuing delays, ...)
 - **Throughput**
 - **Evictions**
- More details in the paper

What is Action?

- At every new page request, the action is to **select a storage device**
- Action can be **easily extended** to any number of storage devices
- Sibyl **evicts** a page from the fast device to the slow device



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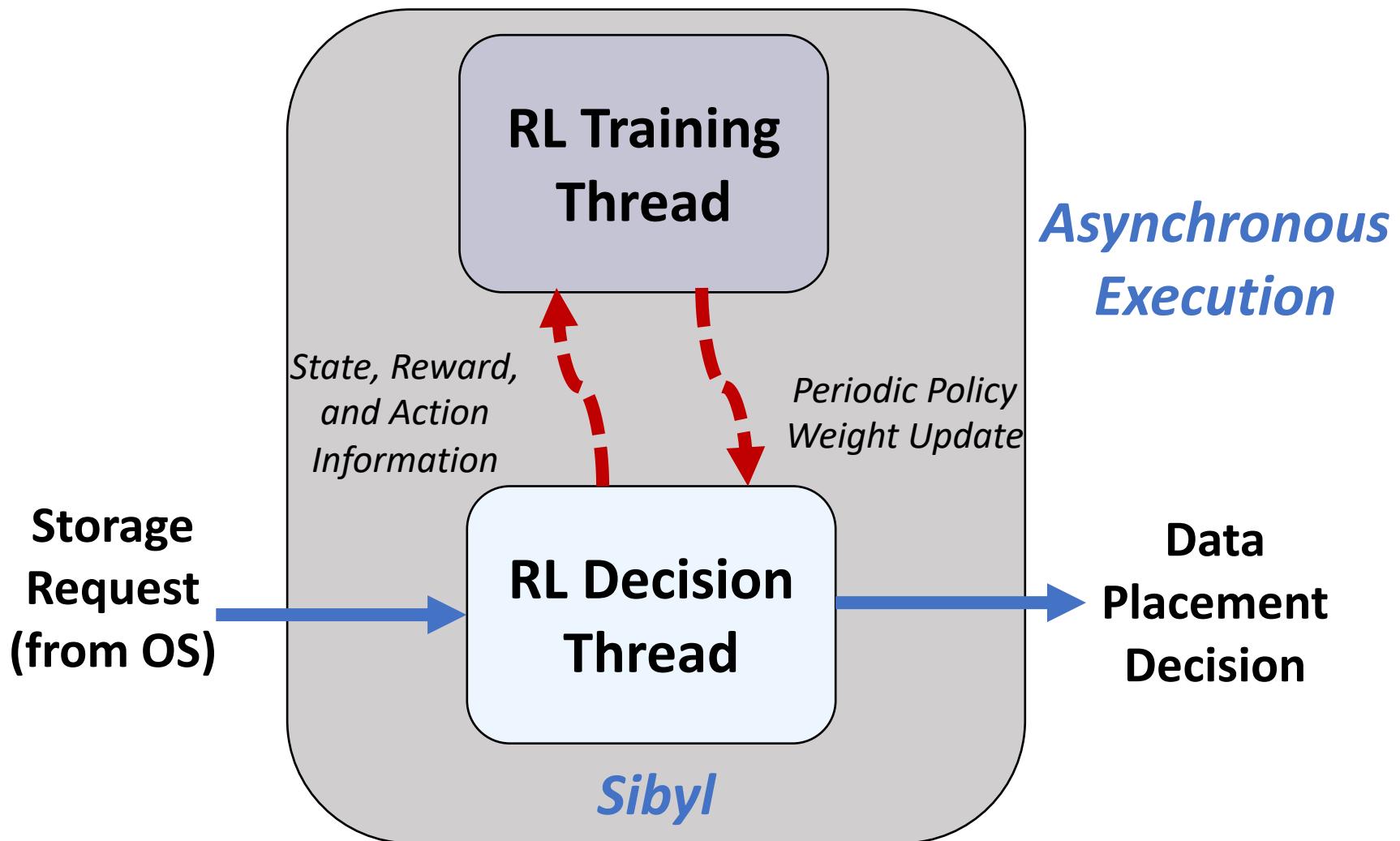
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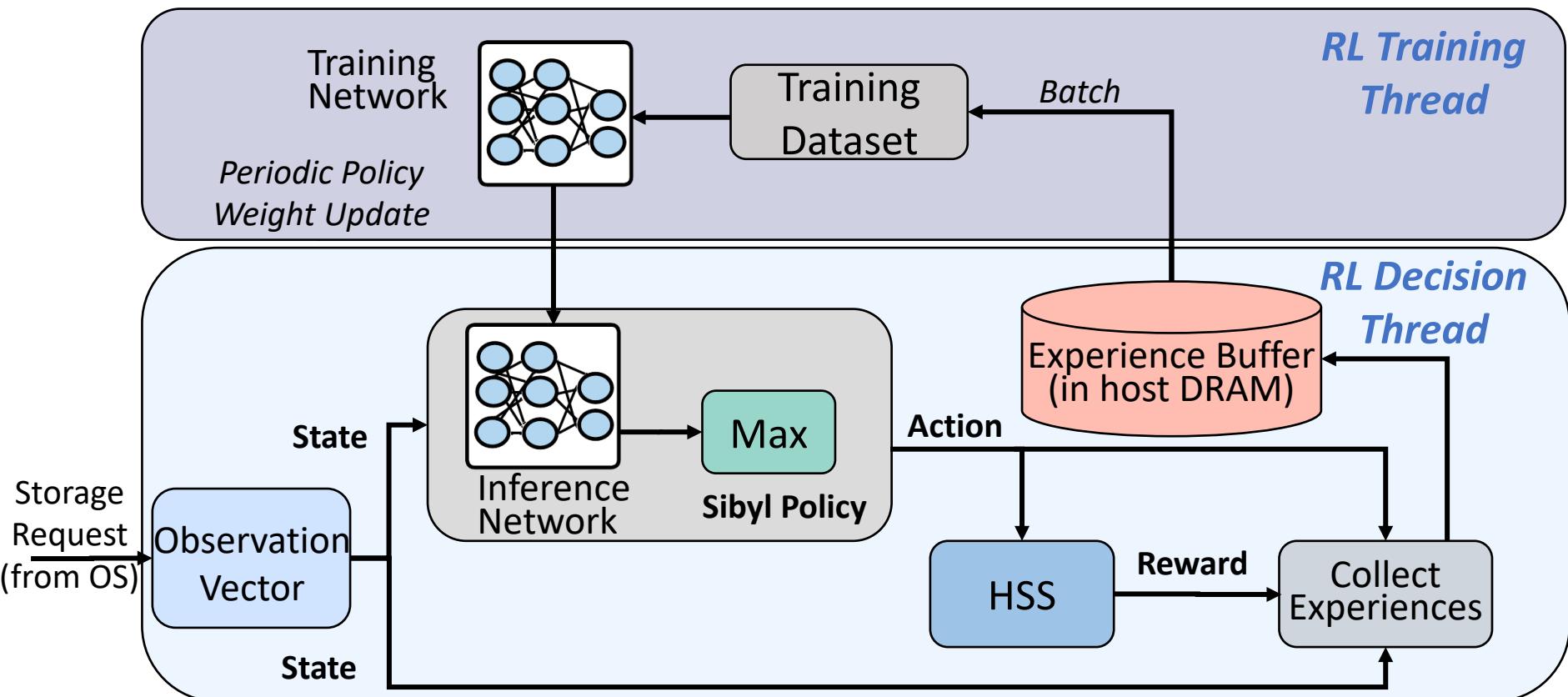
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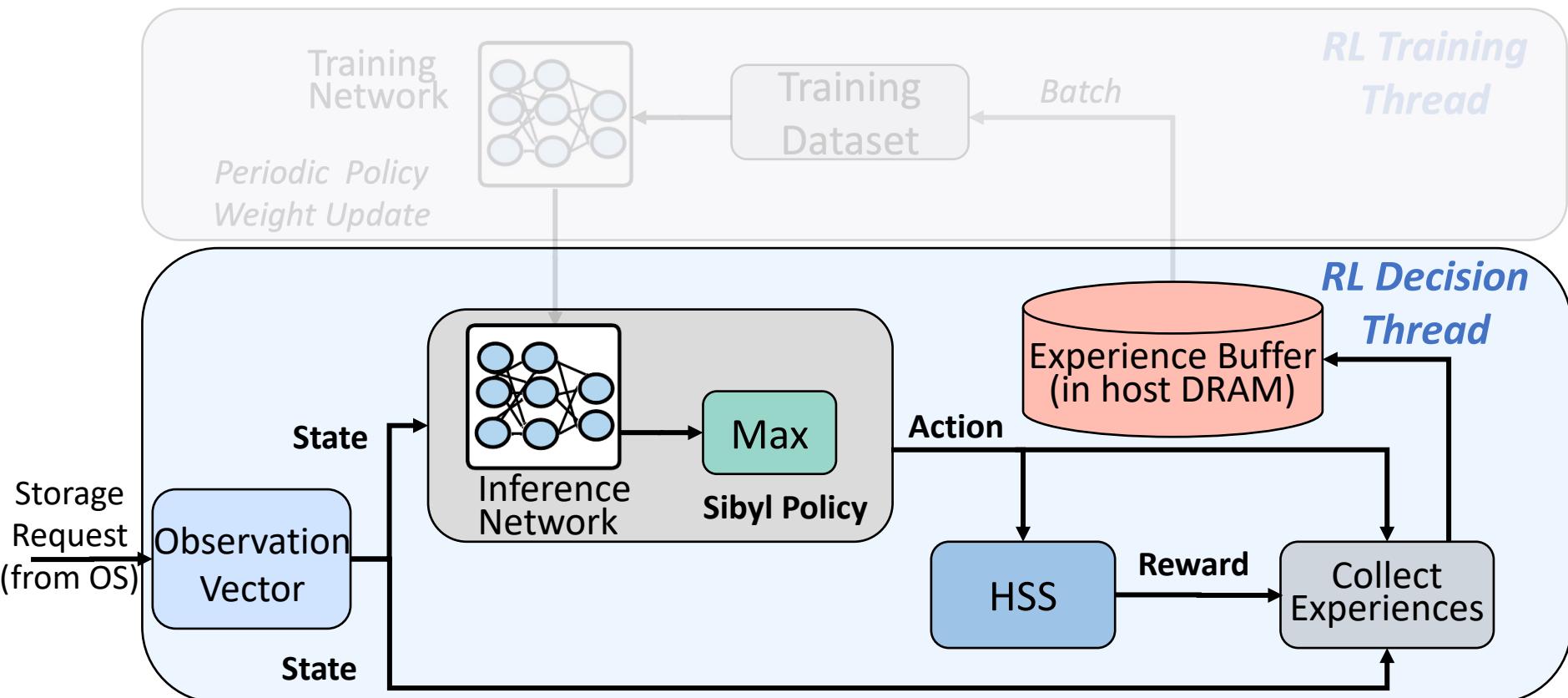
Sibyl Execution



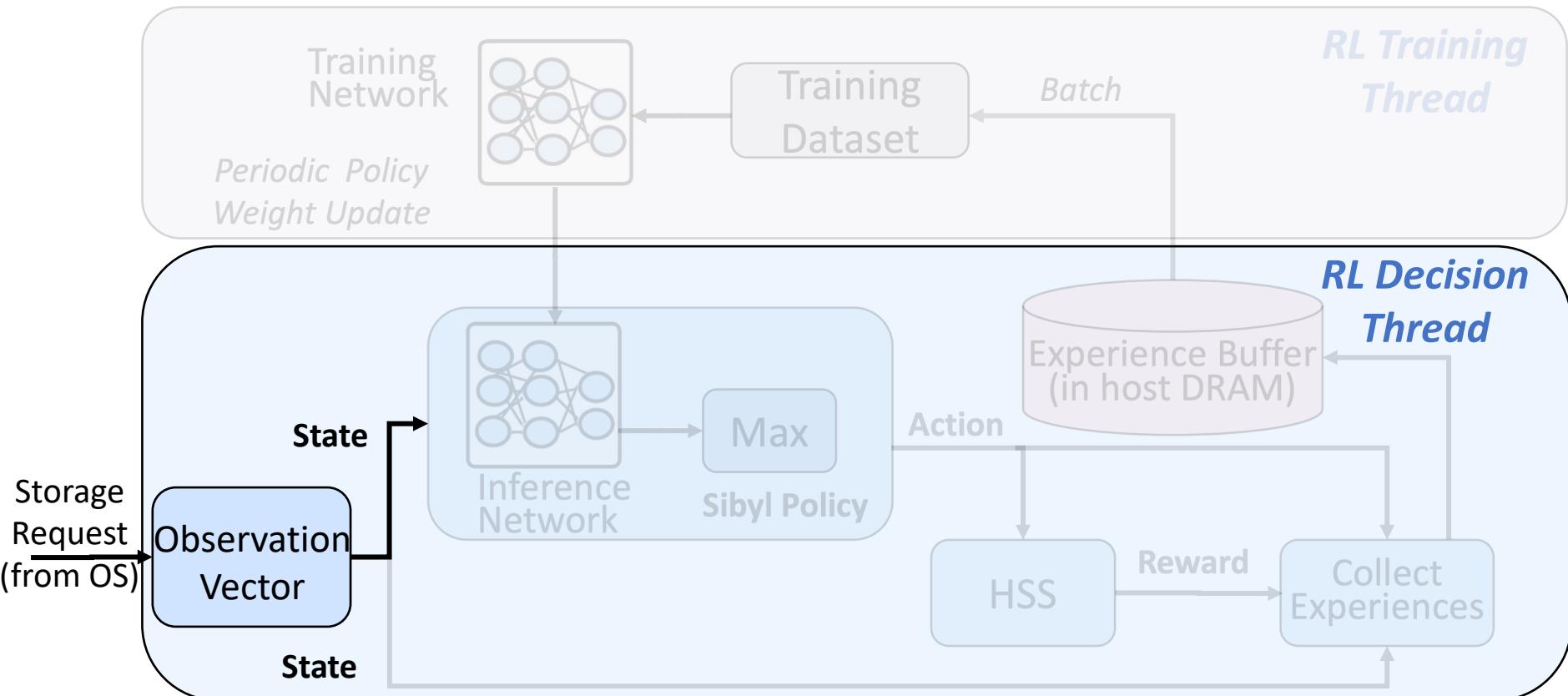
Sibyl Design: Overview



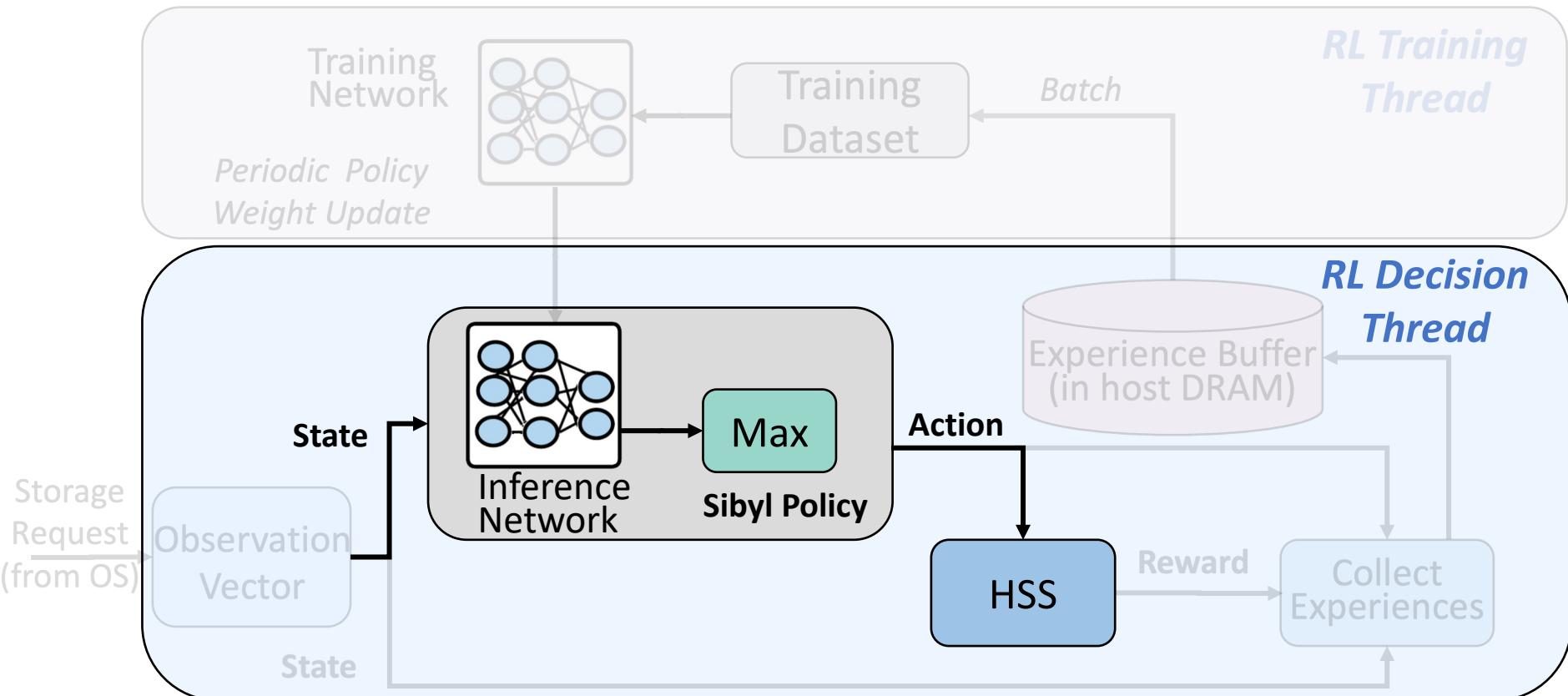
RL Decision Thread



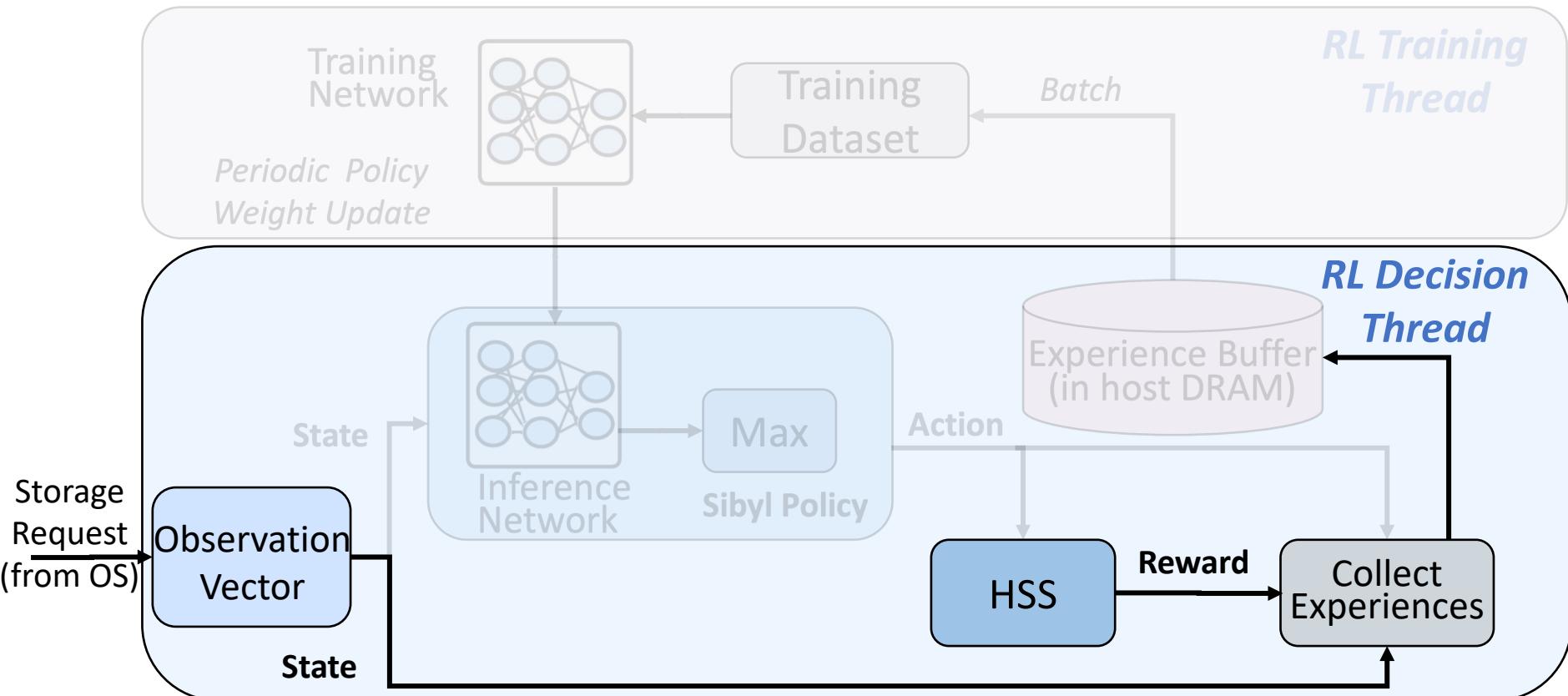
RL Decision Thread



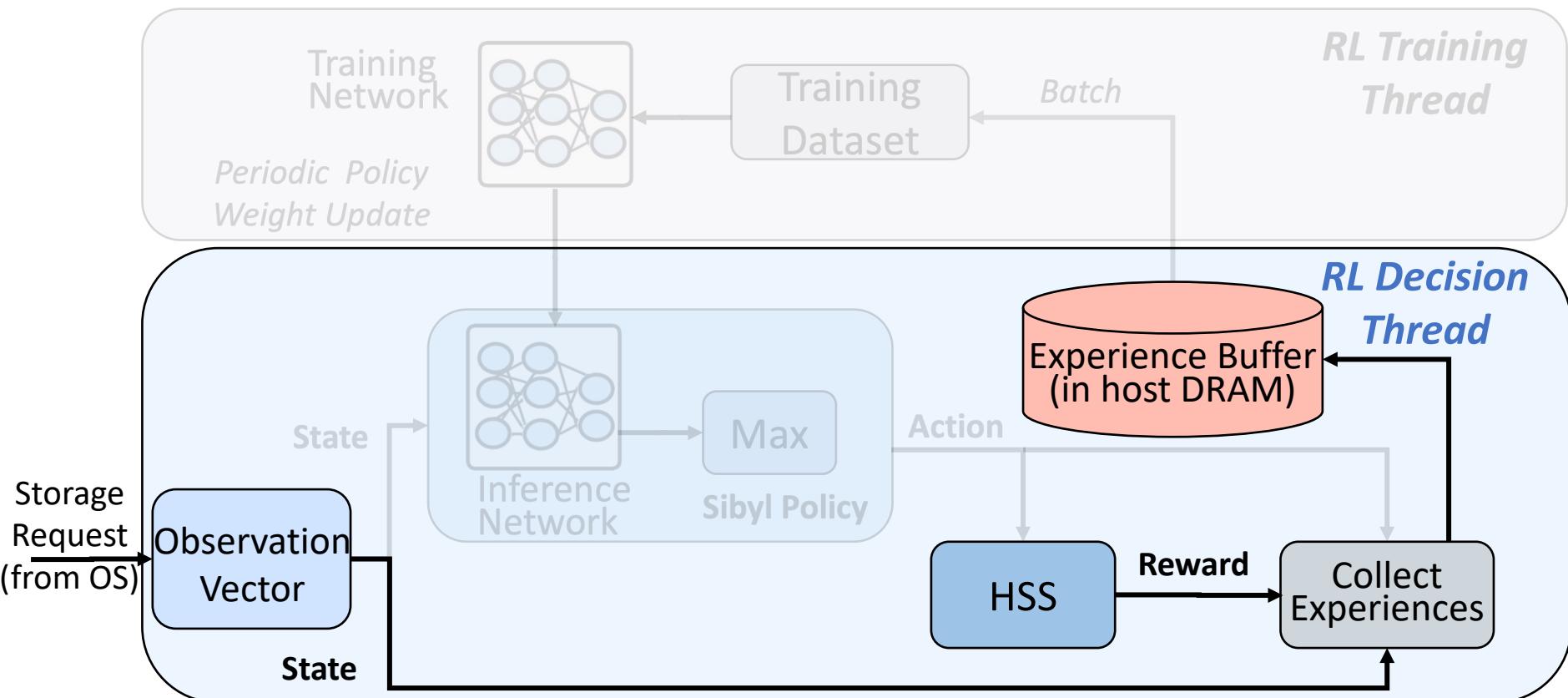
RL Decision Thread



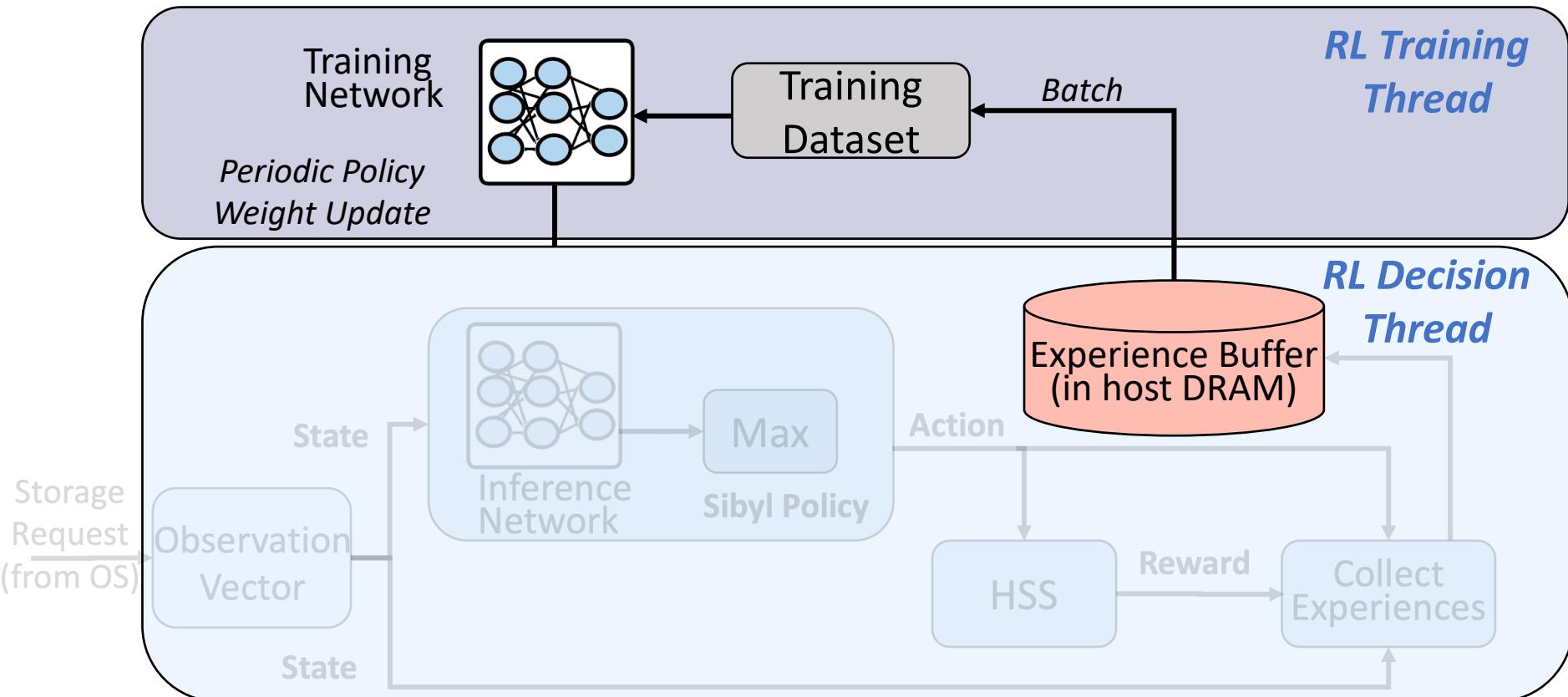
RL Decision Thread



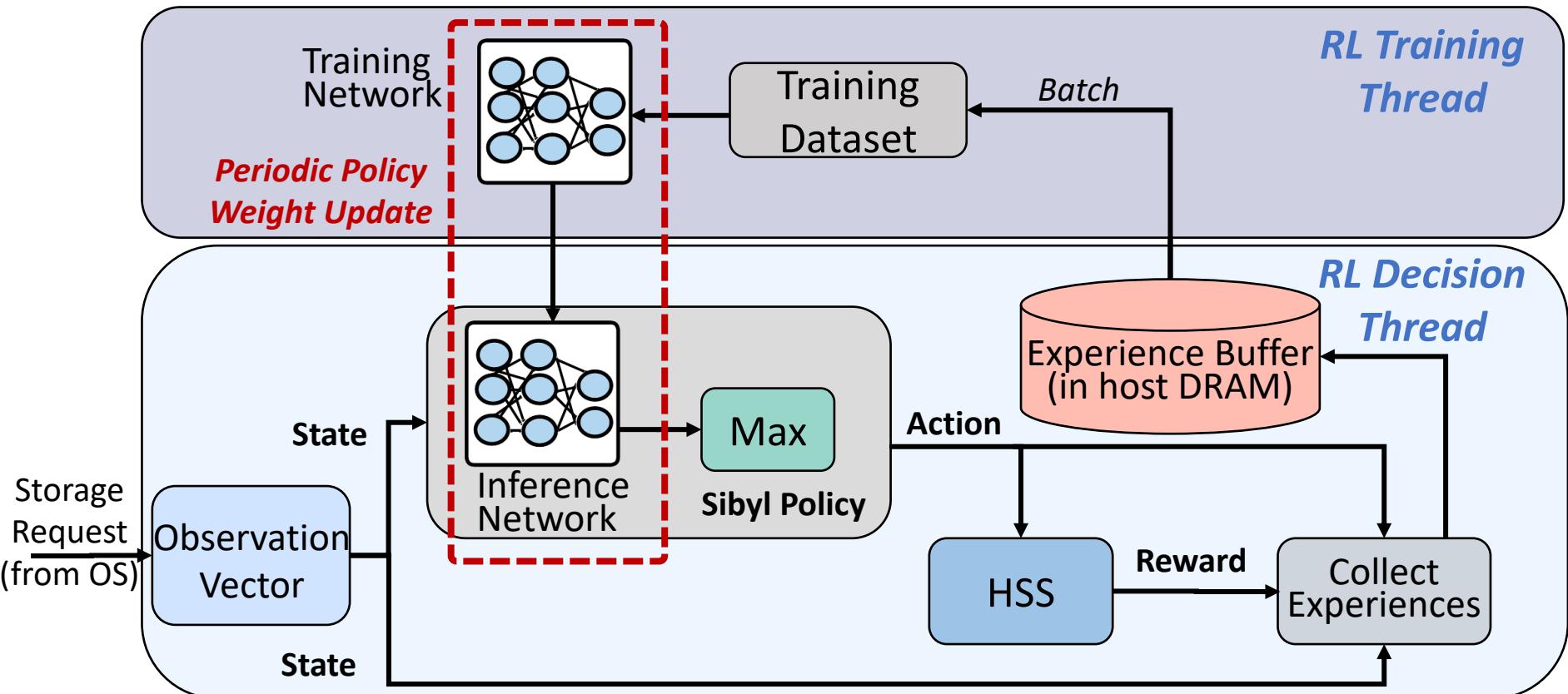
RL Decision Thread



RL Training Thread



Periodic Weight Transfer



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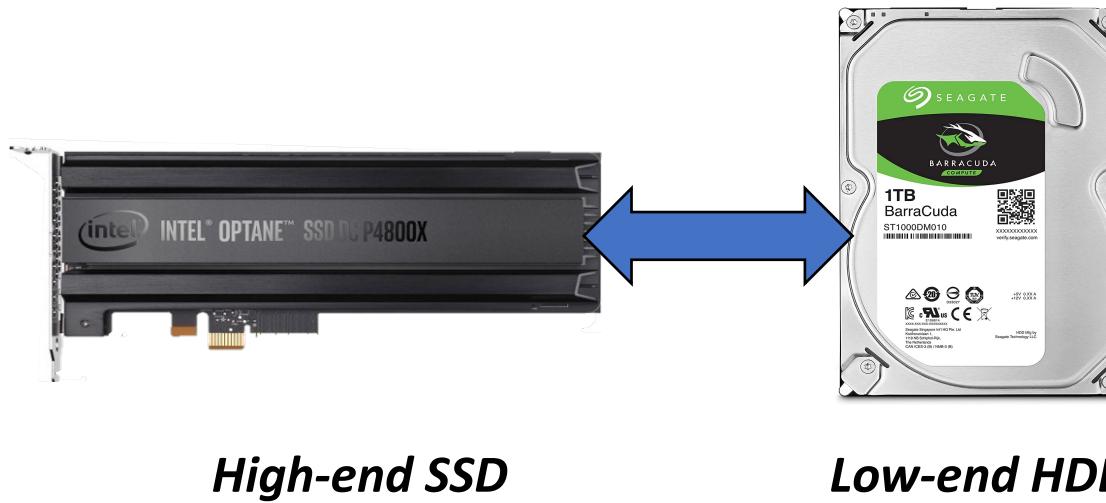
Evaluation Methodology (1/3)

- **Real system** with various HSS configurations
 - Dual-hybrid and tri-hybrid systems

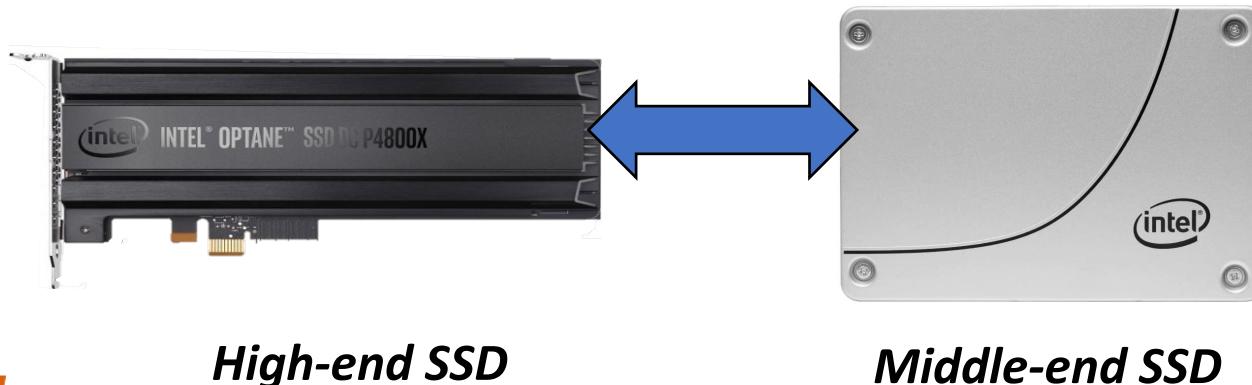


Evaluation Methodology (2/3)

Cost-Oriented HSS Configuration



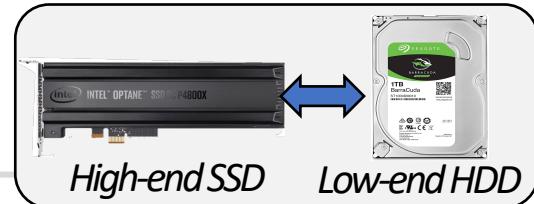
Performance-Oriented HSS Configuration



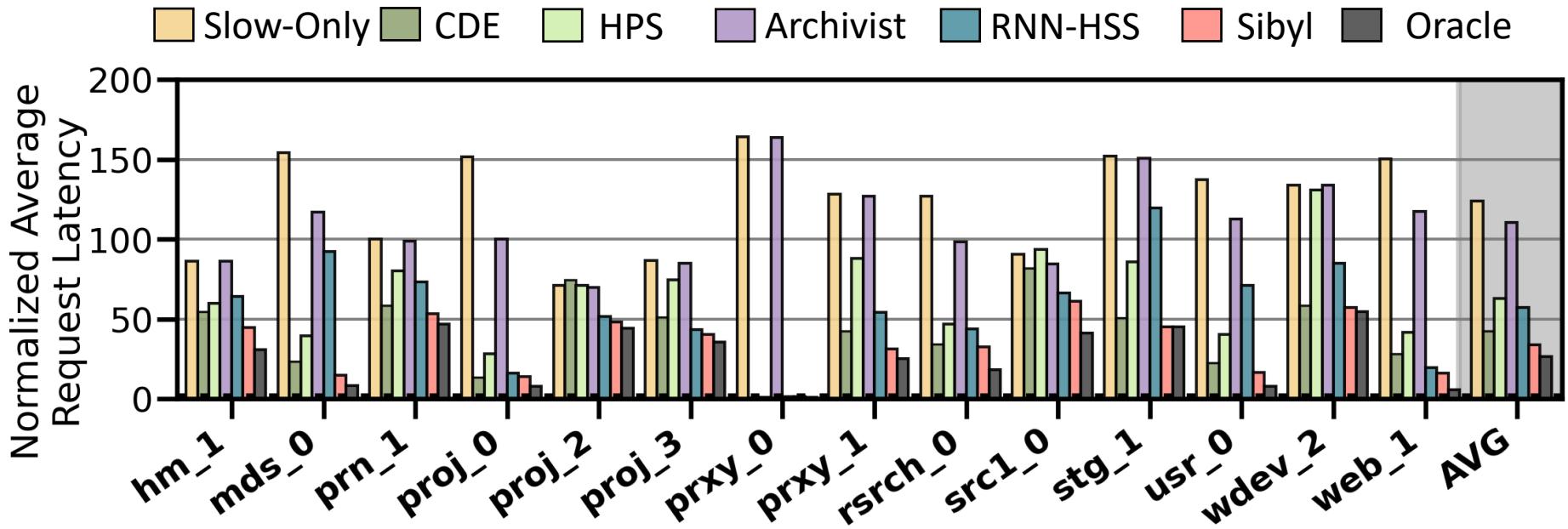
Evaluation Methodology (3/3)

- **18 different workloads** from:
 - MSR Cambridge and Filebench Suites
 - **Four state-of-the-art data placement baselines:**
 - CDE [Matsui+, Proc. IEEE'17]
 - HPS [Meswani+, HPCA'15]
 - Archivist [Ren+, ICCD'19]
 - RNN-HSS [Doudali+, HPDC'19]
-
- The diagram consists of four blue arrows pointing towards the left. The top two arrows are blue and the bottom two are purple. To the right of the top group of arrows is the text *Heuristic-based*. To the right of the bottom group of arrows is the text *Learning-based*.

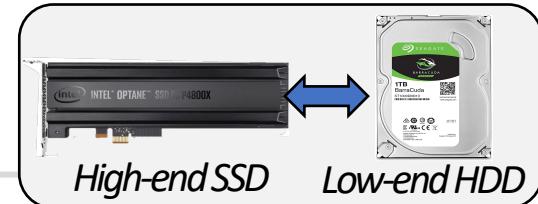
Performance Analysis



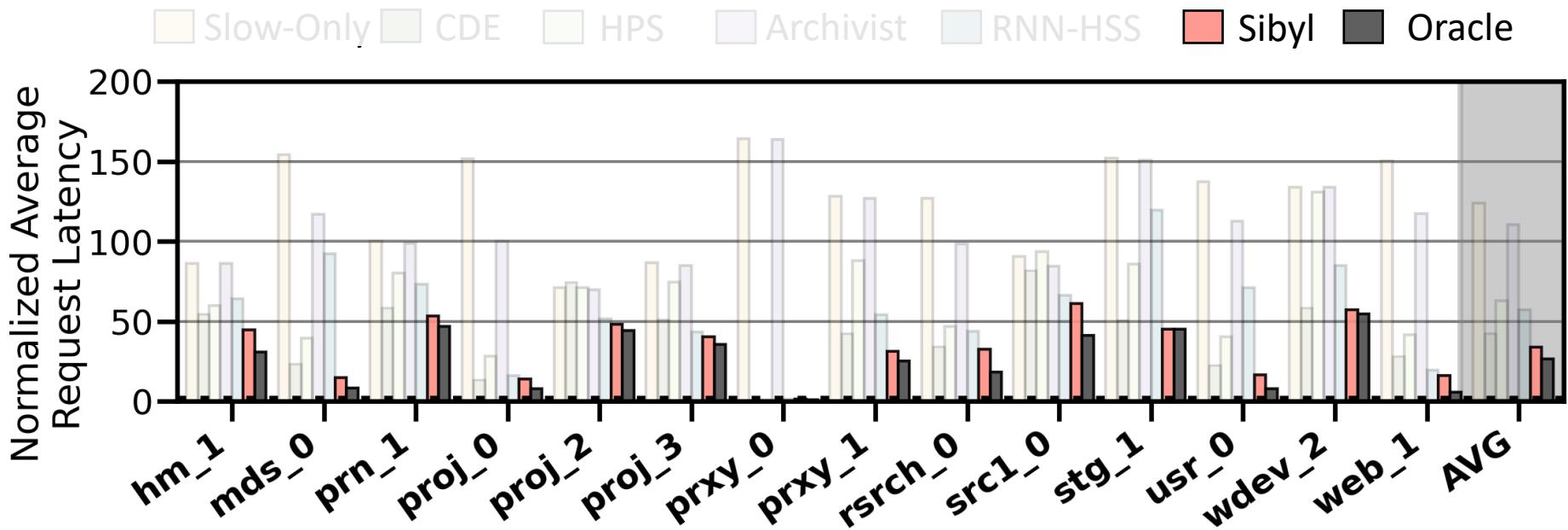
Cost-Oriented HSS Configuration



Performance Analysis

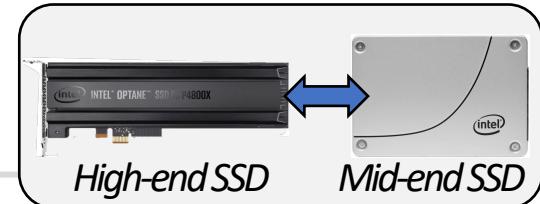


Cost-Oriented HSS Configuration

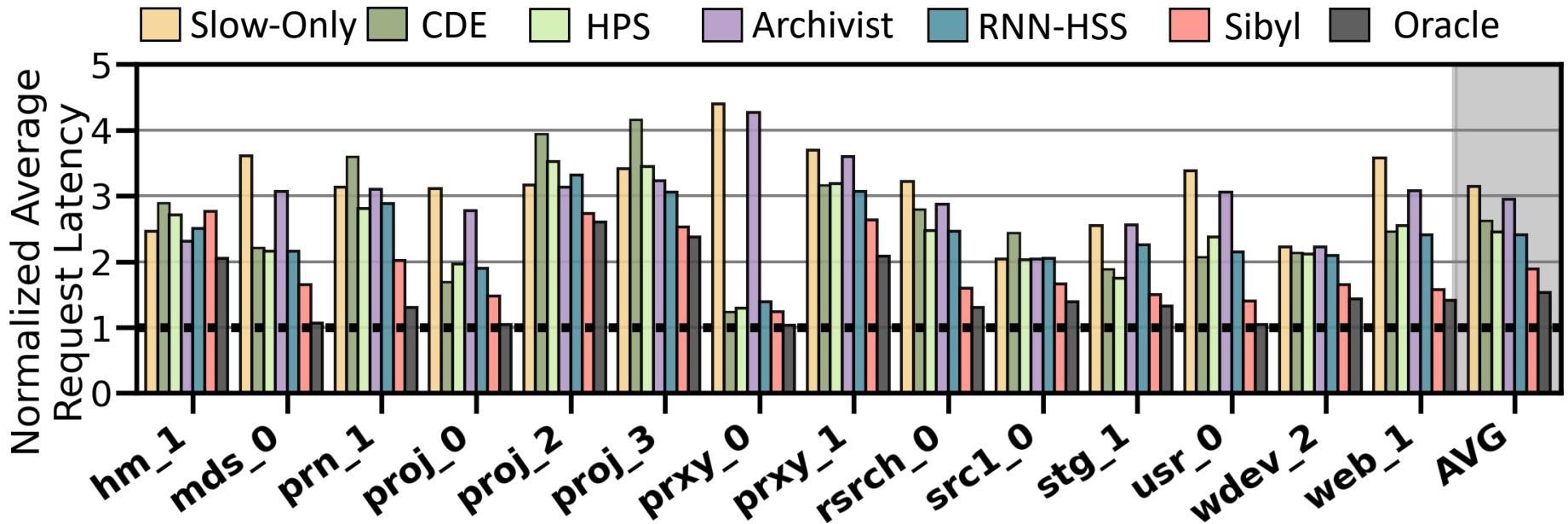


Sibyl consistently **outperforms all the baselines**
for all the workloads

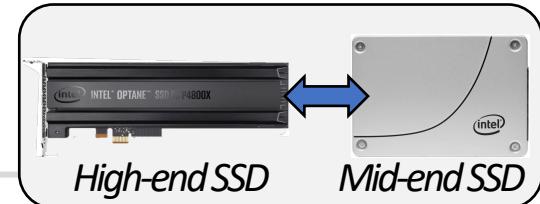
Performance Analysis



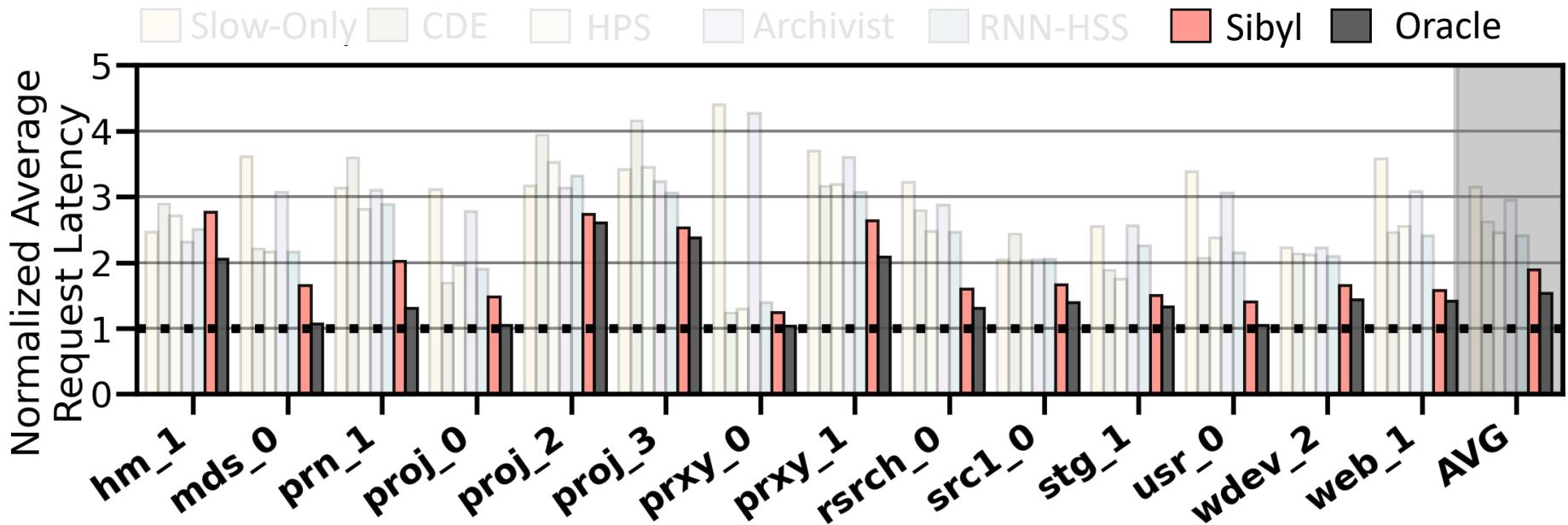
Performance-Oriented HSS Configuration



Performance Analysis

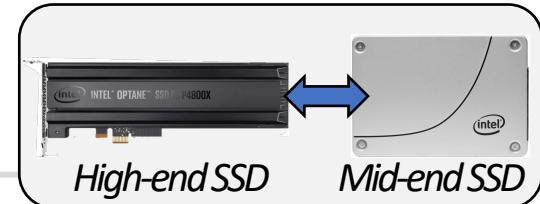


Performance-Oriented HSS Configuration

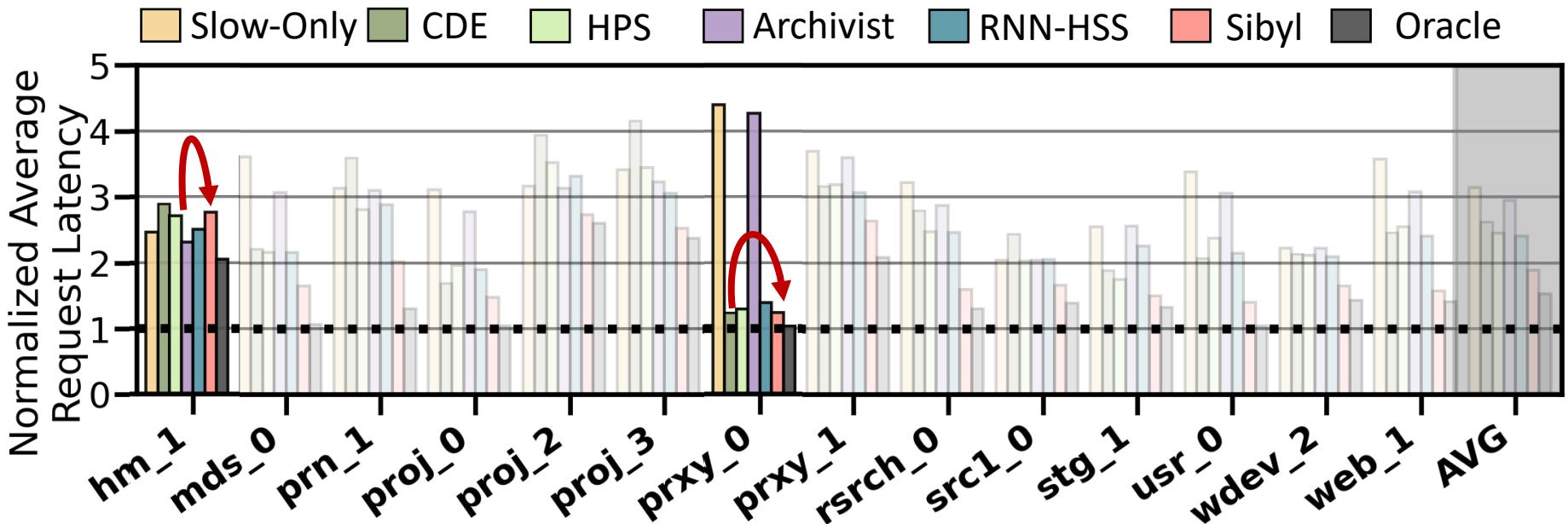


Sibyl provides **21.6% performance improvement** by **dynamically adapting its data placement policy**

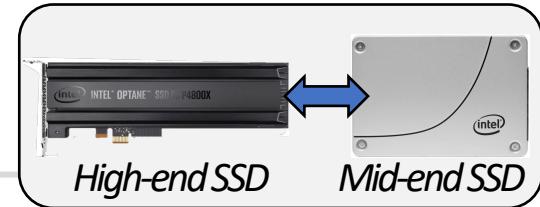
Performance Analysis



Performance-Oriented HSS Configuration



Performance Analysis

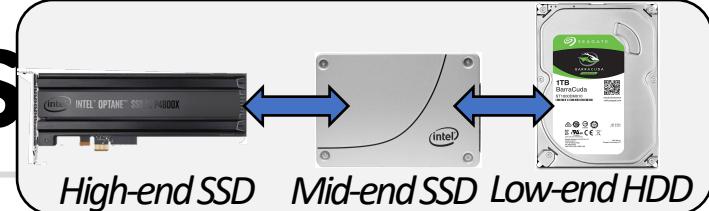


Performance-Oriented HSS Configuration



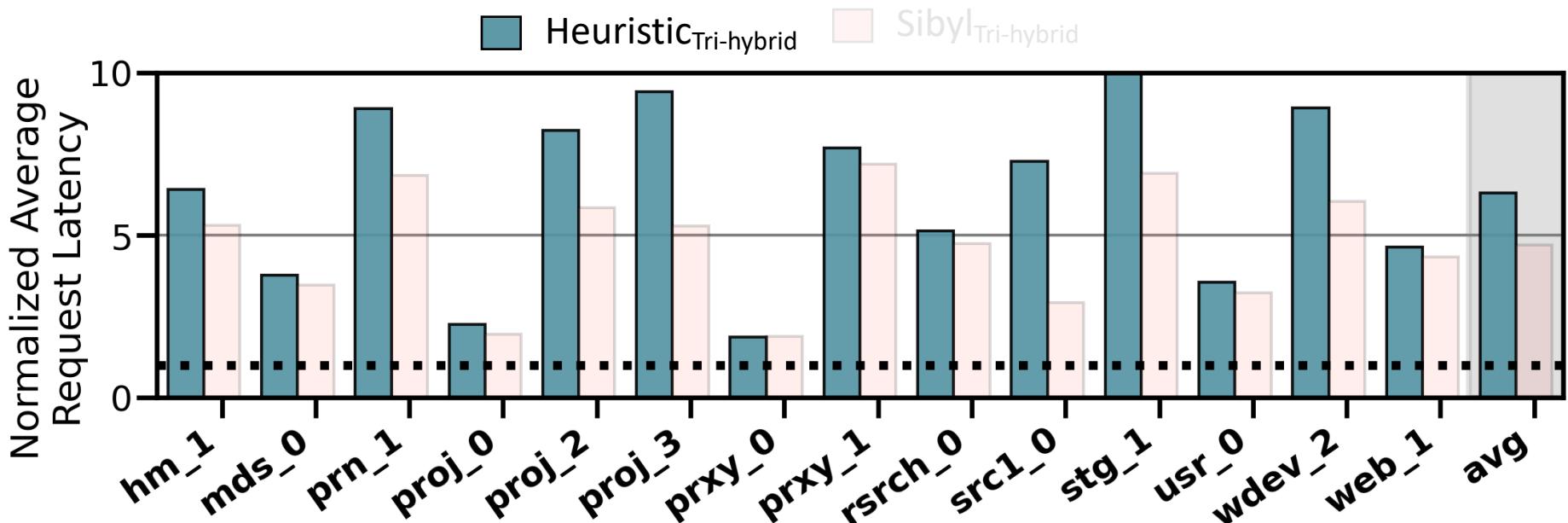
Sibyl achieves **80% of the performance of an oracle policy** that has complete knowledge of future access patterns

Performance on Tri-HSS

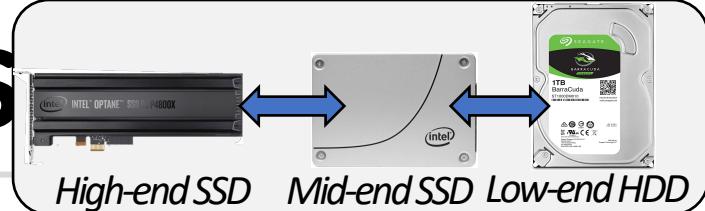


Extending Sibyl for **more devices**:

1. Add a new action
2. Add the remaining capacity of the new device as a state feature

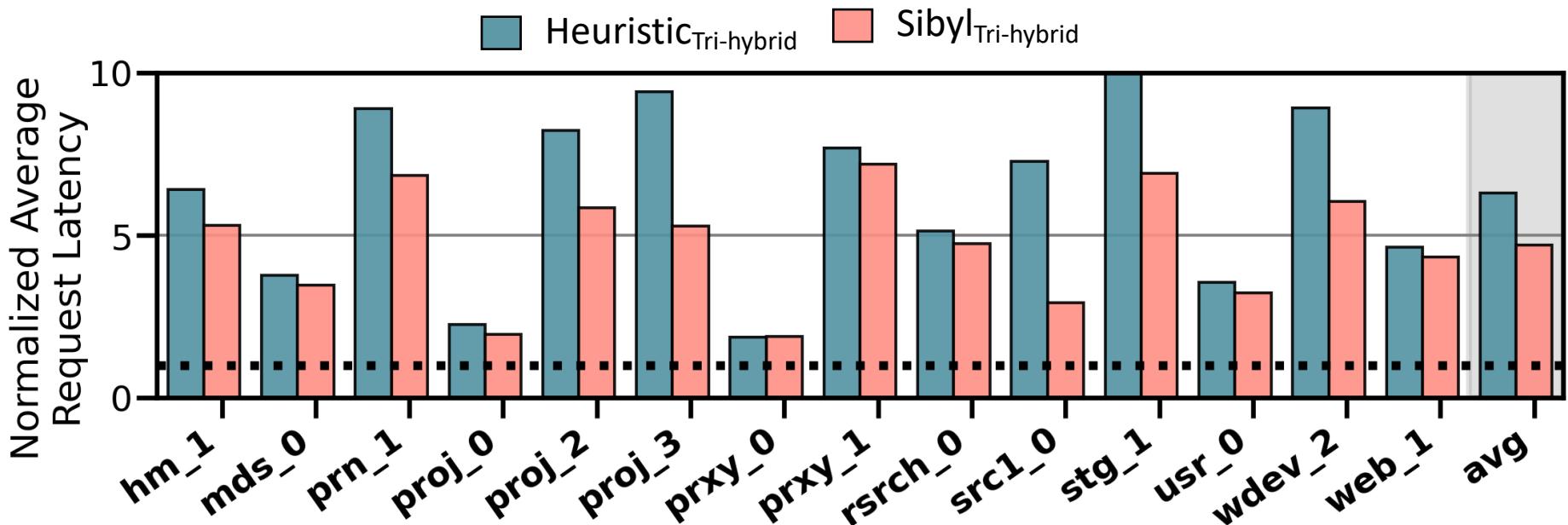


Performance on Tri-HSS

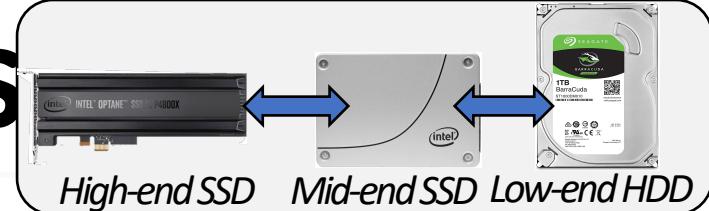


Extending Sibyl for **more devices**:

1. Add a new action
2. Add the remaining capacity of the new device as a state feature



Performance on Tri-HSS



Extending Sibyl for more devices:

1. Add a new action

Sibyl **outperforms** the state-of-the-art data placement policy by **48.2% in a real tri-hybrid system**

Sibyl reduces the system architect's burden by providing **ease of extensibility**

Sibyl's Overhead

- **124.4 KiB** of total storage cost
 - Experience buffer, inference and training network
- **40-bit** metadata overhead per page for state features
- Inference latency of **~10ns**
- Training latency of **~2us**



Small area overhead



Small inference overhead



Satisfies prediction latency

More in the Paper (1/2)

- **Throughput (IOPS) evaluation**
 - Sibyl provides high IOPS compared to baseline policies because it indirectly captures throughput (size/latency)
- Evaluation on **unseen workloads**
 - Sibyl can effectively adapt its policy to highly dynamic workloads
- Evaluation on **mixed workloads**
 - Sibyl provides equally-high performance benefits as in single workloads

More in the Paper (2/2)

- Evaluation on **different features**
 - Sibyl autonomously decides which features are important to maximize the performance
- Evaluation with **different hyperparameter values**
- Sensitivity to **fast storage capacity**
 - Sibyl provides scalability by dynamically adapting its policy to available storage size
- **Explainability analysis** of Sibyl's decision making
 - Explain Sibyl's actions for different workload characteristics and device configurations

More in the Paper (2/2)

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Nastaran Hajinazar¹

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¹ETH Zürich

²Eindhoven University of Technology

³LIRMM, Univ. Montpellier, CNRS

<https://arxiv.org/pdf/2205.07394.pdf>

<https://github.com/CMU-SAFARI/Sibyl>

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Conclusion

- We introduce **Sibyl**, the first reinforcement learning-based data placement technique in hybrid storage systems that provides
 - **Adaptivity**
 - **Easily extensibility**
 - **Ease of design and implementation**
- We evaluated Sibyl on real systems using many different workloads
 - Sibyl **improves performance by 21.6%** compared to the best prior data placement policy in a dual-HSS configuration
 - In a tri-HSS configuration, Sibyl **outperforms** the state-of-the-art-data placement policy by **48.2%**
 - Sibyl achieves **80% of the performance** of an oracle policy with a storage overhead of only **124.4 KiB**

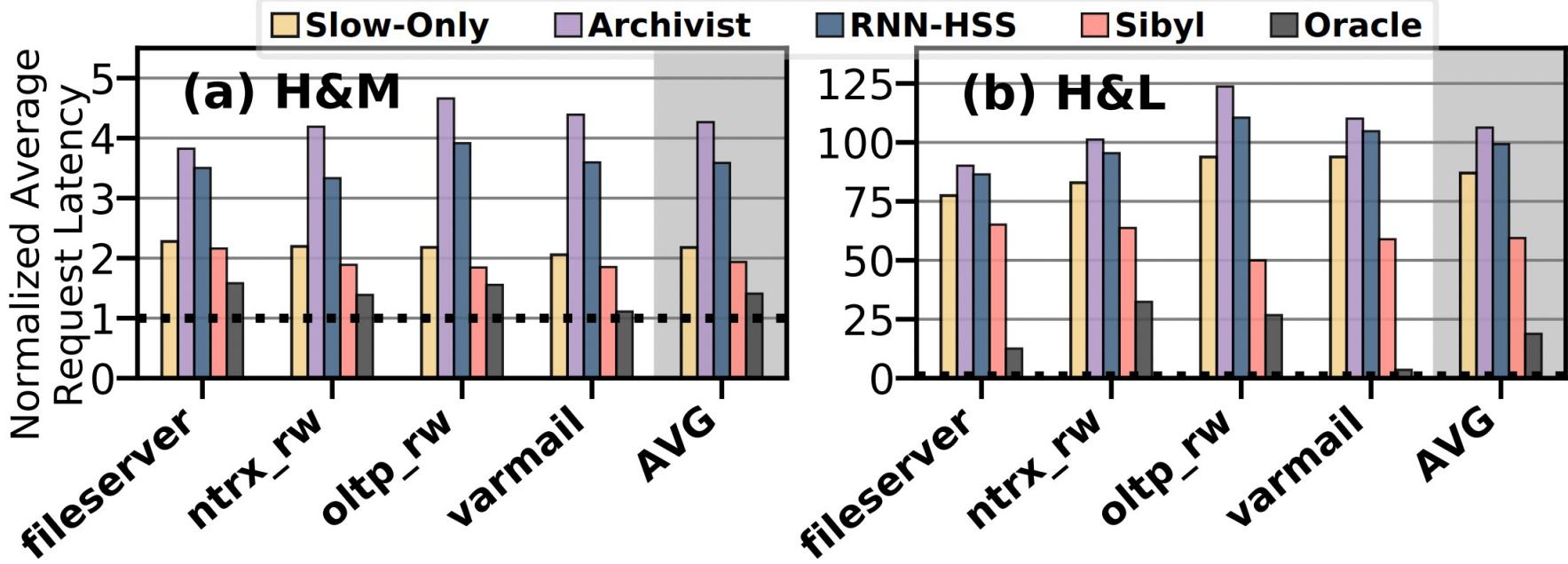
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BACKUP

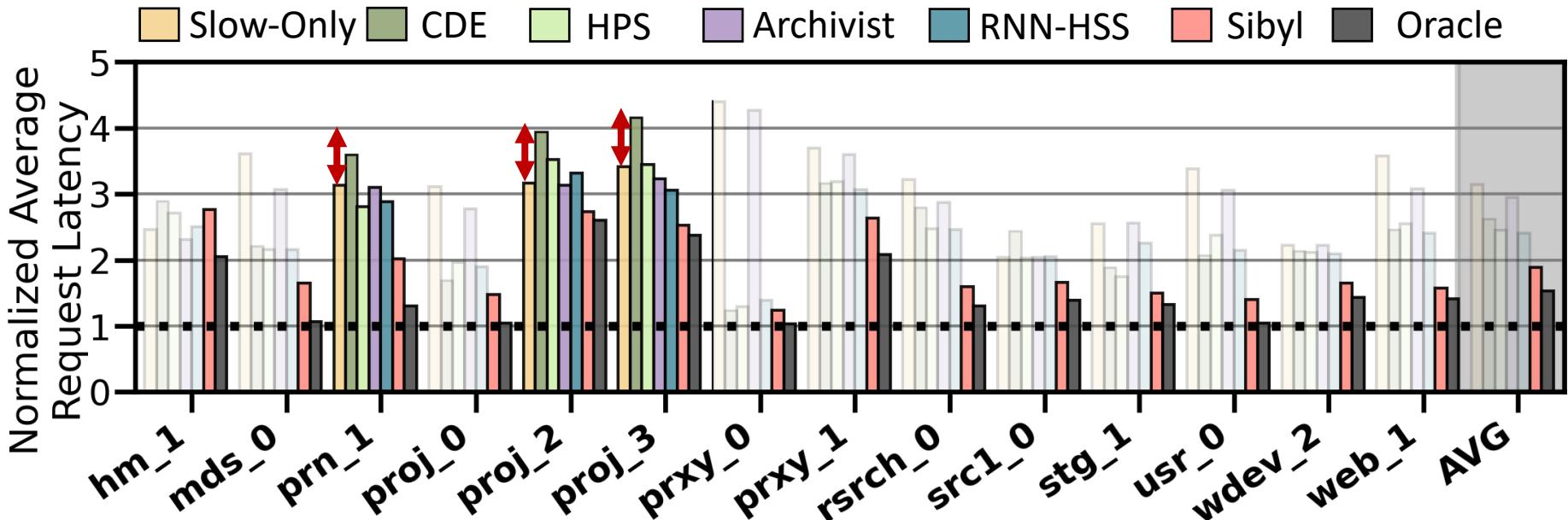
Performance on Unseen Workloads



H&M (H&L) HSS configuration, Sibyl outperforms RNN-HSS and Archivist by 46.1% (54.6%) and 8.5% (44.1%), respectively

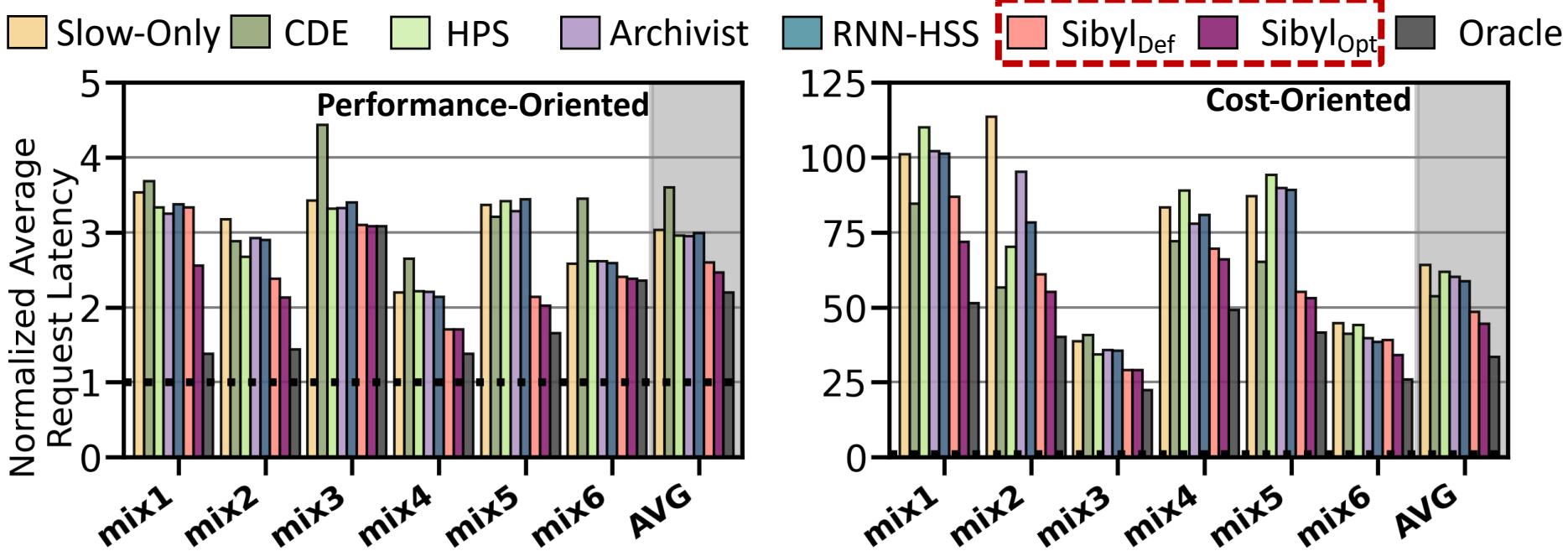
Performance Analysis

Performance-Oriented HSS Configuration

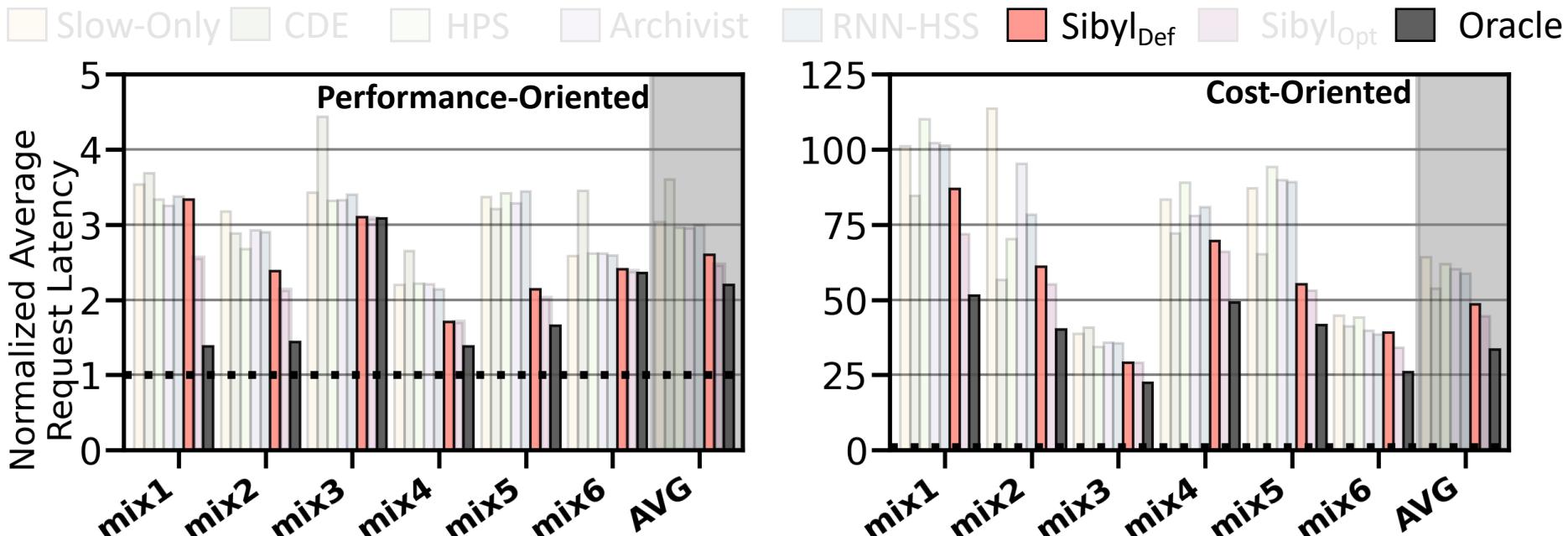


Baseline policies **are ineffective** for many workloads even when compared to Slow-Only

Performance on Mixed Workloads

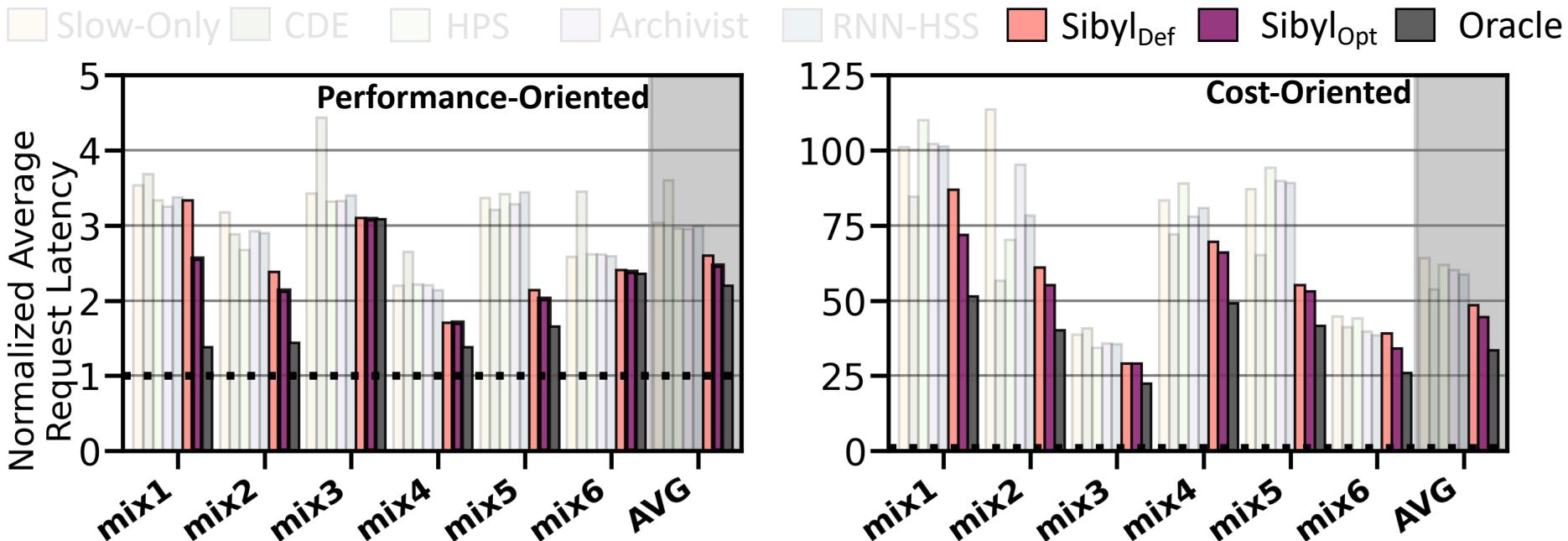


Performance on Mixed Workloads



Sibyl_{Def} **outperforms** baseline data placement techniques by up to **27.9%**

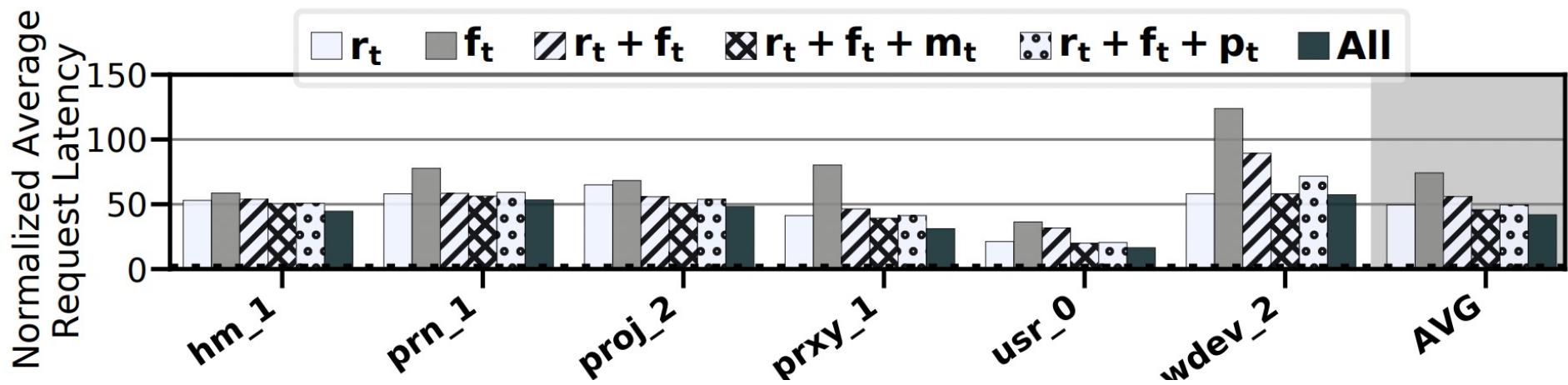
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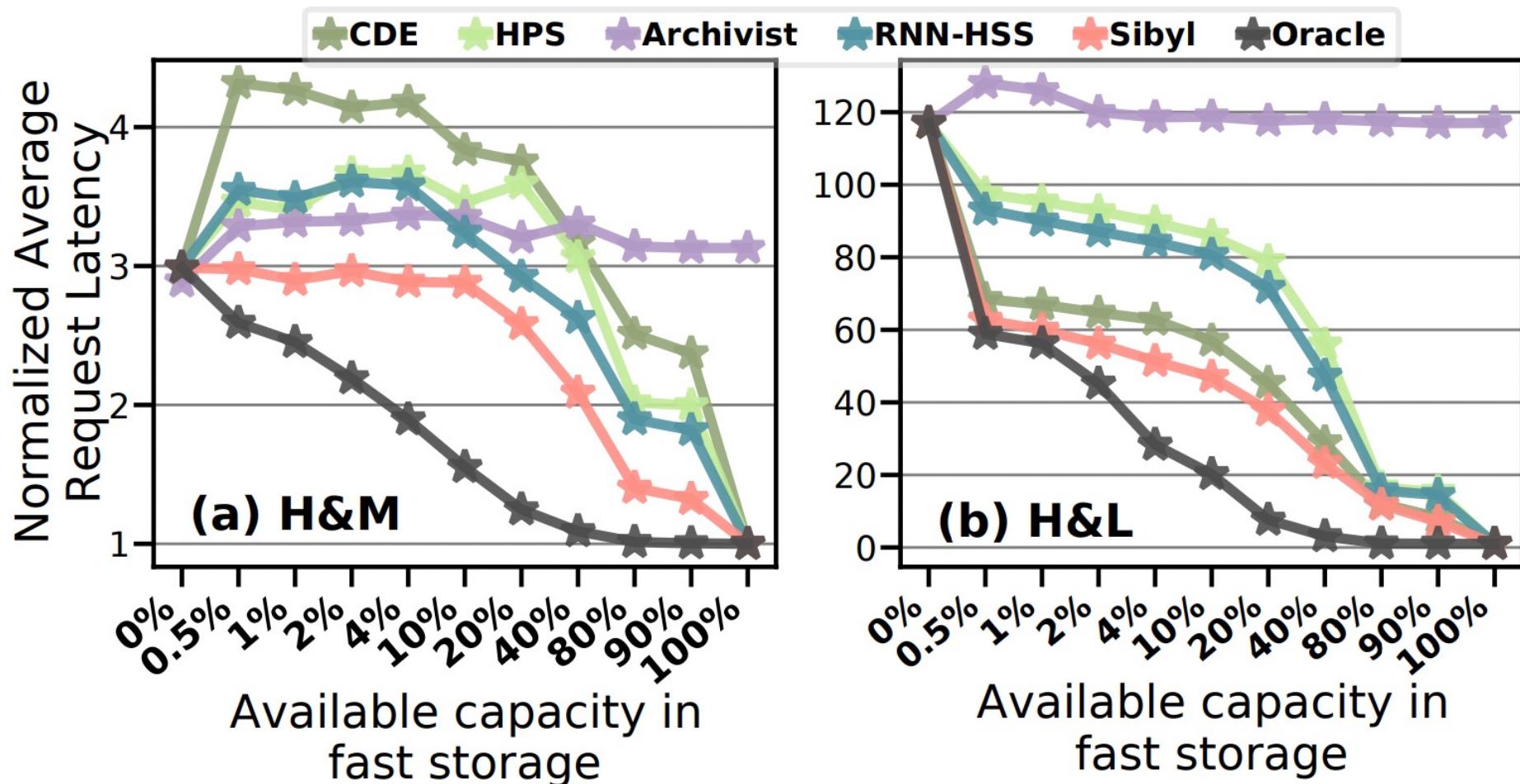
Sibyl_{Opt} **provides 7.2% higher average performance** than Sibyl_{Def}

Performance With Different Features

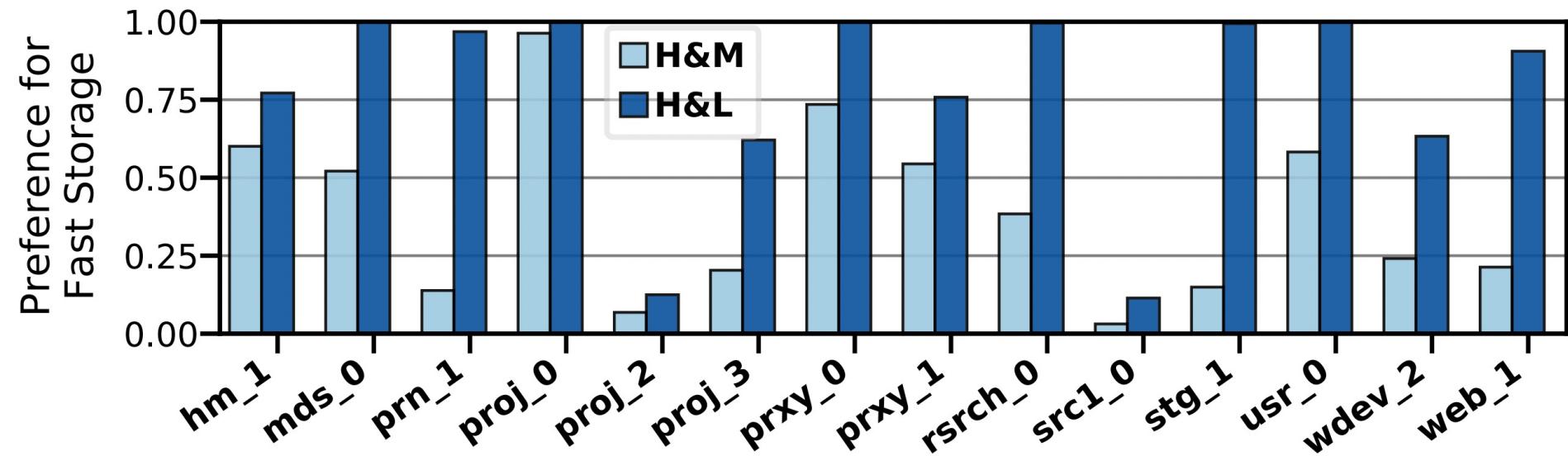


Sibyl autonomously decides which features are important to maximize the performance of the running workload

Sensitivity to Fast Storage Capacity

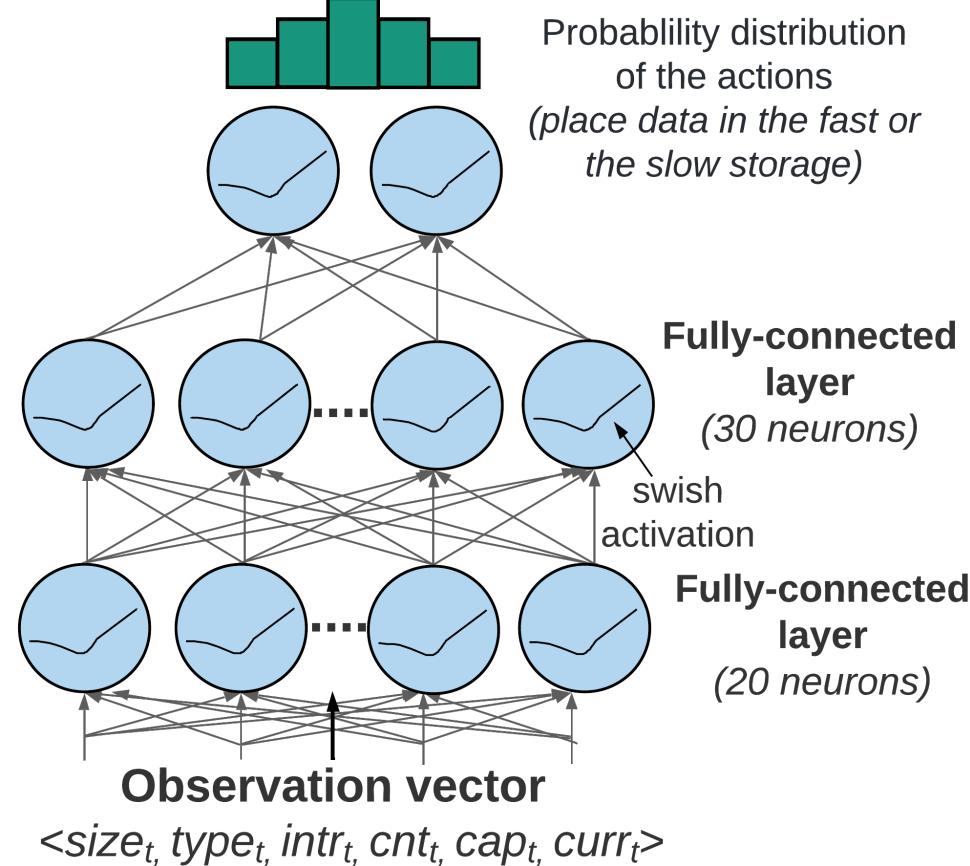


Explainability Analysis



Training and Inference Network

- Training and inference network **allow parallel execution**
- Observation vector as the input
- Produces probability distribution of Q-values



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