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

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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**

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

Talk Outline

Key Shortcomings of Prior Data Placement Techniques

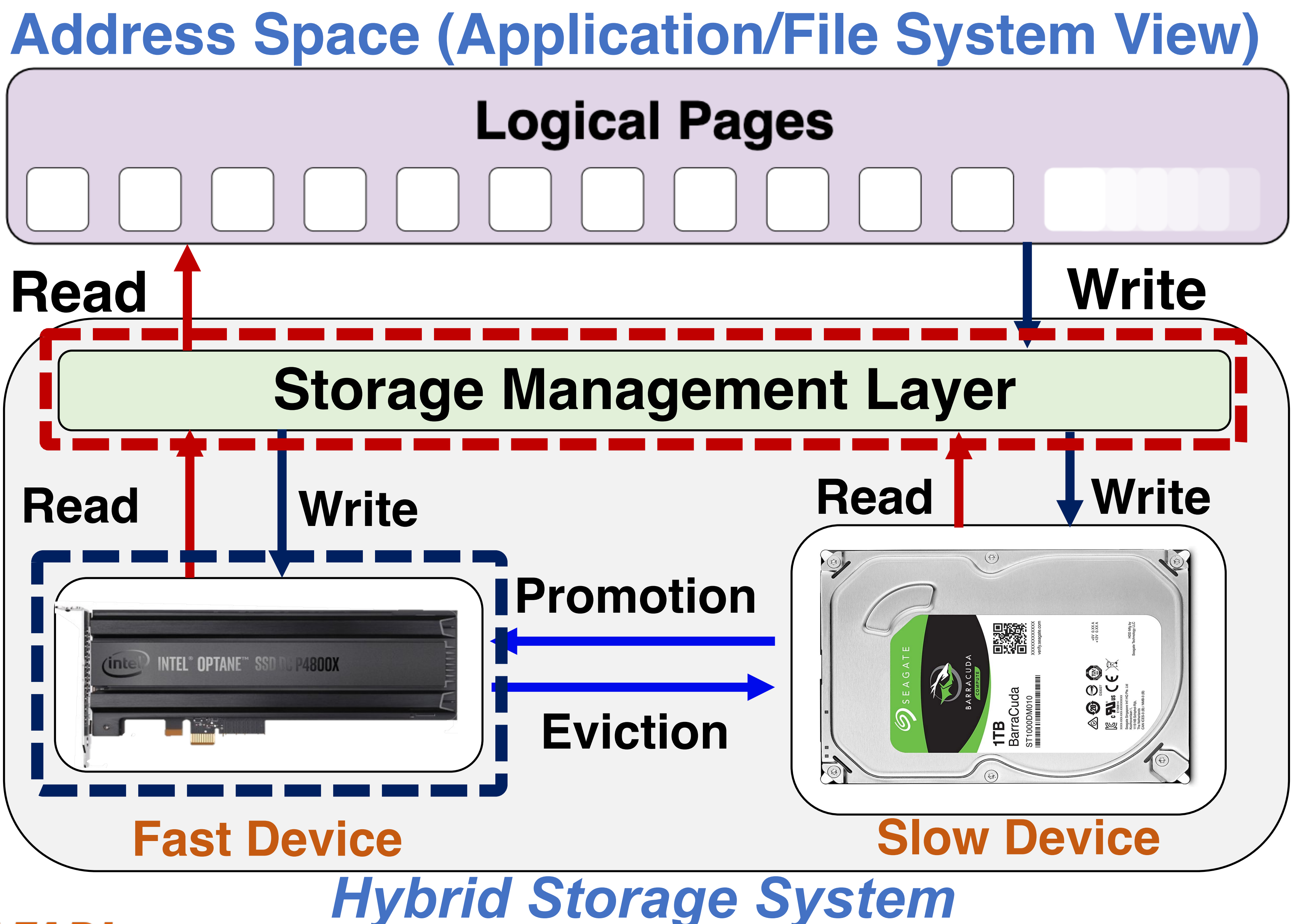
Formulating Data Placement as Reinforcement Learning

Sybil: Overview

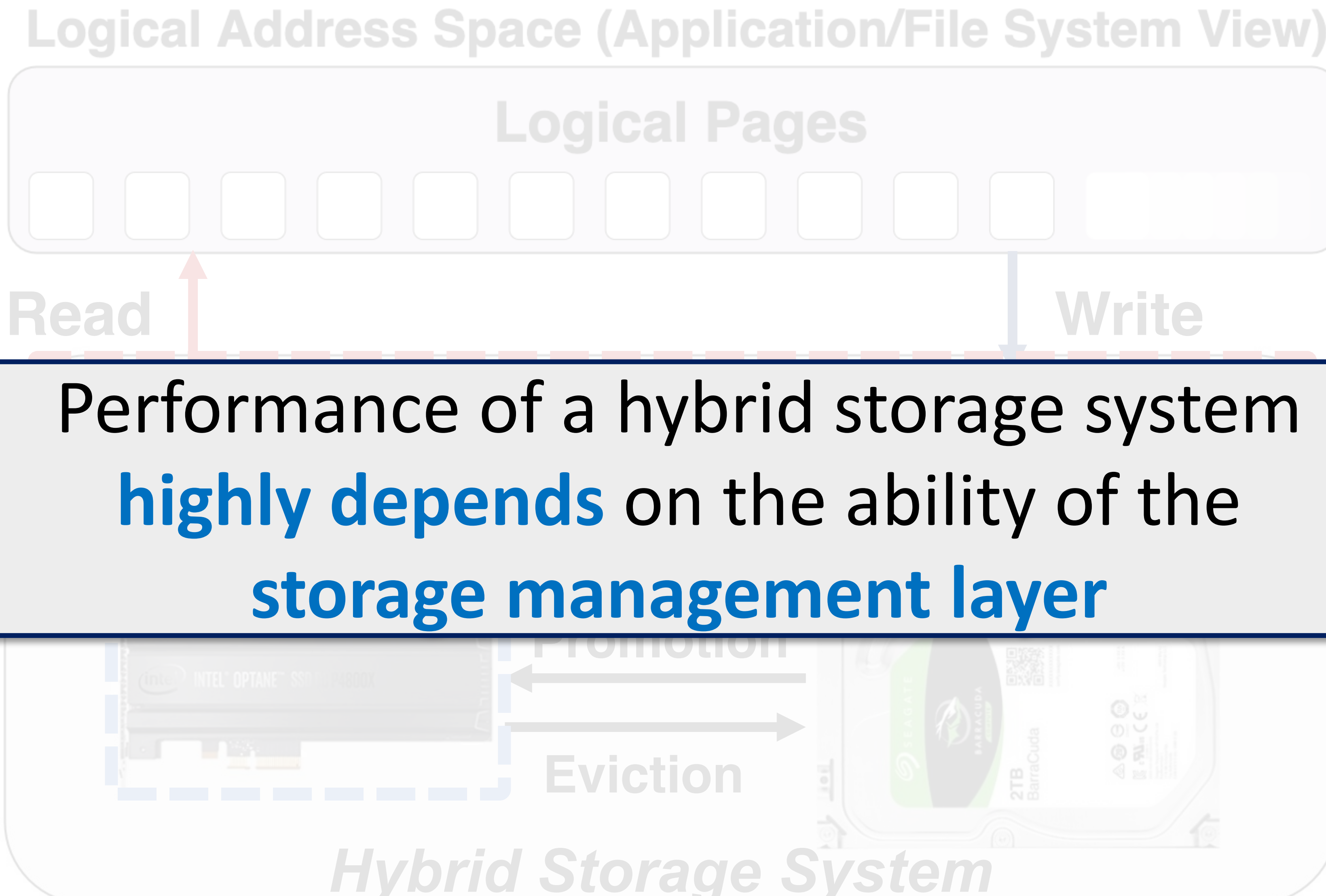
Evaluation of Sybil and Key Results

Conclusion

Hybrid Storage System Basics



Hybrid Storage System Basics



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

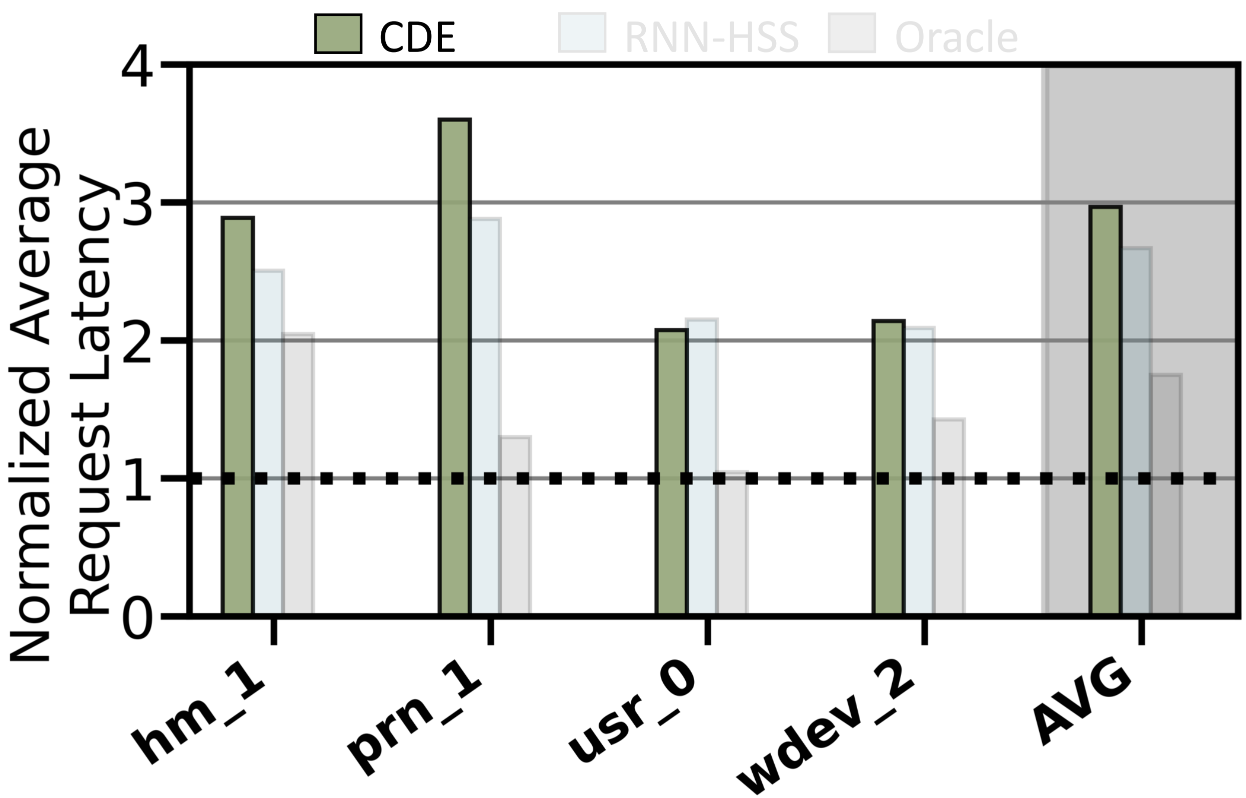
1. Lack of **adaptivity to**:
   a) **Workload changes**
   b) **Changes in device types and configuration**

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

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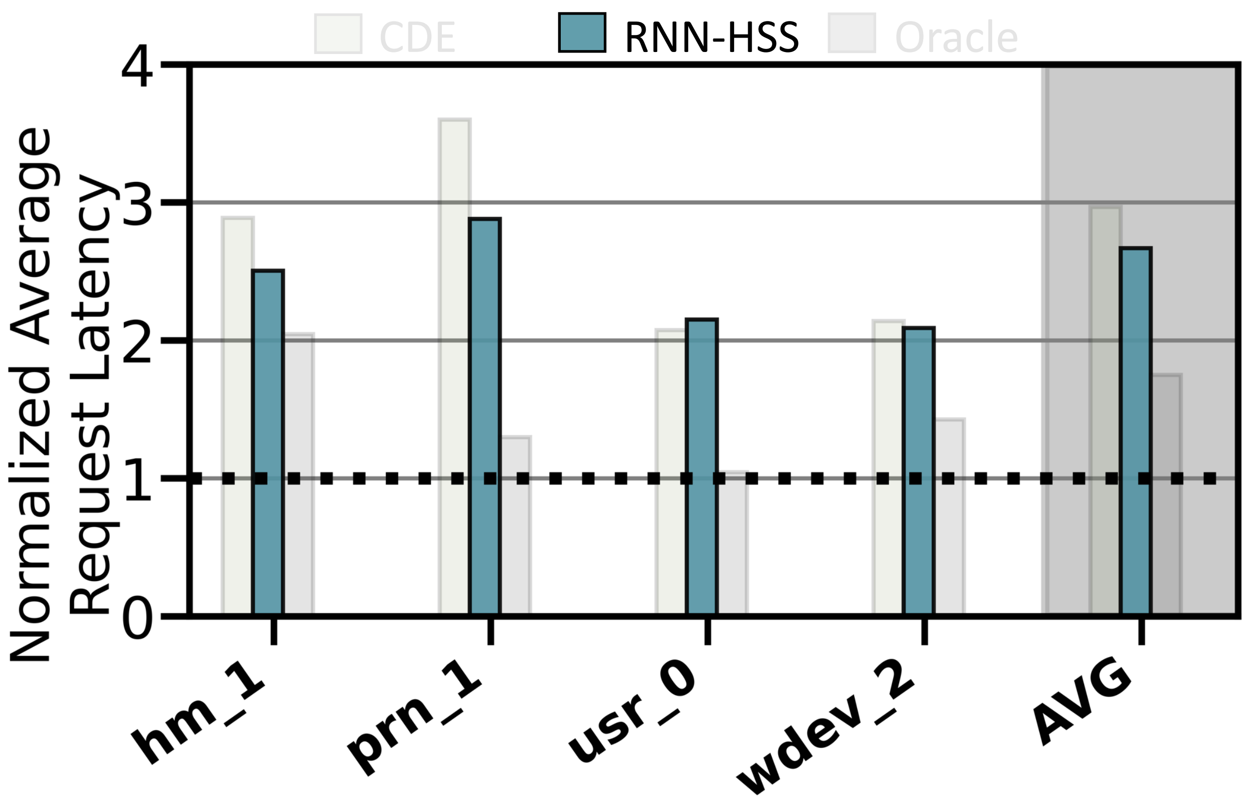

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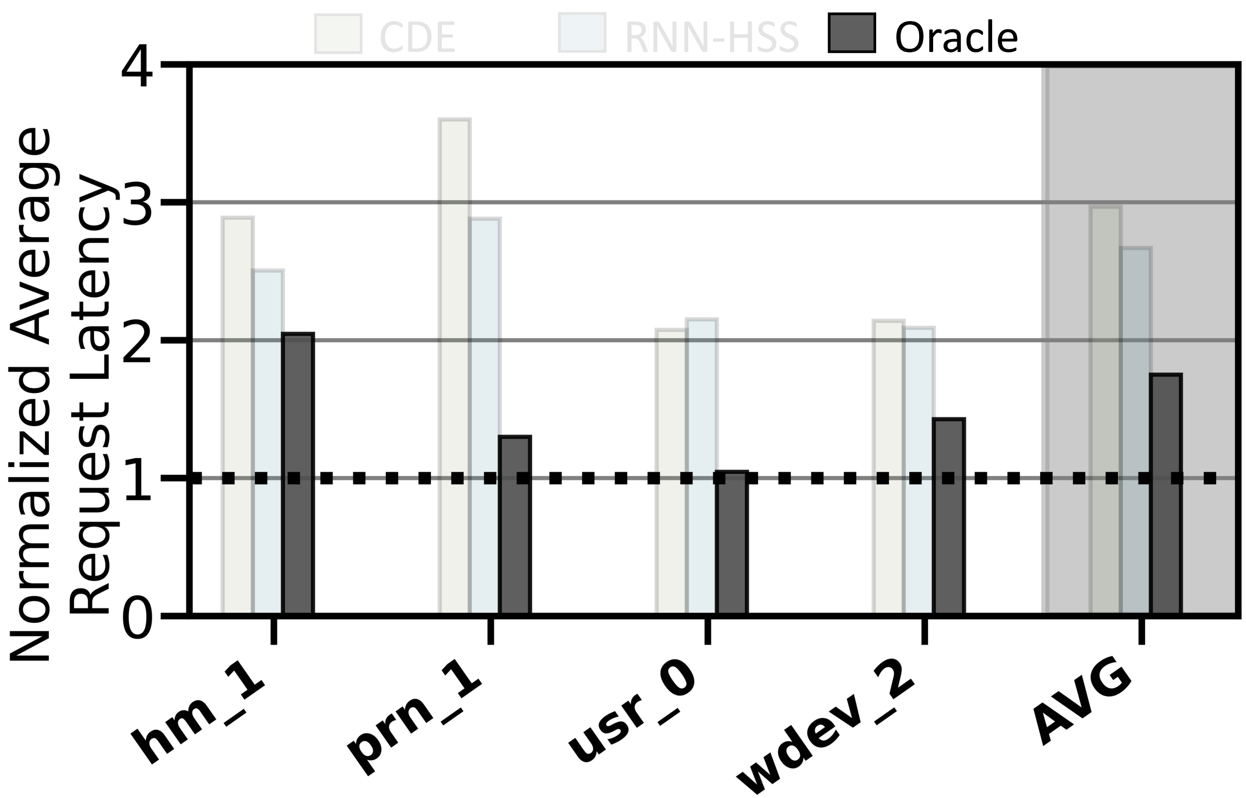

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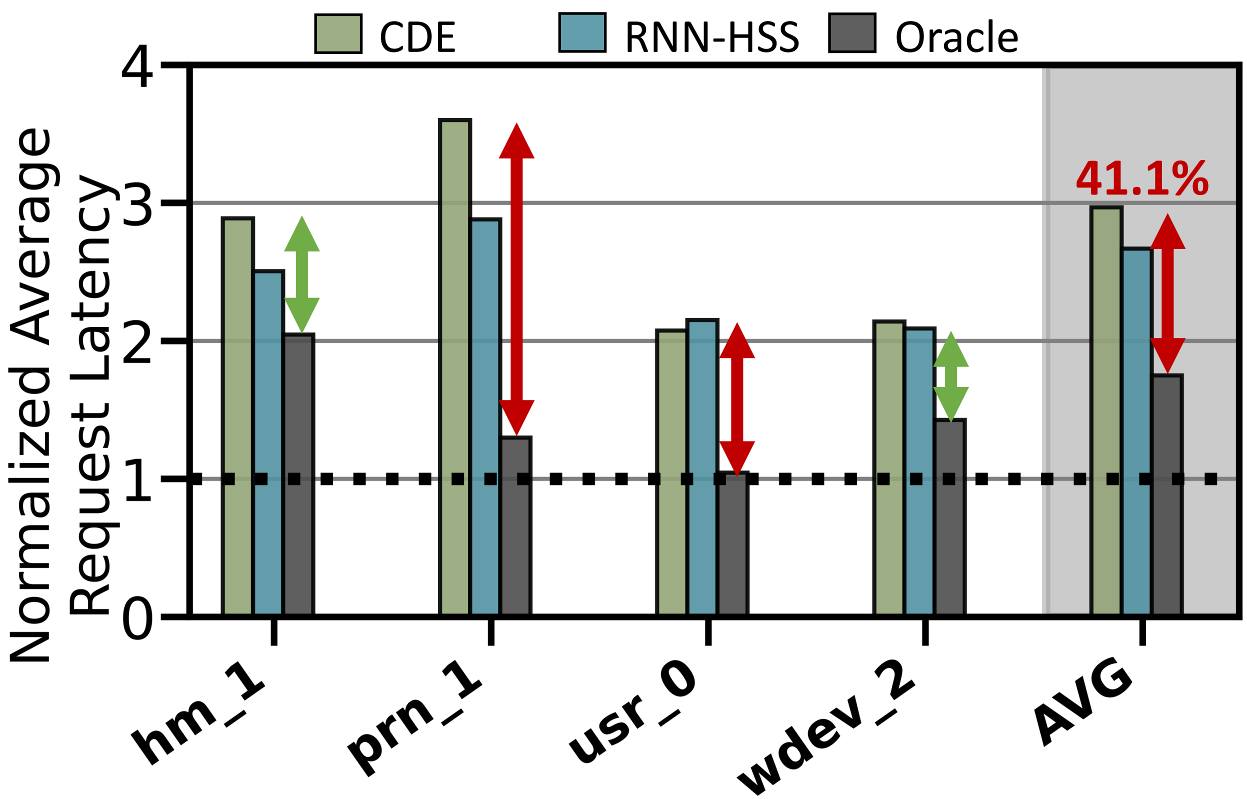
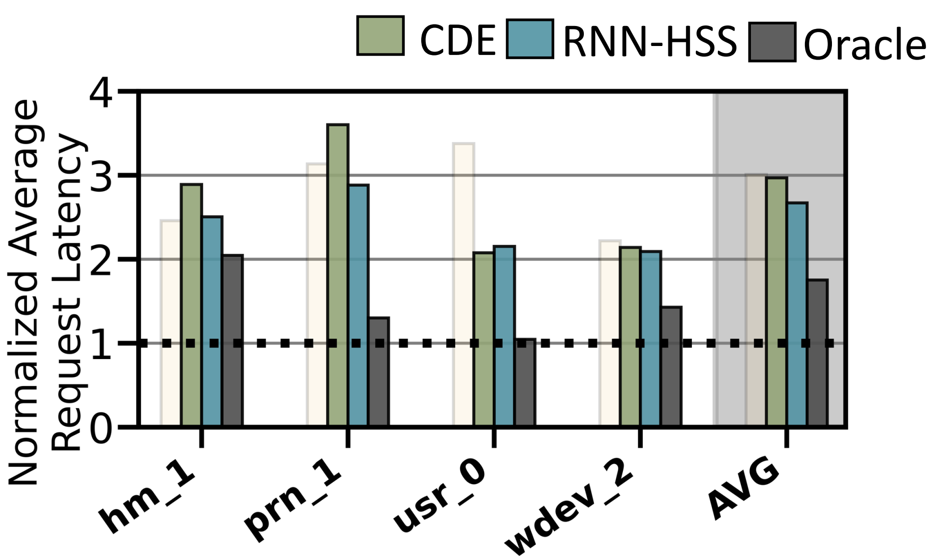


Lack of Adaptivity

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)



HSS Configuration 1

Lack of Adaptivity

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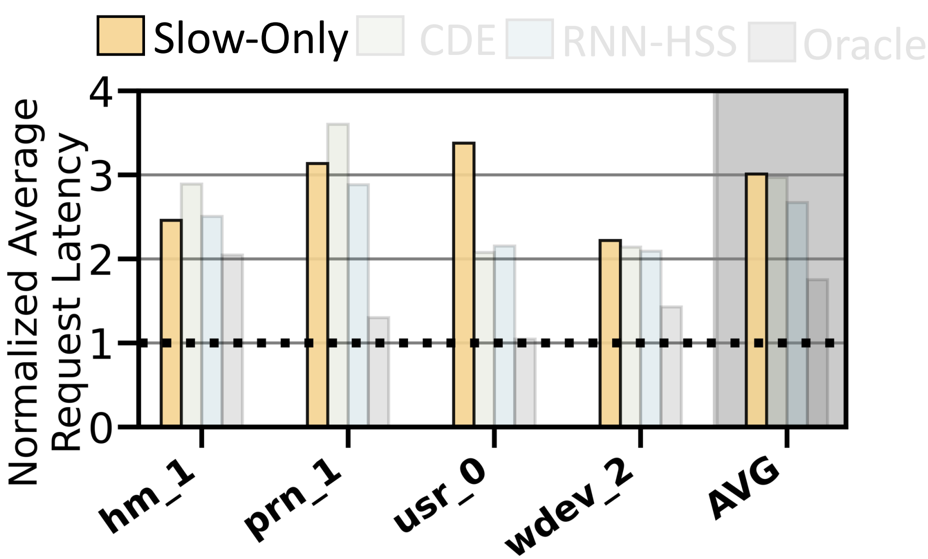

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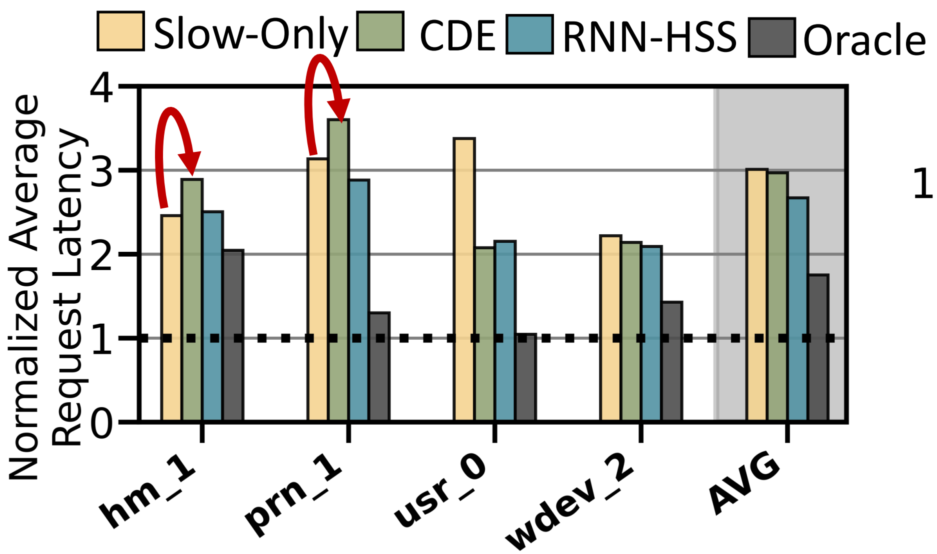
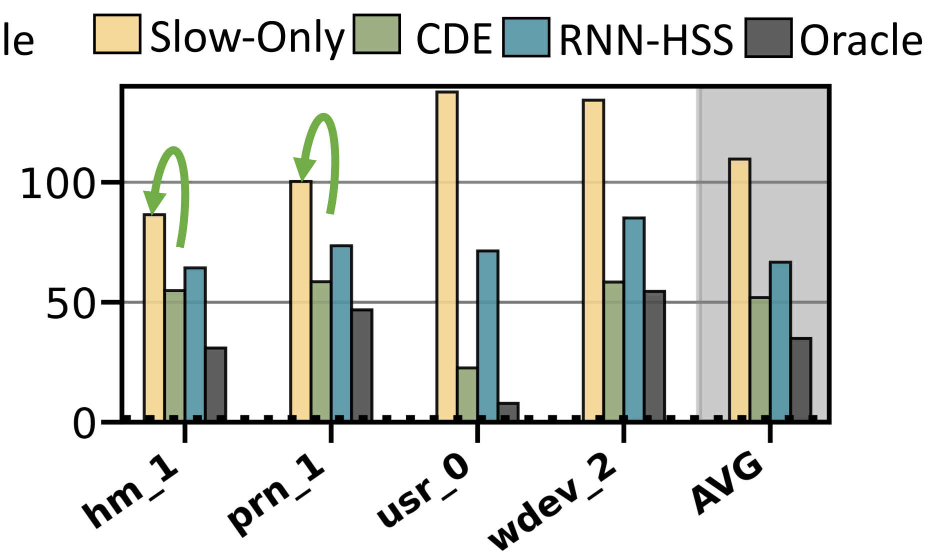


HSS Configuration 1

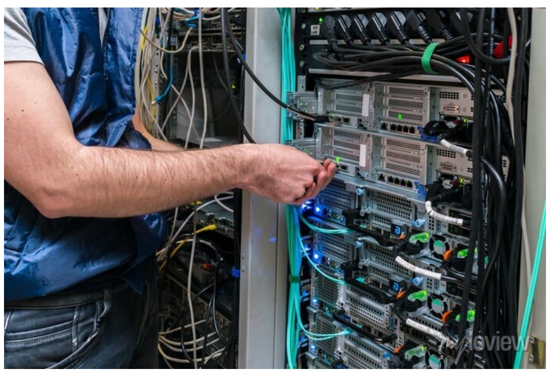


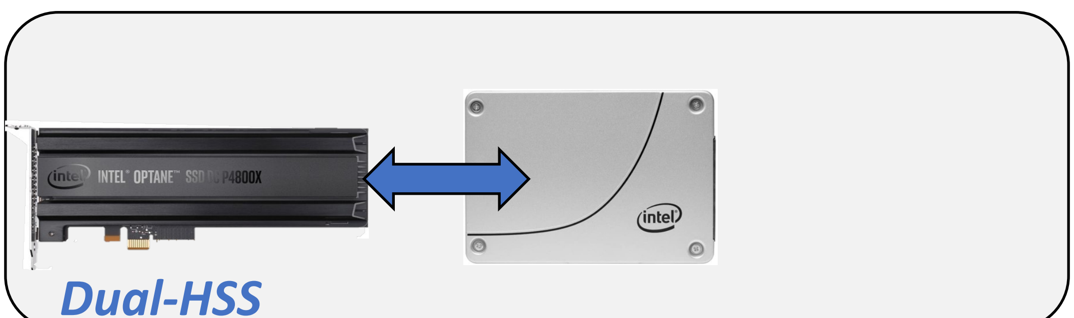
HSS Configuration 2

Lack of Extensibility

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

Change in storage configuration





Lack of Extensibility

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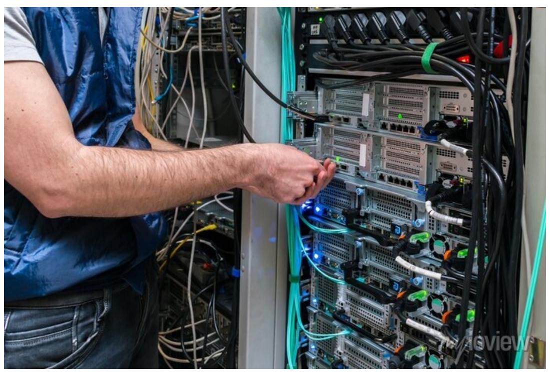
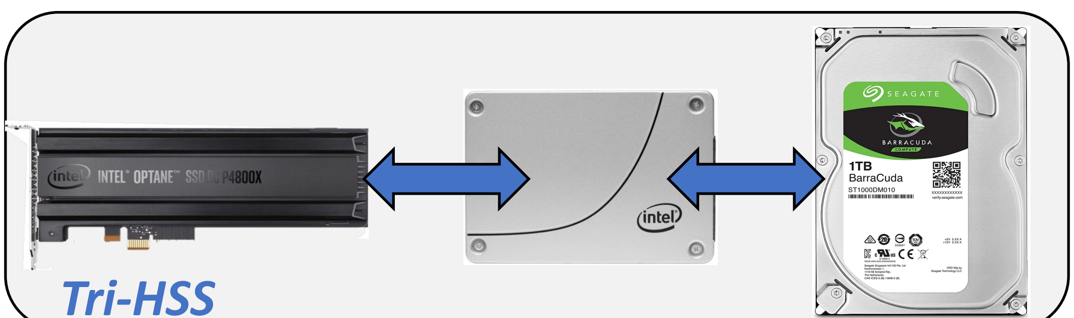
Change in storage configuration



Design a new policy



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**

Sybil is an oracle that makes accurate prophecies
https://en.wikipedia.org/wiki/Sibyl

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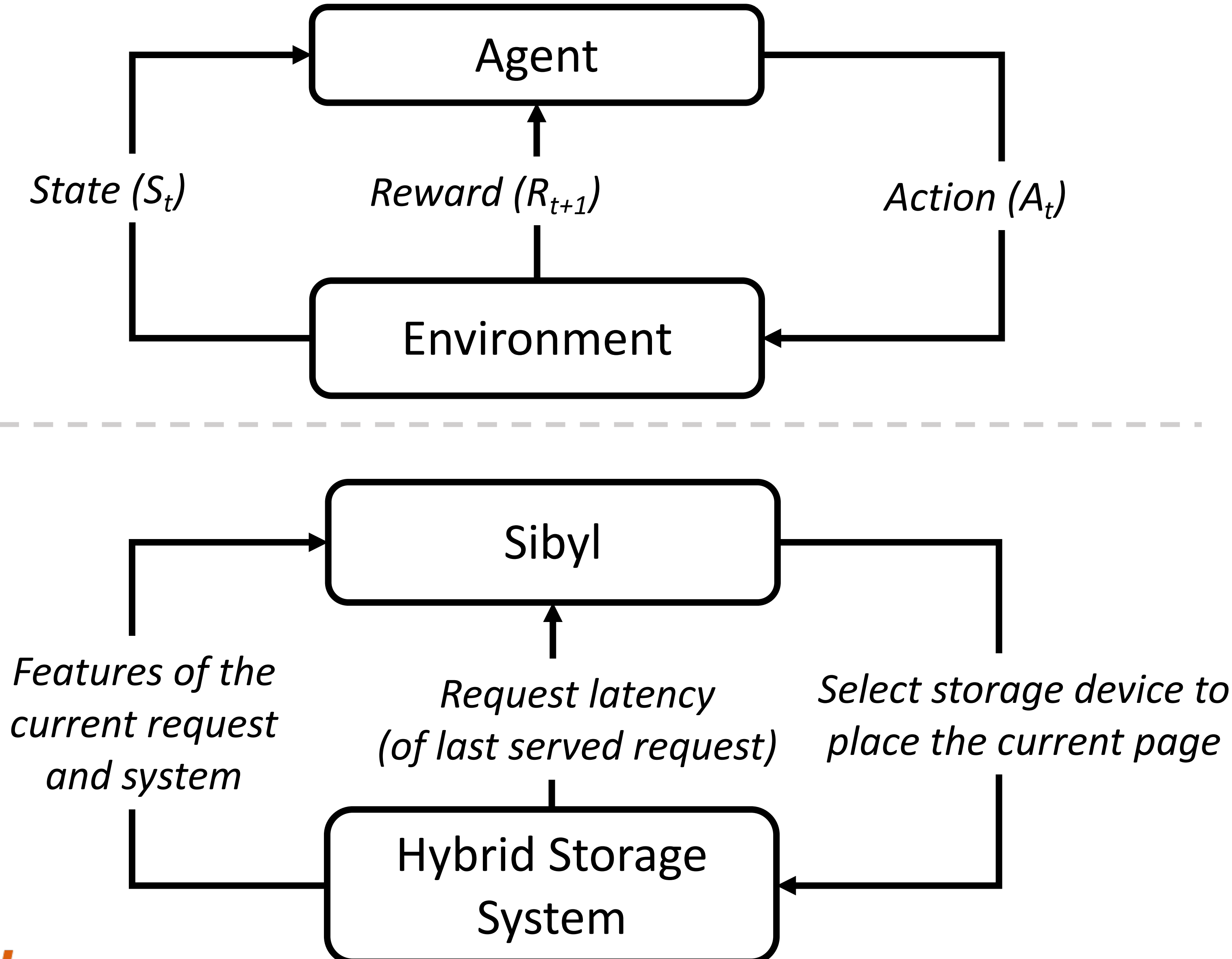
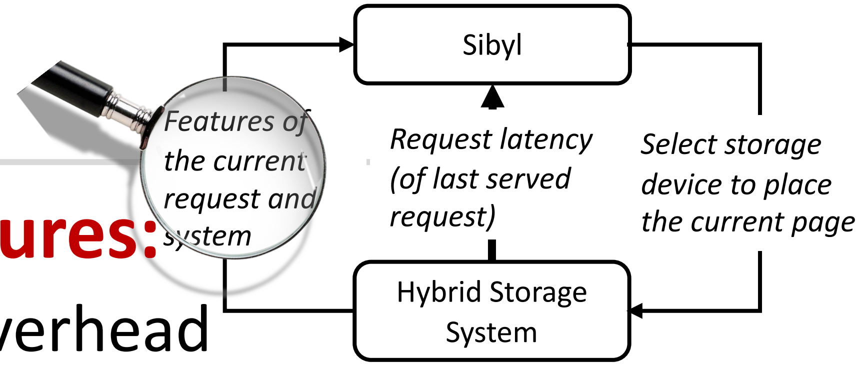
Basics of Reinforcement Learning (RL)

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

Formulating Data Placement as RL



What is State?



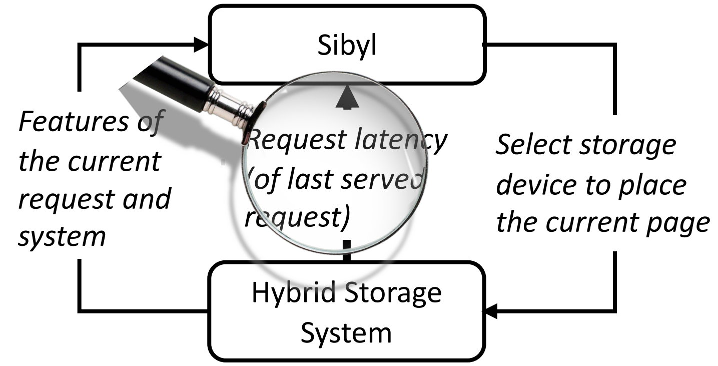
- **Limited number of state features:**
  - Reduce the implementation overhead
  - RL agent is more sensitive to reward

- ***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?



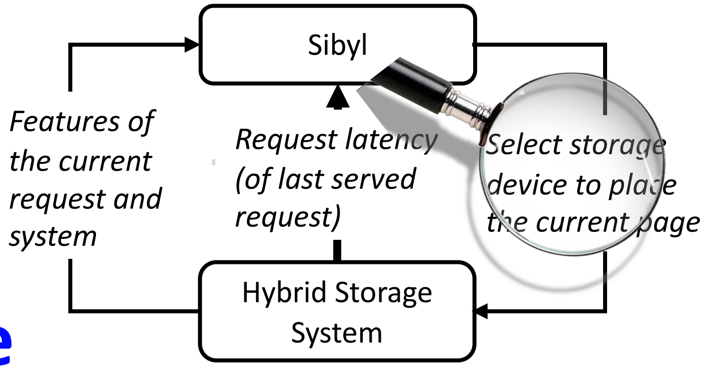
- Defines the **objective** of Sibyl

- 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 learns to **proactively evict or promote** a page

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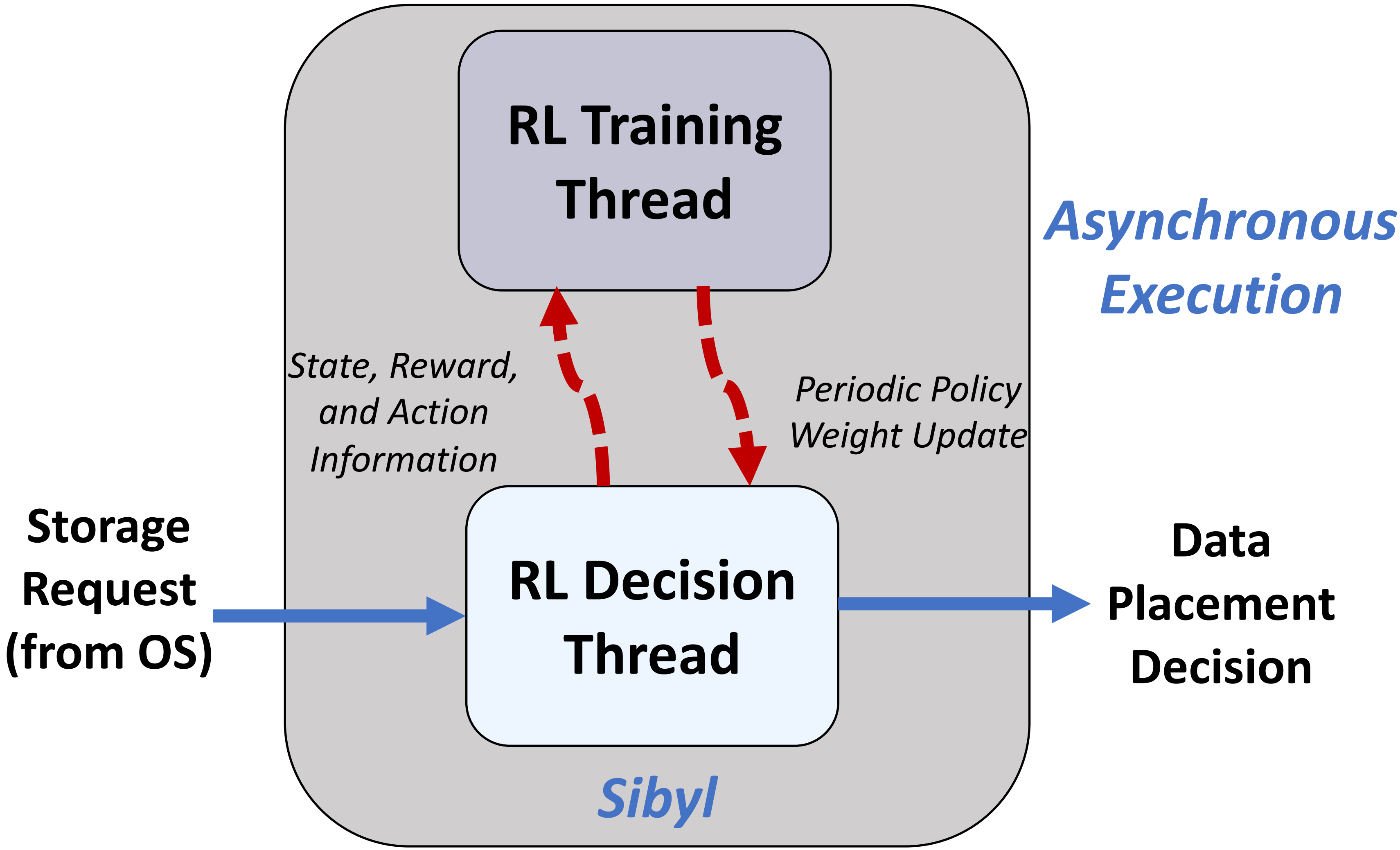
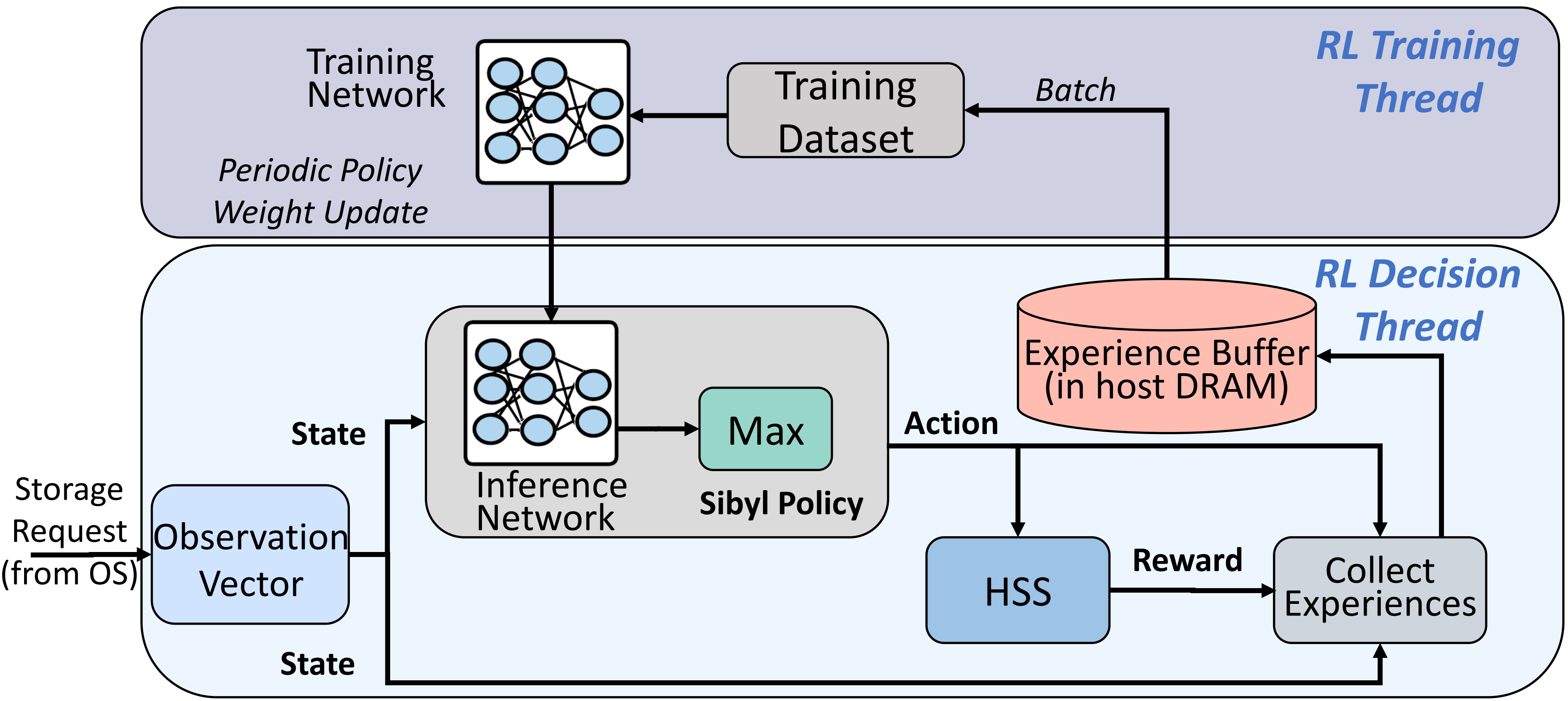
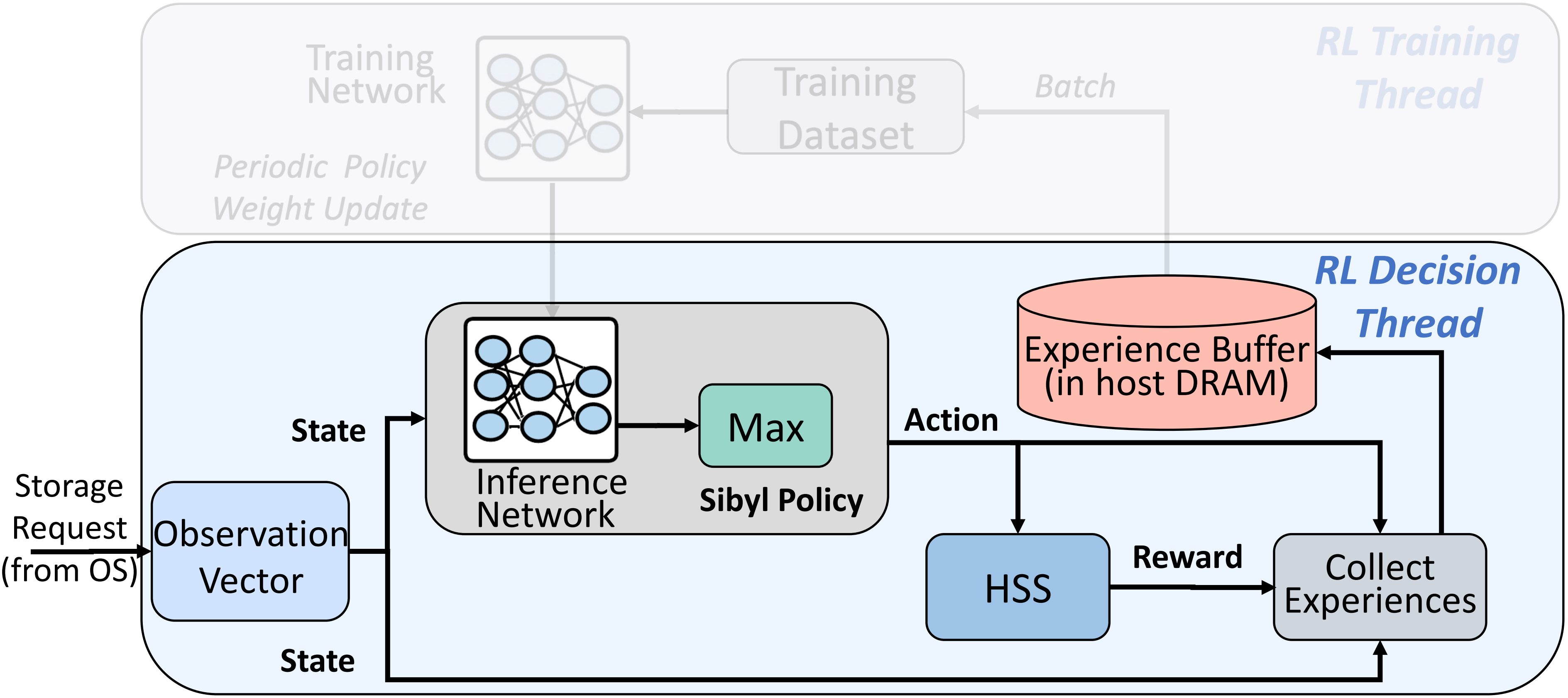
Sibyl Execution



Sibyl Design: Overview



RL Decision Thread



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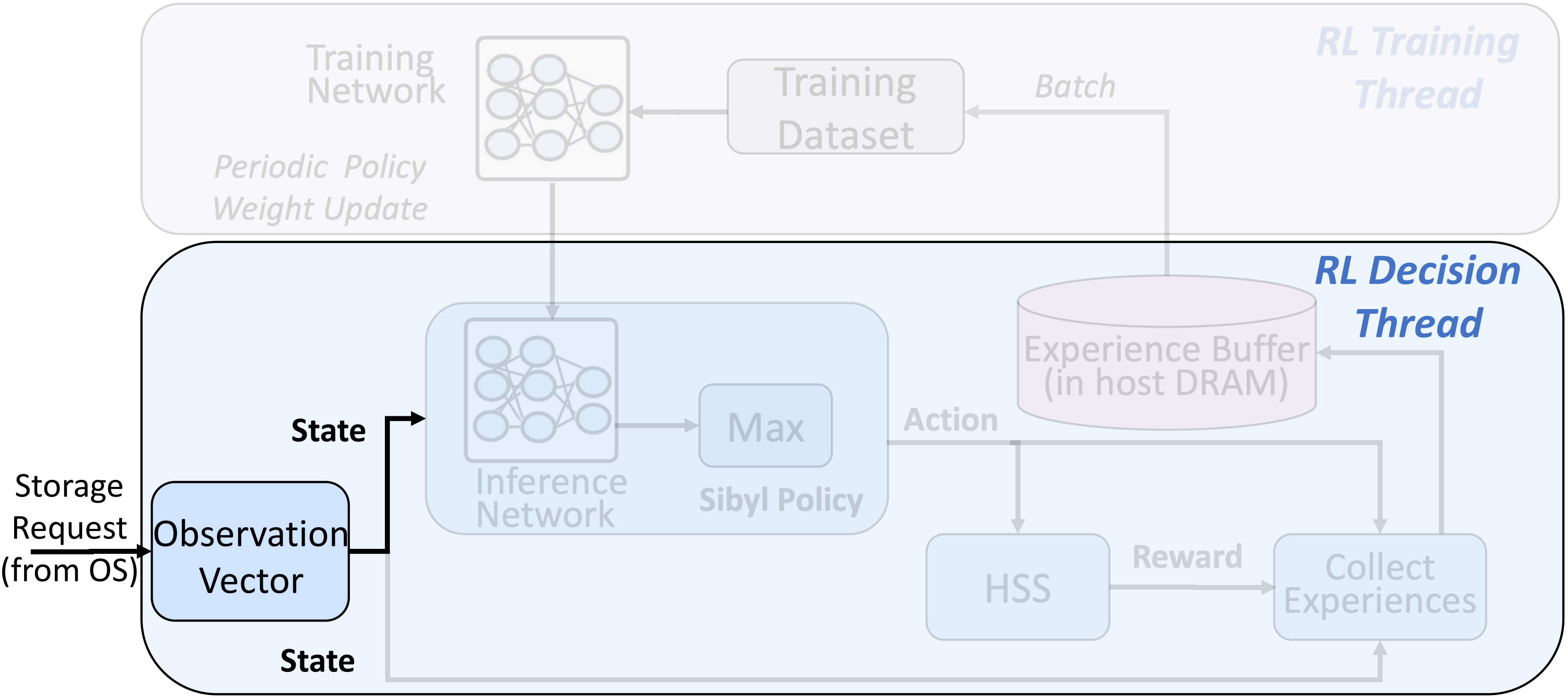

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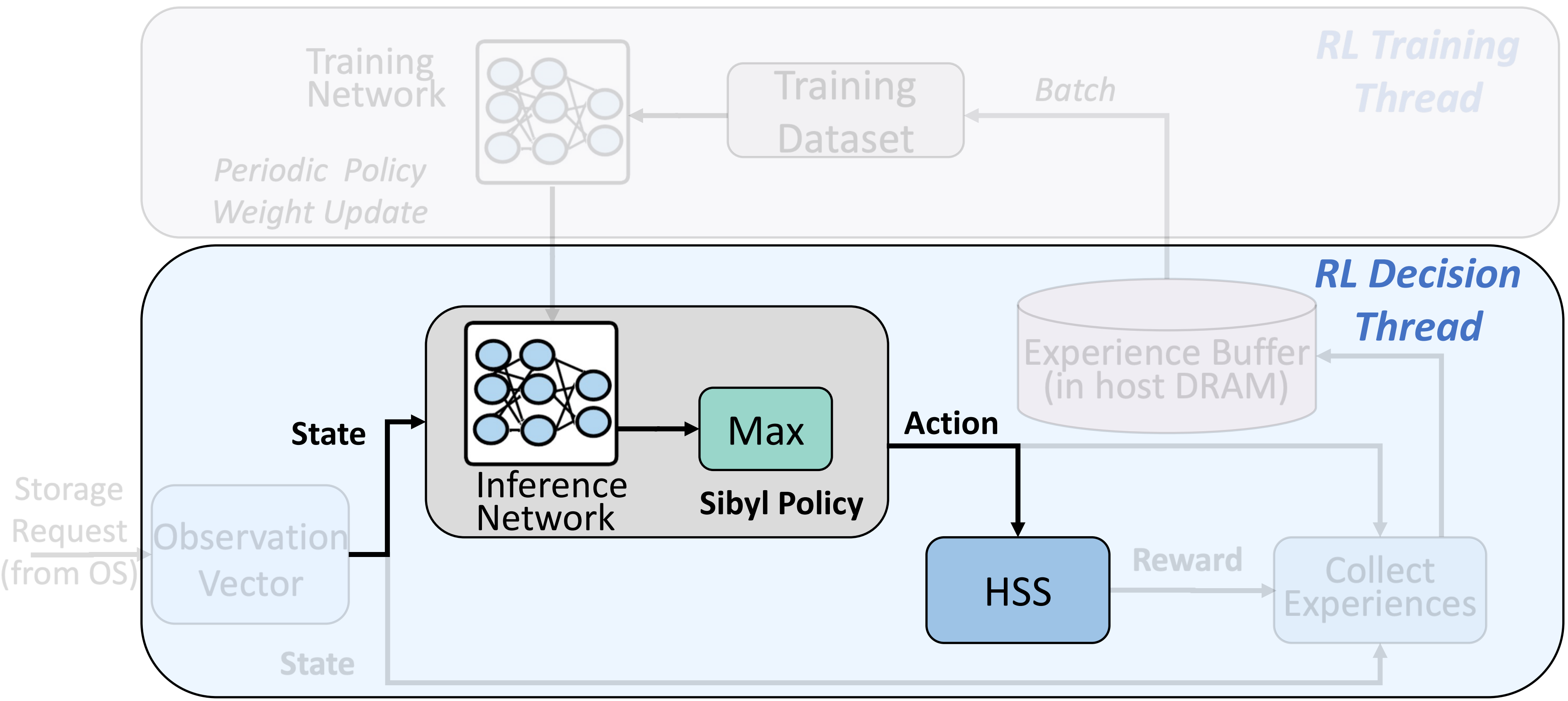

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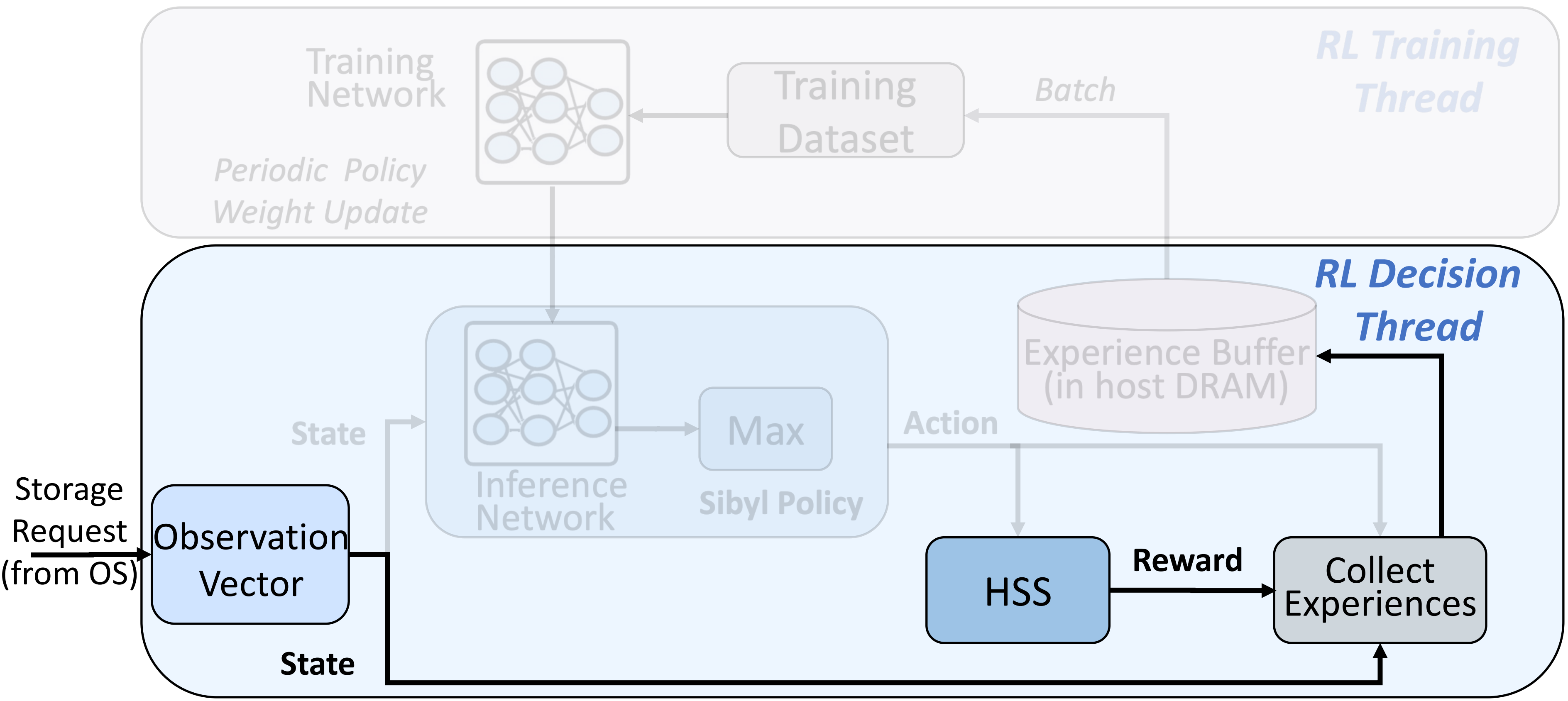
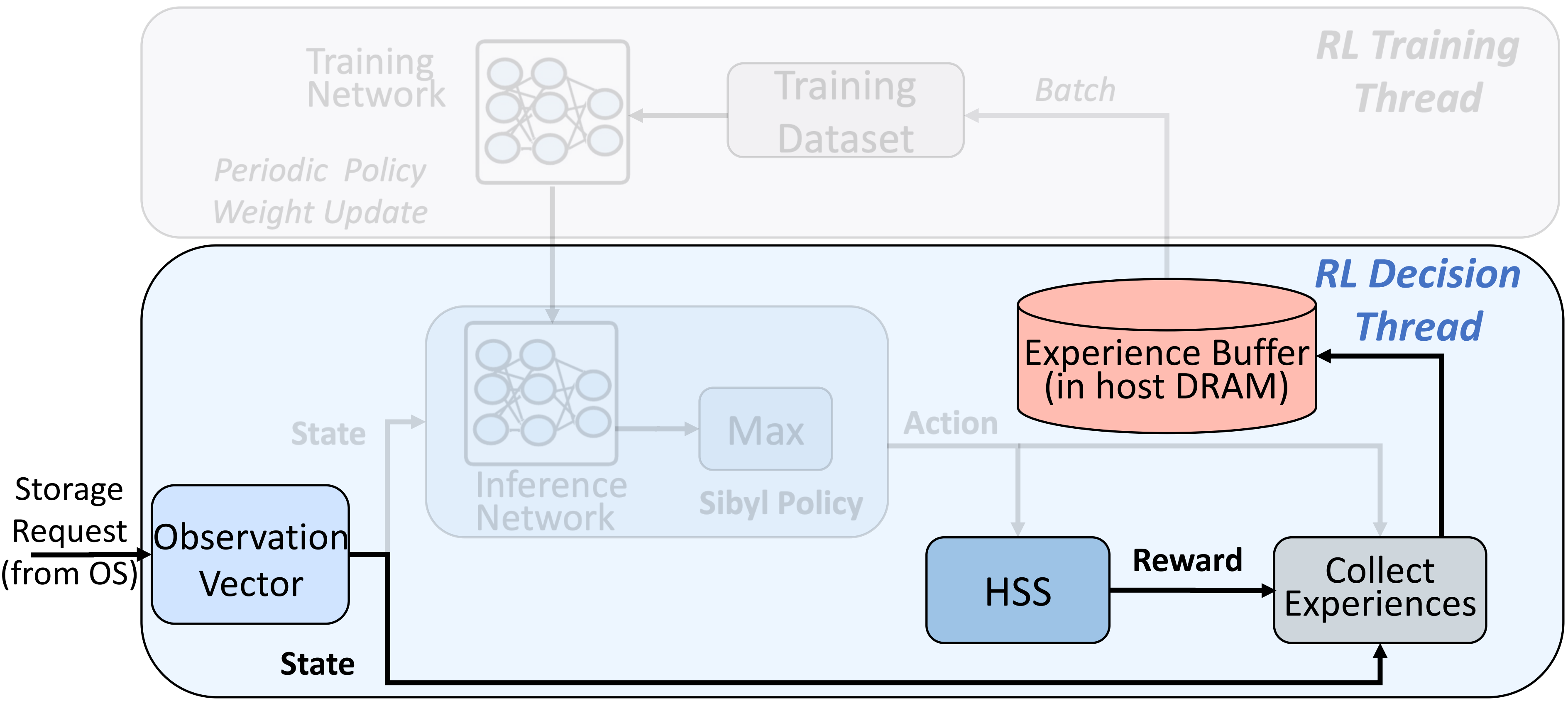
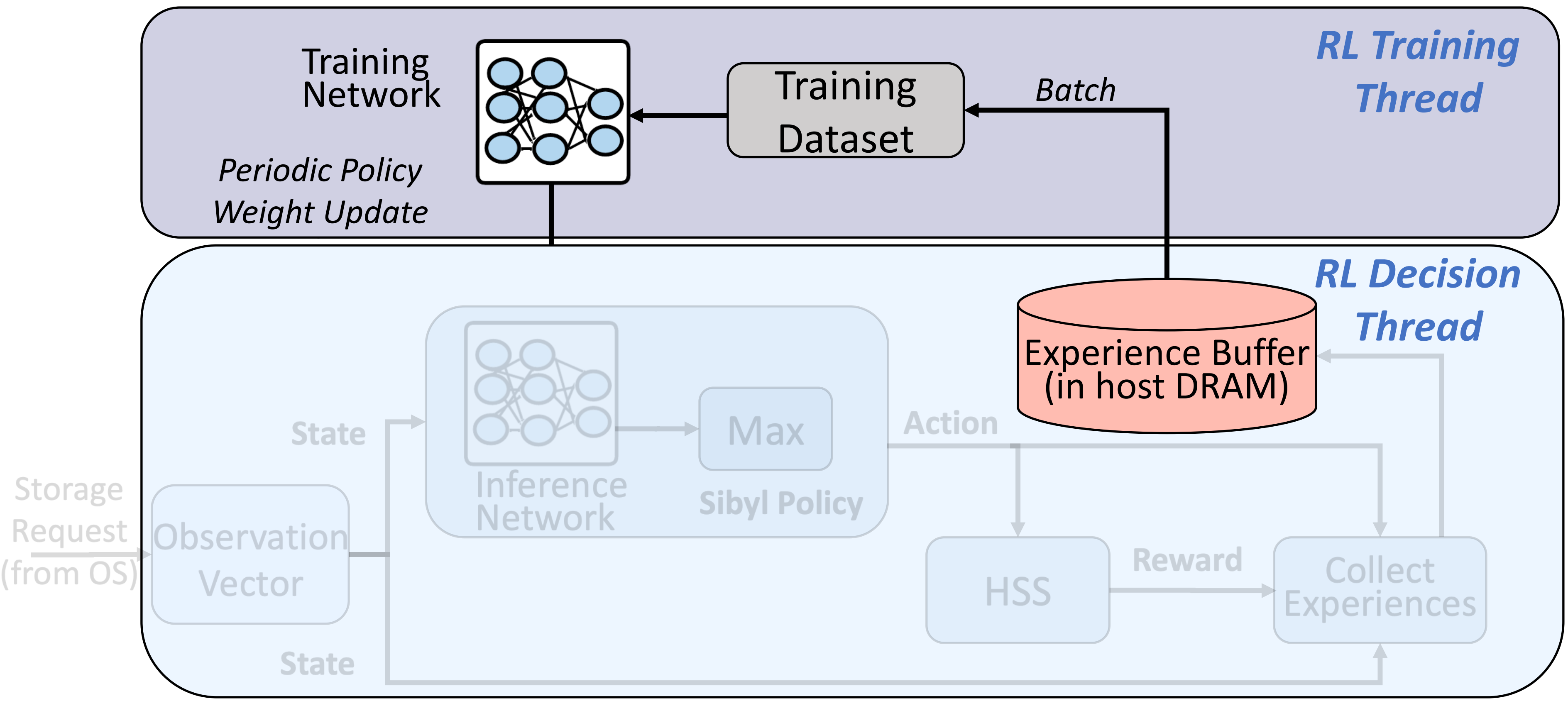


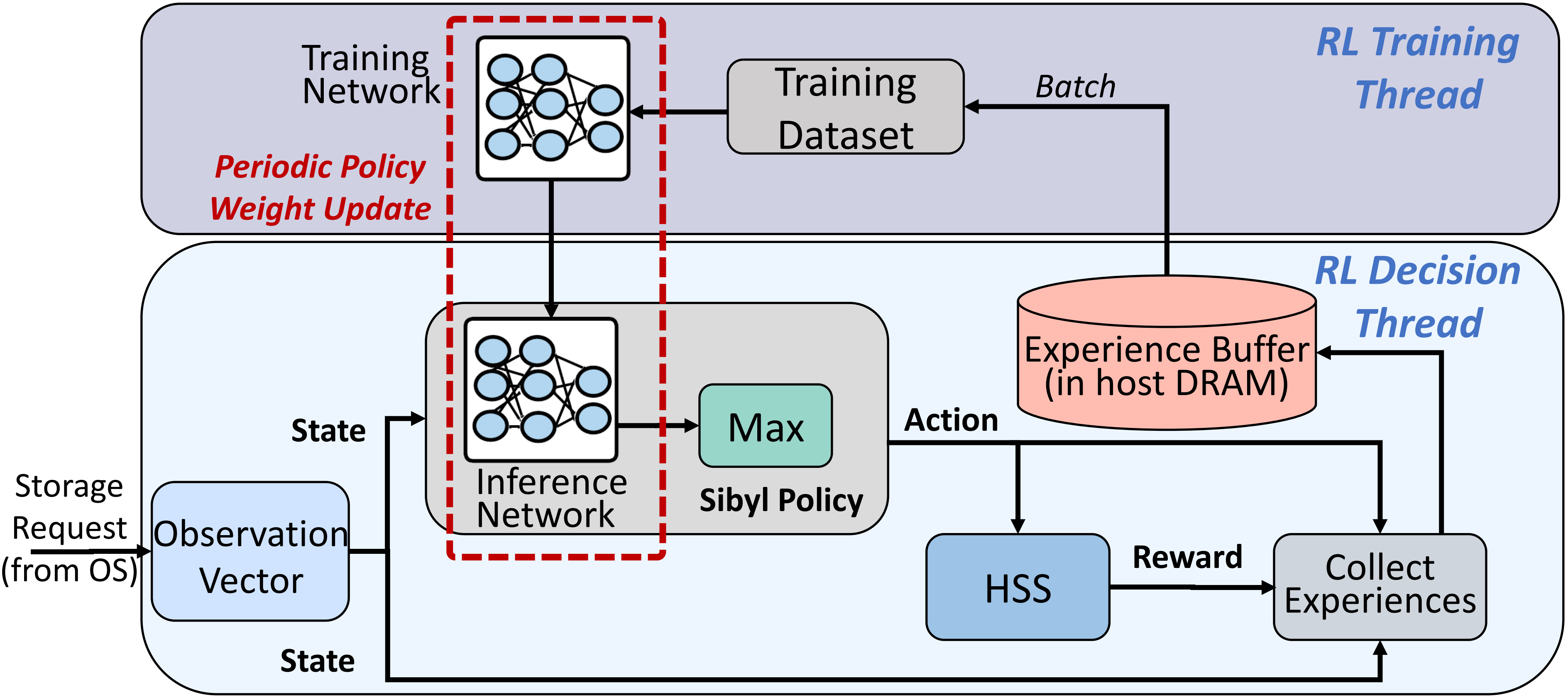
RL Decision Thread



RL Training Thread



Periodic Weight Transfer

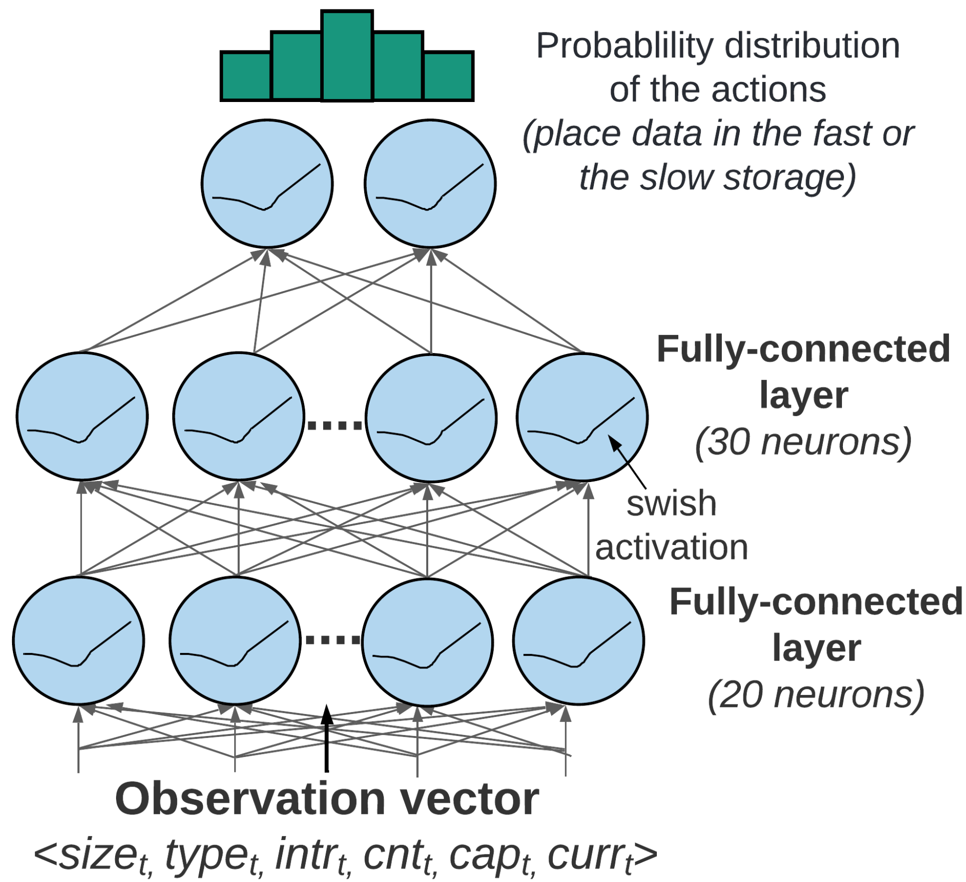


Training and Inference Network

- Training and inference network **allow parallel execution**

- **Observation vector as the input**

- **Produces probability distribution of Q-values**



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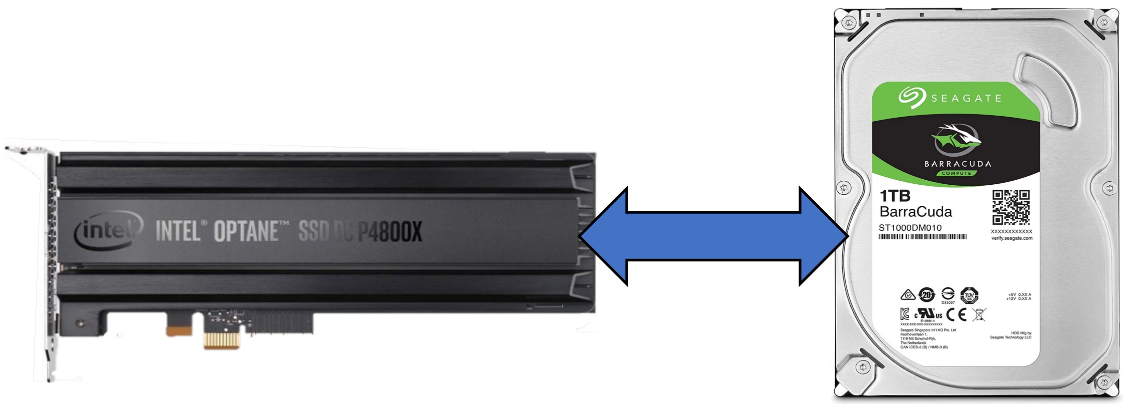
Evaluation Methodology (1/3)

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

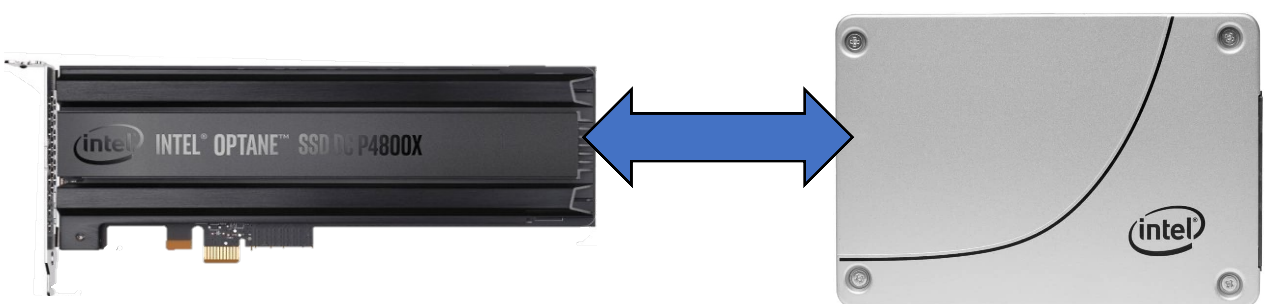
Evaluation Methodology (2/3)

Cost-Oriented HSS Configuration



High-end SSD *Low-end HDD*

Performance-Oriented HSS Configuration



High-end SSD *Middle-end SSD*

Evaluation Methodology (3/3)

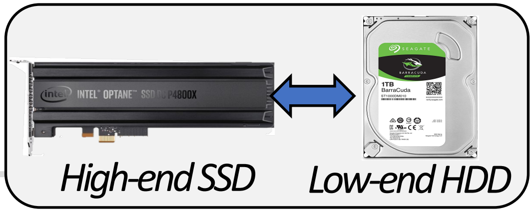
- **18 different workloads** from:
  - MSR Cambridge and Filebench Suites

- **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]

Heuristic-based

Learning-based

Performance Analysis



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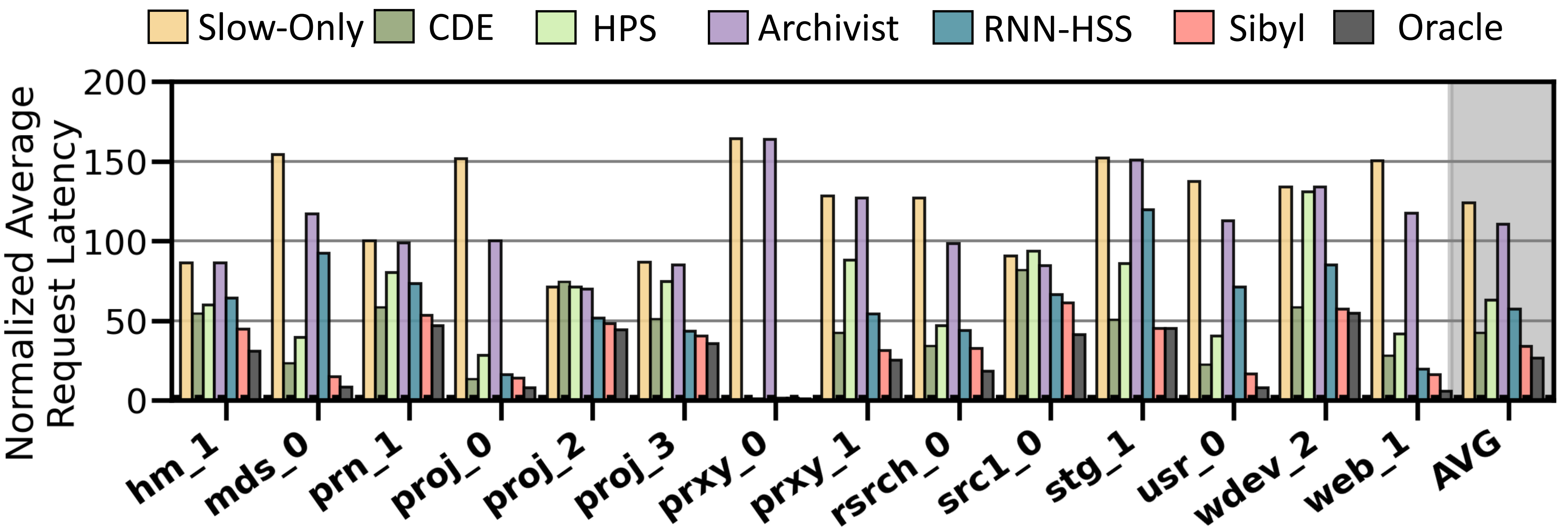
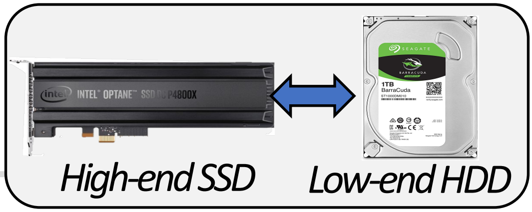


Performance Analysis



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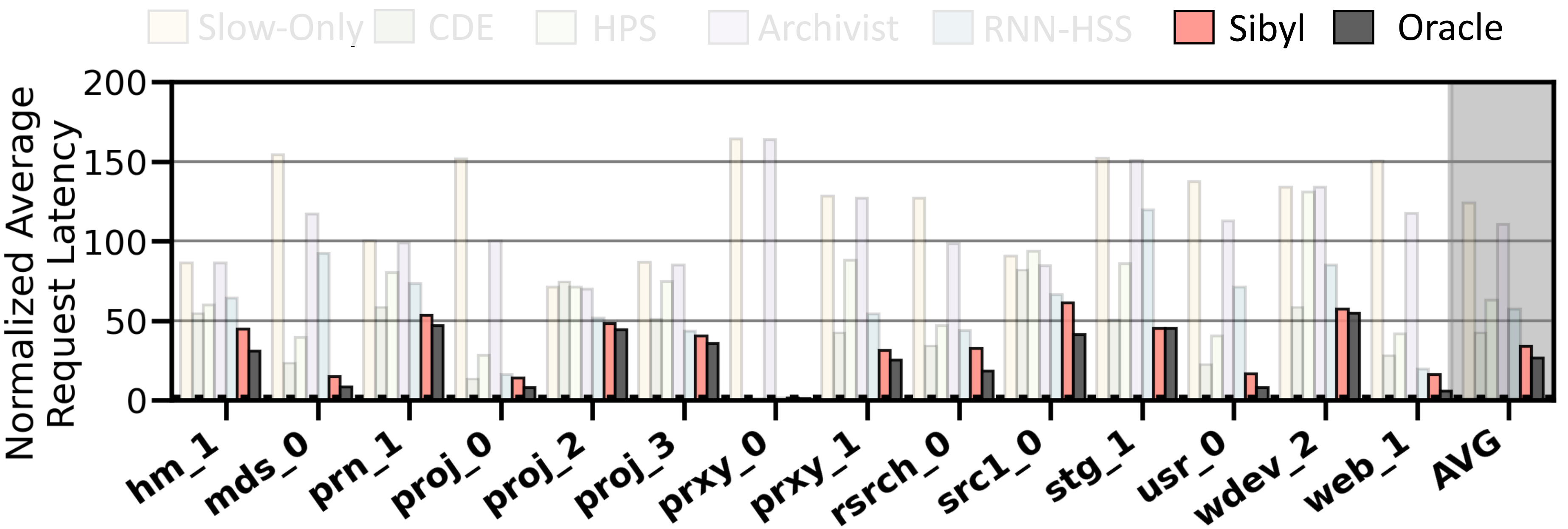
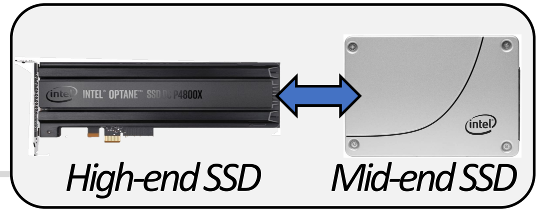
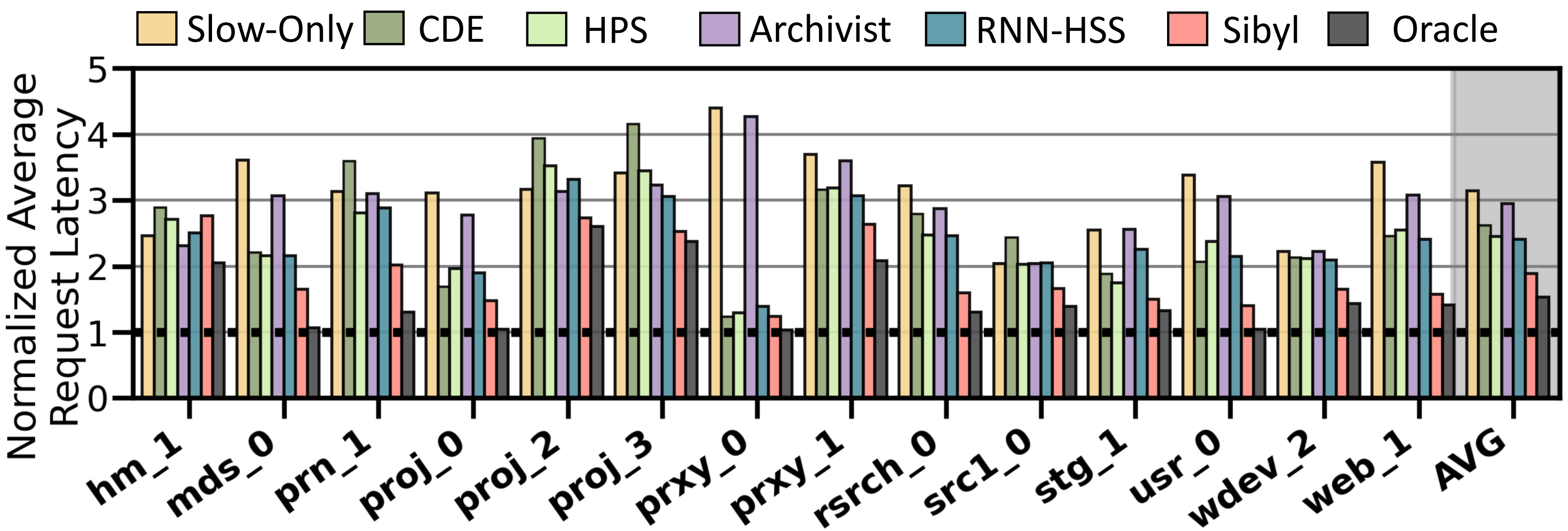


Sibyl consistently **outperforms all the baselines for all the workloads**

Performance Analysis



Performance-Oriented HSS Configuration



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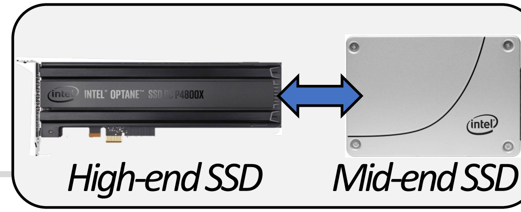
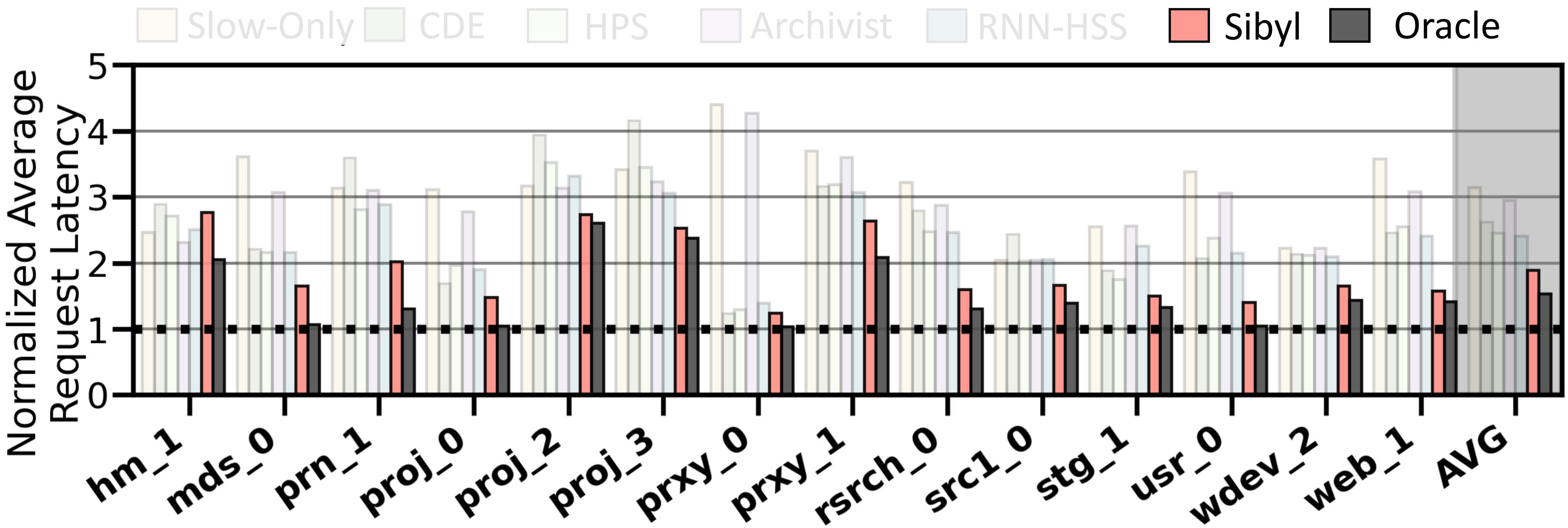
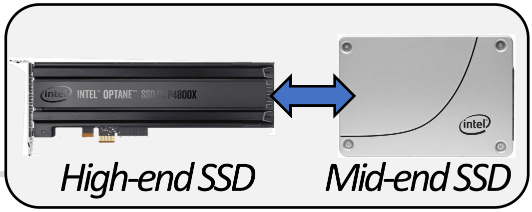


Performance-Oriented HSS Configuration

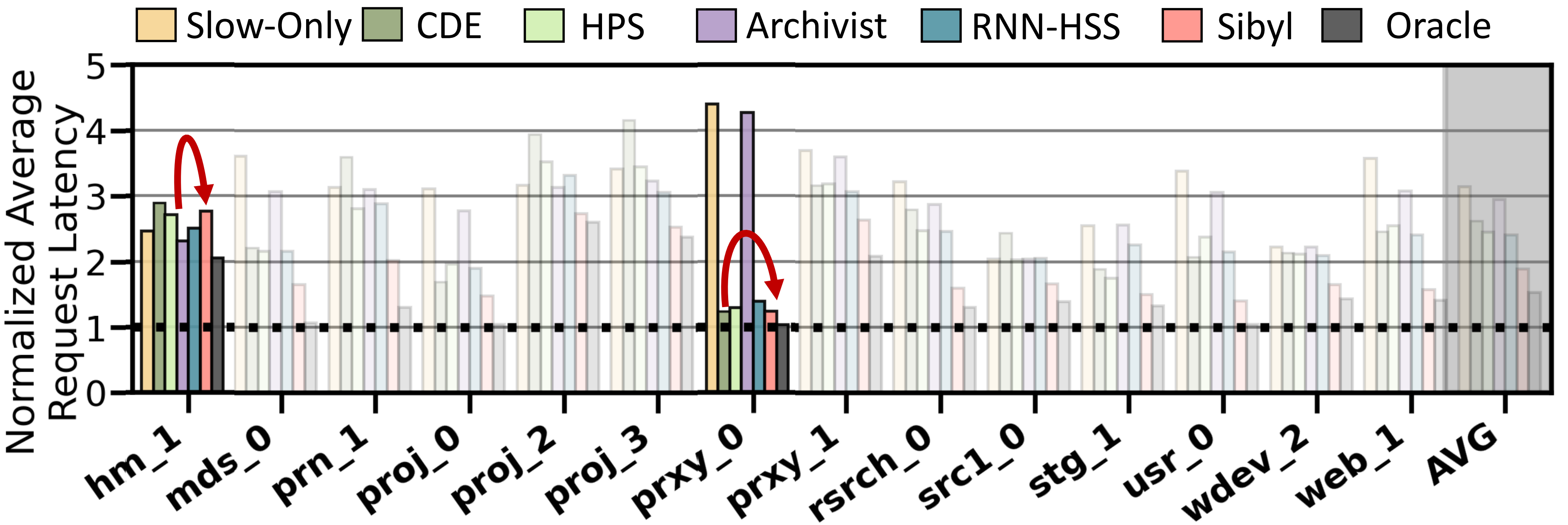


Sibyl provides **21.6% performance improvement** by **dynamically adapting its data placement policy**

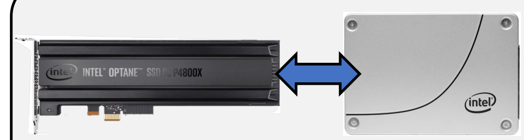
Performance Analysis



Performance-Oriented HSS Configuration



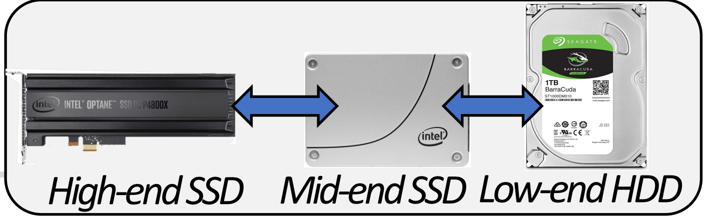
Performance Analysis



Performance-Oriented HSS Configuration

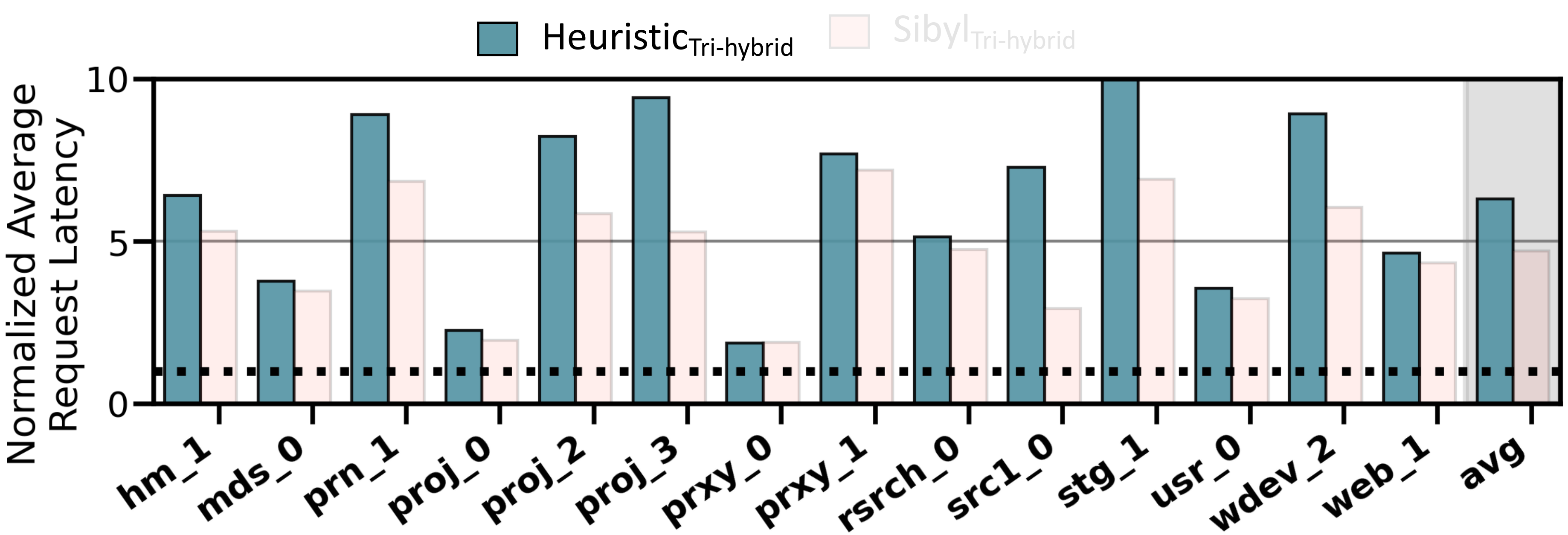
Sibyl achieves **80% of the performance of an oracle policy** that has complete knowledge of future access patterns

Performance on Tri-HSS

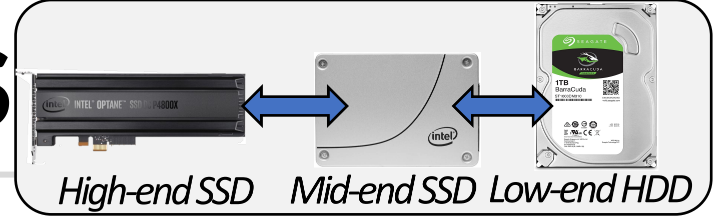


Extending Sibyl for **more devices**:

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



Performance on Tri-HSS



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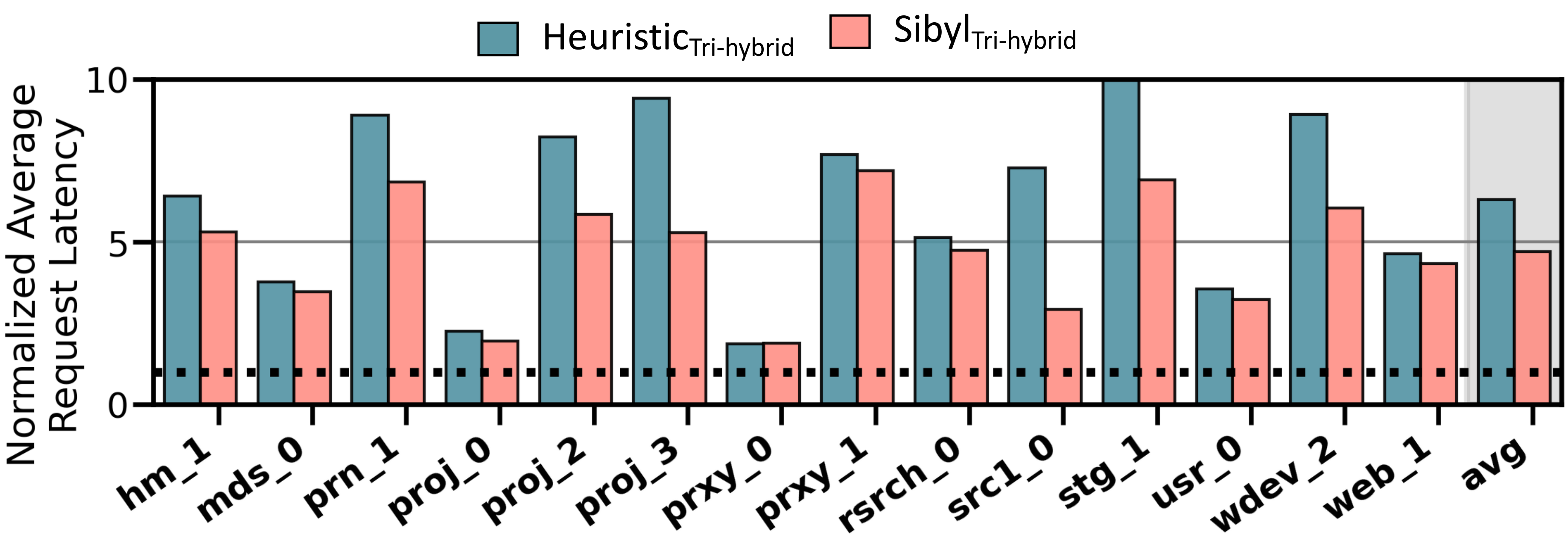
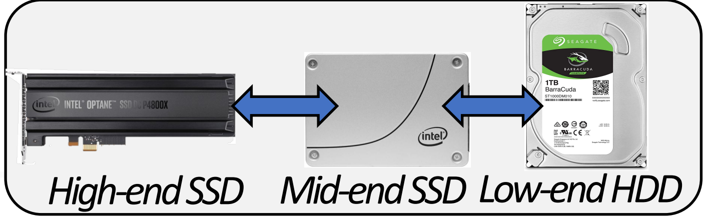


Performance on Tri-HSS



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 Sybil's decision making
  - Explain Sibyl’s actions for different workload characteristics and device configurations

More in the Paper (2/2)

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[1]ETH Zürich [2]Eindhoven University of Technology [3]LIRMM, Univ. Montpellier, CNRS

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

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

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Conclusion

- **We introduced 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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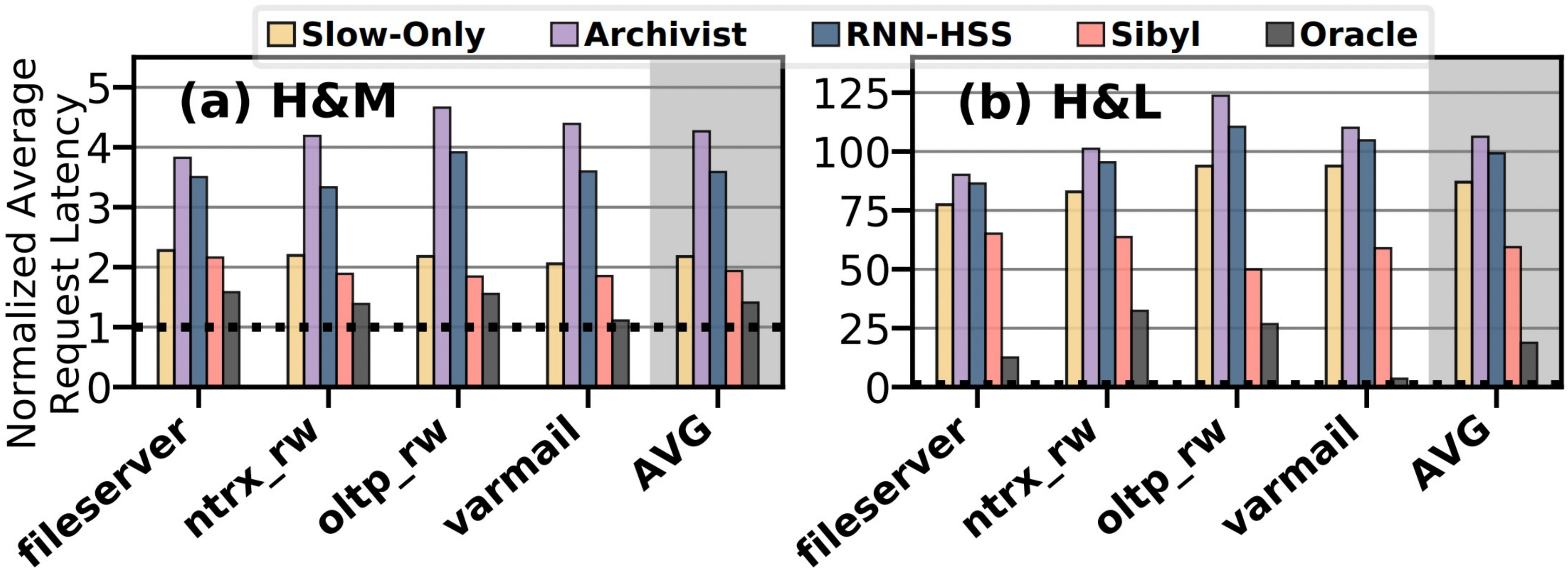
BACKUP

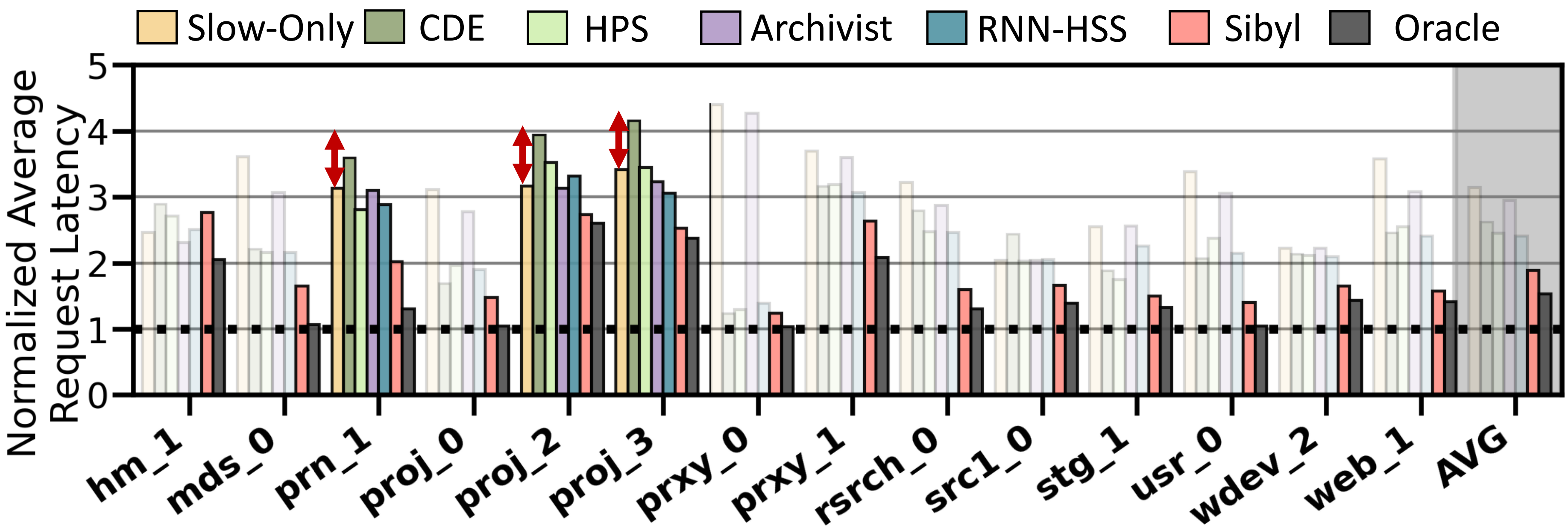
Performance on Unseen Workloads



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

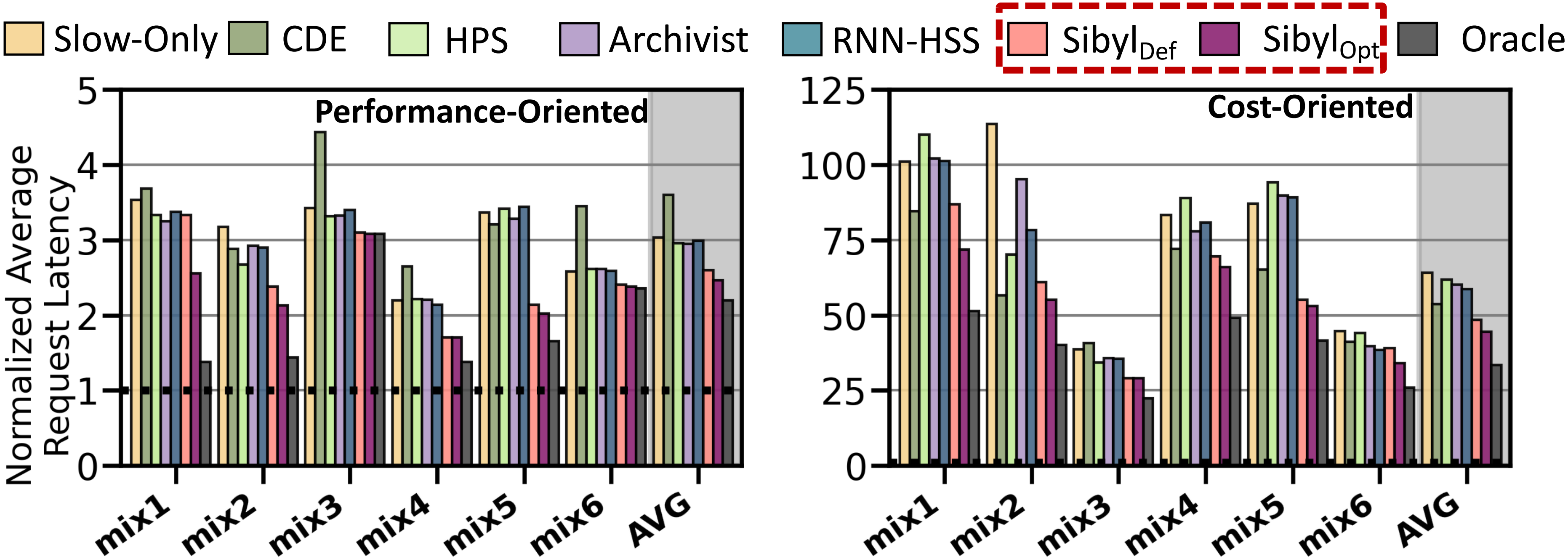
Performance Analysis

Performance-Oriented HSS Configuration

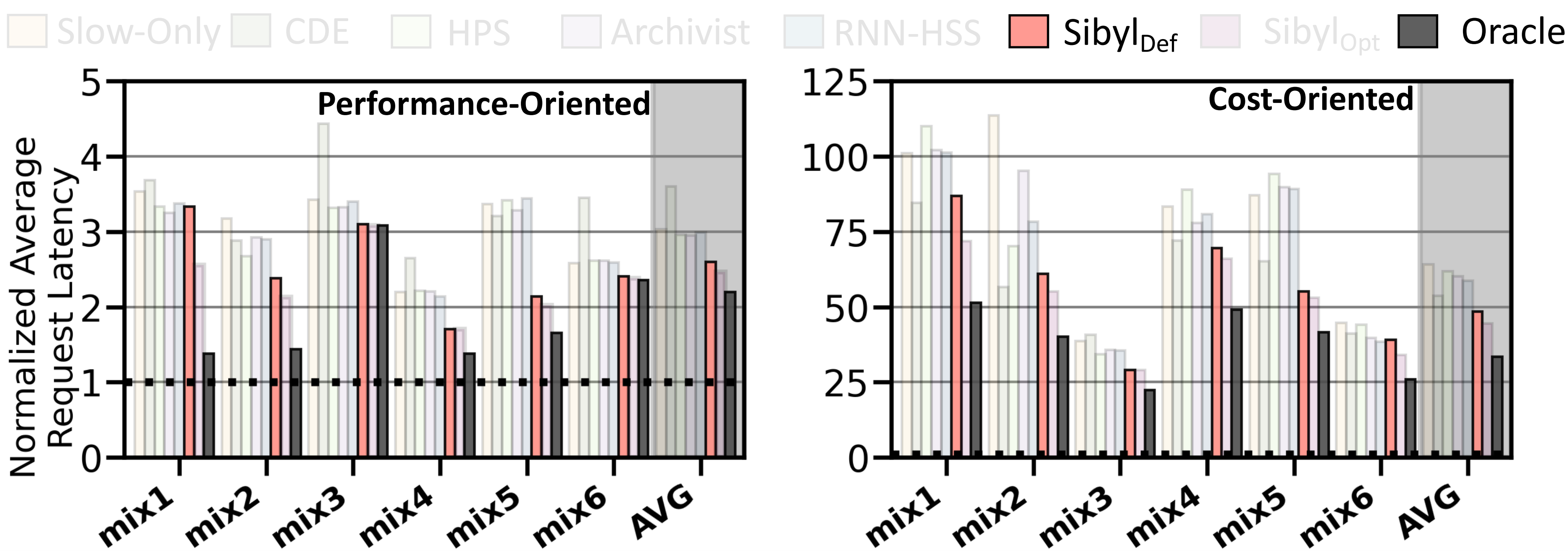


Baseline policies **are ineffective** for many workloads even when compared to Slow-Only

Performance on Mixed Workloads

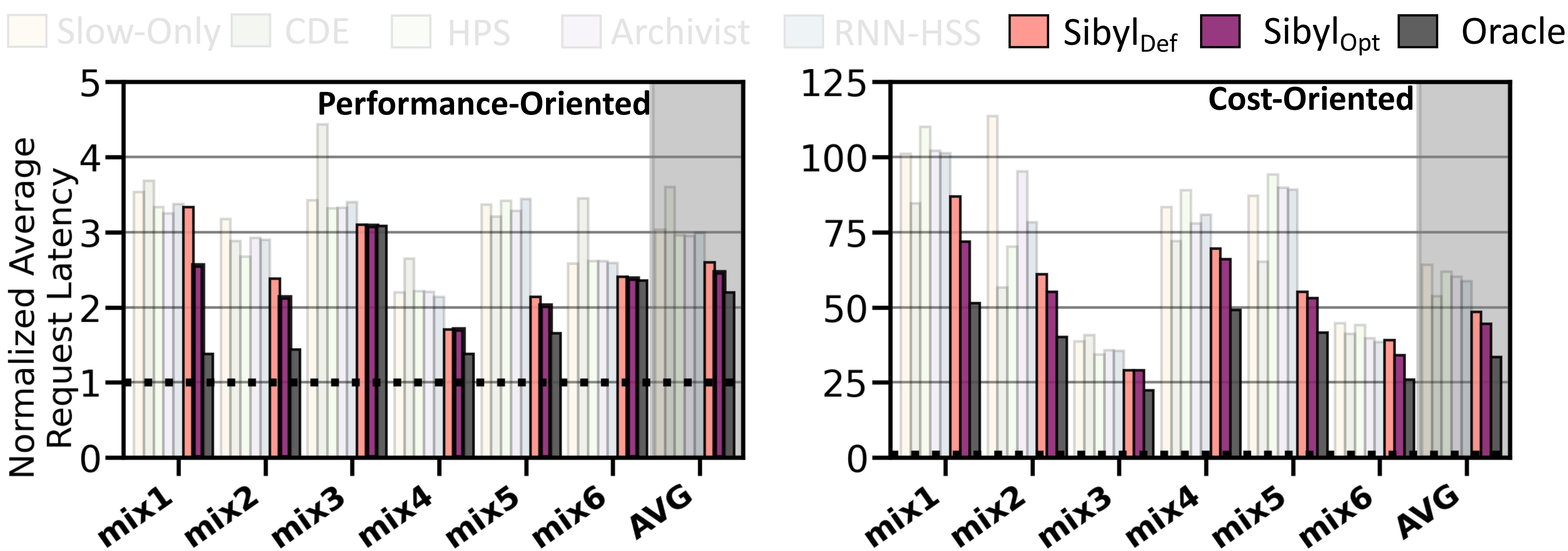


Performance on Mixed Workloads



Sibyl$_{Def}$ **outperforms** baseline data placement techniques by up to **27.9%**

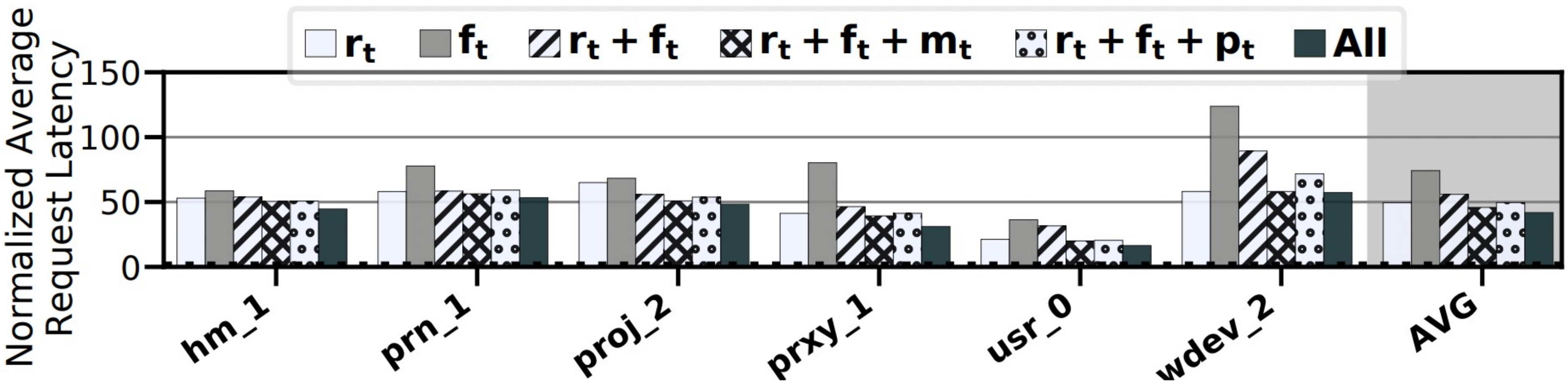
Performance on Mixed Workloads



$\text{Sibyl}_{\text{Def}}$ **outperforms** baseline data placement techniques by up to **27.9%**

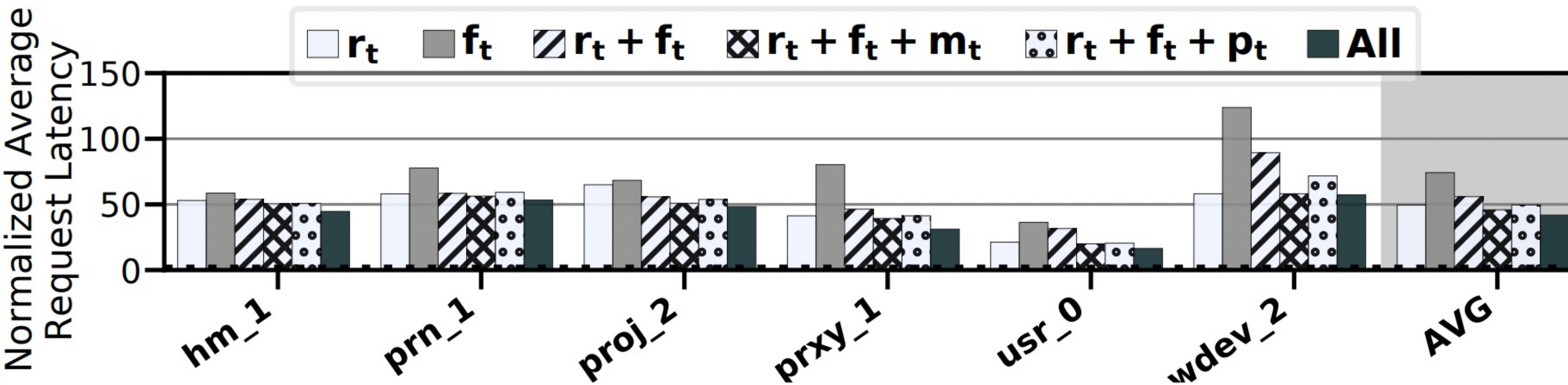
$\text{Sibyl}_{\text{Opt}}$ **provides 7.2% higher average performance** than $\text{Sibyl}_{\text{Def}}$

Performance With Different Features



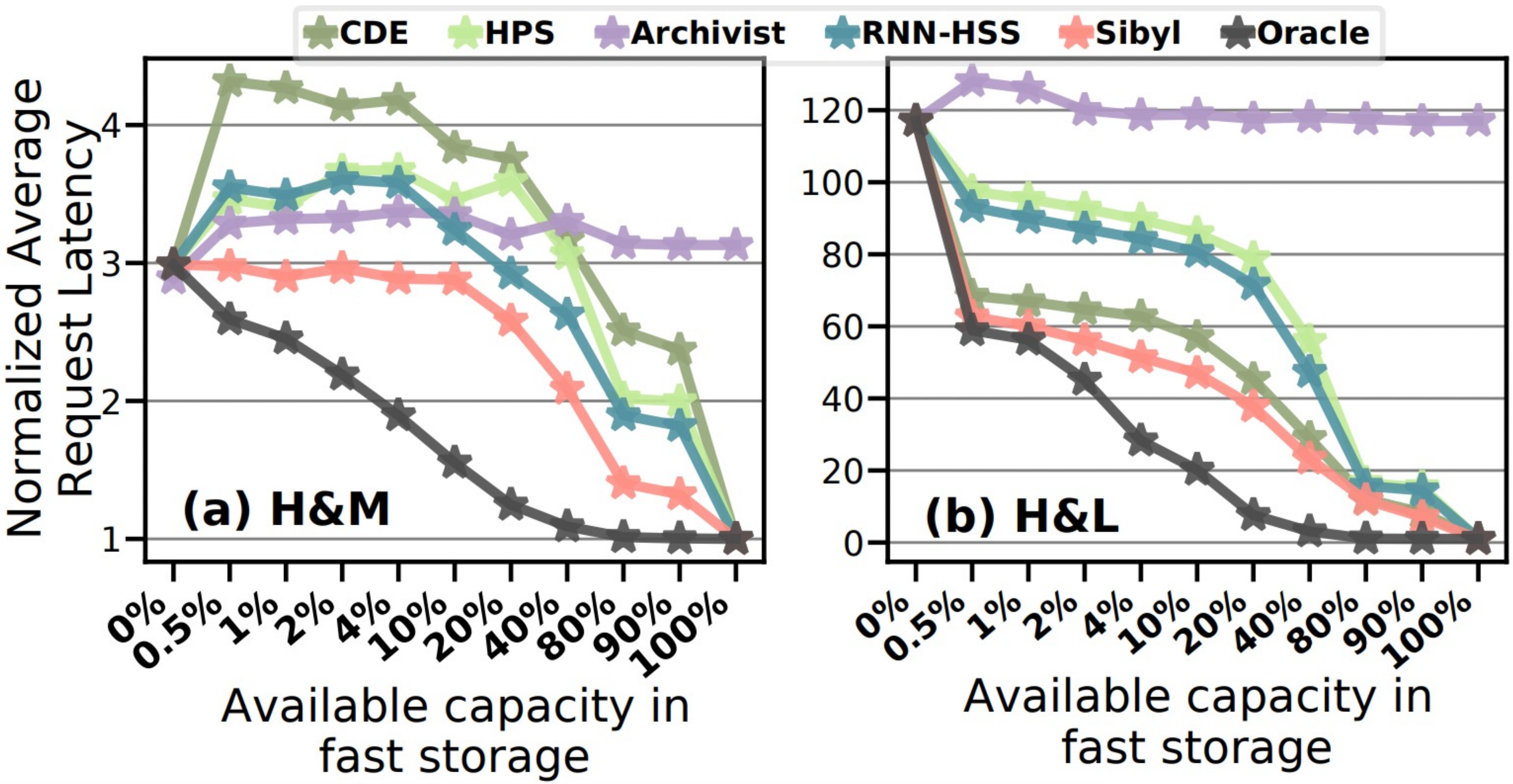
Sibyl autonomously decides which features are important to maximize the performance of the running workload

Performance With Different Features

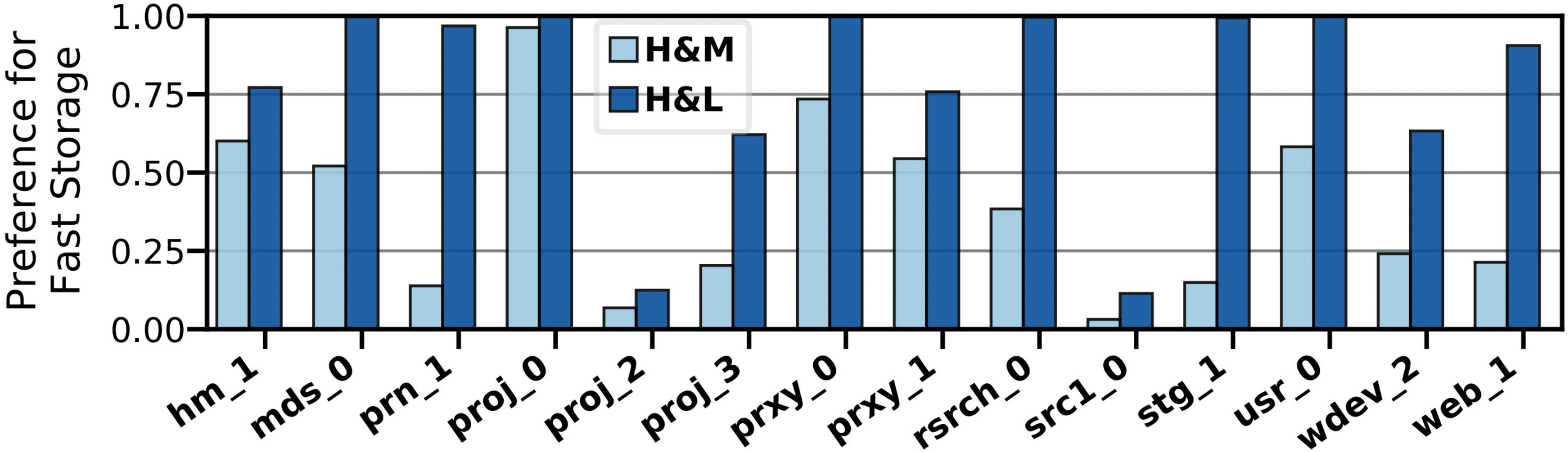


Sibyl autonomously decides which features are important to maximize the performance of the running workload

Sensitivity to Fast Storage Capacity



Explainability Analysis



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