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**

Talk Outline

Key Shortcomings of Prior Data Placement Techniques

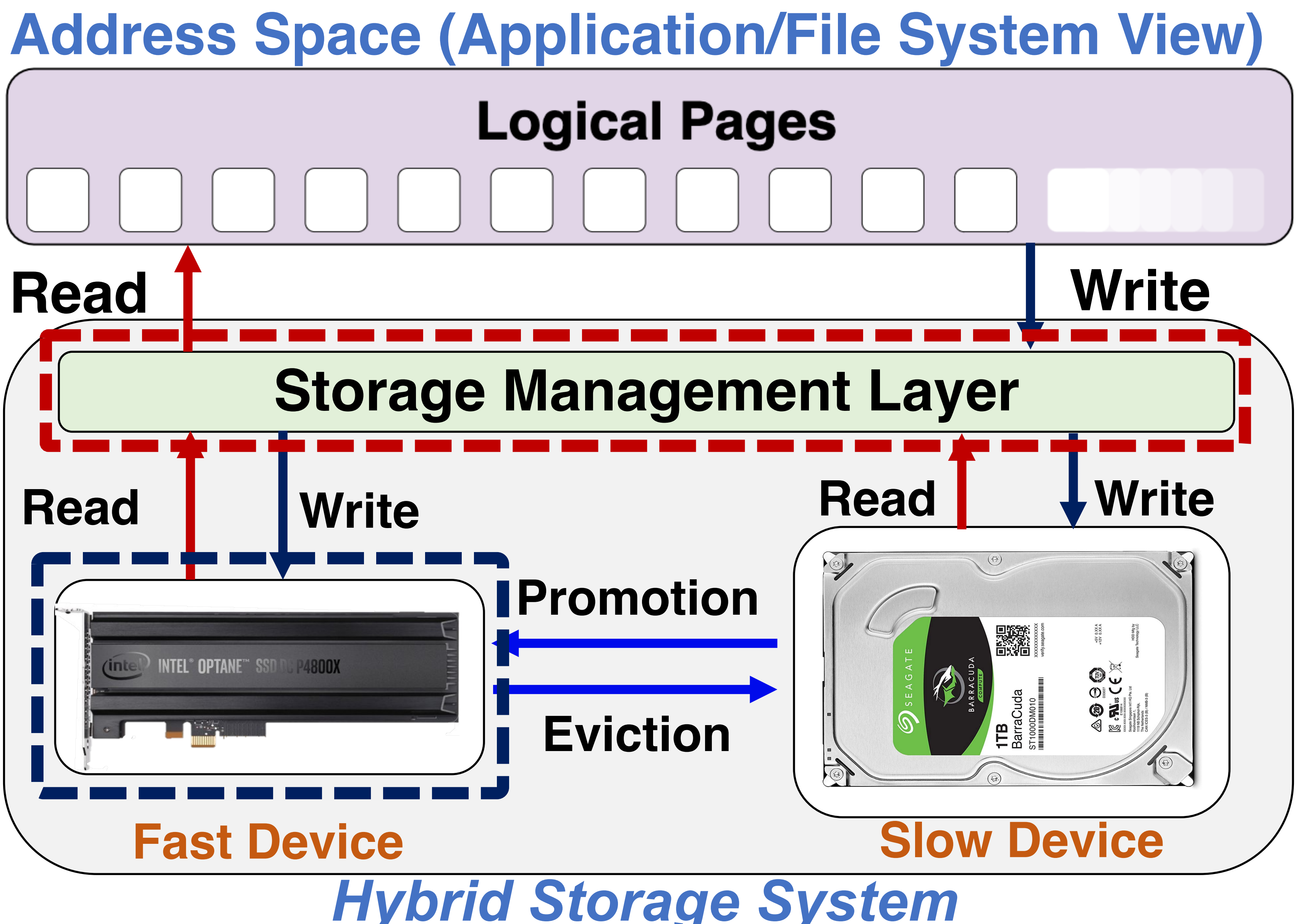
Formulating Data Placement as Reinforcement Learning

Sybil: Overview

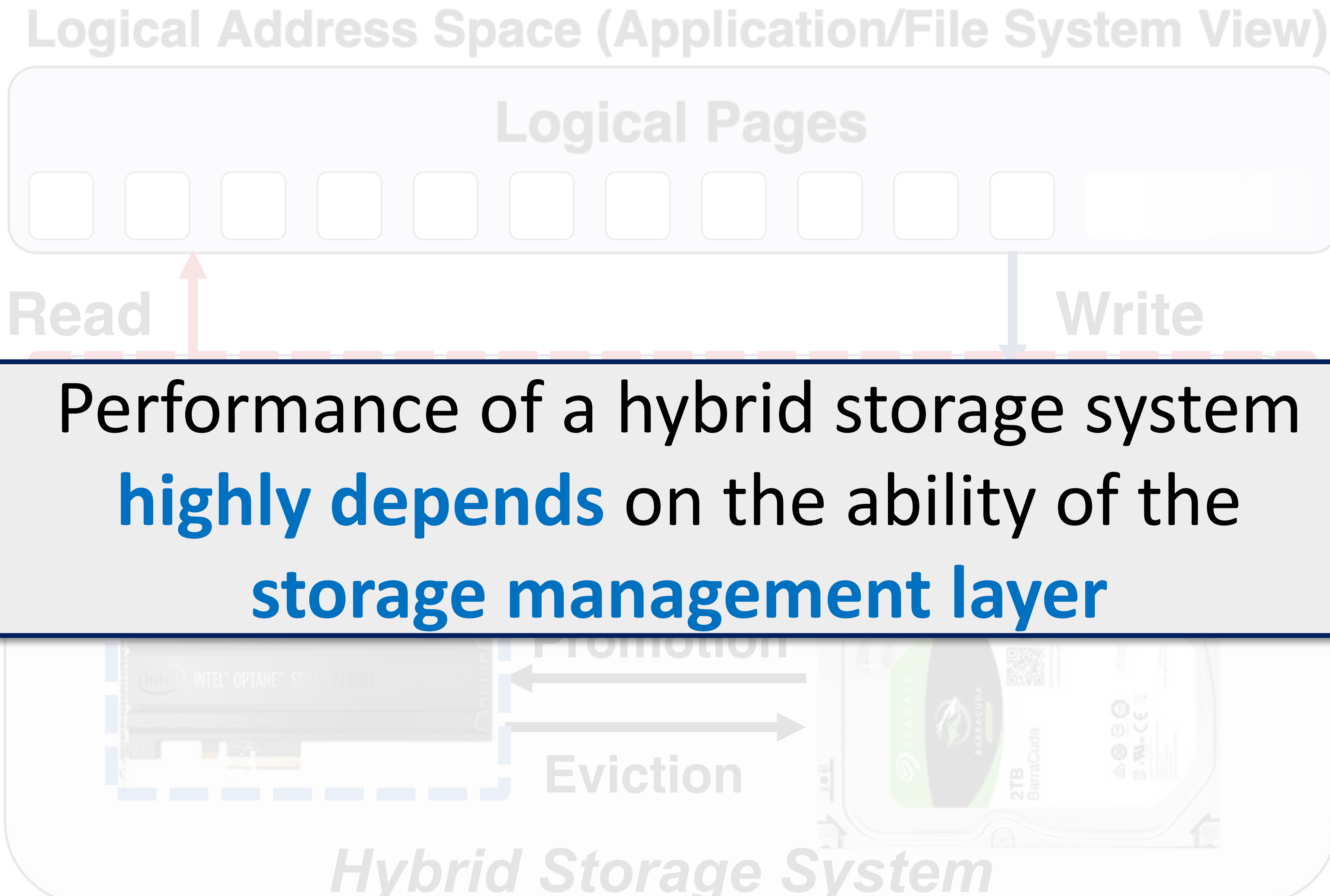
Evaluation of Sybil and Key Results

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

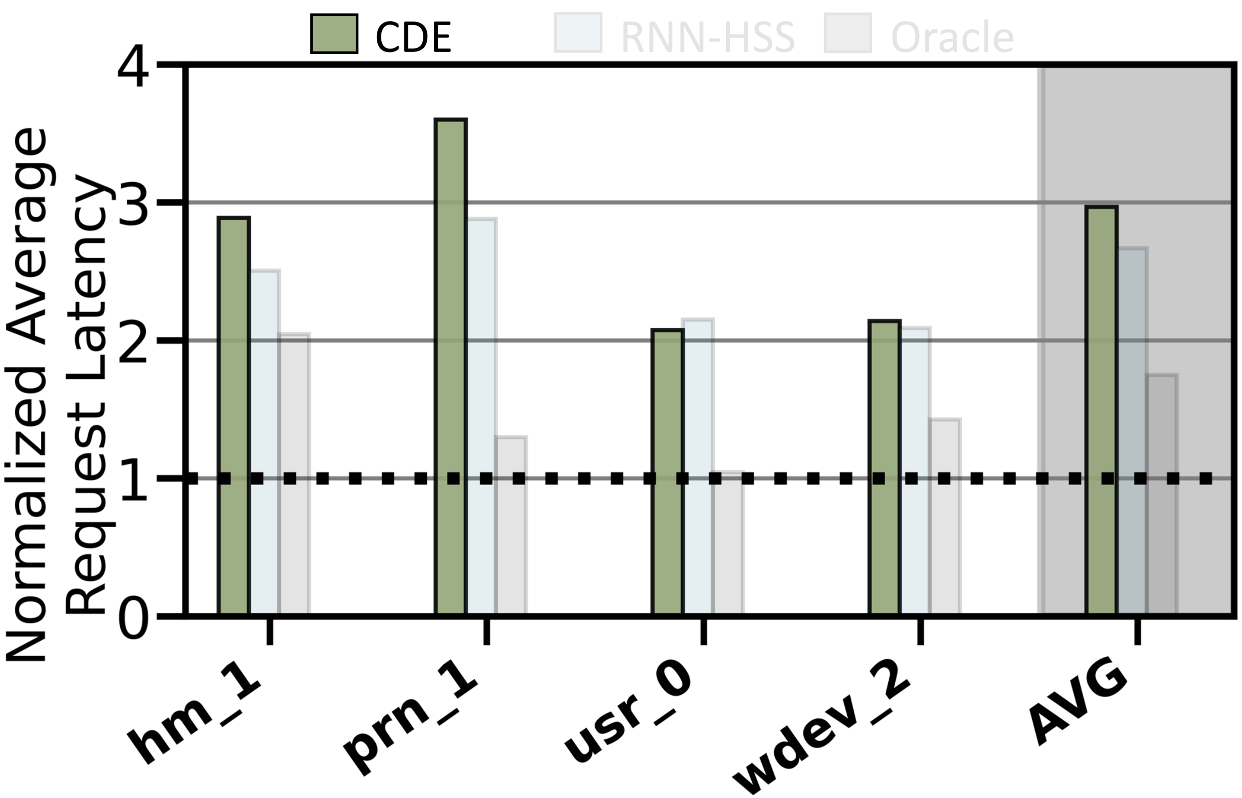
1. Lack of **adaptivity to**:
   a) **Workload changes**
   b) **Changes in device types and configuration**

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**



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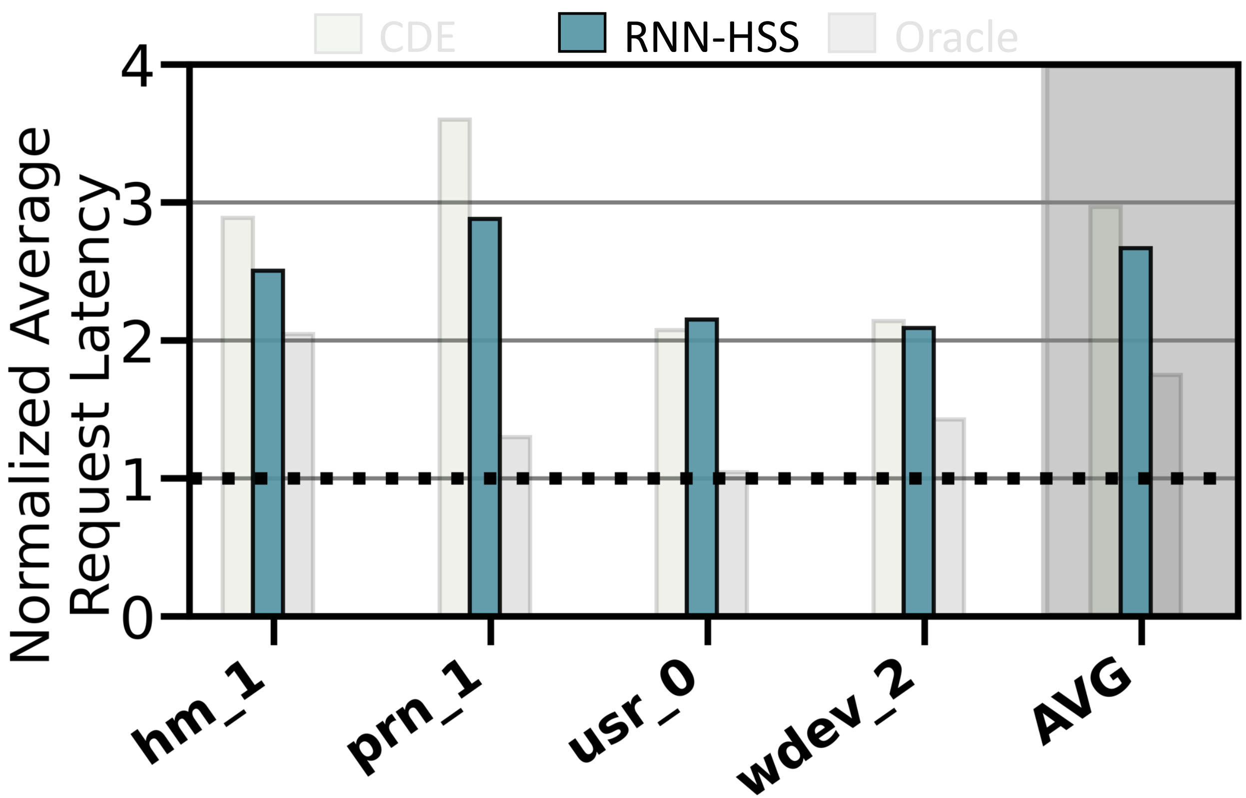

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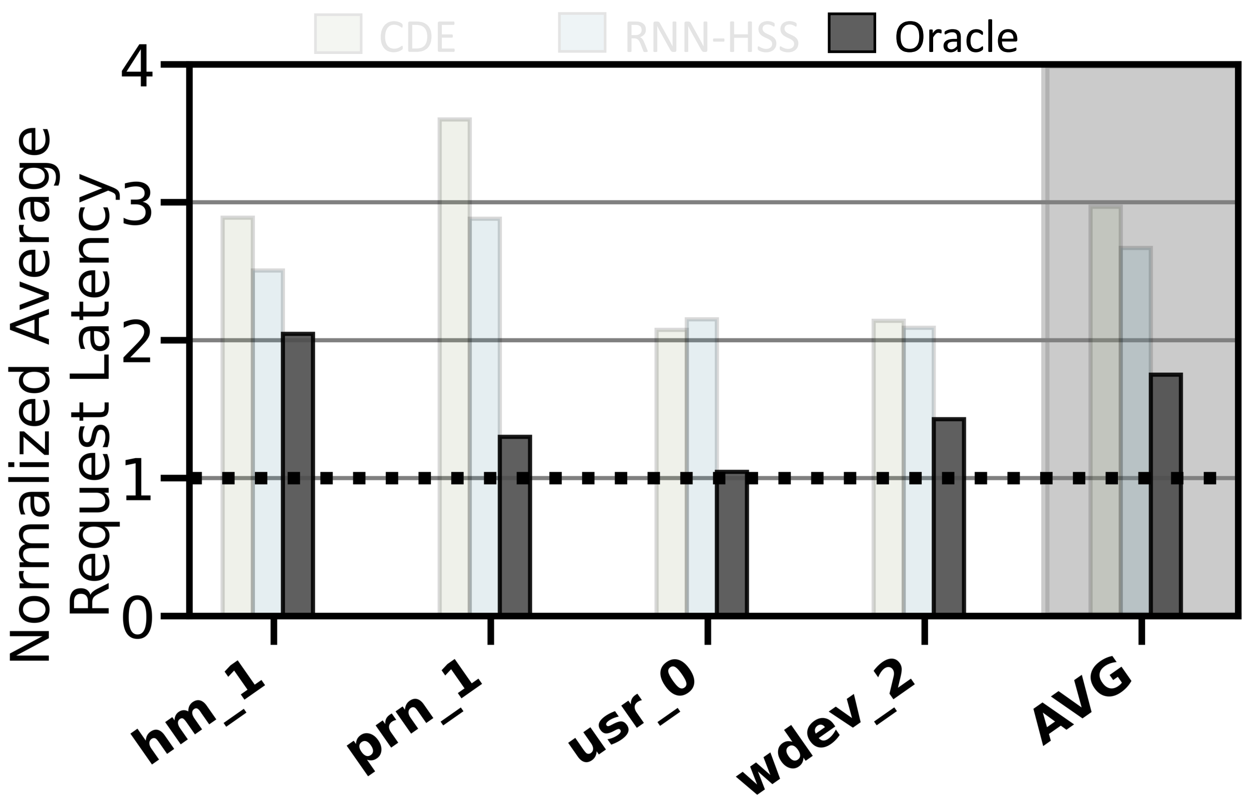

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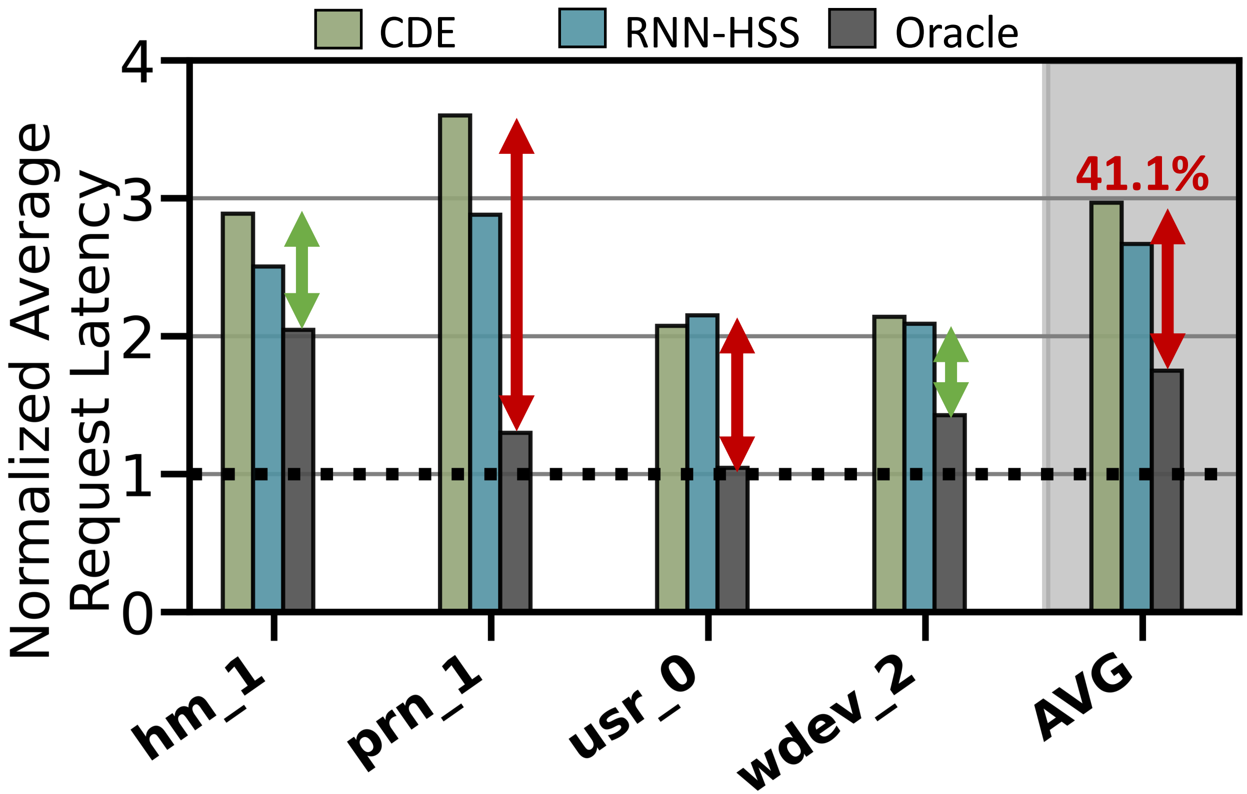
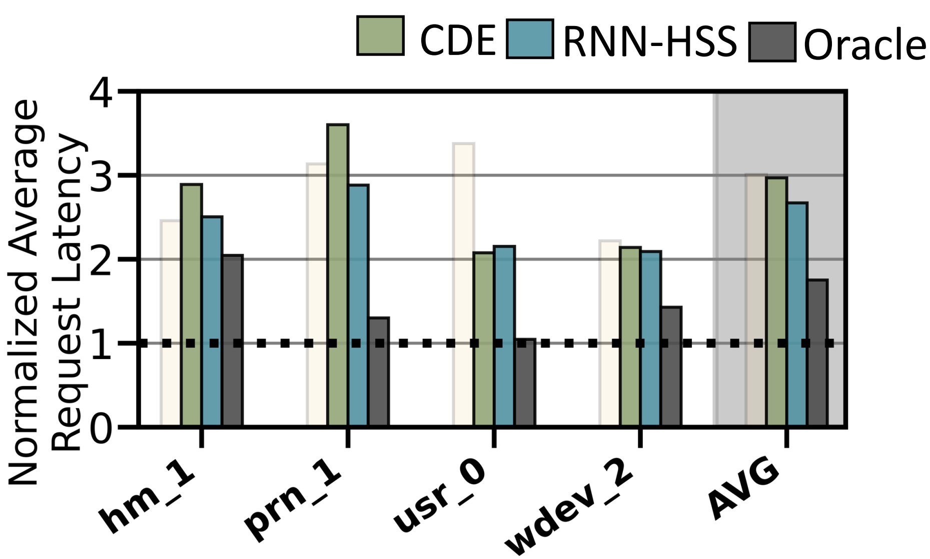


Lack of Adaptivity

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

Changes in Device Types and Configurations

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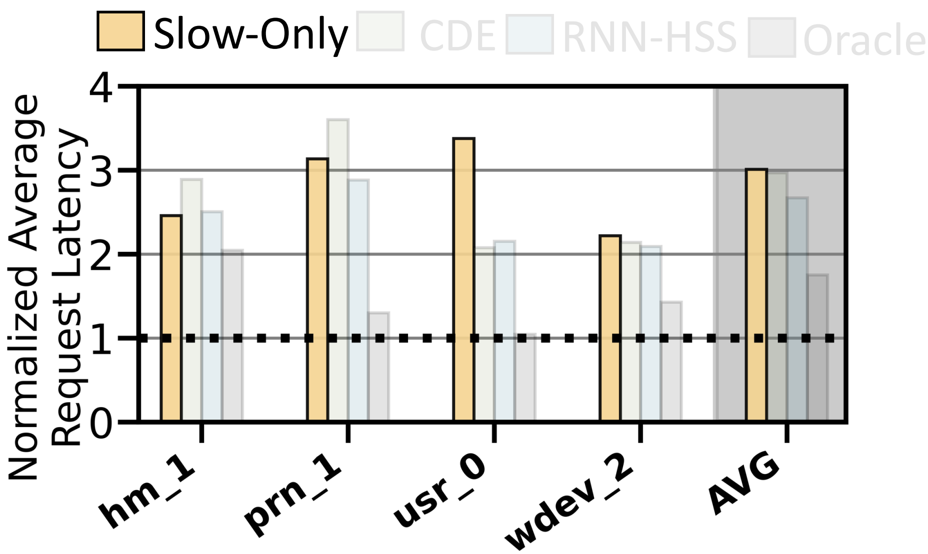

HSS Configuration 1

Lack of Adaptivity

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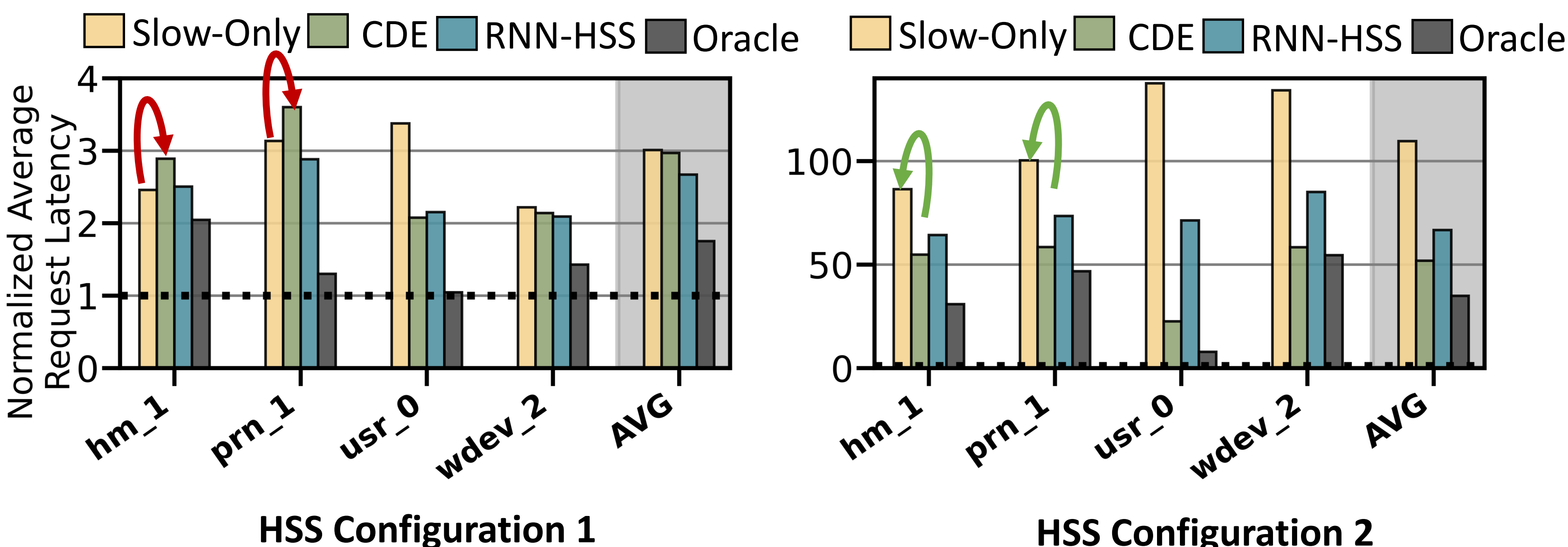
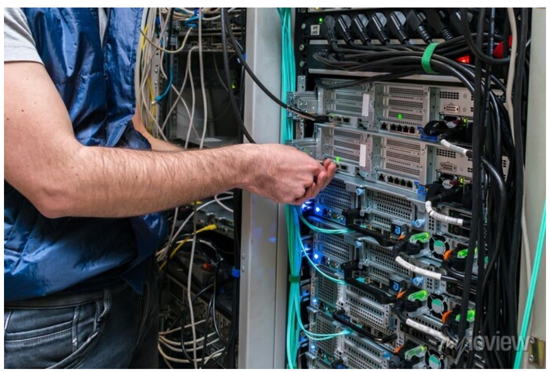
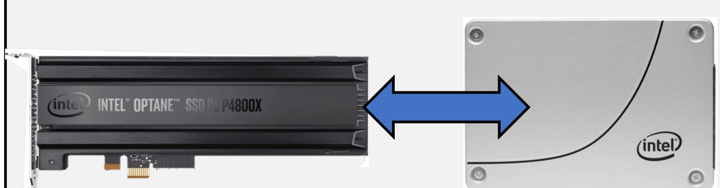


Lack of Extensibility

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

Change in storage configuration



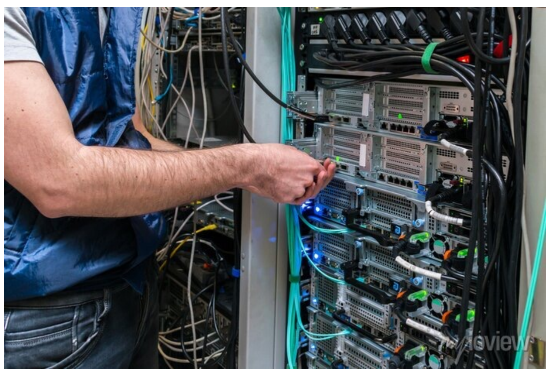


Dual-HSS

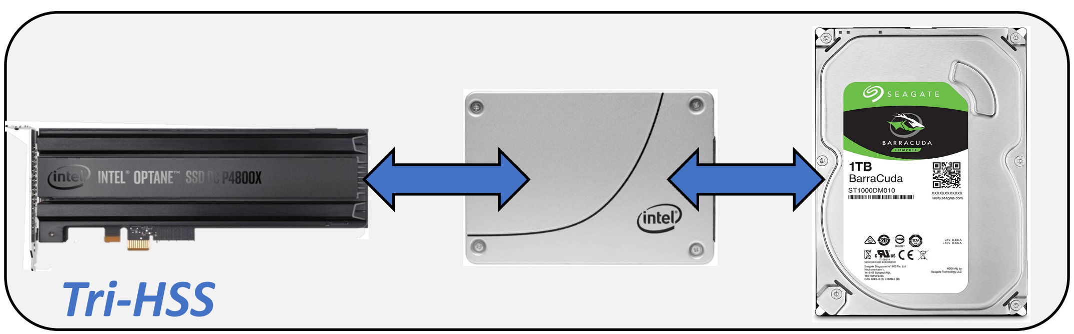
Lack of Extensibility

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

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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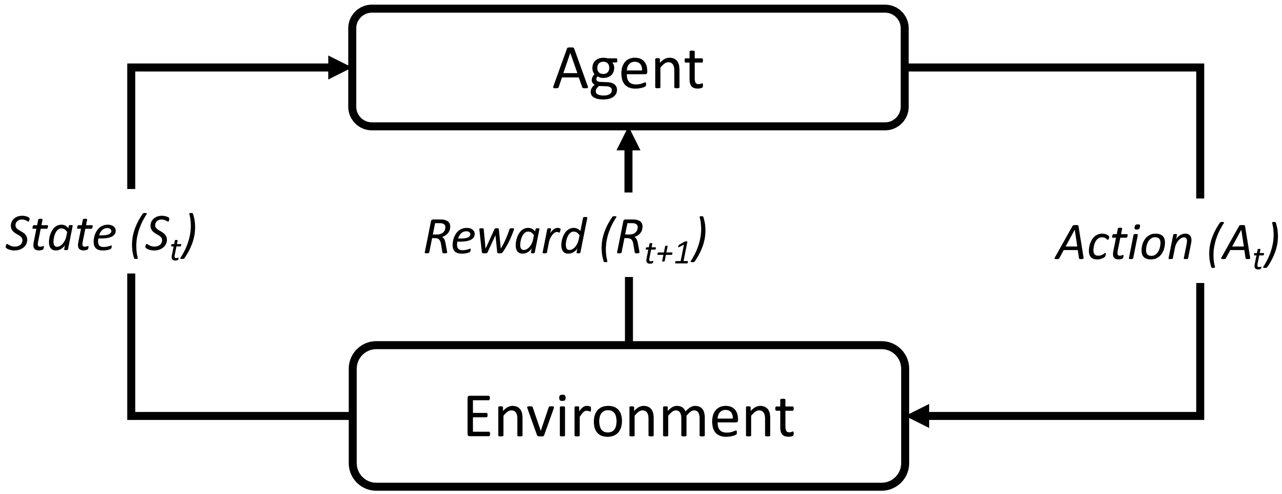
Basics of Reinforcement Learning (RL)

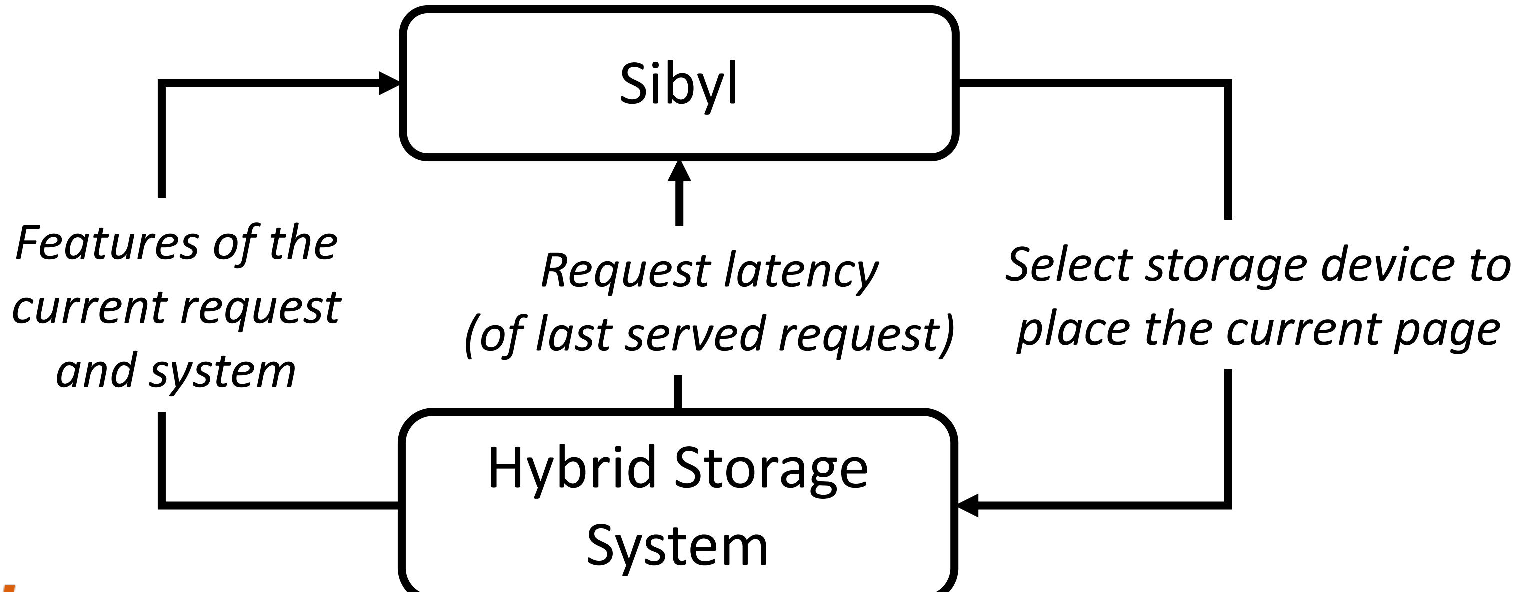
Agent

Environment

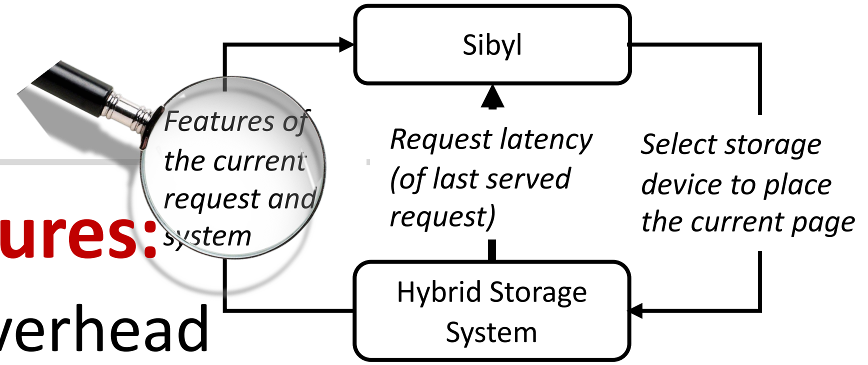
Agent learns to take an **action** in a given **state**
to maximize a numerical **reward**

Formulating Data Placement as RL





What is State?



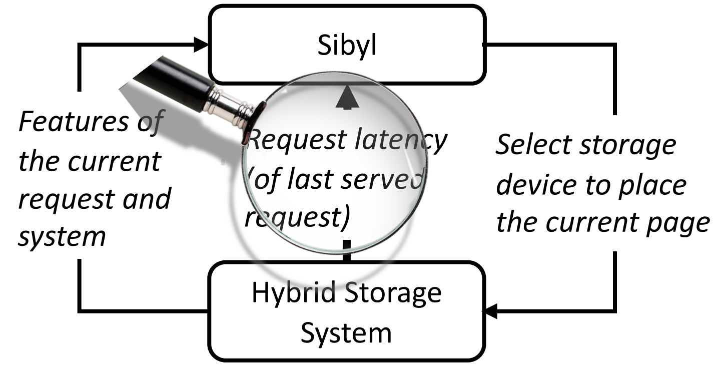
- **Limited number of state features:**
  - Reduce the implementation overhead
  - RL agent is more sensitive to reward

- ***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?



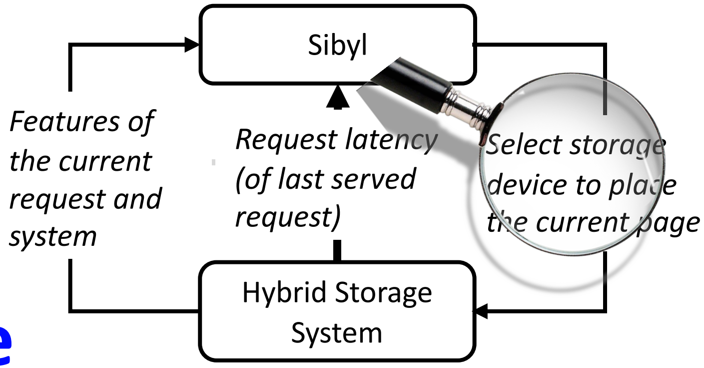
- Defines the **objective** of Sibyl

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

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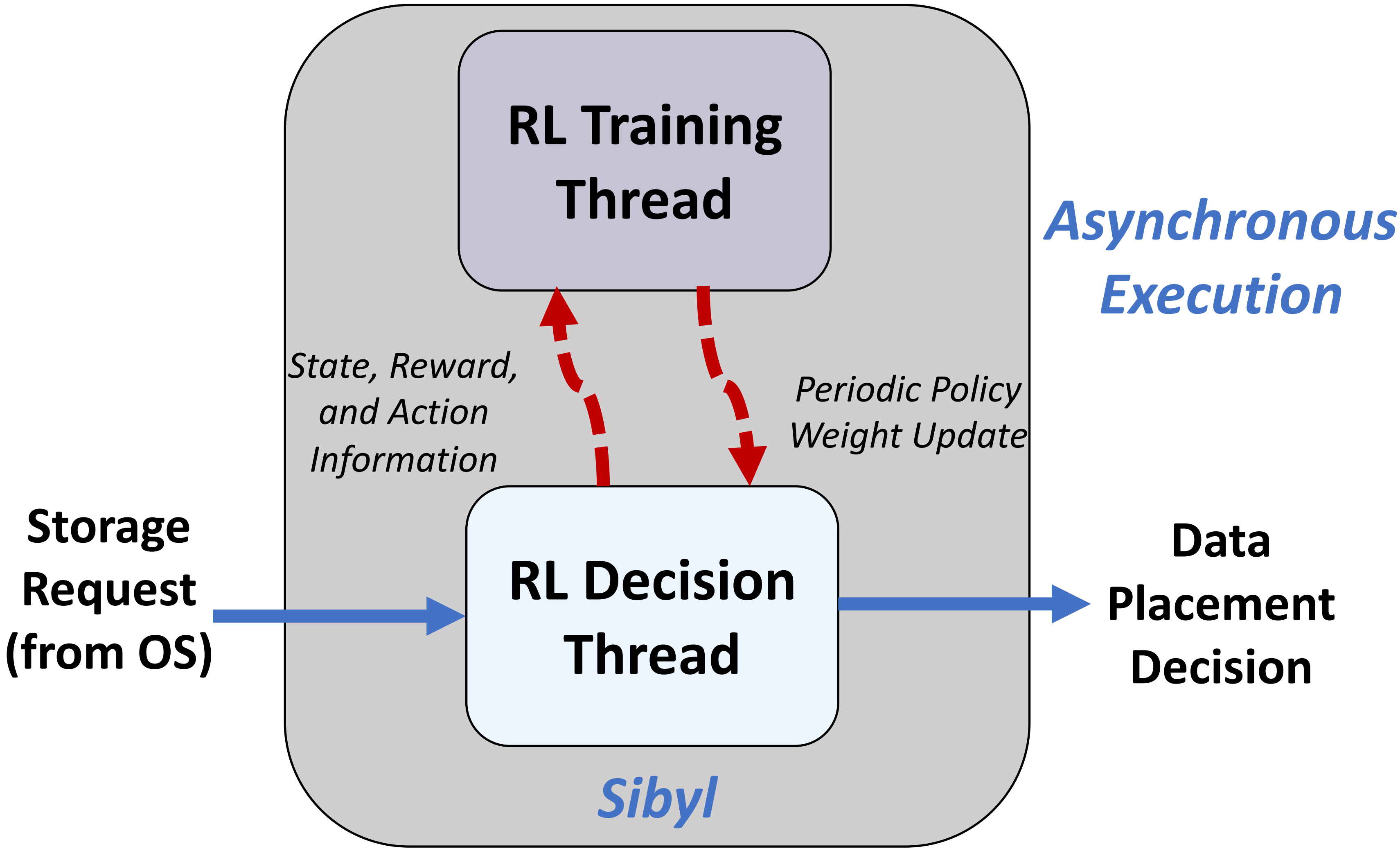
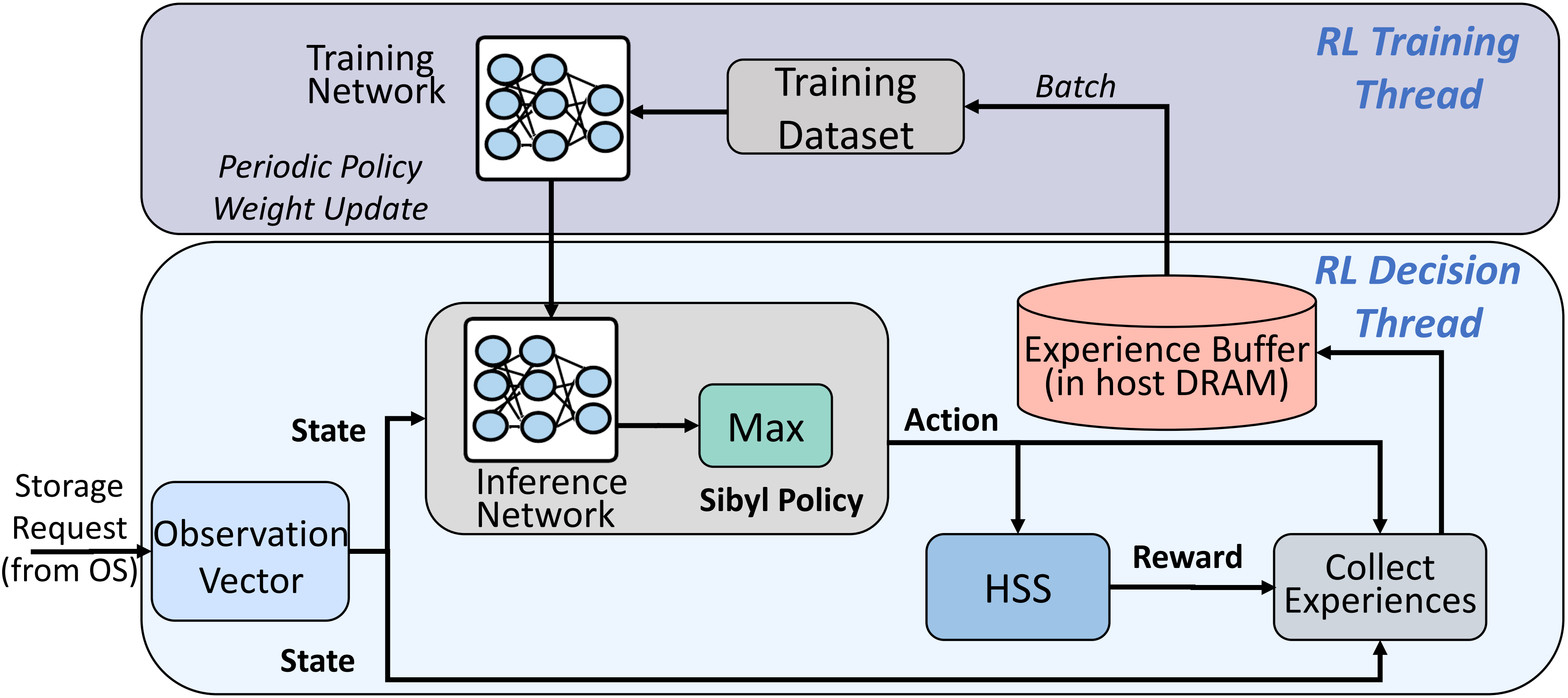
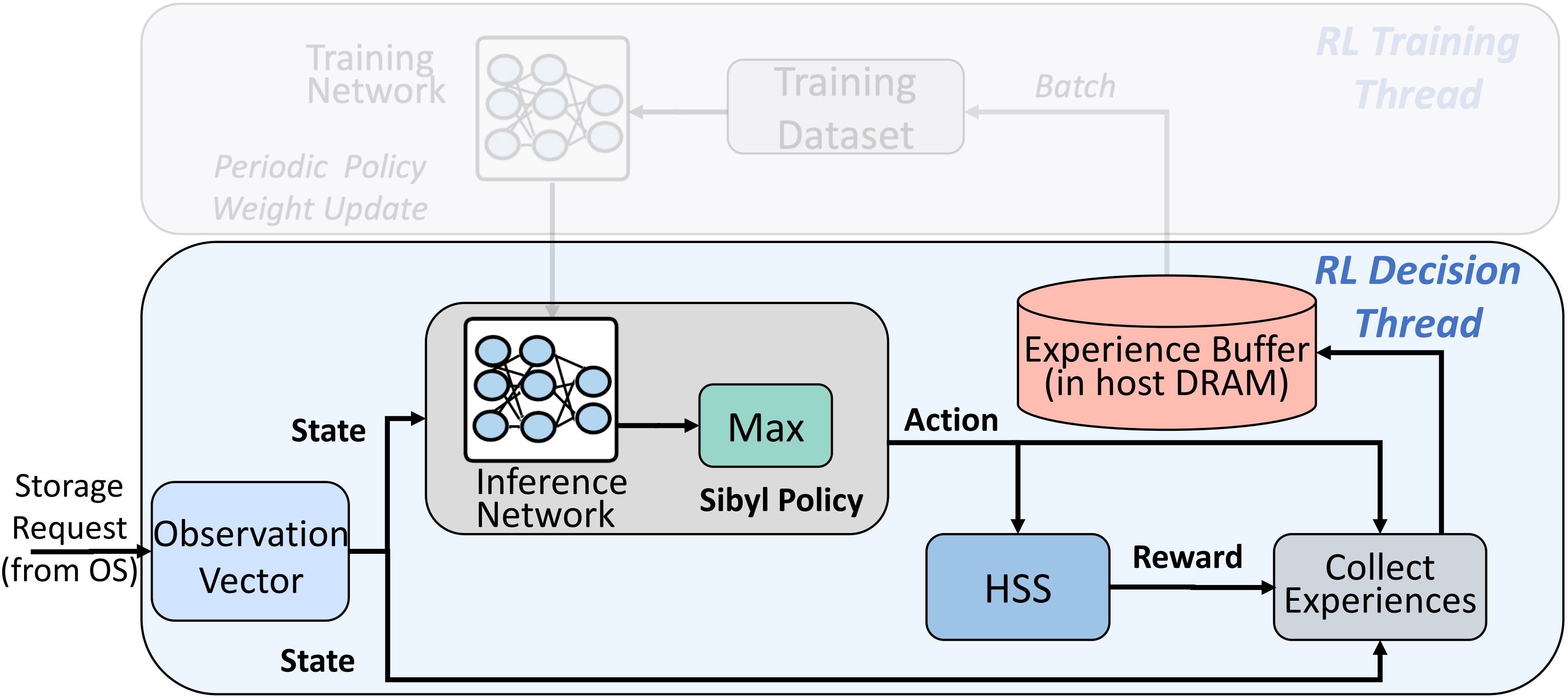
Sibyl Execution



Sibyl Design: Overview



RL Decision Thread



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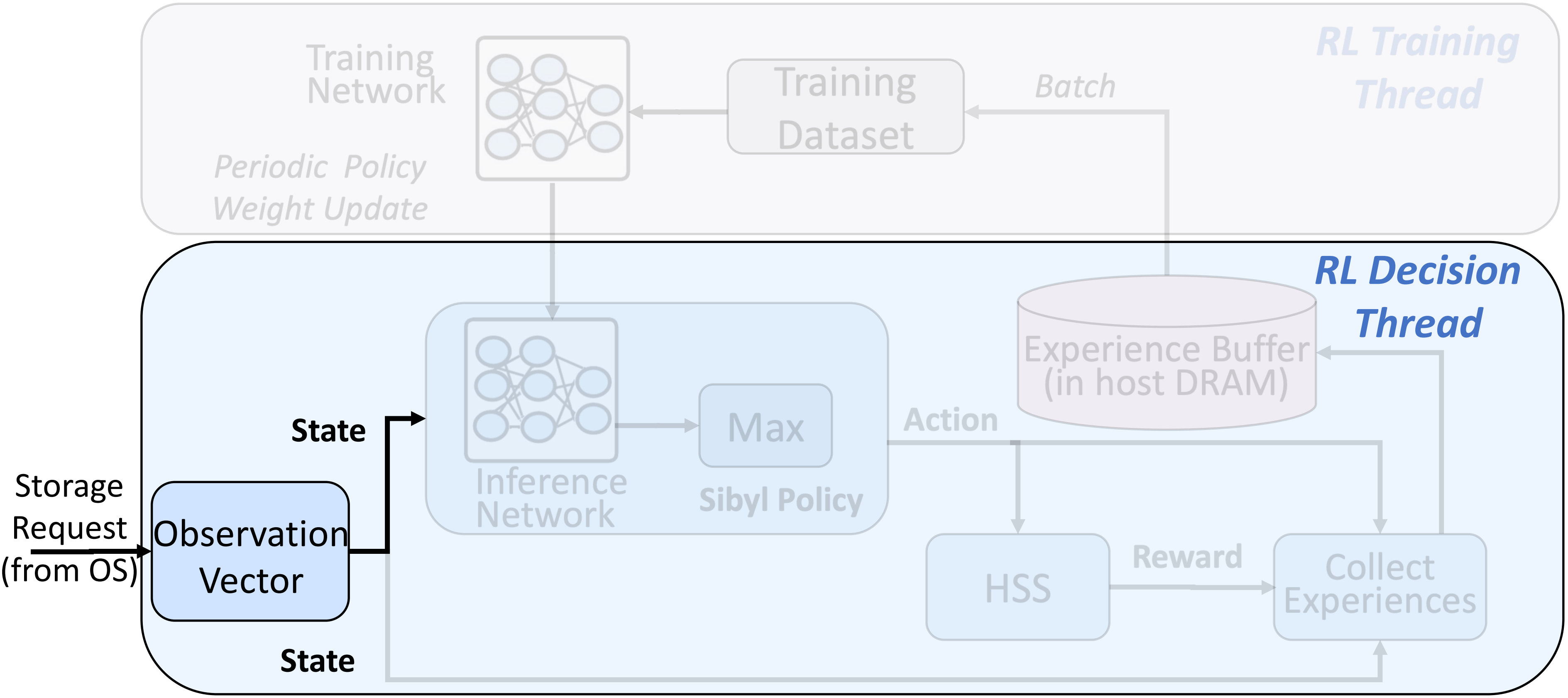

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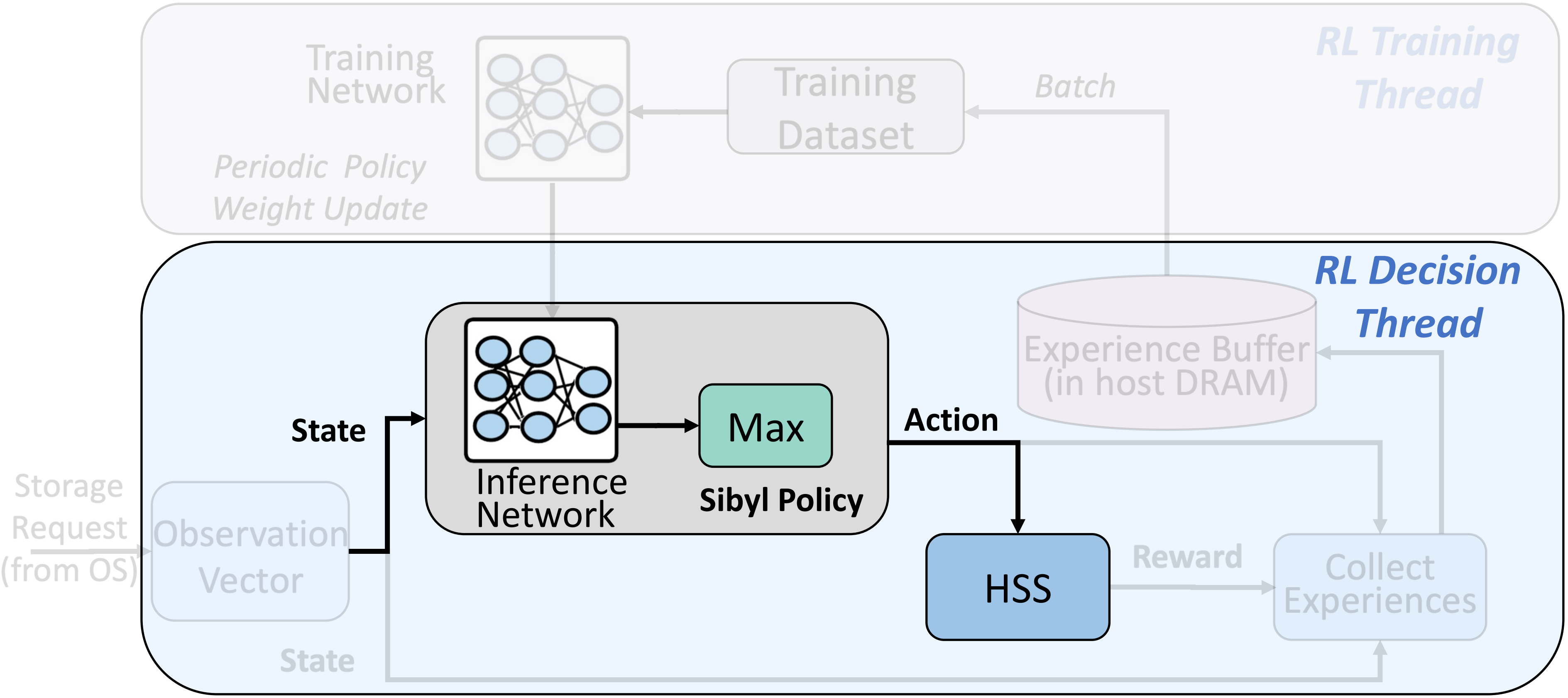

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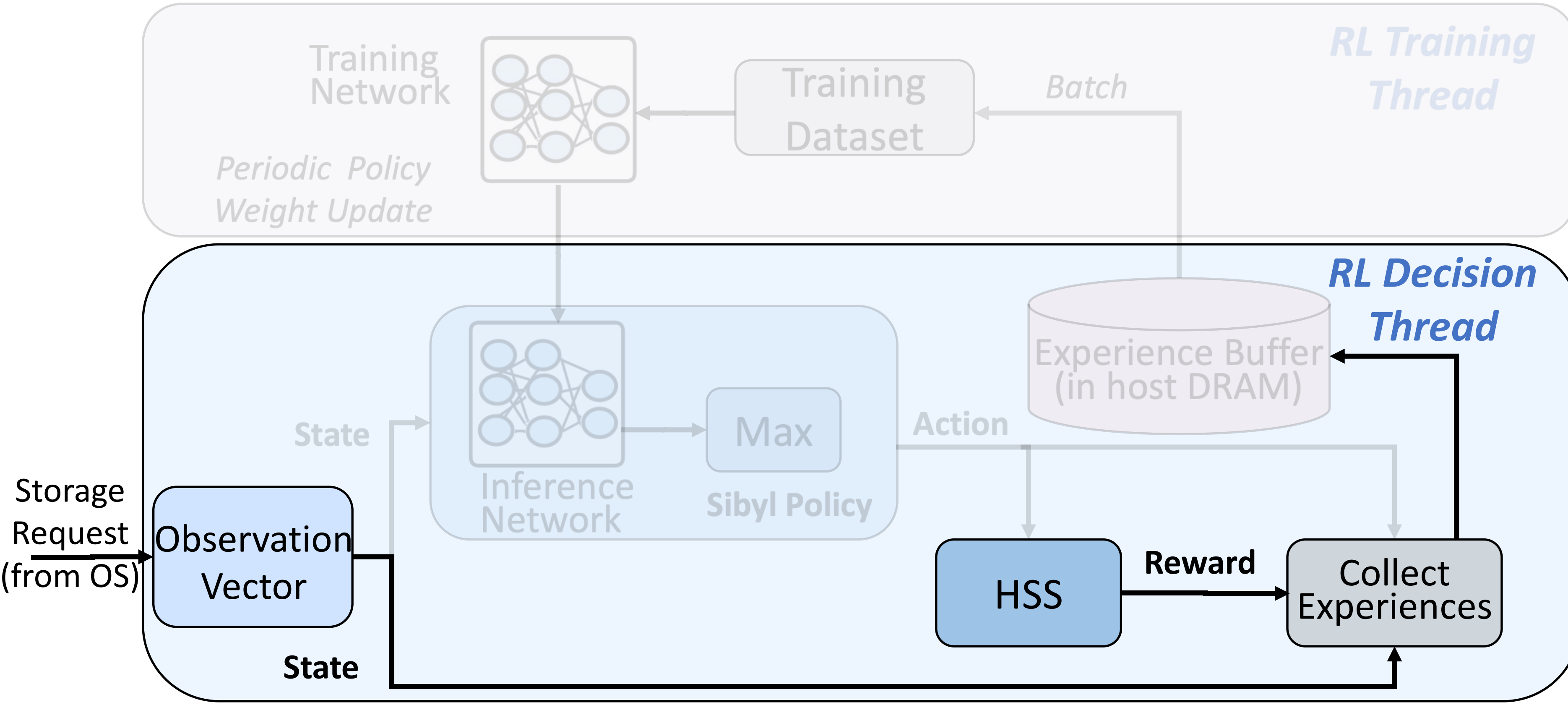
RL Decision Thread



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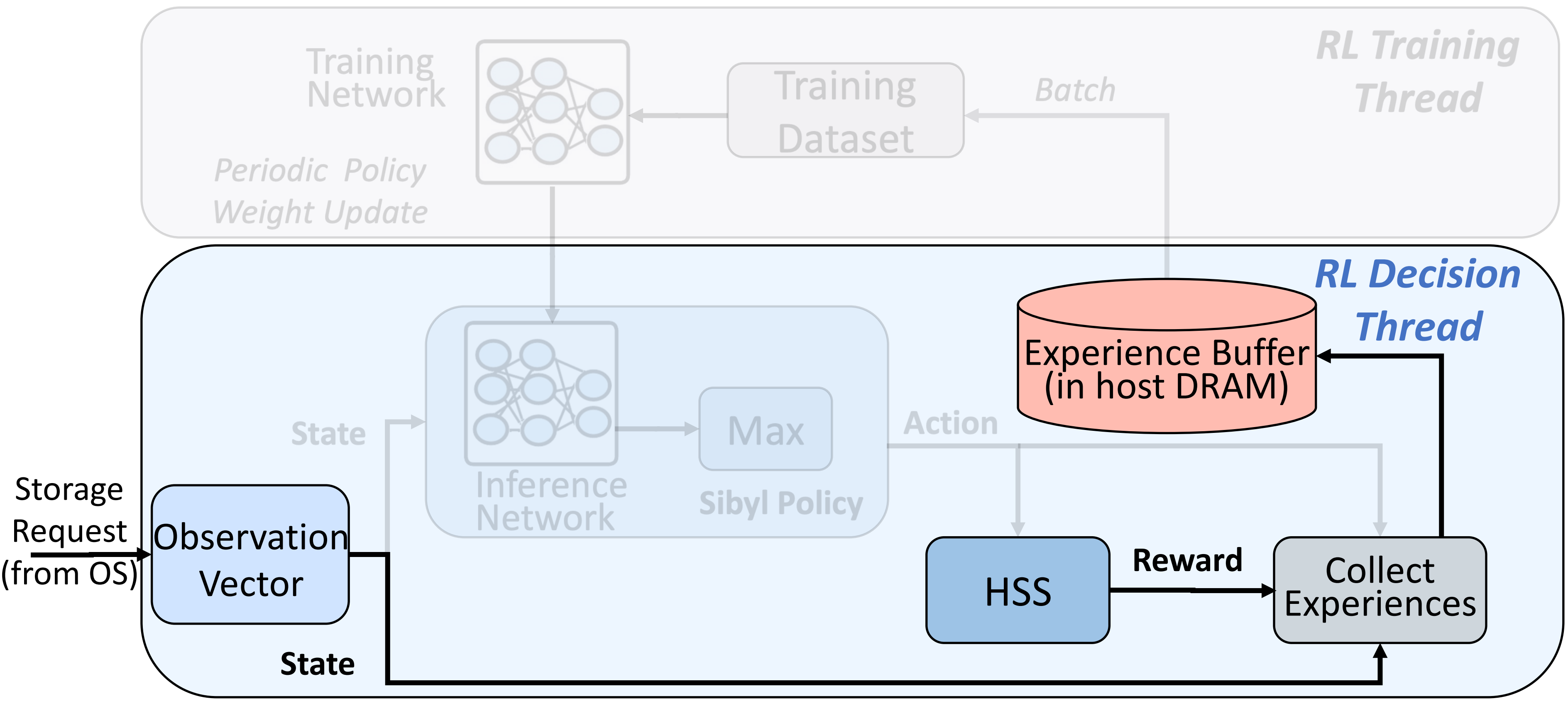
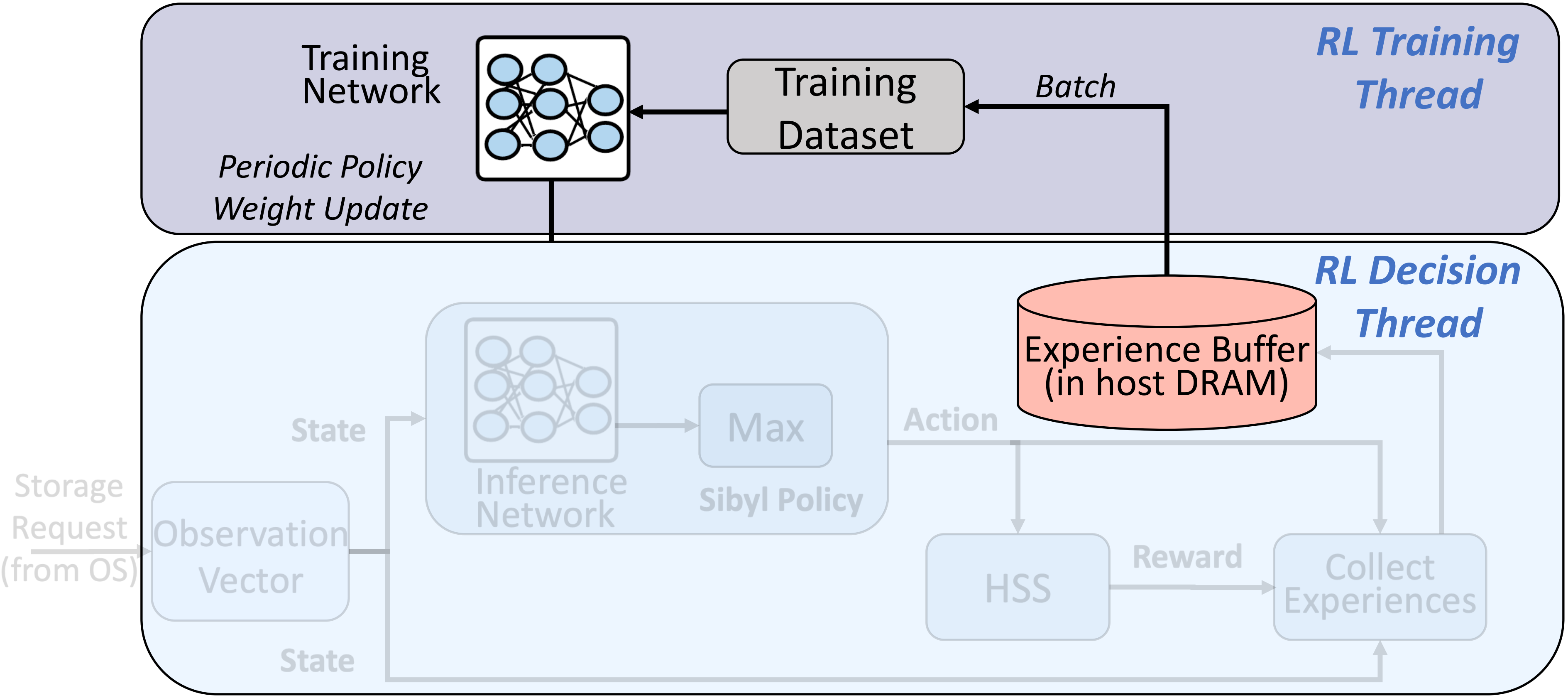
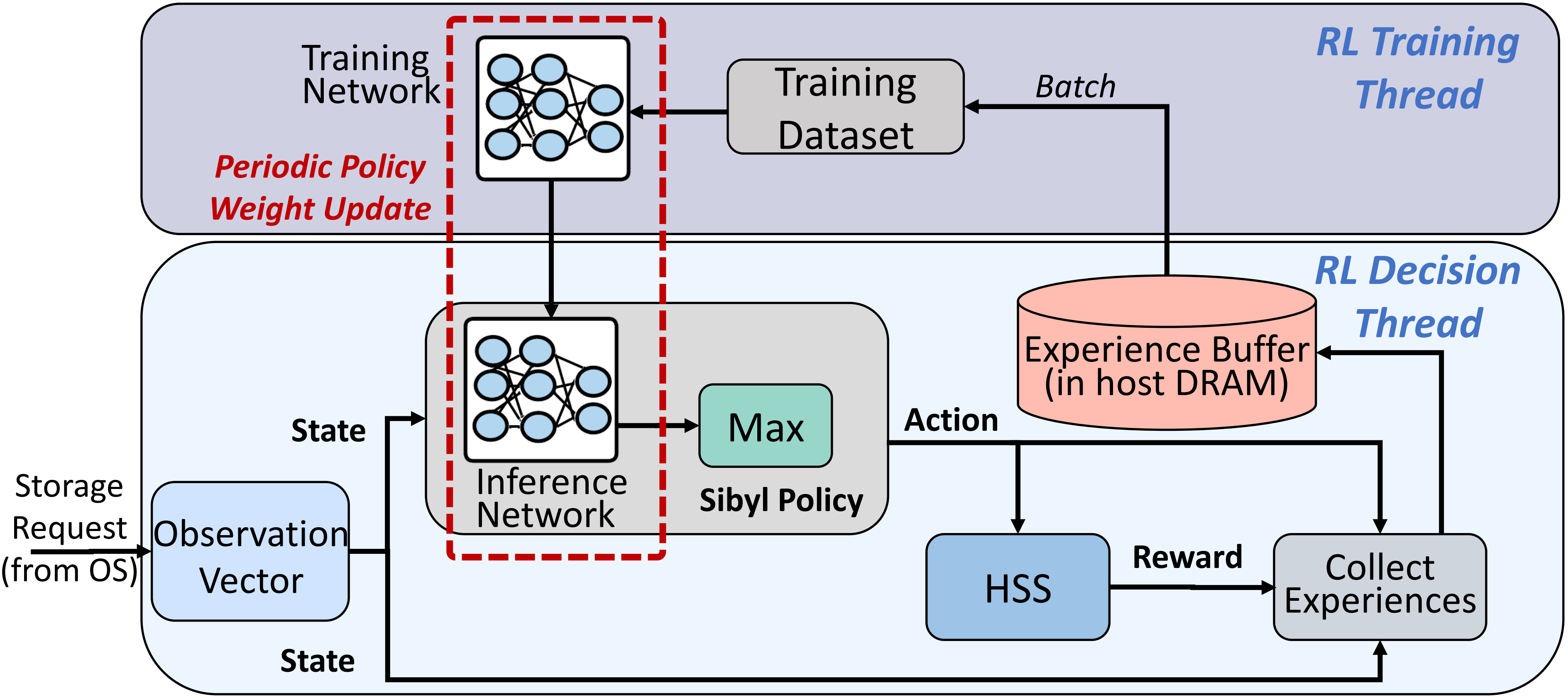


RL Training Thread



Periodic Weight Transfer



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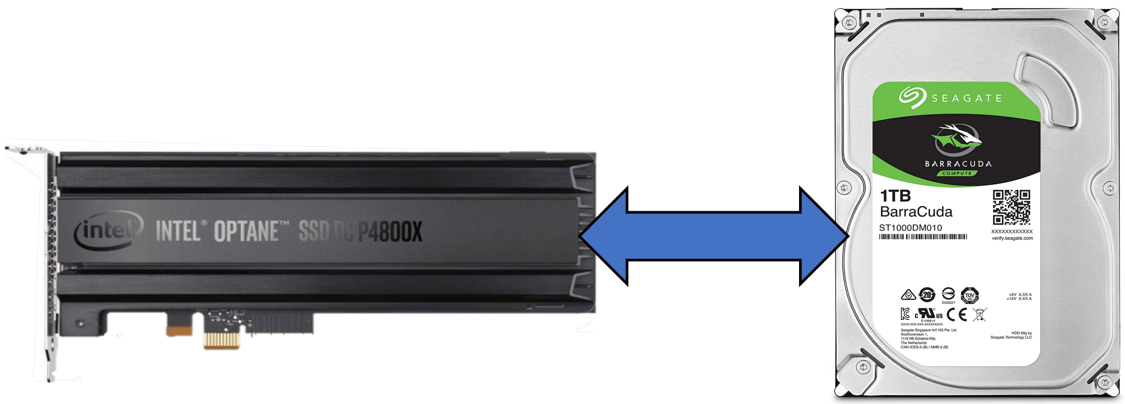
Evaluation Methodology (1/3)

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

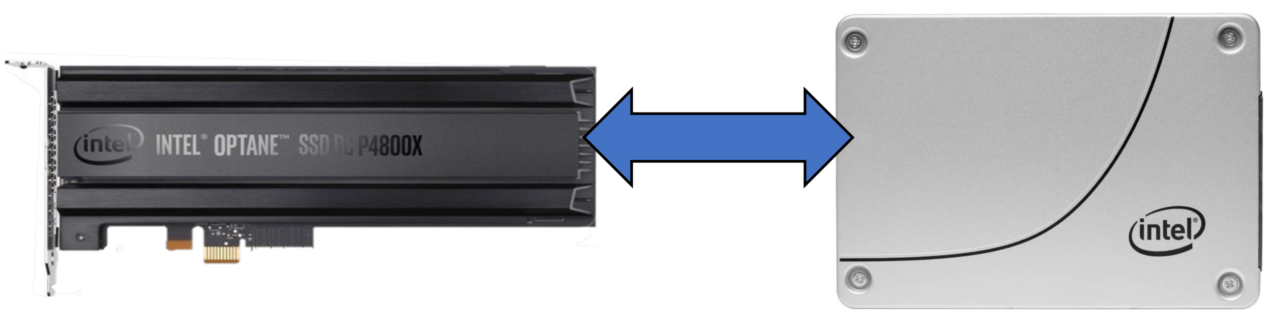
Evaluation Methodology (2/3)

Cost-Oriented HSS Configuration



High-end SSD *Low-end HDD*

Performance-Oriented HSS Configuration



High-end SSD *Middle-end SSD*

Evaluation Methodology (3/3)

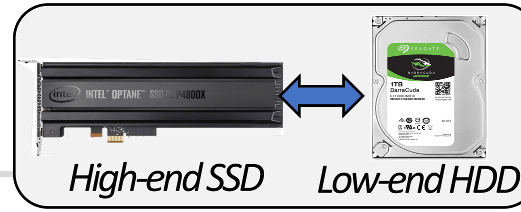
- **18 different workloads** from:
  - MSR Cambridge and Filebench Suites

- **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]

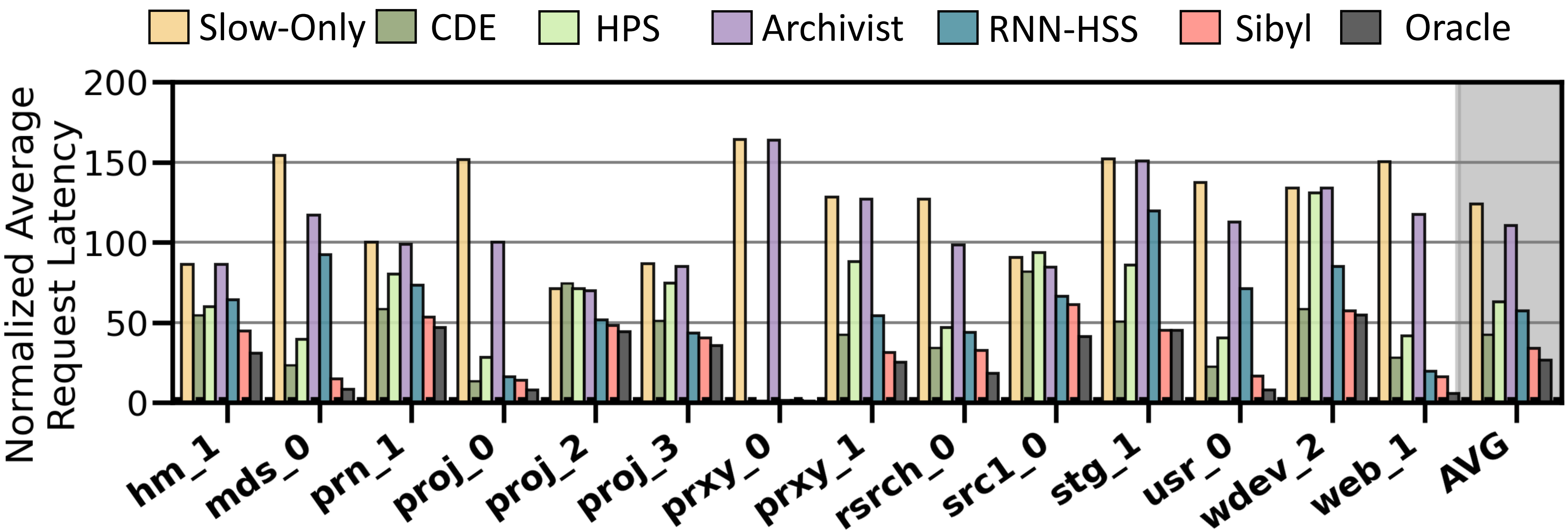
Heuristic-based

Learning-based

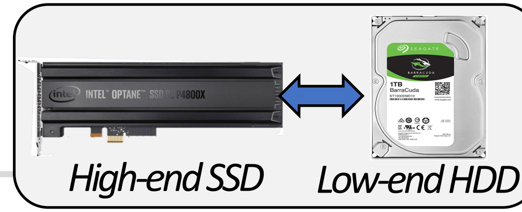
Performance Analysis



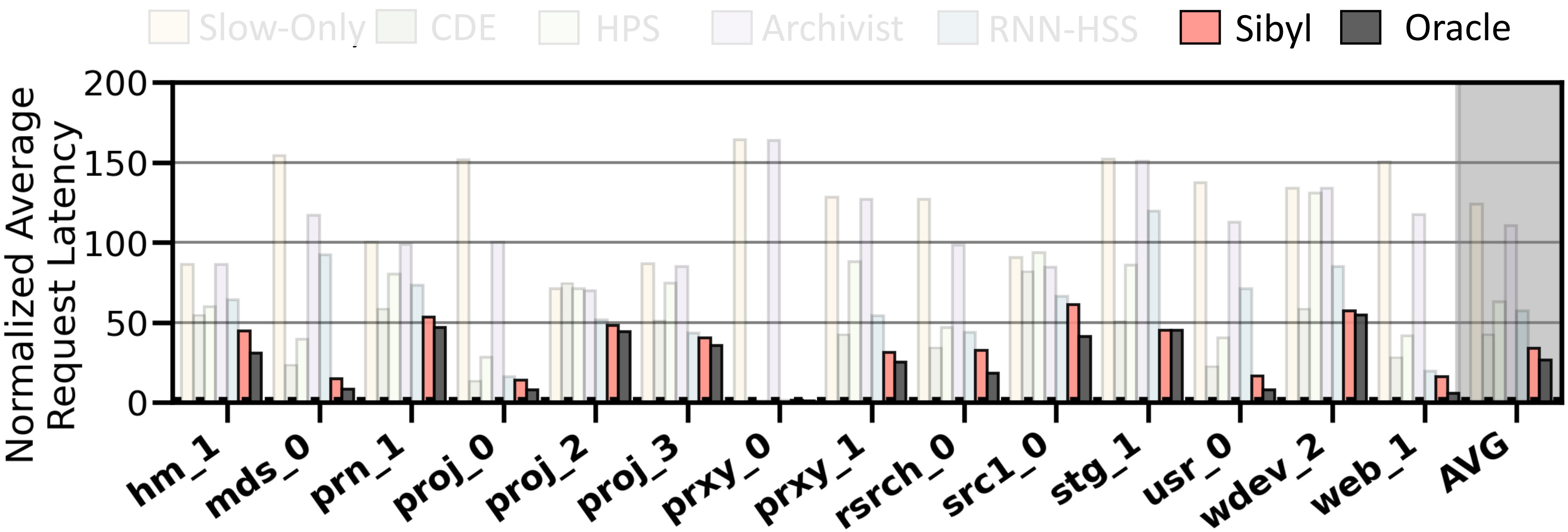
Cost-Oriented HSS Configuration



Performance Analysis

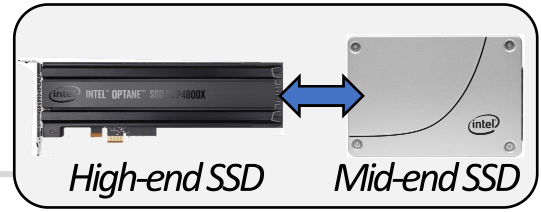


Cost-Oriented HSS Configuration

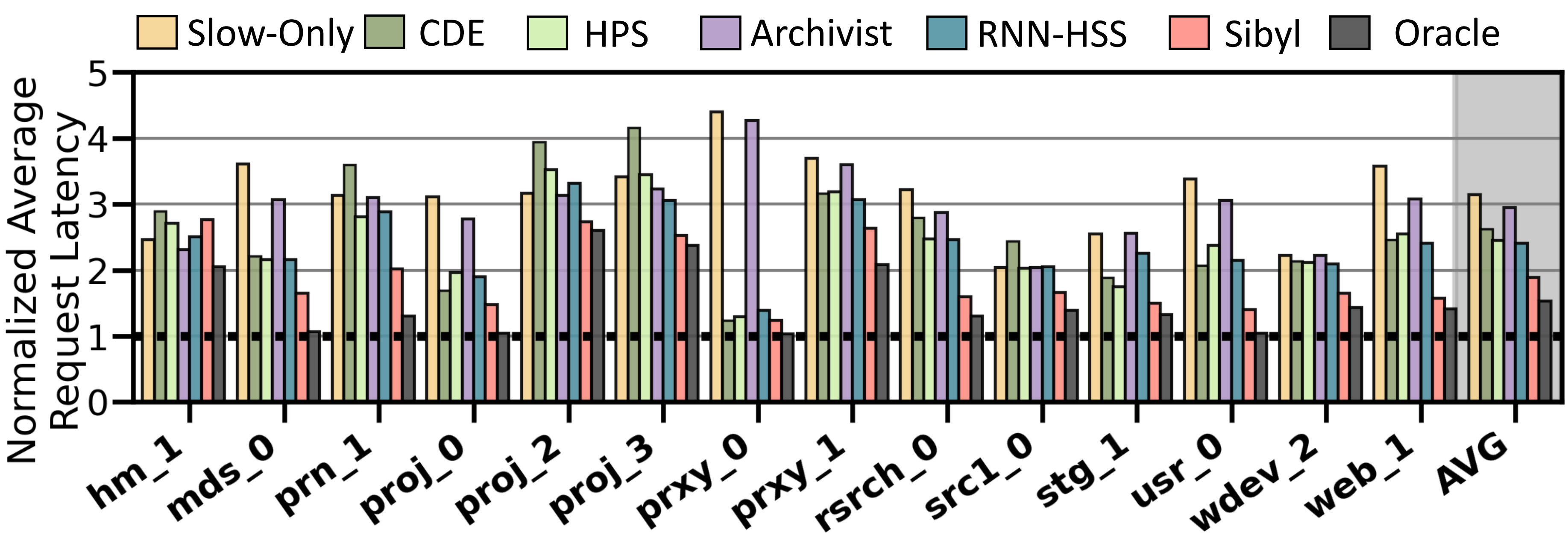


Sibyl consistently **outperforms all the baselines for all the workloads**

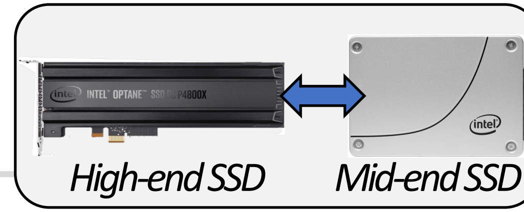
Performance Analysis



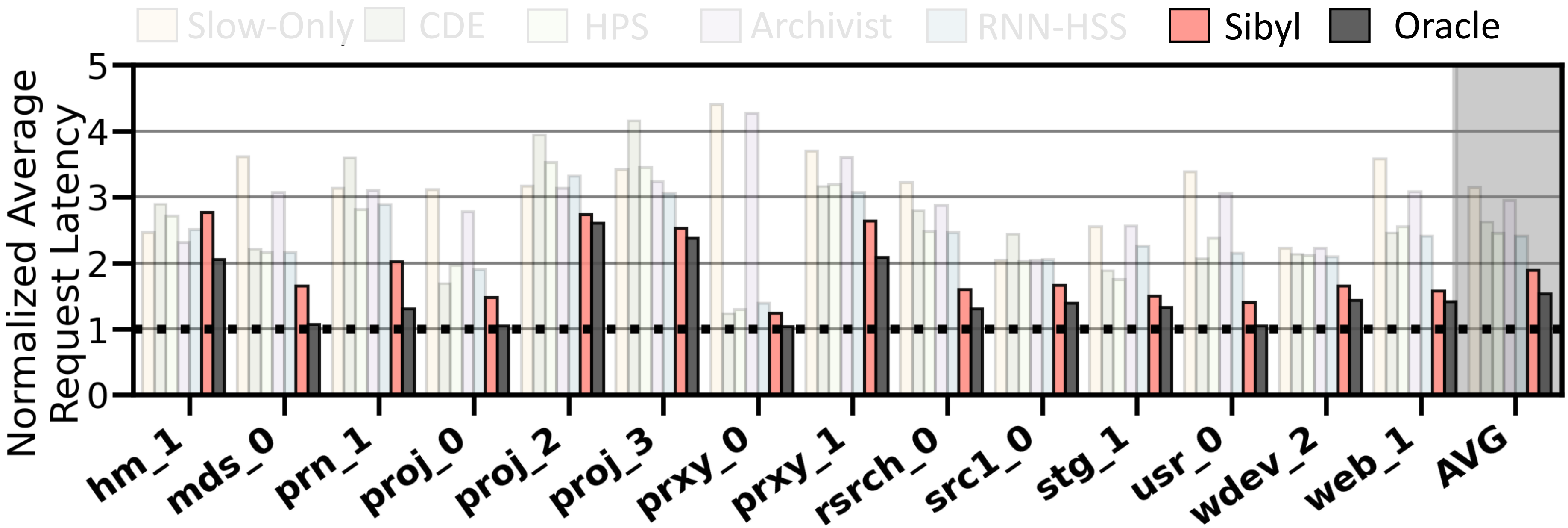
Performance-Oriented HSS Configuration



Performance Analysis

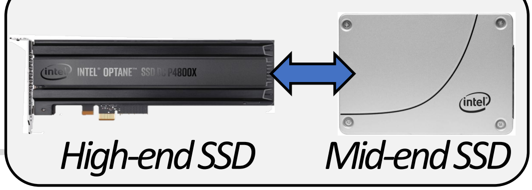


Performance-Oriented HSS Configuration

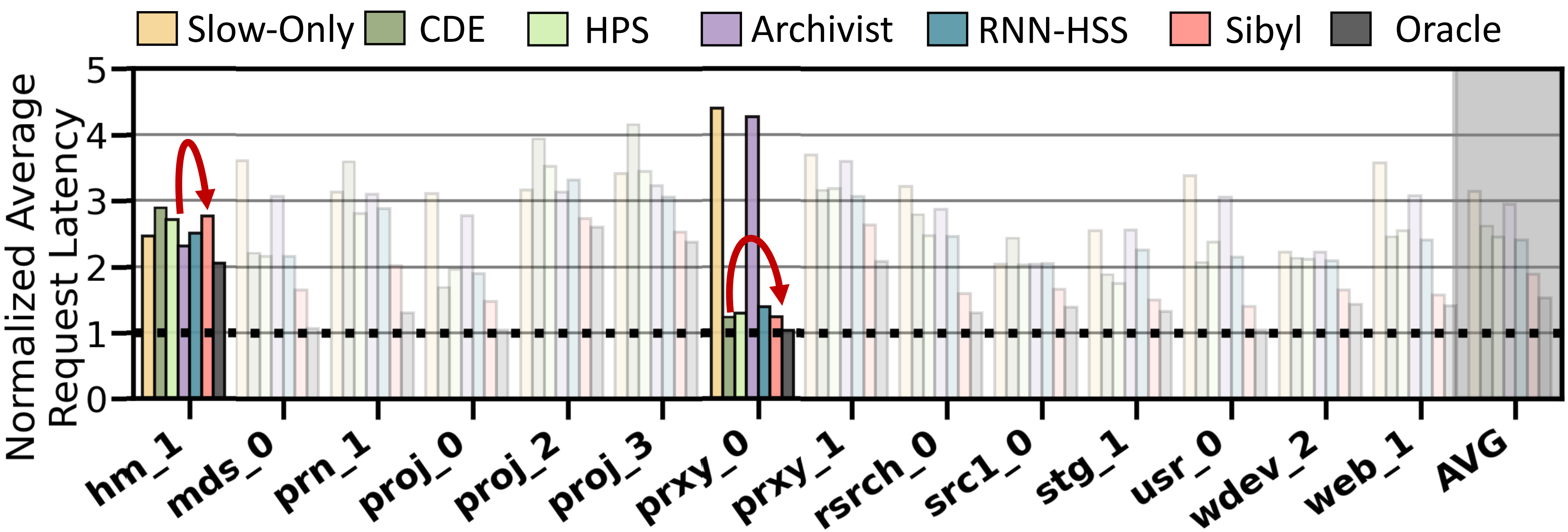


Sibyl provides **21.6% performance improvement** by **dynamically adapting its data placement policy**

Performance Analysis



Performance-Oriented HSS Configuration



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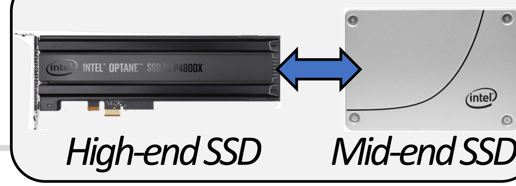
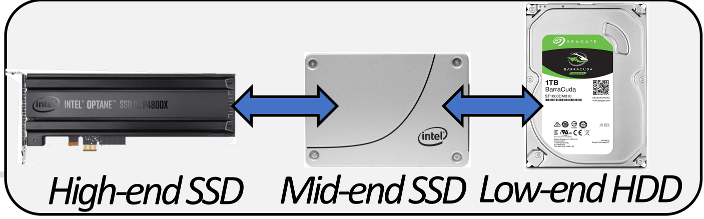
Performance Analysis



Performance-Oriented HSS Configuration

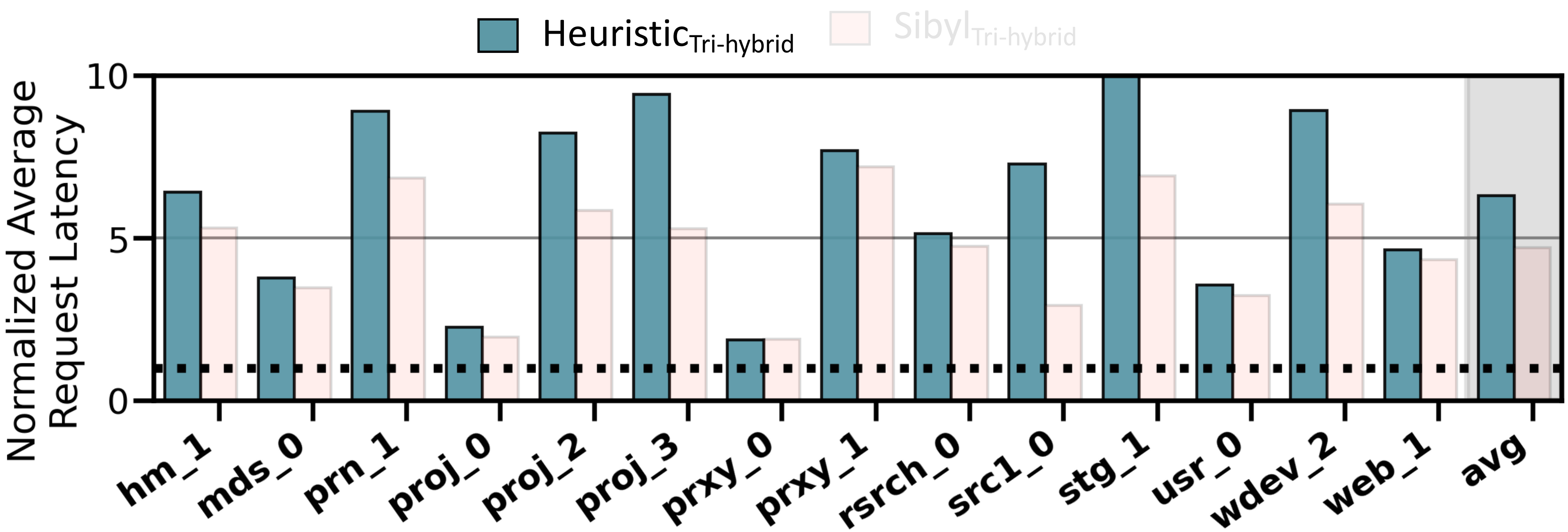
Sibyl achieves **80% of the performance of an oracle policy** that has complete knowledge of future access patterns

Performance on Tri-HSS

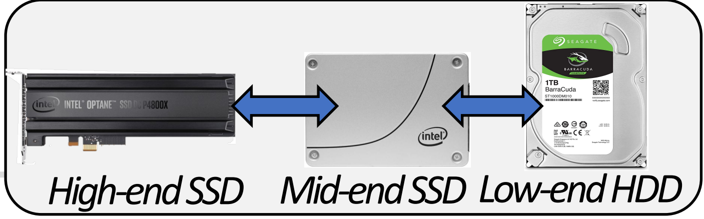


Extending Sibyl for **more devices**:

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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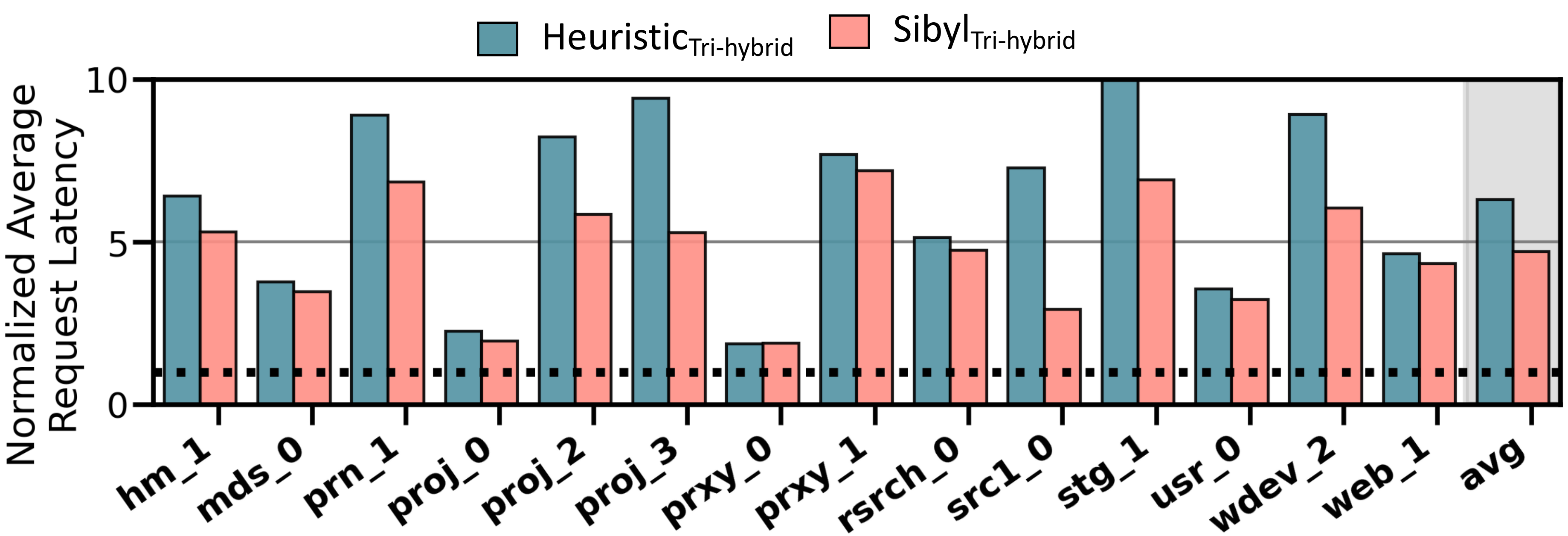
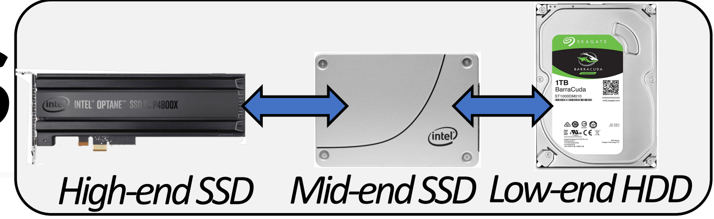


Performance on Tri-HSS



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

Talk Outline

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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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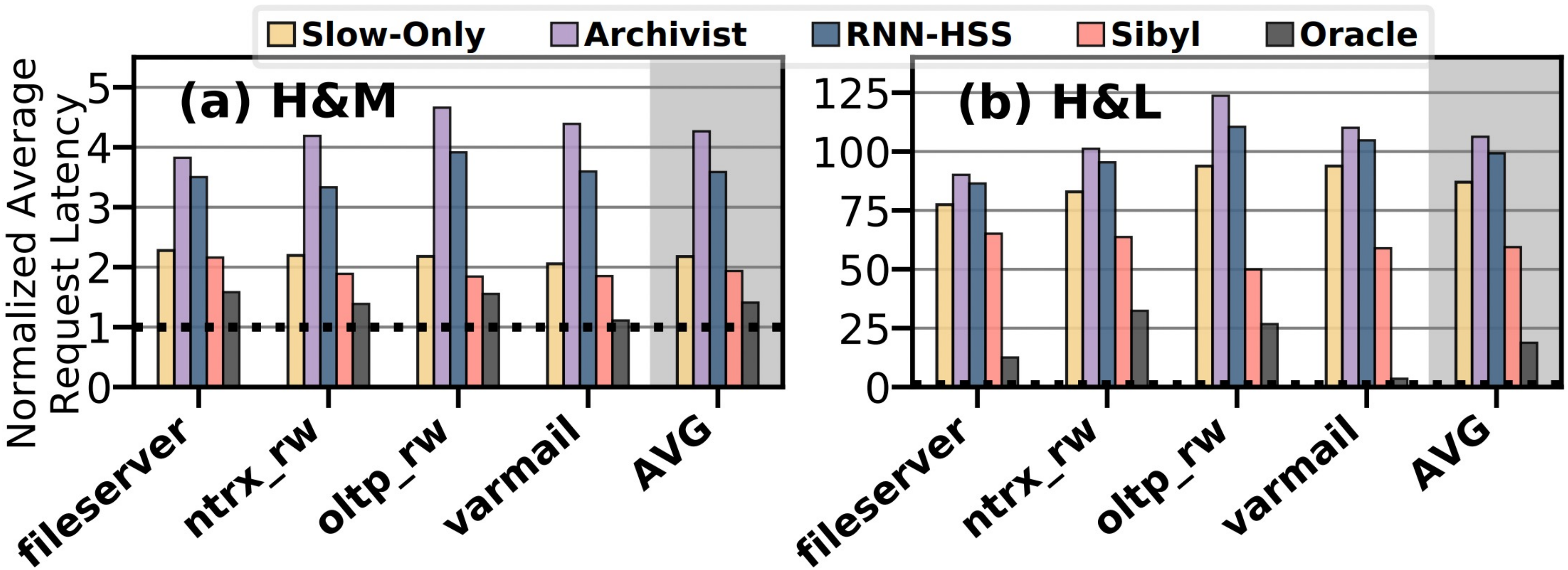
BACKUP

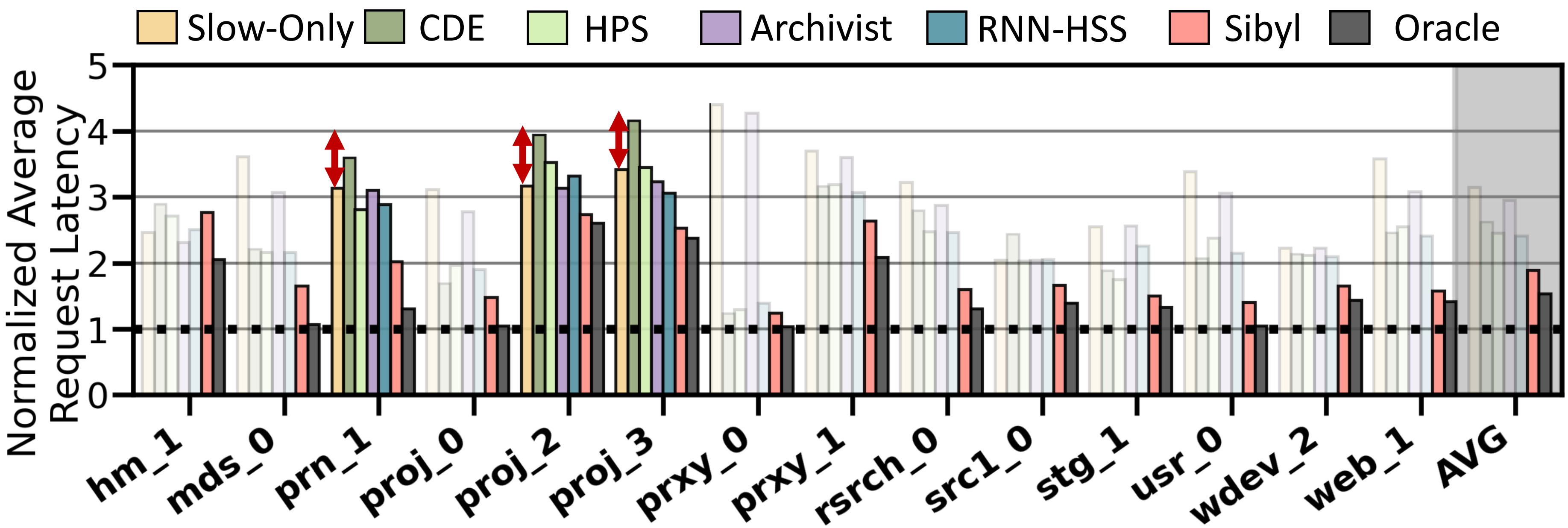
Performance on Unseen Workloads



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

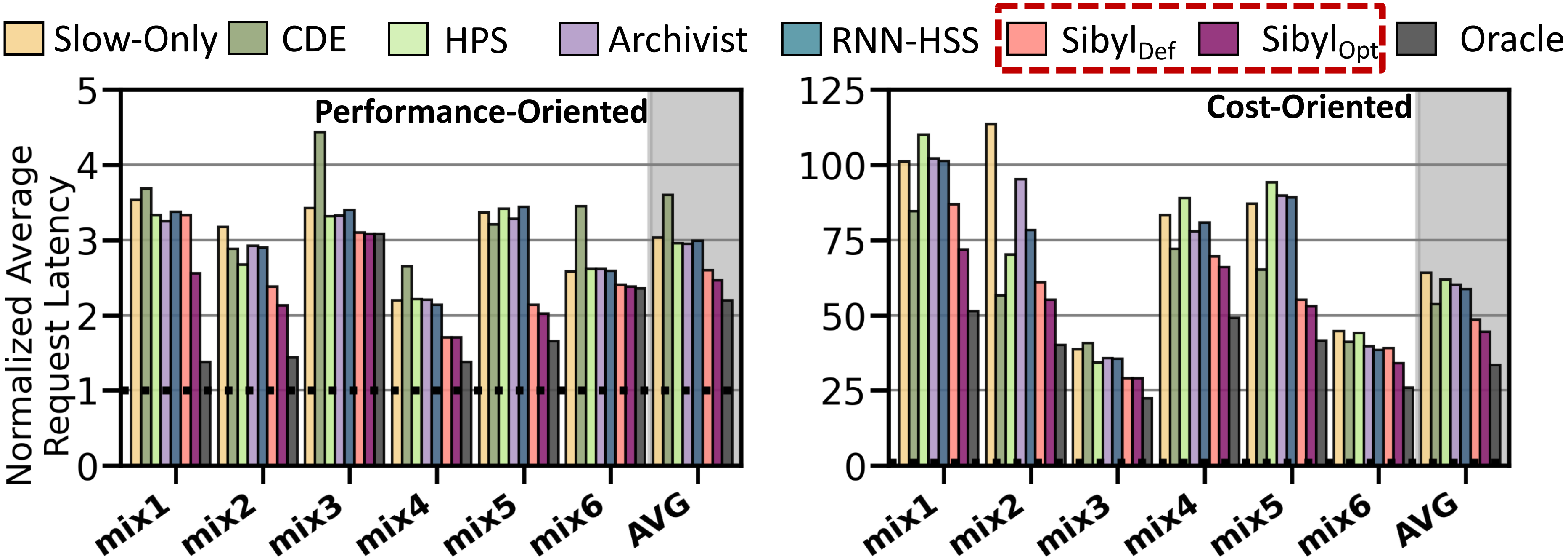
Performance Analysis

Performance-Oriented HSS Configuration

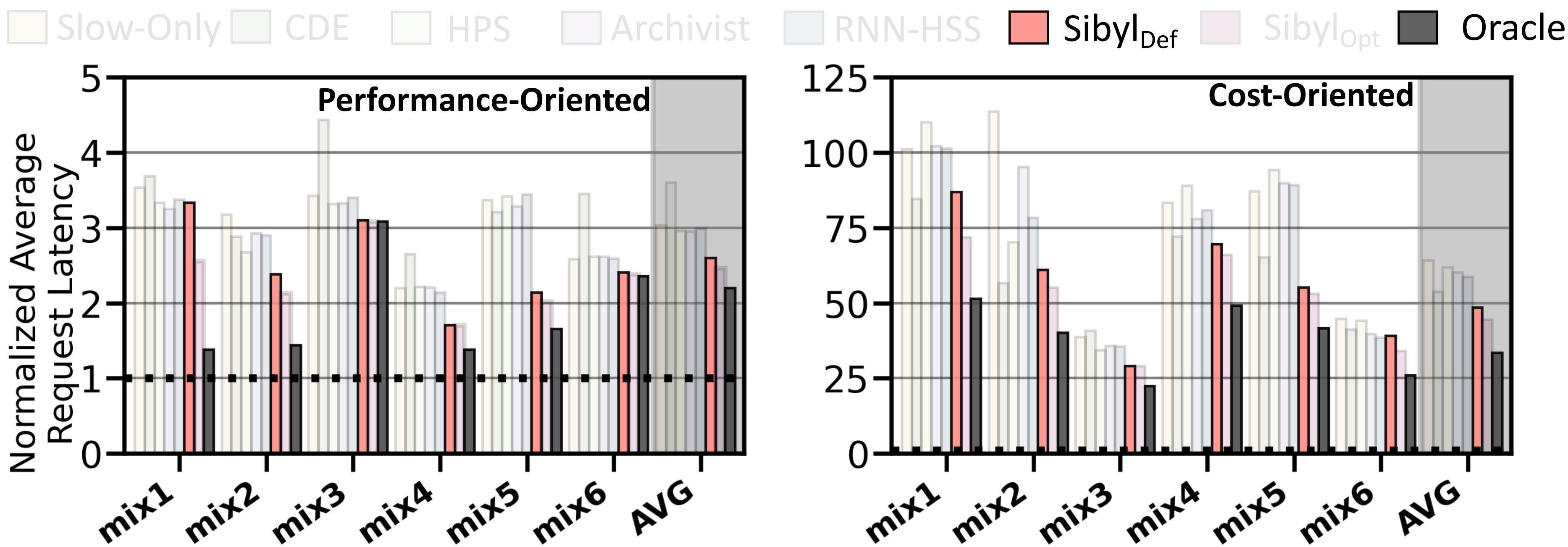


Baseline policies **are ineffective** for many workloads even when compared to Slow-Only

Performance on Mixed Workloads

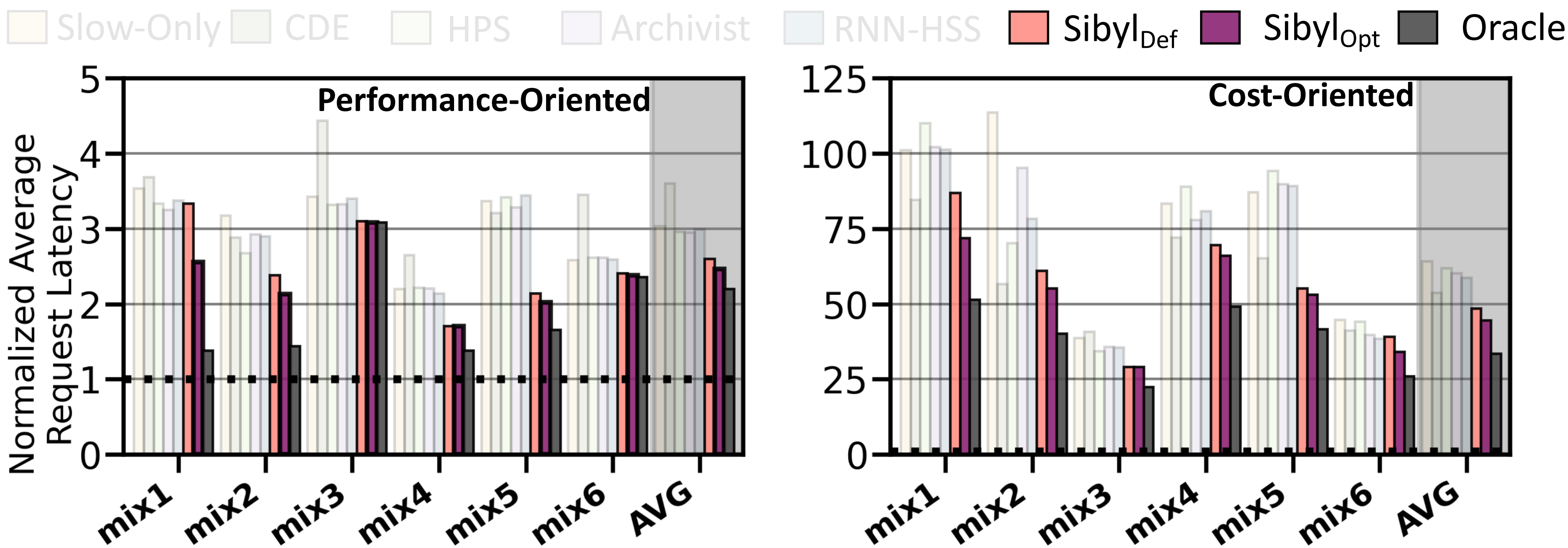


Performance on Mixed Workloads



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

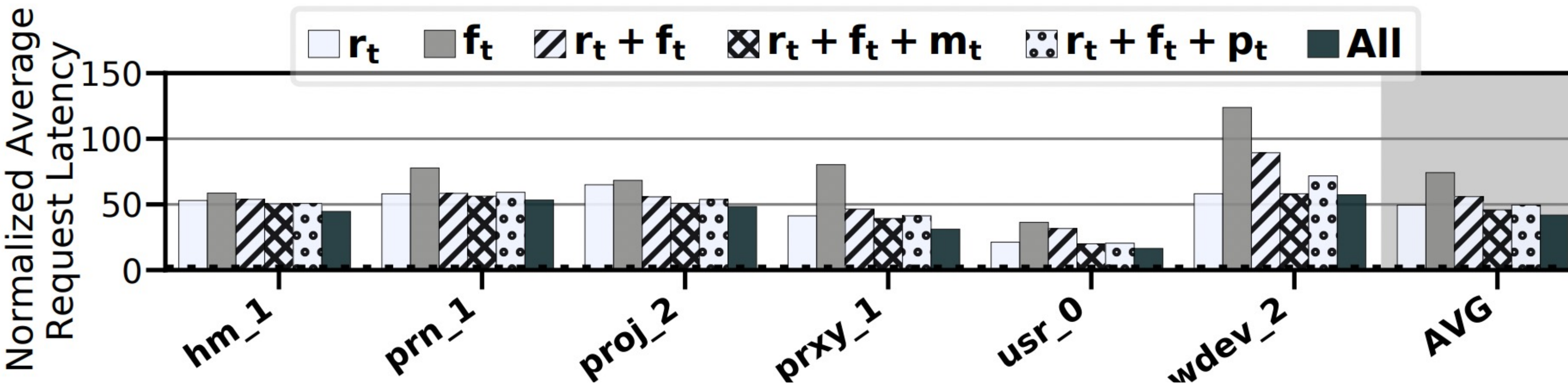
Performance on Mixed Workloads



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

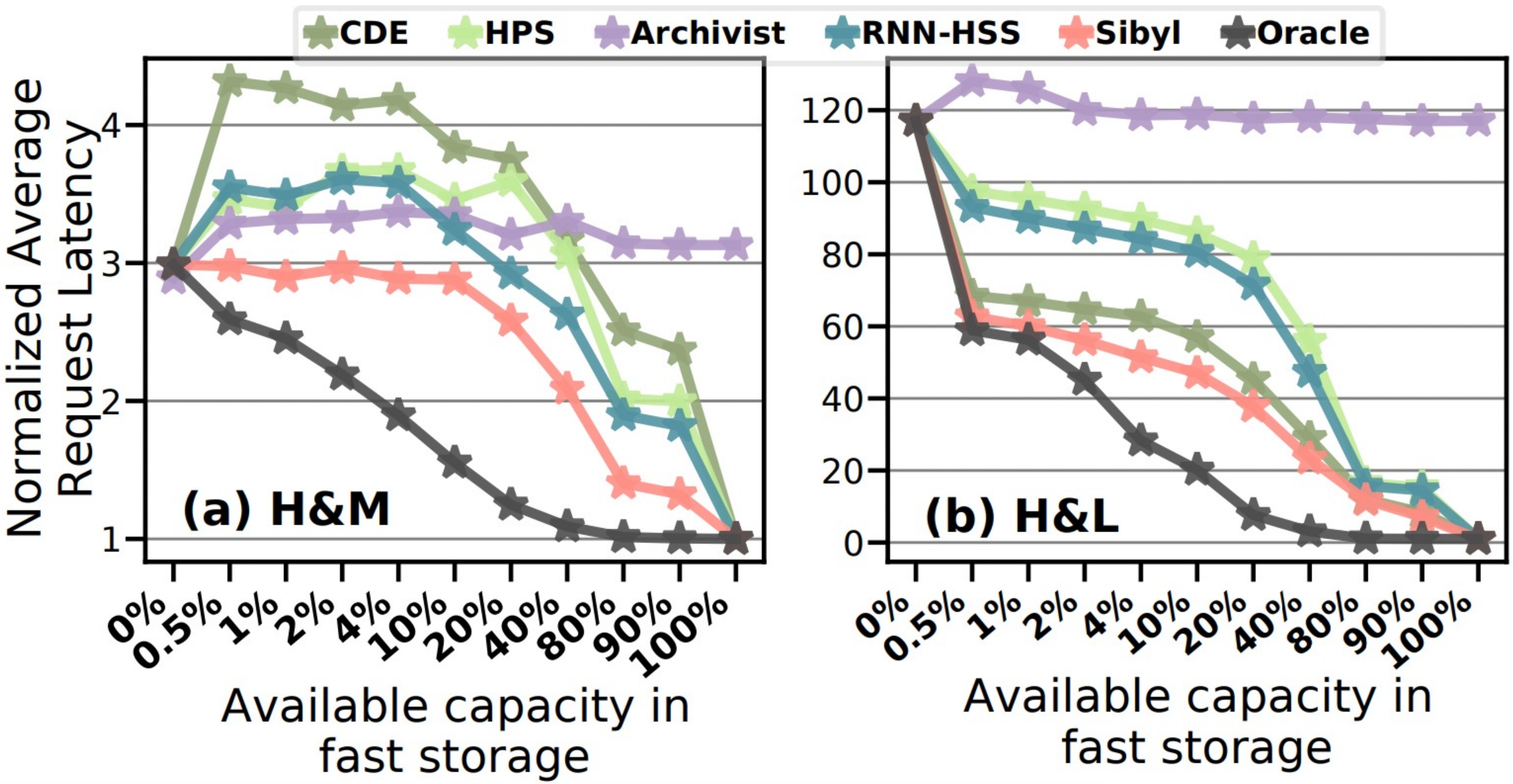
$\text{Sibyl}_{\text{Opt}}$ **provides 7.2% higher average performance** than $\text{Sibyl}_{\text{Def}}$

Performance With Different Features

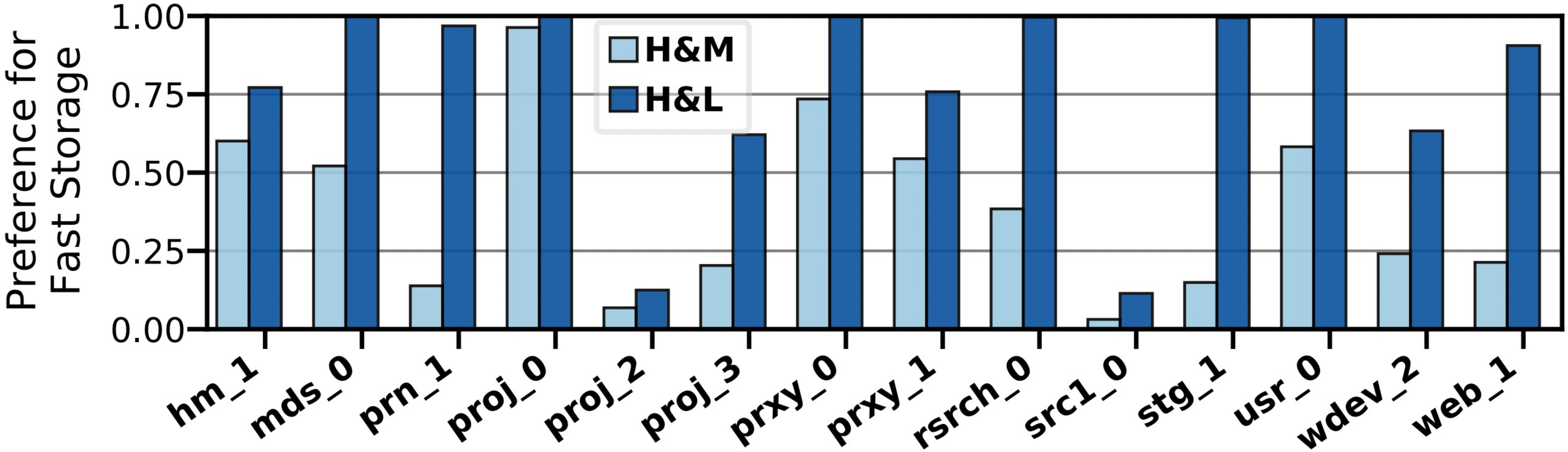


Sibyl autonomously decides which features are important to maximize the performance of the running workload

Sensitivity to Fast Storage Capacity

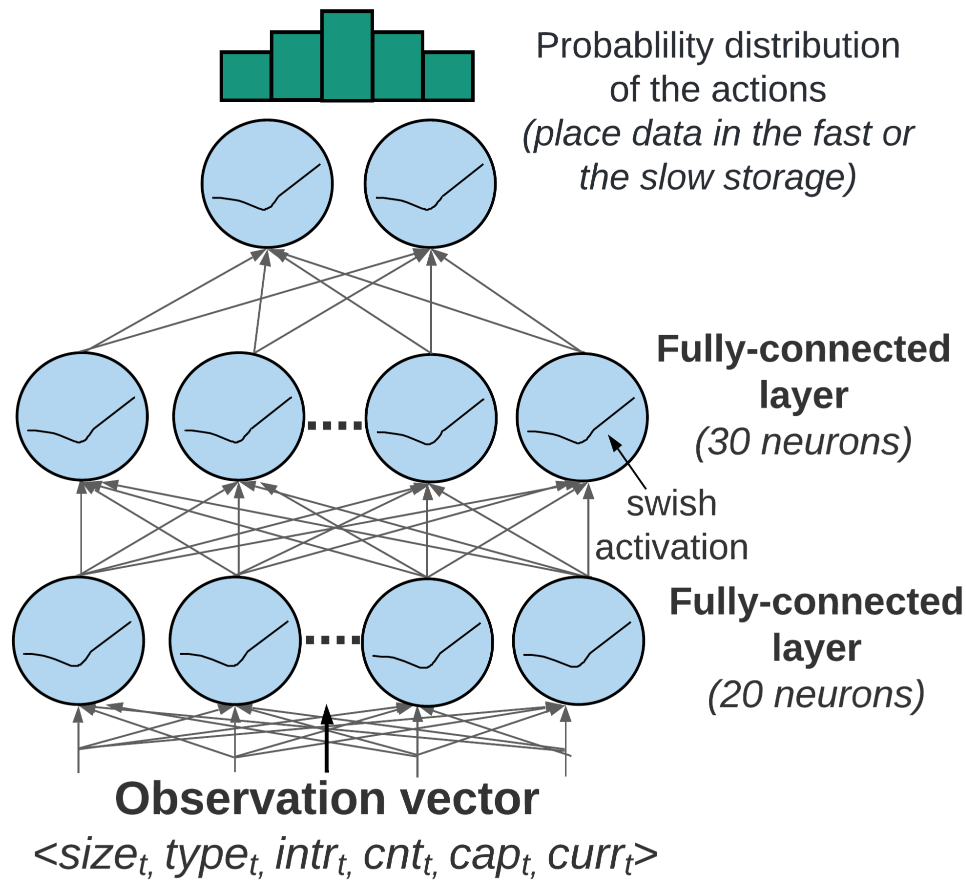


Explainability Analysis



Training and Inference Network

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



Sibyl:
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49th ISCA 2022, New York, USA

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