Symbiosis: The Art of Application and Kernel Cache Cooperation

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Database Systems and Storage Engines

Large scale database systems

- MongoDB / MySQL / CockroachDB

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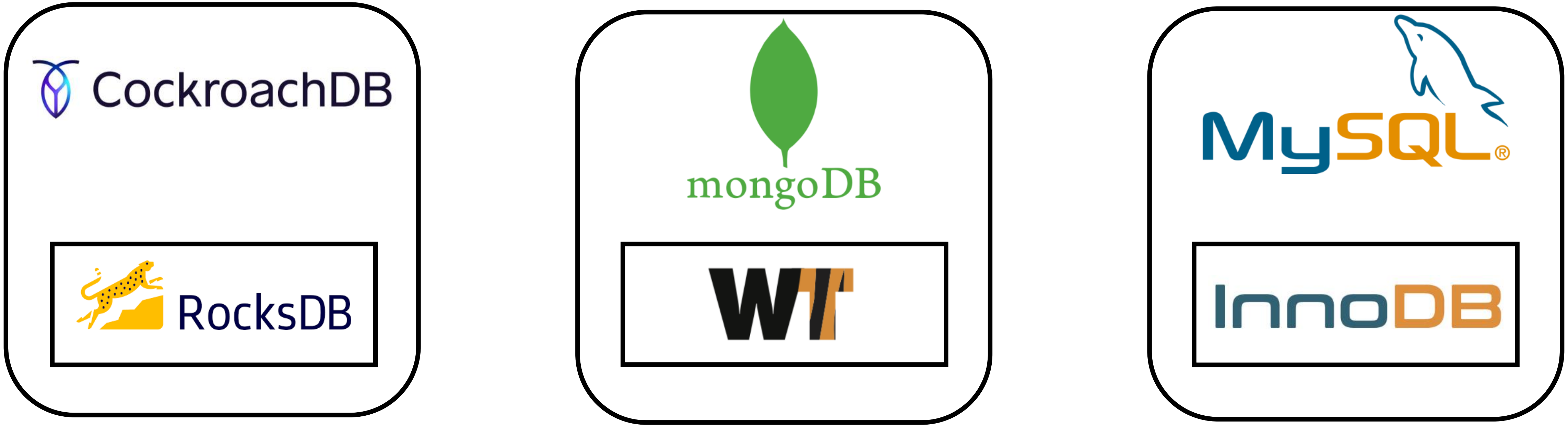
- MongoDB / MySQL / CockroachDB

Storage engines within DB to interact with filesystems

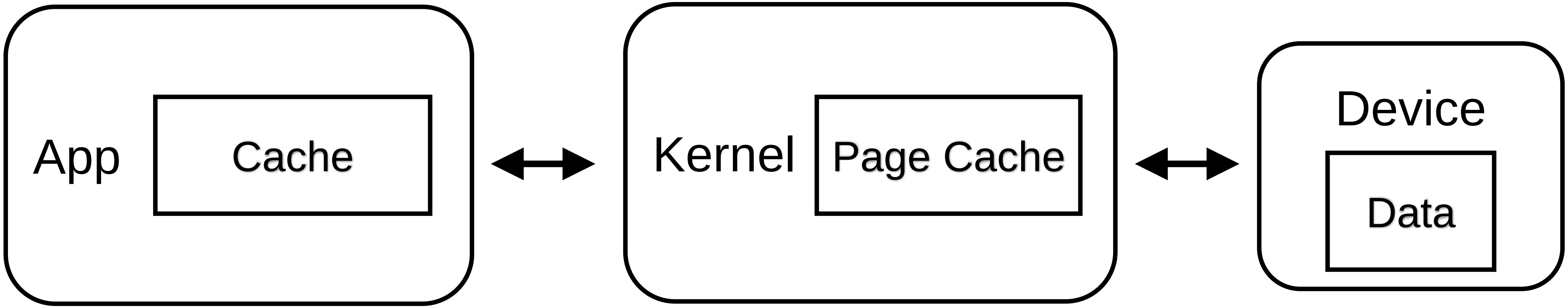
- RocksDB / WiredTiger / InnoDB



Caching in Storage Engine

Cache within the application

An implicit layer of kernel caching

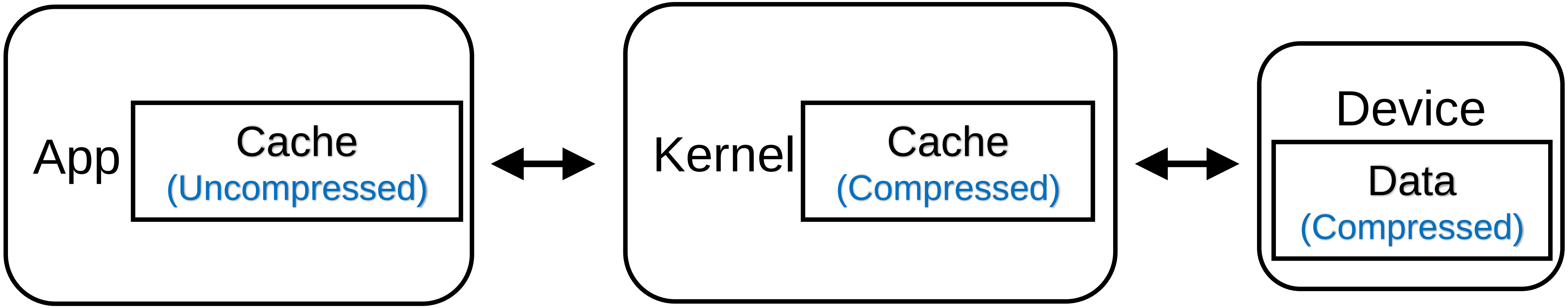


Caching in Storage Engine

Cache within the application

An implicit layer of kernel caching

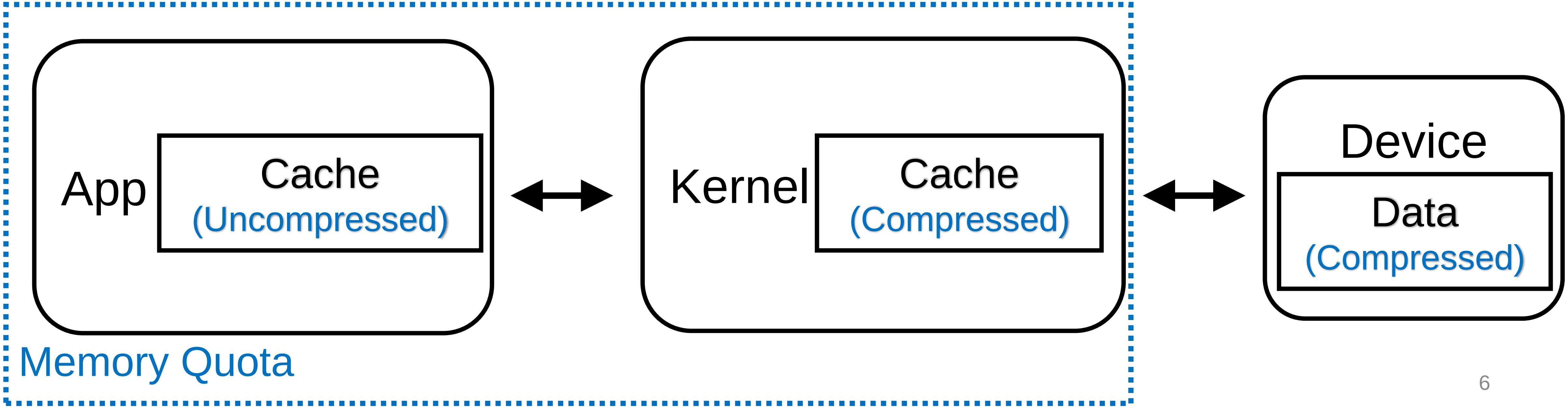
- Stores compressed data



Caching in Storage Engine

Forms a special two-layer cache structure
- Sharing of memory quota

Optimal cache partitioning is important and not trivial
- Yields great benefit
- Depends on various factors



Optimal Cache Partitioning is Hard

App Cache   Kernel Cache

	#1: All to **app cache**	#2: All to **kernel cache**
Configuration		
Performance with **small** working set size		
Performance with **large** working set size		

Optimal Cache Partitioning is Hard

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Optimal Cache Partitioning is Hard

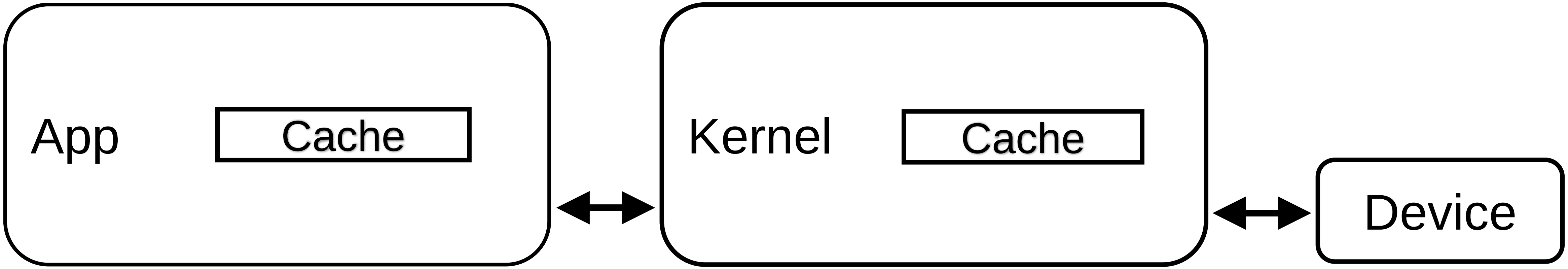
App Cache | Kernel Cache

	#1: All to **app cache**		#2: All to **kernel cache**
Configuration	Memory Quota		Memory Quota
Performance with **small** working set size	**2**	**:**	**1**
Performance with **large** working set size	**1**	**:**	**5**

The best partition could be arbitrary percentage in the middle

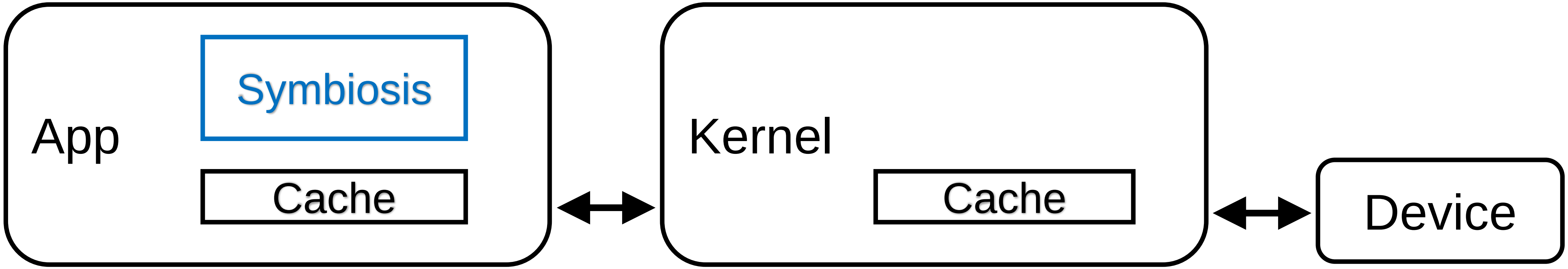
Symbiosis - Adapt Cache Sizes by Simulation

Symbiosis



Symbiosis - Adapt Cache Sizes by Simulation

Symbiosis
- Embedded in the storage engine



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Symbiosis

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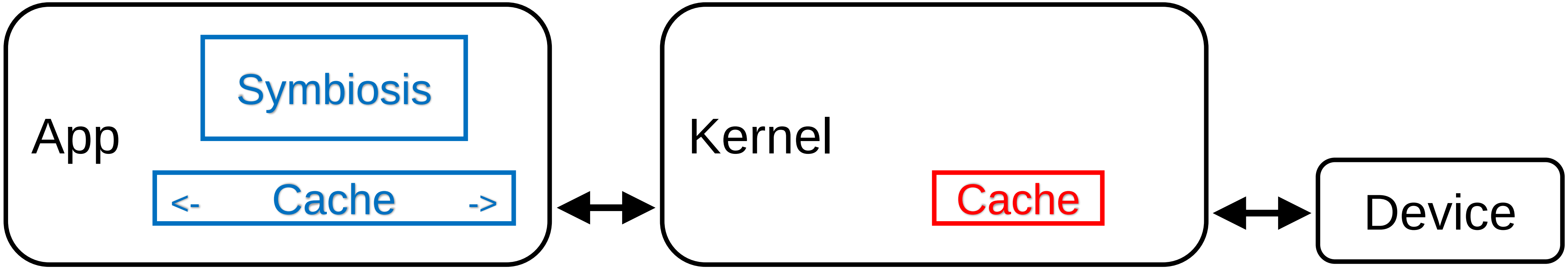
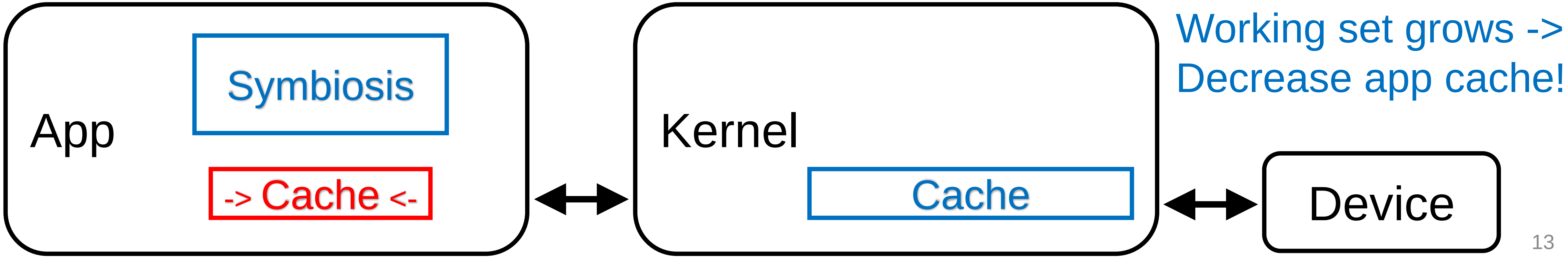


Symbiosis - Adapt Cache Sizes by Simulation

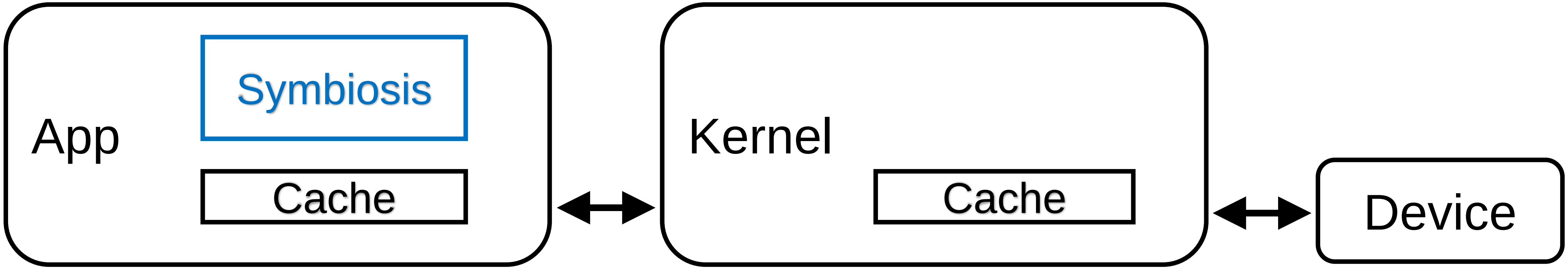
Symbiosis

- Embedded in the storage engine
- Optimizes cache partitioning automatically
- Adapts cache sizes to dynamic workloads



Symbiosis - Adapt Cache Sizes by Simulation

- Integrated into production systems with <1000 LoC
  - LevelDB, RocksDB, WiredTiger
- Performance improvements
  - 1.5x on average for read-heavy workloads
- Online cache simulation with high accuracy and negligible overhead
  - ~0.1% space overhead and ~1% time overhead



Outline

- Overview of Symbiosis
- Key Challenge
  - Simulate accurately with low overhead
- Optimization Techniques
  - Incremental reuse of a single ghost cache
  - Misalignment-aware sampling
  - Guard against unmodeled
- Evaluation
  - Static workloads
  - Dynamic (changing) workloads

Symbiosis - Overview

Detects workload change

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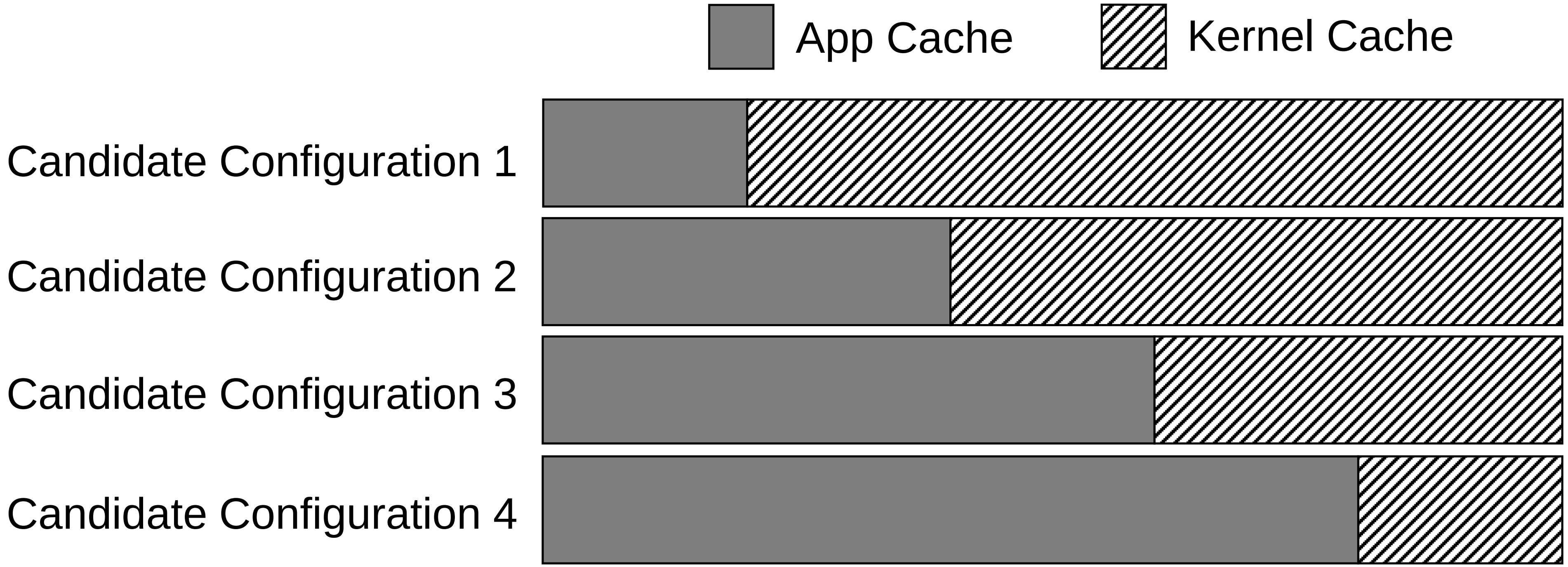
Simulates multiple candidate cache size configurations



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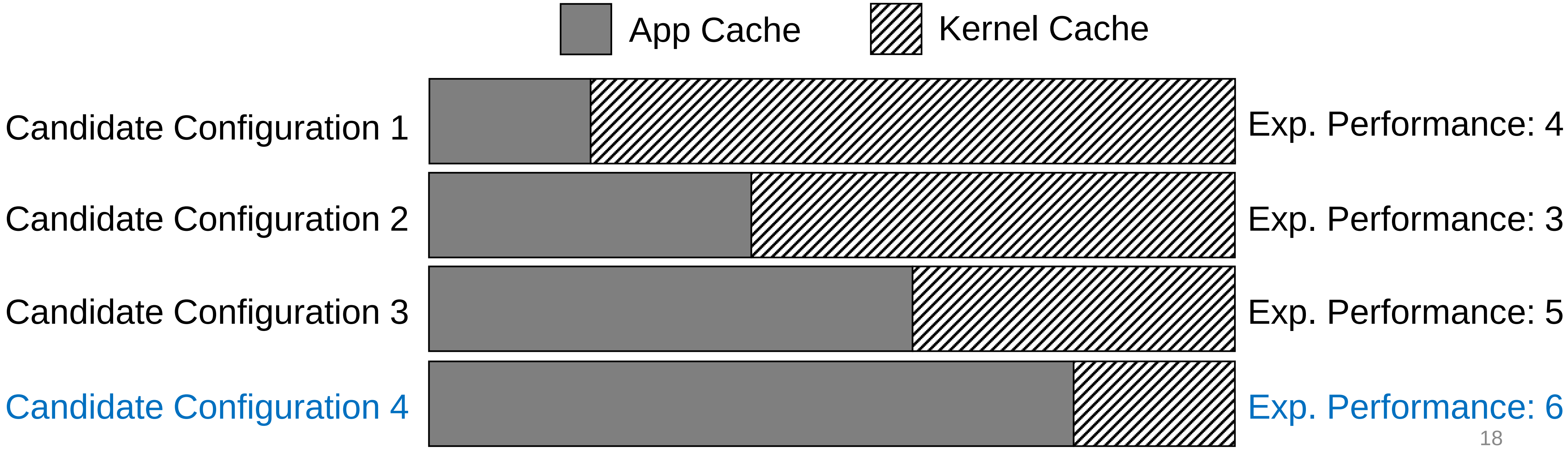


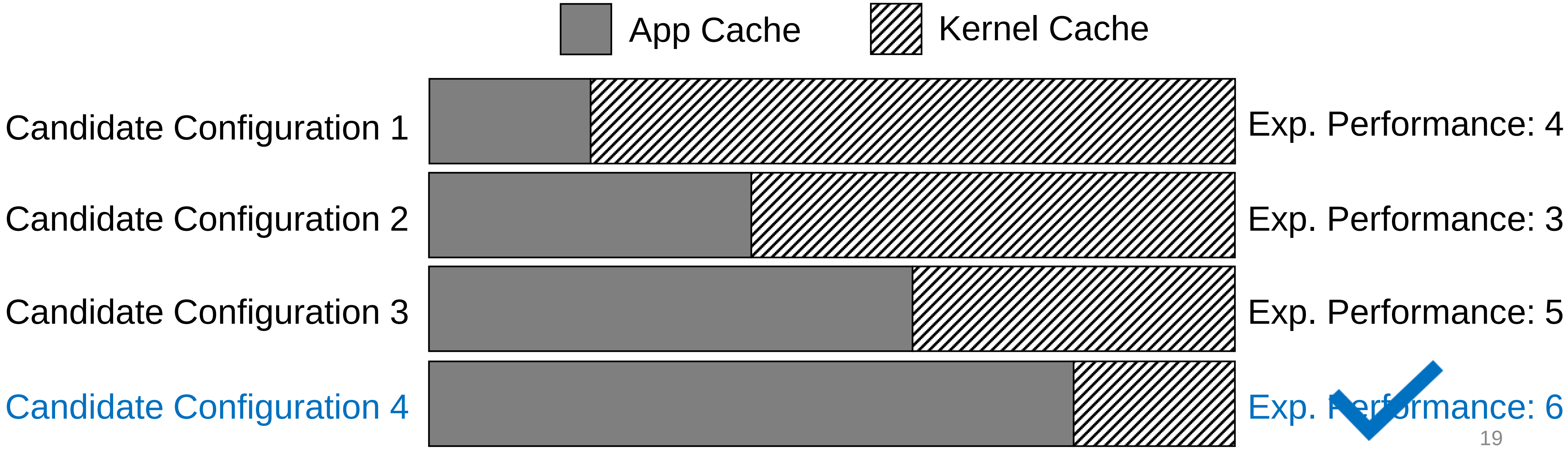
Symbiosis - Overview

Detects workload change

Simulates multiple candidate cache size configurations

Finds the configuration with the best expected performance

Applies the best configuration if it yields enough benefit



Key Challenge

How to simulate accurately?

How to simulate with negligible overhead?

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Tension!

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Tension!

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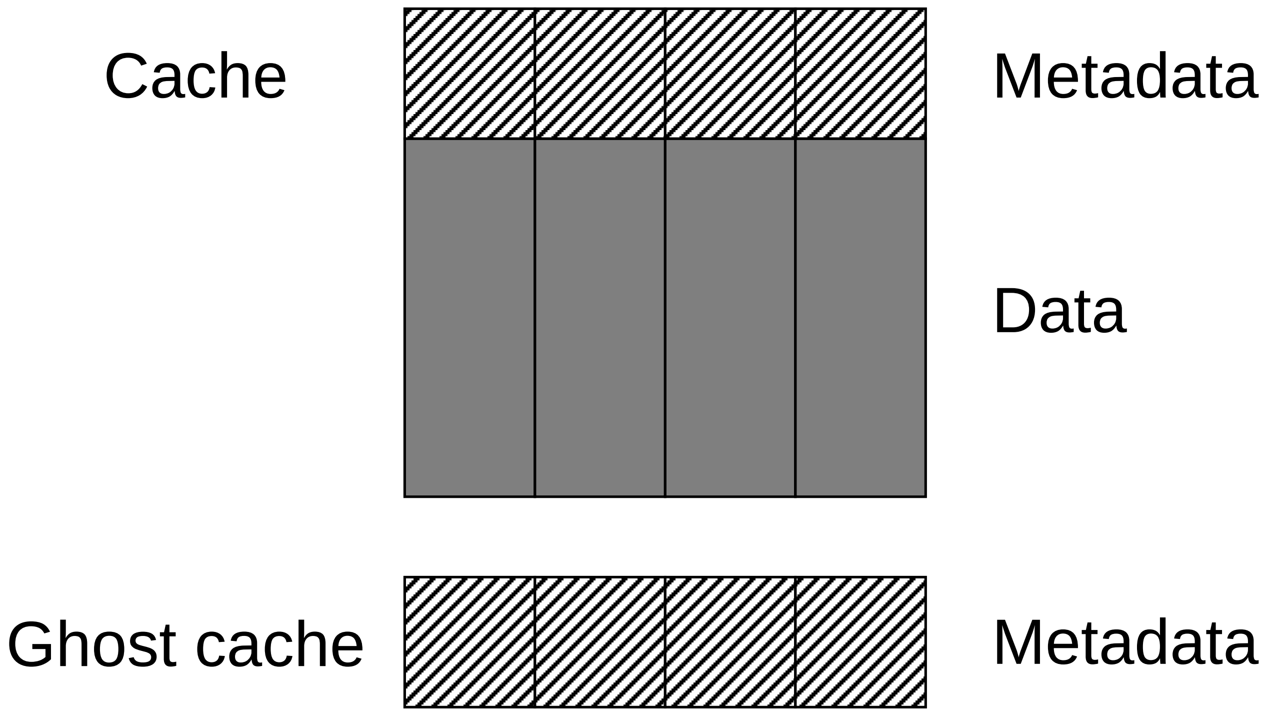
Optimization Techniques

- Incremental reuse of a single ghost cache
- Misalignment-aware sampling
- Guard against unmodeled

Classical Solution - Ghost Cache Simulation

Ghost cache - maintain only cache access metadata

- Useful for cache statistics analysis



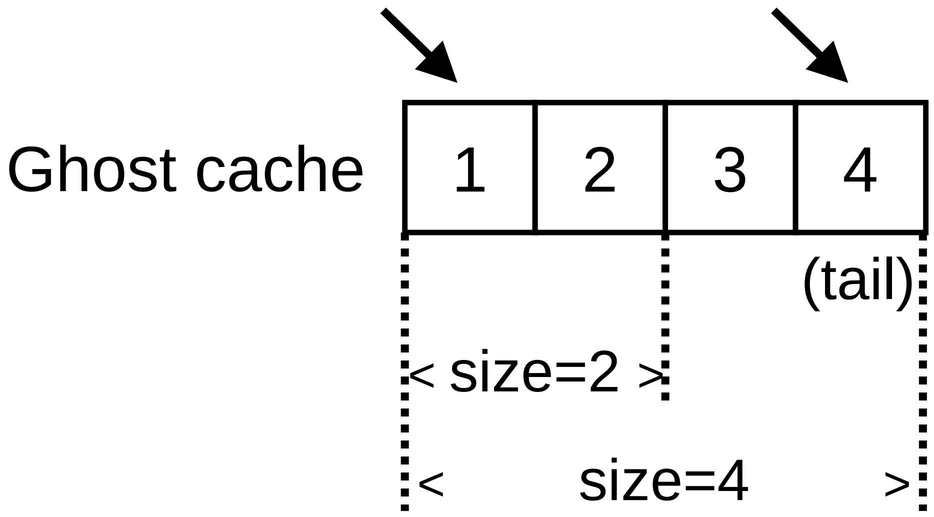
Ghost Cache Simulation - Single Layer

Use a single ghost cache instance

- Largely reduces space and time overhead

Simulate caches of multiple sizes simultaneously

- When the eviction policy has stack property



Ghost Cache Simulation - Two Layers

Simultaneous simulation of caches with different sizes is not feasible

- The second layer sees different access patterns

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1st-layer access trace:

2 1 3 2 3 1 3 1 2 4
2 1 3 2 3 1 2 1 3 4
2 1 3 2 1 3 1 3 2 4

1st-layer Ghost cache

size = 1

1

Ghost Cache Simulation - Two Layers

Simultaneous simulation of caches with different sizes is not feasible

The second layer sees different access patterns

size = 1

1st-layer access trace:
2 1 3 2 3 1 3 1 2 4
2 1 3 2 3 1 2 1 3 4
2 1 3 2 1 3 1 3 2 4

1st-layer Ghost cache $\boxed{1}$

2nd-layer access trace:
2 1 3 2 3 1 3 1 2 4
2 1 3 2 3 1 2 1 3 4
2 1 3 2 1 3 1 3 2 4

Ghost Cache Simulation - Two Layers

Simultaneous simulation of caches with different sizes is not feasible

- The second layer sees different access patterns

1st-layer access trace:

2 1 3 2 3 1 3 1 2 4
2 1 3 2 3 1 2 1 3 4
2 1 3 2 1 3 1 3 2 4

1st-layer Ghost cache (size = 3)

1	2	3

2nd-layer access trace: 4 3 4 2 4

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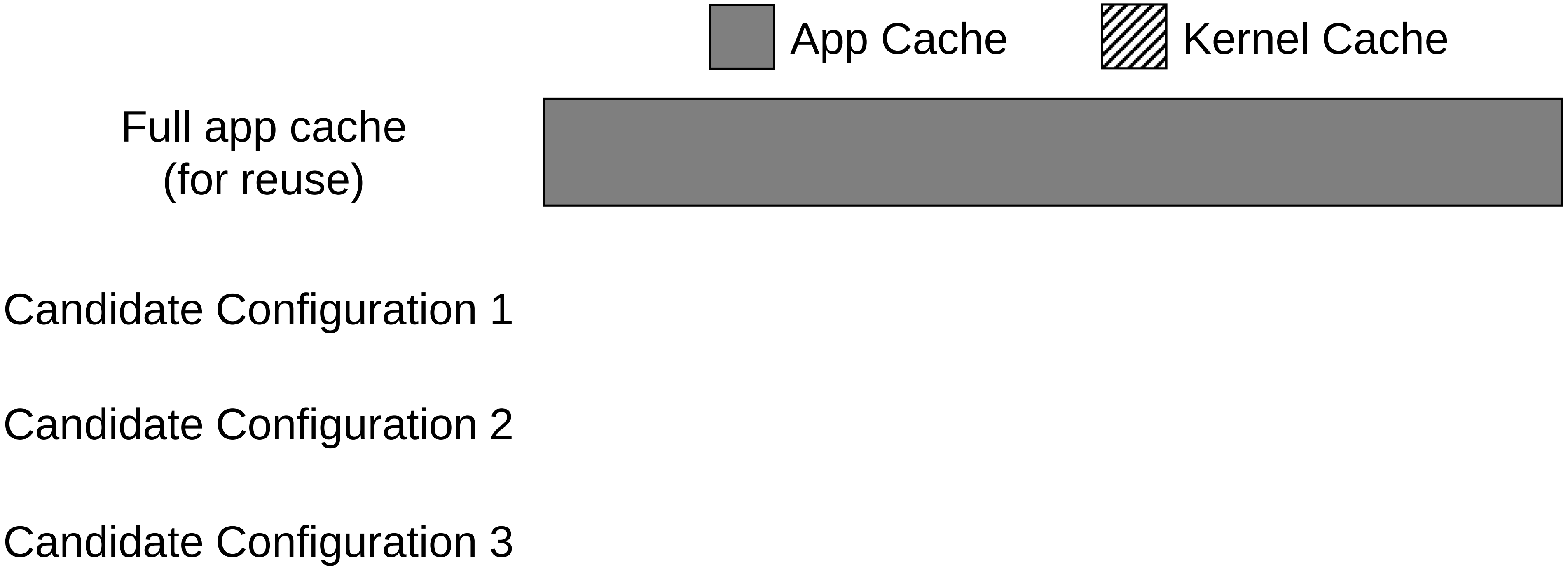

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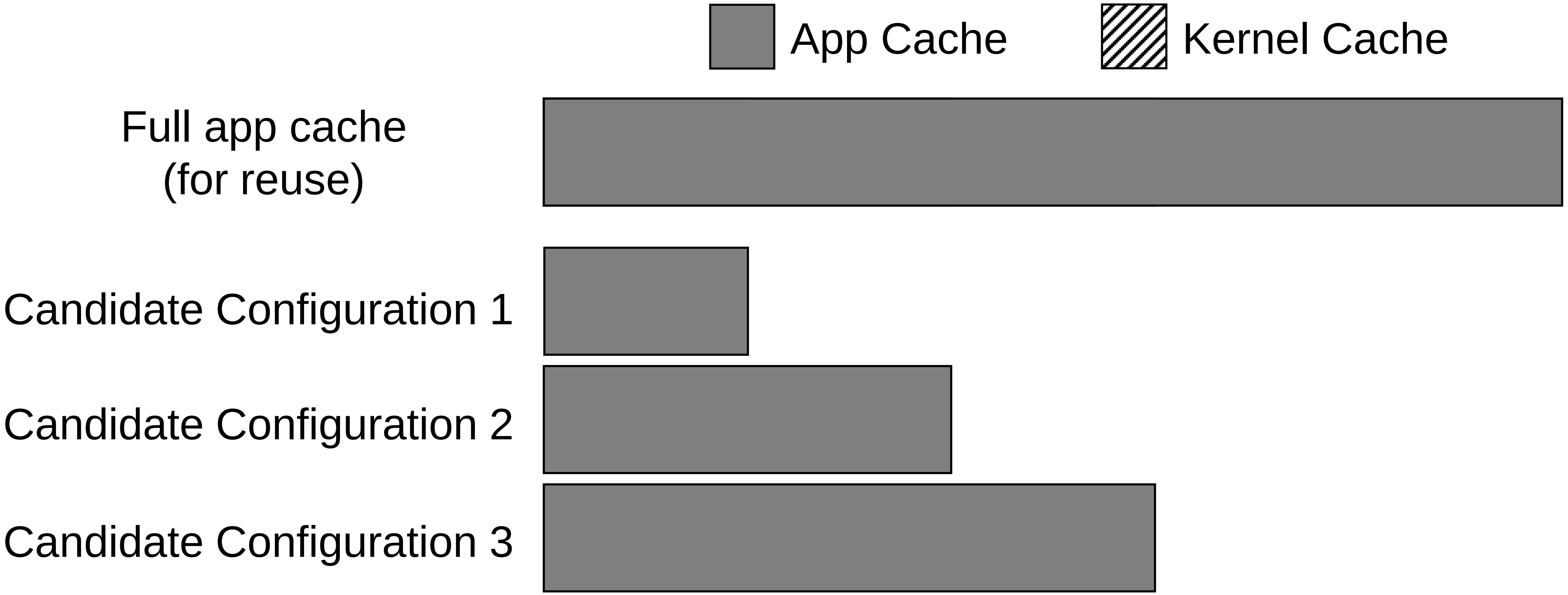
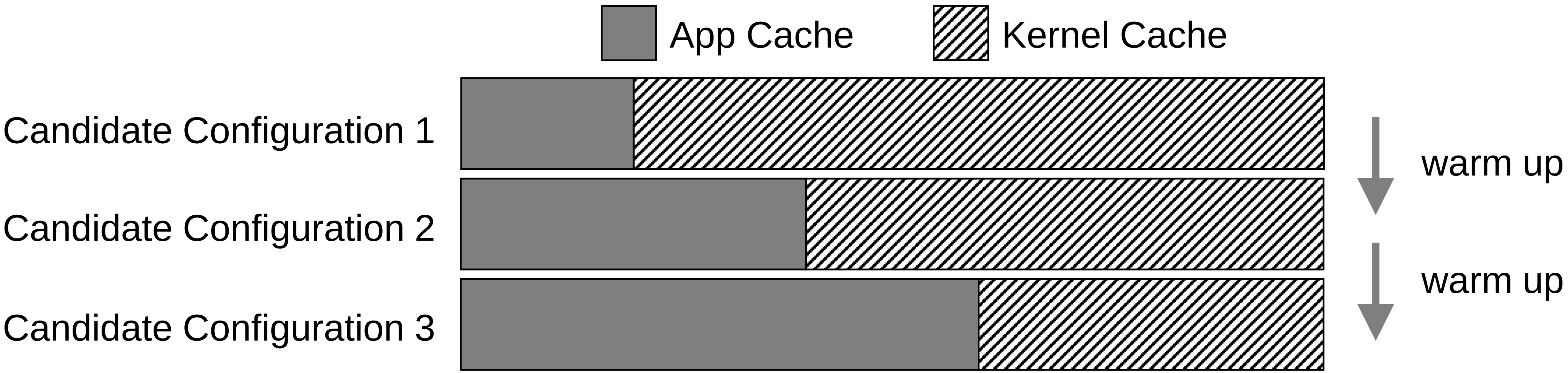


Incremental reuse of a single ghost cache

- Use a single ghost cache instance
  - Largely reduces space and time overhead
- Simulate candidates one at a time
- Minimize warm-up before each simulation
  - Utilize the stack property for the first layer
  - Simulate in the order of increasing application cache size



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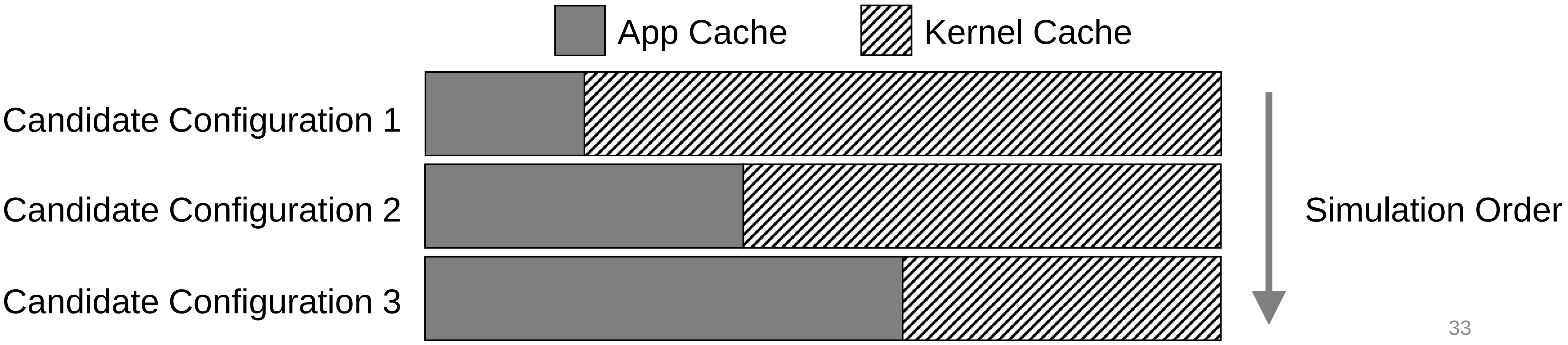
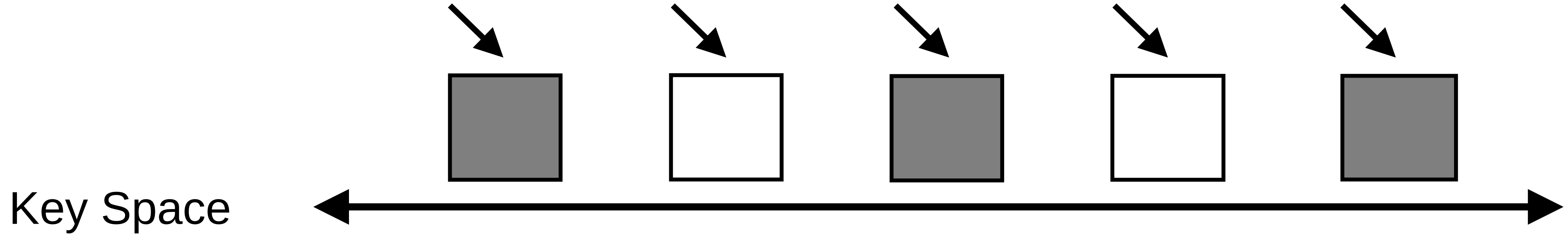


Misalignment-aware Sampling

Key-space sampling

Sample targets in key space and all accesses to the targets

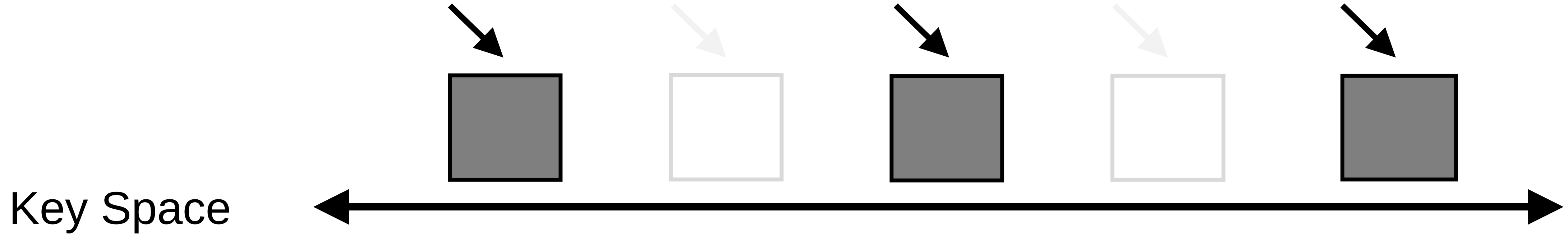


Waldspurger et al. Efficient MRC Construction with SHARDS. 2015 (original key space sampling)

Misalignment-aware Sampling

Key-space sampling

- Samples targets in key space and all accesses to the targets
- Works in normal multi-layer caching



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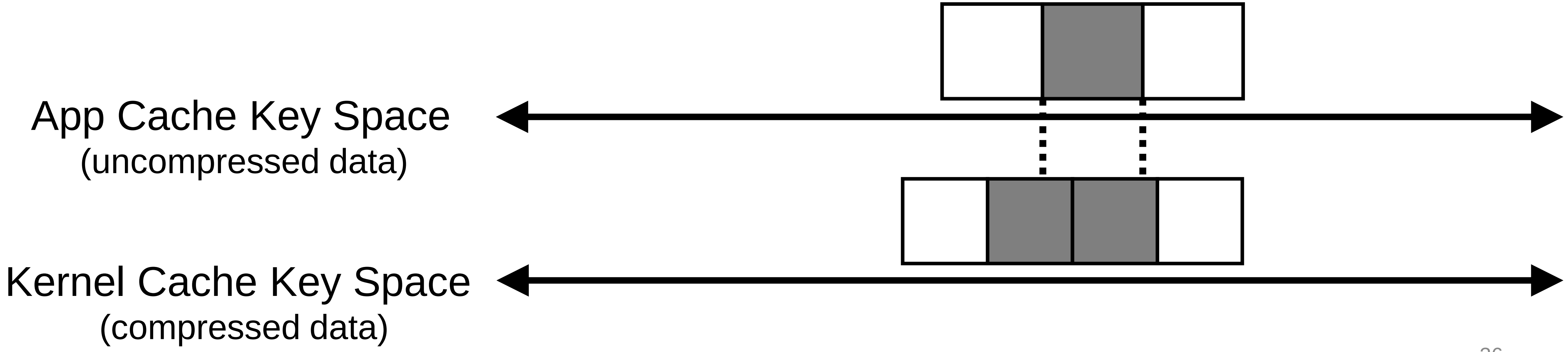
Misalignment-aware Sampling

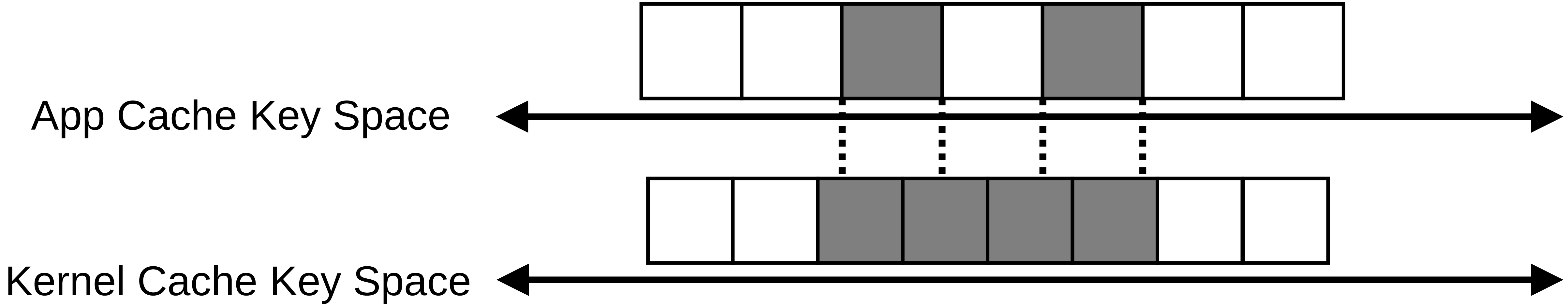
Misalignment - different caching units

- The unit of app cache: app-defined blocks
- The unit of kernel cache: pages
- One unit in the 1st layer corresponds to multiple units in the 2nd layer



Misalignment-aware Sampling

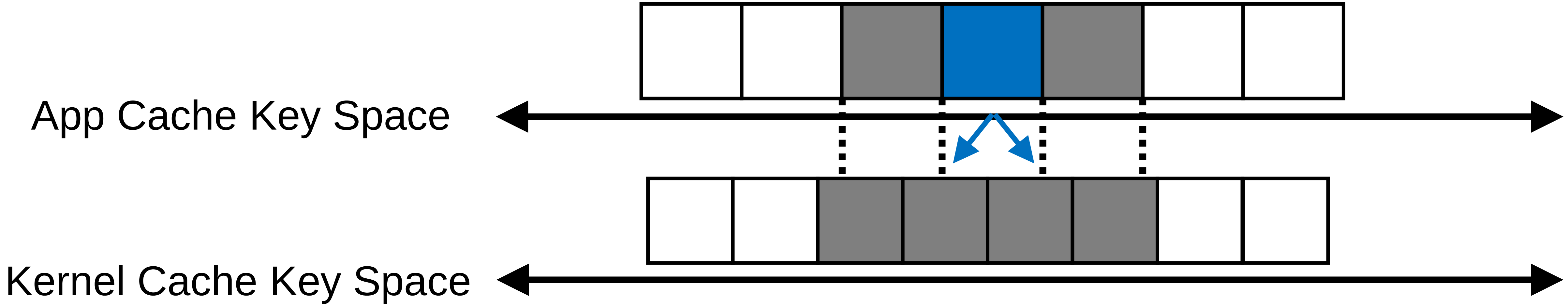
Key-space sampling with misalignment



Misalignment-aware Sampling

Key-space sampling with misalignment

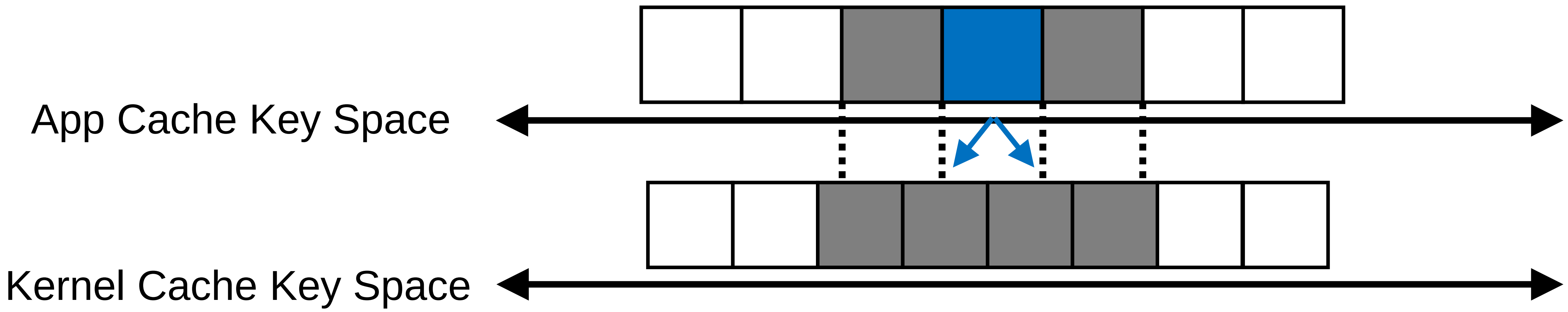
- Hits in the 2nd layer due to accessed neighboring blocks in the 1st layer



Misalignment-aware Sampling

Key-space sampling with misalignment

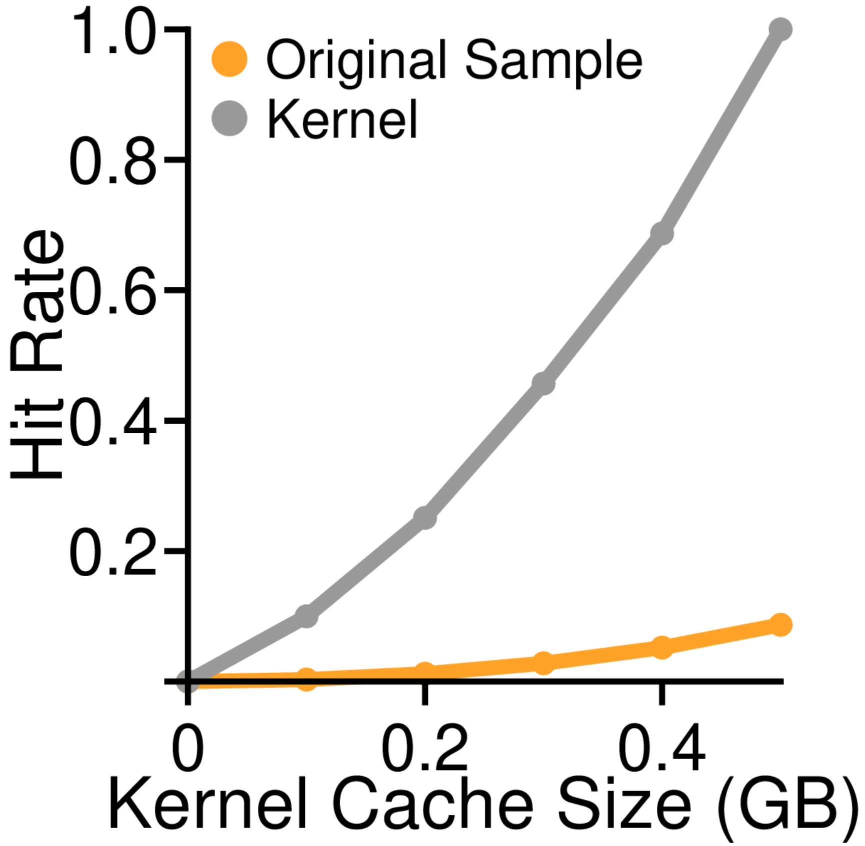
- Hits in the 2nd layer due to accessed neighboring blocks in the 1st layer
- Contiguous targets not all sampled so hits are not counted
- Loses the effects of accessing contiguous pages



Misalignment-aware Sampling

Key-space sampling with misalignment

Much lower kernel cache hit rate



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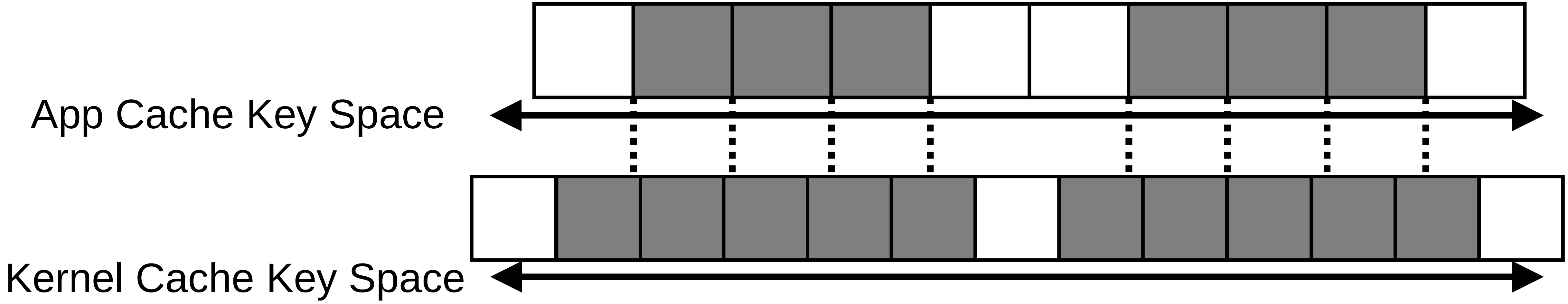
Misalignment-aware Sampling

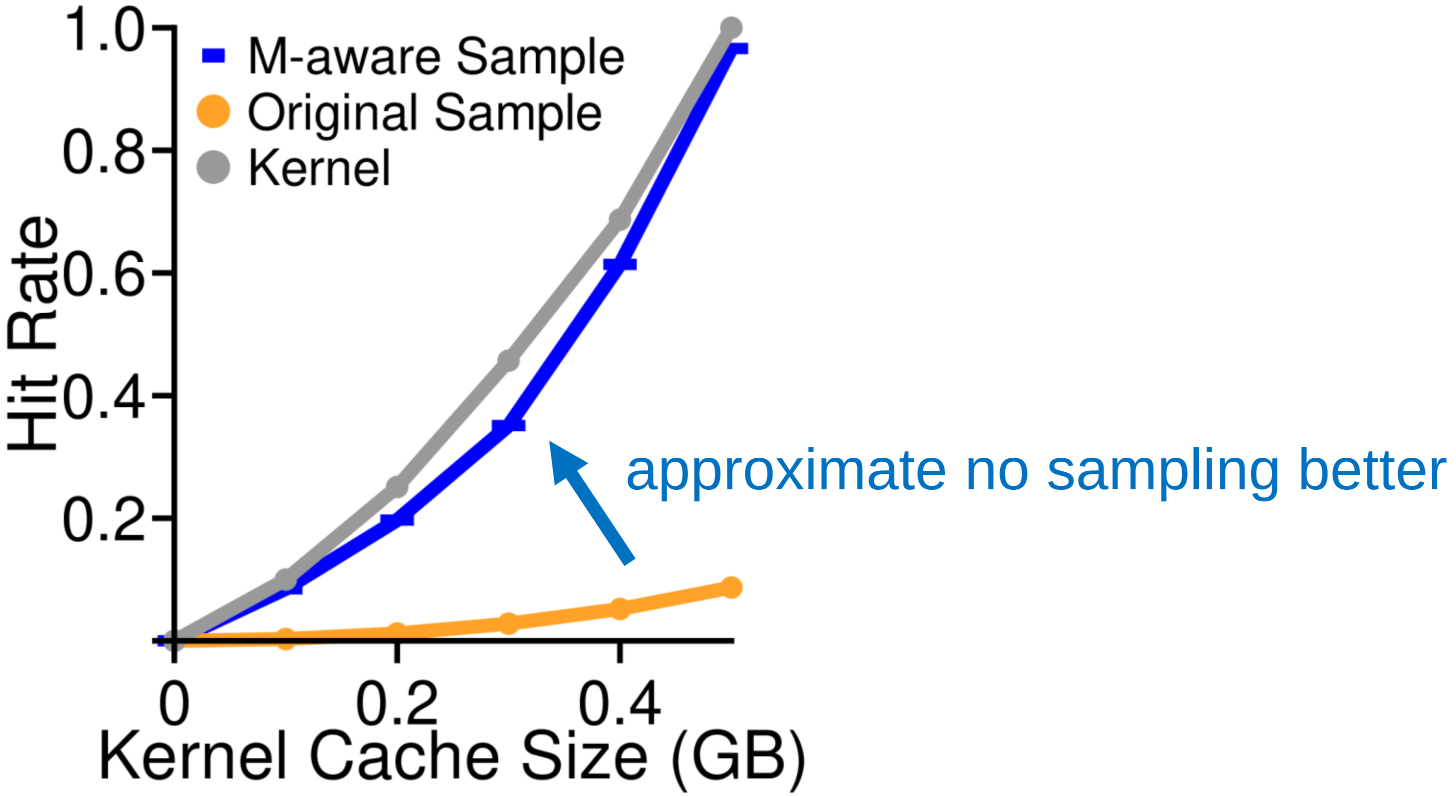
- Misalignment-aware Sampling
  - Sample contiguous targets together to keep the effect of misalignment



Misalignment-aware Sampling

Misalignment-aware Sampling

- Sample contiguous targets together to keep the effect of misalignment
- In Symbiosis, we samples in groups of 32 and the sampling rate is 1/64
- Misalignment-aware sampling is much more accurate



Guard Against Unmodeled Cases

Some kernel features not modeled (e.g., read-ahead)

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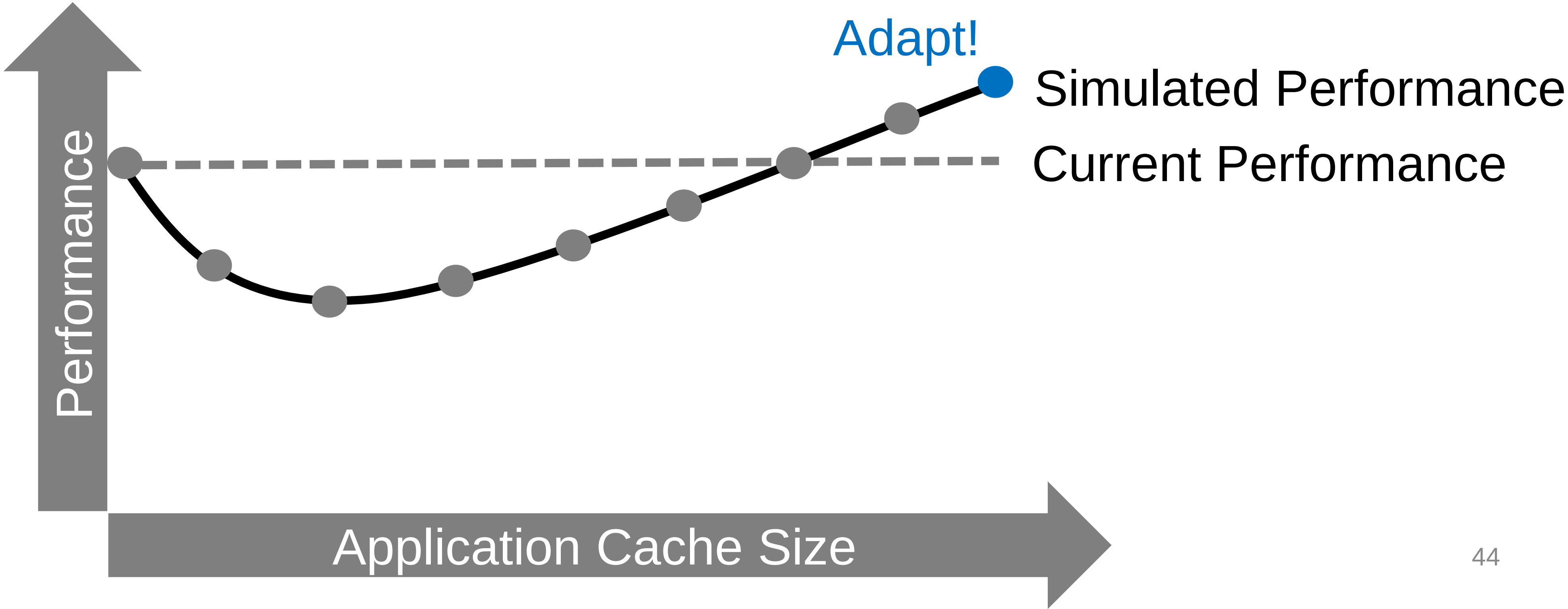
When simulation is accurate



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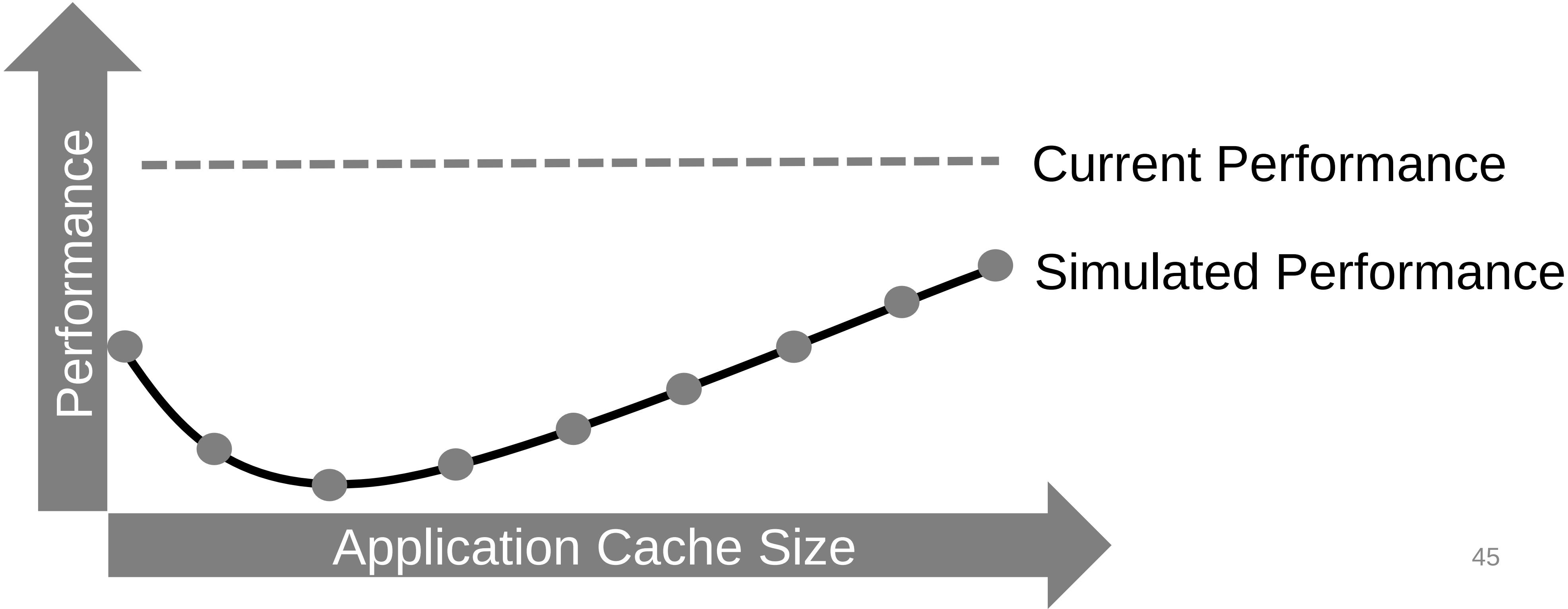
Some kernel features not modeled (e.g., read-ahead)

When simulation is not accurate

Observation: omitting such features usually results in a worse perf.

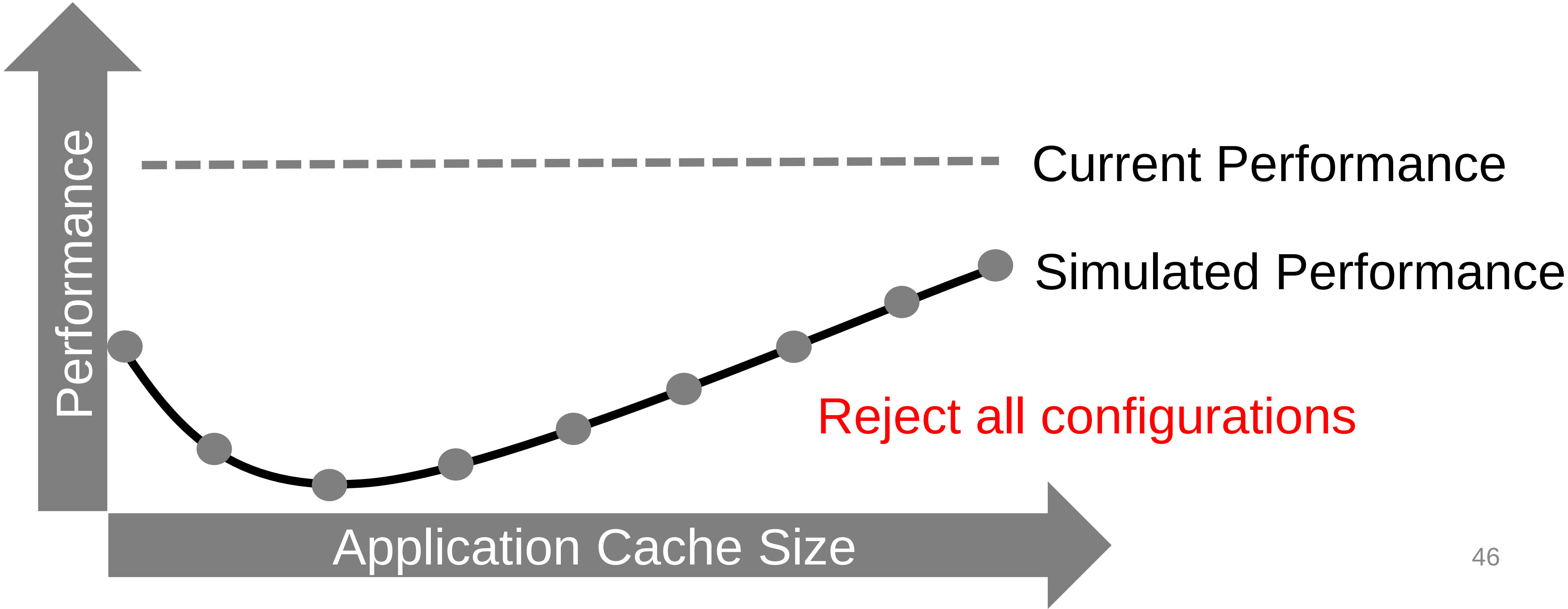


Guard Against Unmodeled Cases

Some kernel features not modeled (e.g., read-ahead)

Observation: omitting such features usually results in a worse perf.

Policy: only adapts when predicted perf. is better than current perf.



Evaluation - Static Workloads

Experiments

Performance with various workloads and environments

Factors		Presented Space	# of parameters
Workloads	Data Set Size	5, 2.5, 1.67, 1.24, 1	4
	Access Pattern	uniform, zipfian, hotspot{30,20,10}	5
Software	Compression Lib.	snappy (default), zstd	2
	Storage Engine	LevelDB, RocksDB, WiredTiger	3
Hardware	CPU Frequency	CPU1: 2.9GHz, CPU2: 2.0GHz	2
	Device Latency	SSD1: ~10us, SSD2: ~70us	2

Results

Improves performance in 98% of 190+ workloads by 1.5x on average

Evaluation - Dynamic Workloads

Experiments

- Performance with abrupt and gradual workload changes
- Performance with real world workloads
- Overhead and tail latency analysis

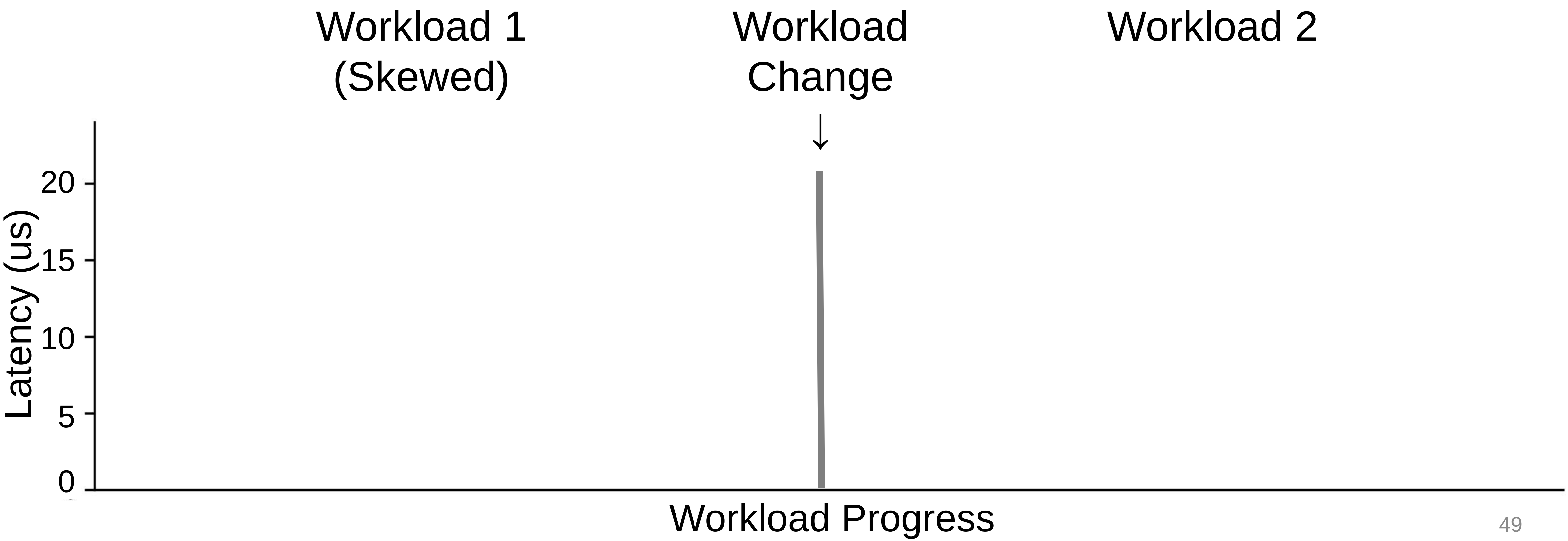
Results

- Symbiosis properly reacts to all of 38 workloads
- Symbiosis incurs 0.1% space overhead and 1% time overhead

Dynamic Workloads - Example

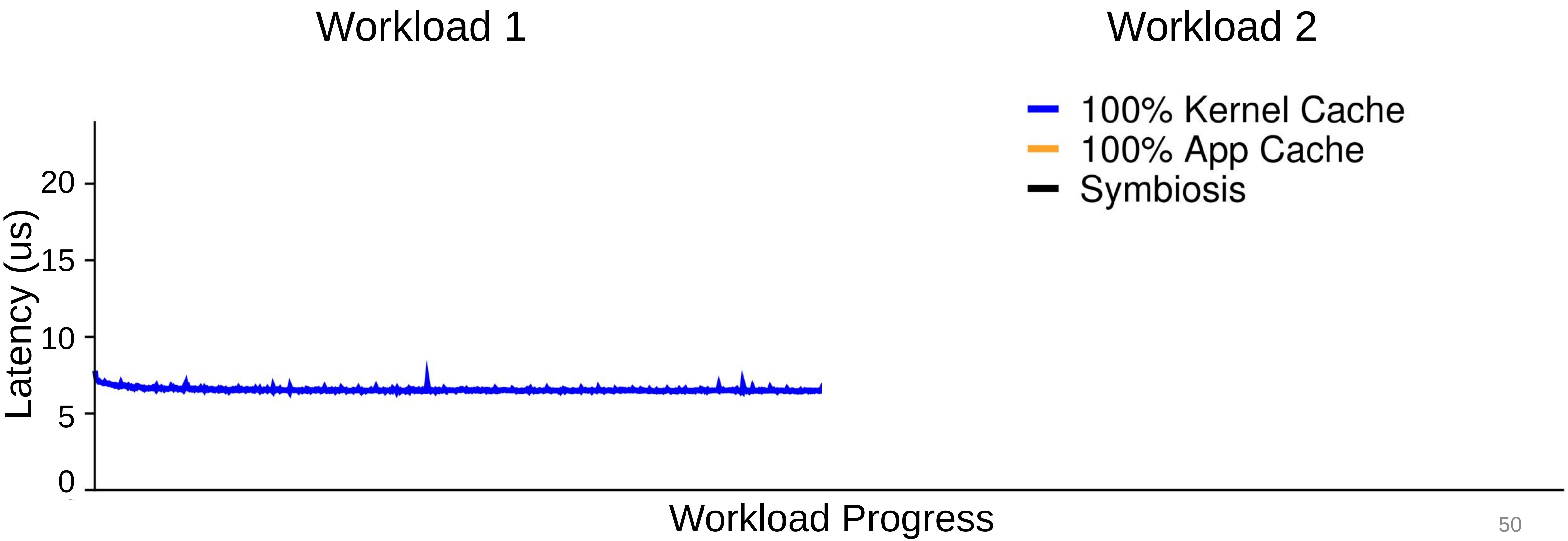
Consists of 2 static workloads

- Workload 1 is very skewed, while workload 2 is less skewed
- Data set fits in memory when compressed, but not when uncompressed



Dynamic Workloads - Example

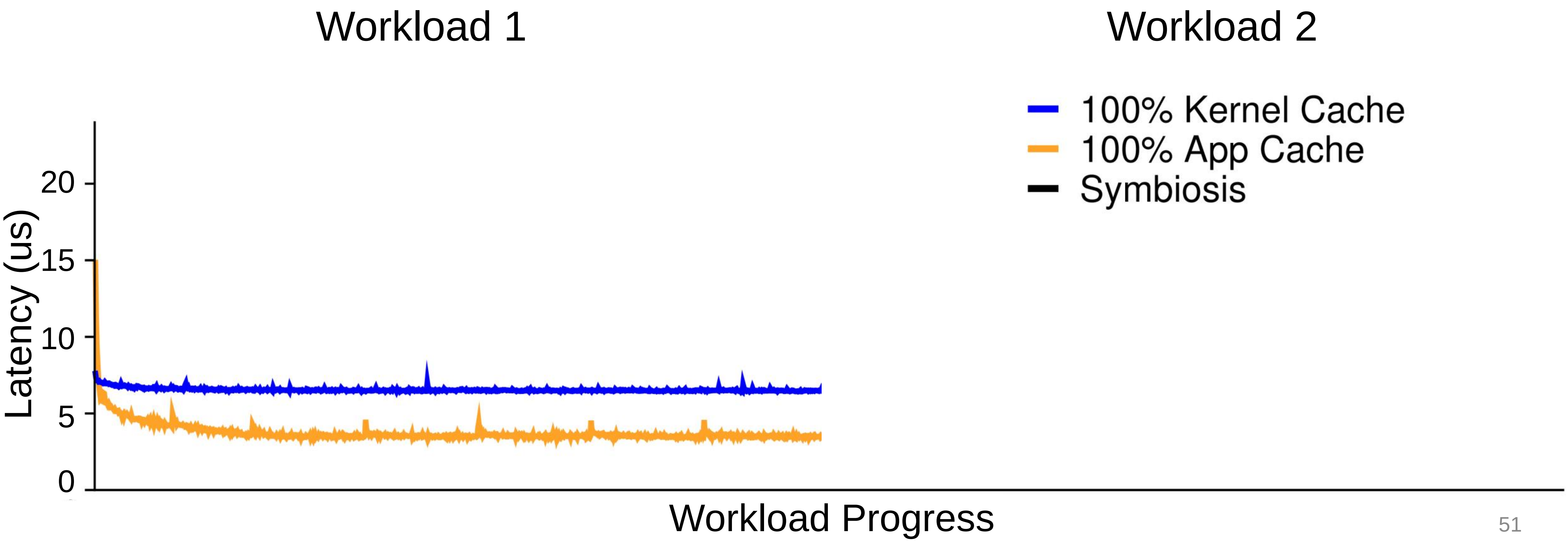
Workload 1



Dynamic Workloads - Example

Workload 1

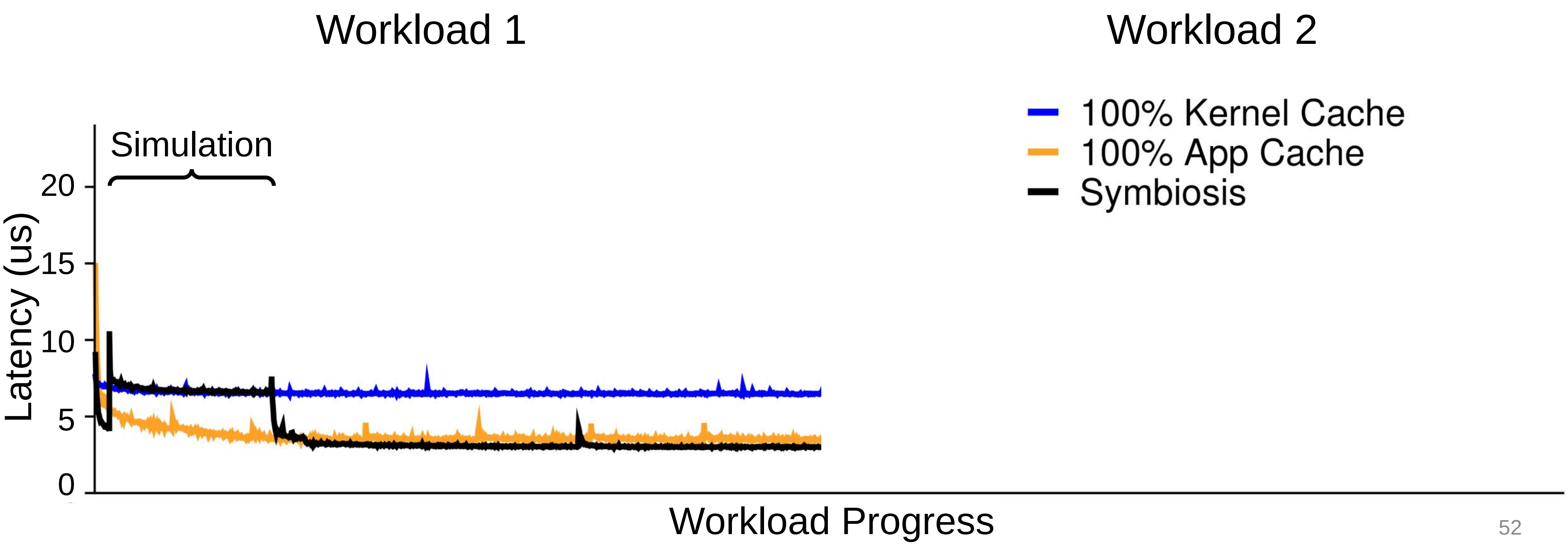
- 100% app cache performs better due to high skewedness



Dynamic Workloads - Example

Workload 1

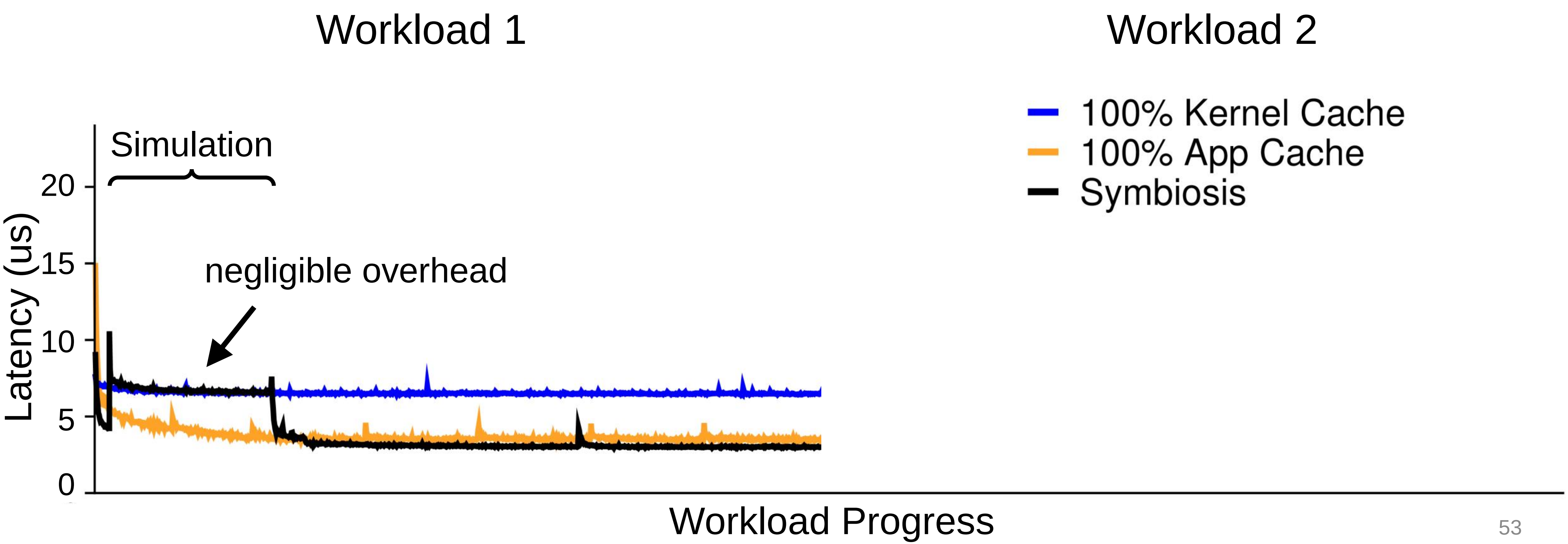
Symbiosis performs best after simulation



Dynamic Workloads - Example

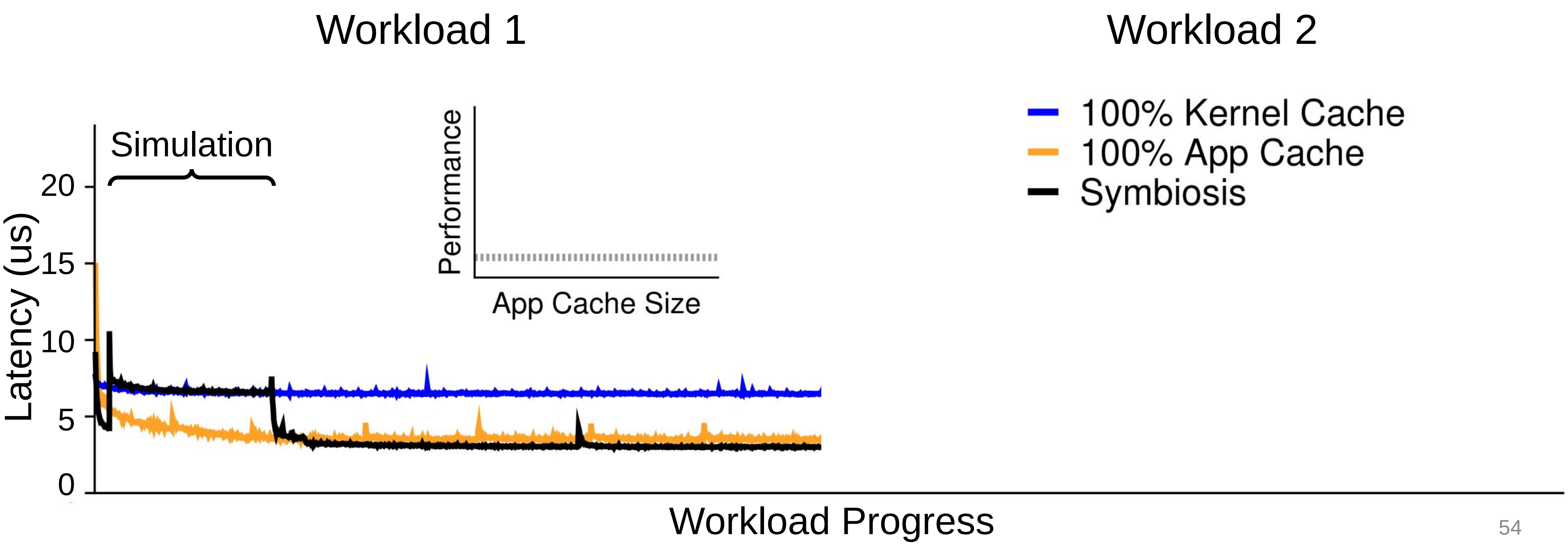
Workload 1

Symbiosis incurs negligible overhead during simulation



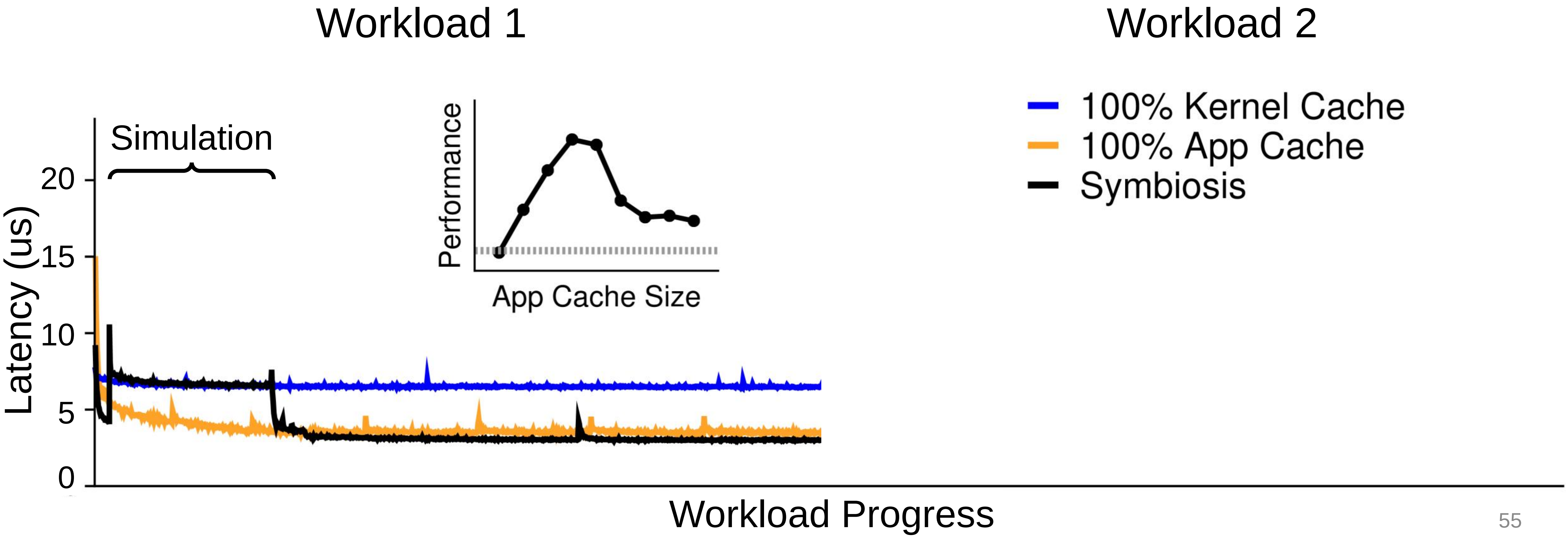
Dynamic Workloads - Example

Workload 1



Dynamic Workloads - Example

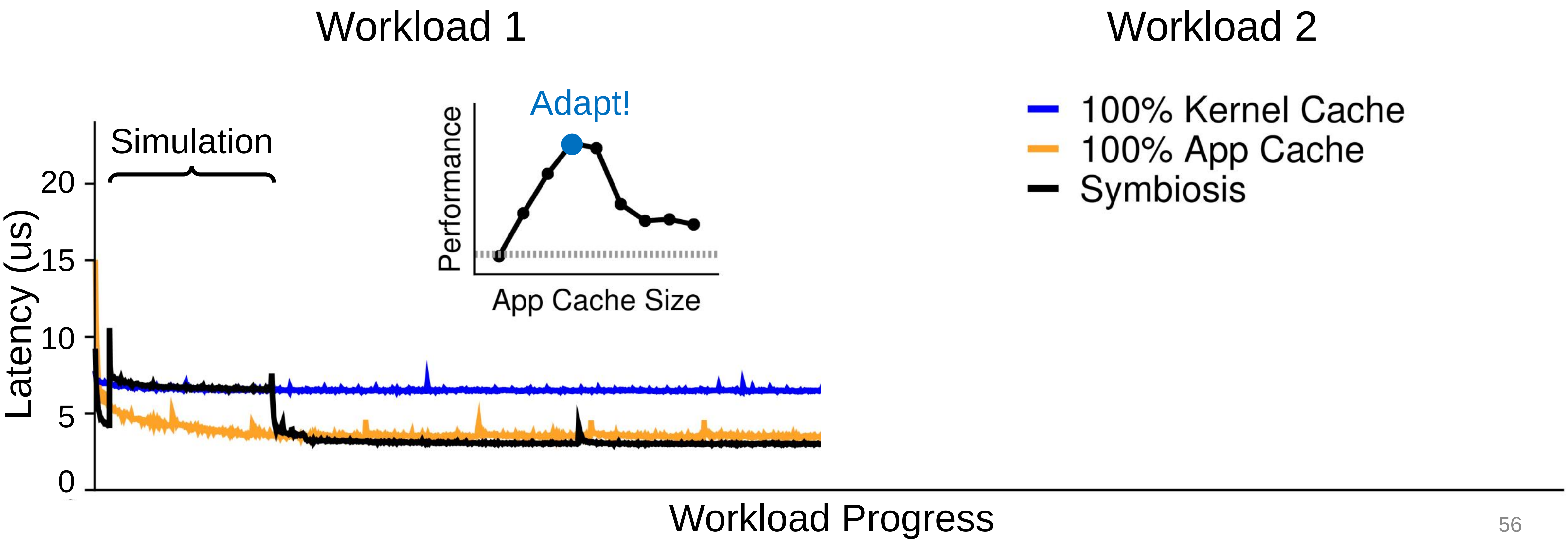
Workload 1



Dynamic Workloads - Example

Workload 1

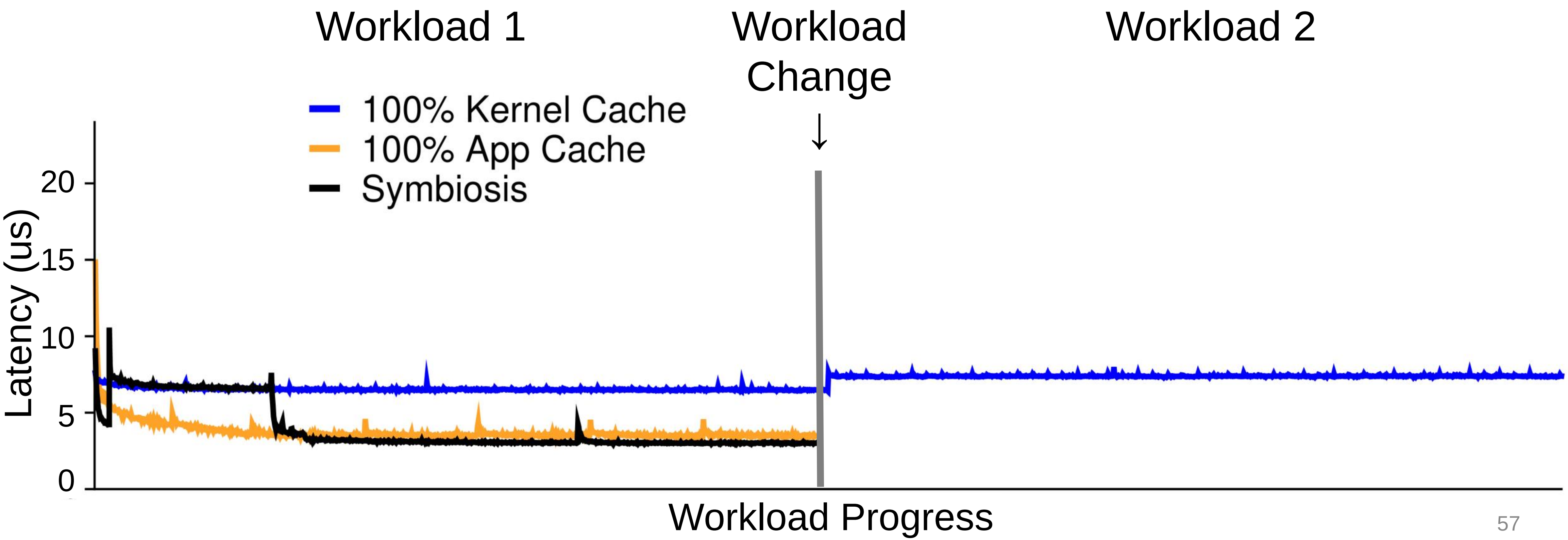
Simulation result: giving ~40% of memory to app cache is the best



Dynamic Workloads - Example

Workload 2

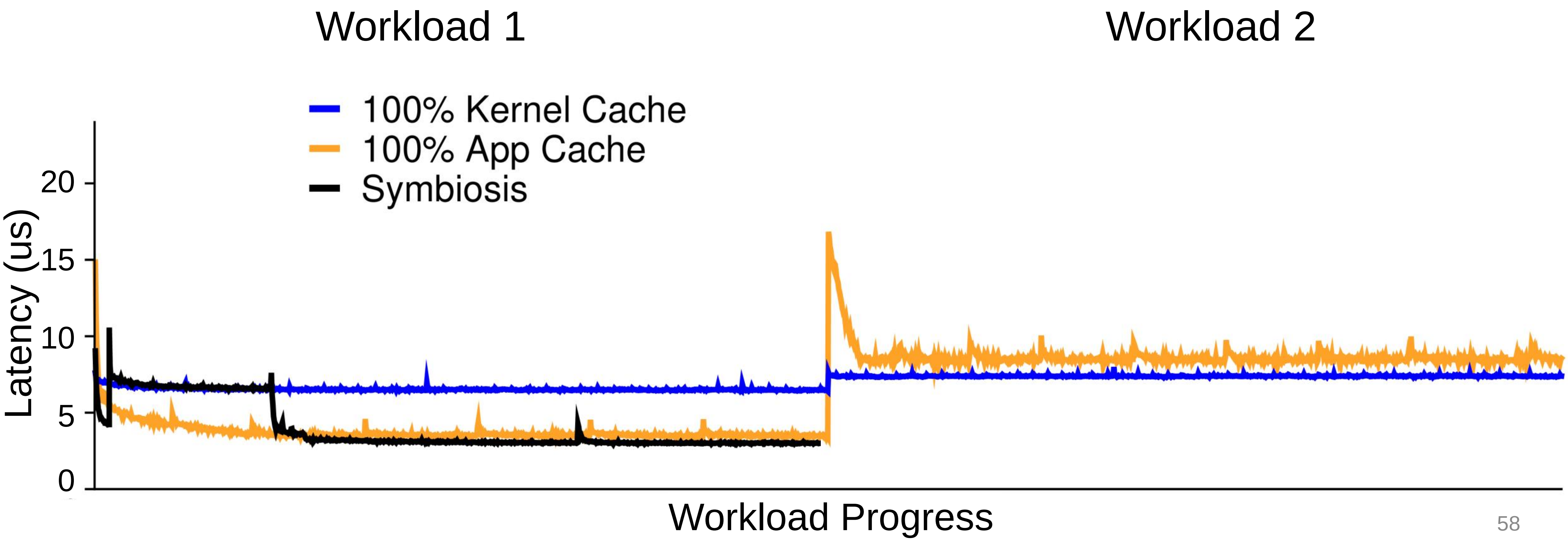
- 100% kernel cache performs similarly



Dynamic Workloads - Example

Workload 2

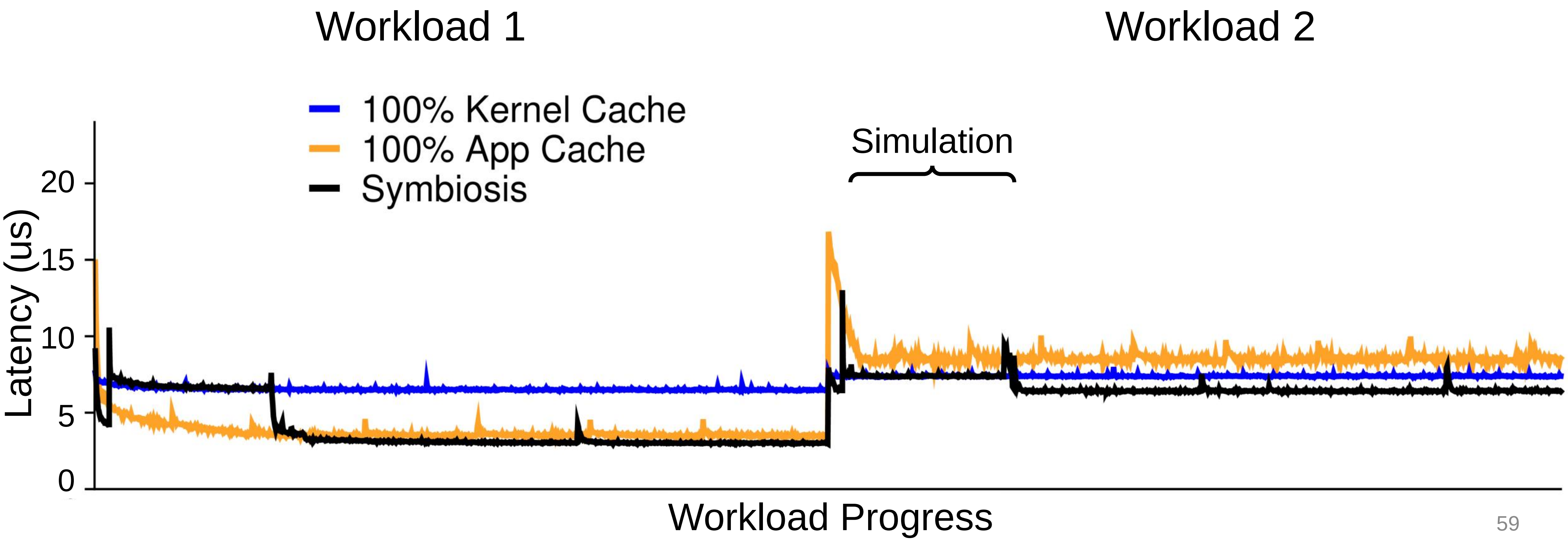
- 100% app cache performs worse due to less skewedness



Dynamic Workloads - Example

Workload 2

Symbiosis maintains the best performance after simulation



Dynamic Workloads - Example

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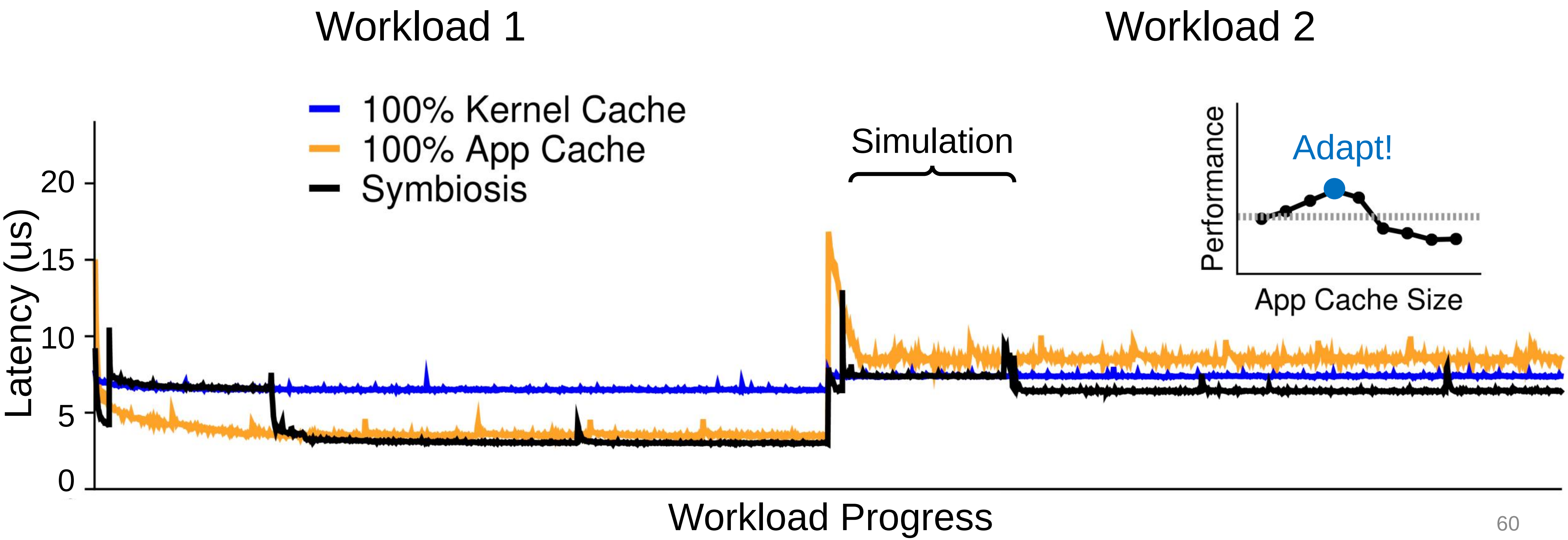

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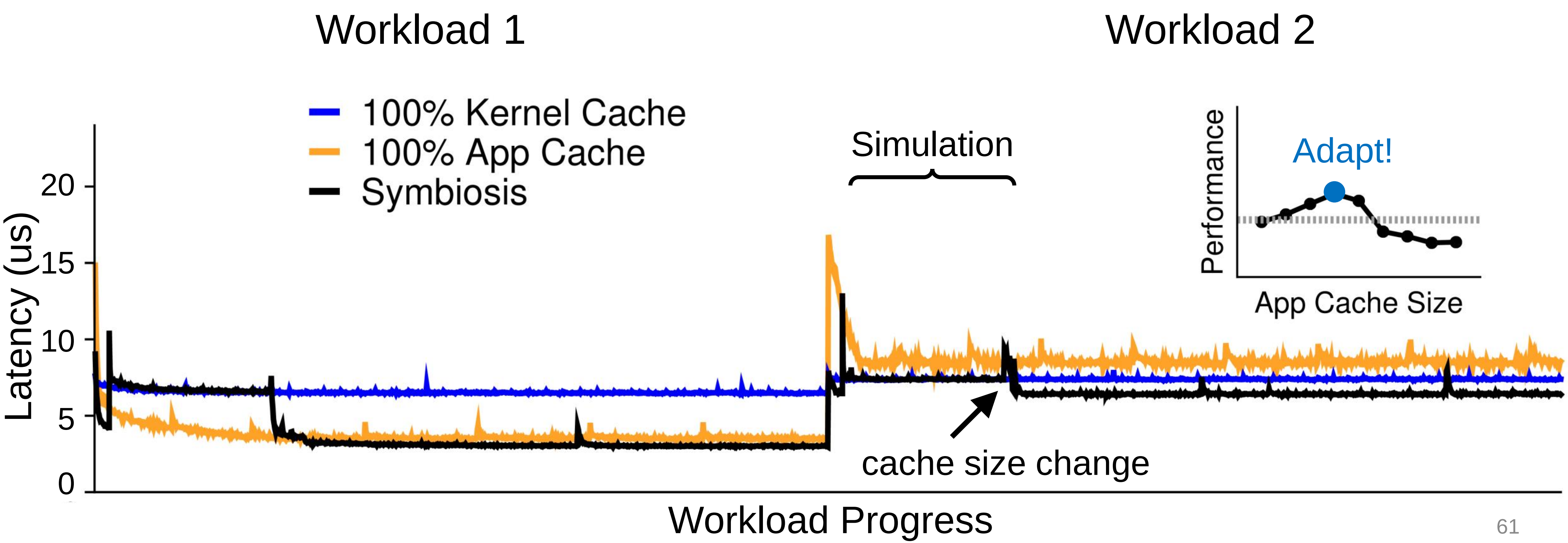

Conclusion

Symbiosis: dynamic cache size adjustment via online simulation

- Integrated into production systems within 1000 LoC
  - LevelDB, RocksDB, WiredTiger
- Adapts to various workloads and reacts to workload changes
  - Performs well on 190+ static workloads and 38 dynamic workloads
- Delivers excellent performance with negligible overhead
  - 1.5x gain on average for read-heavy workloads
  - 0.1% space overhead and 1% time overhead

Conclusion

Simulation-based online performance tuning

- A tuning approach that does not rely on machine learning
- Deep understanding and careful optimizations are necessary
- Potential parameter tuning beyond cache sizes

Thank You for Listening!

See the paper for:

- Offline simulation study
- Detailed implementation and evaluation

Symbiosis source code

- https://github.com/daiyifandanny/Symbiosis