Reducing Bloom Filter CPU Overhead in LSM-Trees on Modern Storage Devices

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presentation at DAMON 2021

Log-Structured Merge Trees

Widely adopted because they balance read performance and ingestion

RocksDB

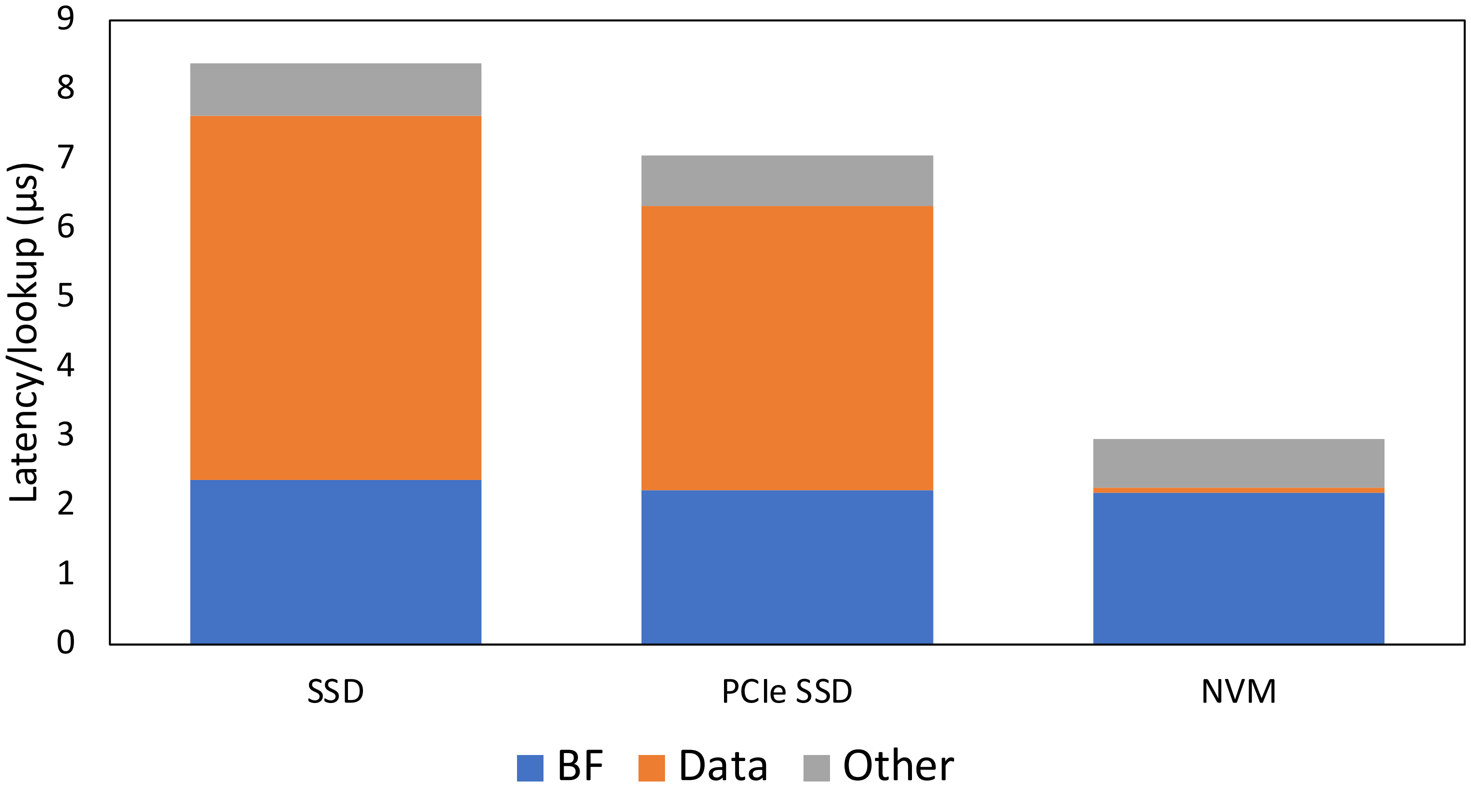
amazon DynamoDB

APACHE HBASE

levelDB

cassandra

Where does the time go?



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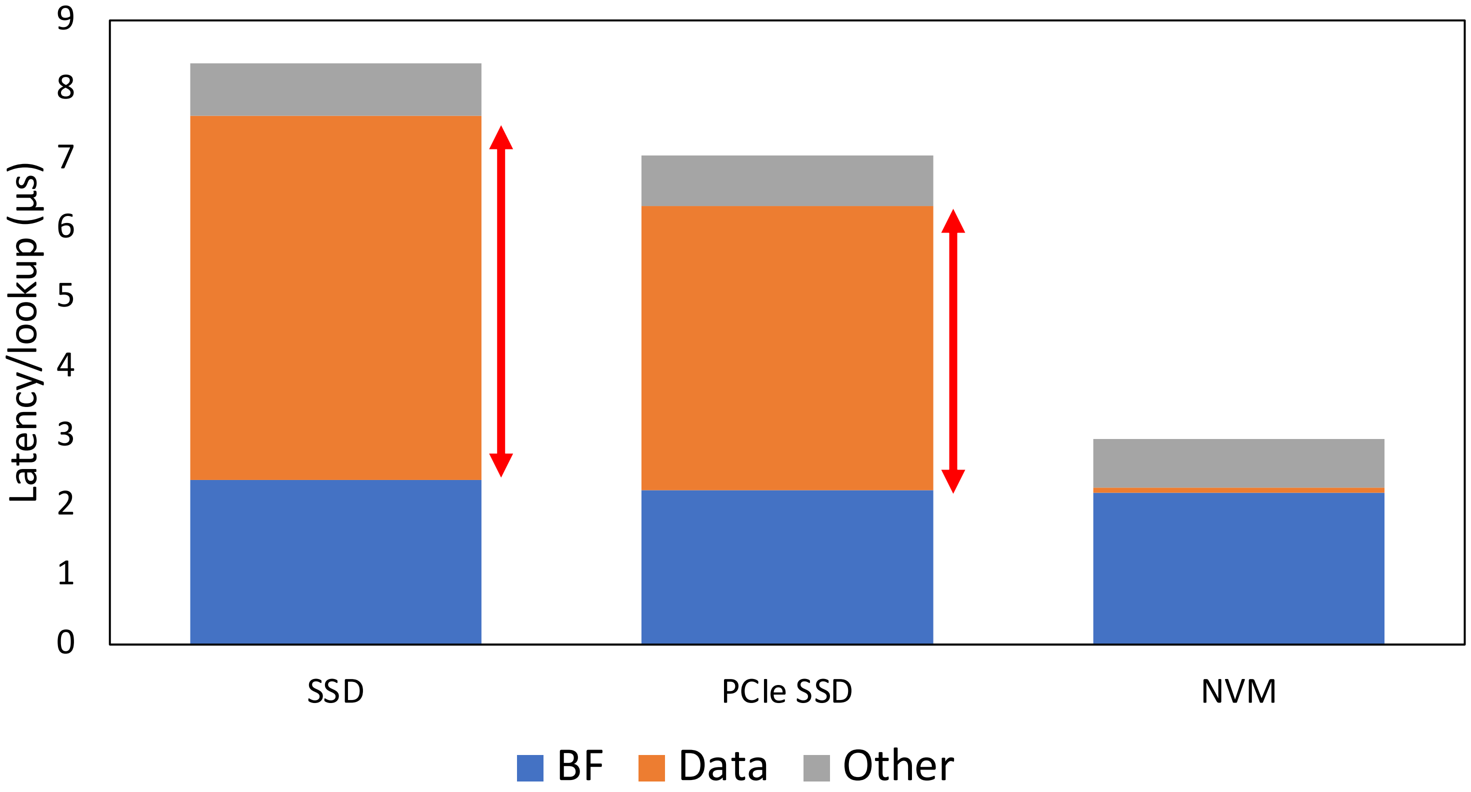

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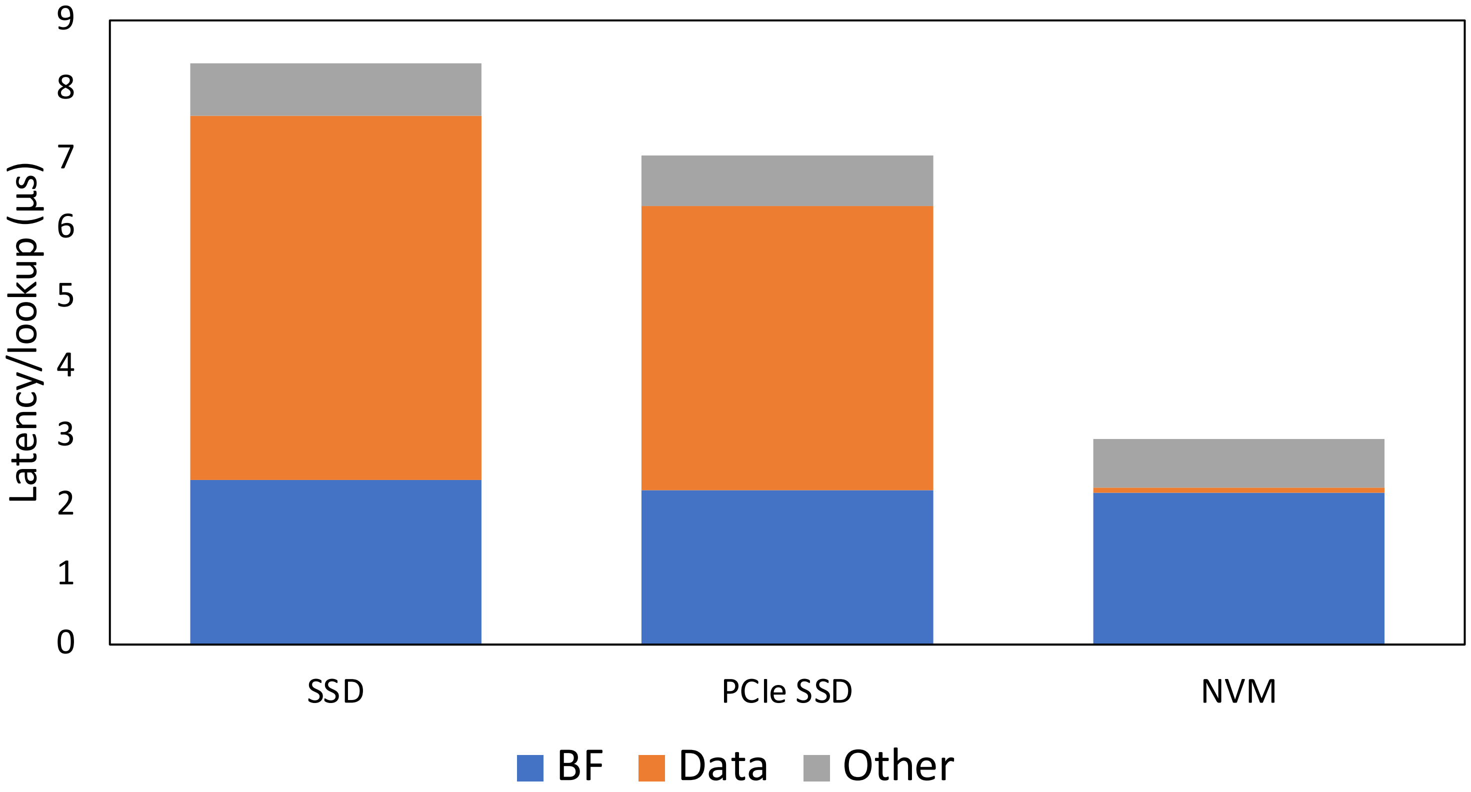
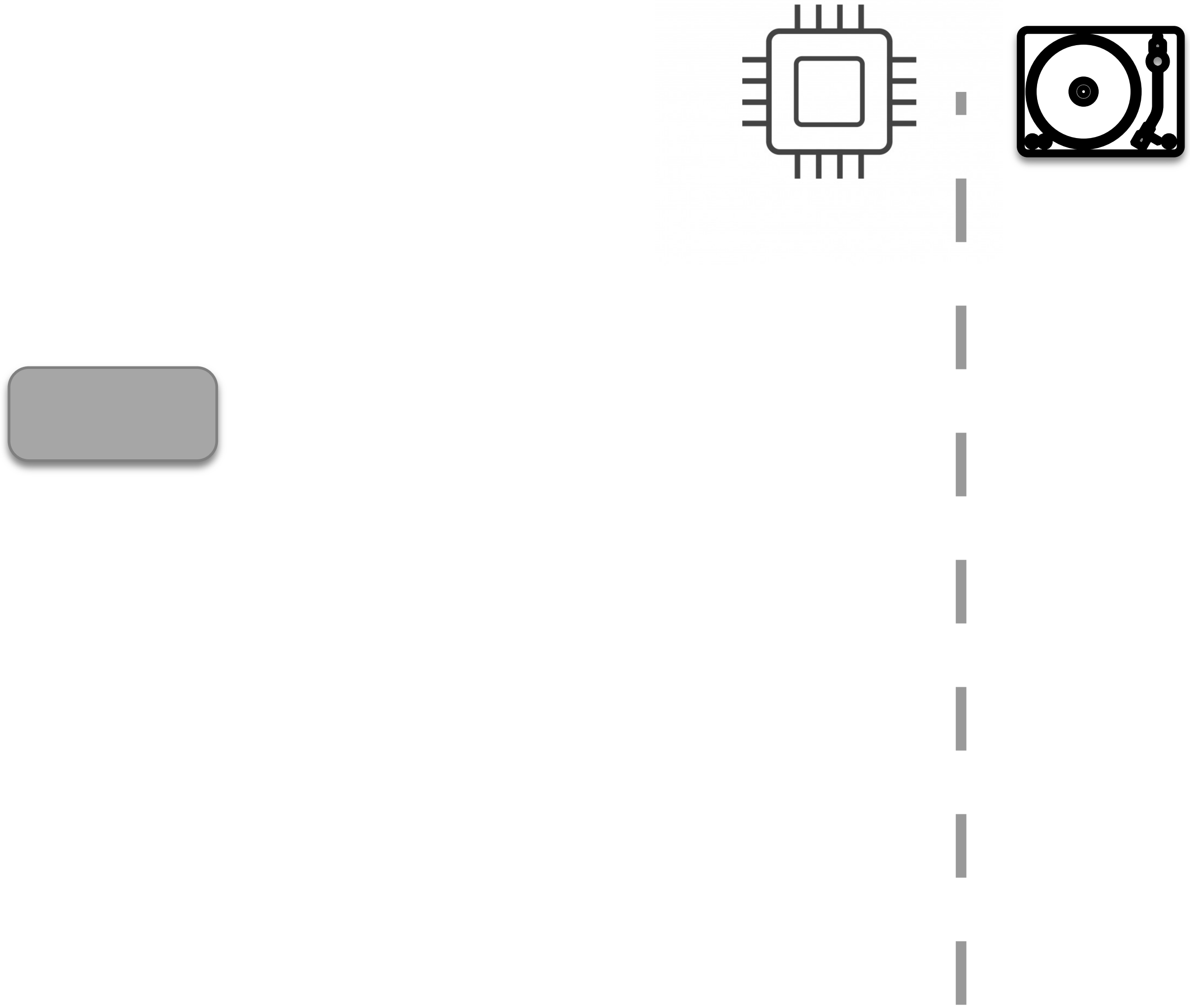


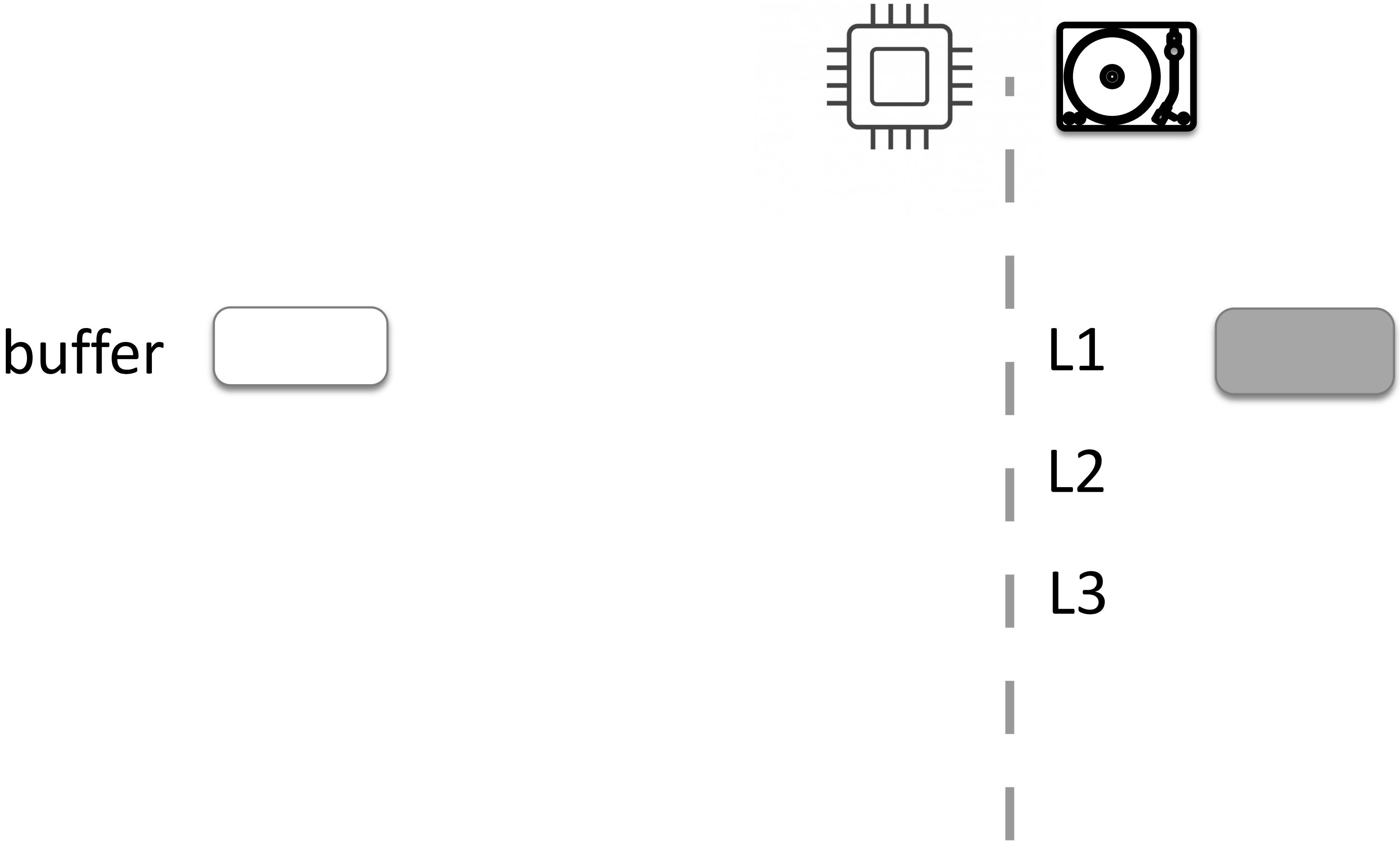
The time spent on Bloom filters dominates for faster storage.

Log-Structured Merge Trees

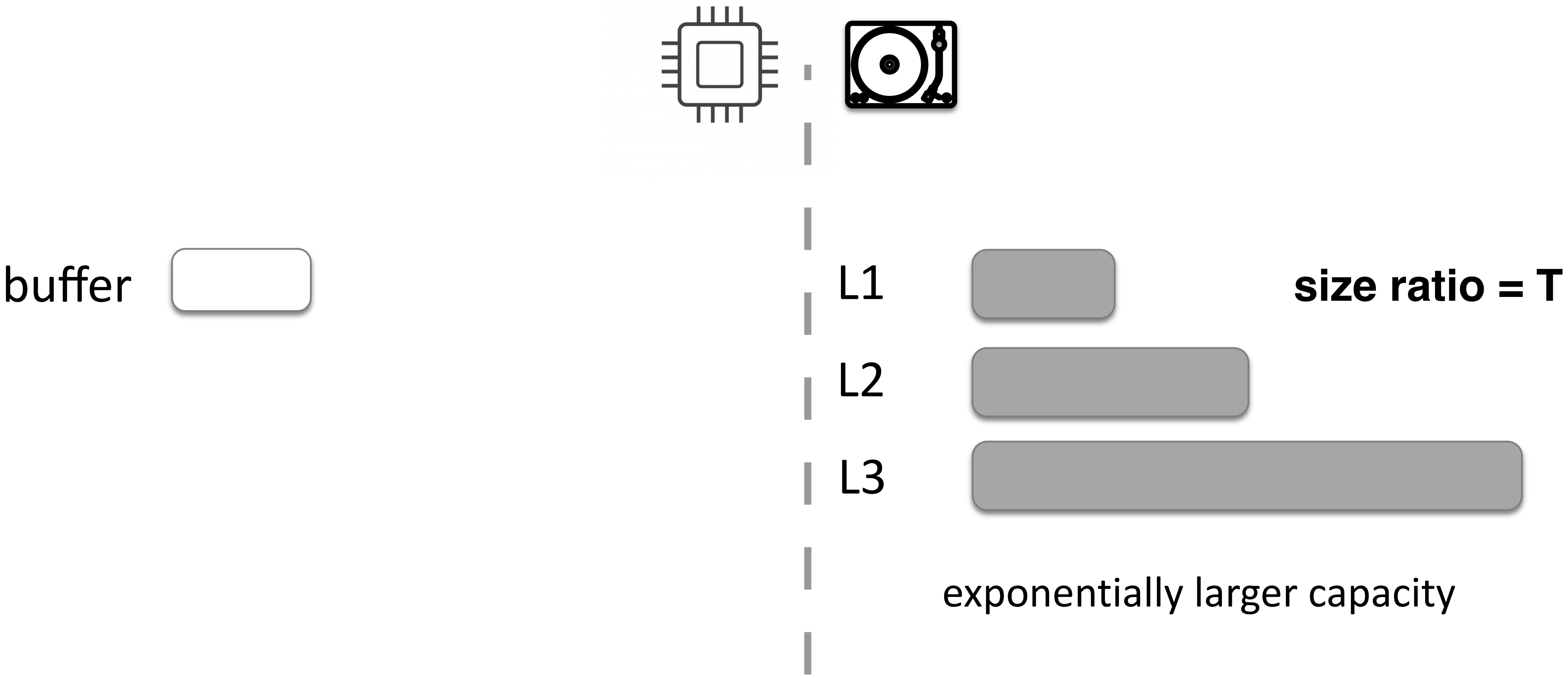


buffer

Log-Structured Merge Trees



Log-Structured Merge Trees



buffer

L1

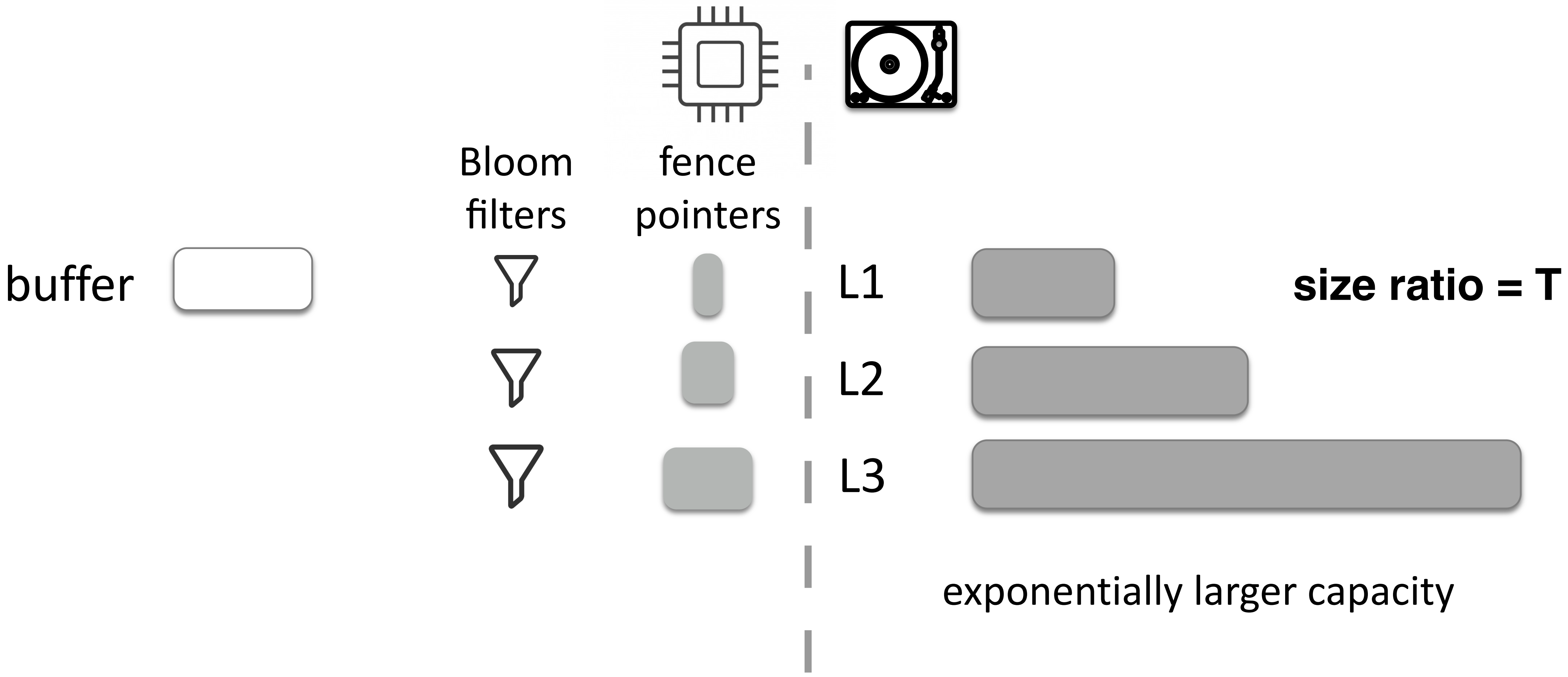
L2

L3

size ratio = T

exponentially larger capacity

Log-Structured Merge Trees



Bloom filters

fence pointers

buffer

L1

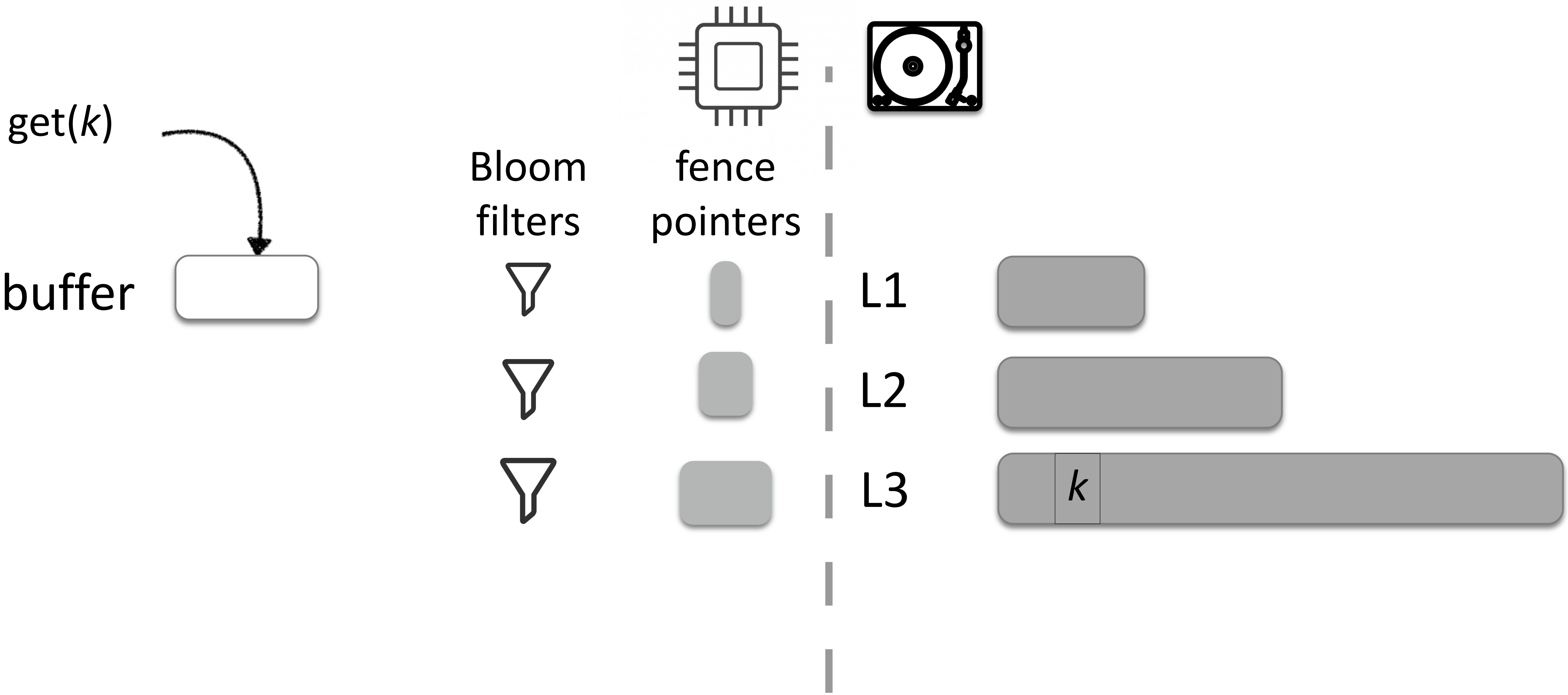
L2

L3

size ratio = T

exponentially larger capacity

Log-Structured Merge Trees



get(*k*)

Bloom filters

fence pointers

buffer

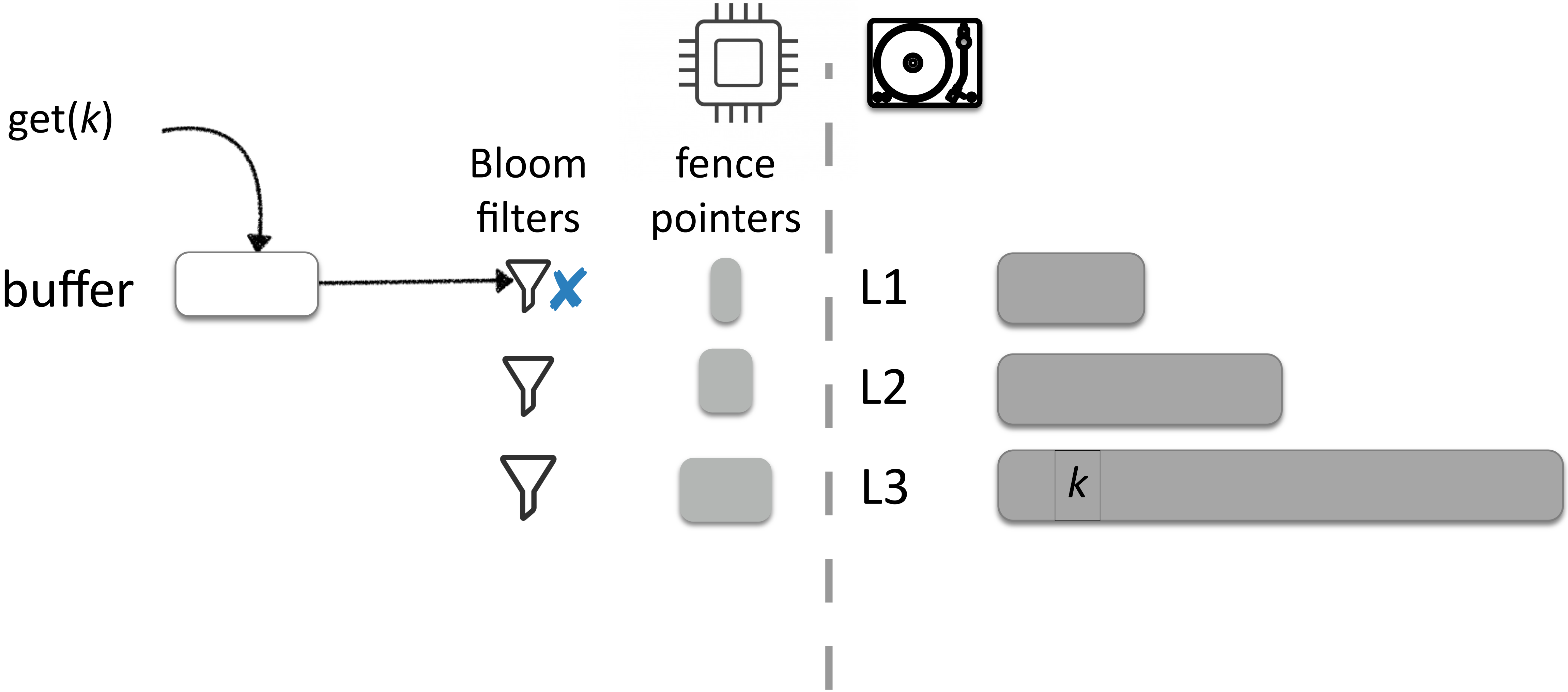
L1

L2

L3

k

Log-Structured Merge Trees



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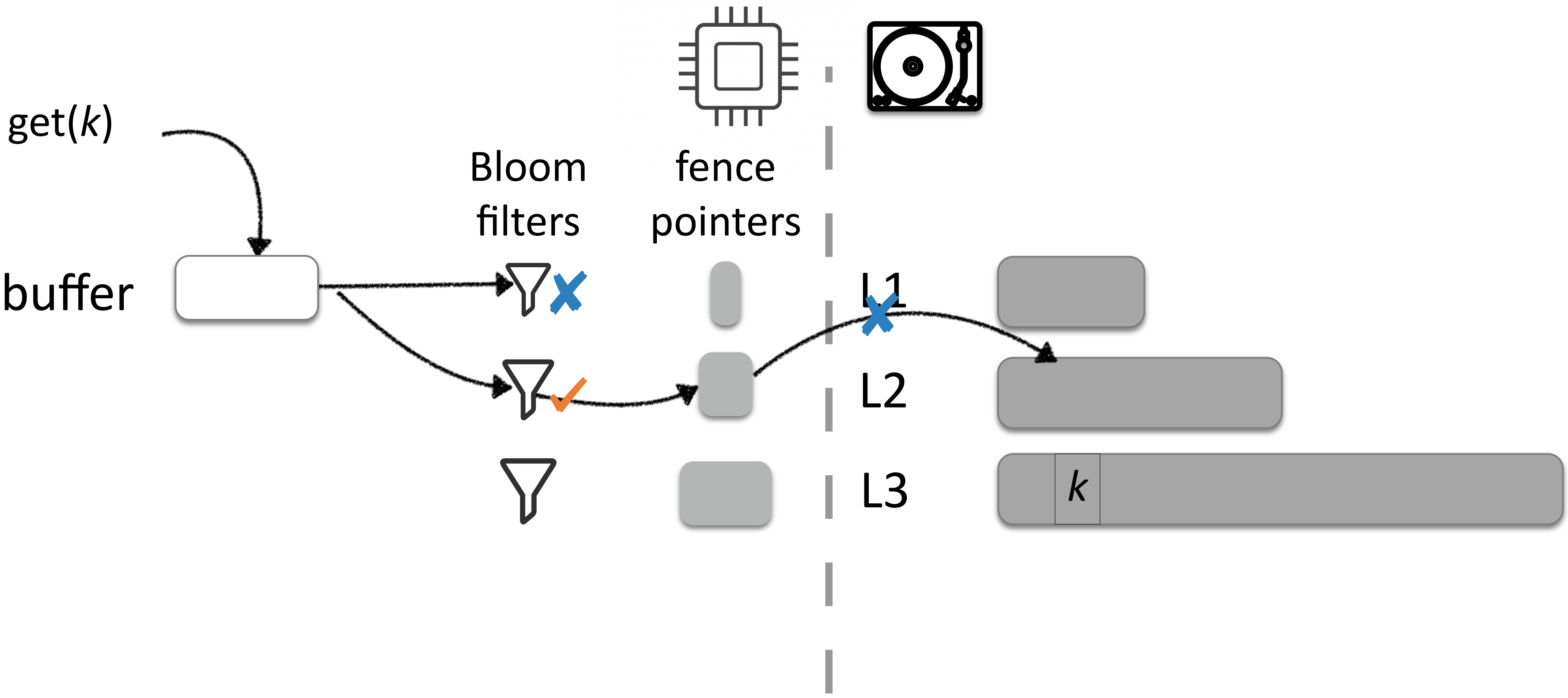

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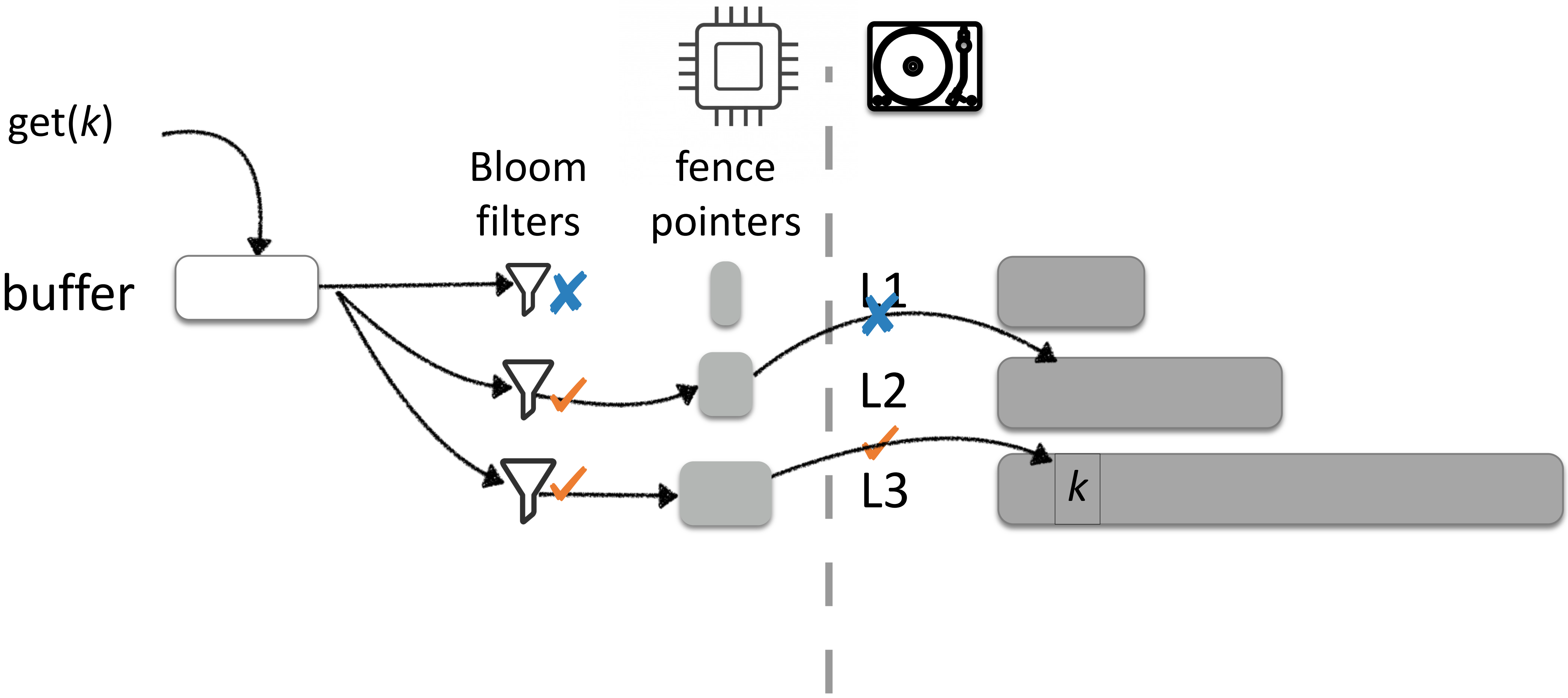

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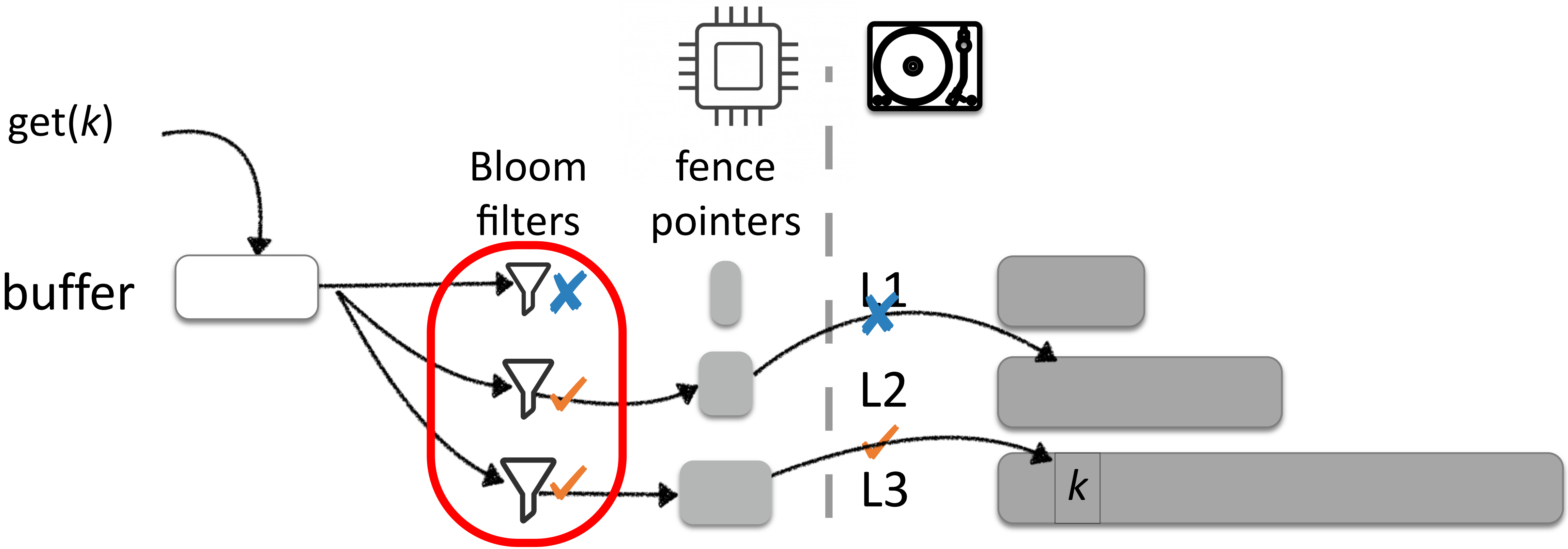
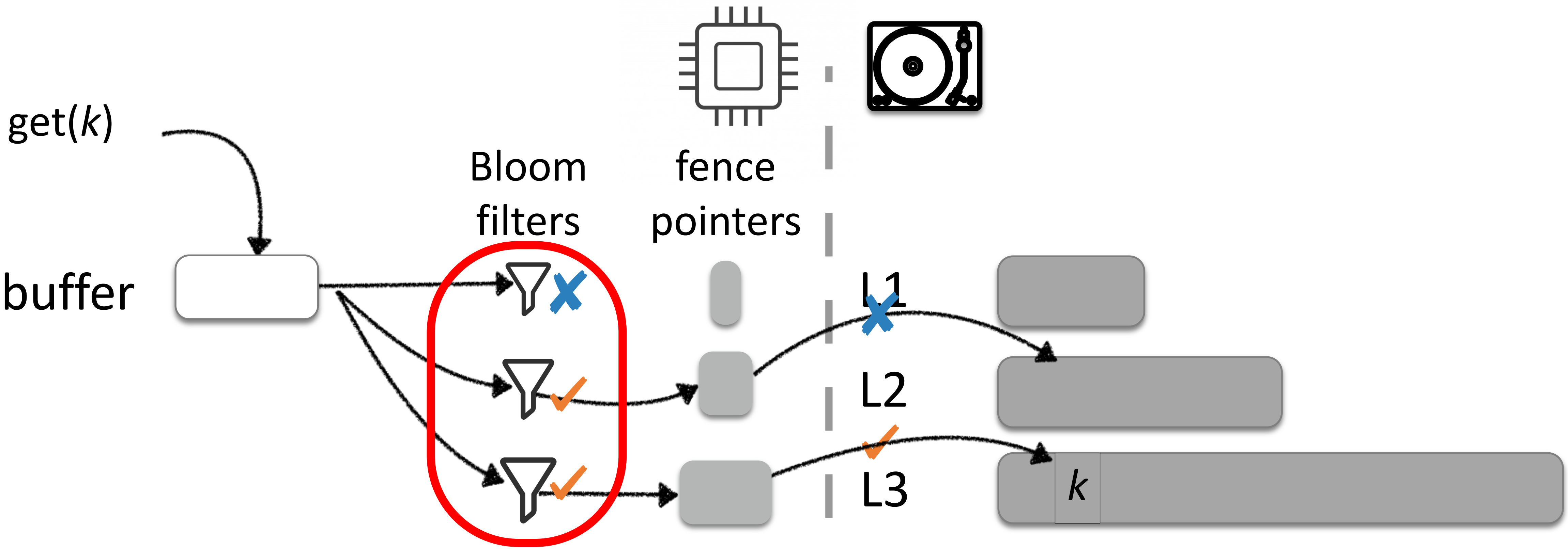


All queries use a BF!

Log-Structured Merge Trees



All queries use a BF!

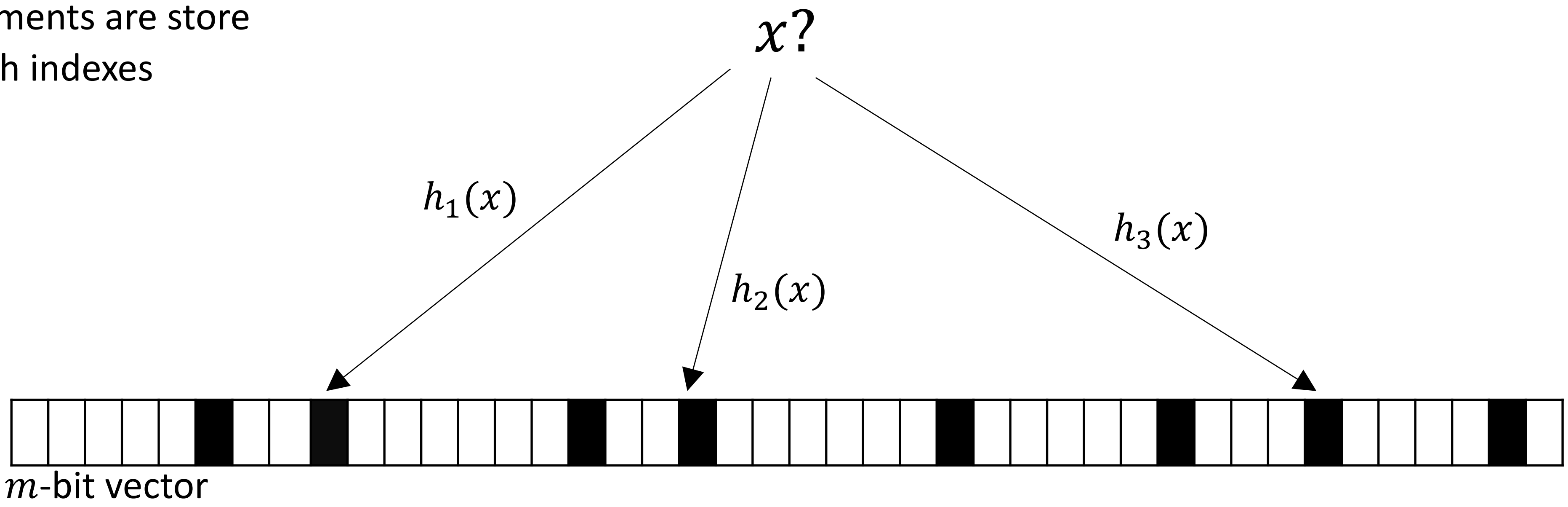
What is the cost of querying a Bloom filter?

Bloom Filter Query Cost

m-bit vector

n elements are store

k hash indexes



the fraction of empty queries

$$k \cdot \underline{T_H} + \underline{T_P} + \alpha \cdot f_p \cdot T_D + (1-\alpha) \cdot \underline{T_D}$$

Hashing time Probing time Data access time

Bloom Filter Query Cost

m-bit vector

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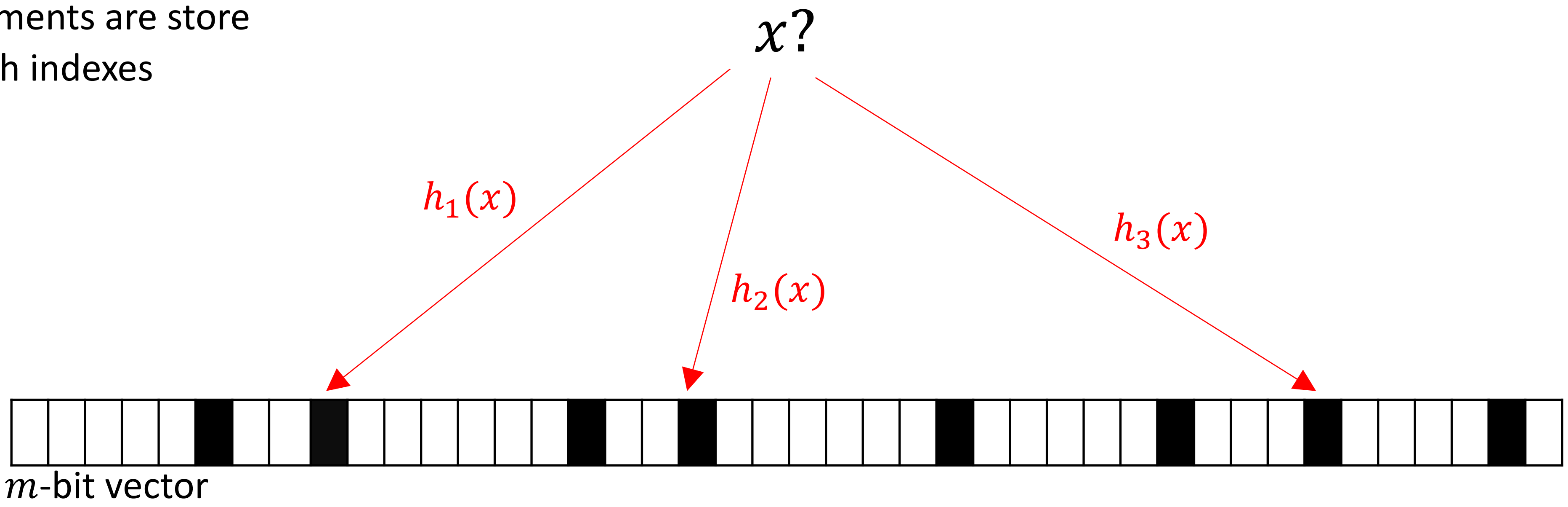

$$\underline{k \cdot T_H} + T_P + \alpha \cdot f_p \cdot T_D + (1 - \alpha) \cdot T_D$$

Bloom Filter Query Cost

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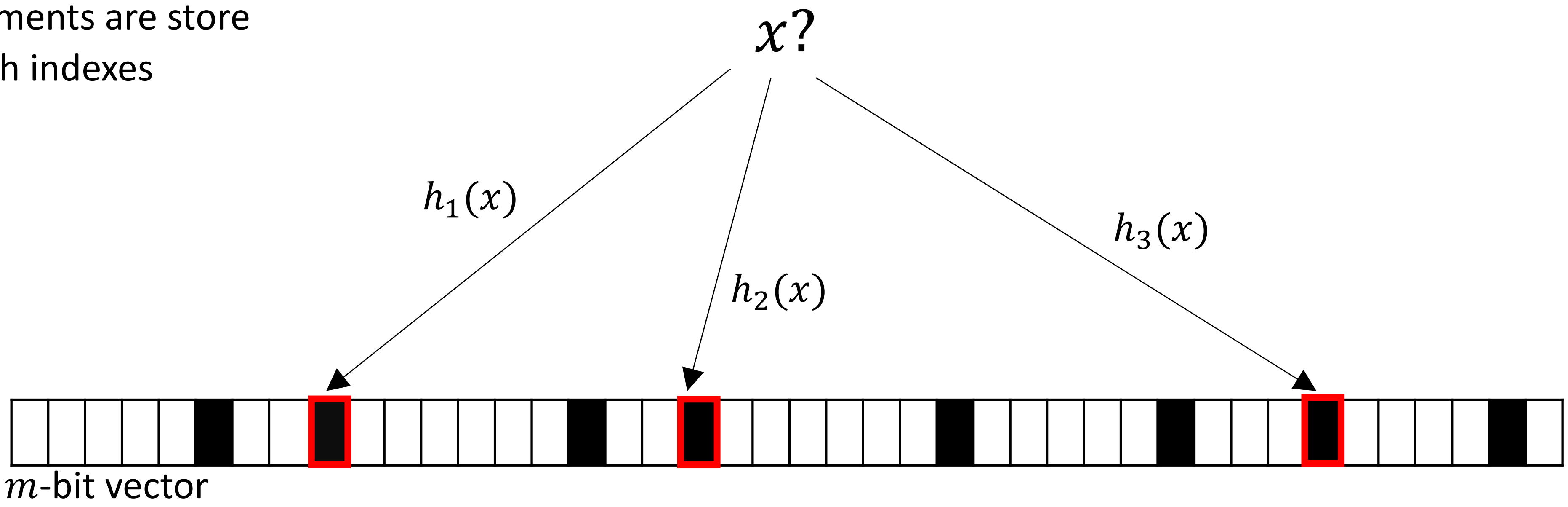

$$k \cdot T_H + \underline{T_P} + \alpha \cdot f_p \cdot T_D + (1-\alpha) \cdot T_D$$

α → the fraction of empty queries

Bloom Filter Query Cost

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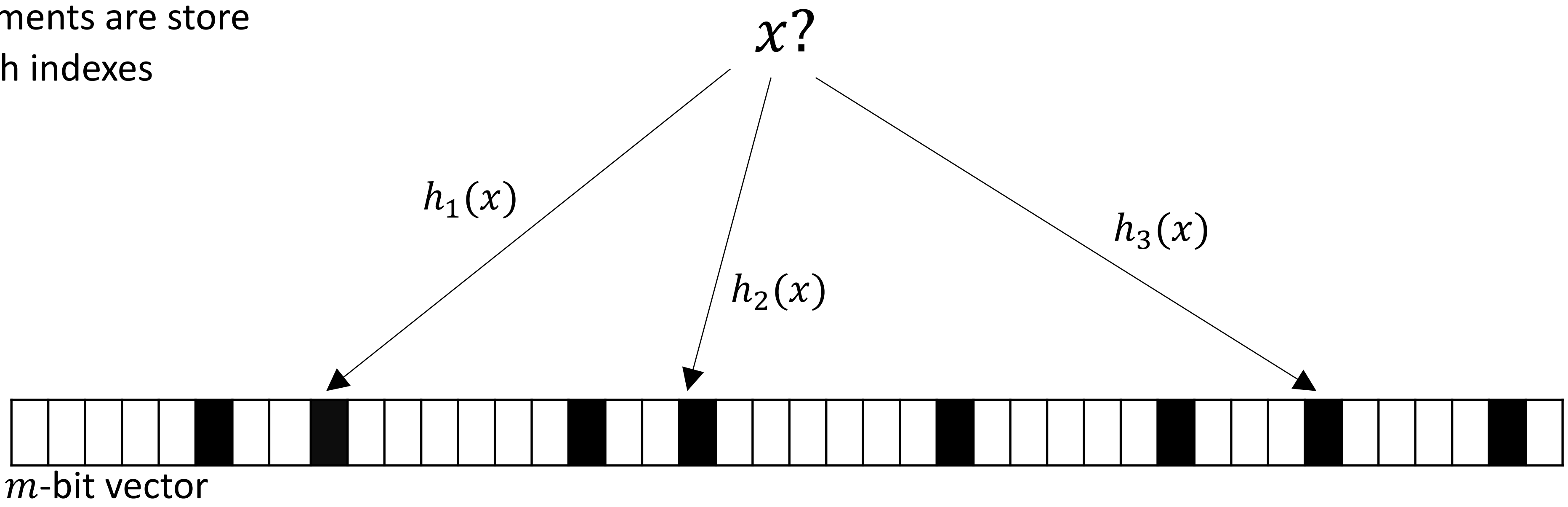

$$k \cdot T_H + T_P + \underline{\alpha \cdot f_p \cdot T_D + (1-\alpha) \cdot T_D}$$

the fraction of empty queries

Bloom Filter Query Cost

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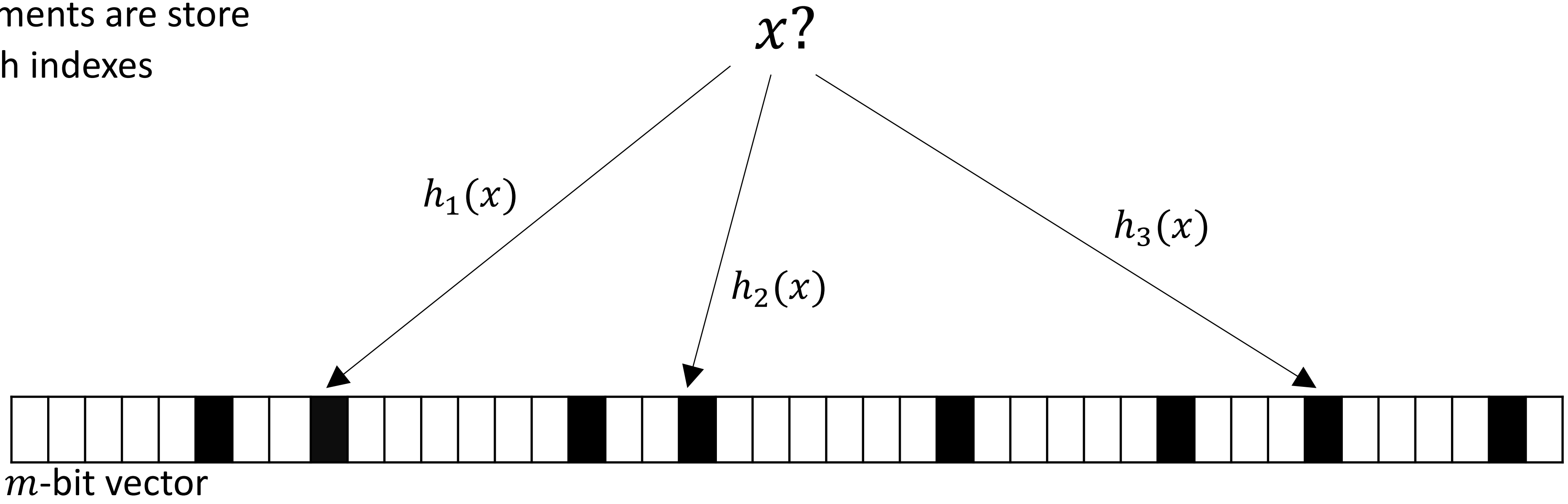


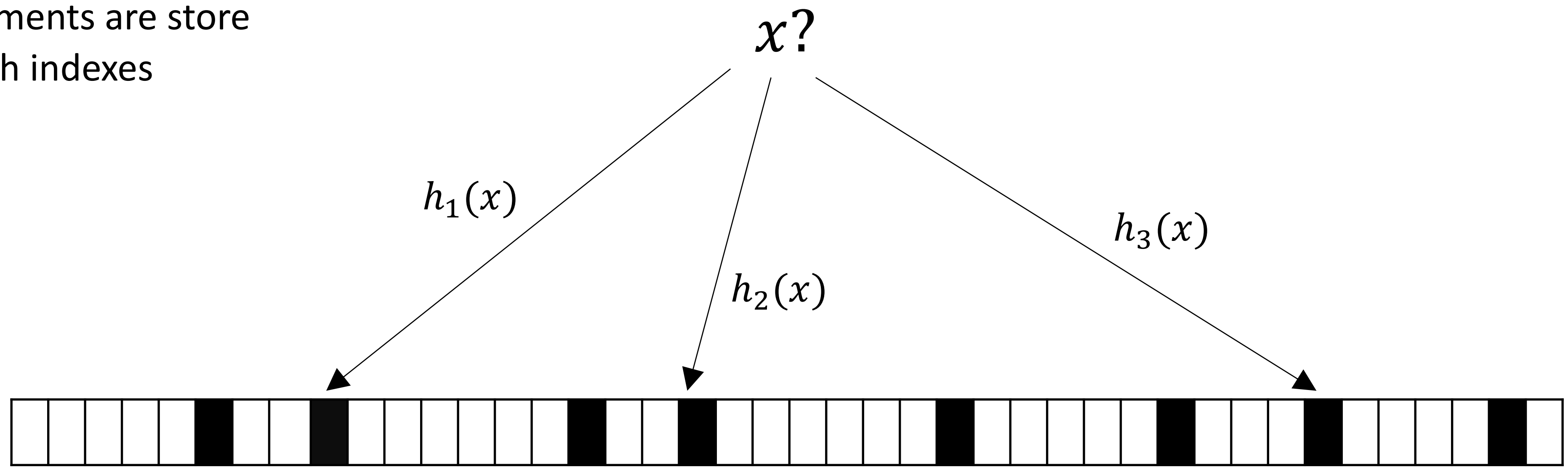
$$k \cdot T_H + T_P + \underbrace{\alpha \cdot f_p \cdot T_D}_{\text{empty}} + \underbrace{(1-\alpha) \cdot T_D}_{\text{non-empty}}$$

Bloom Filter Query Cost

m-bit vector

n elements are store

k hash indexes



m-bit vector

$$\boxed{k \cdot T_H} + T_P + \alpha \cdot f_p \cdot T_D + (1 - \alpha) \cdot T_D$$

Bloom Filter Query Cost

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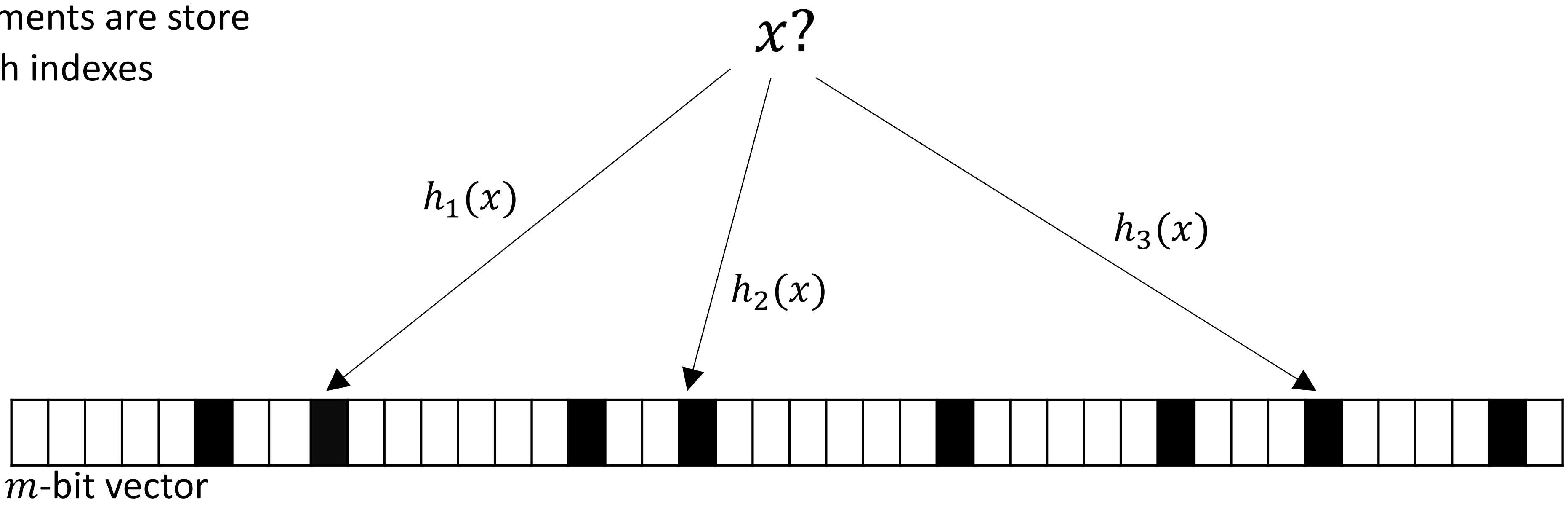


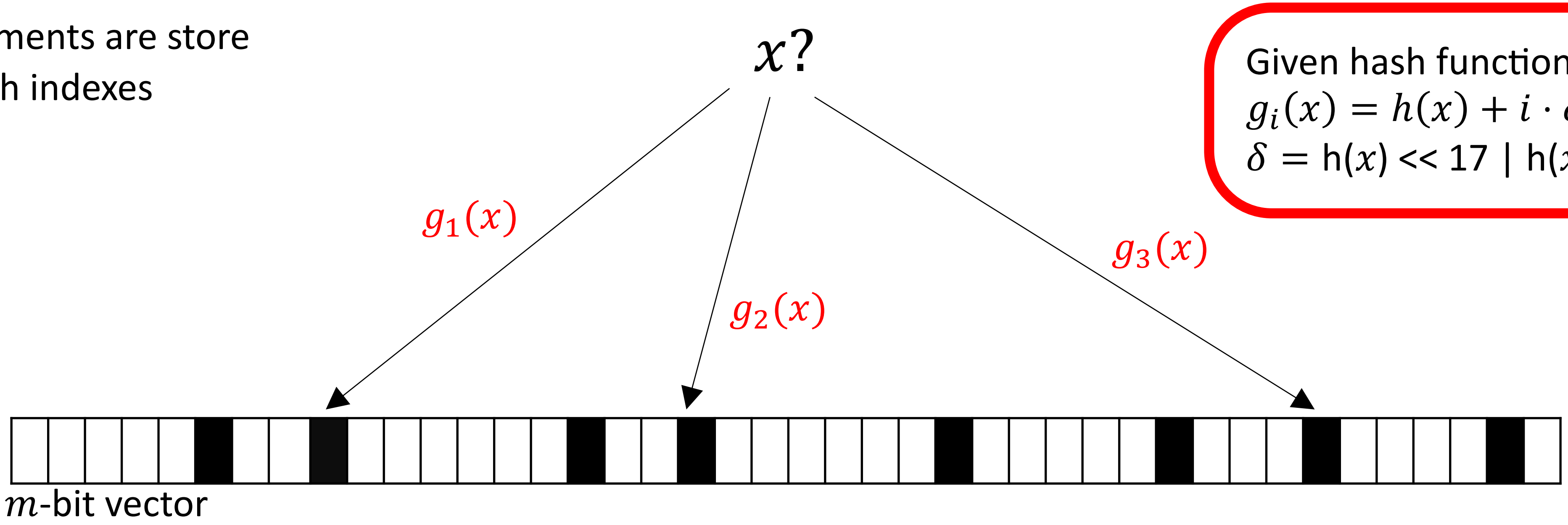
$$\boxed{k \cdot T_H} + T_P + \alpha \cdot f_p \cdot T_D + (1 - \alpha) \cdot T_D$$

→ a single hash function,
followed by much cheaper bitwise operations

Bloom Filter Query Cost

m-bit vector
n elements are store
k hash indexes

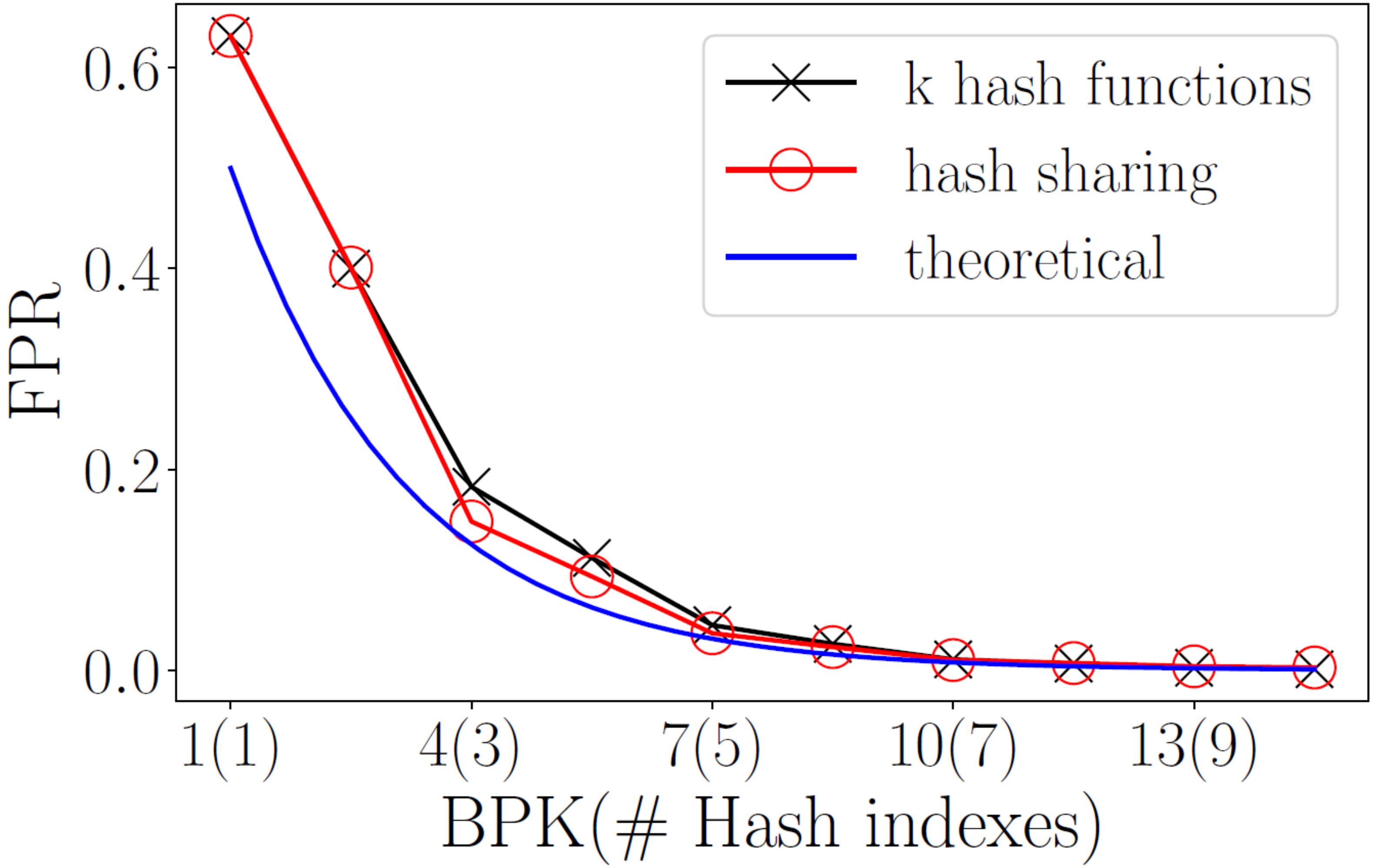
Given hash function, h
$g_i(x) = h(x) + i \cdot \delta$
δ = h(x) << 17 | h(x) >> 15



$$\cancel{k} \cdot T_H + T_P + \alpha \cdot f_p \cdot T_D + (1-\alpha) \cdot T_D$$

Bloom Filter False Positive Rate

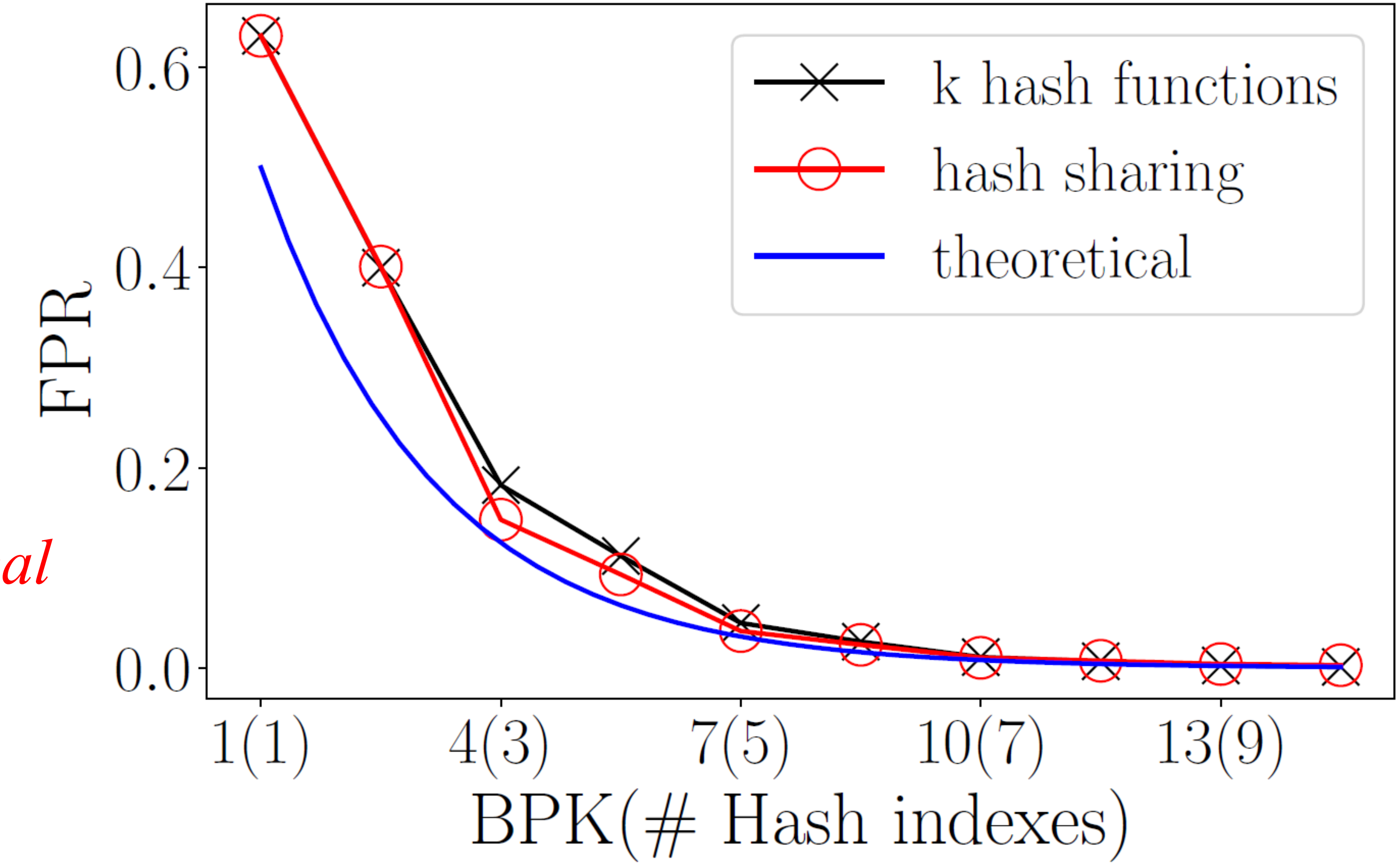
k vs. single hash function



Bloom Filter False Positive Rate

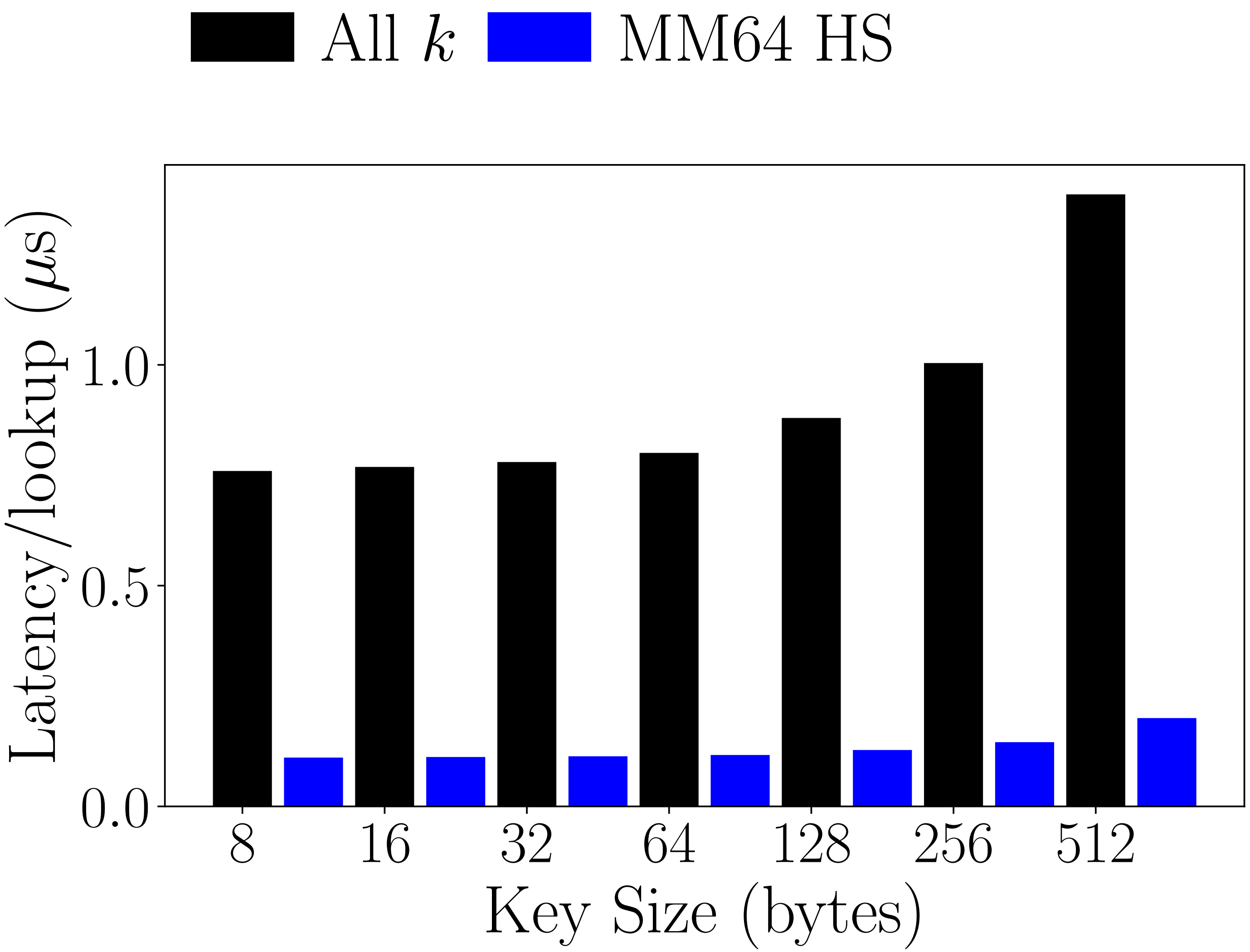
k vs. single hash function

FPR close-to-theoretical



Bloom Filter Lookup Latency

k vs. single hash function



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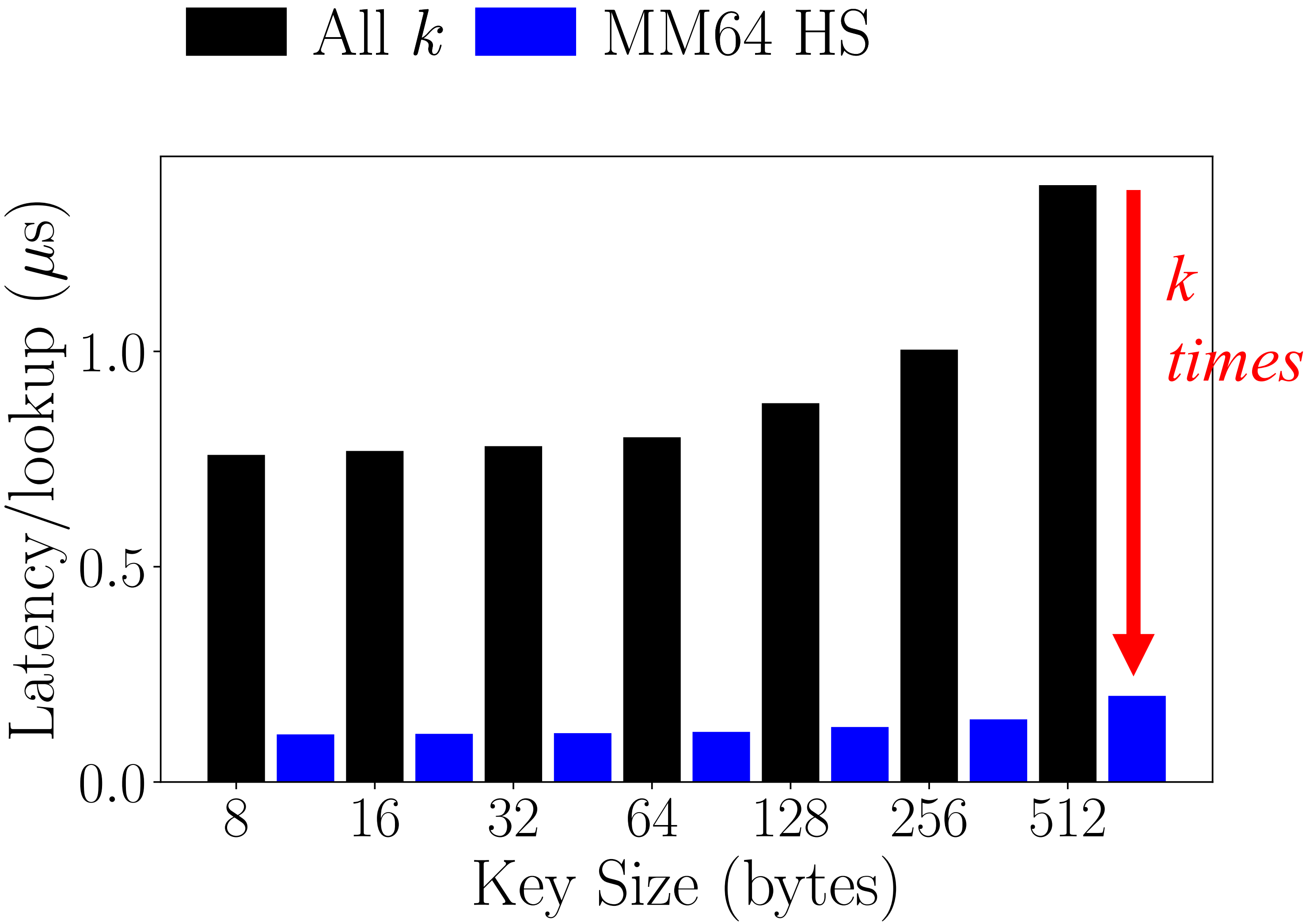

What is the Lookup Cost in LSM-Trees?

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Leveling

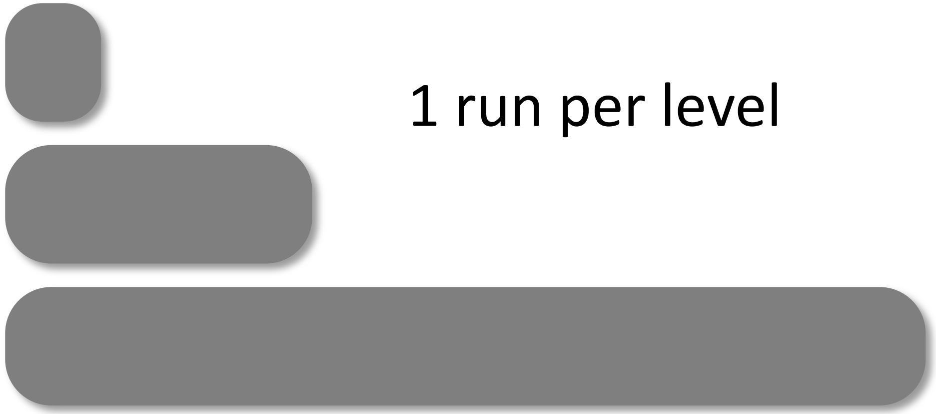
read-optimized

Tiering

write-optimized

Leveling

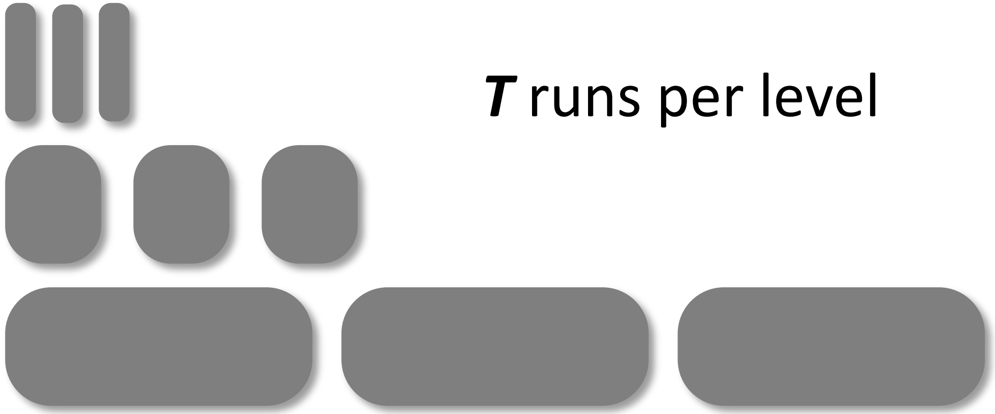
read-optimized



1 run per level

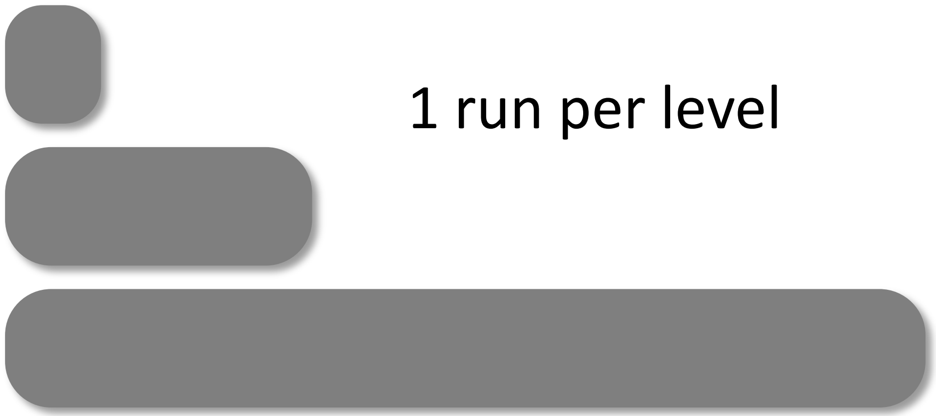
Tiering

write-optimized



T runs per level

Lookup Cost in a Leveled LSM-Tree



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Lookup cost in level i, $\mathcal{T}(i)$

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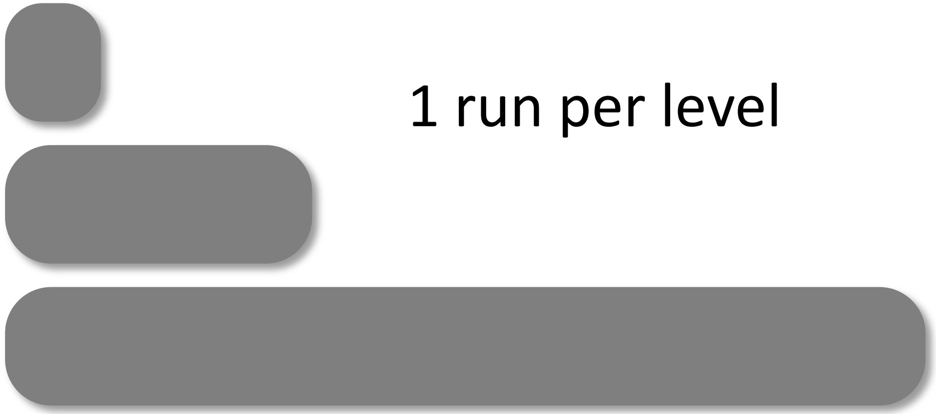

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Lookup cost in level i, $\mathcal{T}(i)$

- empty (α_i)

$$\alpha_i \cdot (T_H + T_P + f_p \cdot T_D)$$

- non-empty ($1 - \alpha_i$)

$$(1 - \alpha_i) \cdot (T_H + T_P + T_D)$$

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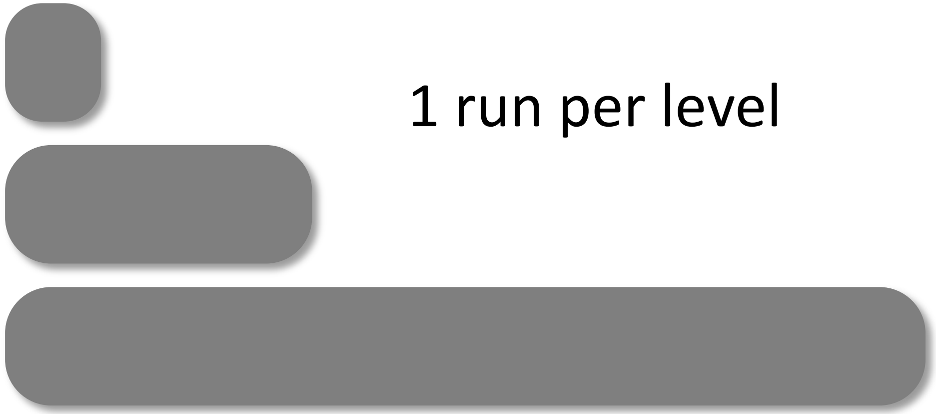

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$\boxed{+}$

$$\mathcal{T}(i) = T_H + T_P + \alpha_i \cdot f_p \cdot T_D + (1 - \alpha_i) \cdot T_D$$

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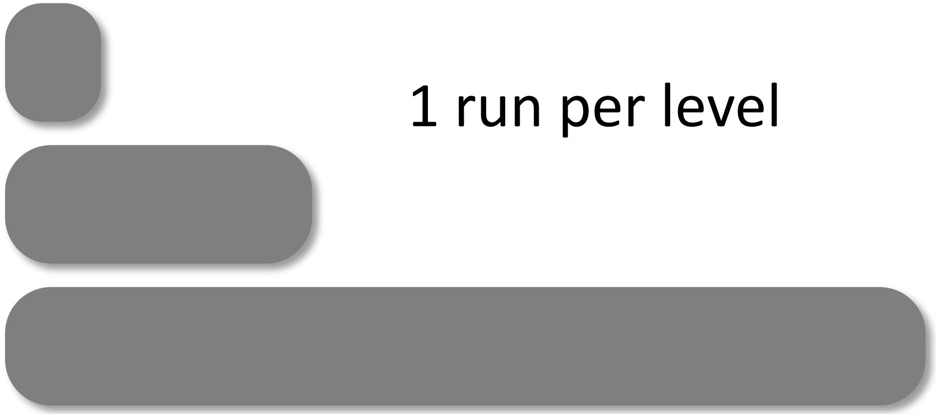

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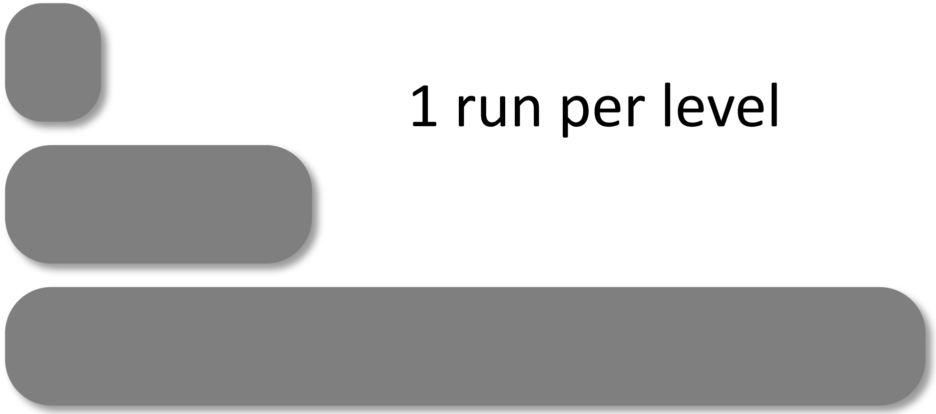
$\boxed{+}$

$$cost \approx \left(L - \frac{1-\alpha}{T-1}\right) \cdot (T_H + T_P) + \left(L - \frac{1-\alpha}{T-1} - 1 + \alpha\right) \cdot (f_p \cdot T_D) + (1-\alpha) \cdot T_D$$

Lookup Cost in a Leveled LSM-Tree



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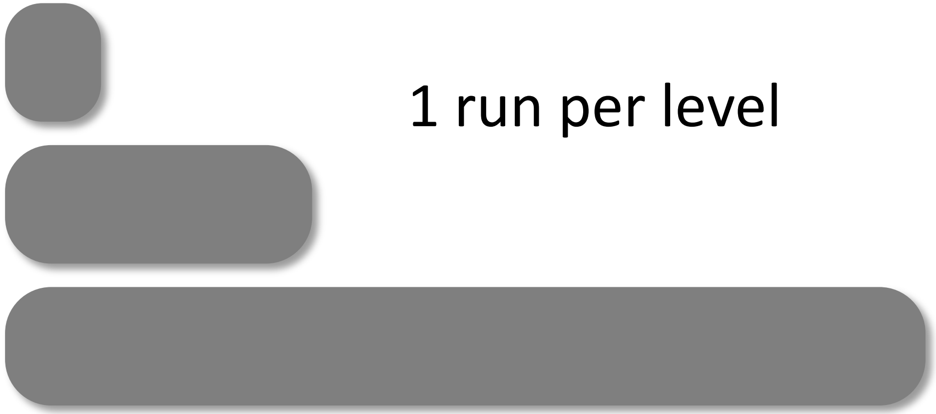
$+$

$$cost \approx \underbrace{\left(L - \frac{1-\alpha}{T-1}\right) \cdot (T_H + T_P)}_{\text{Bloom filter cost}} + \left(L - \frac{1-\alpha}{T-1} - 1 + \alpha\right) \cdot (f_p \cdot T_D) + (1 - \alpha) \cdot T_D$$

Lookup Cost in a Leveled LSM-Tree



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Lookup cost in level i, $\mathcal{T}(i)$

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  $$\alpha_i \cdot (T_{BF} + f_p \cdot T_D)$$

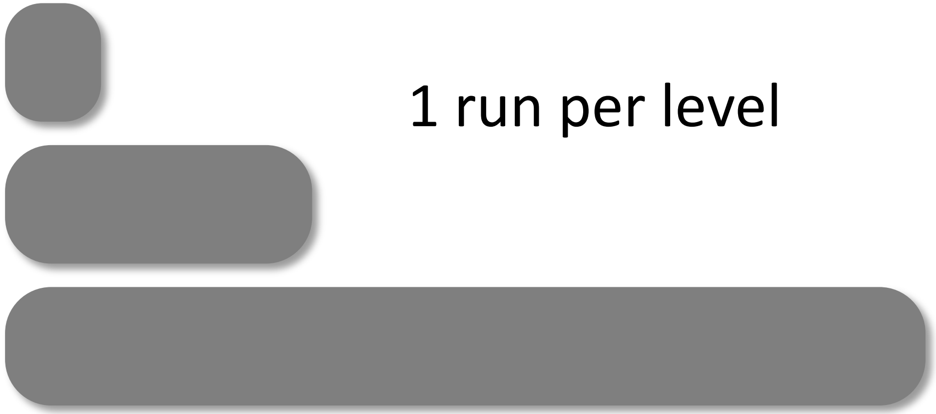
- non-empty ($1-\alpha_i$)

  $$(1-\alpha_i) \cdot (T_{BF} + T_D)$$

$$\boxed{+}$$

$$cost \approx \underbrace{\left(L - \frac{1-\alpha}{T-1}\right) \cdot (T_H + T_P)}_{\text{Bloom filter cost}} + \underbrace{\left(L - \frac{1-\alpha}{T-1} - 1 + \alpha\right) \cdot (f_p \cdot T_D)}_{\text{Data access due to false positives}} + (1-\alpha) \cdot T_D$$

Lookup Cost in a Leveled LSM-Tree



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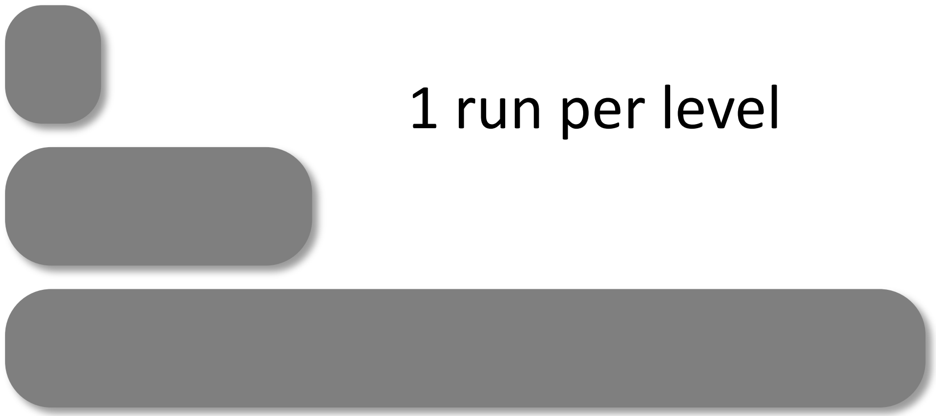
Lookup Cost in a Leveled LSM-Tree



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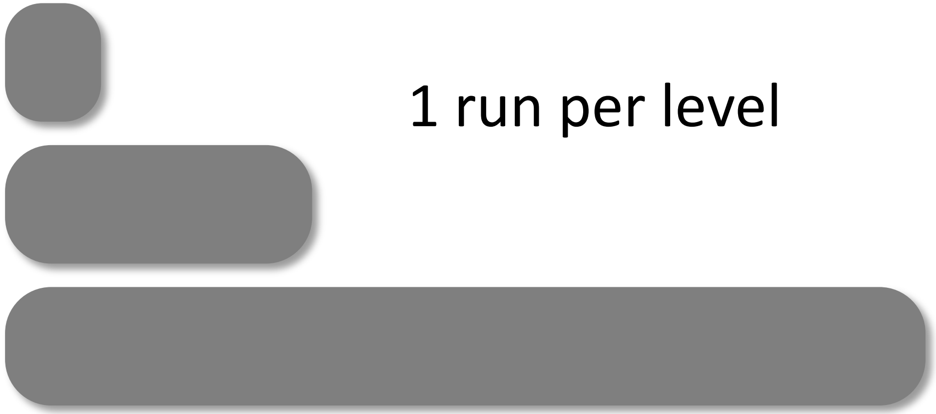
$\boxed{+}$

$$cost \approx \overset{\propto L}{\boxed{\left(L - \frac{1-\alpha}{T-1}\right) \cdot (T_H + T_P)}} + \left(L - \frac{1-\alpha}{T-1} - 1 + \alpha\right) \cdot (f_p \cdot T_D) + (1 - \alpha) \cdot T_D$$

Hashing accumulates as L grows (larger data size)

Lookup Cost in a Leveled LSM-Tree



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$$(1 - \alpha_i) \cdot (T_{BF} + T_D)$$

$$\boxed{+}$$

$$cost \approx \left(L - \frac{1-\alpha}{T-1}\right) \cdot (T_{BF}) + \left(L - \frac{1-\alpha}{T-1} - 1 + \alpha\right) \cdot (f_p \cdot T_D) + \boxed{(1-\alpha) \cdot T_D}$$

Hashing is more prominent for empty queries

Storage Access vs. Hashing

Operation	Latency	Normalized
4KB access on SDD	113 μs	706×
4KB access on PCIe SDD	10 μs	62.5×
4KB access on emulated NVM	**250 ns**	**1.56×**
4KB access on Memory	160 ns	1×
Murmur Hash of 1KB	235 ns	1.47×

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10% faster than NVM

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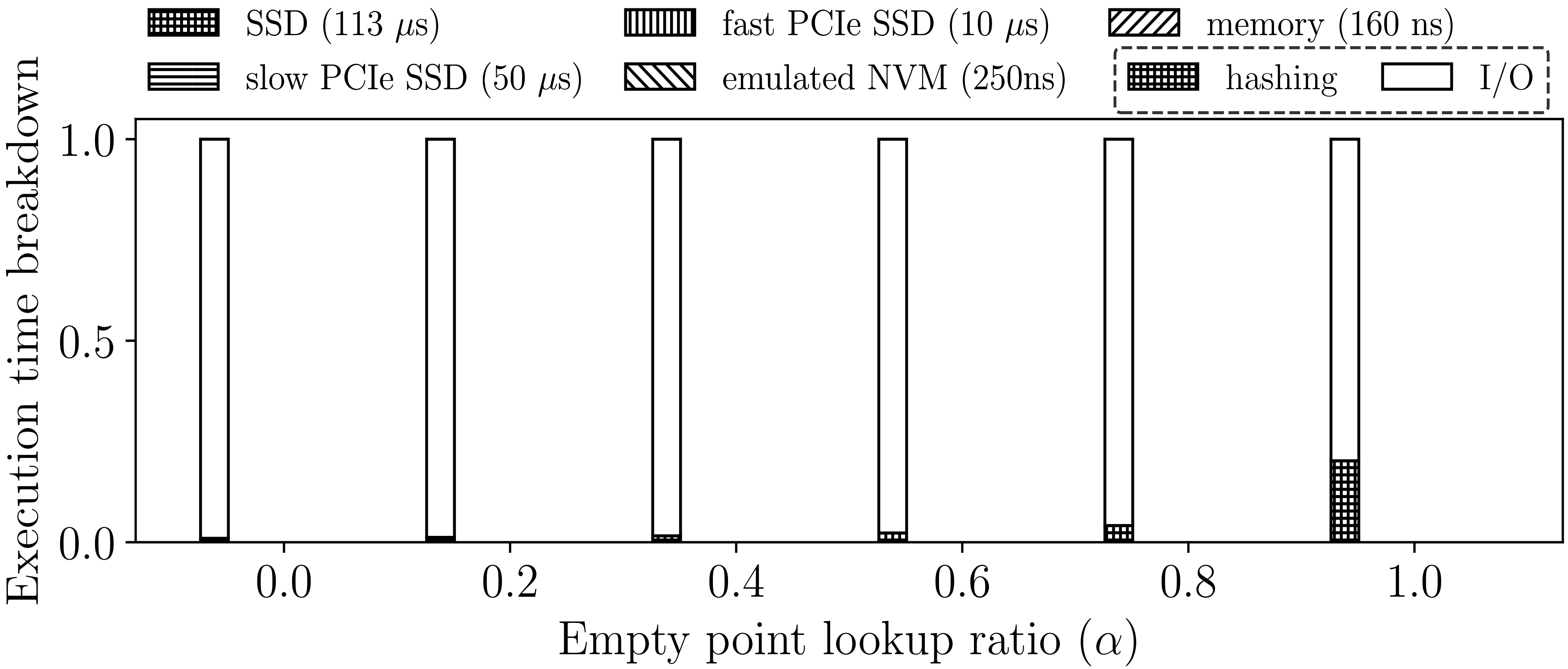
10% faster than NVM

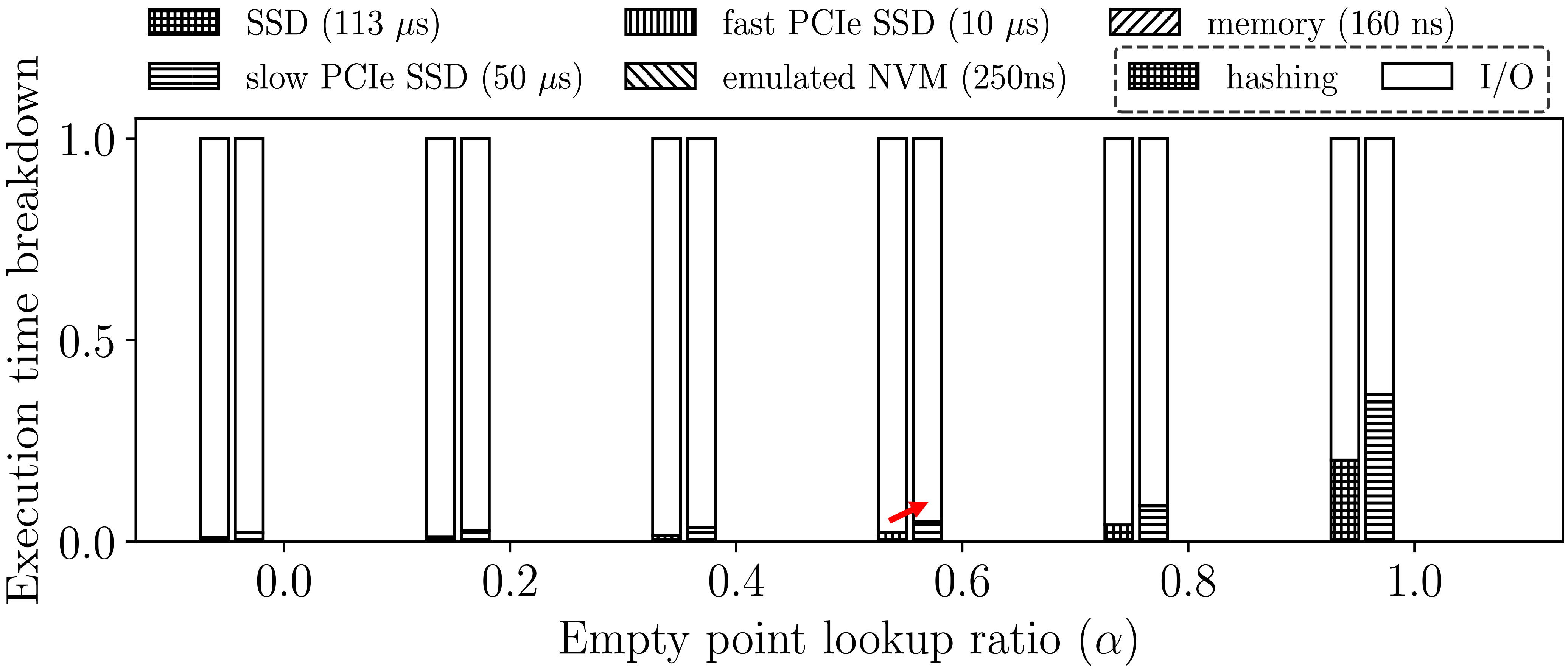
What is the time spent hashing as we move to faster devices?

Hashing Overhead in a Leveled LSM-Tree



In SSDs, hashing is over 10% for all empty lookups

Hashing Overhead in a Leveled LSM-Tree



Hashing is getting more dominant

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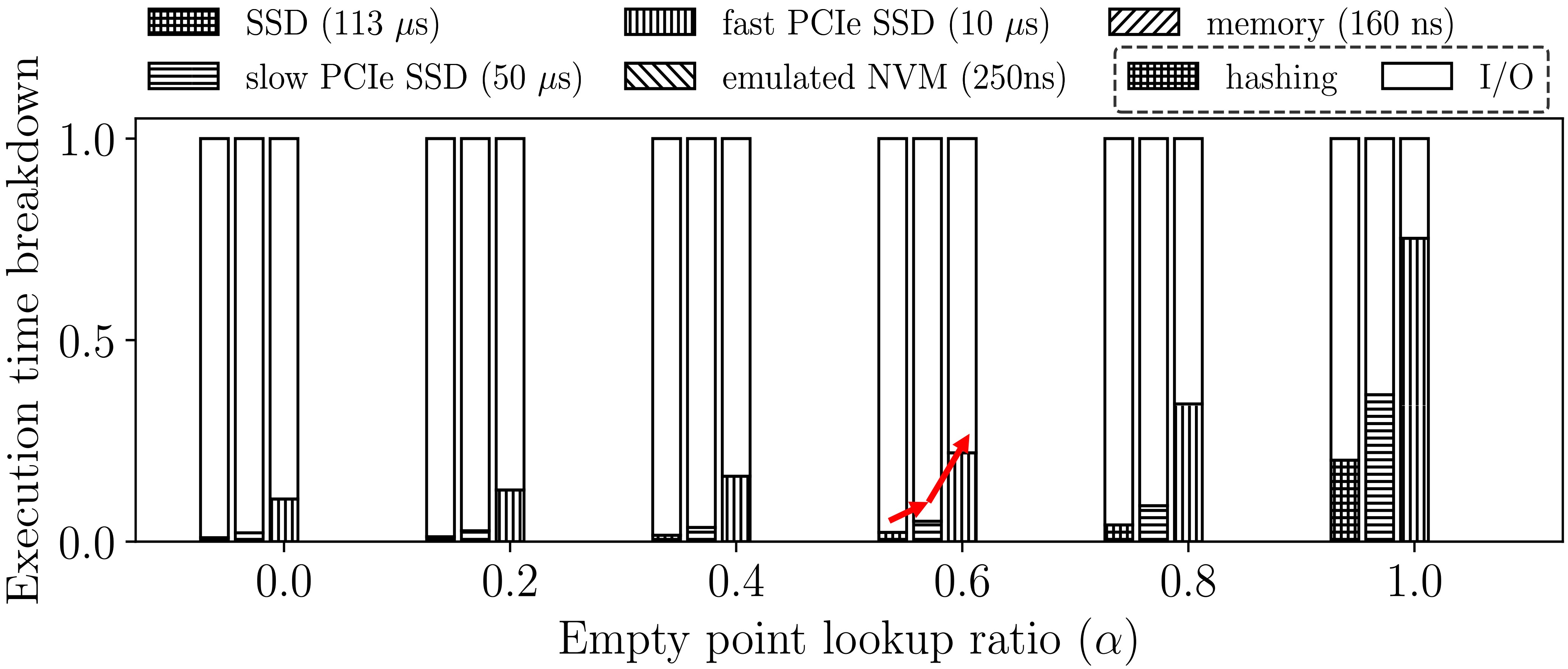

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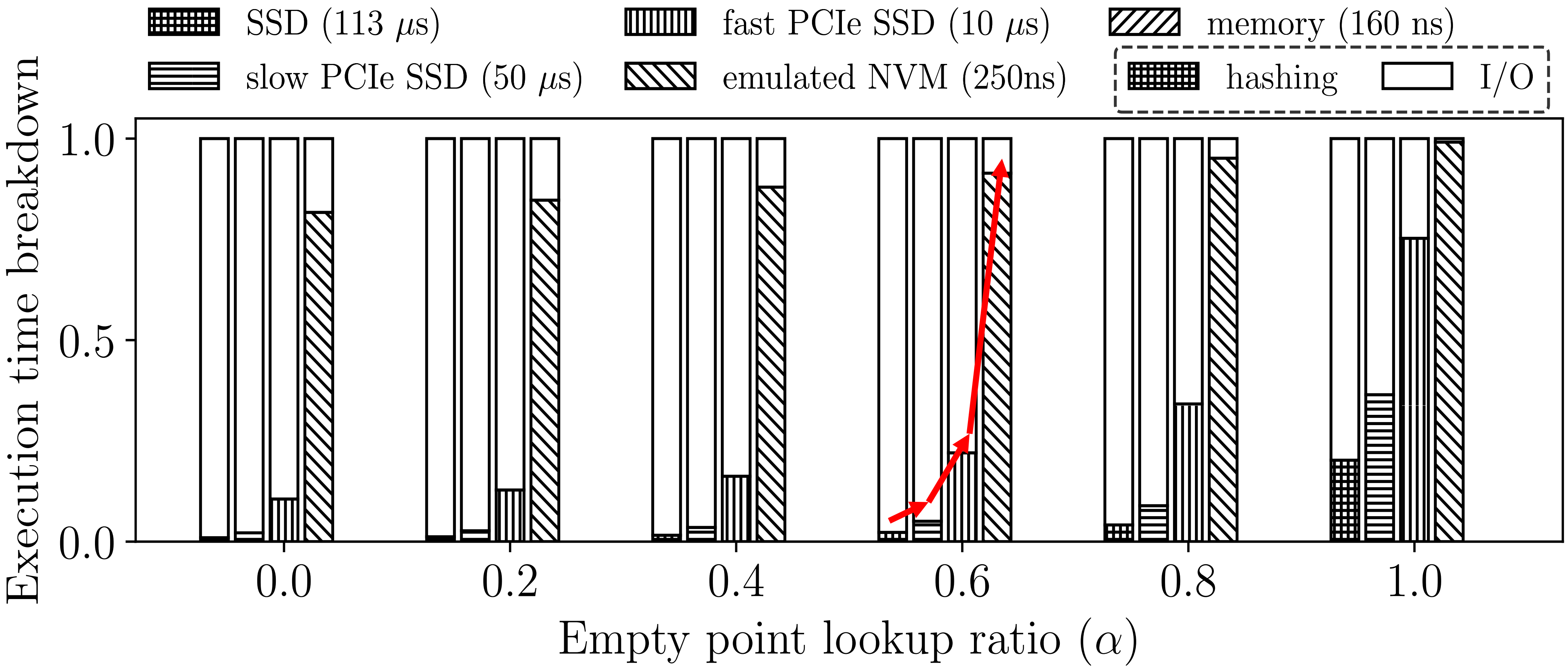

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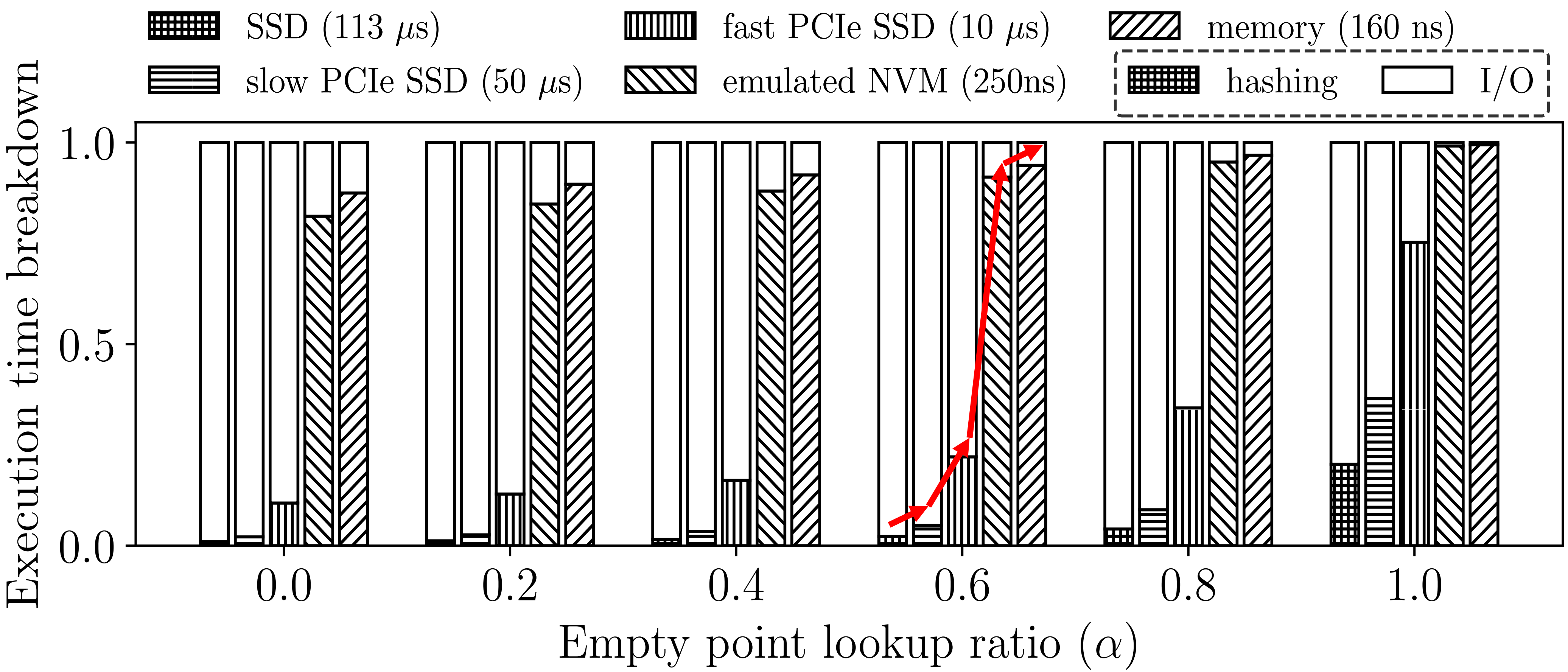
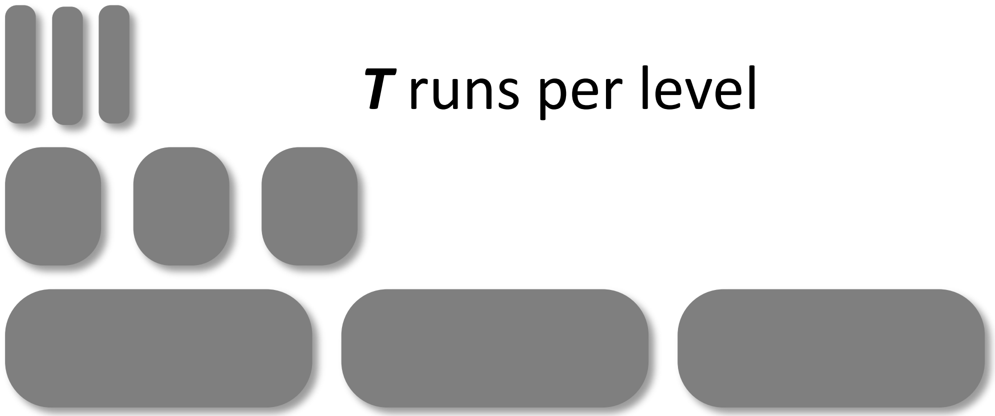


Hashing is getting more dominant

Lookup Cost in a Tiered LSM-Tree



T runs per level

Lookup cost in level i, $\mathcal{T}(i)$

- empty (α_i)

  $\alpha_i \cdot T \cdot (\,T_H + T_P + f_p \cdot T_D)$

- non-empty $(1 - \alpha_i)$

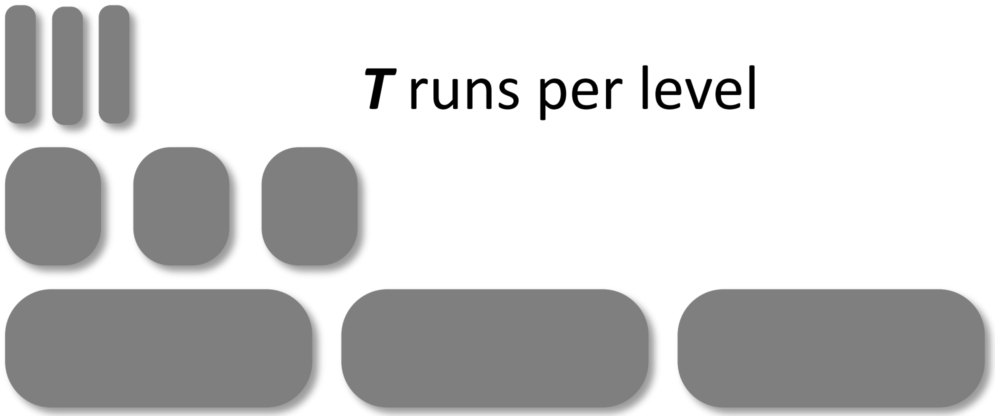
  $(1-\alpha_i) \cdot \dfrac{T+1}{2} \cdot (\,T_H + T_P) + (1-\alpha_i) \cdot T_D$

$cost \;\approx \left(T \cdot L - \frac{T+1}{2}(1-\alpha)\right) \cdot (T_{BF})$ **Bloom filter cost**

$+ \left(T \cdot L - (1-\alpha) \cdot (T+1)\right) \cdot \left(f_p \cdot T_D\right)$ **Data access due to false positives**

$+ (1-\alpha) \cdot\; T_D$ **Data access**

Lookup Cost in a Tiered LSM-Tree



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Lookup cost in level i, $\mathcal{T}(i)$

- empty (α_i)

  $\alpha_i \cdot T \cdot (\, T_H + T_P + f_p \cdot T_D)$

- non-empty $(1 - \alpha_i)$

  $(1 - \alpha_i) \cdot \dfrac{T+1}{2} \cdot (\, T_H + T_P) + (1 - \alpha_i) \cdot T_D$

$$cost \approx \overset{\propto T \cdot L}{\boxed{\left(T \cdot L - \frac{T+1}{2}(1-\alpha)\right) \cdot (T_H + T_P)}}$$

Bloom filter cost

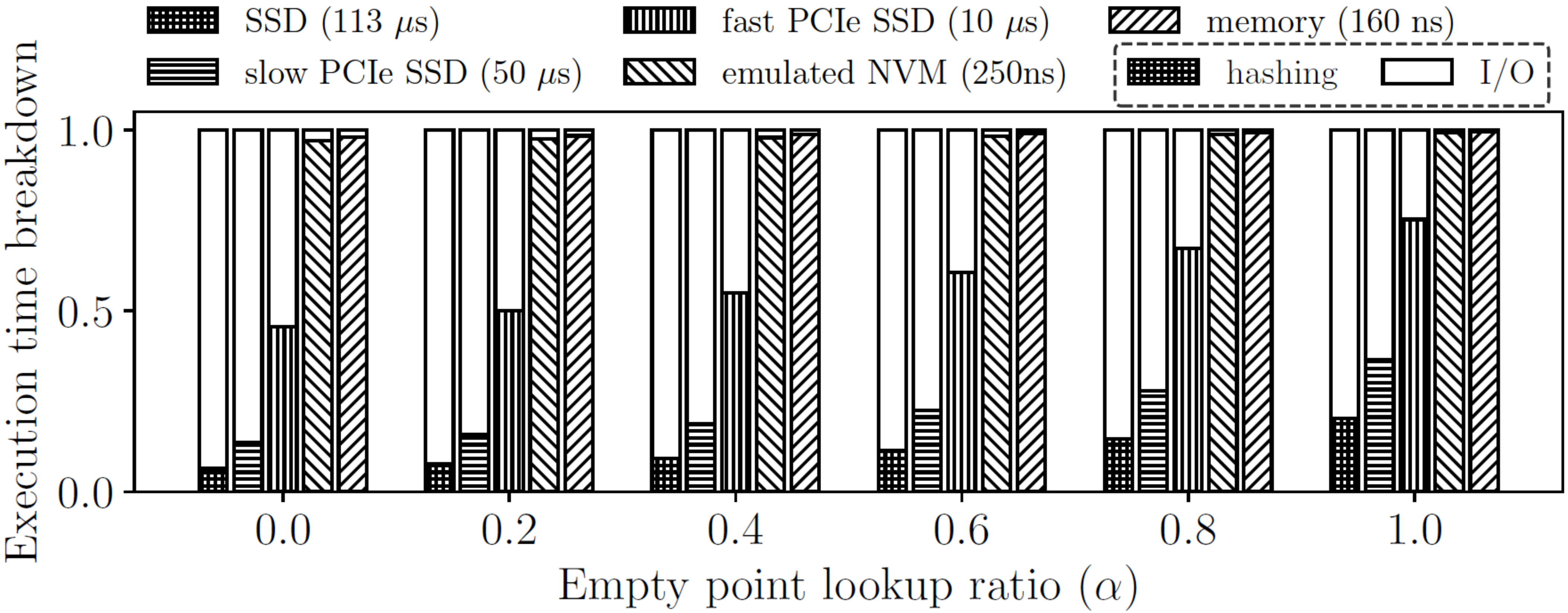
$$+ \left(T \cdot L - (1-\alpha) \cdot (T+1)\right) \cdot \left(f_p \cdot T_D\right)$$

Data access due to false positives

$$+ (1-\alpha) \cdot T_D$$

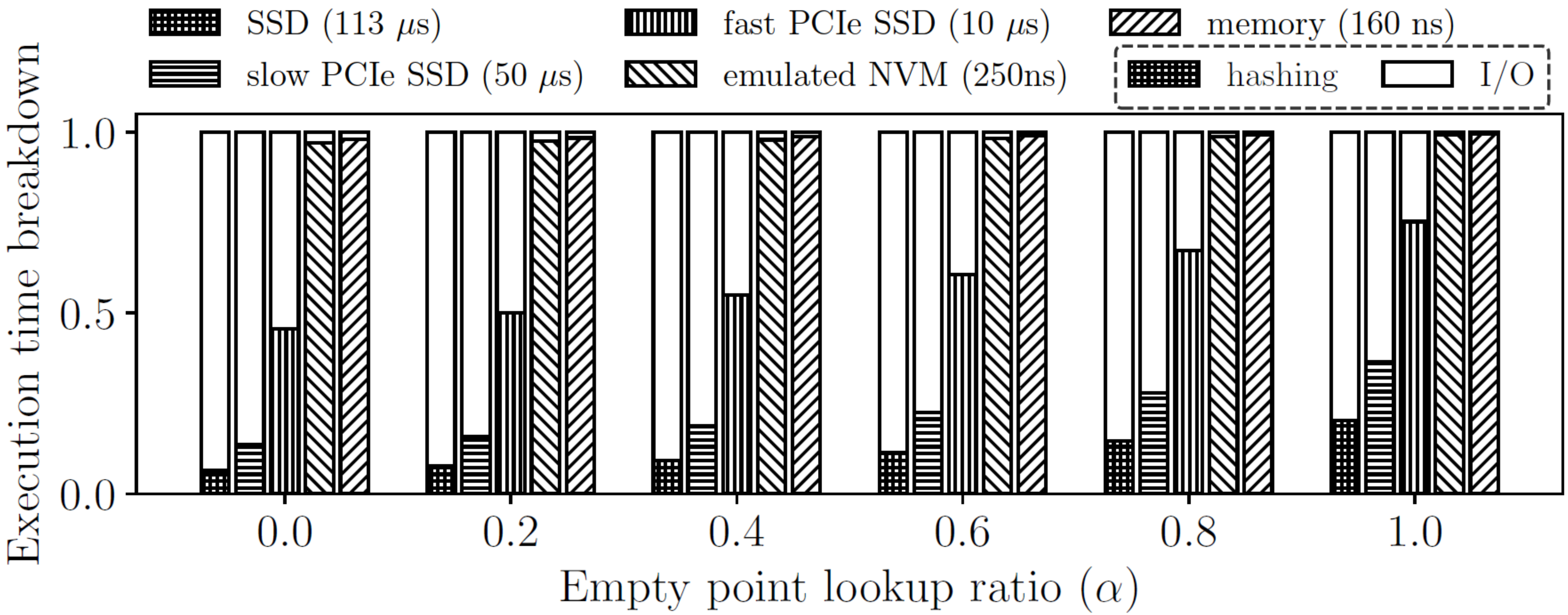
Data access

Hashing Overhead in a Tiered LSM-Tree



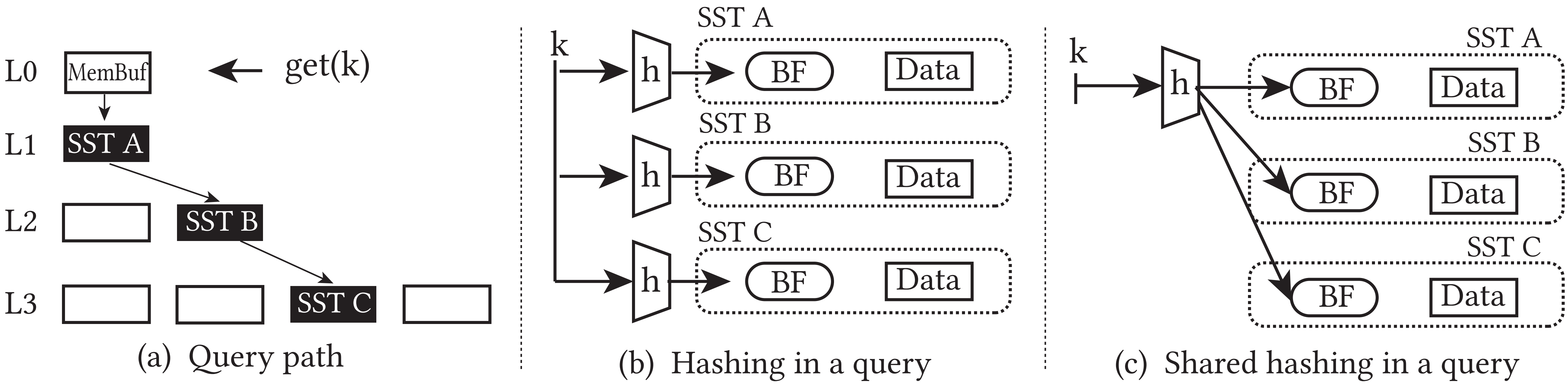
Similar, but hashing is more pronounced.

Hashing Overhead in a Tiered LSM-Tree



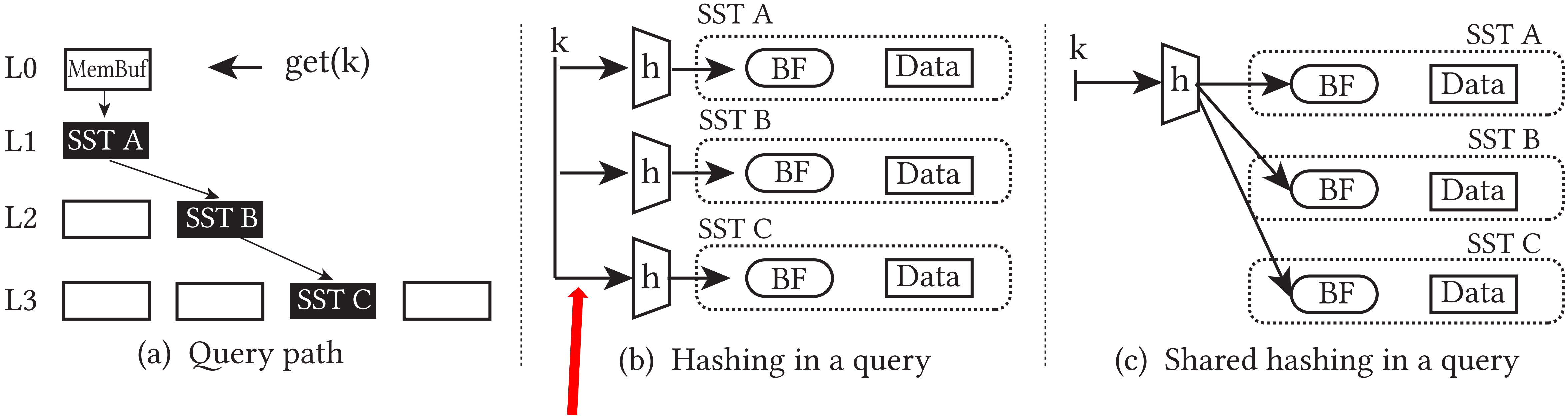
How can we reduce the hashing overhead in LSM-trees?

Hash Sharing in Leveled LSM-Trees



(a) Query path (b) Hashing in a query (c) Shared hashing in a query

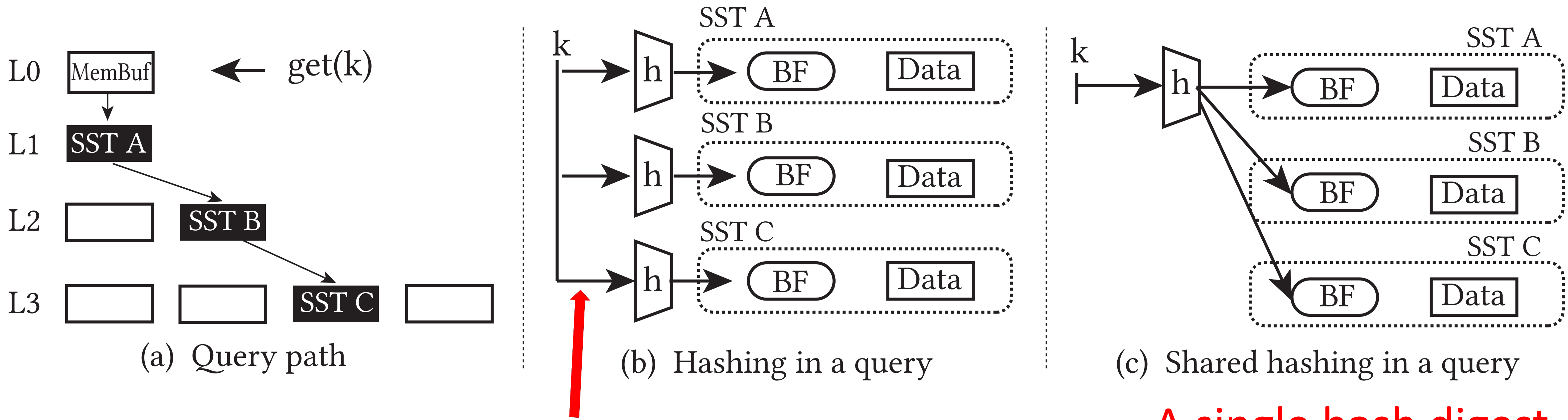
Hash Sharing in Leveled LSM-Trees



(a) Query path (b) Hashing in a query (c) Shared hashing in a query

The same hash function is calculated multiple times which brings CPU overhead.

Hash Sharing in Leveled LSM-Trees



(a) Query path

(b) Hashing in a query

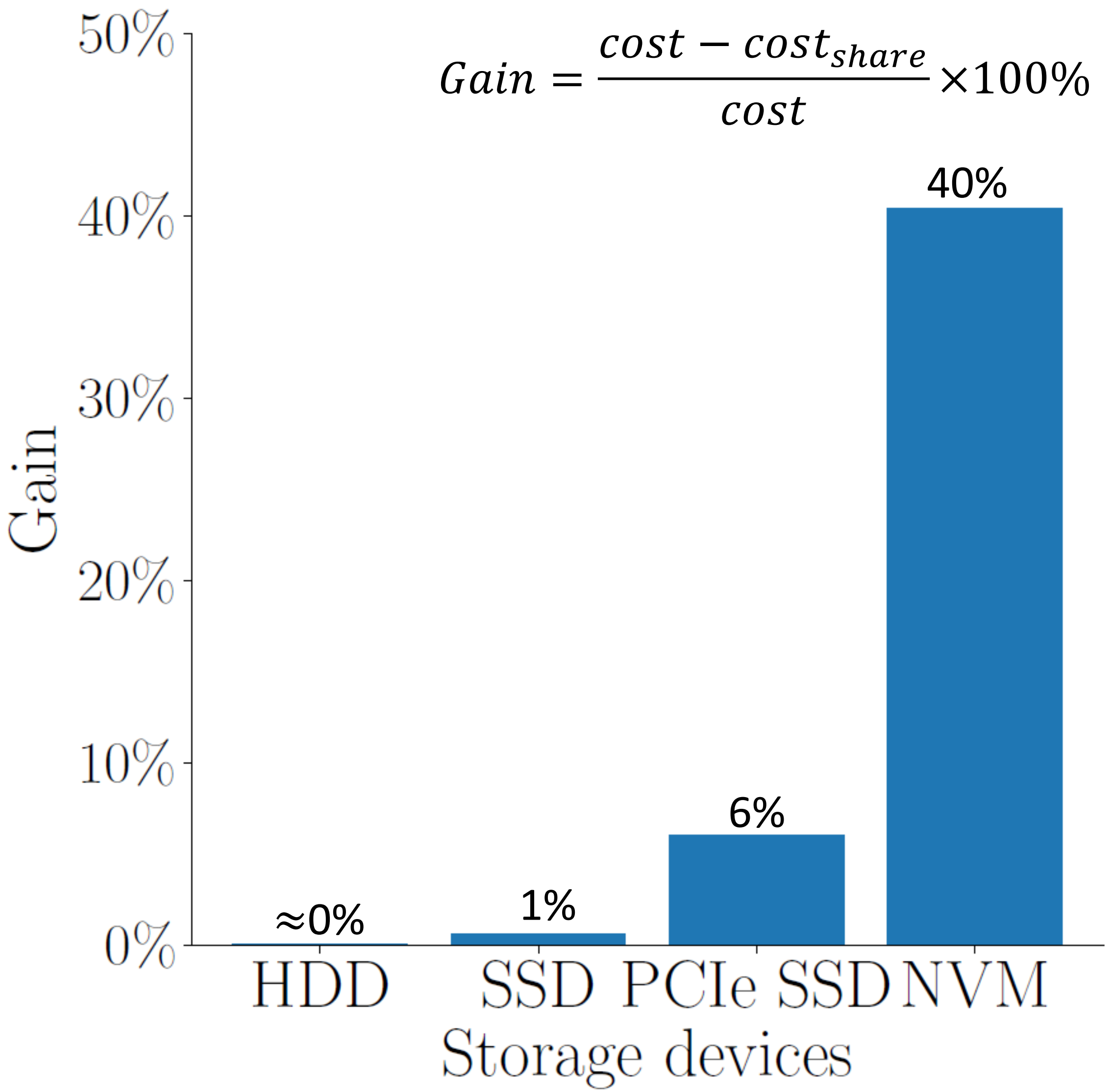
(c) Shared hashing in a query

The same hash function is calculated multiple times which brings CPU overhead.

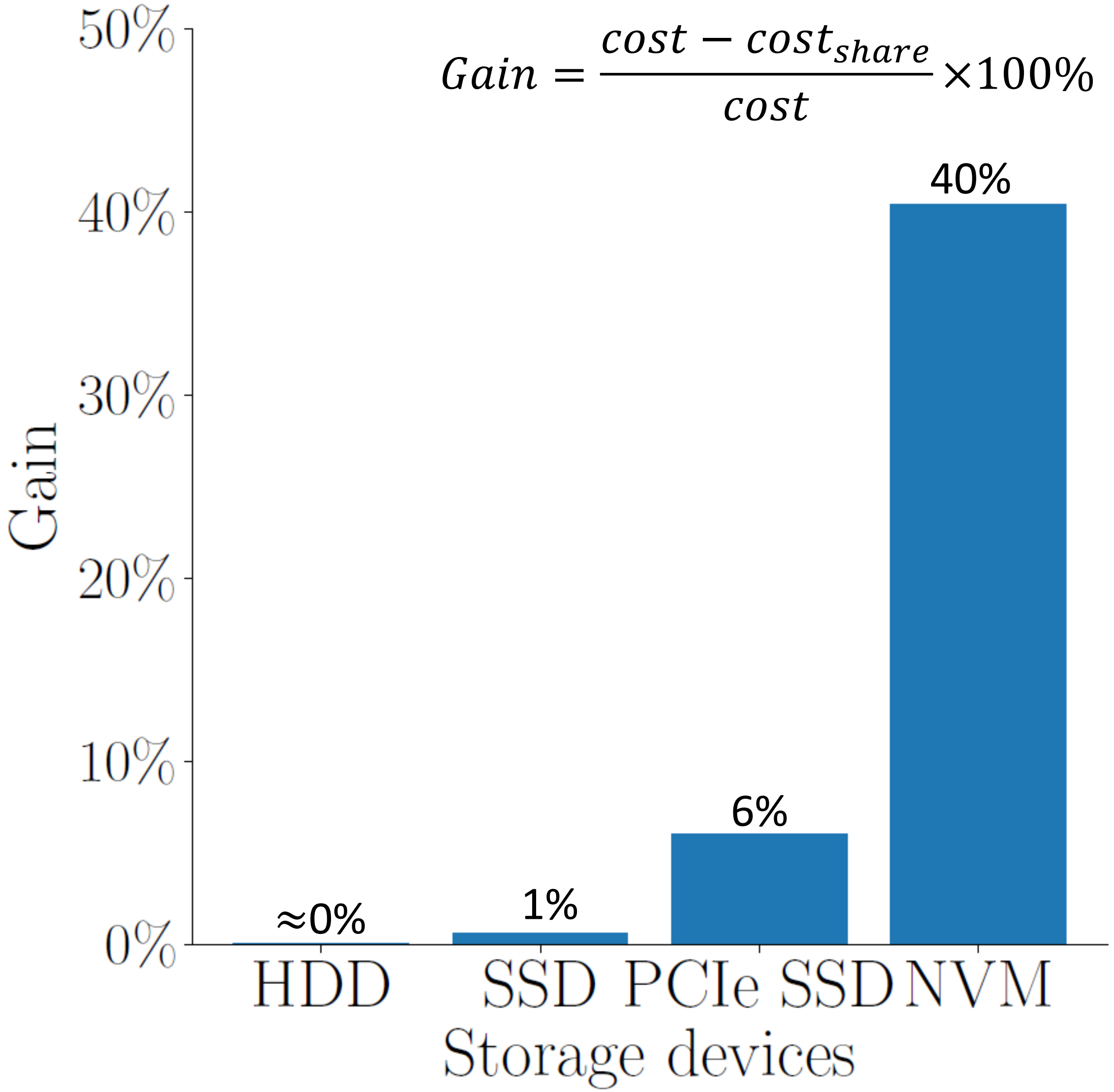
A single hash digest can be reused to avoid expensive hash calculations.

Theoretical Gain w.r.t. Evolving Storage Devices

$$Gain = \frac{cost - cost_{share}}{cost} \times 100\%$$



Theoretical Gain w.r.t. Evolving Storage Devices



$$Gain = \frac{cost - cost_{share}}{cost} \times 100\%$$

The gain increases rapidly for faster storage devices

Experiment Setting

Build an LSM prototype (RocksDB's fast local BF).

1M point queries (report avg latency of 5 experiments)

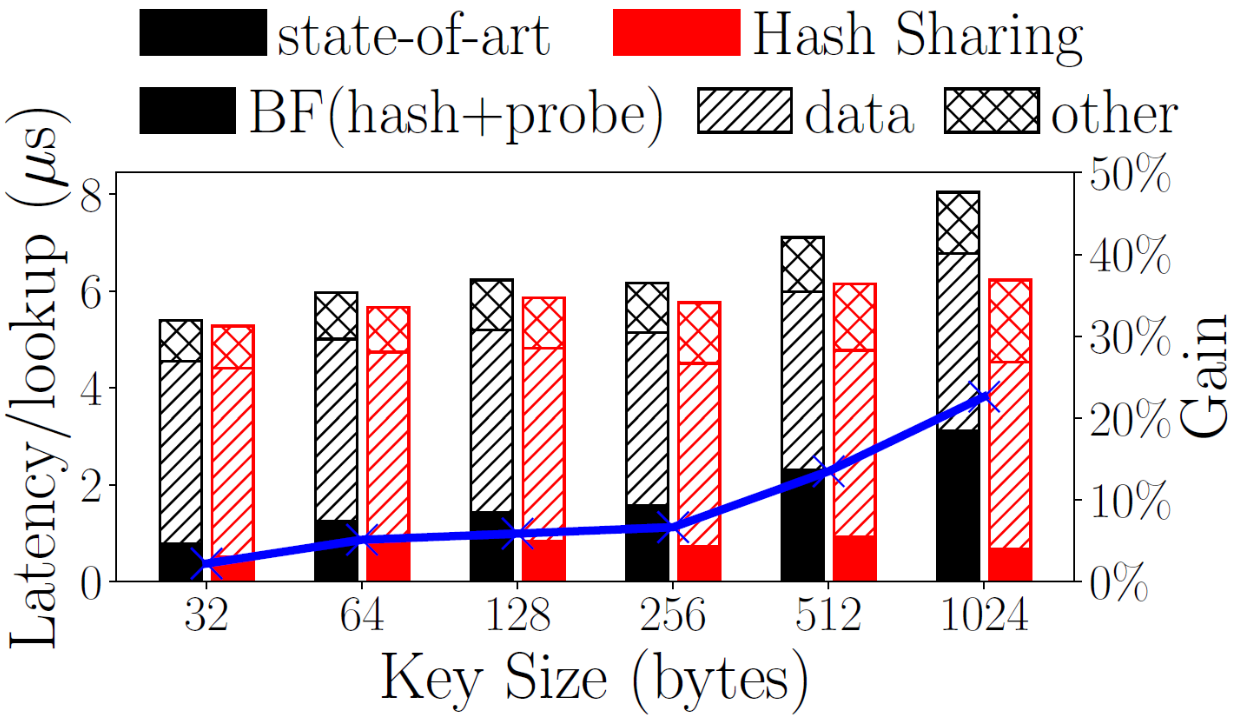
Use PCIe SSD (10 μs) with direct I/O by default

	Parameters	Default Value
Workload	Entry size (key + value)	1KB-2KB
	Data volume	22GB
	Empty query ratio (α)	100%
	Query distribution	Uniform
LSM	File size	2 MB
	Size ratio	10
	Bits per key	10

Impact of the key size

Workload: Entry size: 2KB, #Entries: 11M
Tuning: Bits per key: 10, Size ratio: 10, Storage: PCIe SSD

Uniform Query Distribution



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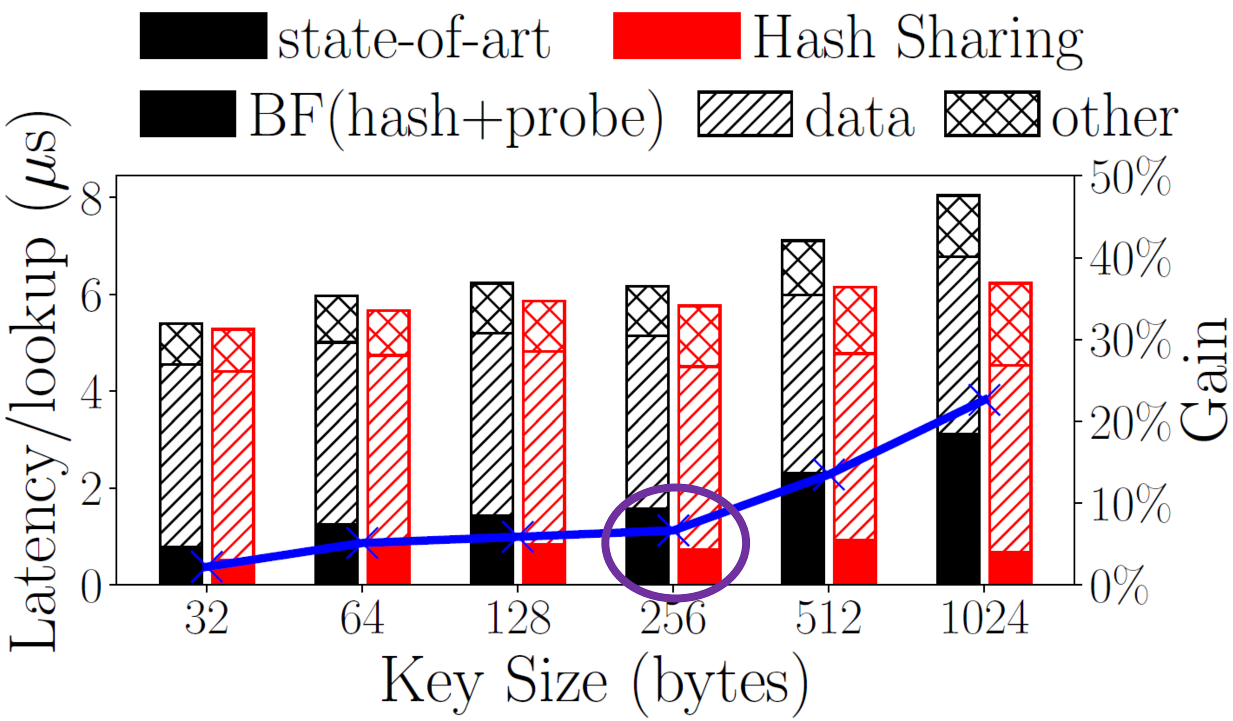
Uniform Query Distribution



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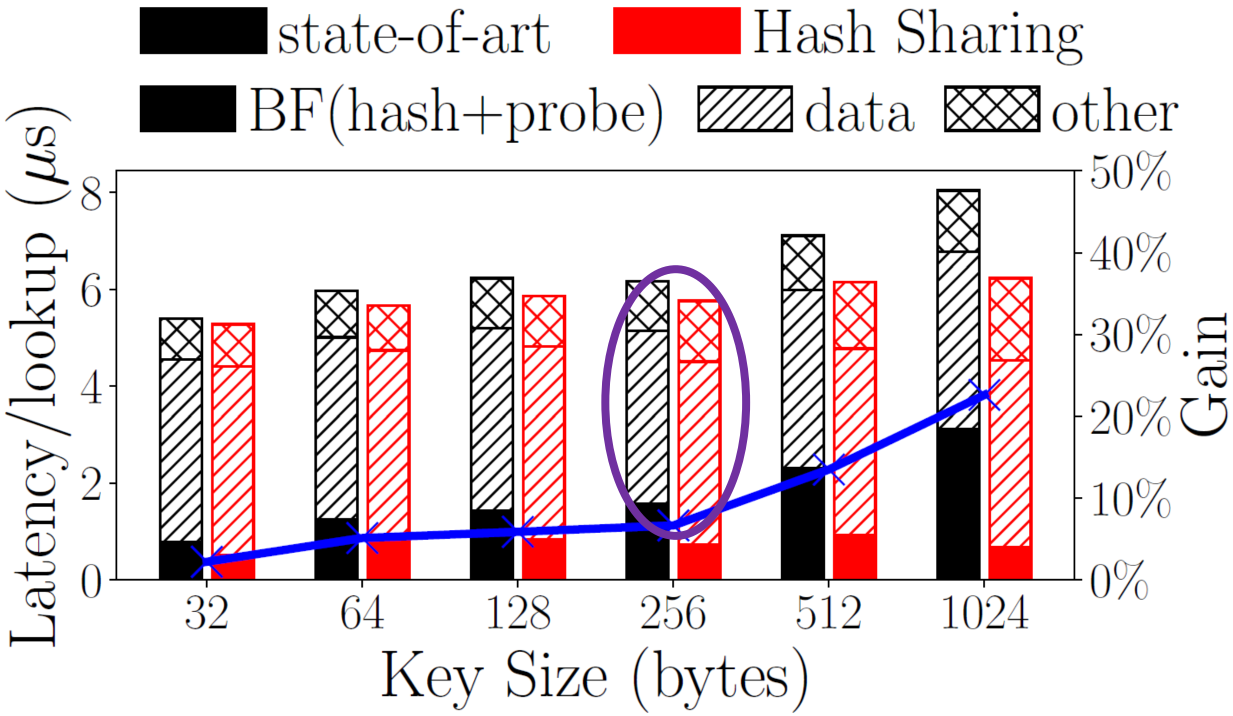

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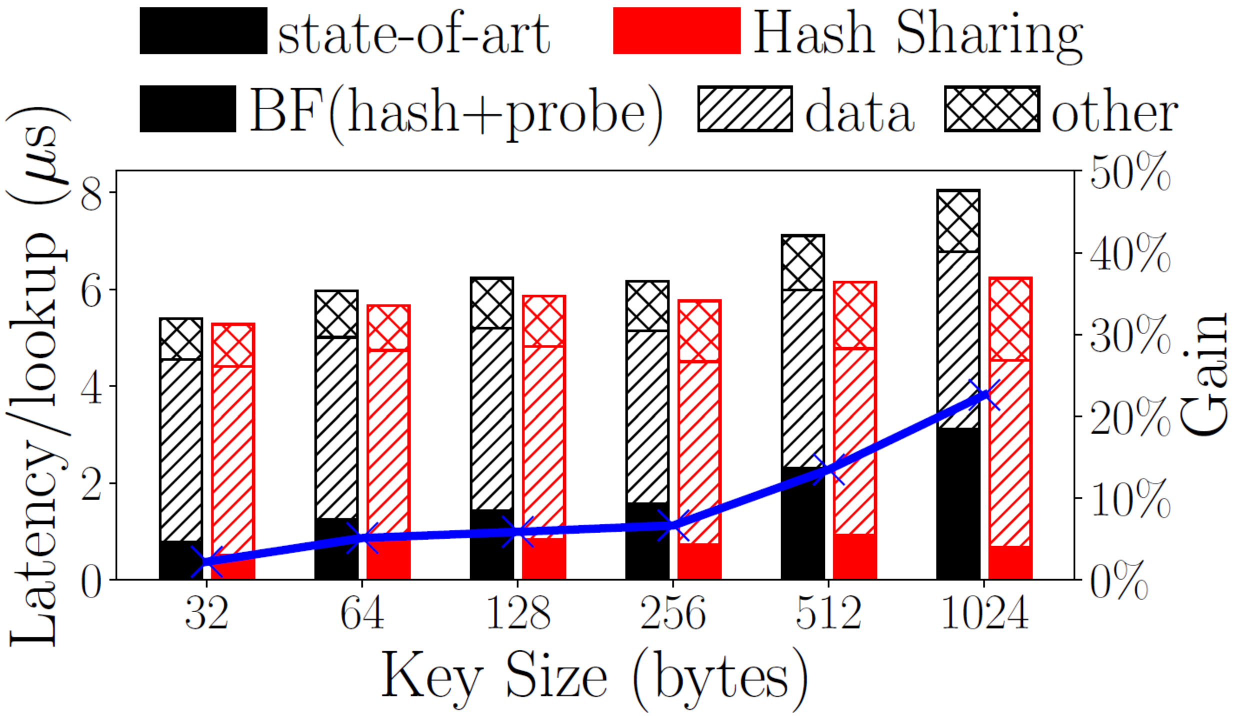

As key size grows, the gain increases up to 20%

Impact of the key size

Workload: Entry size: 2KB, #Entries: 11M
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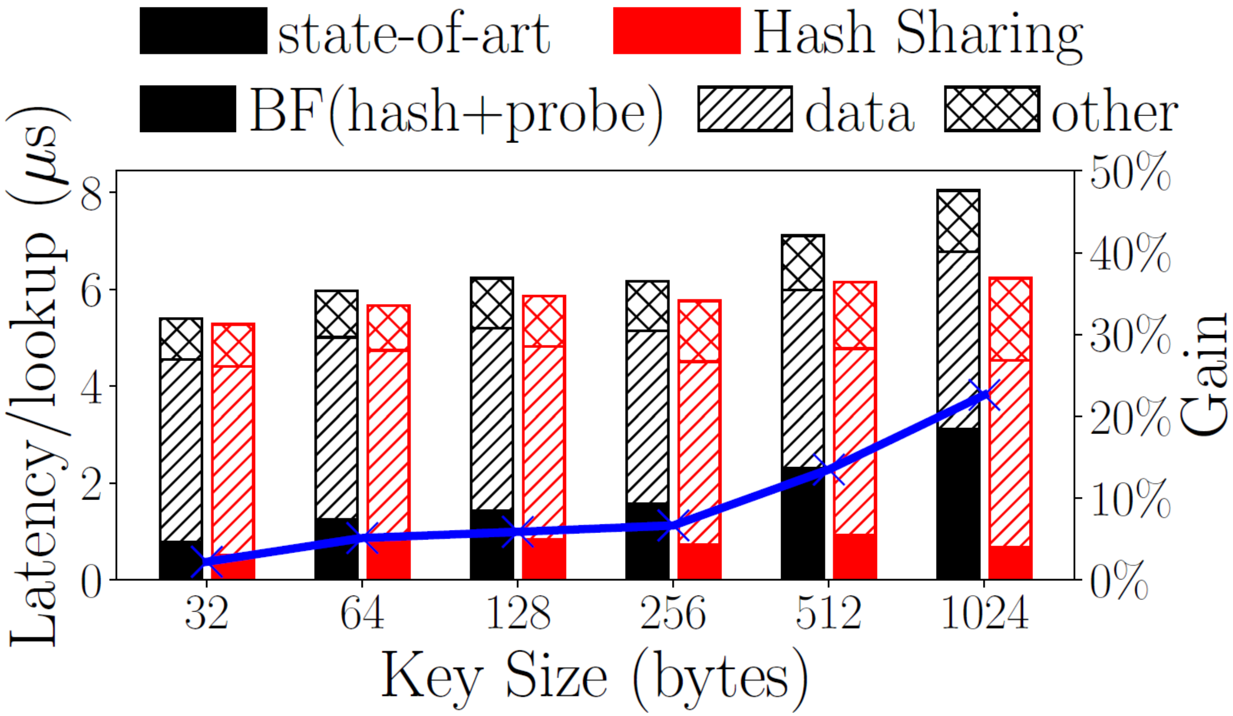
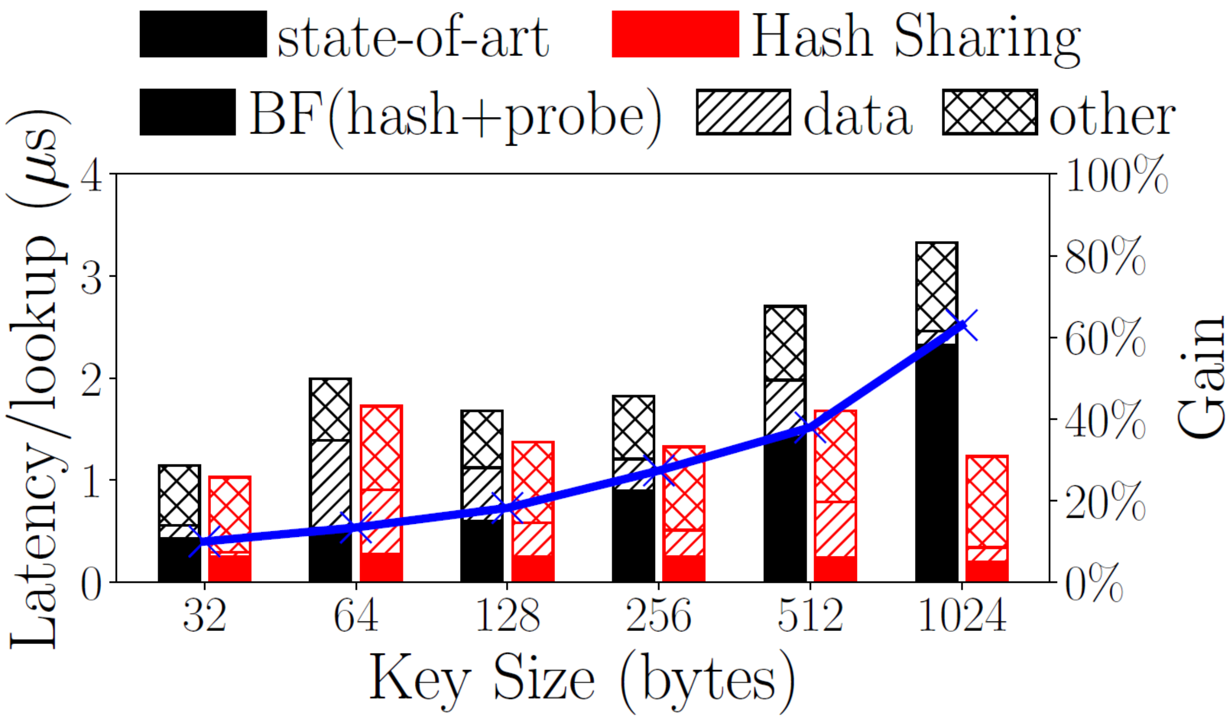
Uniform Query Distribution



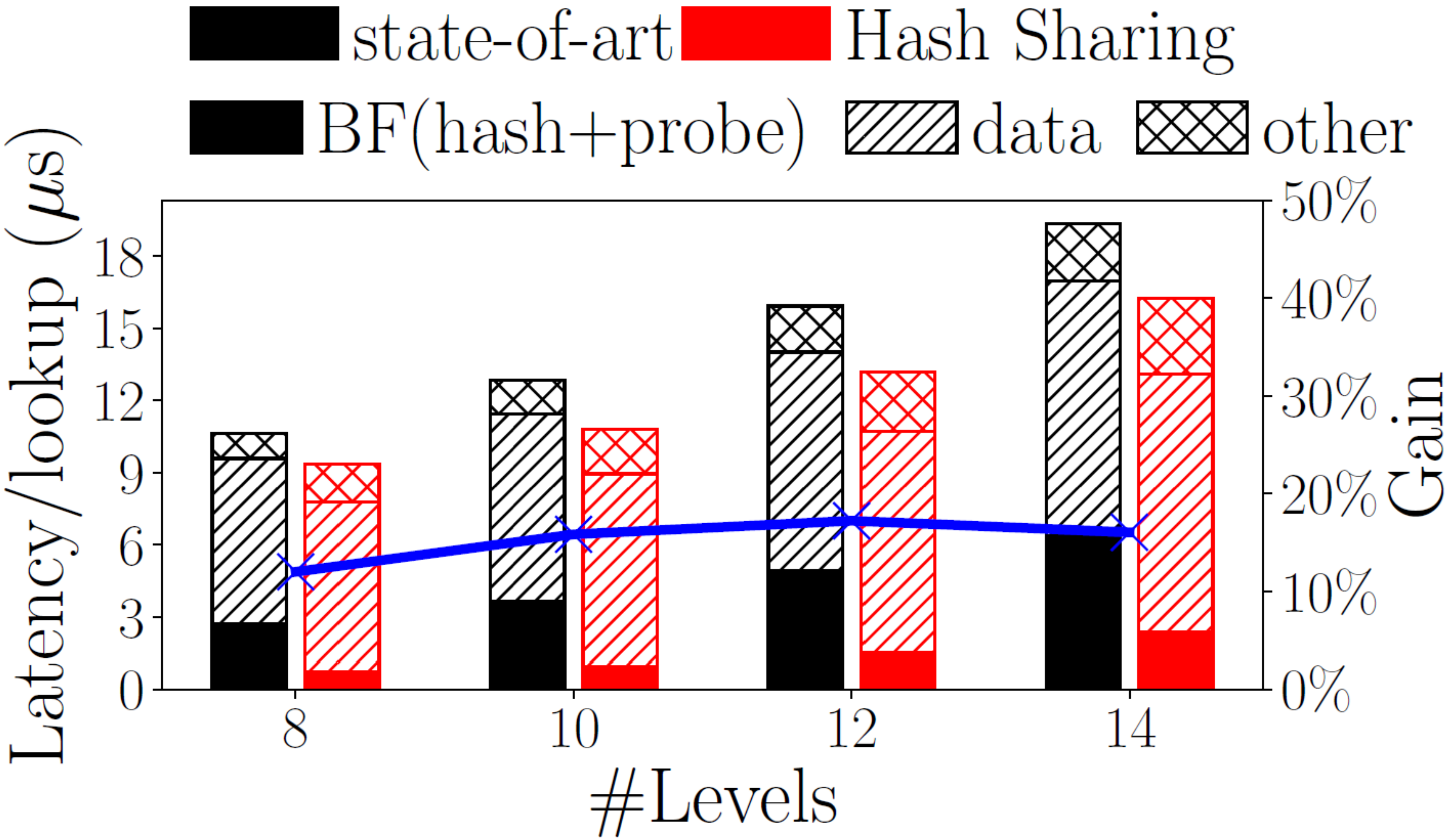
Zipfian Query Distribution



As key size grows, the gain increases up to 20%

For skewed empty query workload, the gain increases up to 60%

Impact of #levels



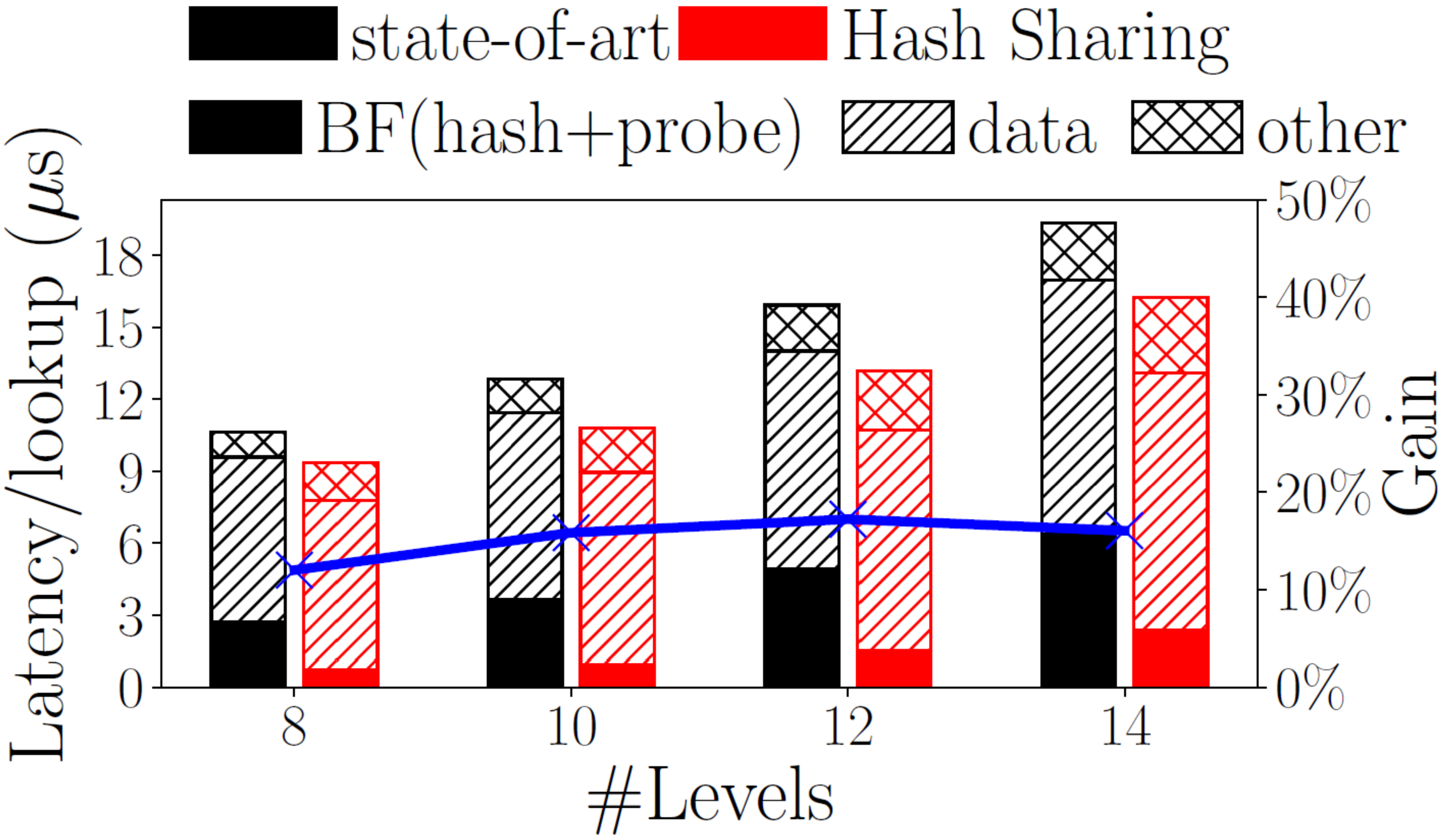
Workload:
- Key size: 64B
- Entry size: 1KB
- #Entries: 22M

Tuning:
- Bits per key: 10
- Size ratio: 2

Storage: PCIe SSD

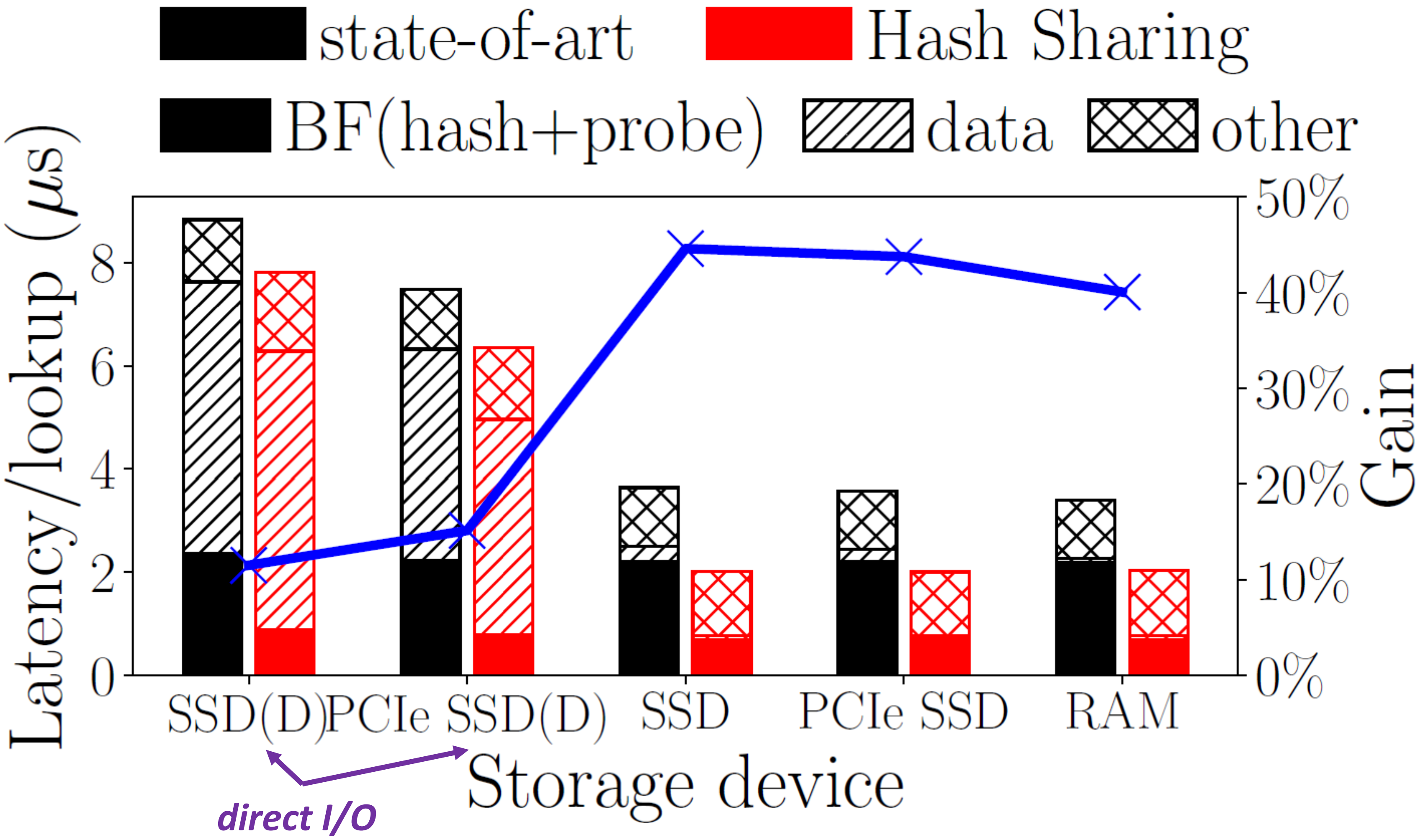
Impact of #levels

Workload:
Key size: 64B
Entry size: 1KB
#Entries: 22M
Tuning:
Bits per key: 10
Size ratio: 2
Storage: PCIe SSD



The gain initially increases as #level grows, and then plateaus

Impact of storage device



Workload:

Key size: 64B

Entry size: 1KB

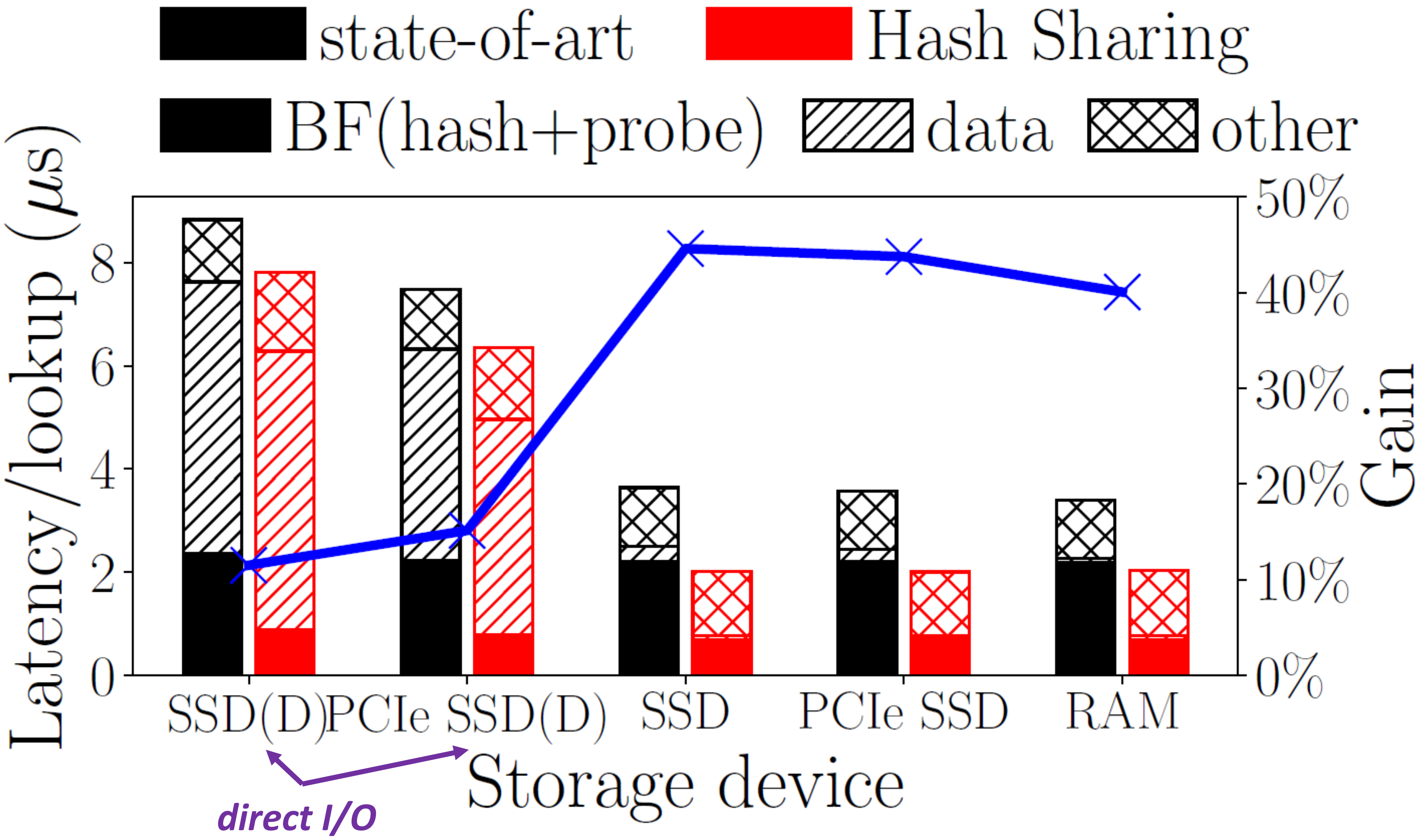
#Entries: 22M

Tuning:

Bits per key: 10

Size ratio: 10

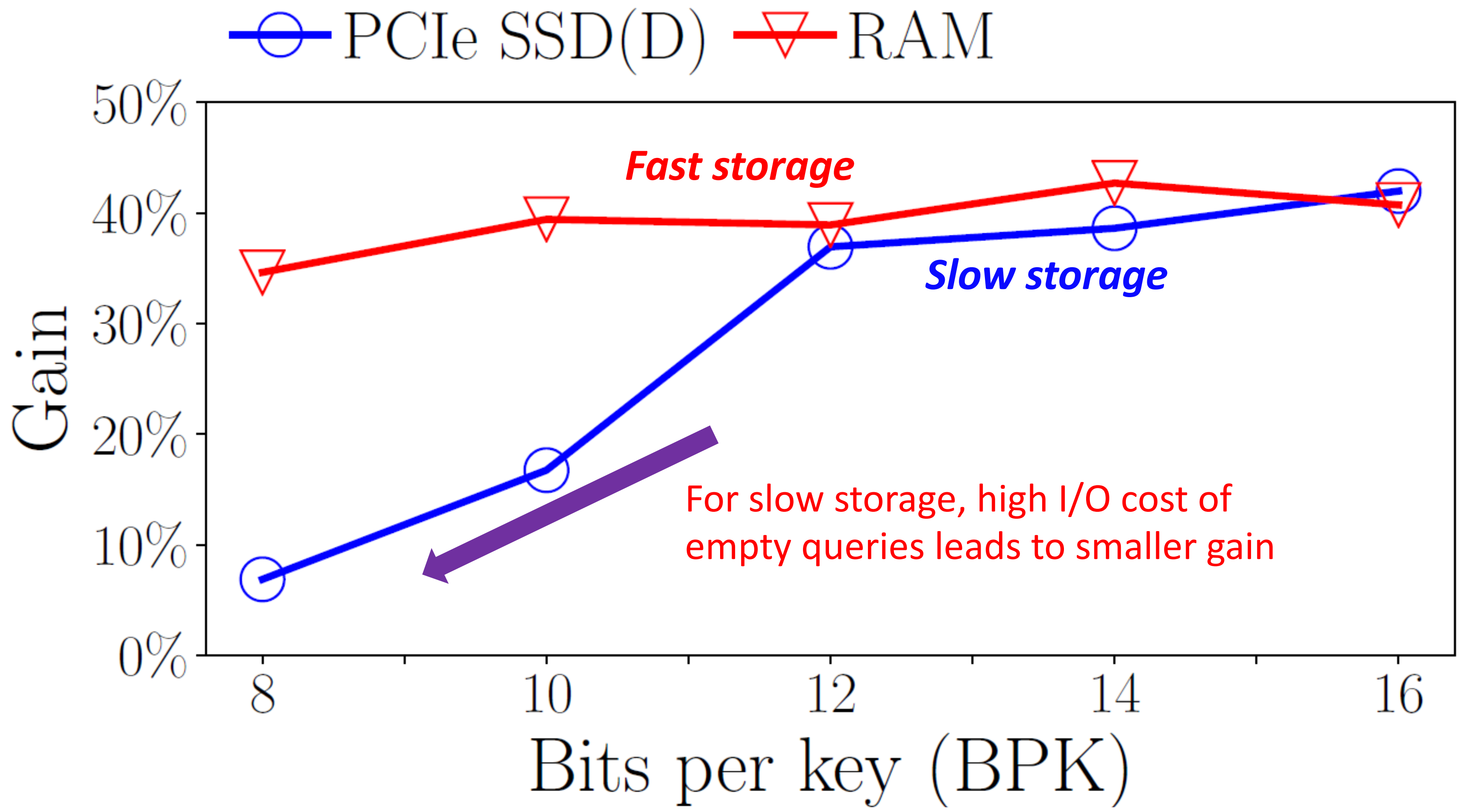
Impact of storage device



Workload:
Key size: 64B
Entry size: 1KB
#Entries: 22M
Tuning:
Bits per key: 10
Size ratio: 10

Hash sharing leads to higher gain for faster storage.

Impact of the I/O cost of empty queries



Fast storage

Slow storage

For slow storage, high I/O cost of empty queries leads to smaller gain

High *I/O cost of empty queries* Low

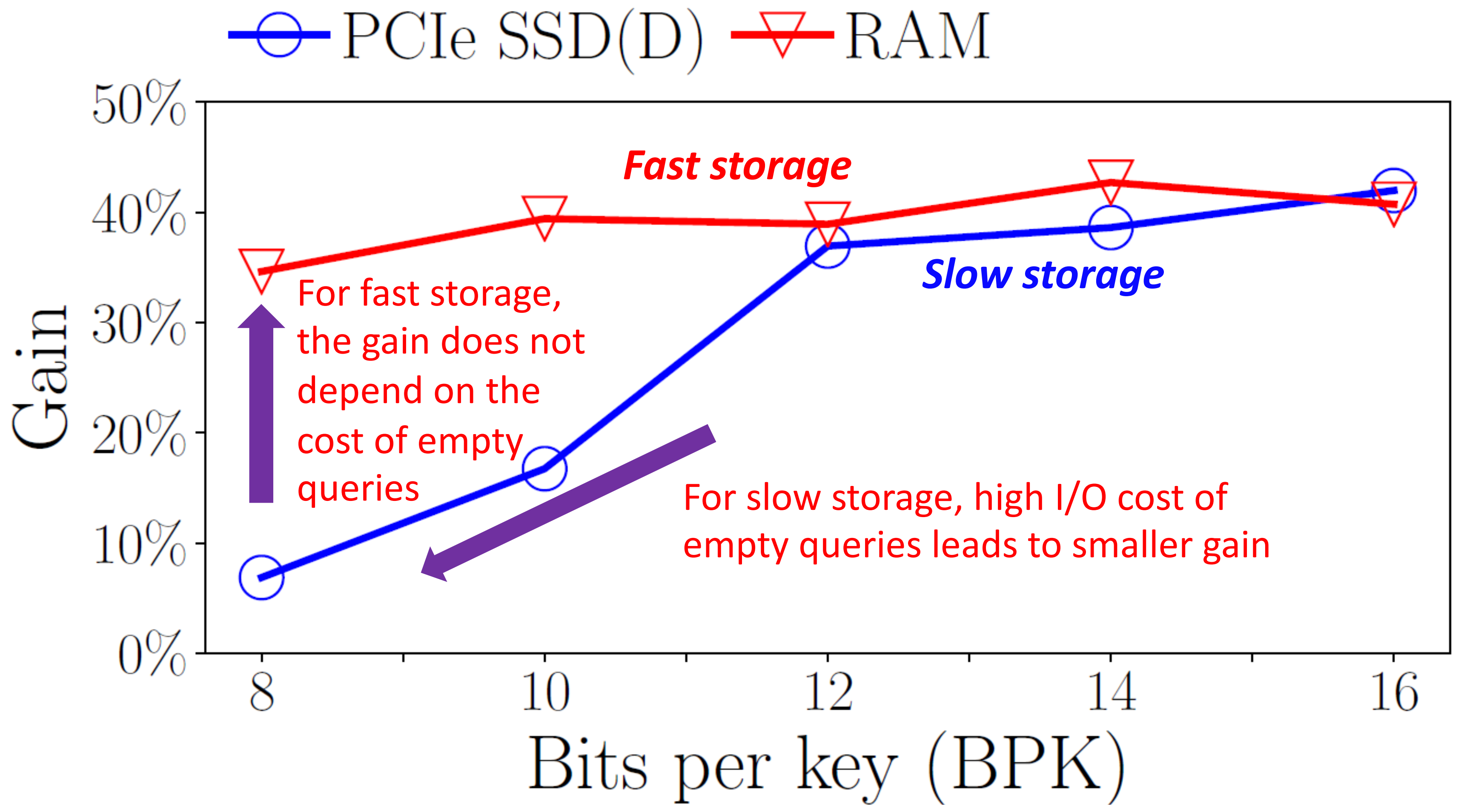
Workload:

- Entry size: 1KB
- #Entries: 22M
- Empty query ratio (α) : 1

Tuning:

- Bits per key: 10
- Size ratio: 10

Impact of the I/O cost of empty queries



Fast storage

Slow storage

For fast storage, the gain does not depend on the cost of empty queries

For slow storage, high I/O cost of empty queries leads to smaller gain

High *I/O cost of empty queries* Low

Workload:

Entry size: 1KB

#Entries: 22M

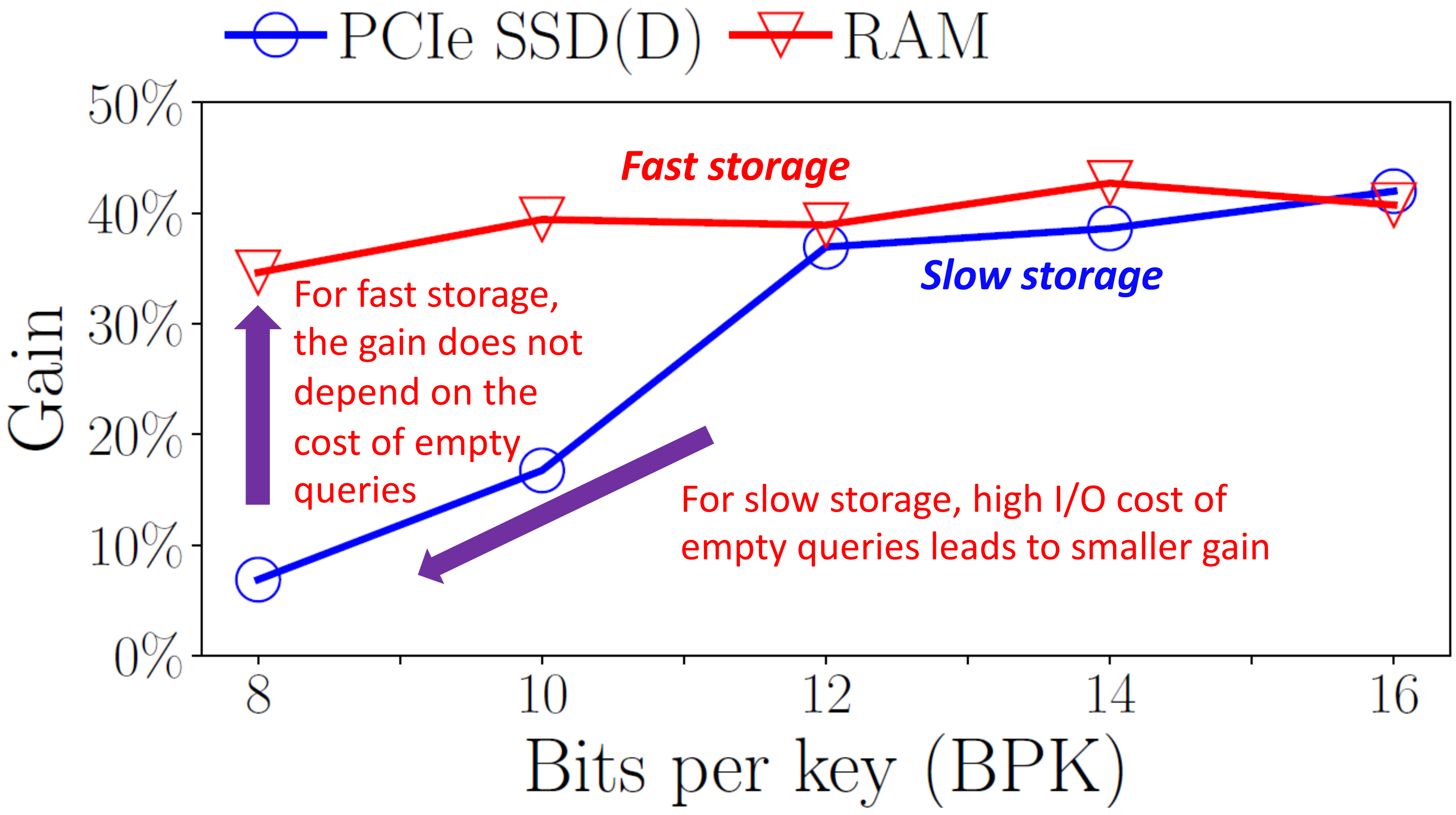
Empty query ratio (α) : 1

Tuning:

Bits per key: 10

Size ratio: 10

Impact of the I/O cost of empty queries



Fast storage

Slow storage

For fast storage, the gain does not depend on the cost of empty queries

For slow storage, high I/O cost of empty queries leads to smaller gain

High *I/O cost of empty queries* Low

Workload:
- Entry size: 1KB
- #Entries: 22M
- Empty query ratio (α) : 1

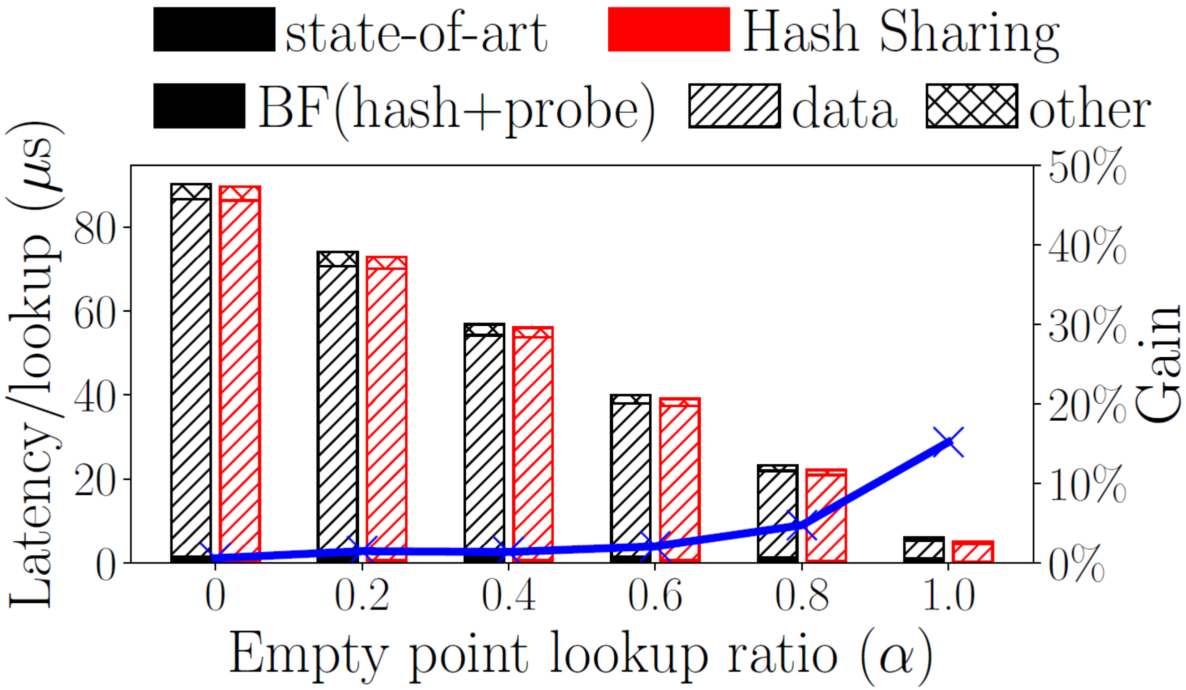
Tuning:
- Bits per key: 10
- Size ratio: 10

Fast storage leads to high gain. Even for slower storage, if the cost of empty queries is low (low FPR), the gain is high

Impact of empty lookup ratio ($\boldsymbol{\alpha}$)

Workload: Entry size: 1KB, #Entries: 22M
Tuning: Bits per key: 10, Size ratio: 10

Storage: PCIe SSD (D)



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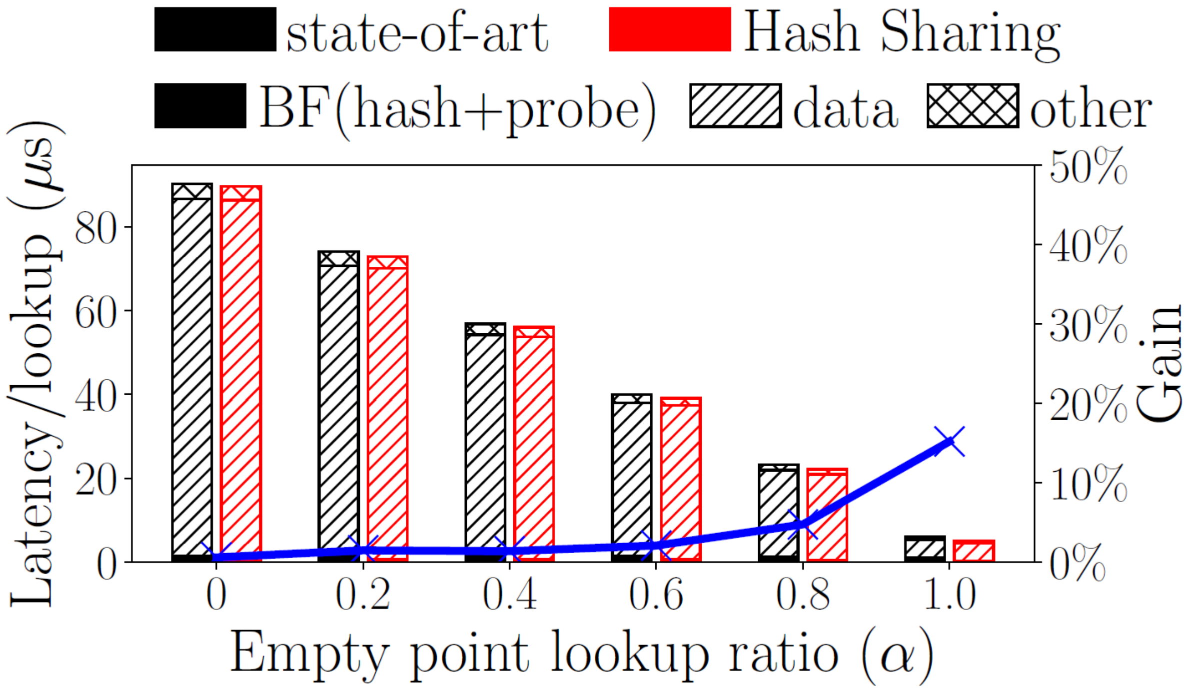

The gain on PCIe SSD increases as α increases

Impact of empty lookup ratio (α)

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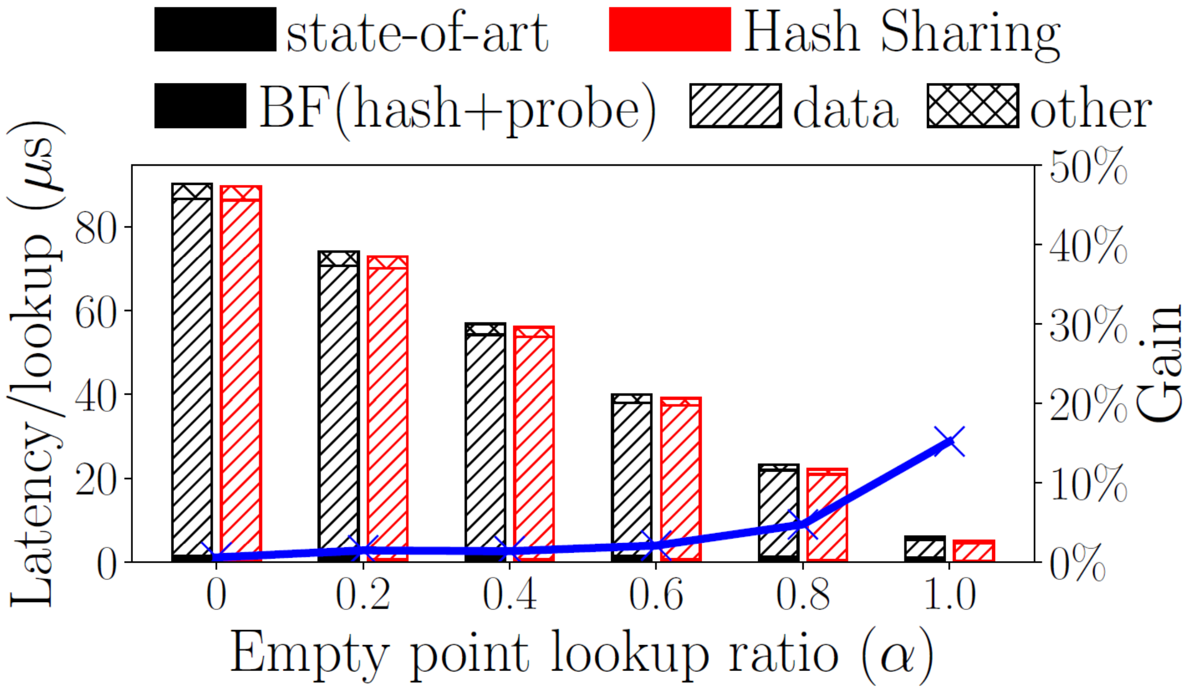
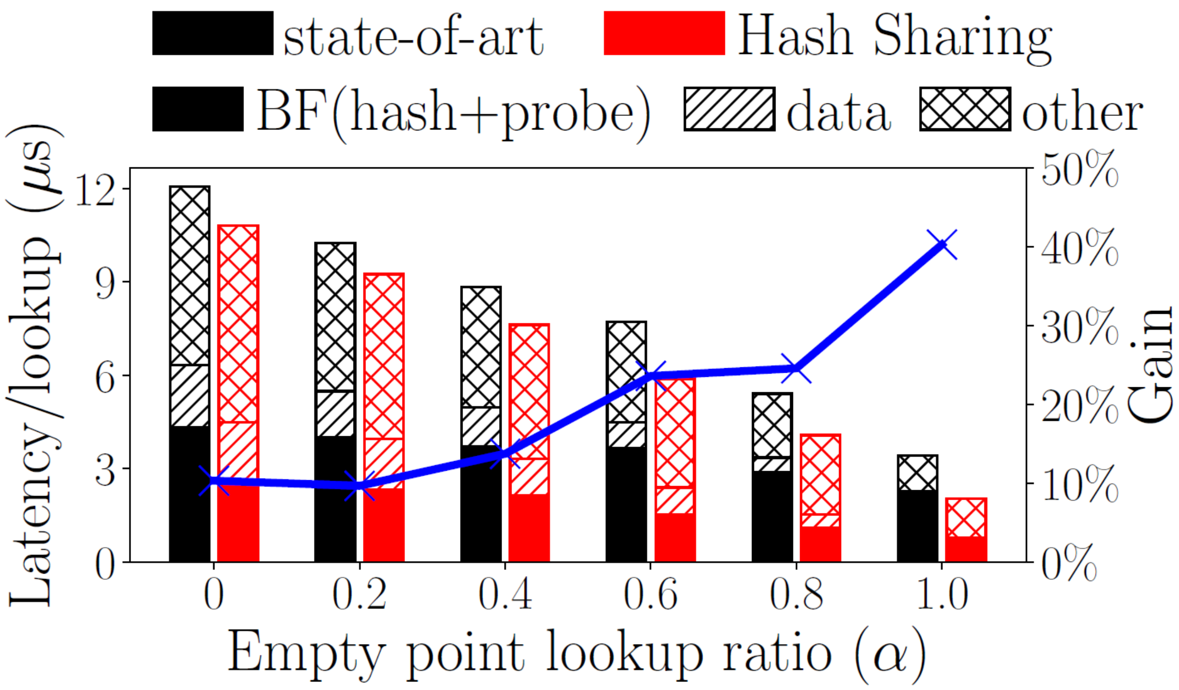
Storage: PCIe SSD (D)



Storage: RAM disk



The gain on PCIe SSD increases as α increases

The benefit is pronounced when it comes to a RAM disk

Impact of empty lookup ratio (α)

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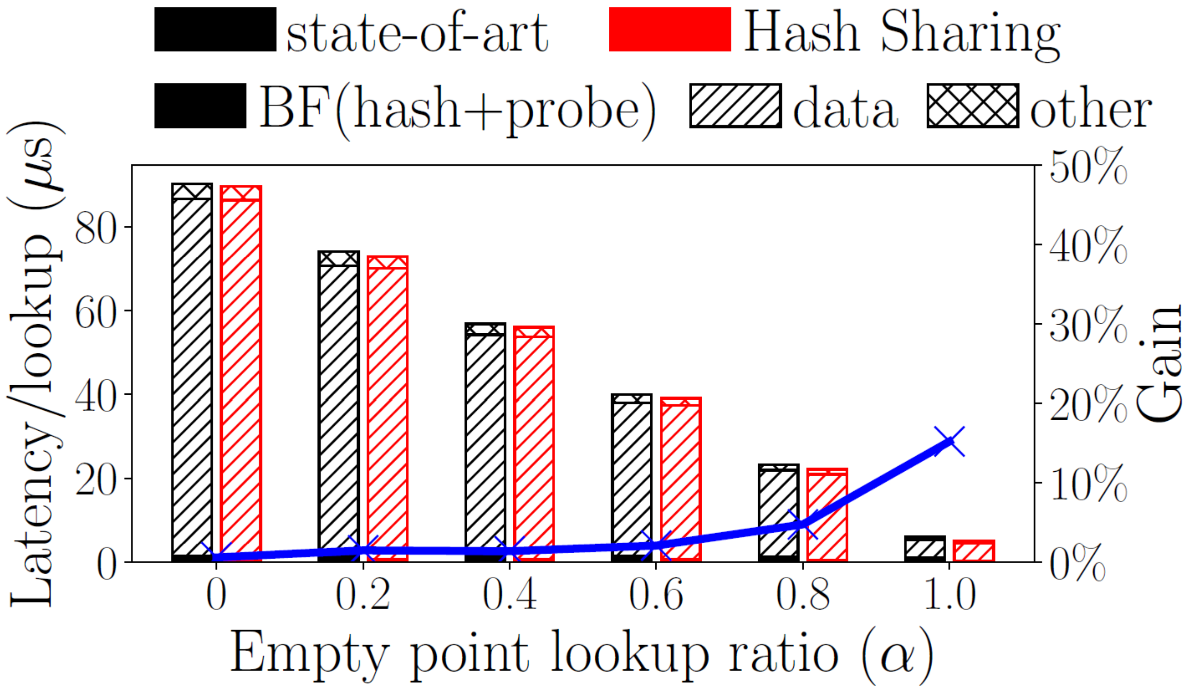
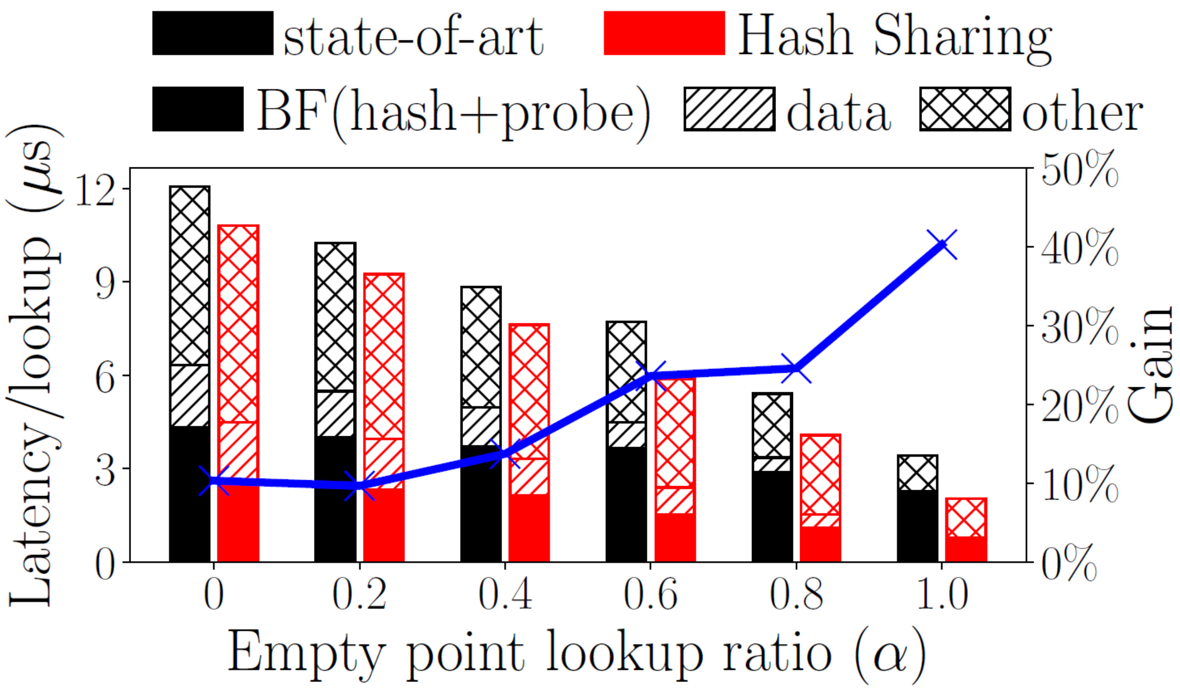


Storage: RAM disk



The gain on PCIe SSD increases as α increases

The benefit is pronounced when it comes to a RAM disk

Overall, hash sharing has more impact for faster devices which is further exacerbated for empty queries.

Conclusion

- ☐ BFs dominate LSM query latency for fast storage

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- ❑ Develop a query cost model to quantify and predict the amount of time on hashing and data accessing

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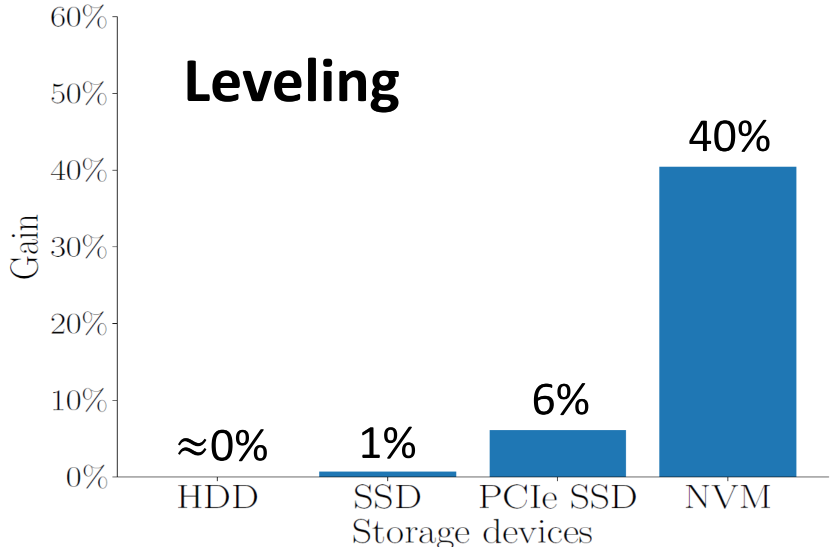
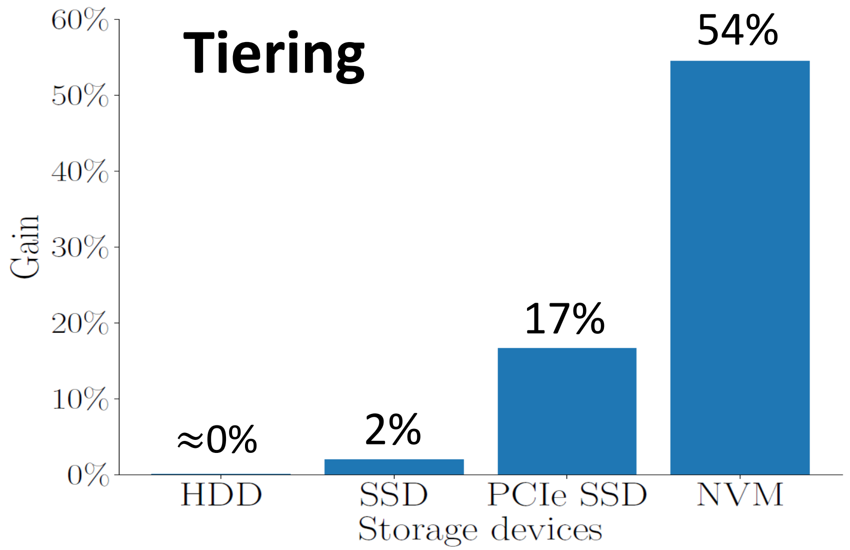
❑ Develop a query cost model to quantify and predict the amount of time on hashing and data accessing

❑ Reduce hashing, by sharing it across BFs and levels, leading to performance gains up to 40%





Conclusion

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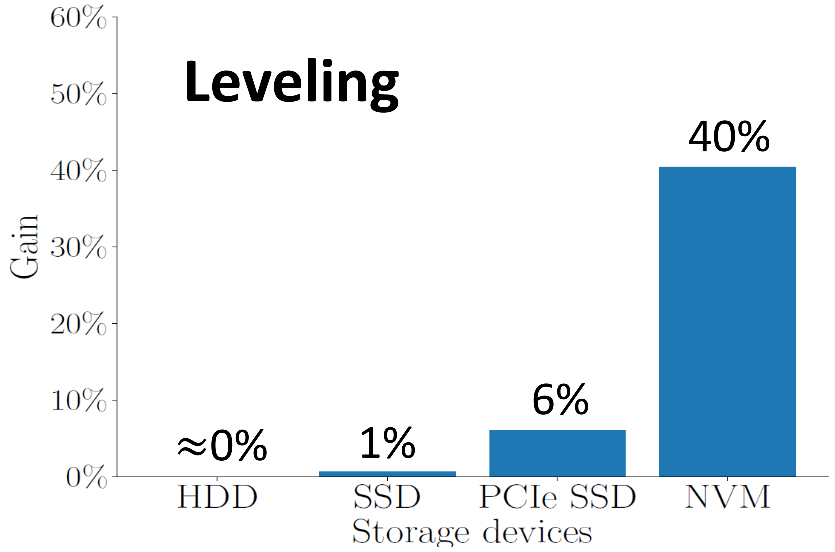

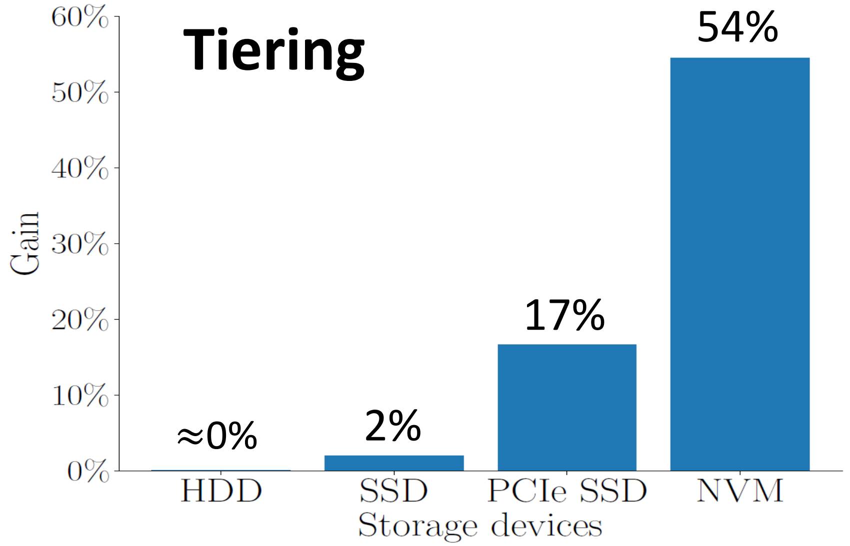

Thank you!

https://github.com/BU-DiSC/BF-Shared-Hashing