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CS 561: **Data Systems Architectures**

class 5

Bloom Filters in LSM trees

Zichen Zhu

https://bu-disc.github.io/CS561/

Slides credited to ***Juhyoung Mun*** and ***Manos Athanassoulis***

Log-Structured Merge Trees

Widely adopted because they balance read performance and ingestion

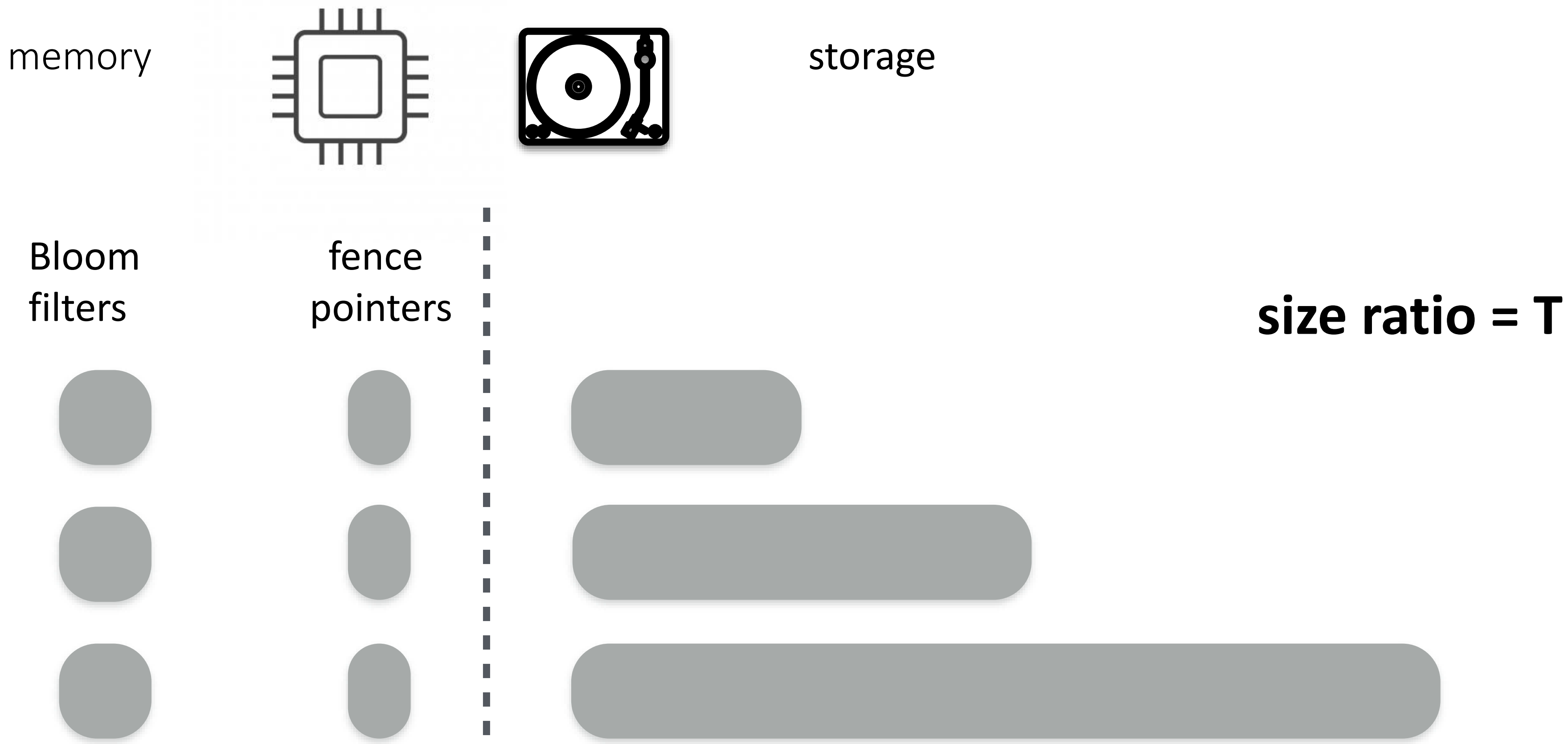
levelDB RocksDB

APACHE HBASE

amazon DynamoDB

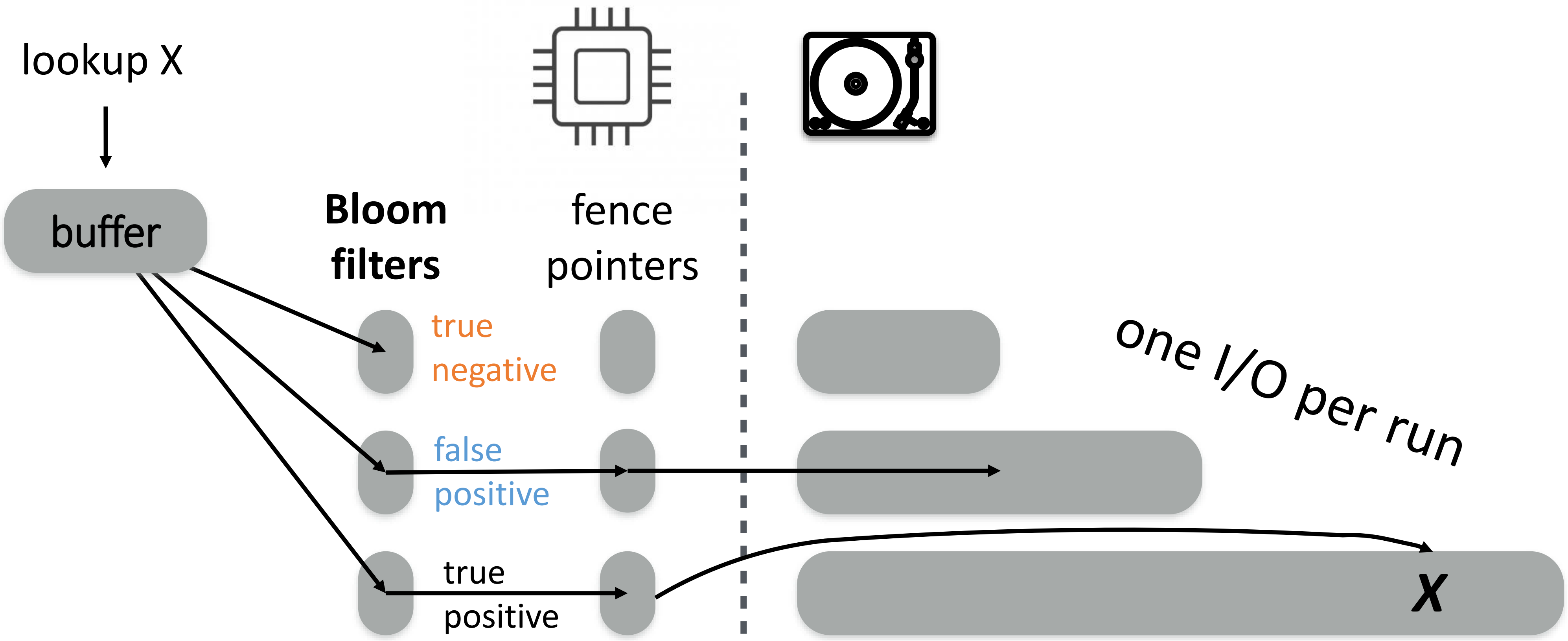
cassandra

Log-Structured Merge Trees



exponentially larger capacity

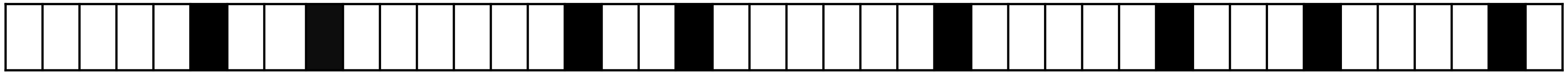
Log-Structured Merge Trees



Bloom Filter

m-bit vector
n elements are store
k hash indexes

y?



m-bit vector

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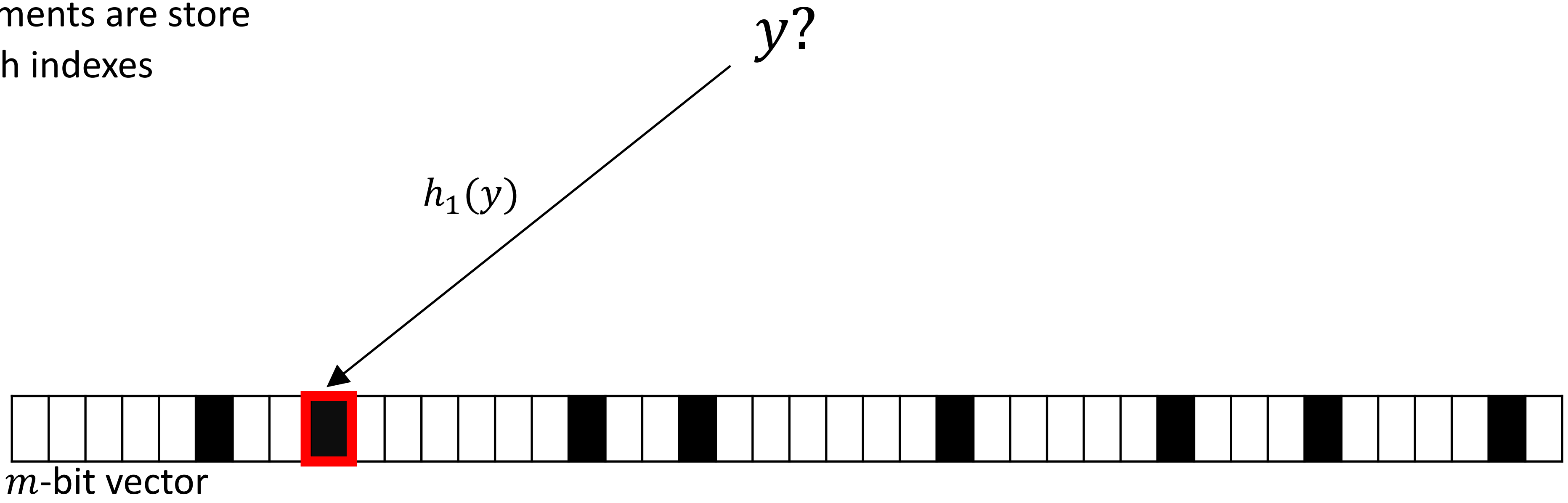

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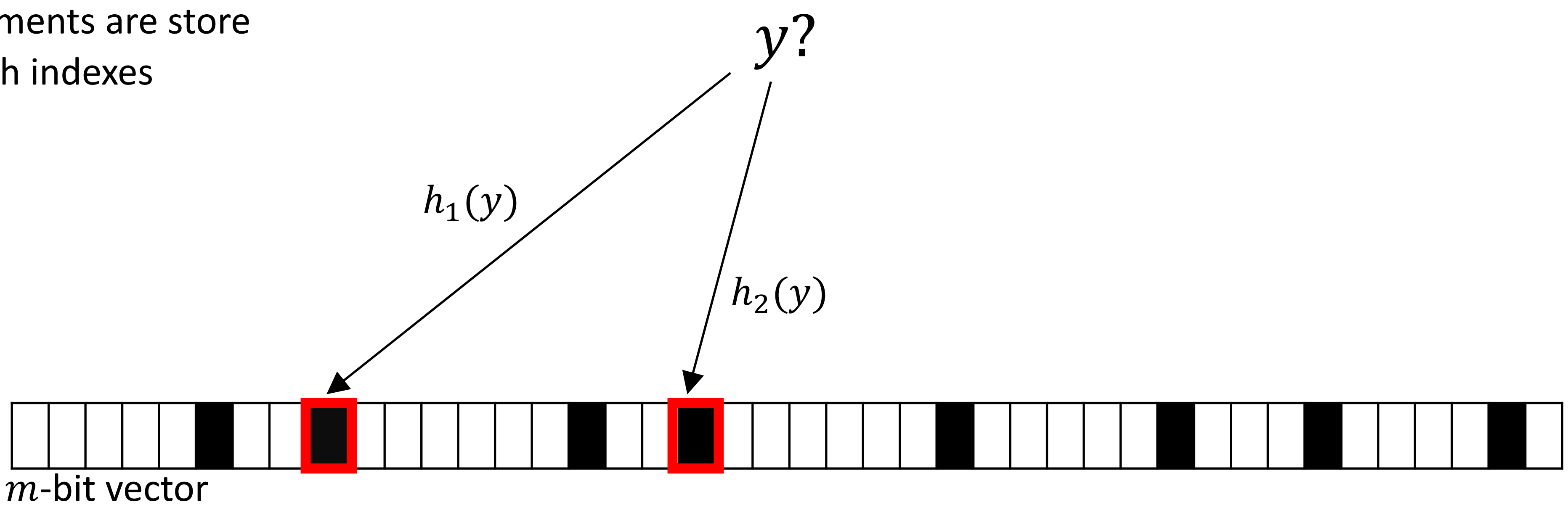

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Bloom Filter

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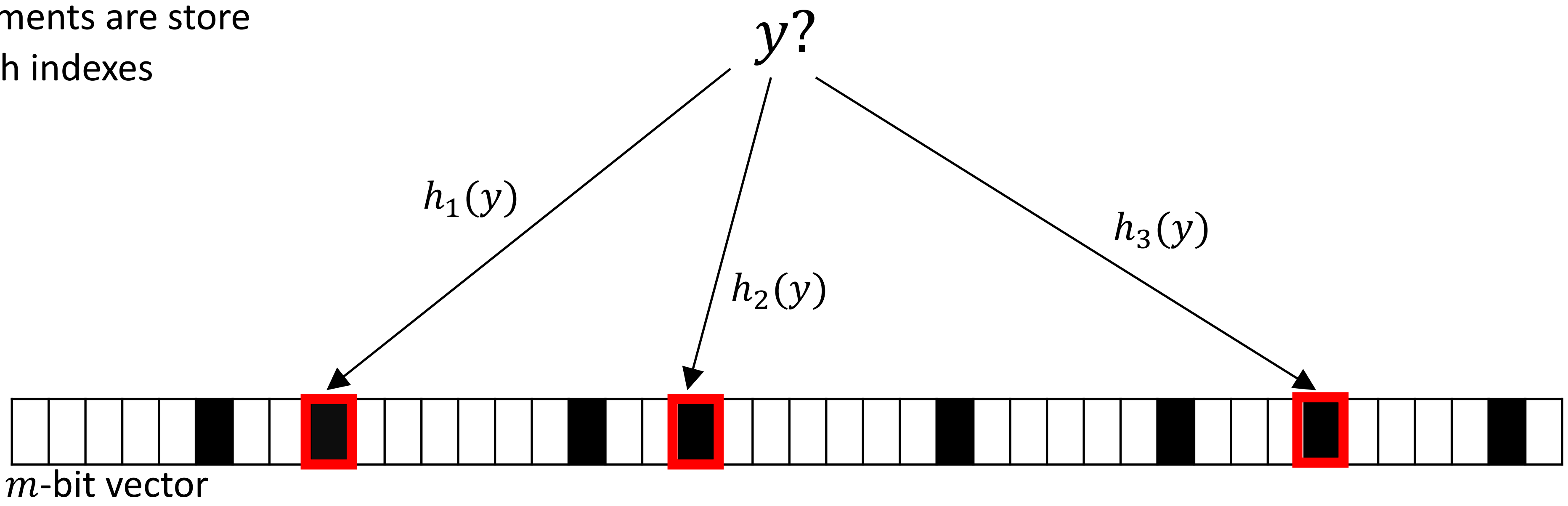

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Bloom Filter

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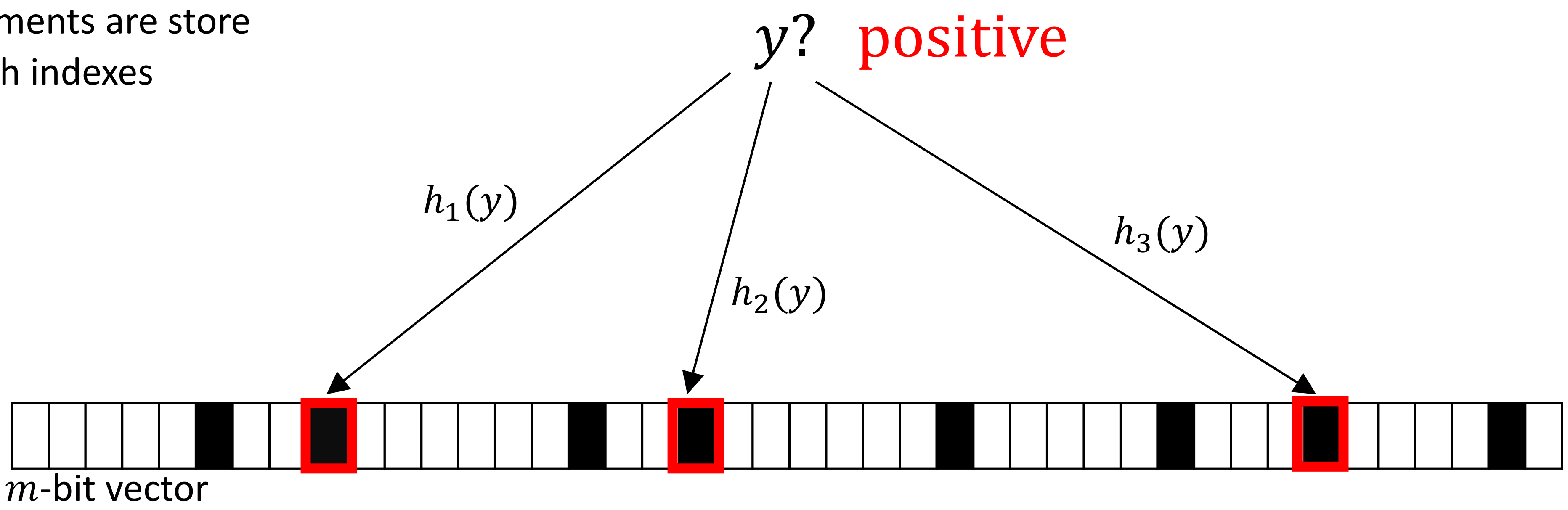

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Bloom Filter

m-bit vector
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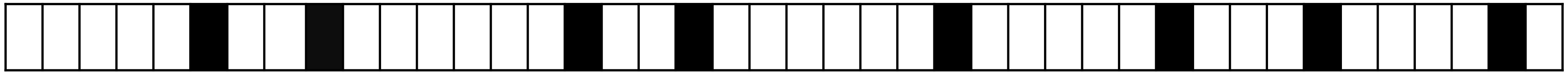
k hash indexes

x?



m-bit vector

Bloom Filter

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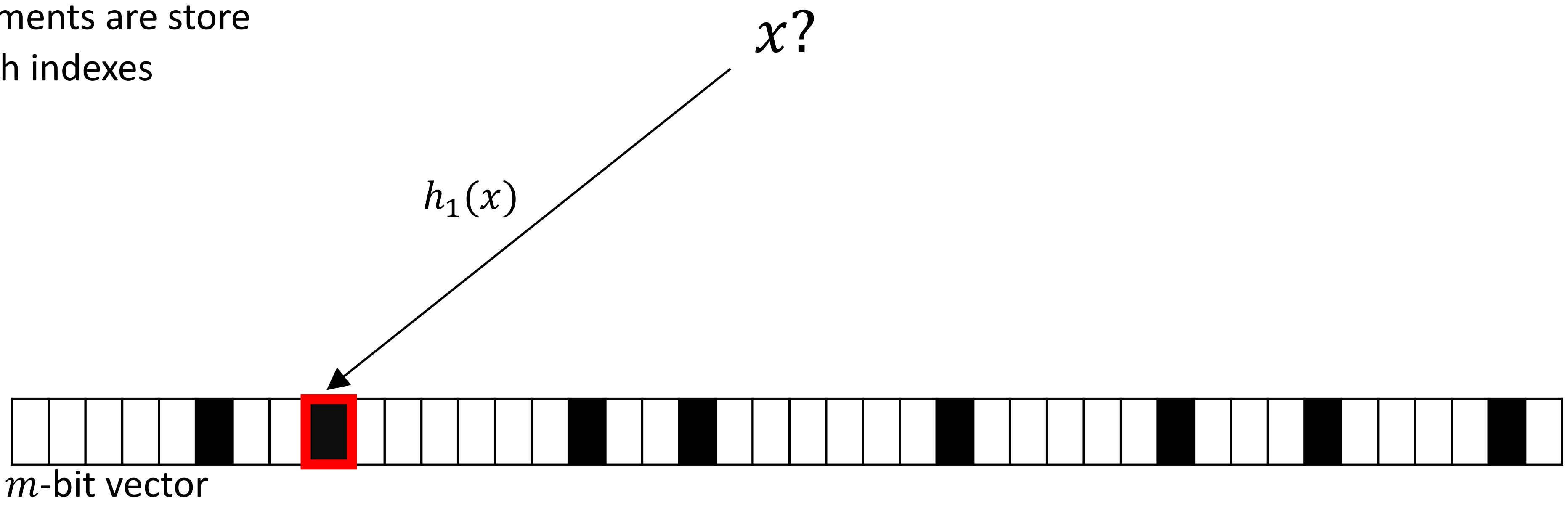
n elements are store
k hash indexes



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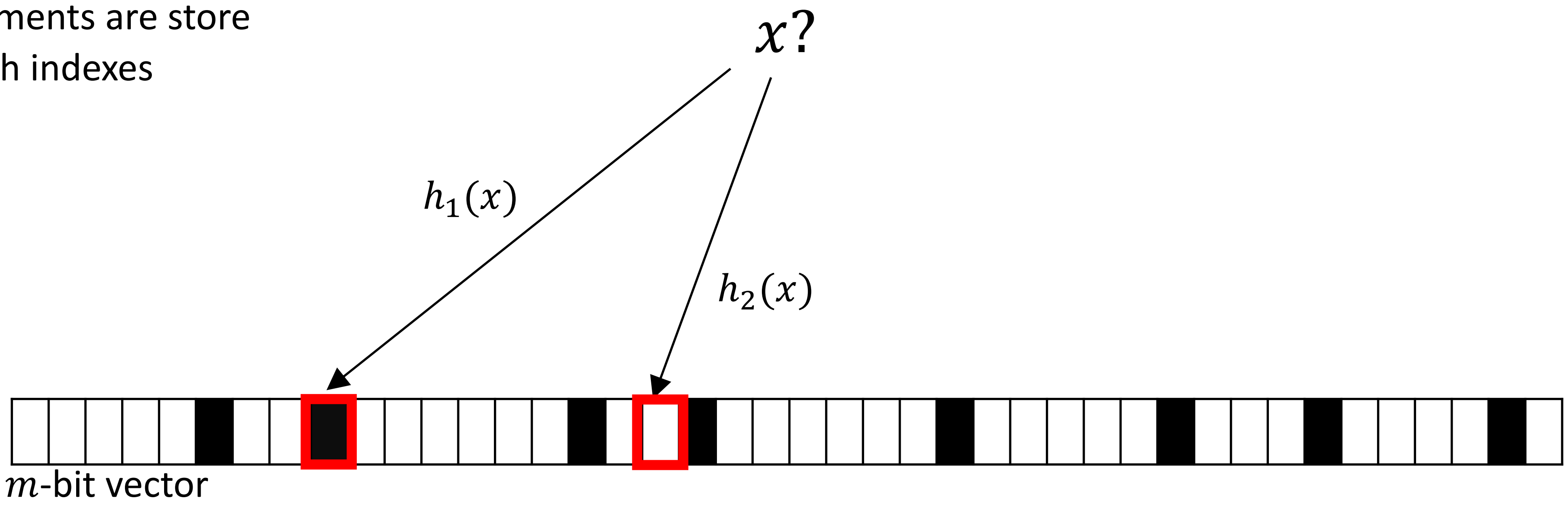

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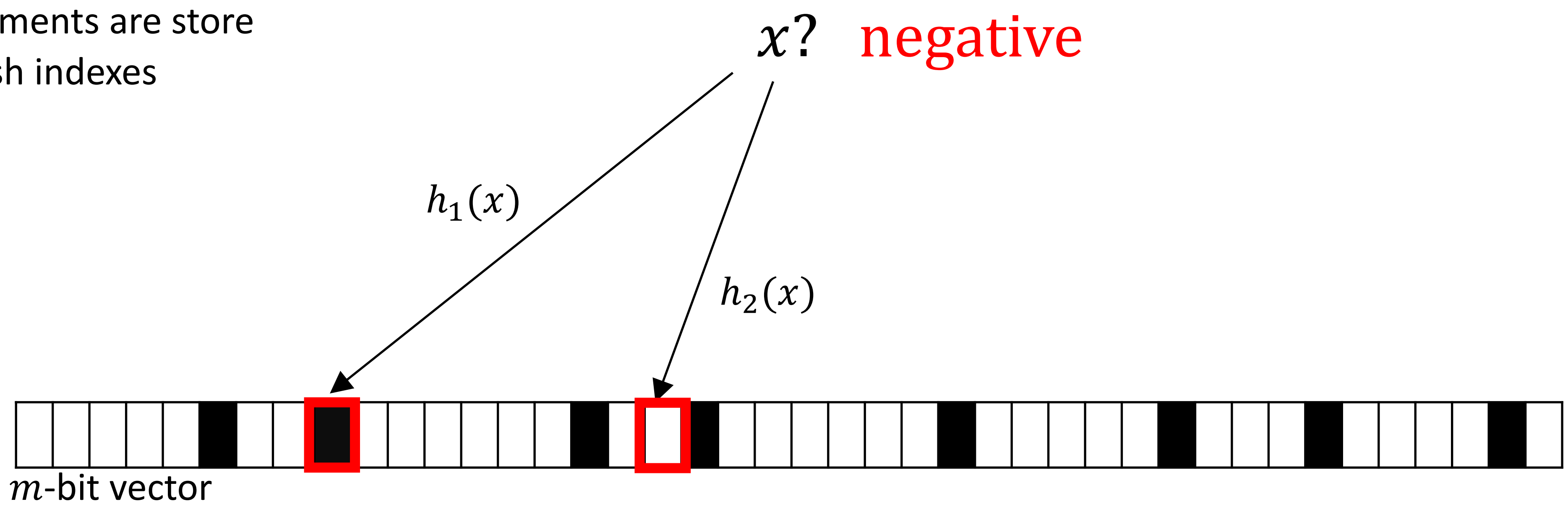

$$\text{false positive } p = e^{-\frac{\text{bits } M}{\text{entries } N} \cdot ln(2)^2}$$

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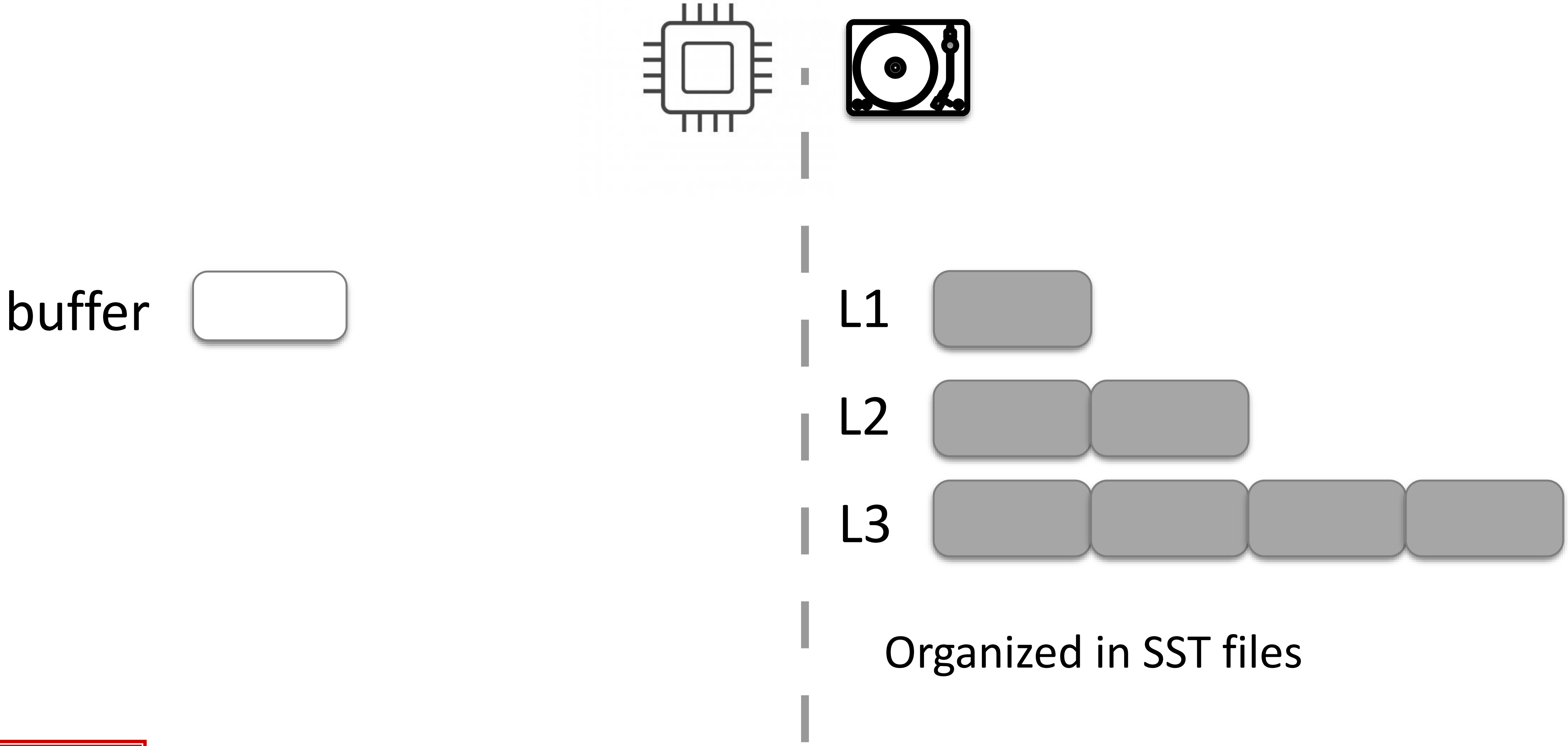
Log-Structured Merge Trees



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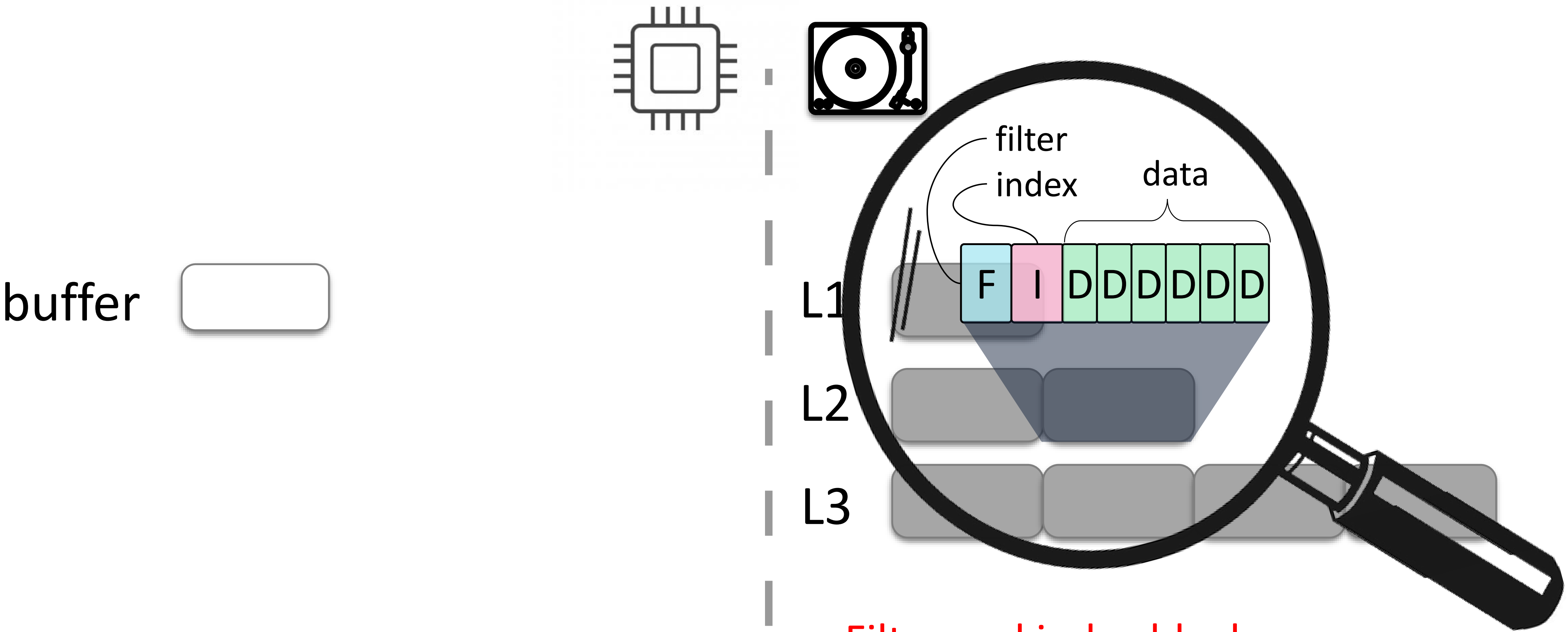

Filter and index blocks
to enhance the lookup performance

Memory Pressure in LSM-trees

Memory vs. Storage

Metric	DRAM				HDD				SATAFlash SSD	
	1987	1997	2007	2018	1987	1997	2007	2018	2007	2018
Unit price($)	5k	15k	48	80	30k	2k	80	49	1k	415
Unit capacity	1MB	1GB	1GB	16GB	180MB	9GB	250GB	2TB	32GB	800GB
$/MB	5k	14.6	0.05	0.005	83.33	0.22	0.0003	0.00002	0.03	0.0005
Random IOPS	–	–	–	–	5	64	83	200	6.2k	67k (r)/20k (w)
Sequential b/w (MB/s)	–	–	–	–	1	10	300	200	66	500 (r)/460 (w)

The Five-Minute Rule 30 Years Later and Its Impact on the Storage Hierarchy, Communications of the ACM, 2019

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The price drop in memory has been slower than storage

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The price drop in memory has been slower than storage making it hard to maintain the same memory-to-data ratio

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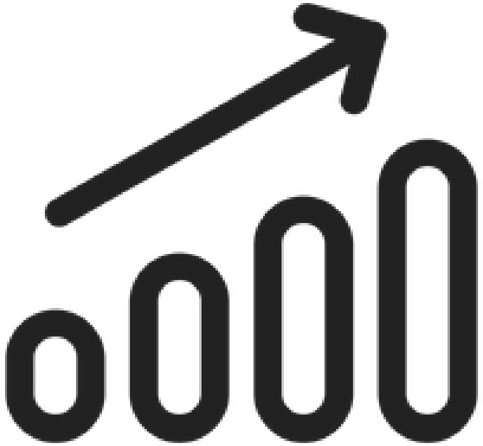
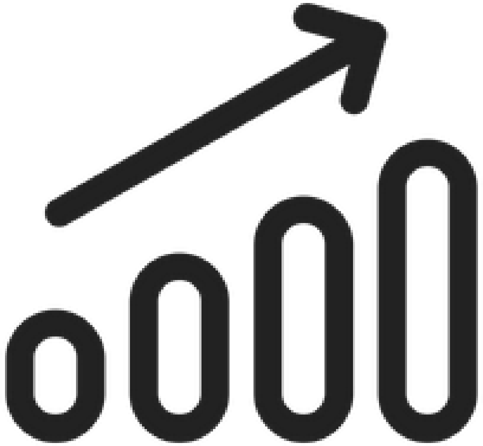
Memory Pressure in LSM-trees



Data size ↑

Memory Pressure in LSM-trees



Data size ↑

For 1TB data,
1.3GB filter &17.2GB index

11% space amplification,
1KB entry, 64B key, bpk 10

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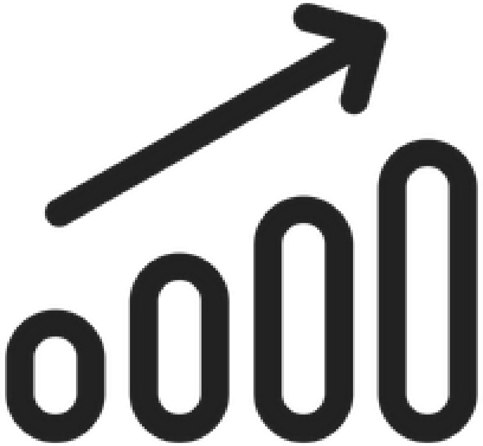
Memory Pressure in LSM-trees



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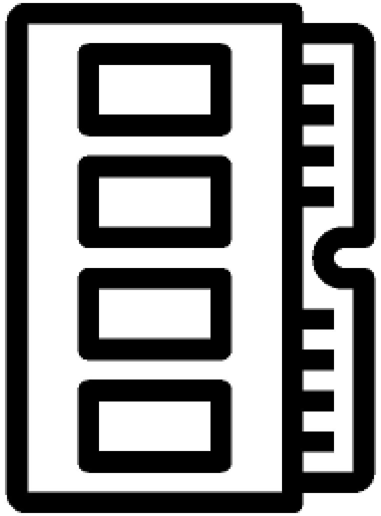

memory-to-data ratio ↓

Memory pressure

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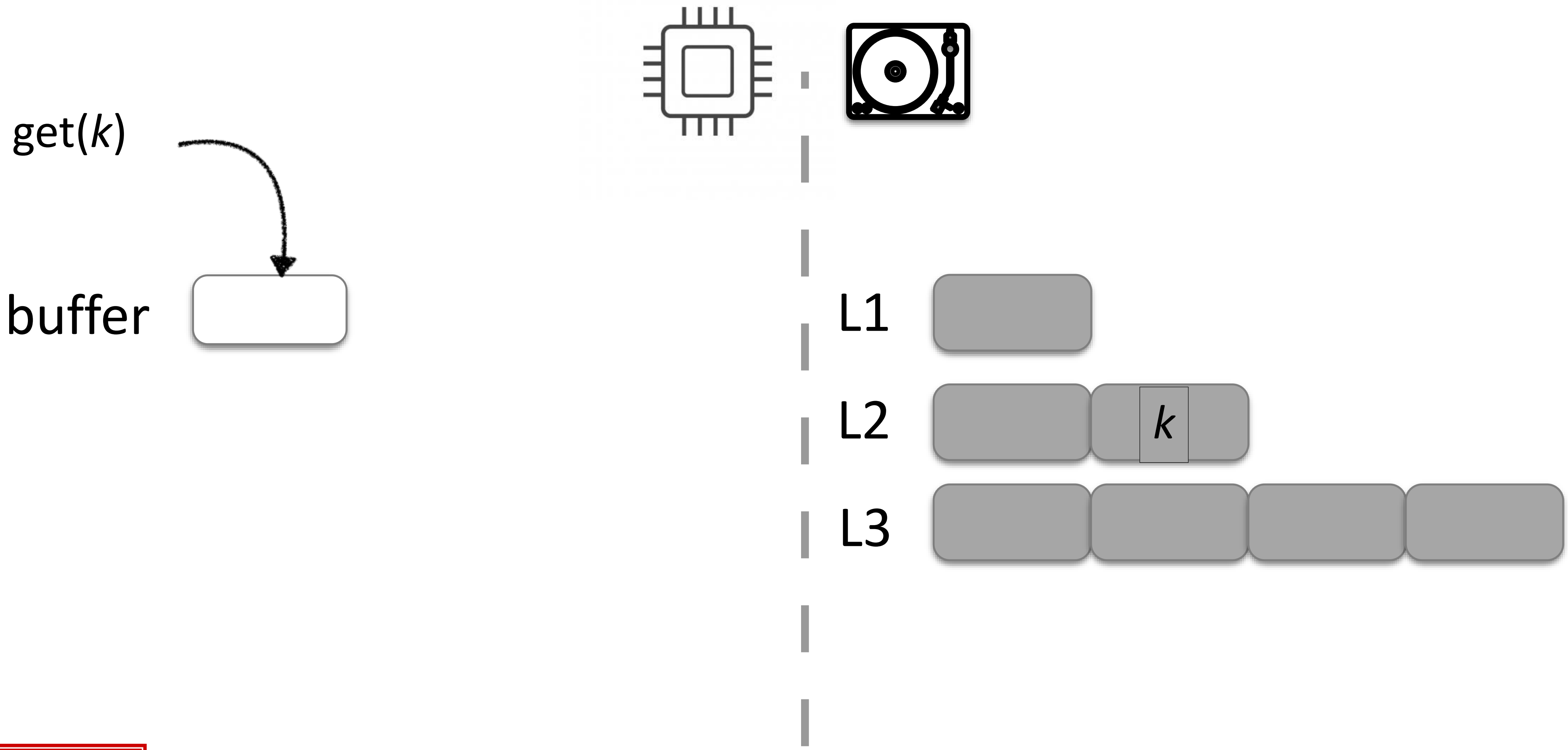
Log-Structured Merge Trees



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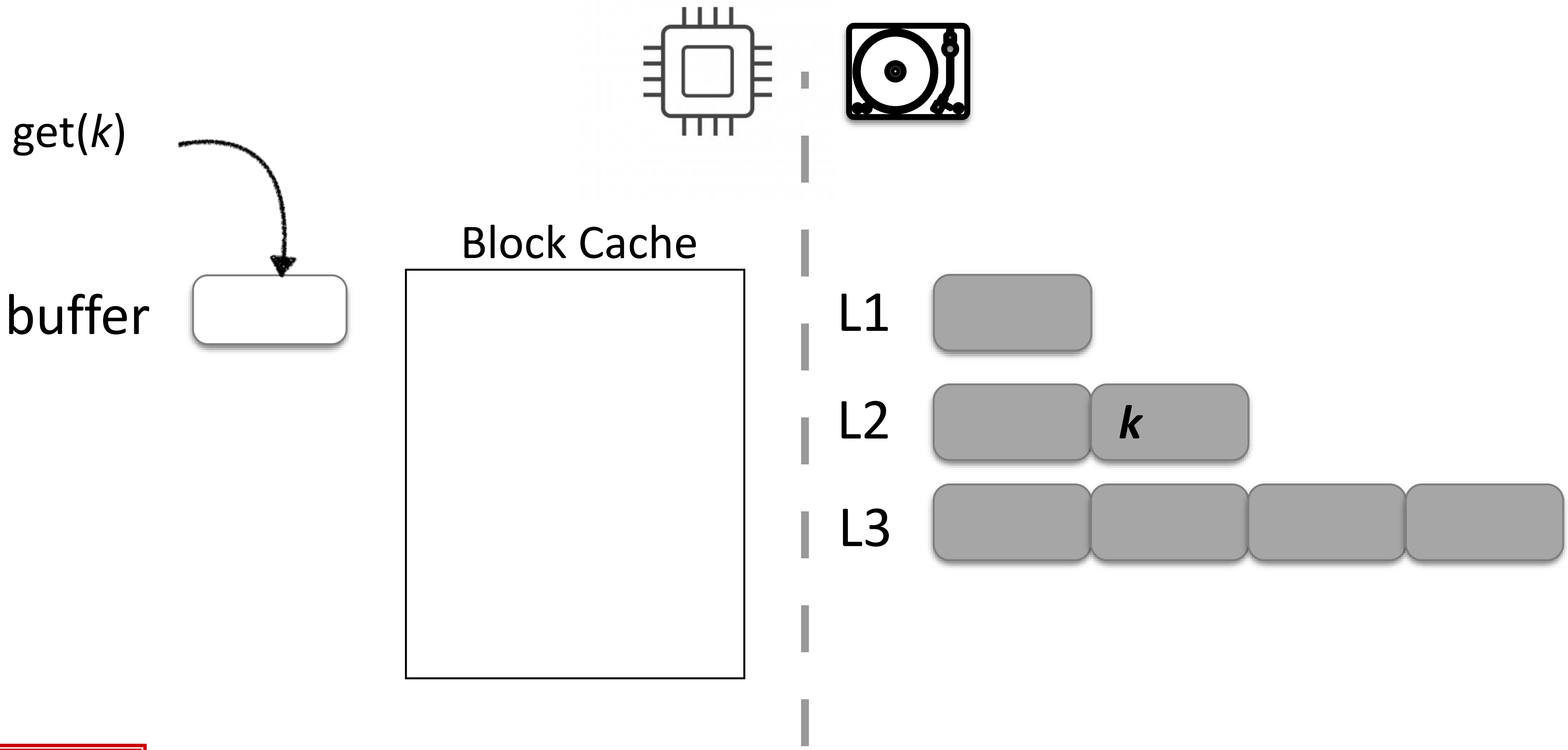

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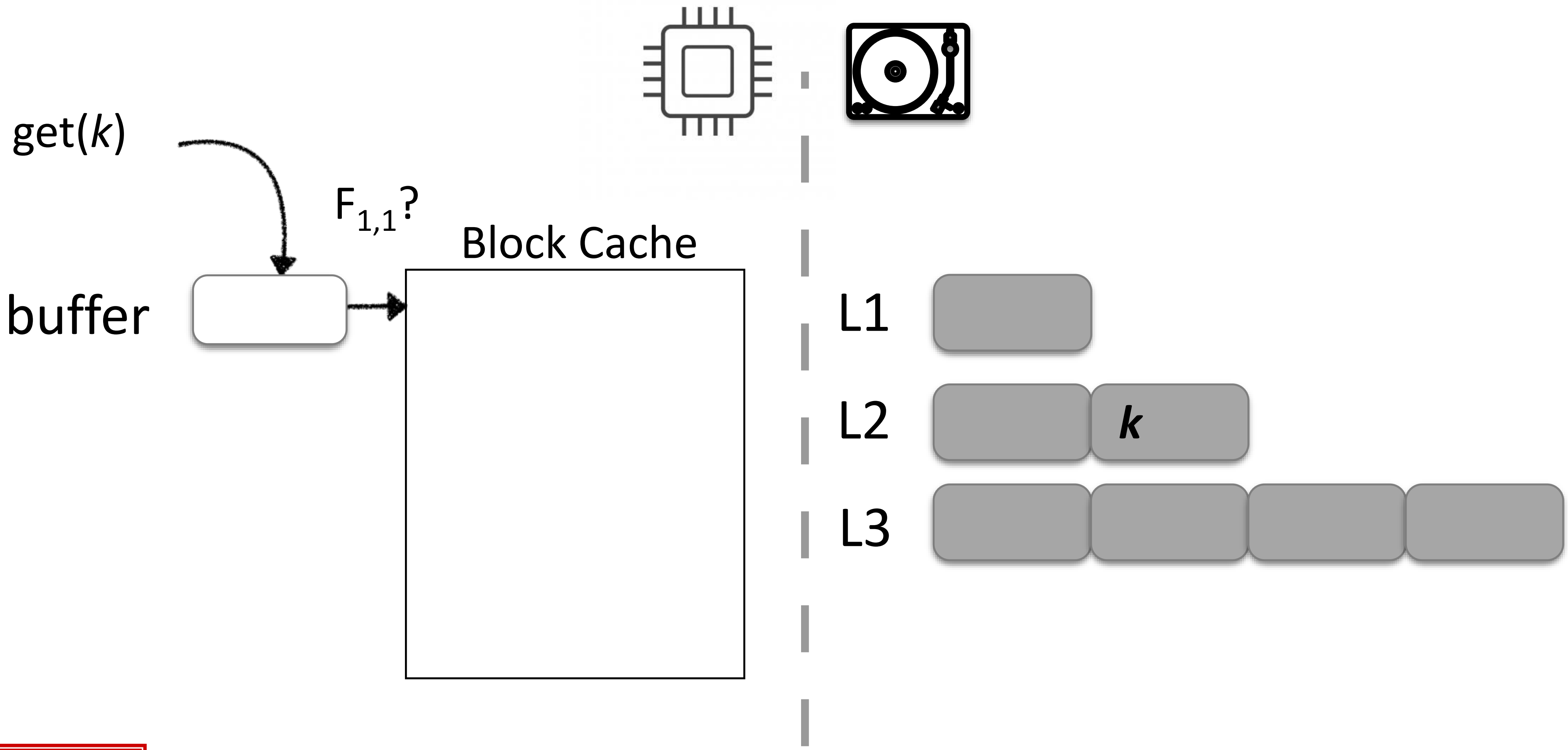

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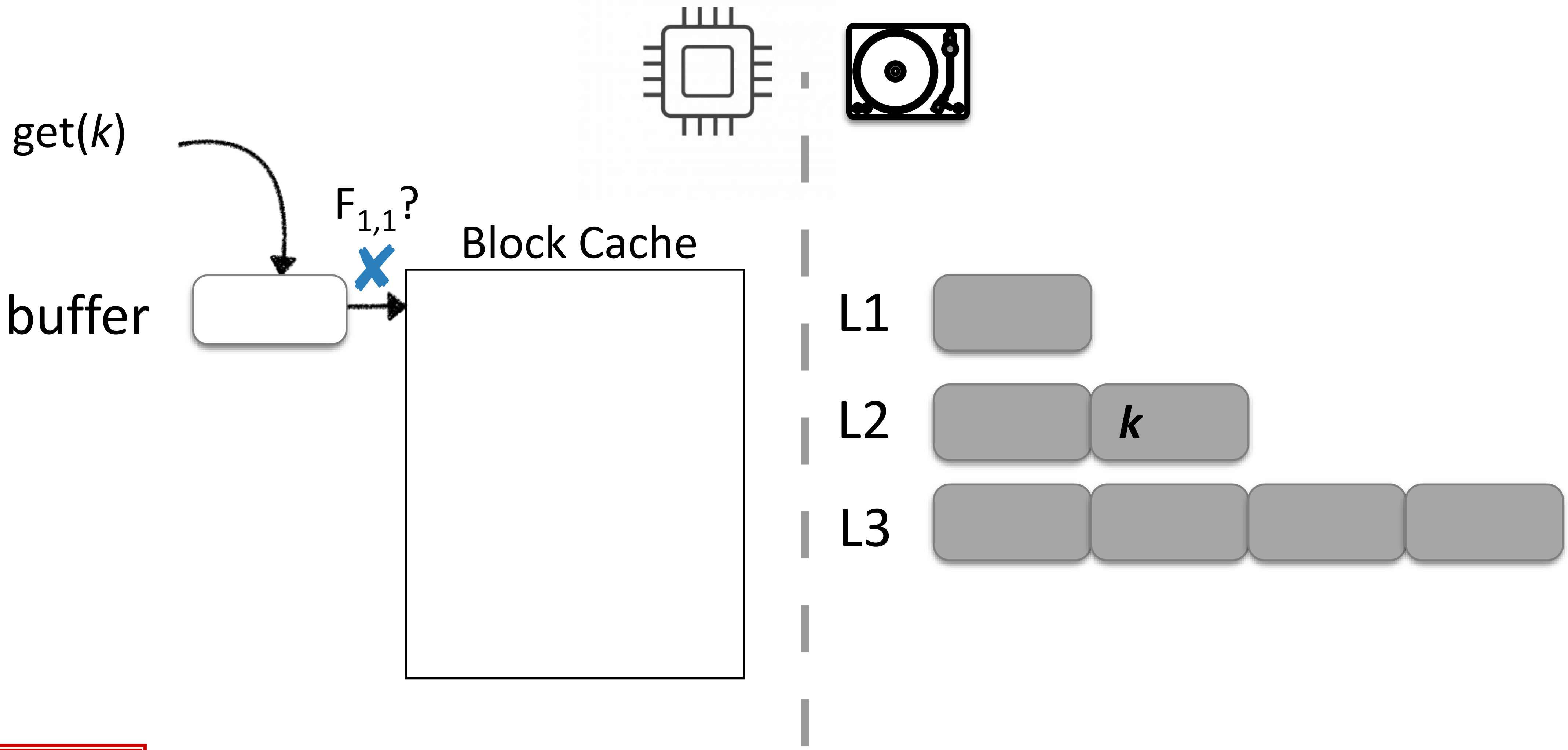

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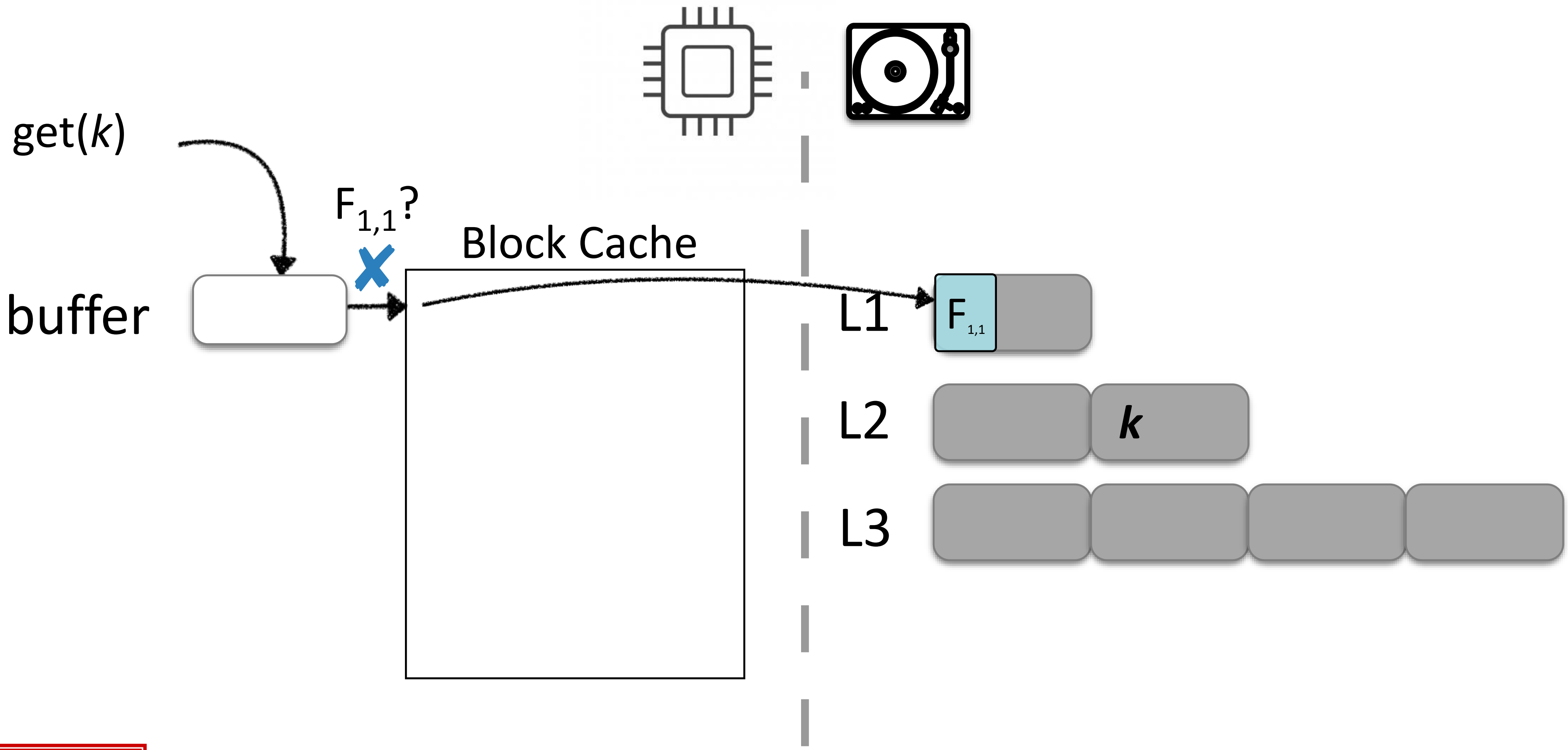

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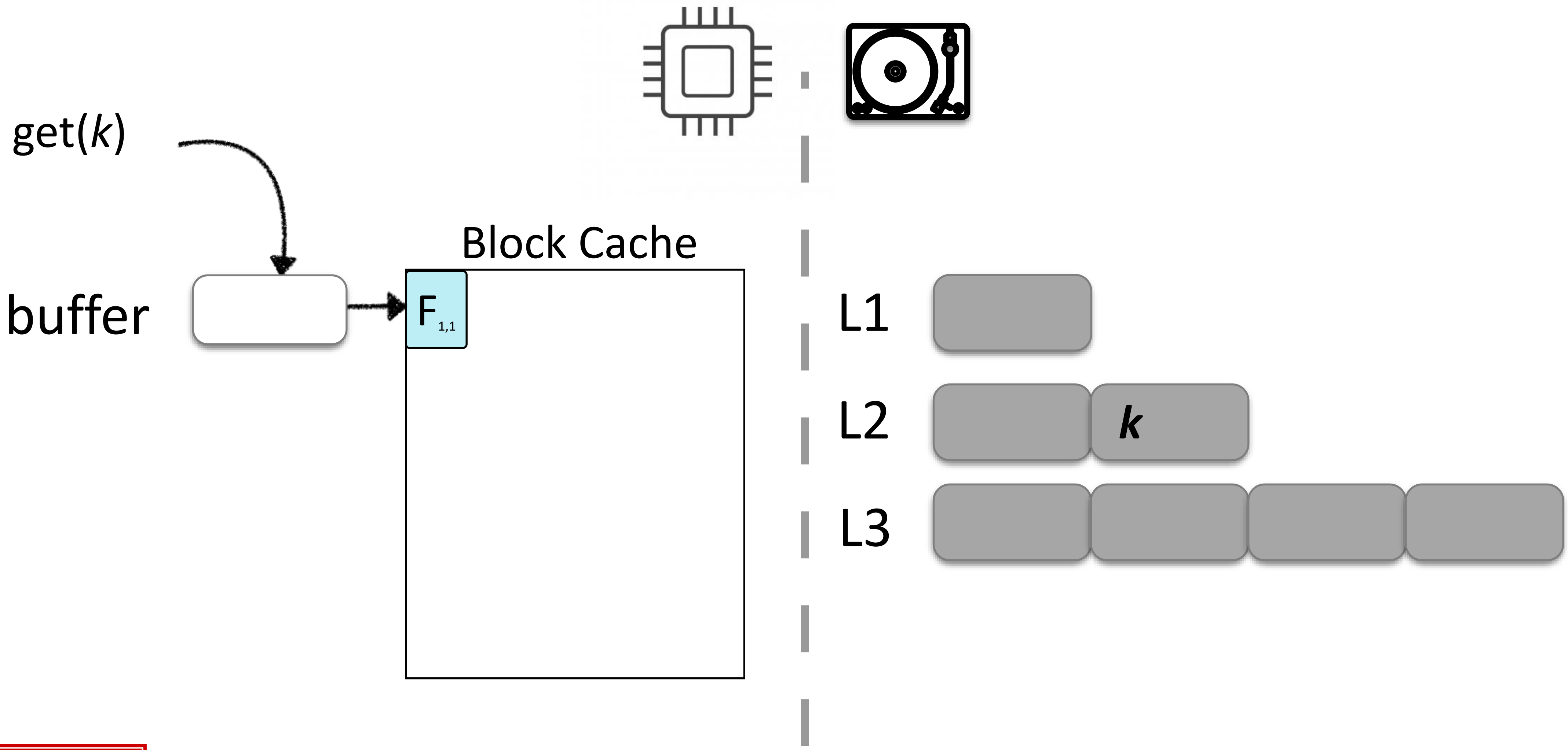

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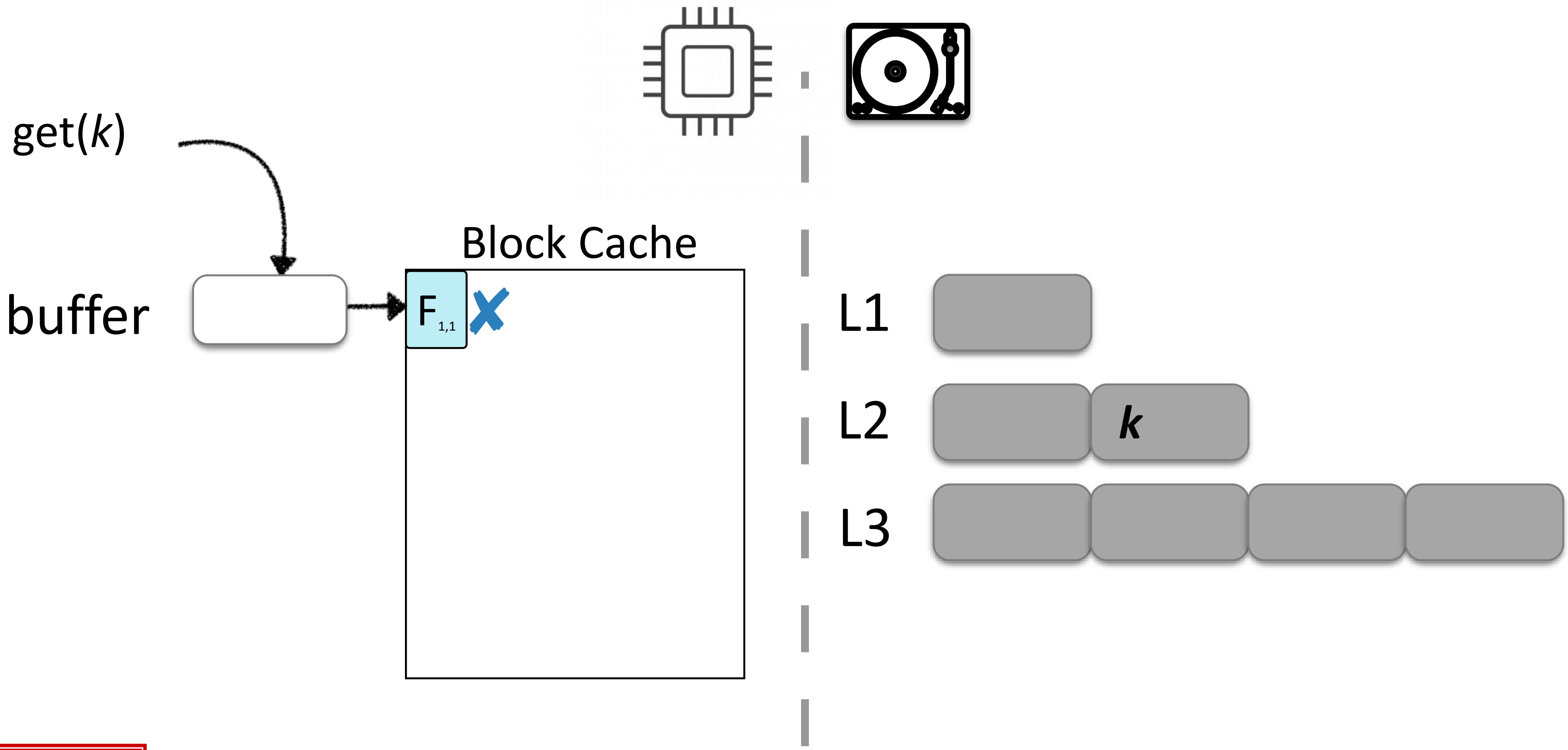

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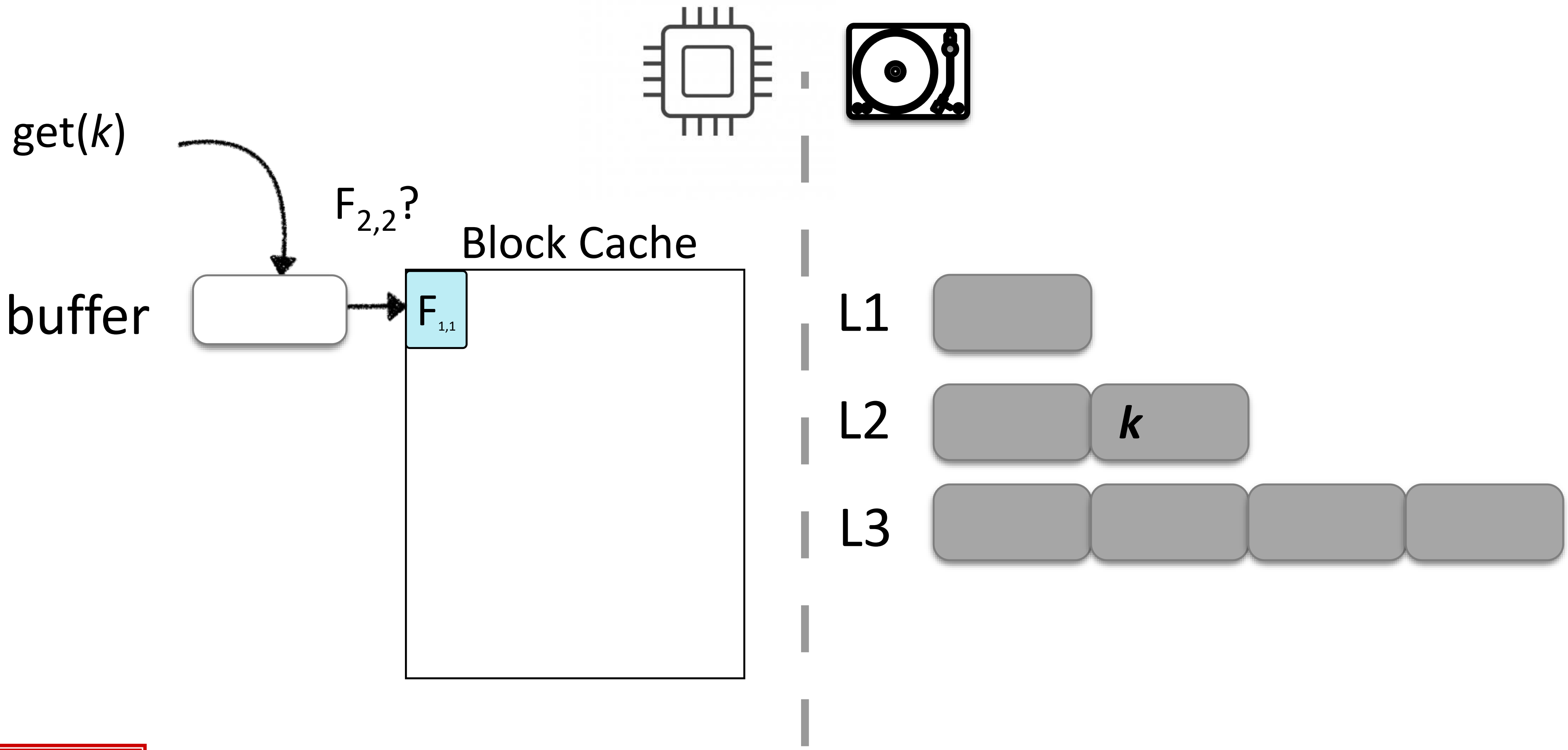

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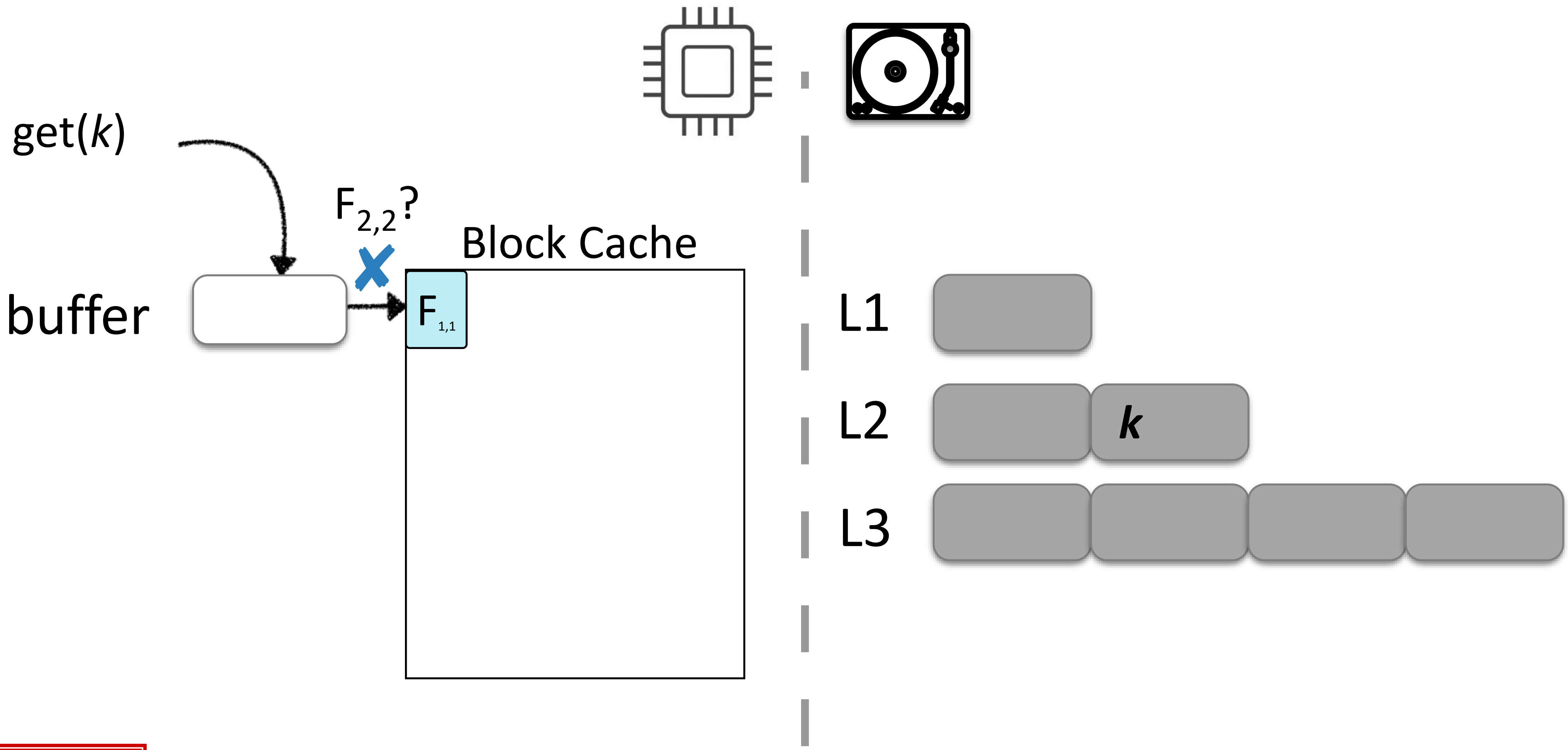

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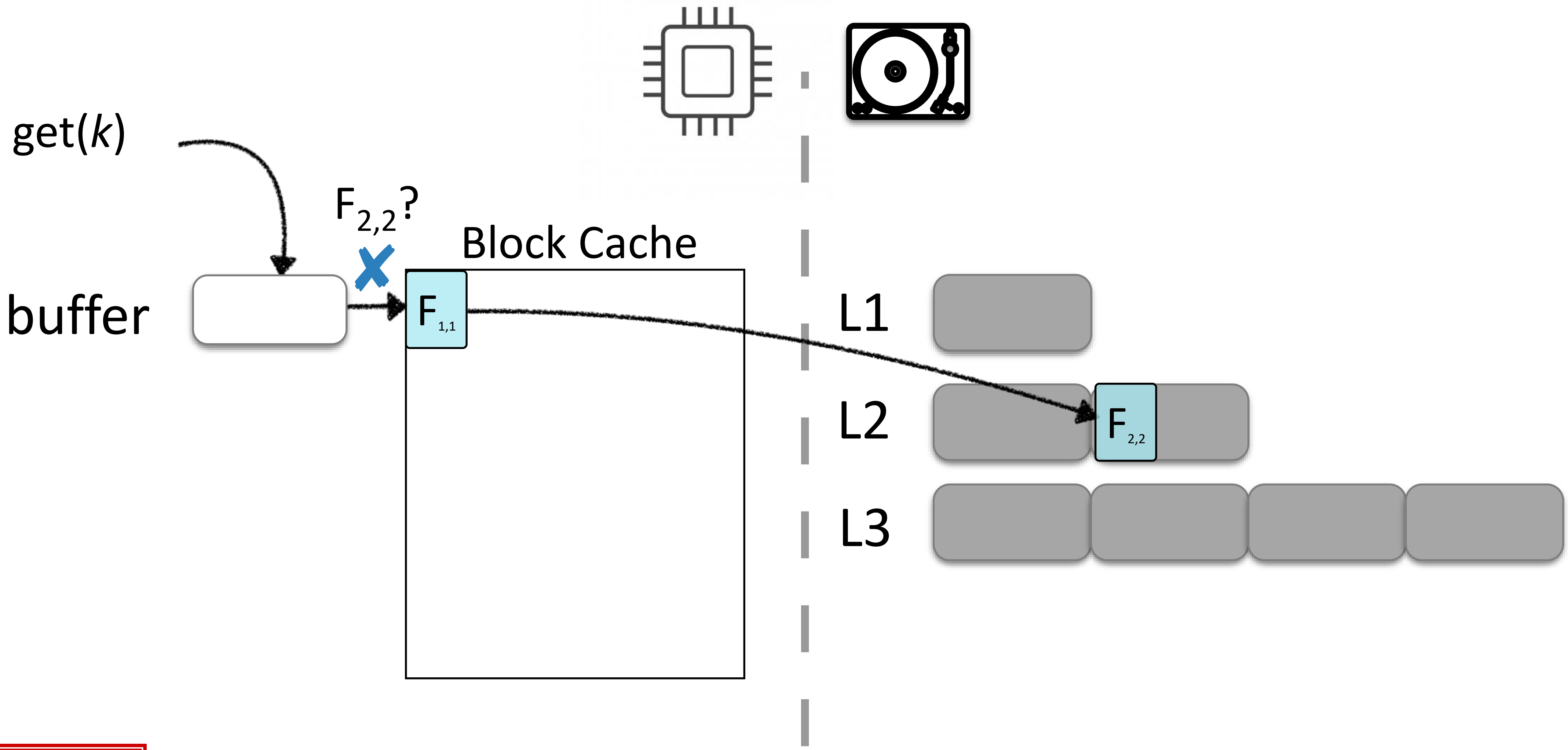

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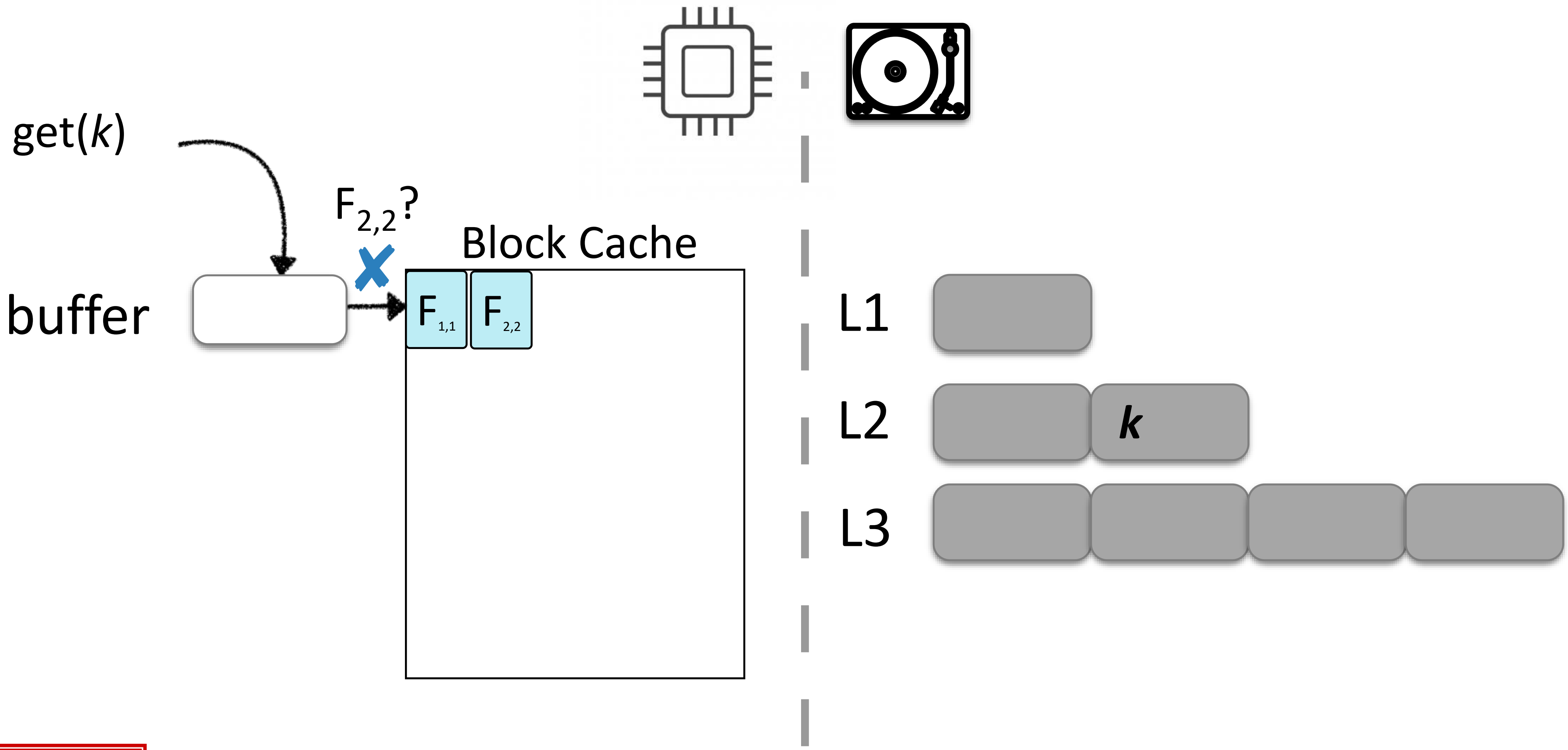

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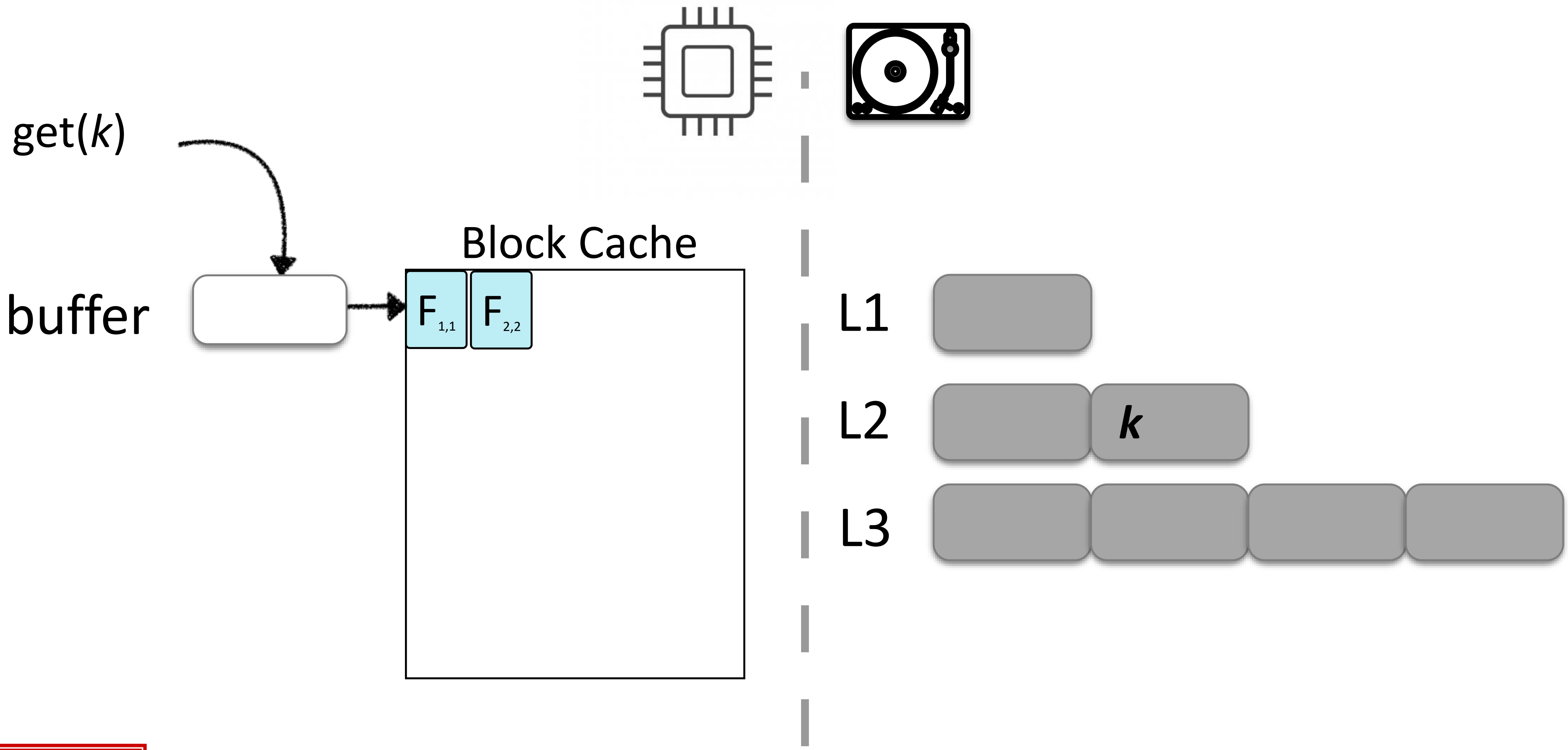

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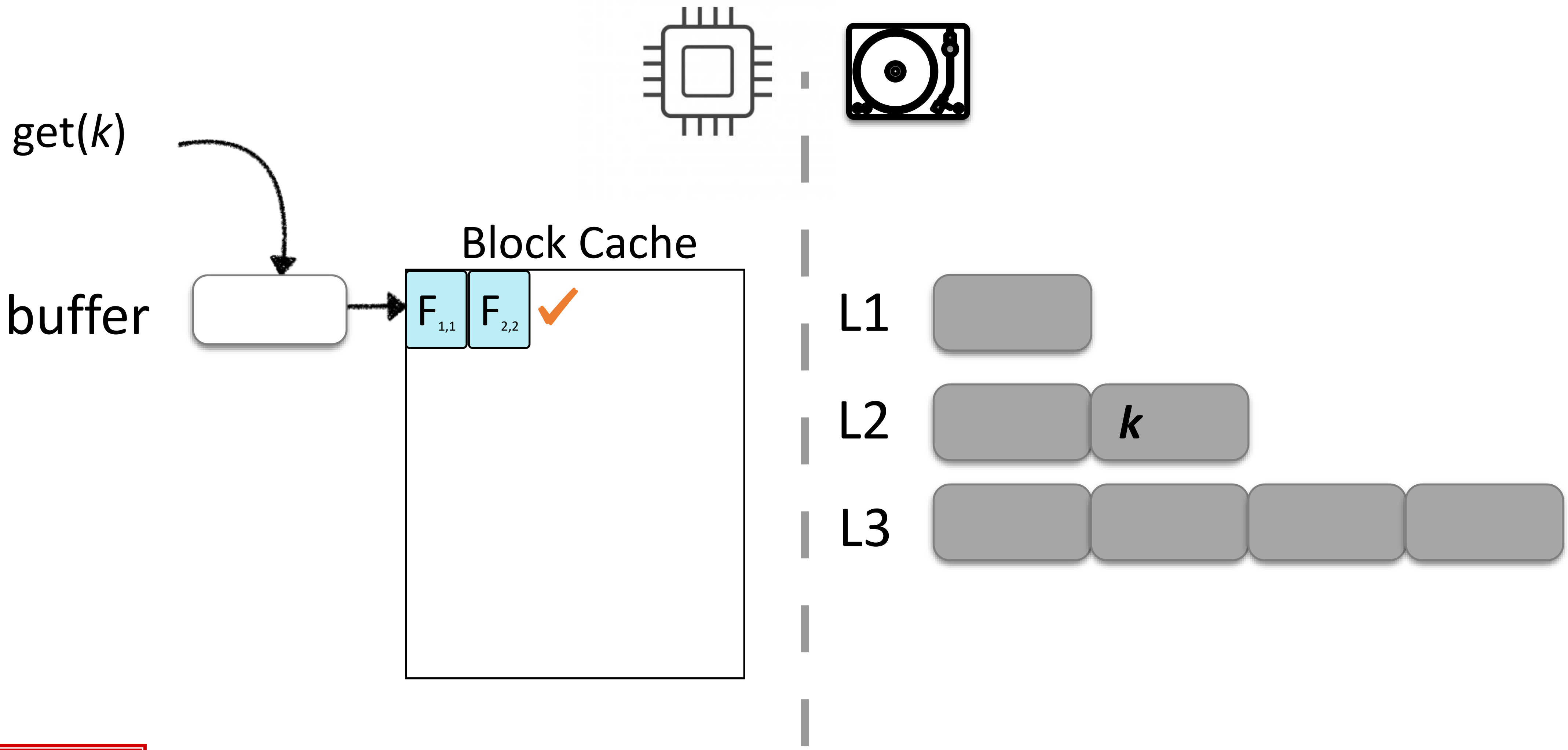

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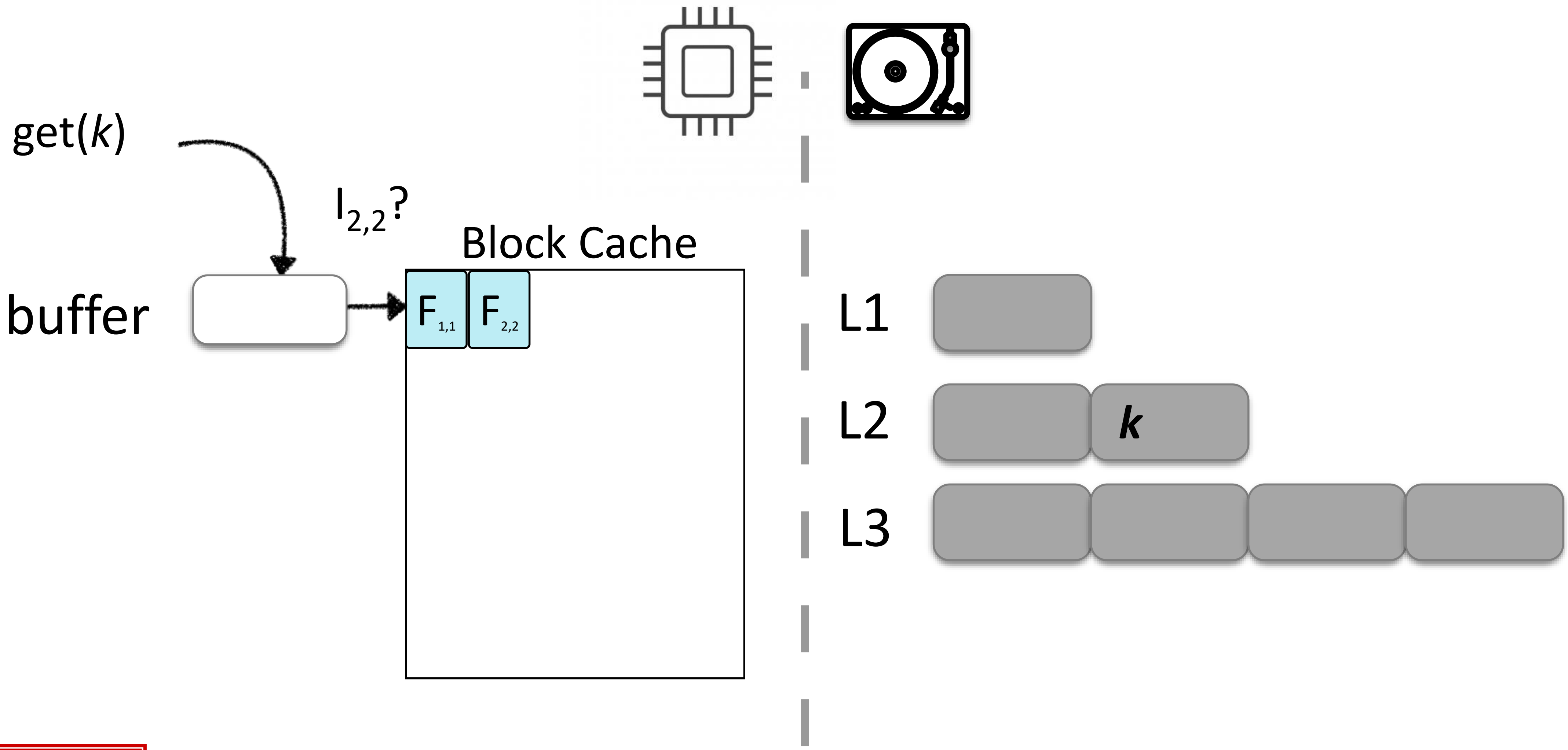

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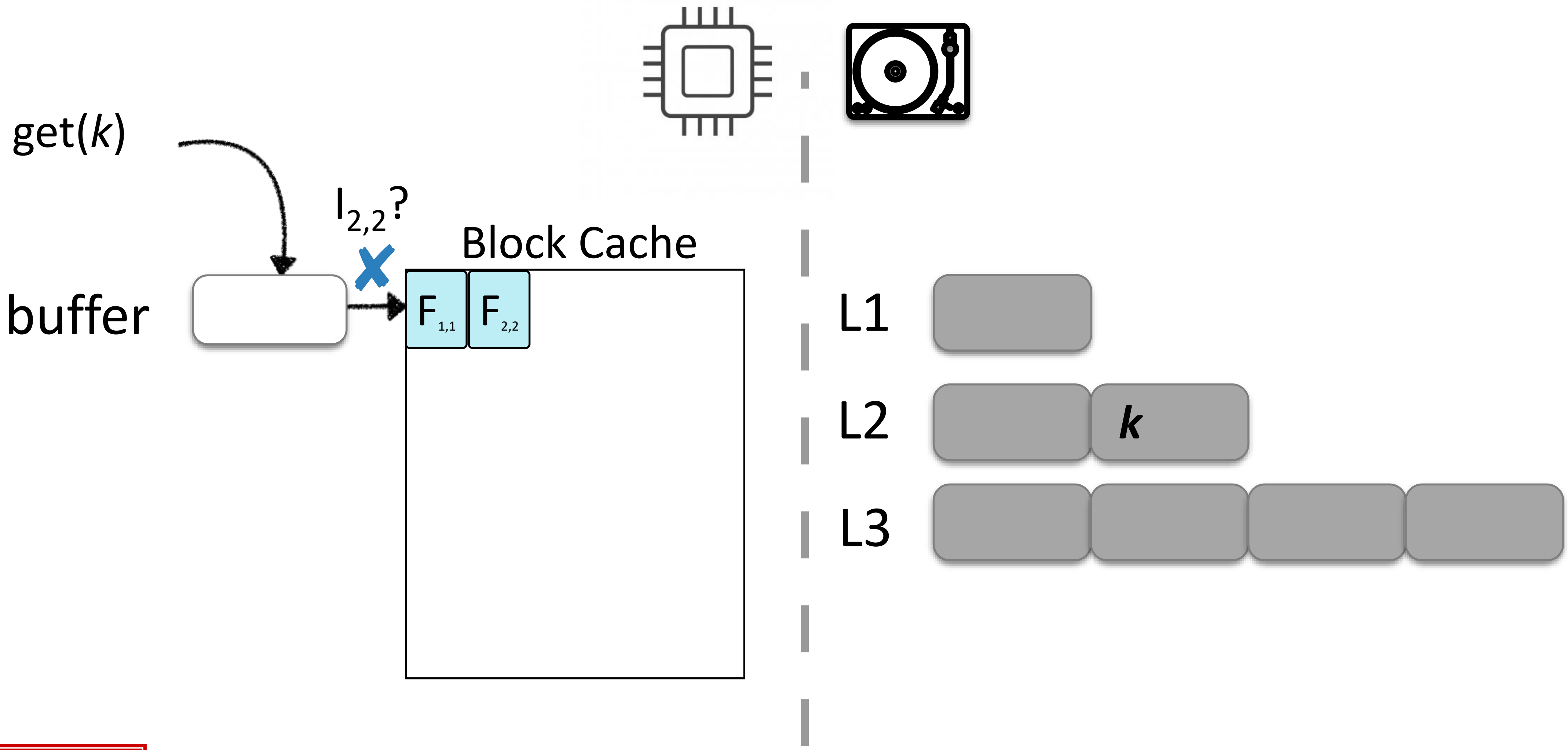

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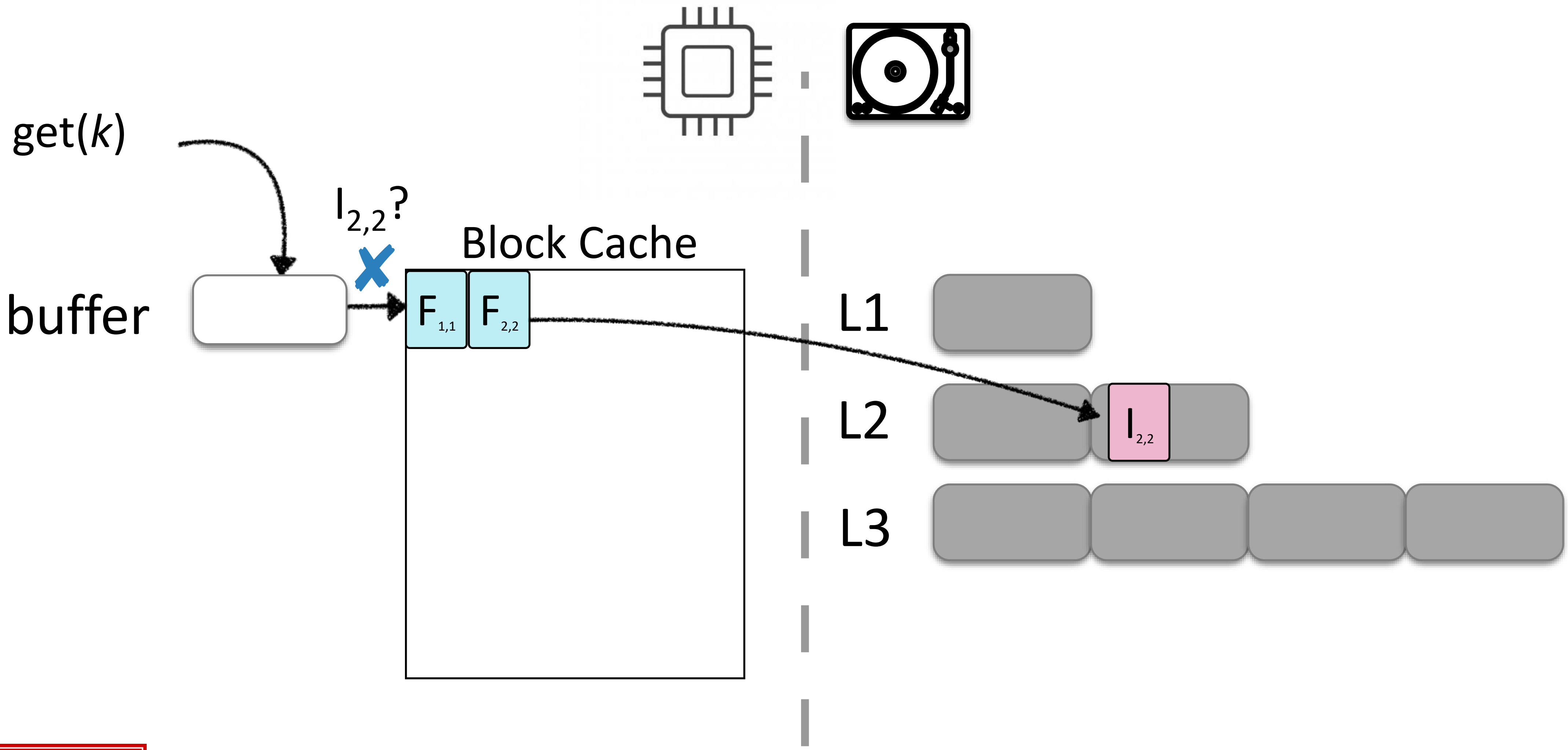

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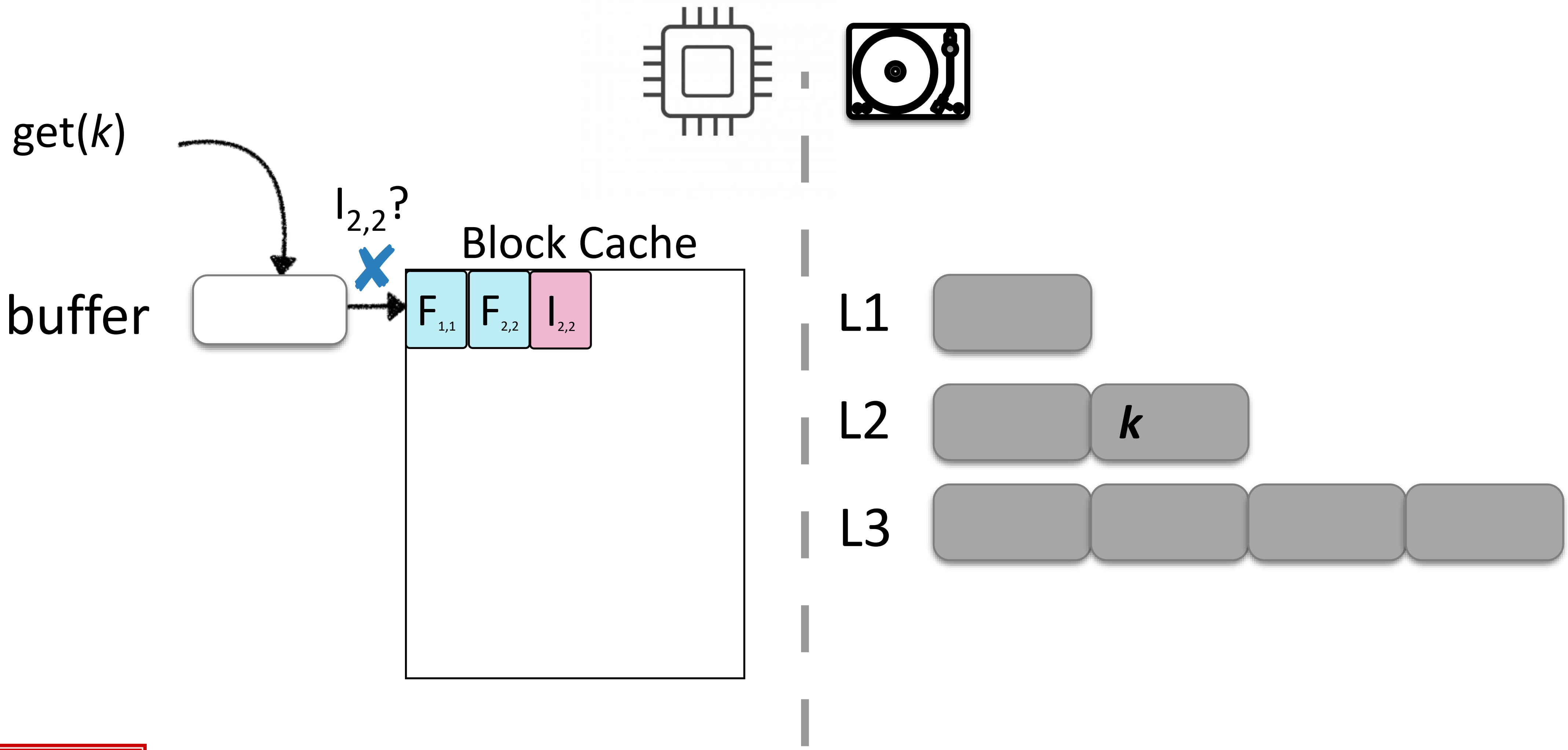

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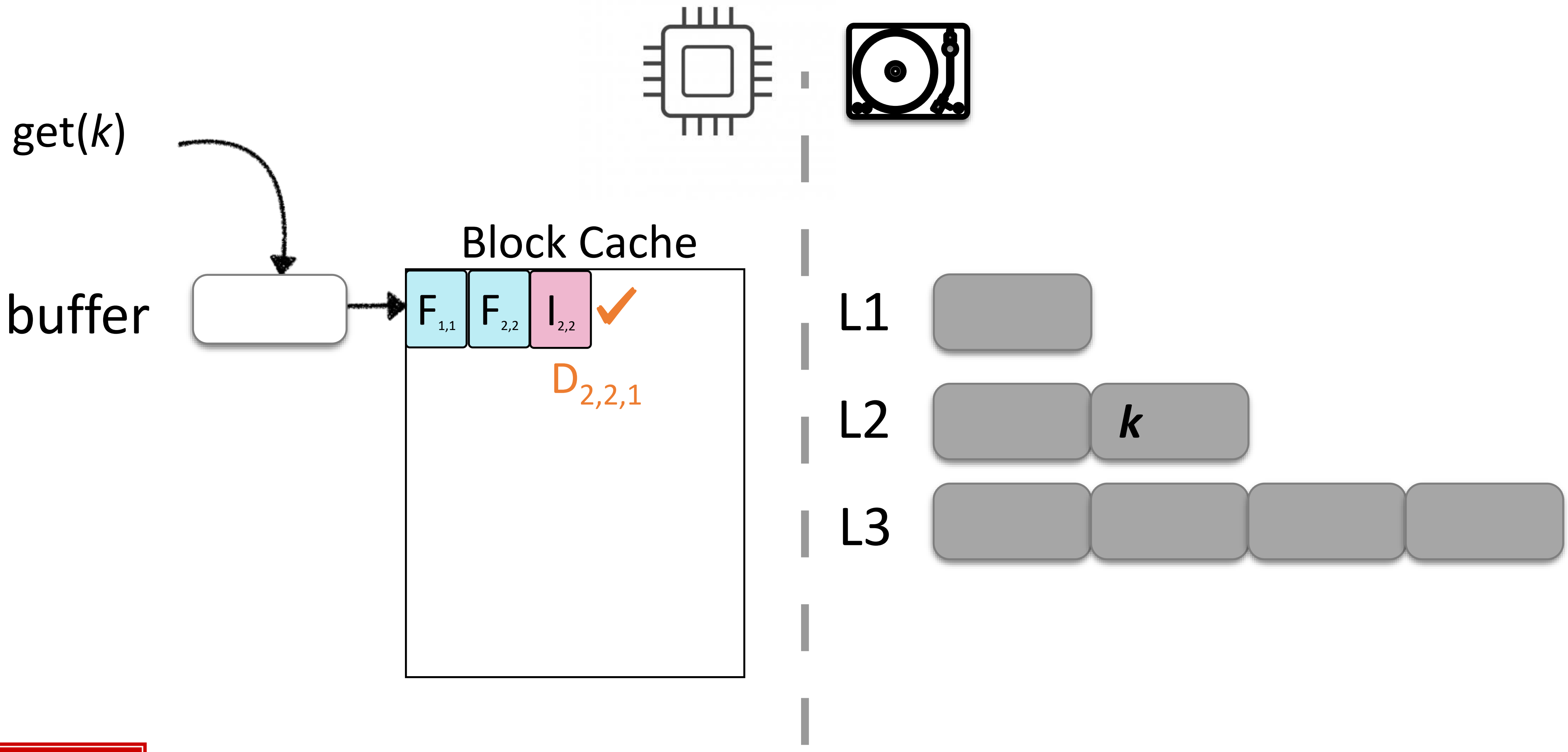

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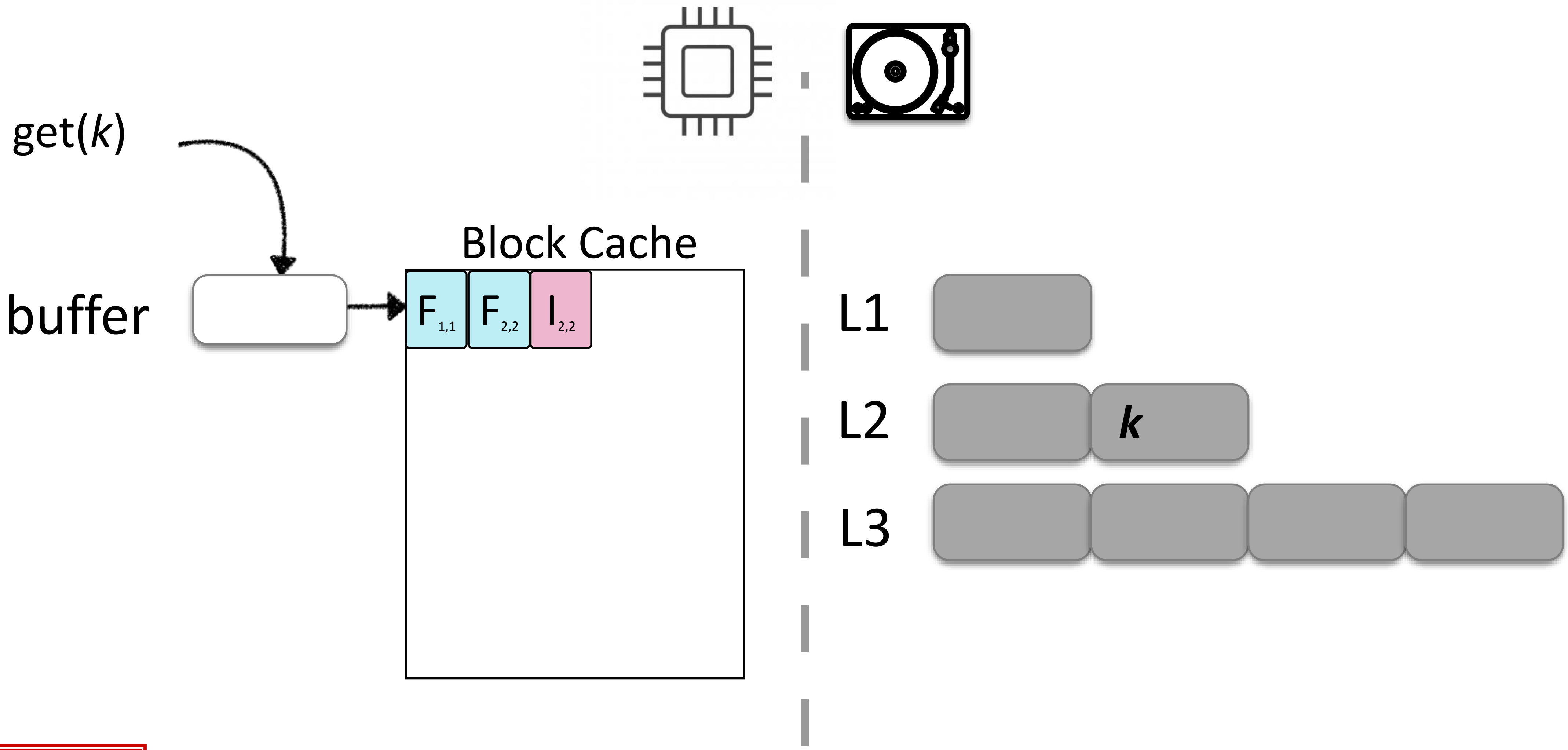

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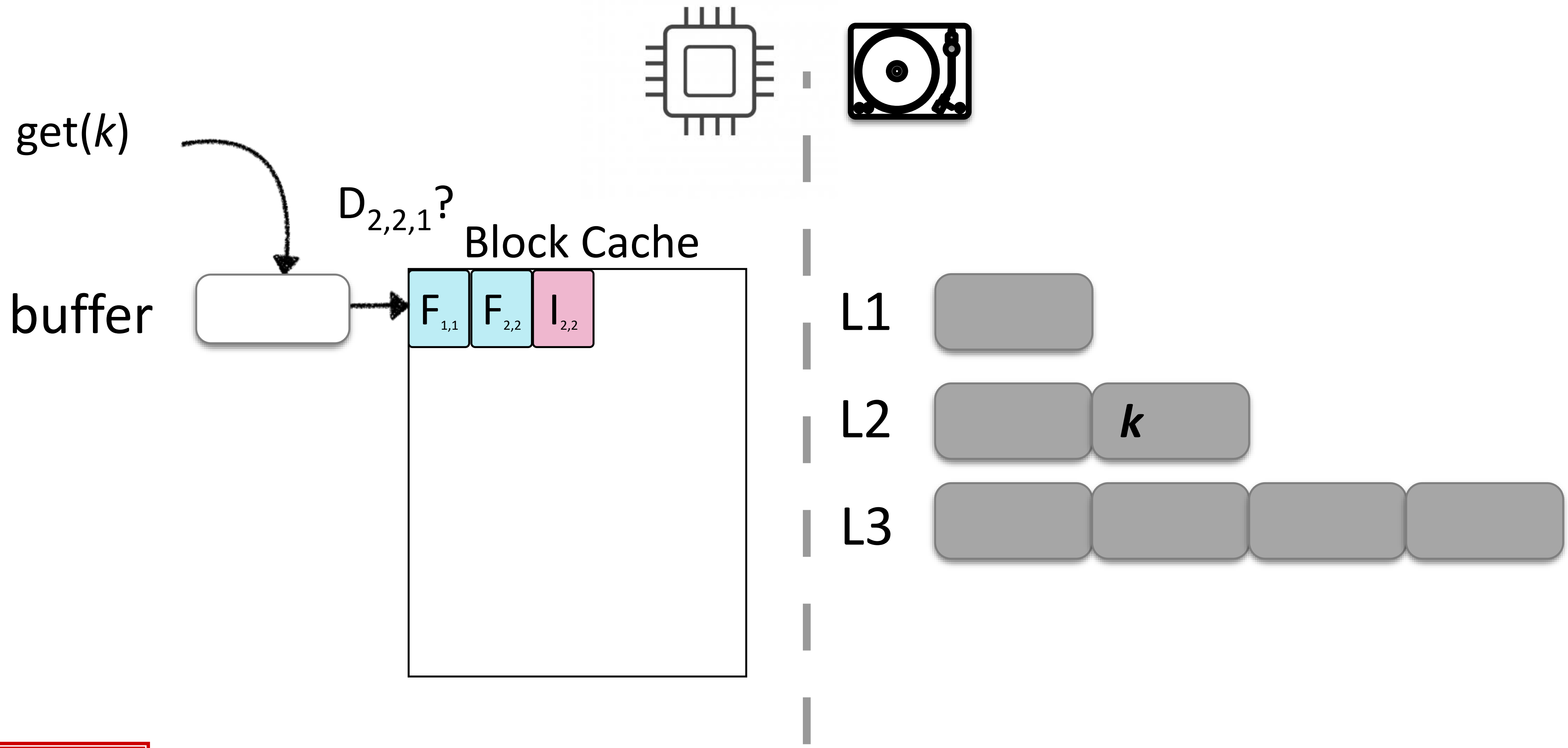

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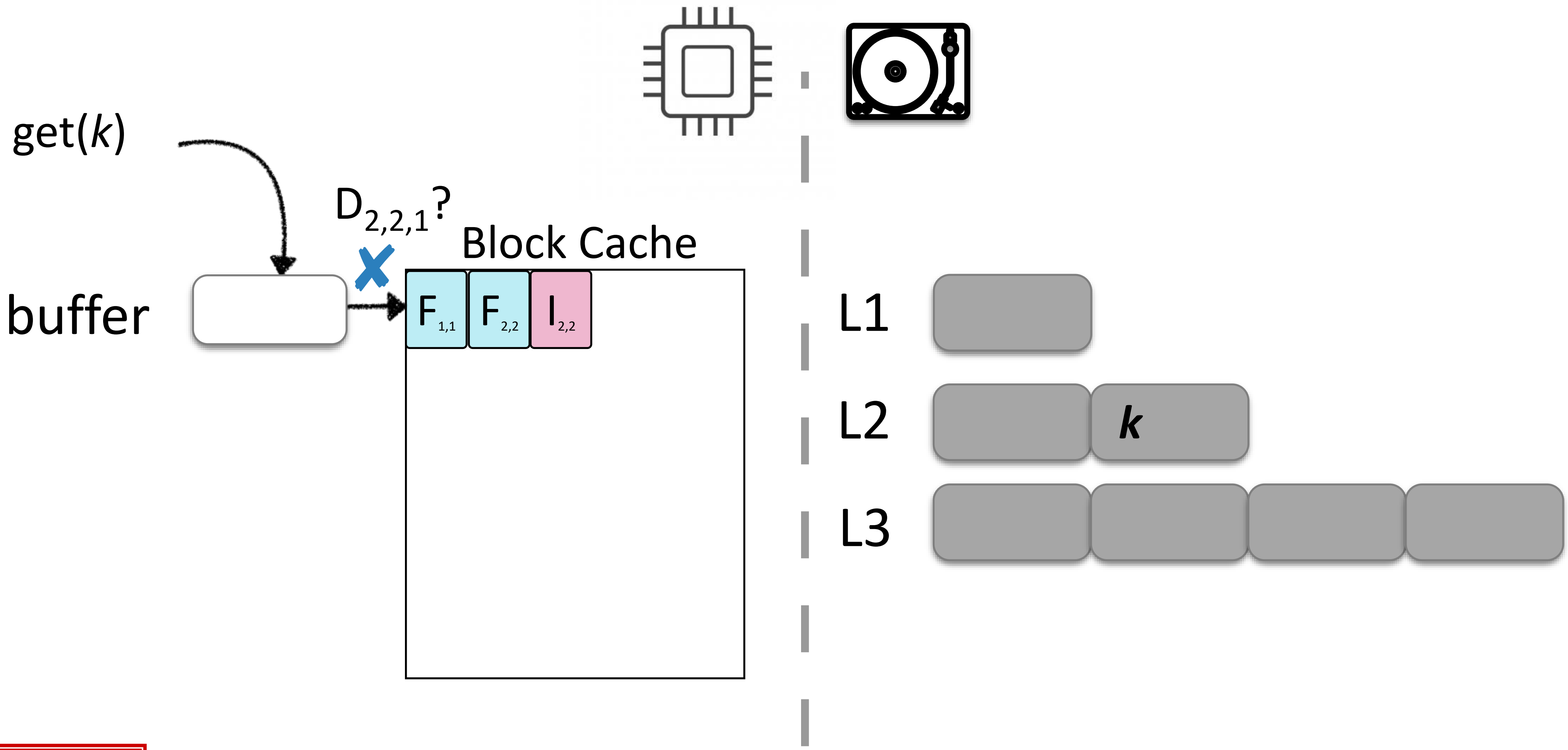

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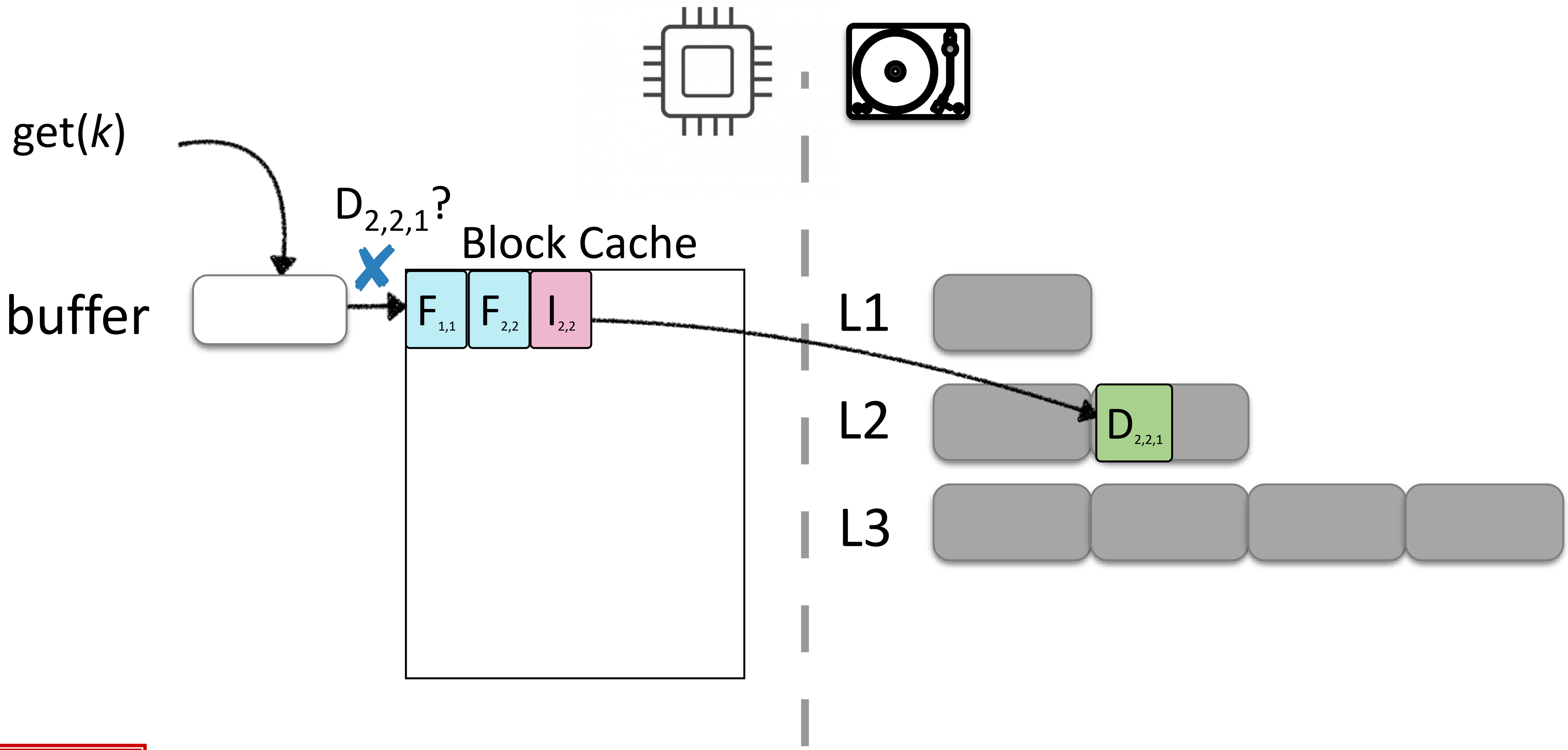

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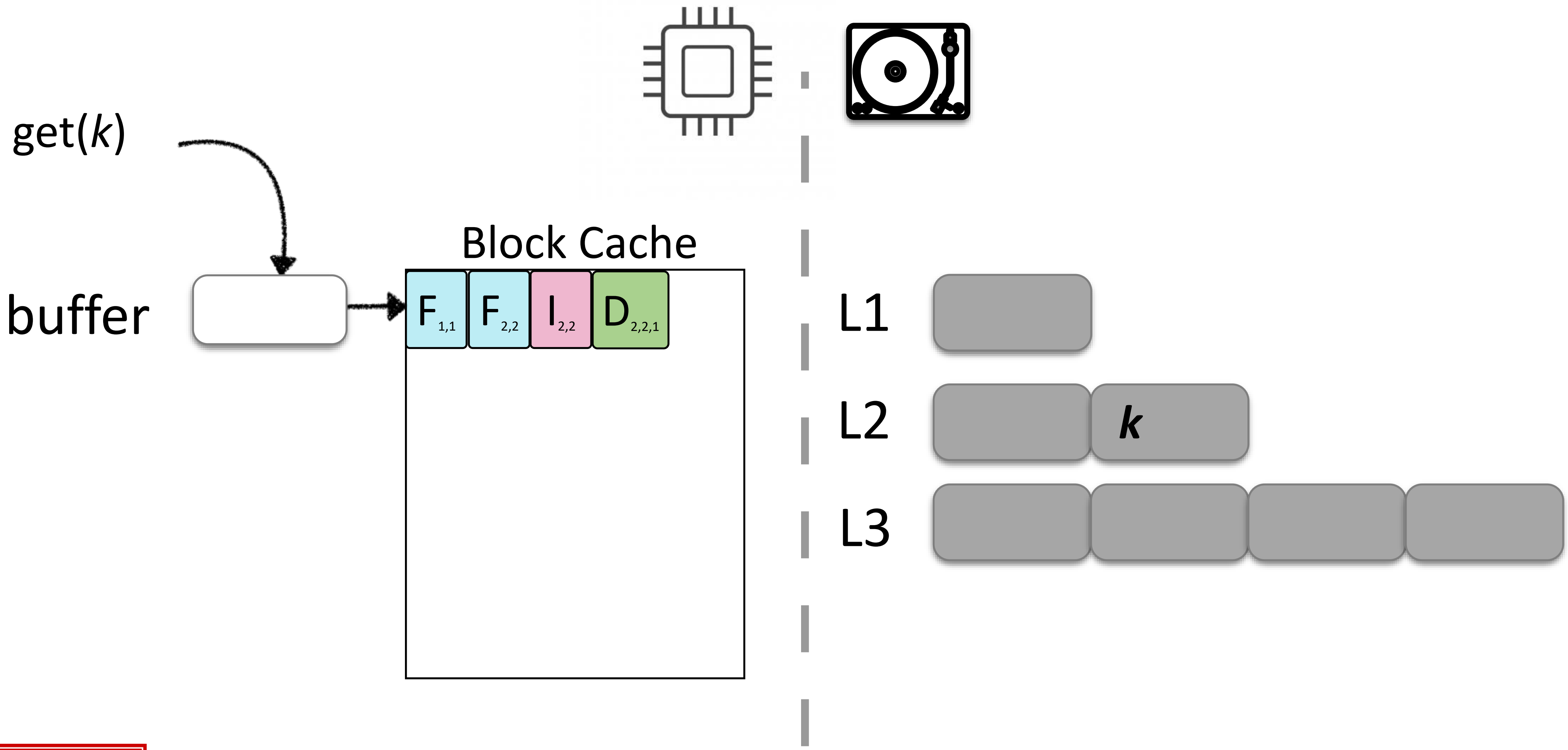

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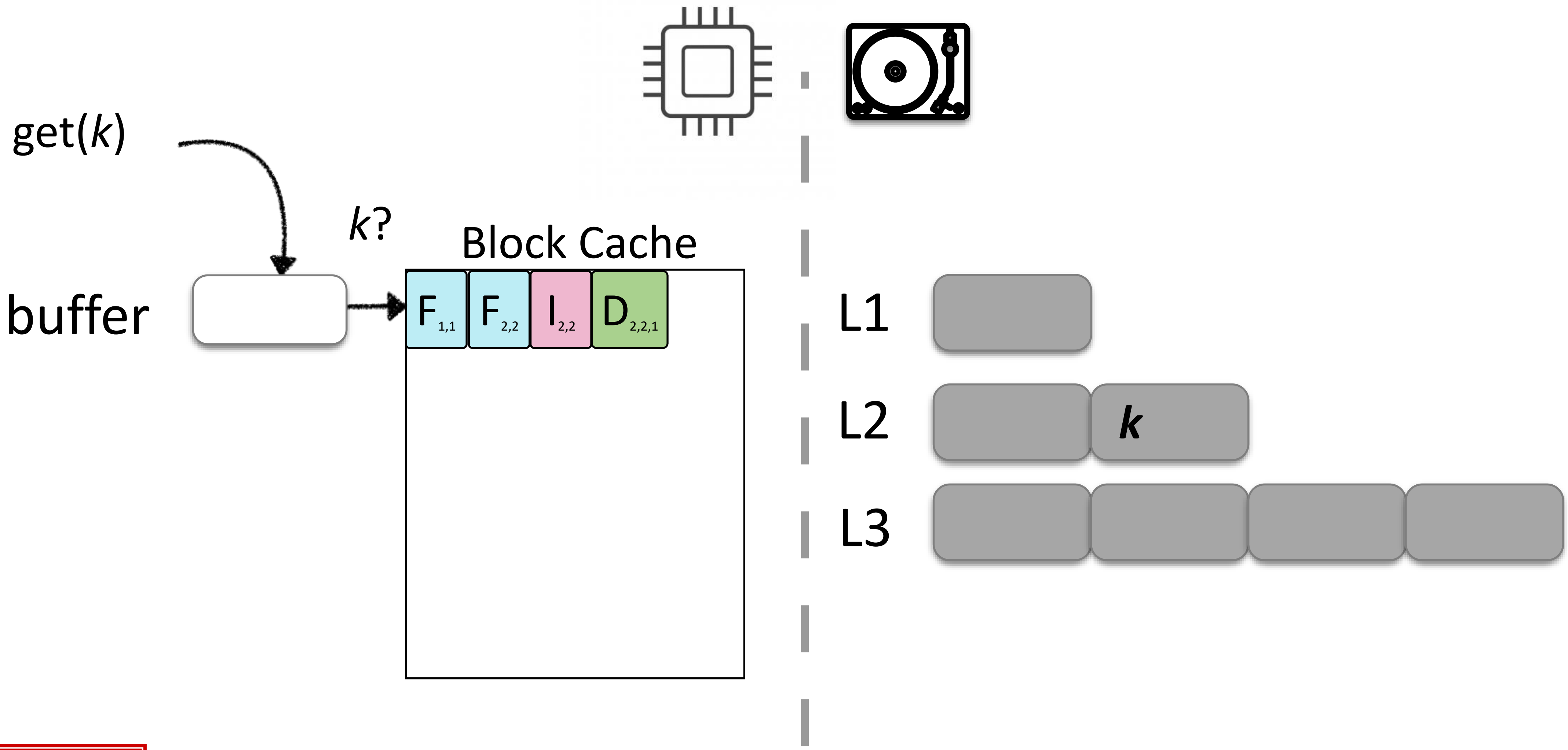

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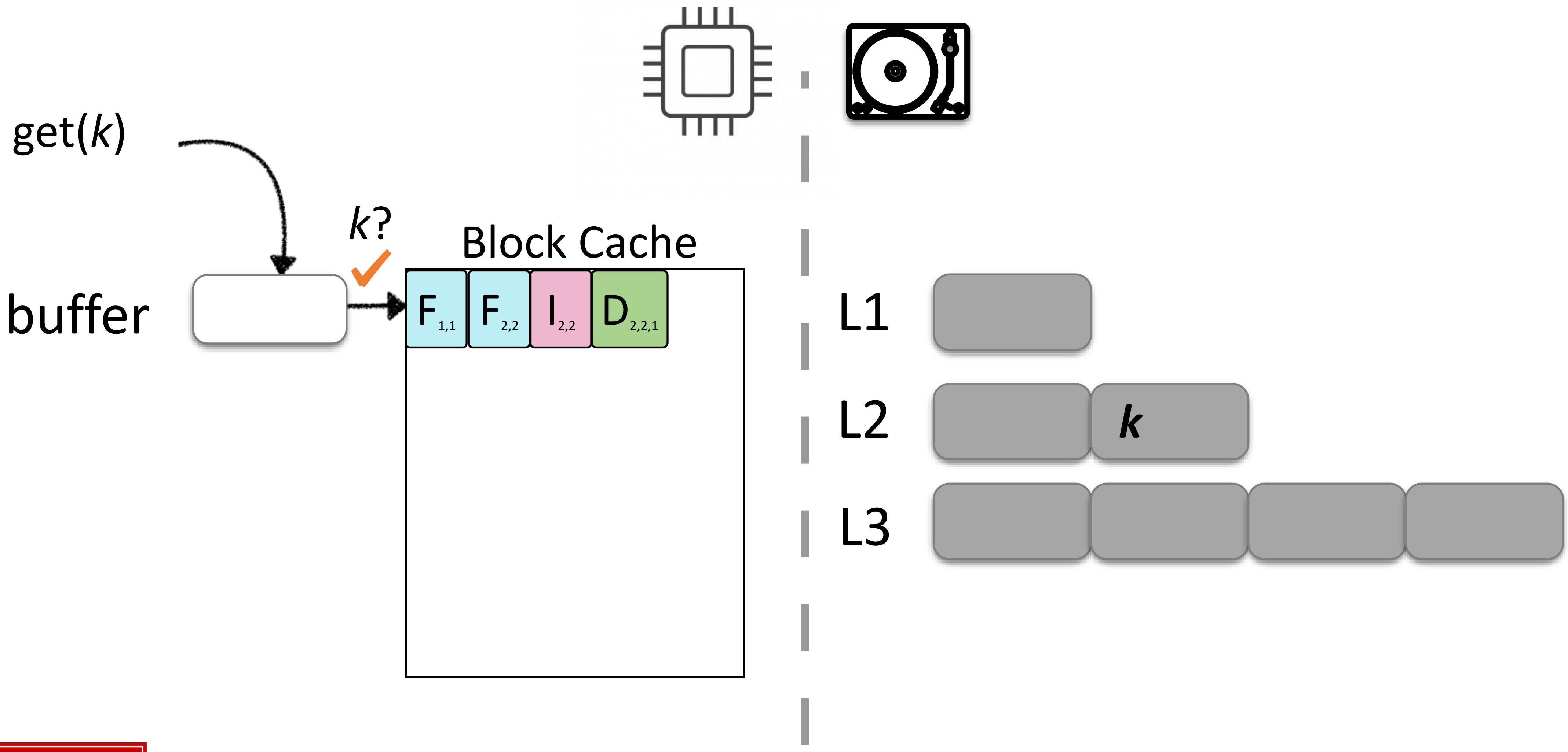

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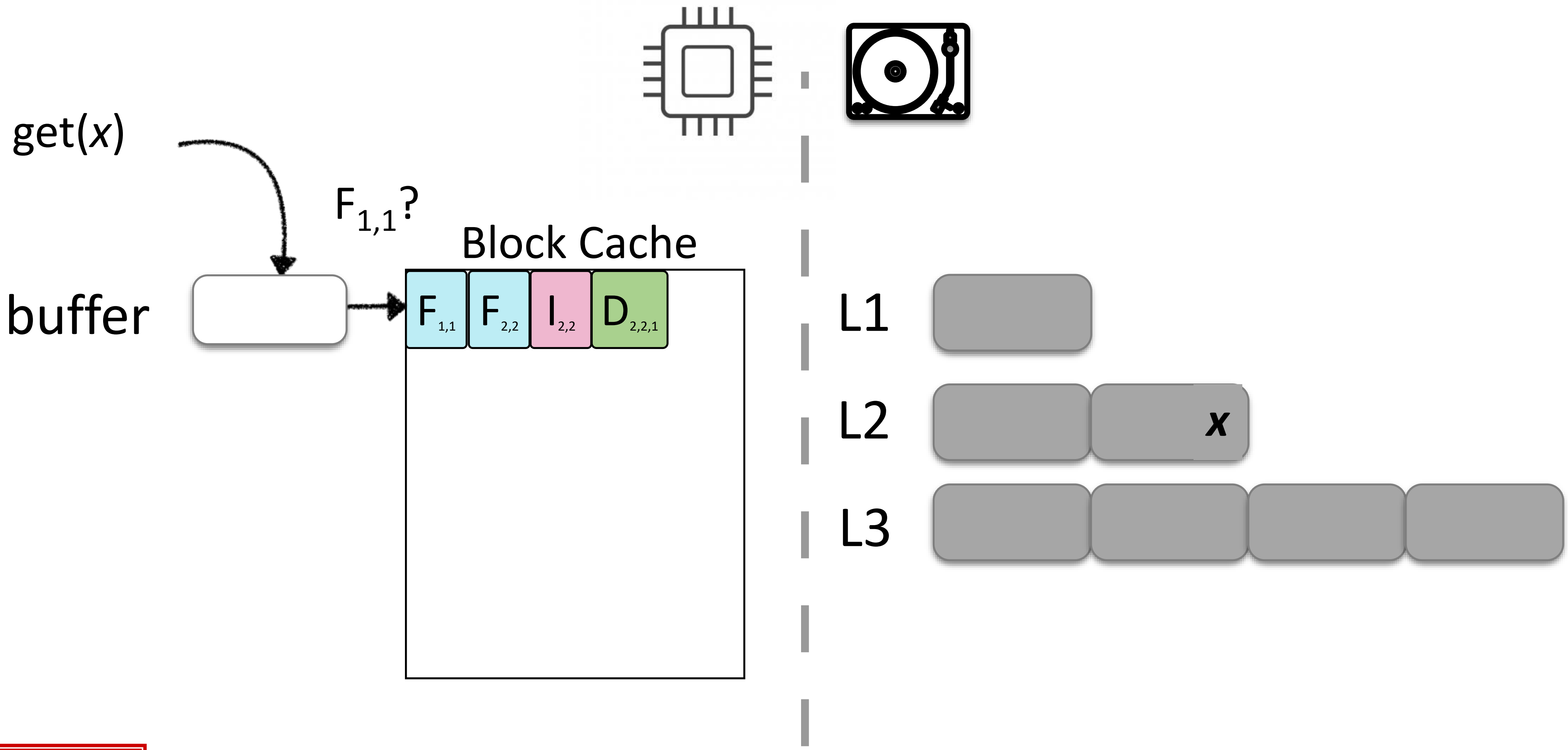

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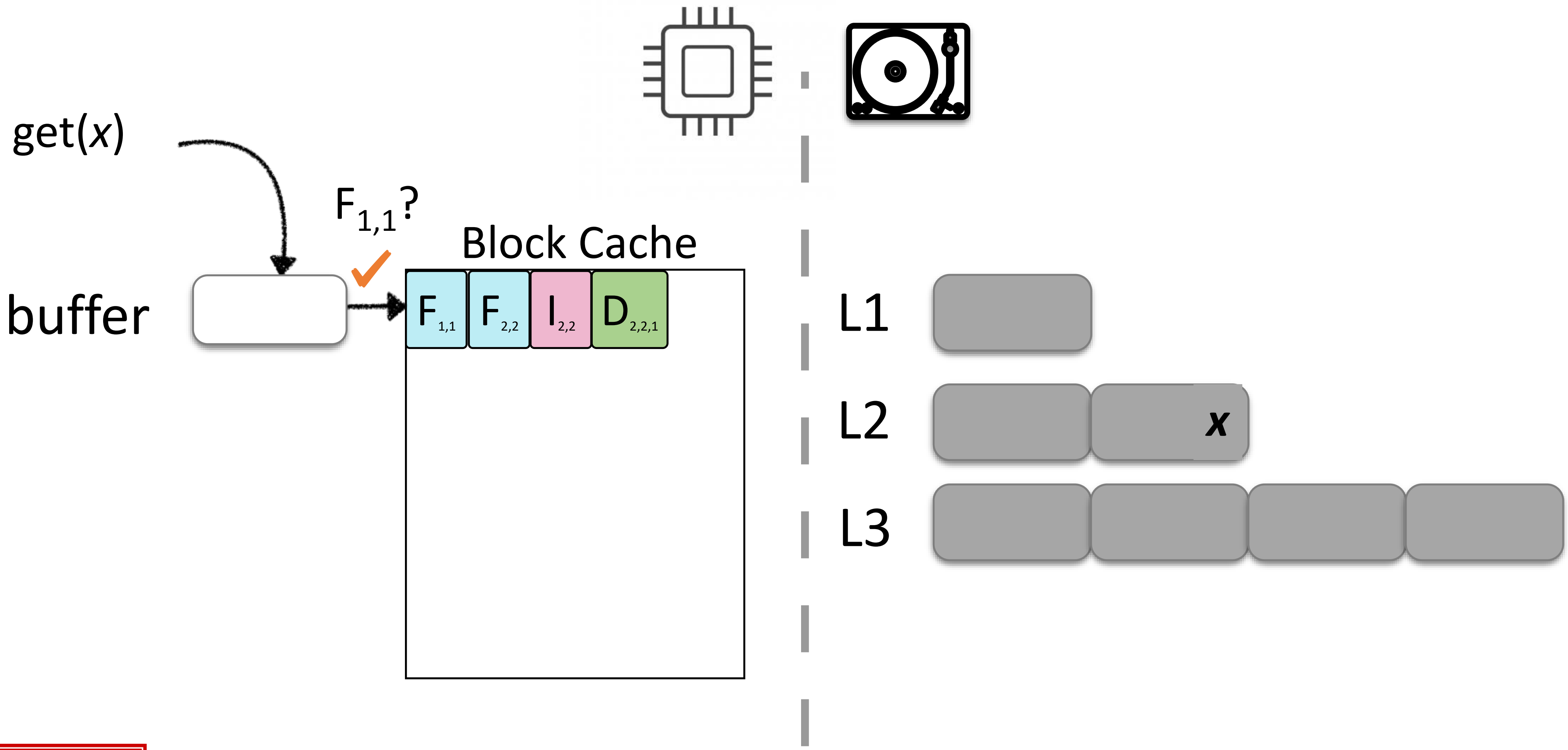

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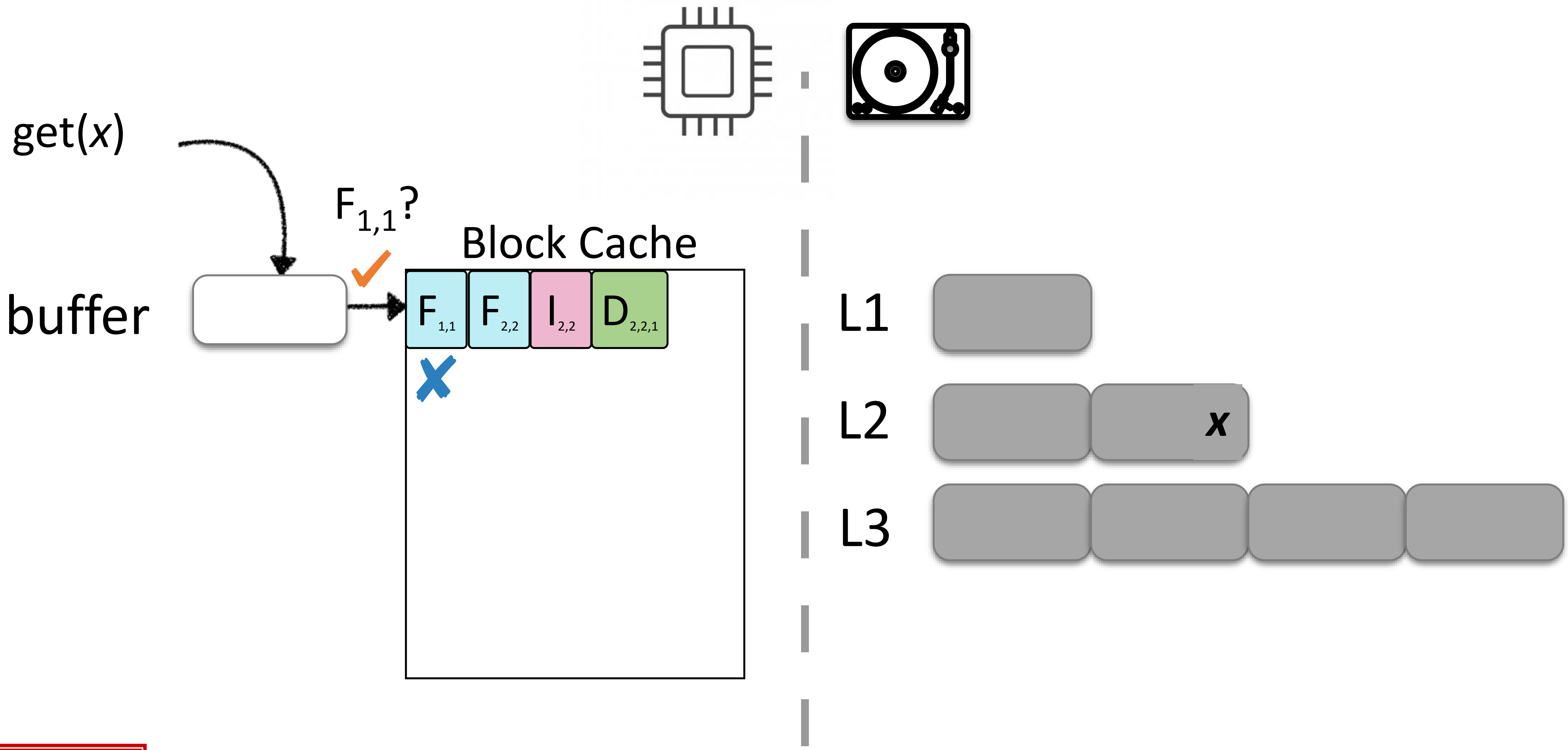

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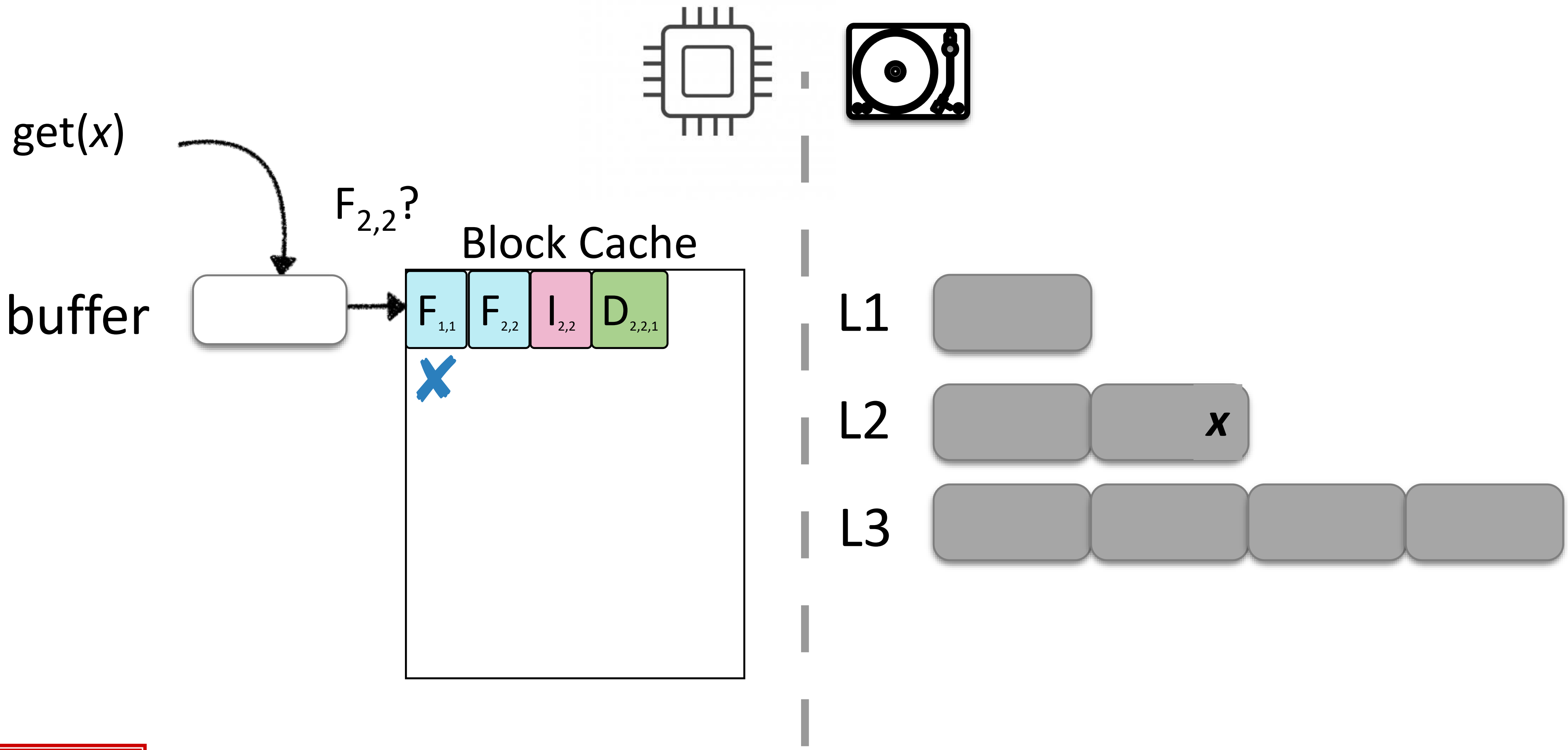

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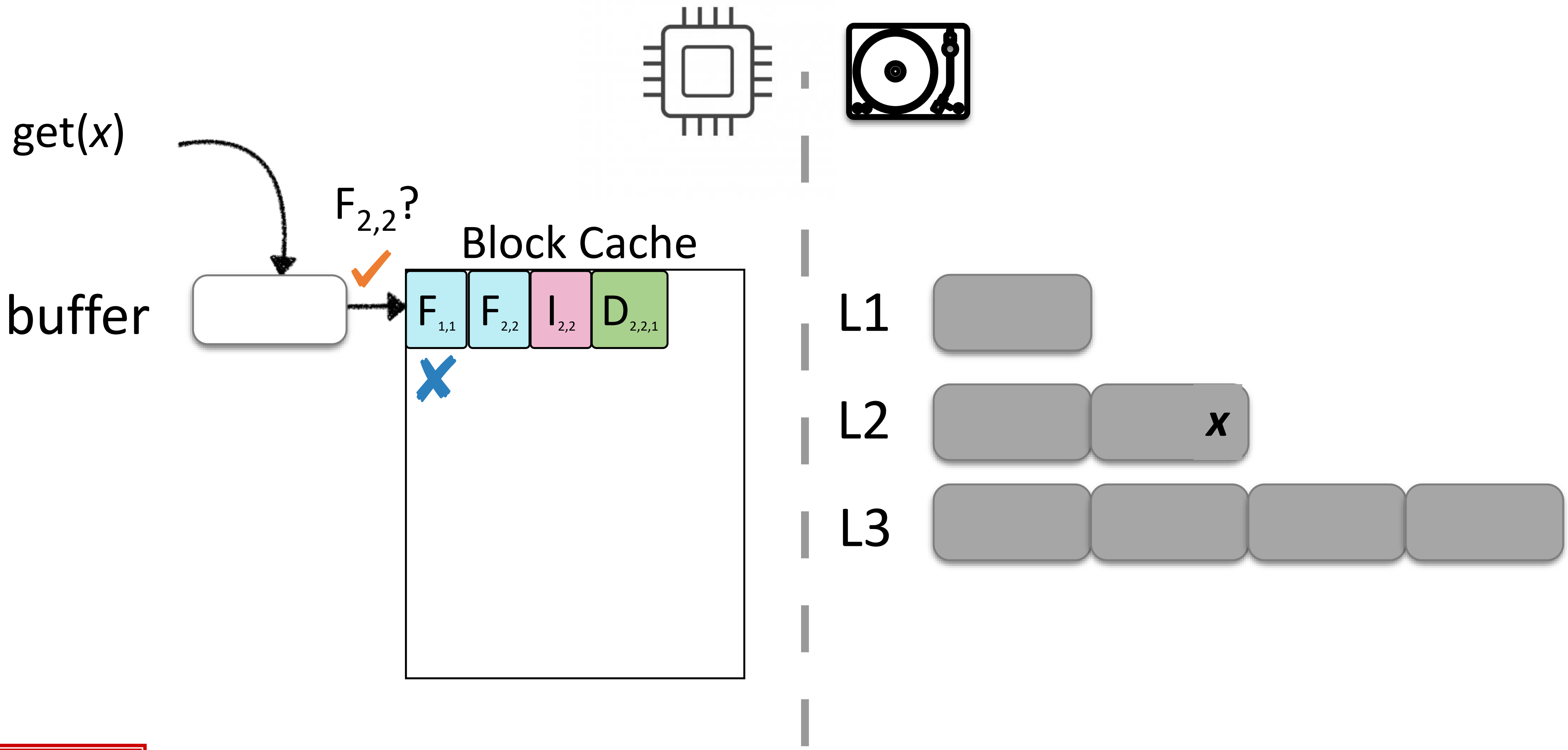

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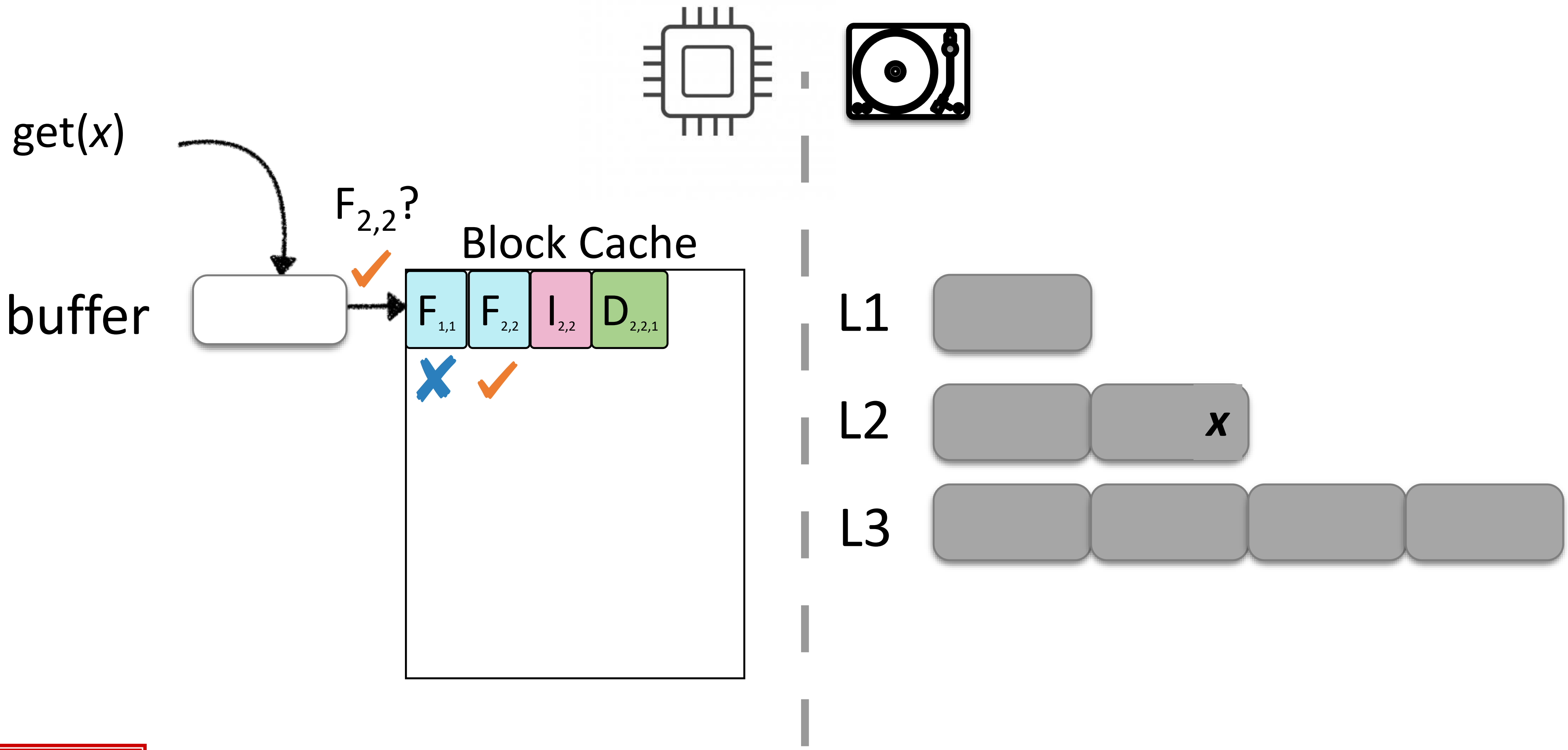

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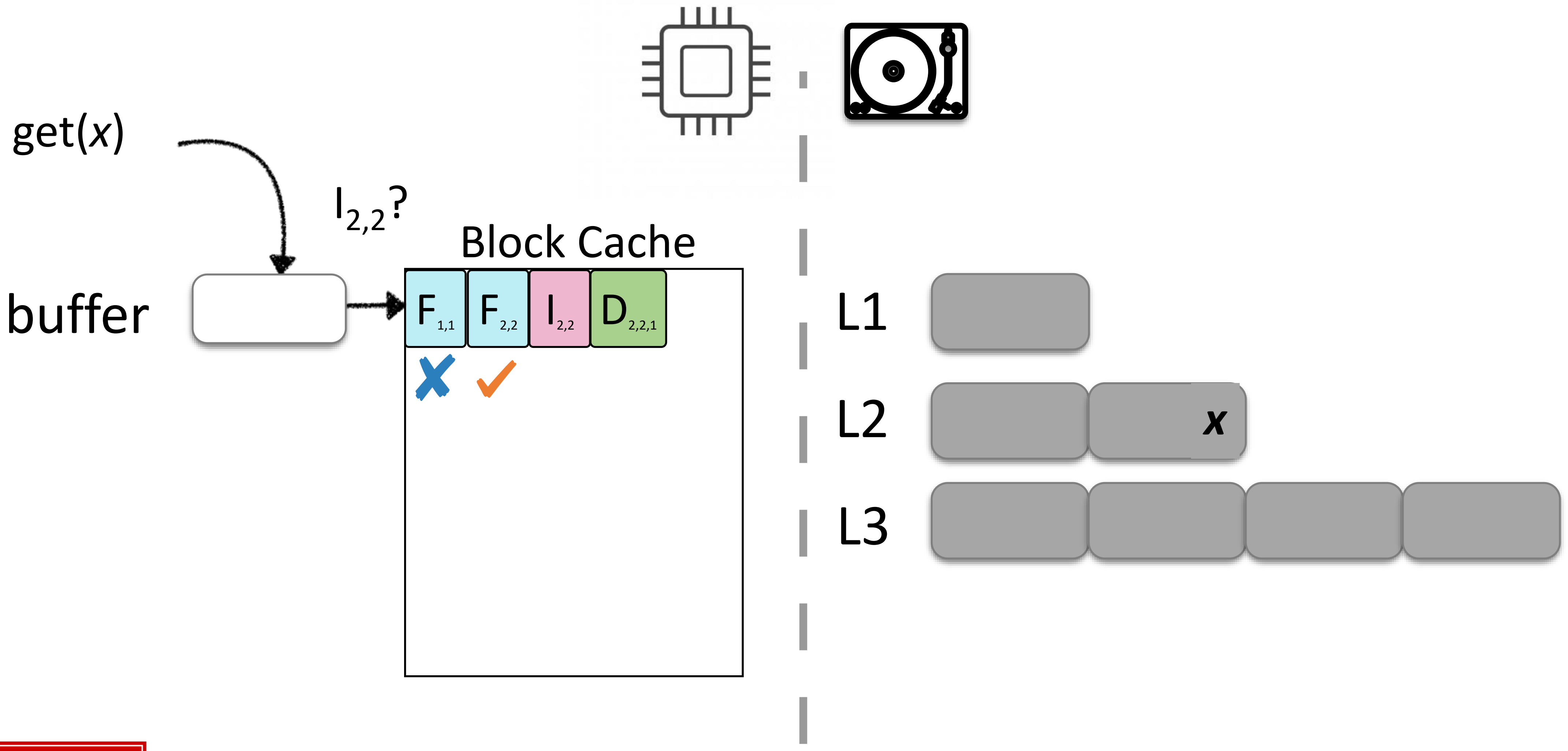

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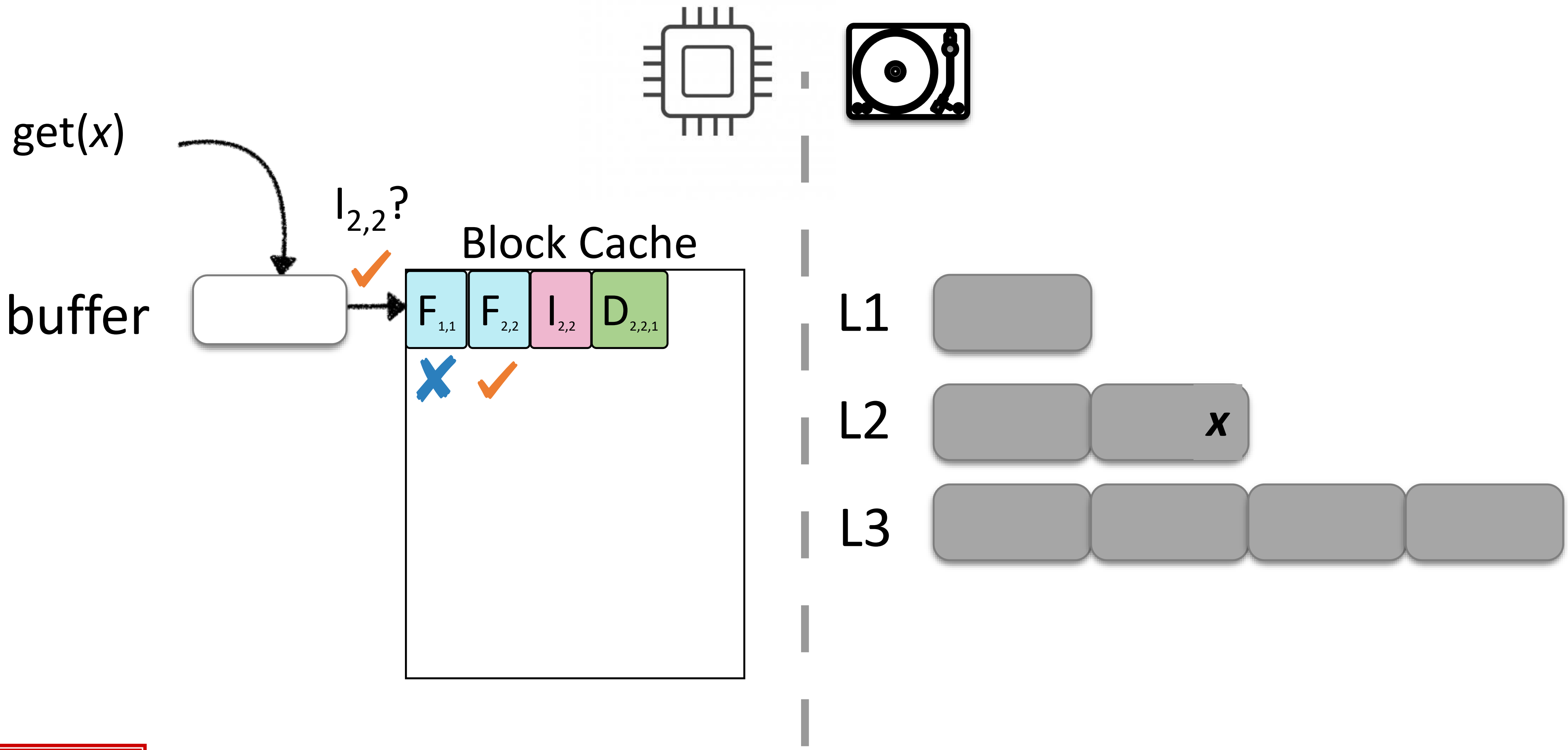

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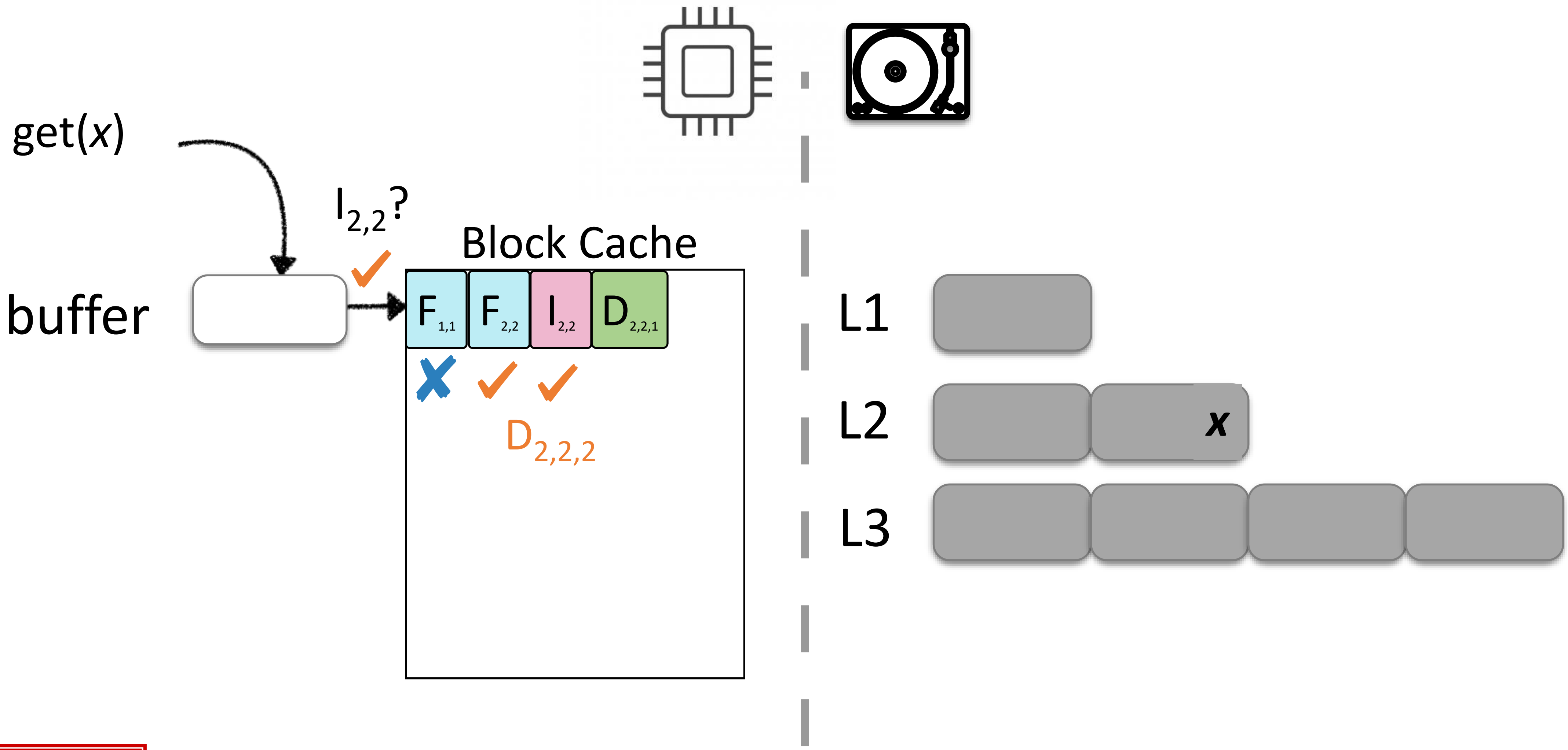

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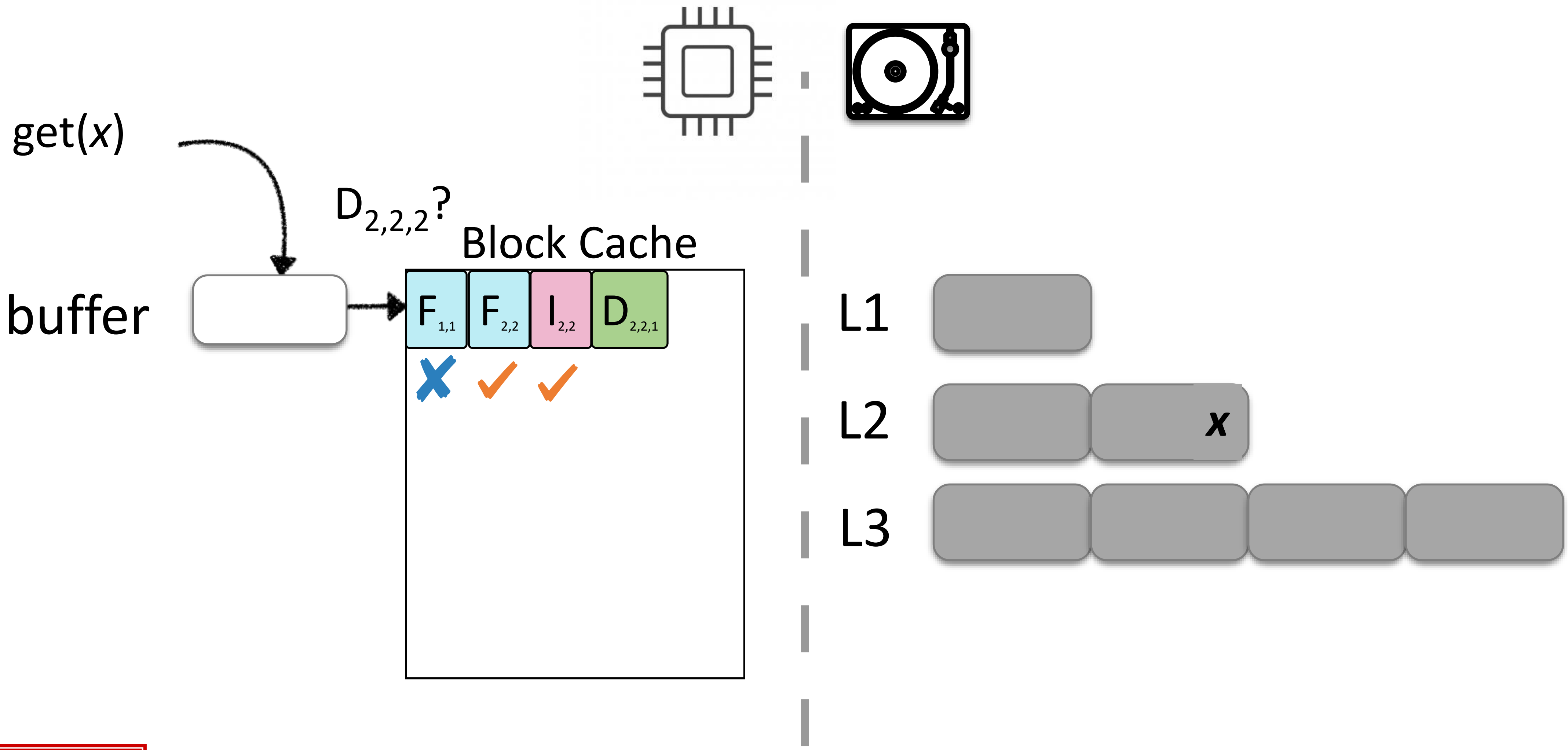

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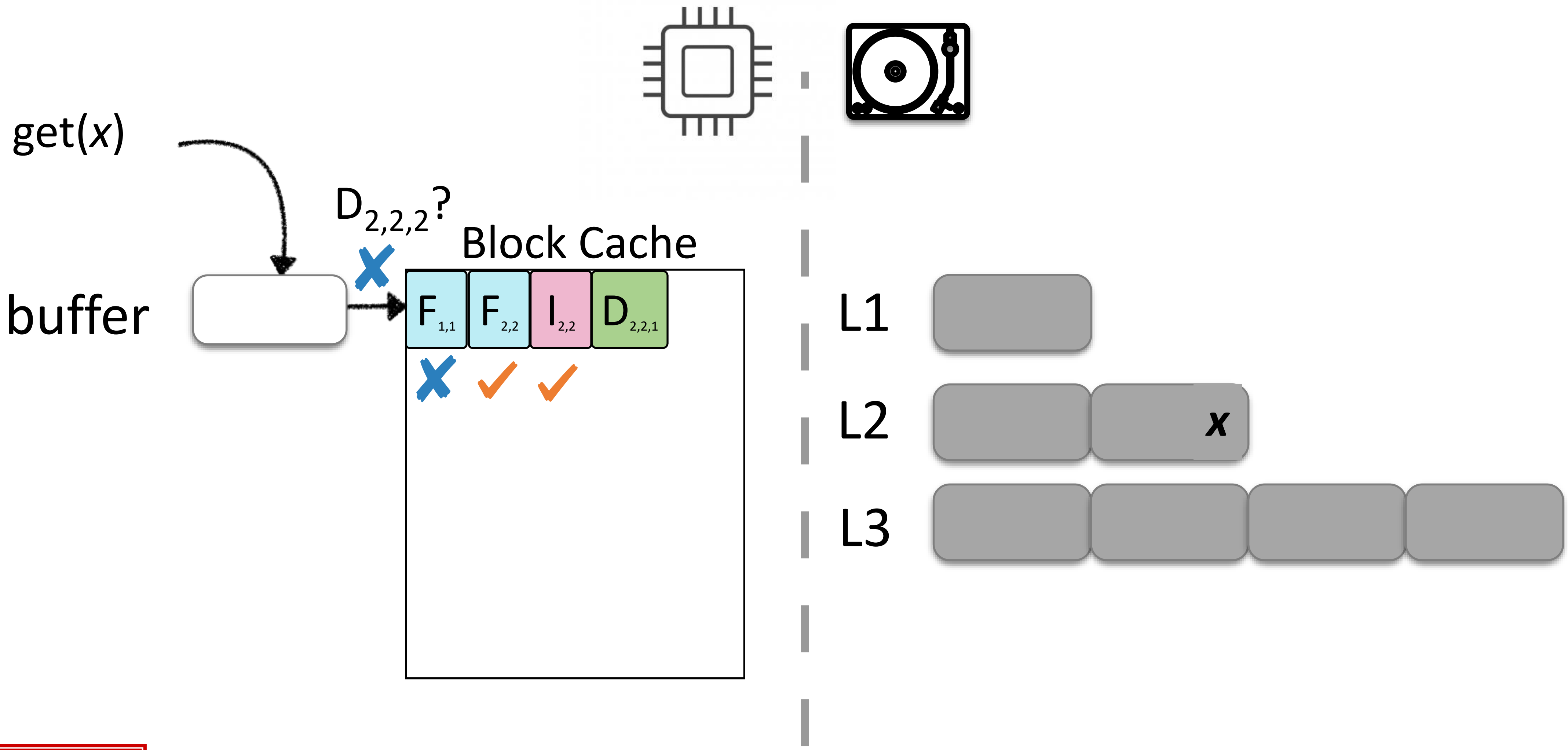

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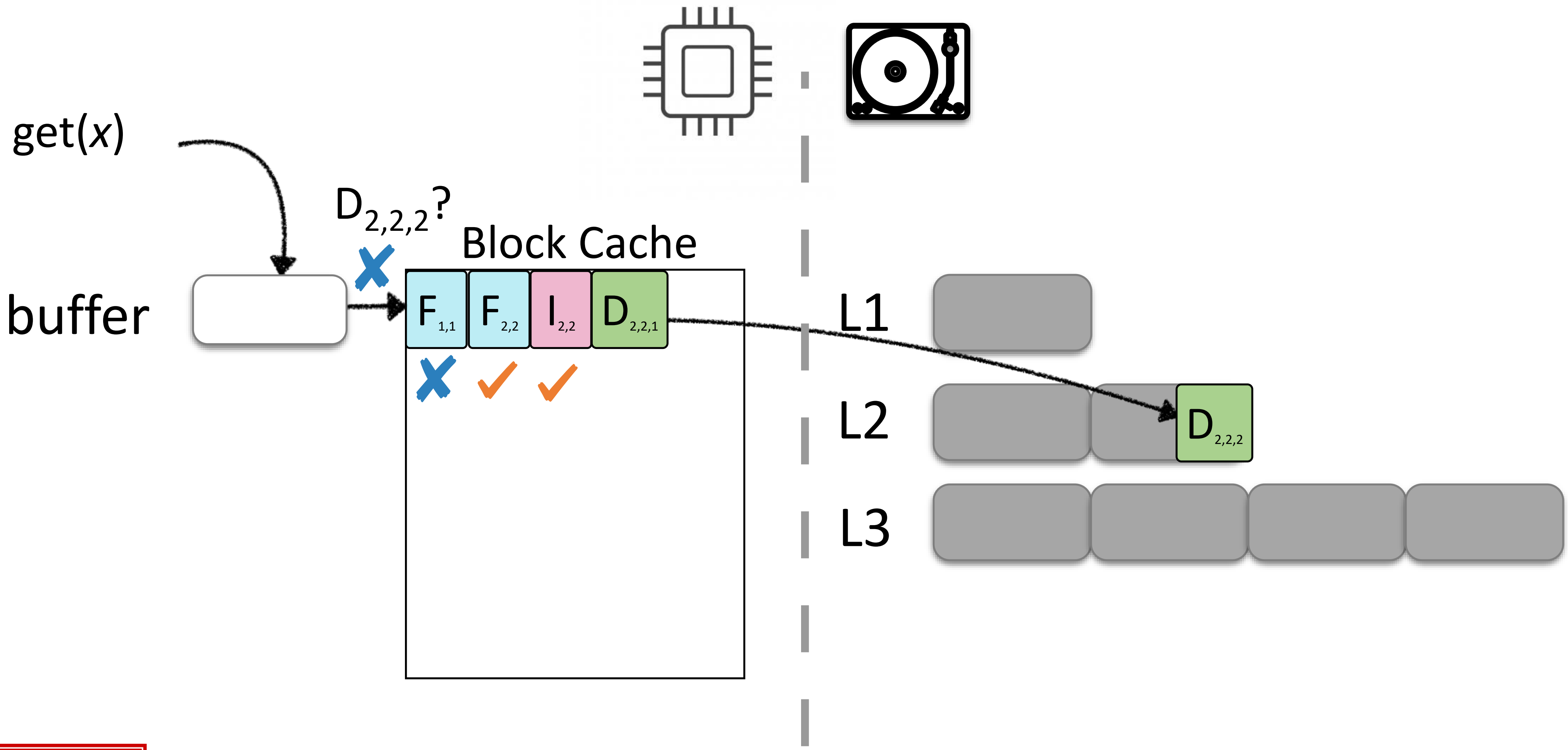

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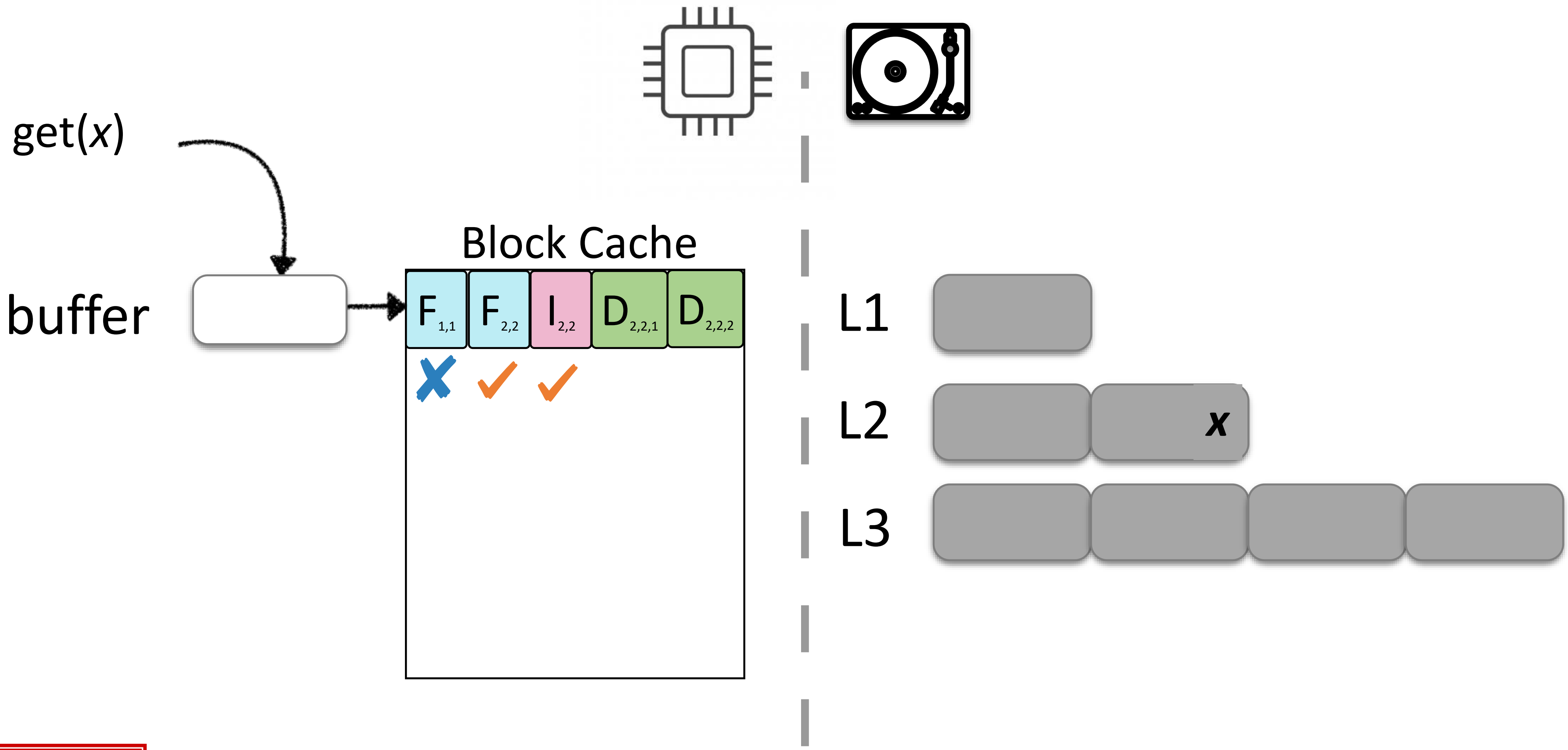

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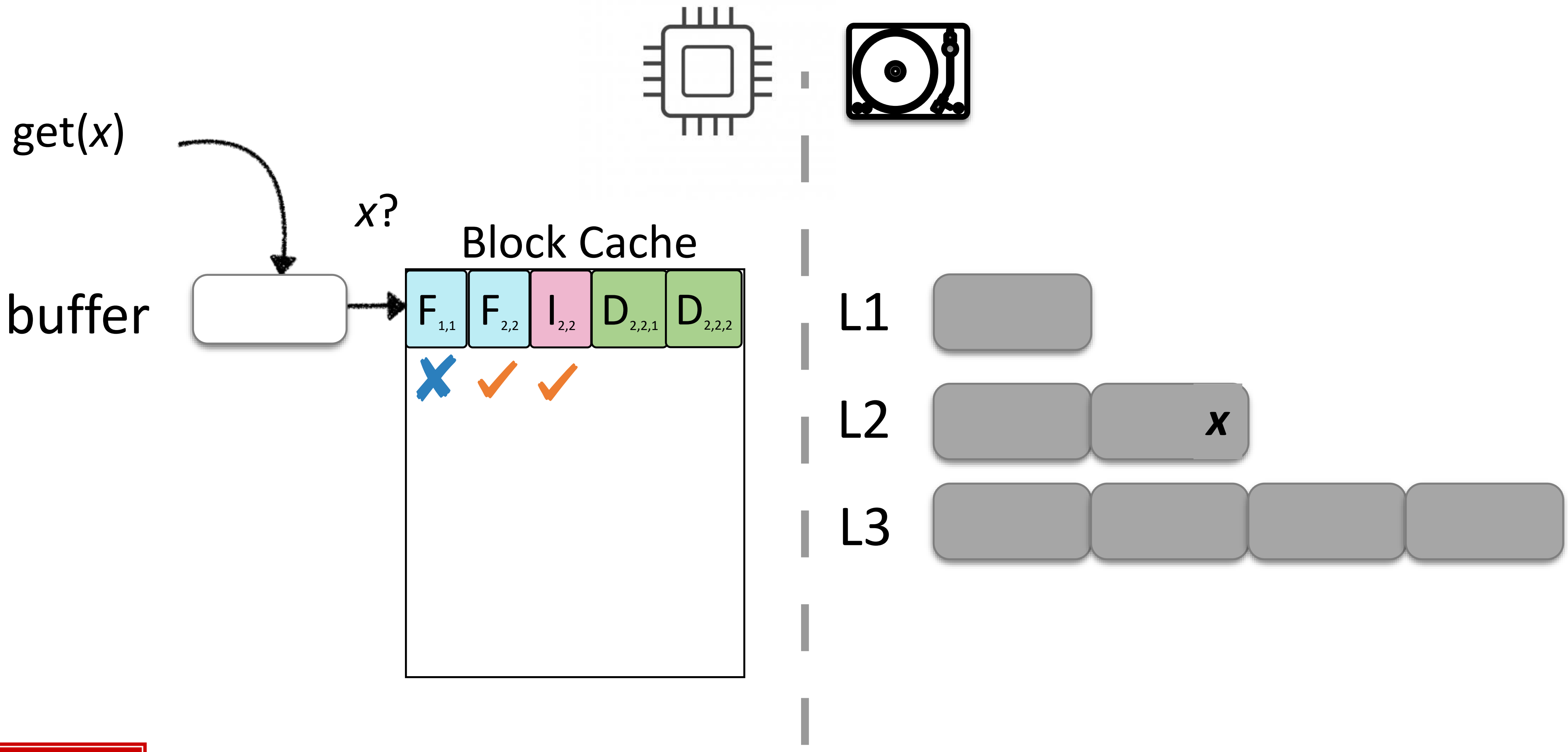

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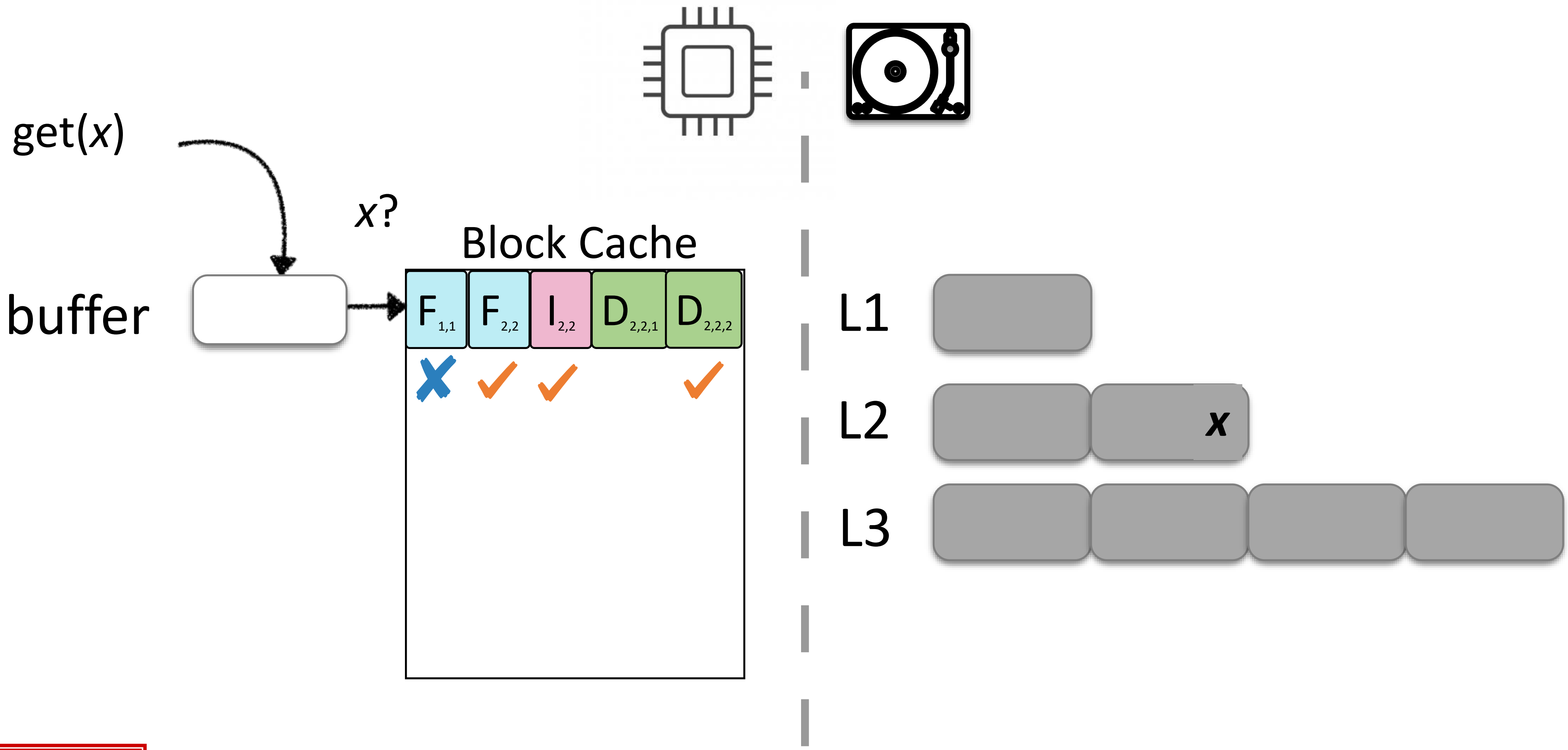

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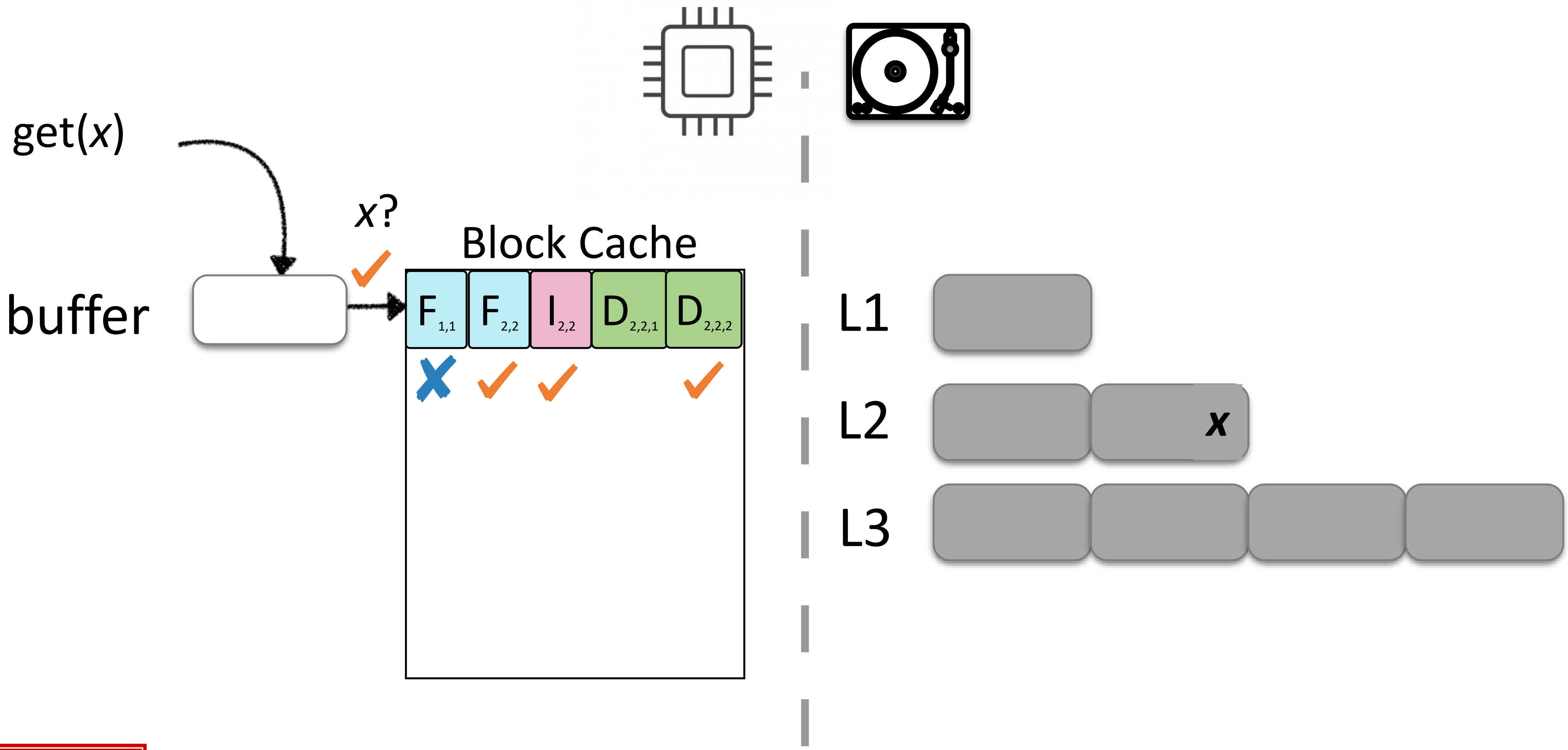

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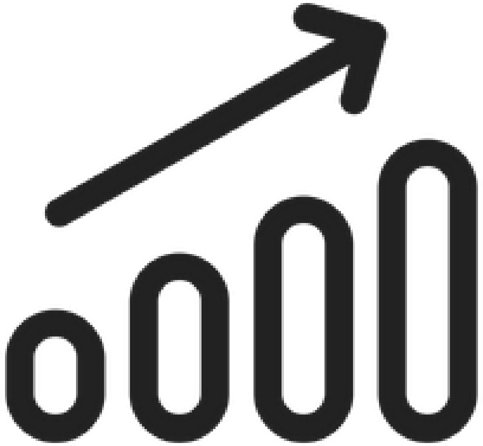
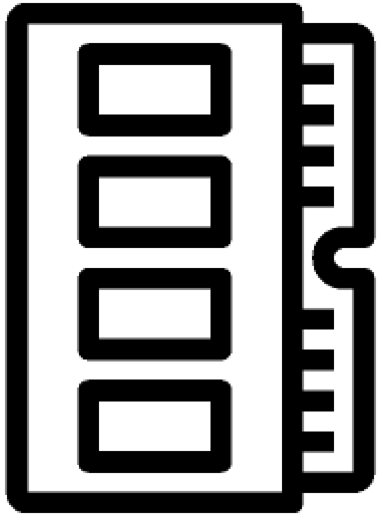
Memory Pressure in LSM-trees



Data size ↑

For 1TB data,
1.3GB filter &17.2GB index

11% space amplification,
1KB entry, 64B key, bpk 10



memory-to-data ratio ↓

Memory pressure

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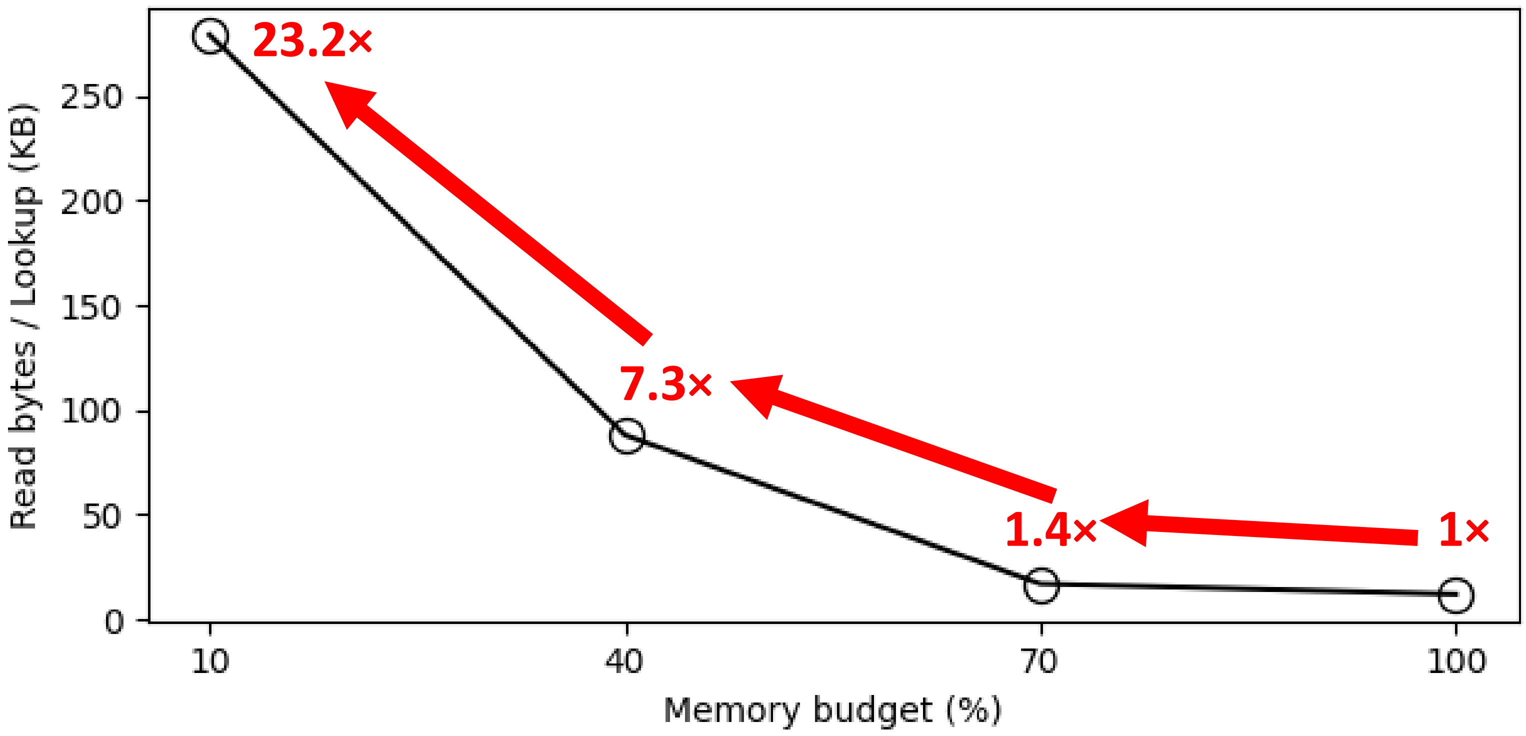
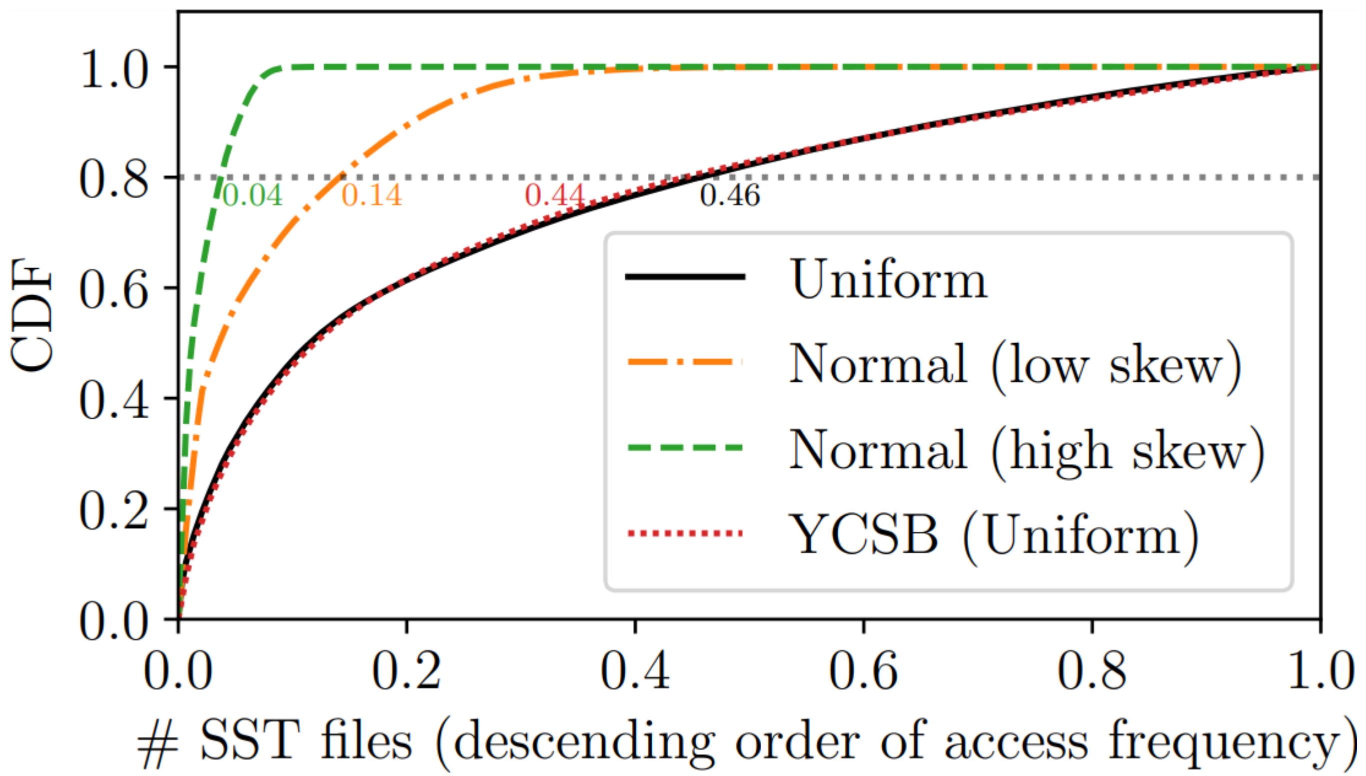
Lookup cost under memory pressure



As the available memory decreases, the read bytes per query increase rapidly.

Are all filter blocks equally important?

Access Frequency Patterns



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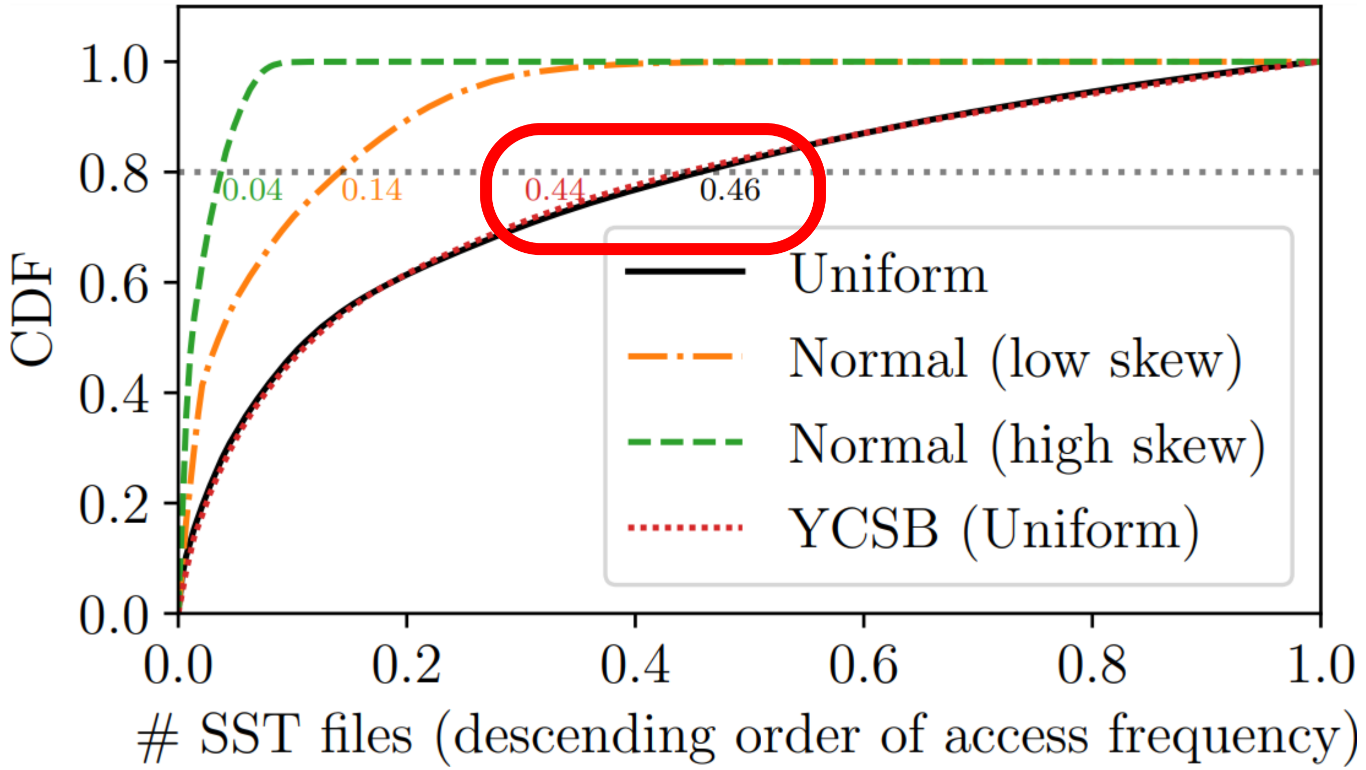
Access Frequency Patterns



Even in a perfectly uniform workload,
80% of the lookups *are directed to* ***44~46% of the SST files***

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[Monkey, SIGMOD 2017]

worst-case I/O cost

memory

Bloom filters

$\boldsymbol{p}$

$\boldsymbol{p}$

$\boldsymbol{p}$

$$O\left(\sum \boldsymbol{p}\right)$$

$$\text{false positive } \boldsymbol{p} = e^{-\frac{\text{bits } M}{\text{entries } N} \cdot ln(2)^2}$$

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memory

Bloom filters

$\boldsymbol{p}$

$\boldsymbol{p}$

$\boldsymbol{p}$

[Monkey, SIGMOD 2017]

worst-case I/O cost

$$O\left(log(N) \cdot e^{-M/N}\right)$$

can we do better?

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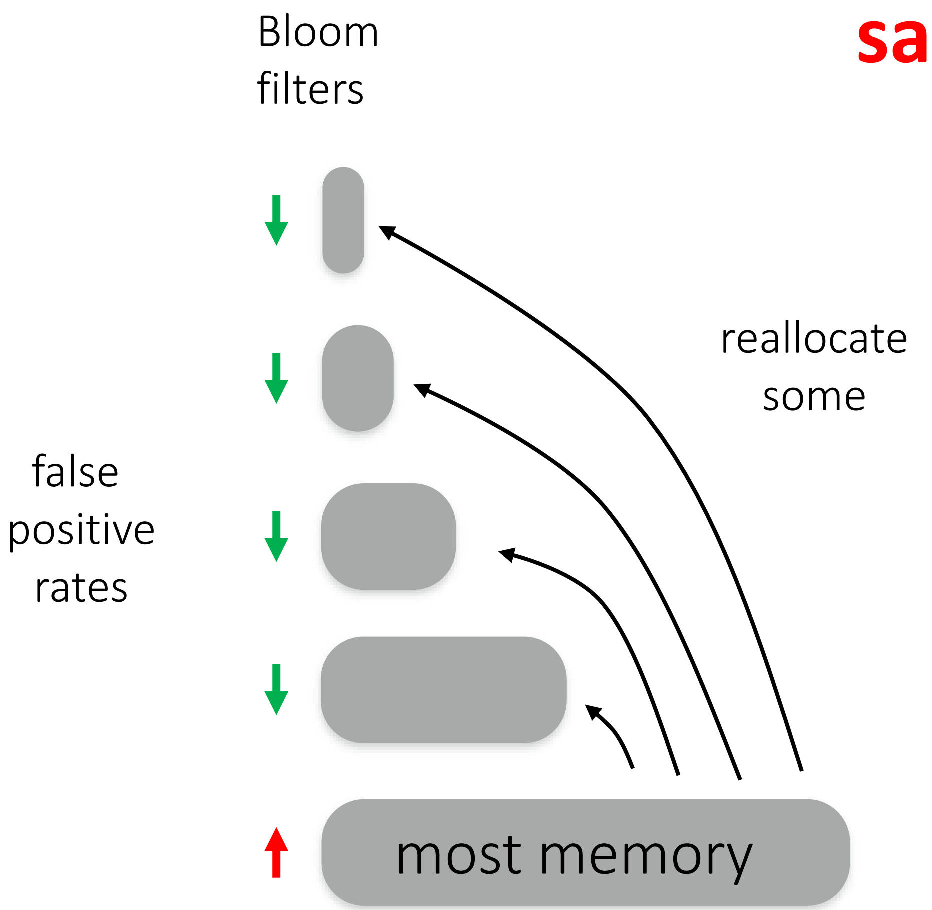
same memory, fewer I/O



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[Monkey, SIGMOD 2017]

relax | model | optimize

$0 < p_2 < 1$

$0 < p_1 < 1$

$0 < p_0 < 1$

$$\text{lookup cost} = \sum p_i$$

$$\text{memory footprint} = f(p_0, p_1, \dots)$$

in terms of $\boldsymbol{p_0}, \boldsymbol{p_1}, \dots$

Bloom filters

memory footprint

[Monkey, SIGMOD 2017]

…

p_2

false positive rates

p_1

p_0

$$\text{false positive } p = e^{-\frac{\text{bits } M}{\text{entries } N} \cdot ln(2)^2}$$

$$\Downarrow$$

$$\text{bits}(\boldsymbol{p}, \boldsymbol{N}) = -\frac{ln(\boldsymbol{p})}{ln(2)^2} \cdot \boldsymbol{N}$$

$$\text{lookup cost} = \sum p_i$$

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[Monkey, SIGMOD 2017]

Bloom filters

memory footprint

$$\text{bits}(\boldsymbol{p}, \boldsymbol{N}) = -\frac{ln(\boldsymbol{p})}{ln(2)^2} \cdot \boldsymbol{N}$$

…

…

false positive rates		
	p_2	$\text{bits}(p_2, N/T^2)$
	p_1	$\text{bits}(p_1, N/T)$
	p_0	$\text{bits}(p_0, N\ )$

$$\text{lookup cost} = \sum p_i$$

$$\text{memory} = -\frac{\boldsymbol{N}}{ln(2)^2} \cdot \sum \frac{ln(p_i)}{T^i}$$

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74

[Monkey, SIGMOD 2017]

Bloom filters

minimize: $\text{lookup cost} = \sum p_i$

…

p_2

false positive rates

p_1

p_0

w.r.t. $\boldsymbol{M} = -\frac{\boldsymbol{N}}{ln(2)^2} \cdot \sum \frac{ln(p_i)}{\boldsymbol{T}^i}$

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[Monkey, SIGMOD 2017]

Monkey

Bloom filters

…

p_0/T^2

p_0/T

p_0

false positive rates

exponential decrease

State-of-the-art

Bloom filters

…

p

p

p

same

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[Monkey, SIGMOD 2017]

Monkey

Bloom filters

...

State-of-the-art

Bloom filters

...

false positive rates

Monkey		State-of-the-art
...	$<$	...
p_0/T^2	$<$	p
p_0/T	$<$	p
p_0	$>$	p

$$\text{lookup cost} = \sum p_i \quad < \quad = \sum p$$

$$= O\left(e^{-M/N}\right) \qquad = O\left(log(N) \cdot e^{-M/N}\right)$$

asymptotic win

lookup cost increases at slower rate as data grows

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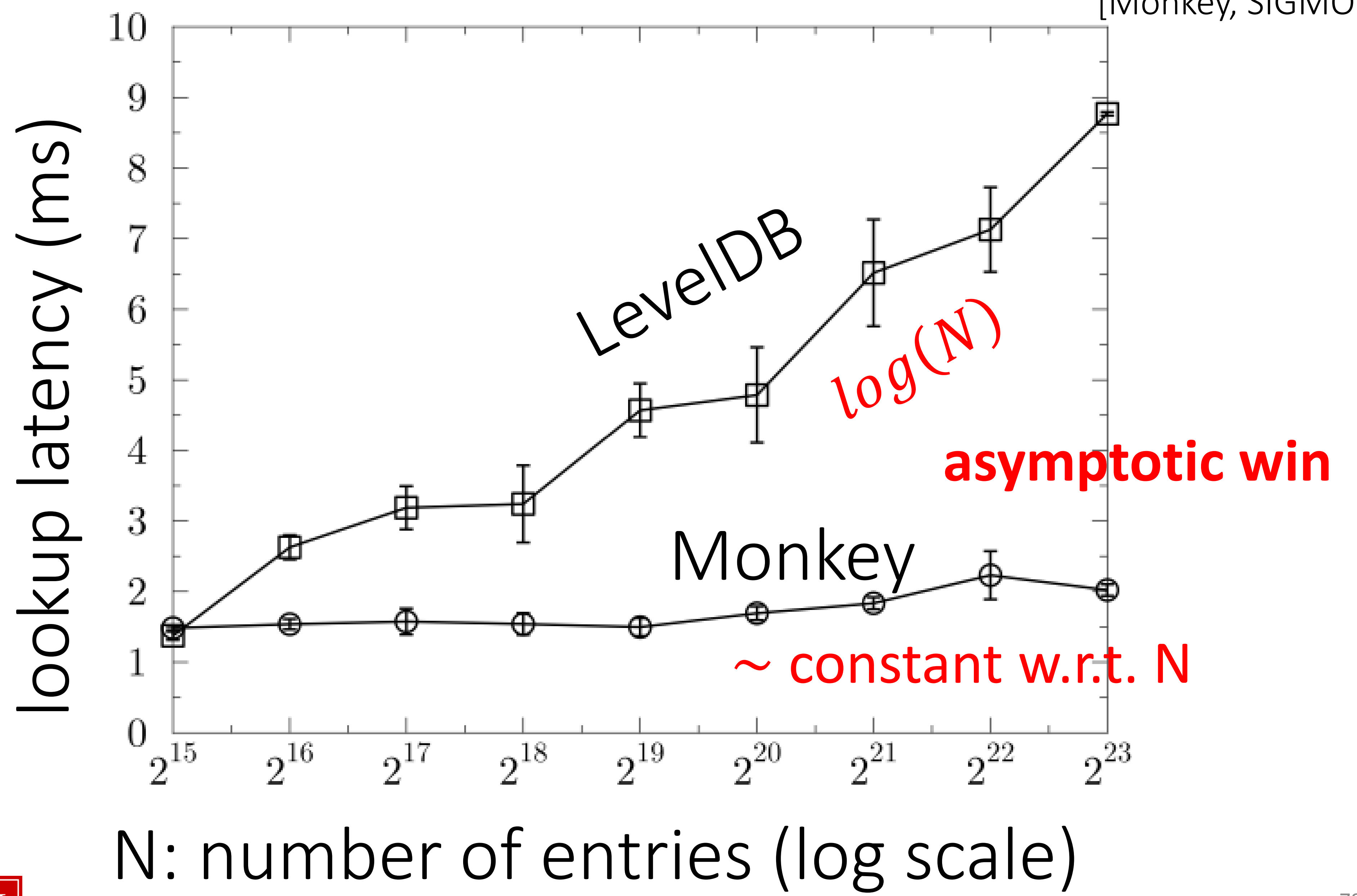
[Monkey, SIGMOD 2017]



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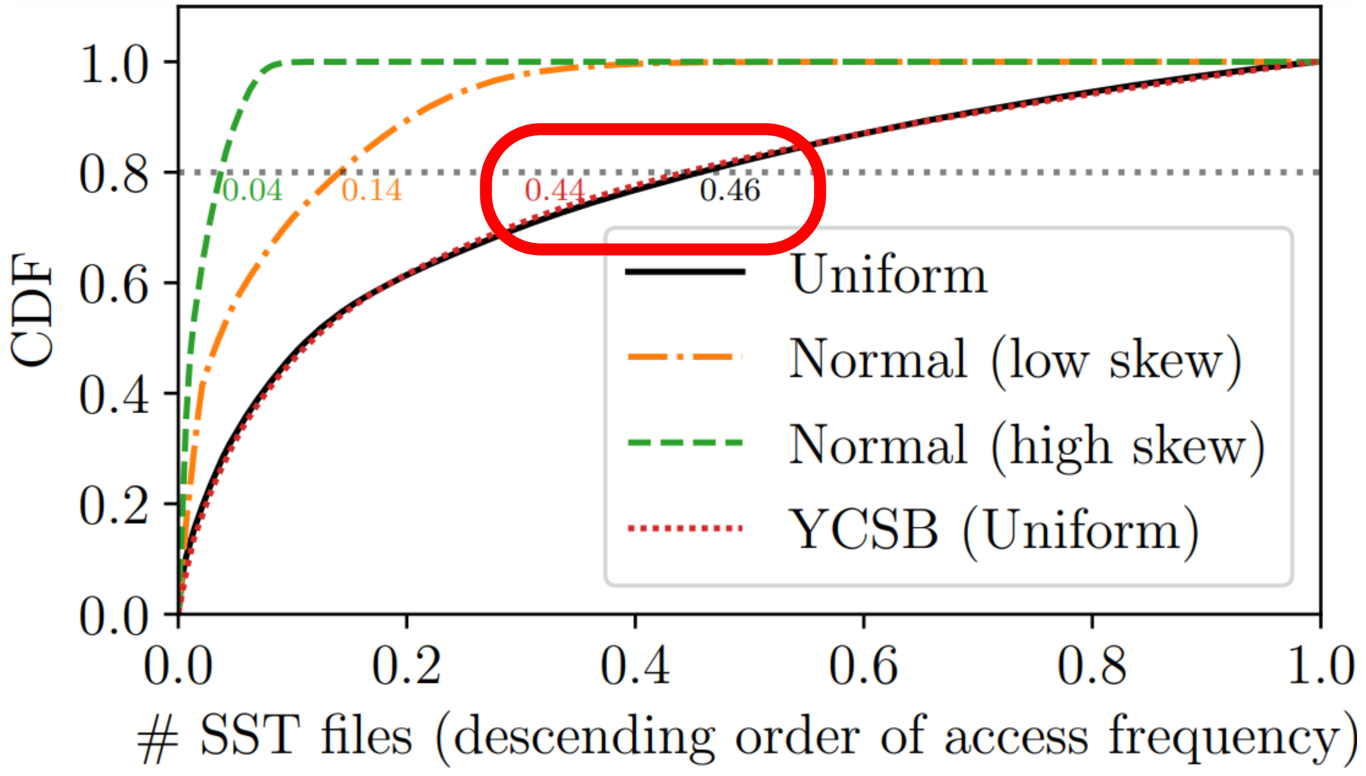
Access Frequency Patterns



Even in a perfectly uniform workload,

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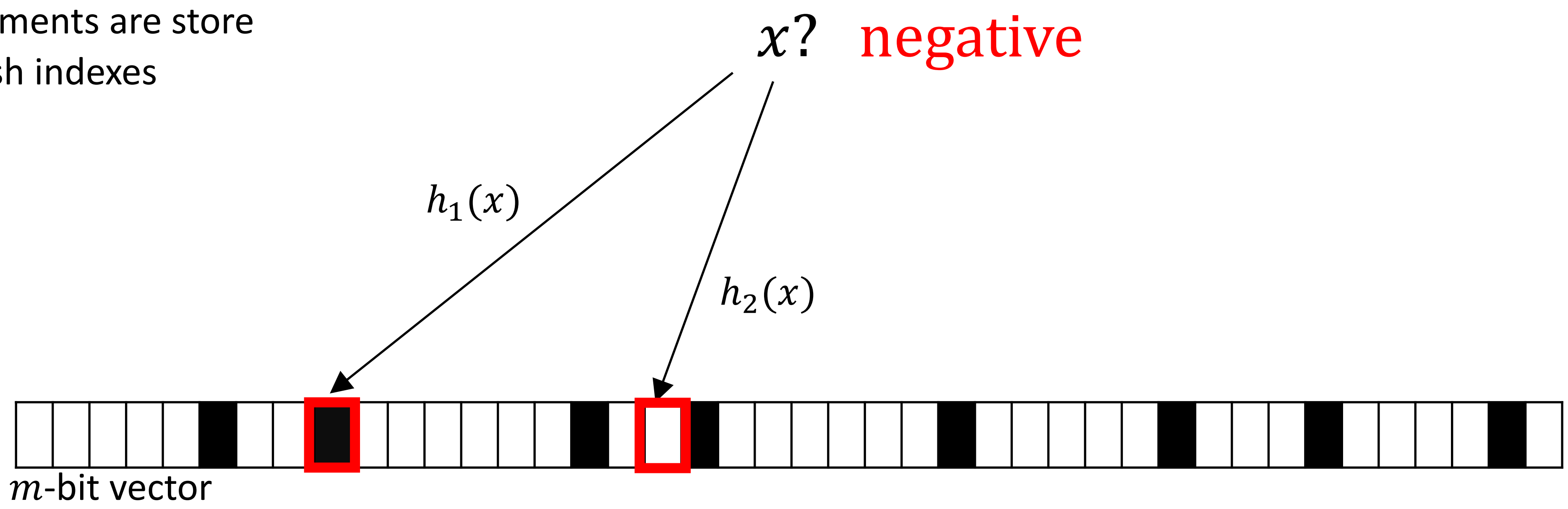
Bloom Filter

m-bit vector
n elements are store
k hash indexes



Bloom Filter

m-bit vector
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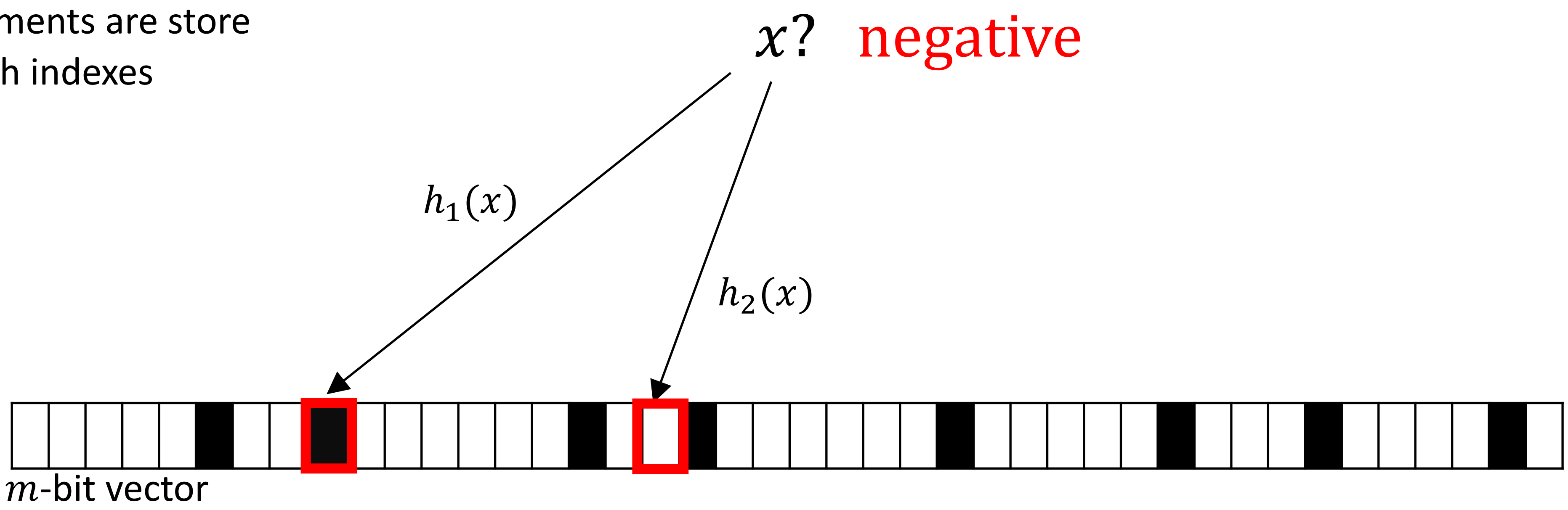

Is the entire filter useful?

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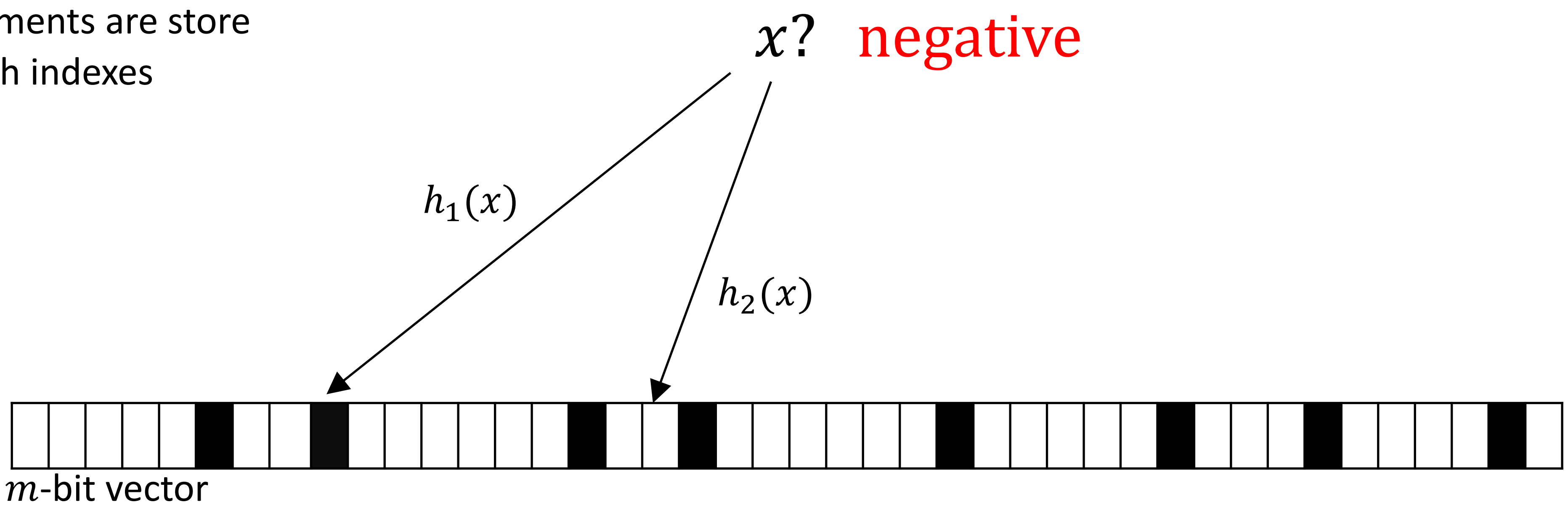
Bloom Filter

m-bit vector
n elements are store
k hash indexes



$$probes_{empty} = 1 + \frac{1}{2} + \frac{1}{2^2} + \dots + \frac{1}{2^{k-1}} = \sum_{d=1}^{k} \frac{1}{2^{k-1}} = 2 - \frac{1}{2^{k-1}}$$

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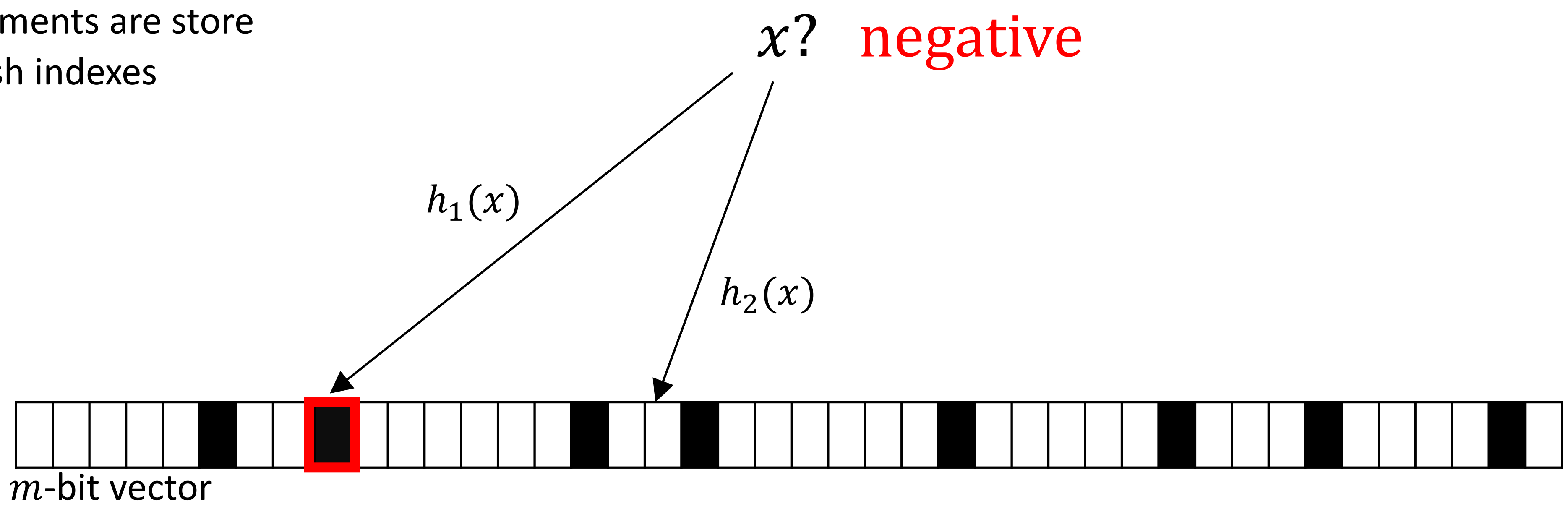
Bloom Filter

m-bit vector

n elements are store

k hash indexes



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Bloom Filter

m-bit vector

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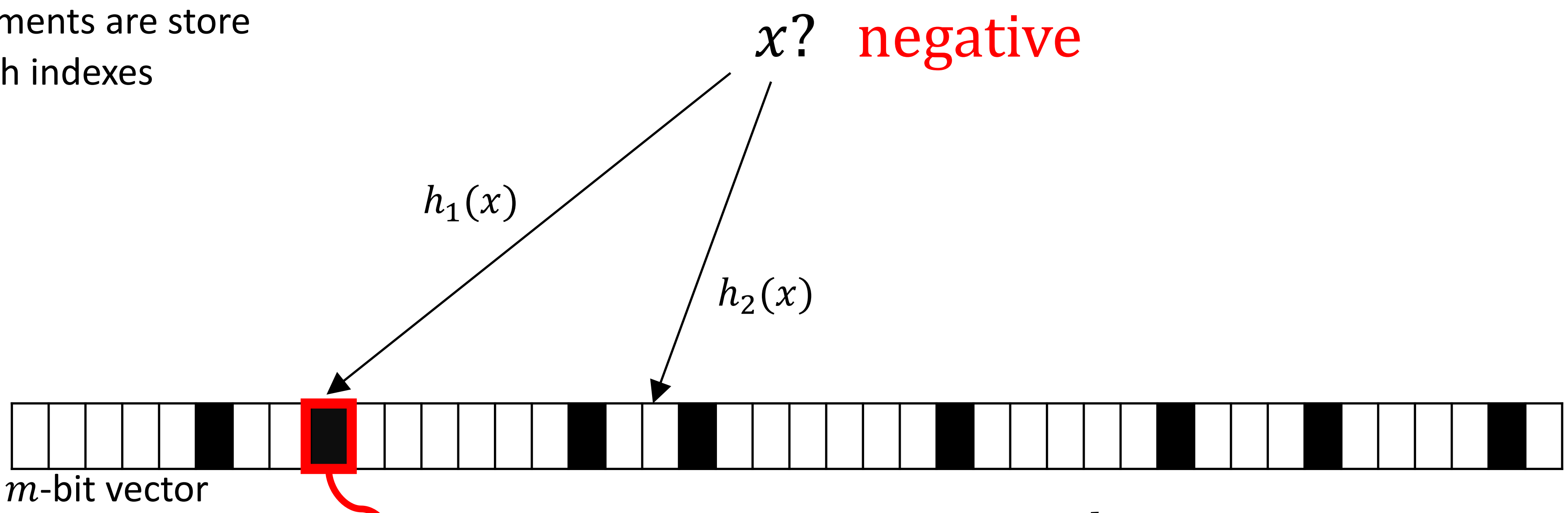

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Bloom Filter

m-bit vector

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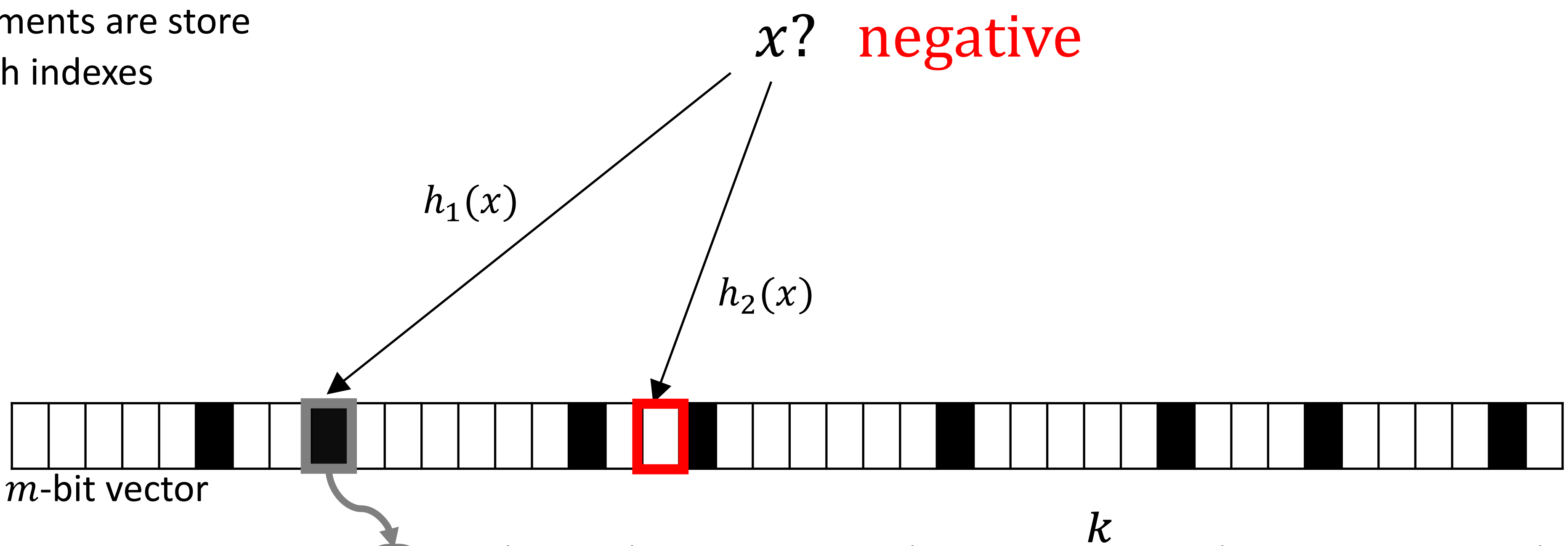
k hash indexes



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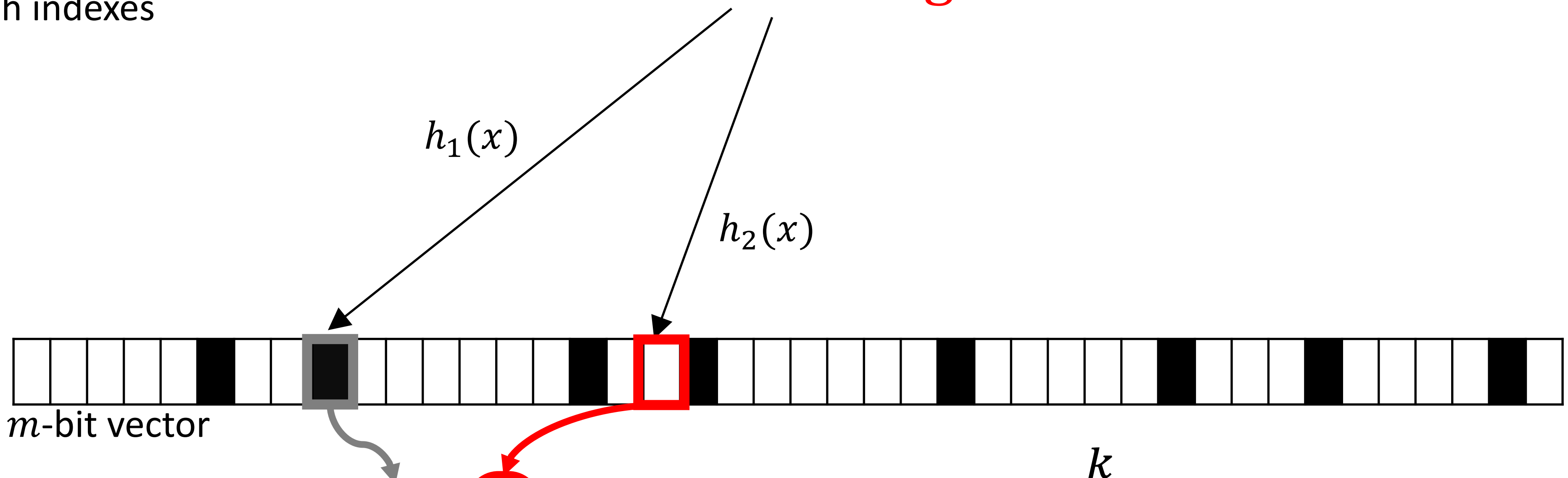
Bloom Filter

m-bit vector

n elements are store

k hash indexes

x? negative



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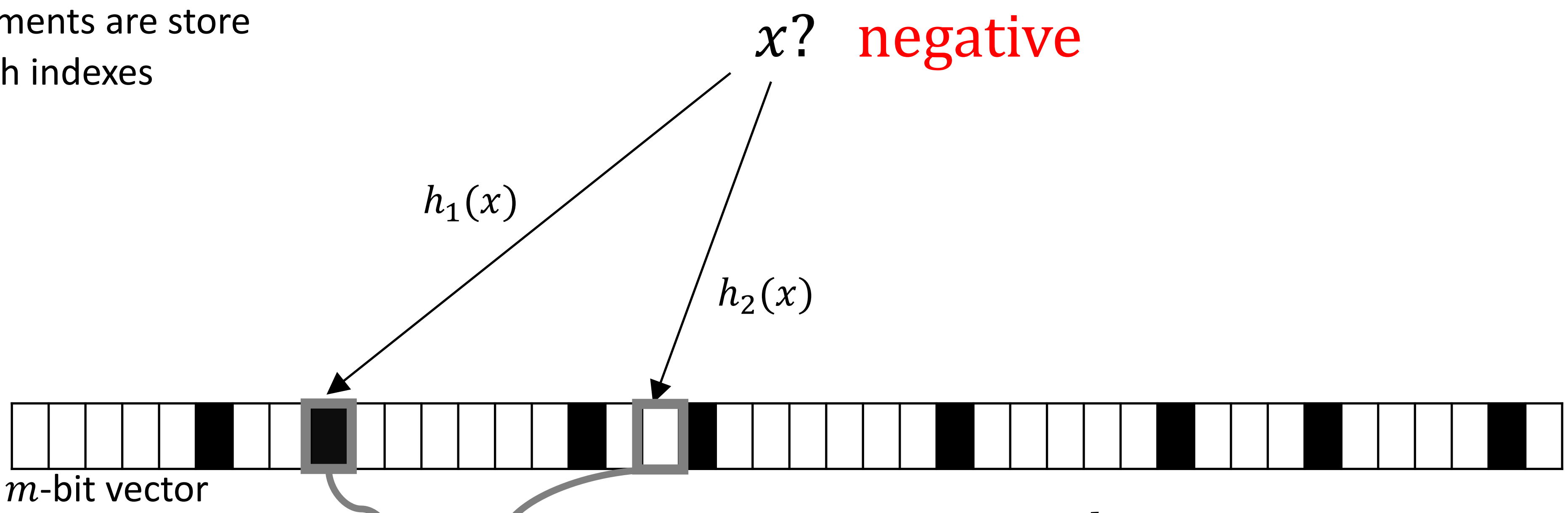
Bloom Filter

m-bit vector
n elements are store
k hash indexes



$$probes_{empty} = 1 + \frac{1}{2} + \underbrace{\frac{1}{2^2} + \cdots + \frac{1}{2^{k-1}}}_{\text{for all } k \text{ hash indexes}} = \sum_{d=1}^{k} \frac{1}{2^{k-1}} = 2 - \frac{1}{2^{k-1}}$$

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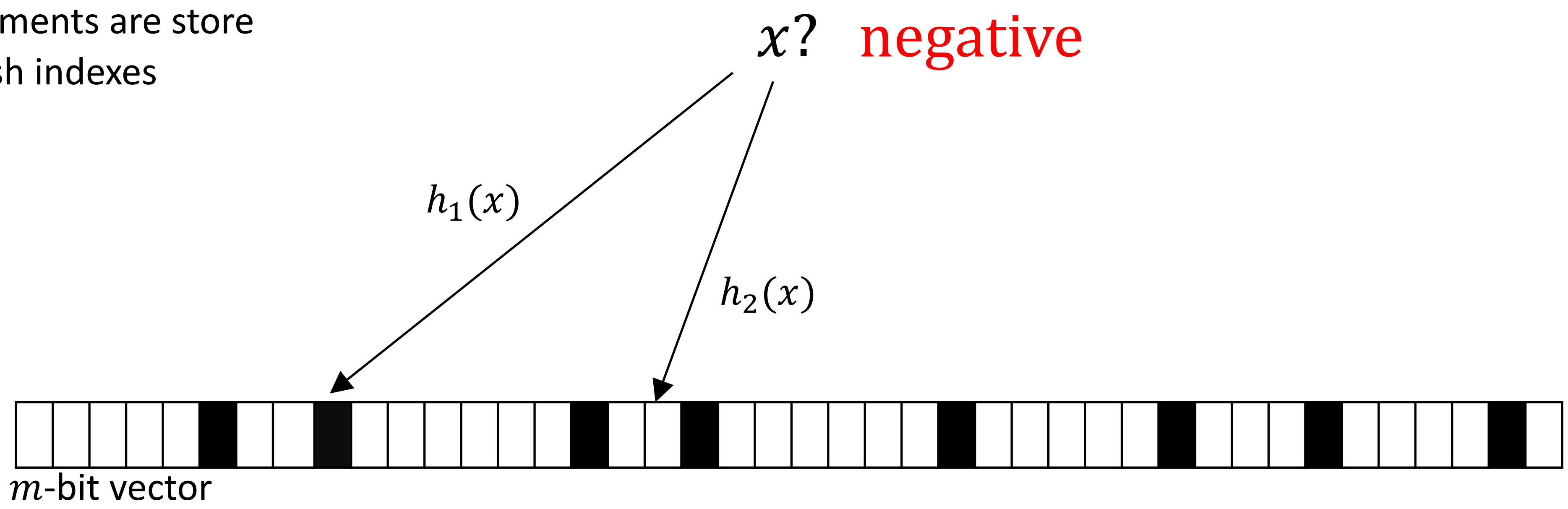
Bloom Filter

m-bit vector
n elements are store
k hash indexes



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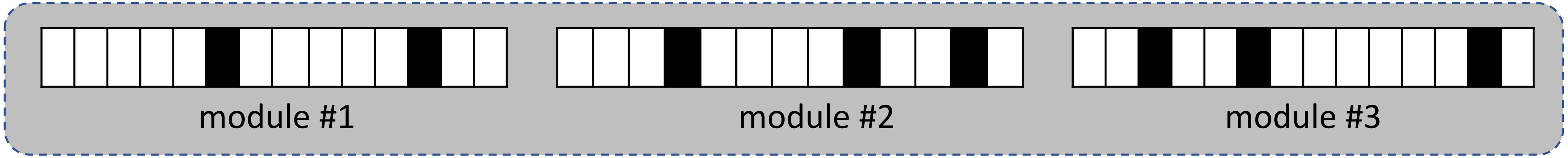
Modular Bloom Filter

m-bit vector
n elements are store
k hash indexes
d modules



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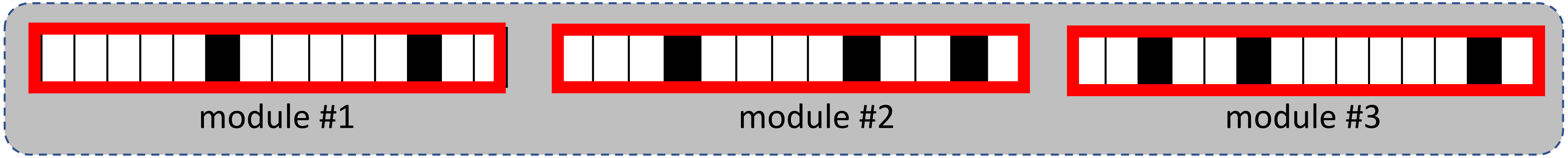
Modular Bloom Filter

m-bit vector
n elements are store
k hash indexes
d modules



An MBF is a collection of D Bloom filters

- m_d-bit vector
- n elements
- k_d hash indexes

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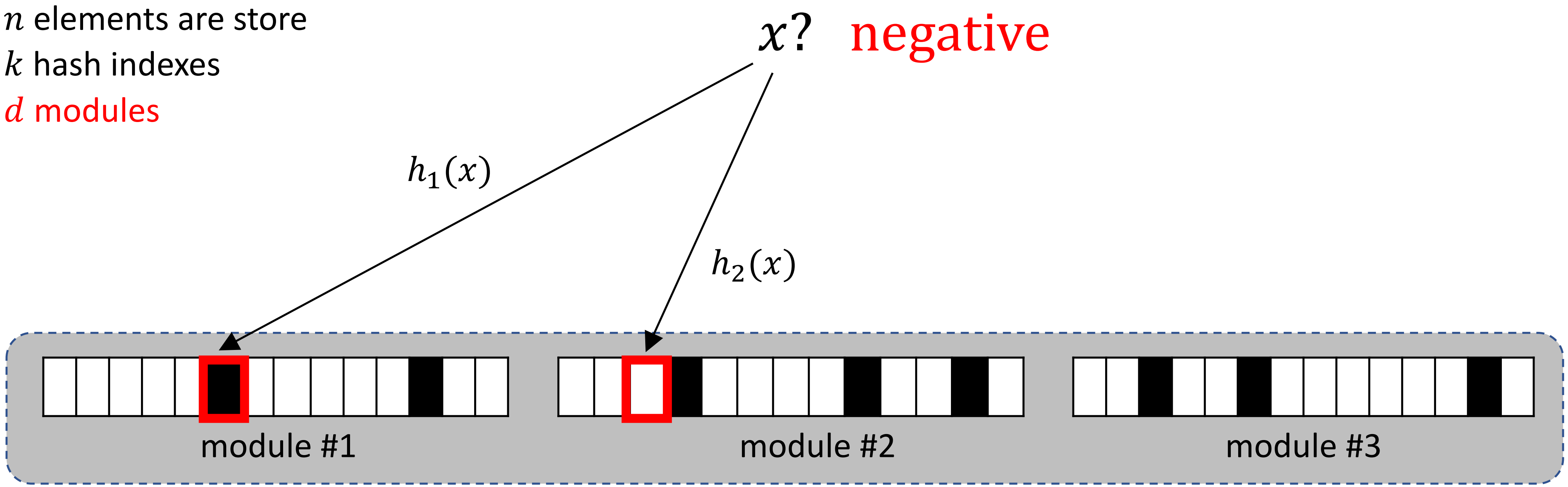
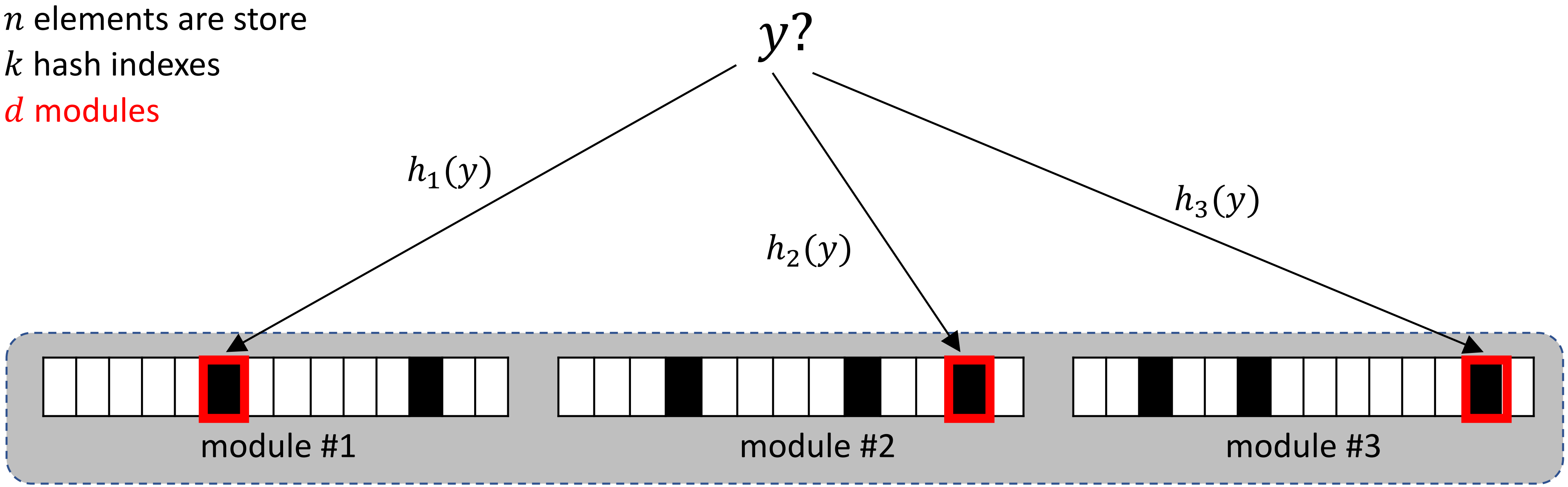
Modular Bloom Filter

m-bit vector
n elements are store
k hash indexes
d modules



Modular Bloom Filter

m-bit vector
n elements are store
k hash indexes
d modules



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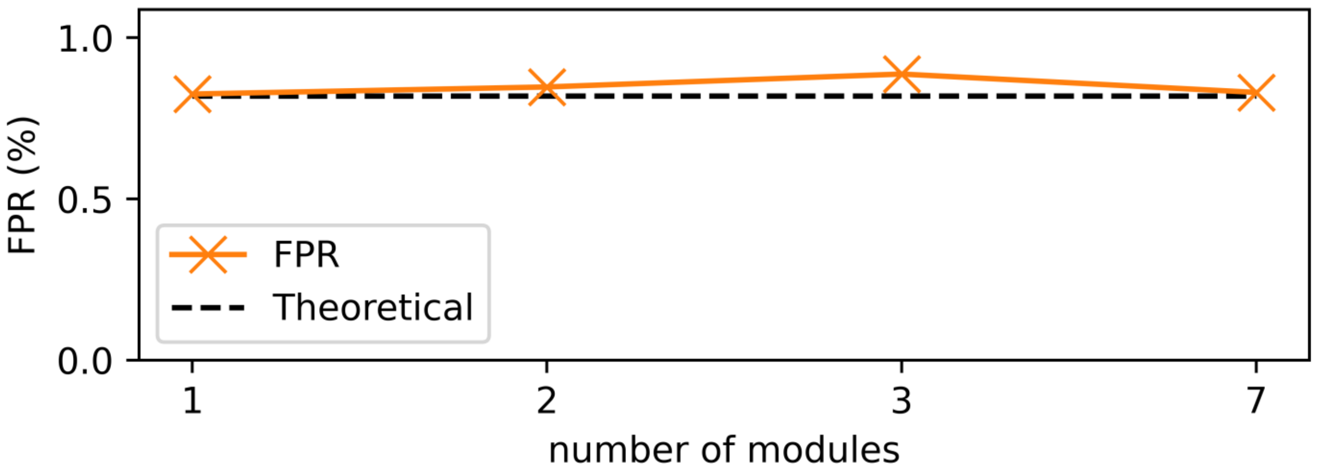
Modular Bloom Filter

False positive rate

FPR close-to-theoretical



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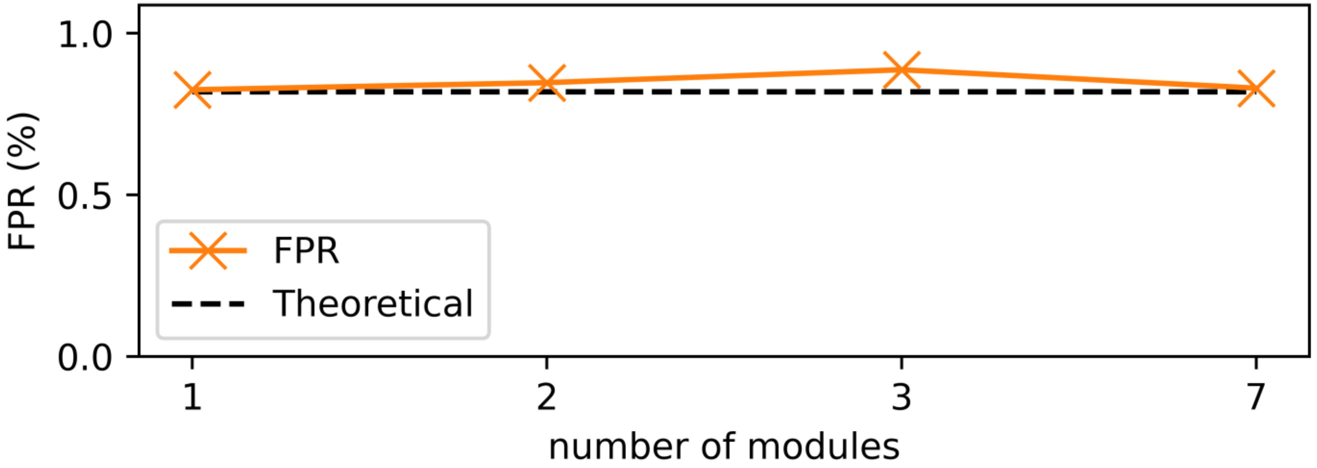
Modular Bloom Filter

False positive rate

FPR close-to-theoretical

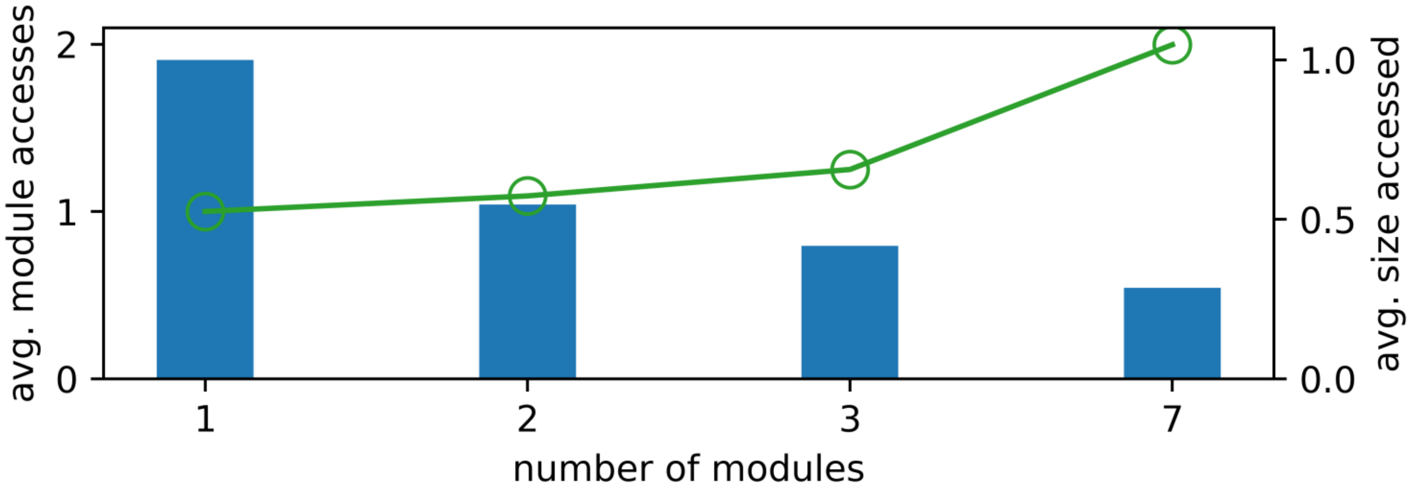


Avg. # of module accesses

vs.

Avg. size accessed

Less memory requirement



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Modular Bloom Filter

m-bit vector
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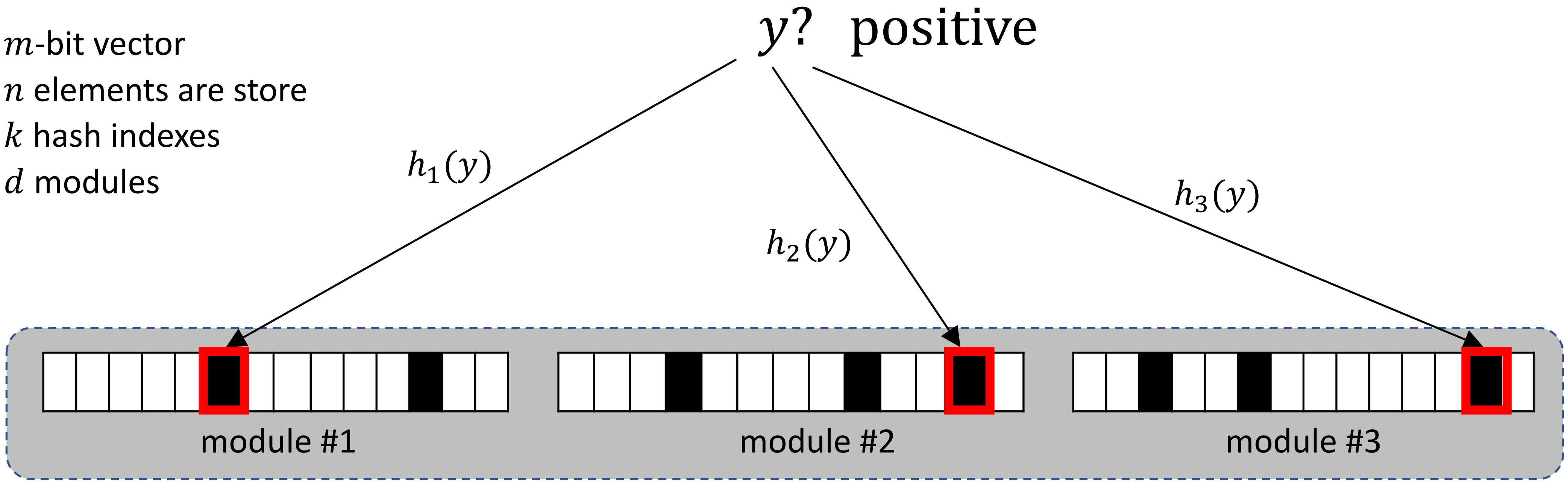
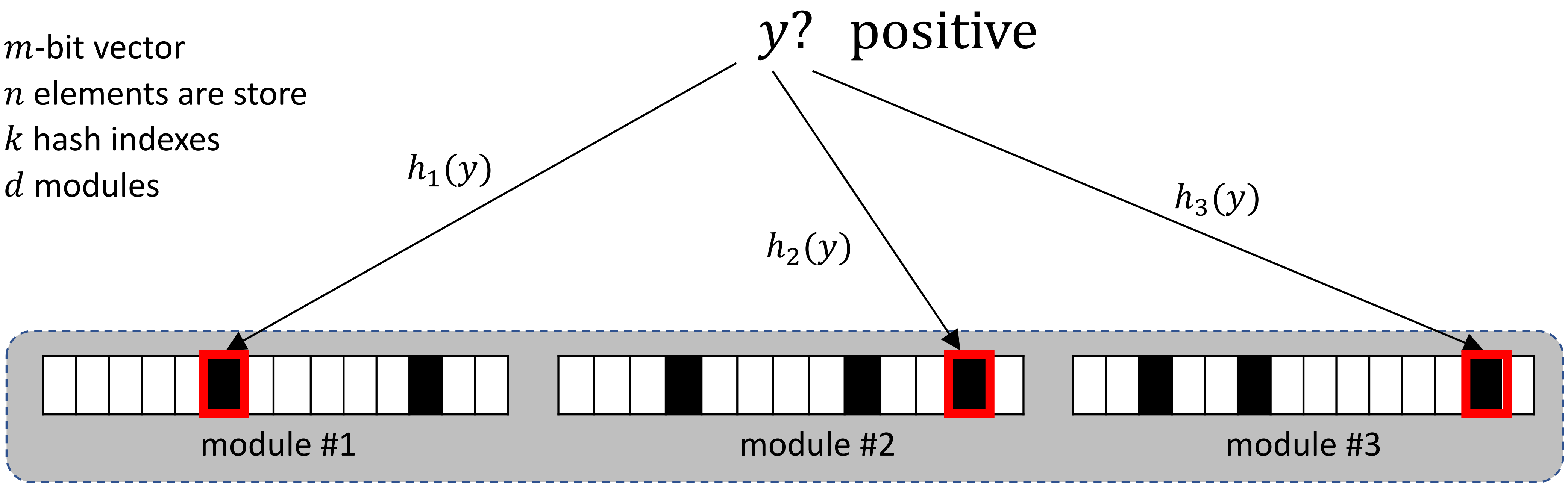
k hash indexes
d modules



MBFs are not useful for positive queries.

Modular Bloom Filter

m-bit vector
n elements are store
k hash indexes
d modules



MBFs are not useful for positive queries.

What if we know something more about the queries?

Skipping Modules

Utility : a measure of the benefit of a filter or a module

$$u_{l,i,d} = expIO_{l,i,d} - expIO_{l,i,d-1}$$

The expected number of I/Os that can be reduced by using d-th module

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Skipping Modules

Utility : a measure of the benefit of a filter or a module

$$u_{l,i,d} = expIO_{l,i,d} - expIO_{l,i,d-1}$$

The expected number of I/Os that can be reduced by using d-th module

Expected number of I/Os

$$expIO_{l,i,d} = \underbrace{\beta_{l,i}}_{\text{access frequency}} \cdot \left(\underbrace{\alpha_{l,i}}_{\text{non-empty queries}} + \underbrace{(1-\alpha_{l,i}) \cdot f_{sm}^{d}}_{\text{false positives from empty queries}}\right)$$

l-th level
i-th SST file
d-th module
f_{sm}: FPR of a single module

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Skipping Modules

Skipping Modules *based on their utilities*

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Skipping Modules

***Skipping Modules** based on their utilities*

$u_{l,i,d}$ = explO(l,i,d) – explO(l,i,d-1)

if $u_{l,i,d} < threshold_d$ **then**
 return *true*

else
 result = QueryModule(key, $module_{l,i,d}$)

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Modular Bloom filter

&

Skipping Algorithm

&

Sharing Hashing

+

LSM-tree

Modular Bloom filter

&

Skipping Algorithm

&

Sharing Hashing

+

LSM-tree

Sharing Hashing with Modular Bloom filters (SHaMBa)

Experimental Evaluation

Experiment Settings

- LSM-tree tuning

Term	Value	Explanation
E	64	entry size (B)
K	32	key size (B)
B	64	block size (#entries)
P	1024	buffer size/file size (#blocks)
T	4	size ratio
b	10	bits per key for filters

- Size of blocks

Term	Value	Explanation
S_D	4	data block size (KB)
S_I	32	index block size (KB)
S_F	80	filter block size (KB)

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Approaches Tested

- Tuning knobs of SHaMBa

Term	Value
number of modules	1, ***2***, 3, or 7
Size of each module	***equal***
skipping algorithm	none, partial ($\mathcal{P}$), or ***full ($\mathcal{F}$)***

- Approaches Tested
  - *state-of-the-art*
  - *SHaMBa-eq*
  - *SHaMBa-eq-*$\mathcal{P}$
  - *SHaMBa-eq-*$\mathcal{F}$

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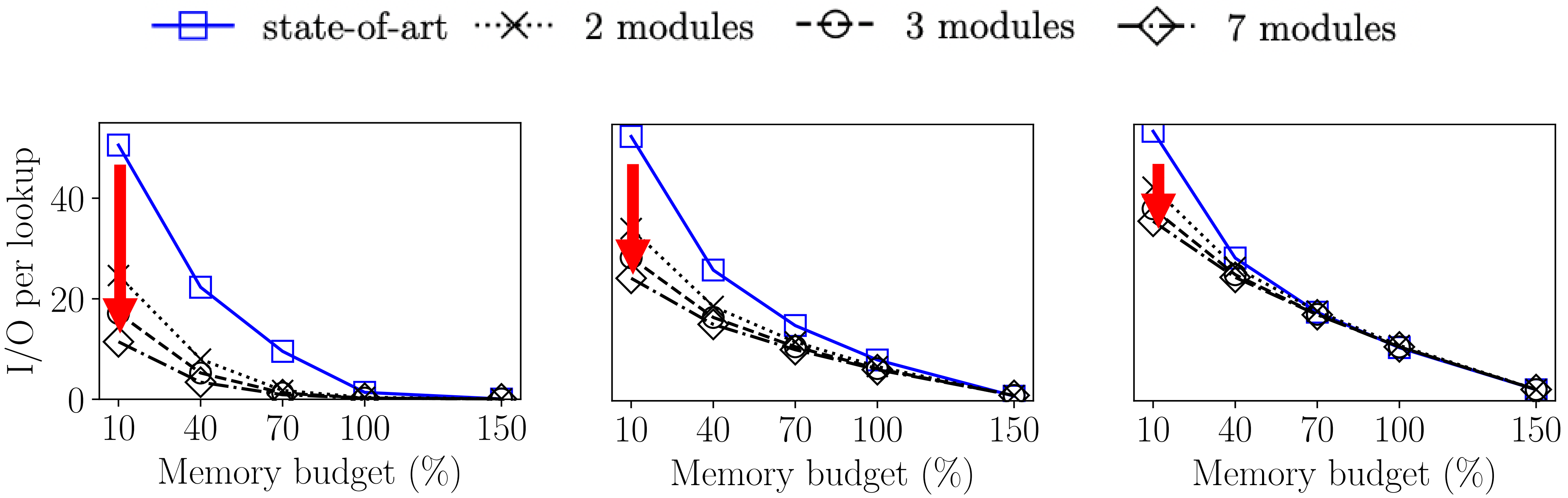
Impact of number of modules

Workload: Uniform, Entry size: 64B, #Entries: 30K
Tuning: no skipping algorithm, equal sized modules



all empty

half empty

all non-empty

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Workload: Uniform, Entry size: 64B, #Entries: 30K
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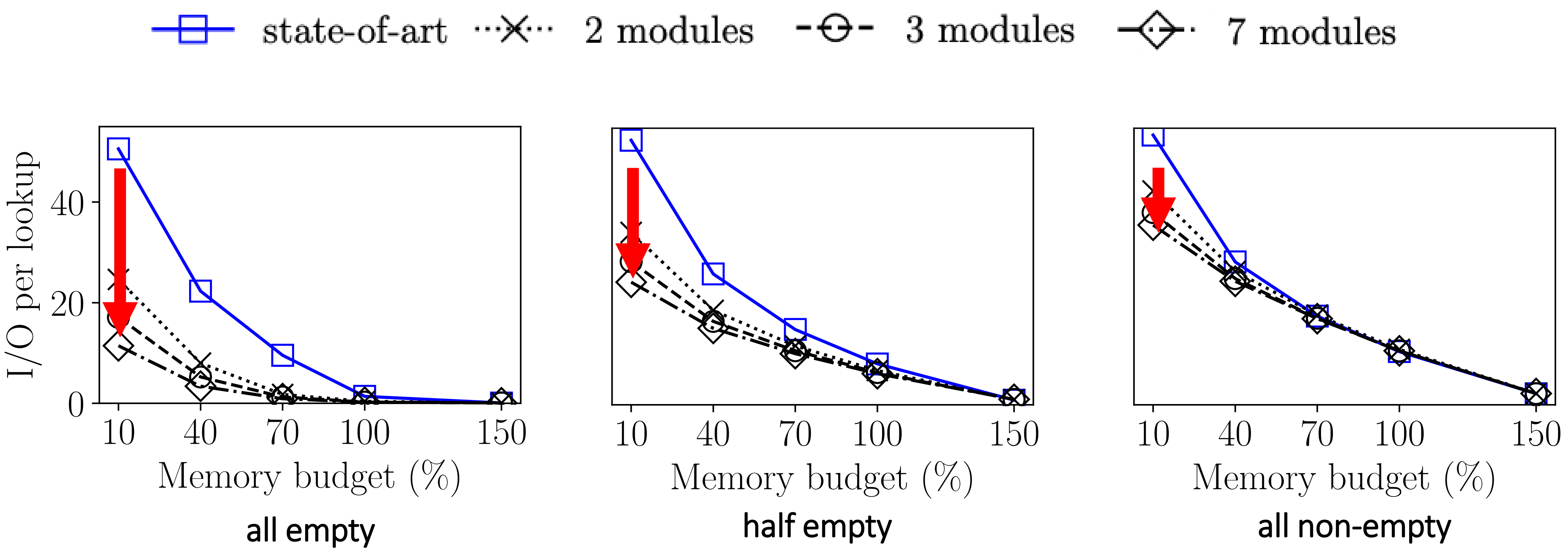

SHaMBa enhances the lookup performance for empty queries

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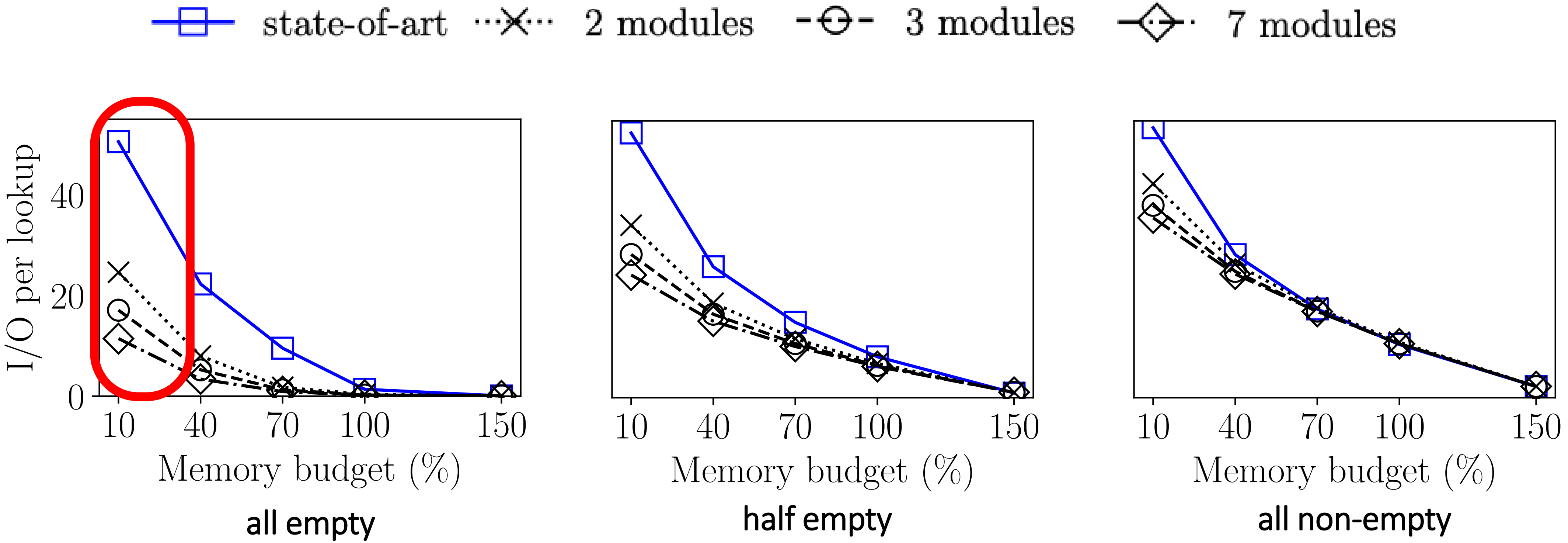

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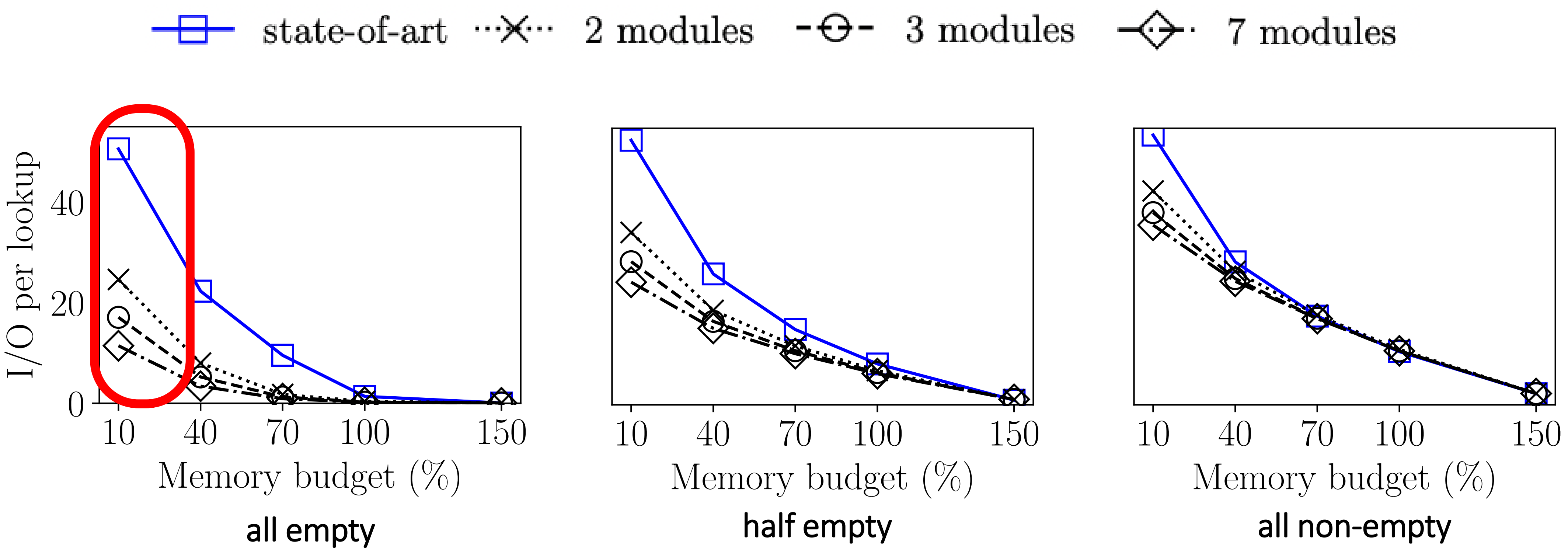
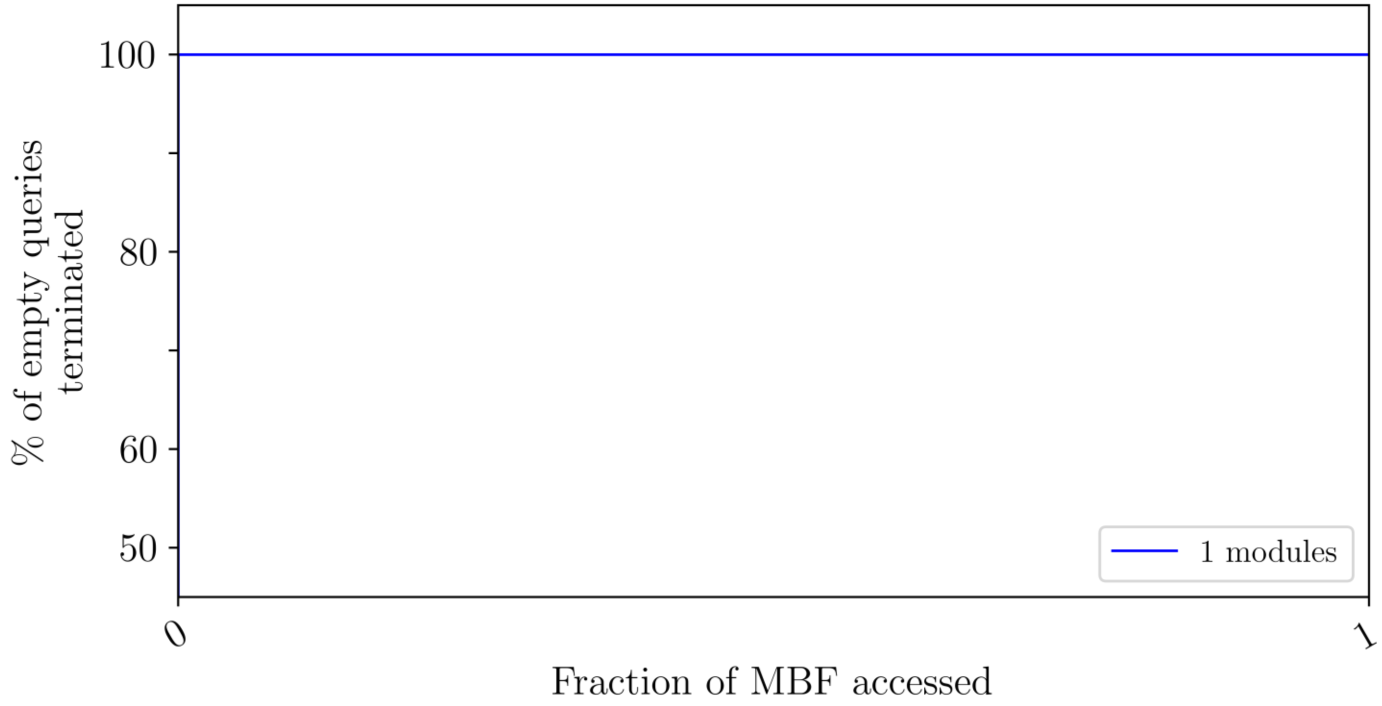


SHaMBa performs best with smaller modules

Impact of number of modules



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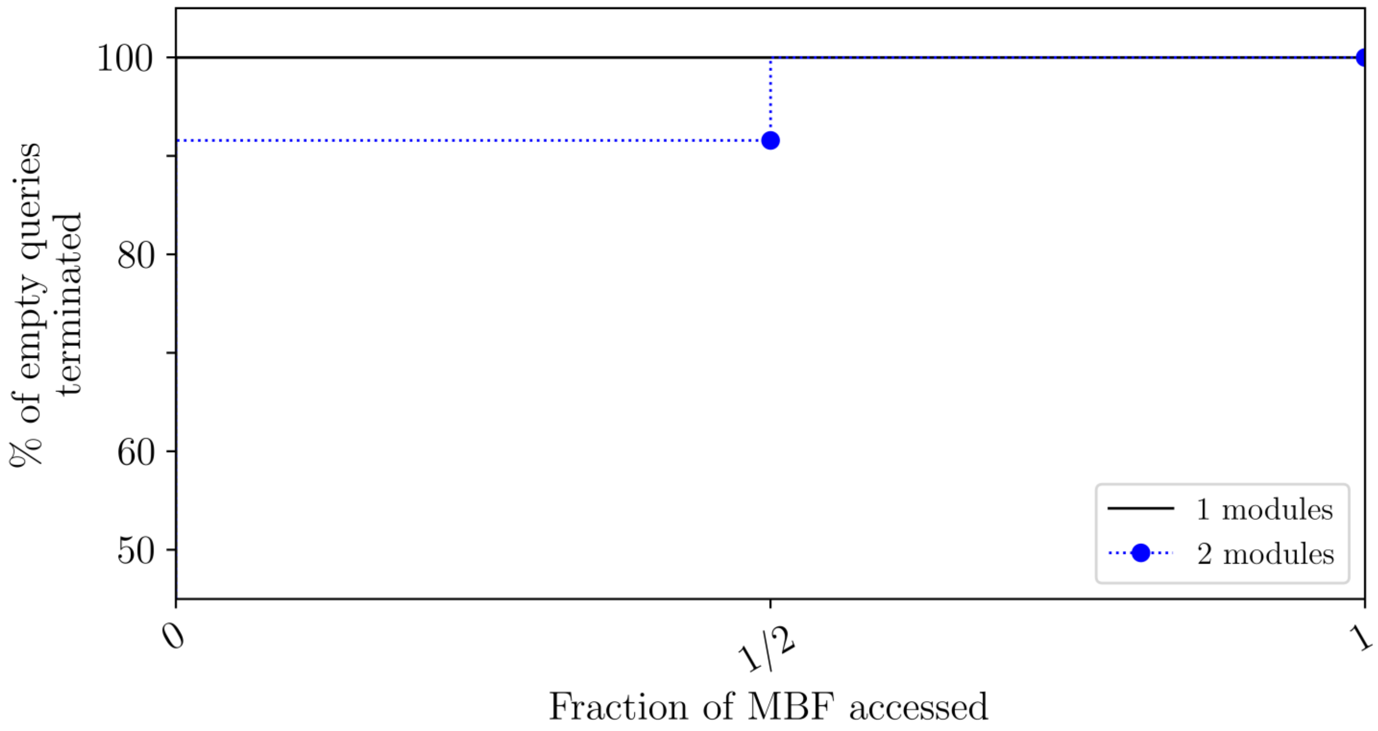
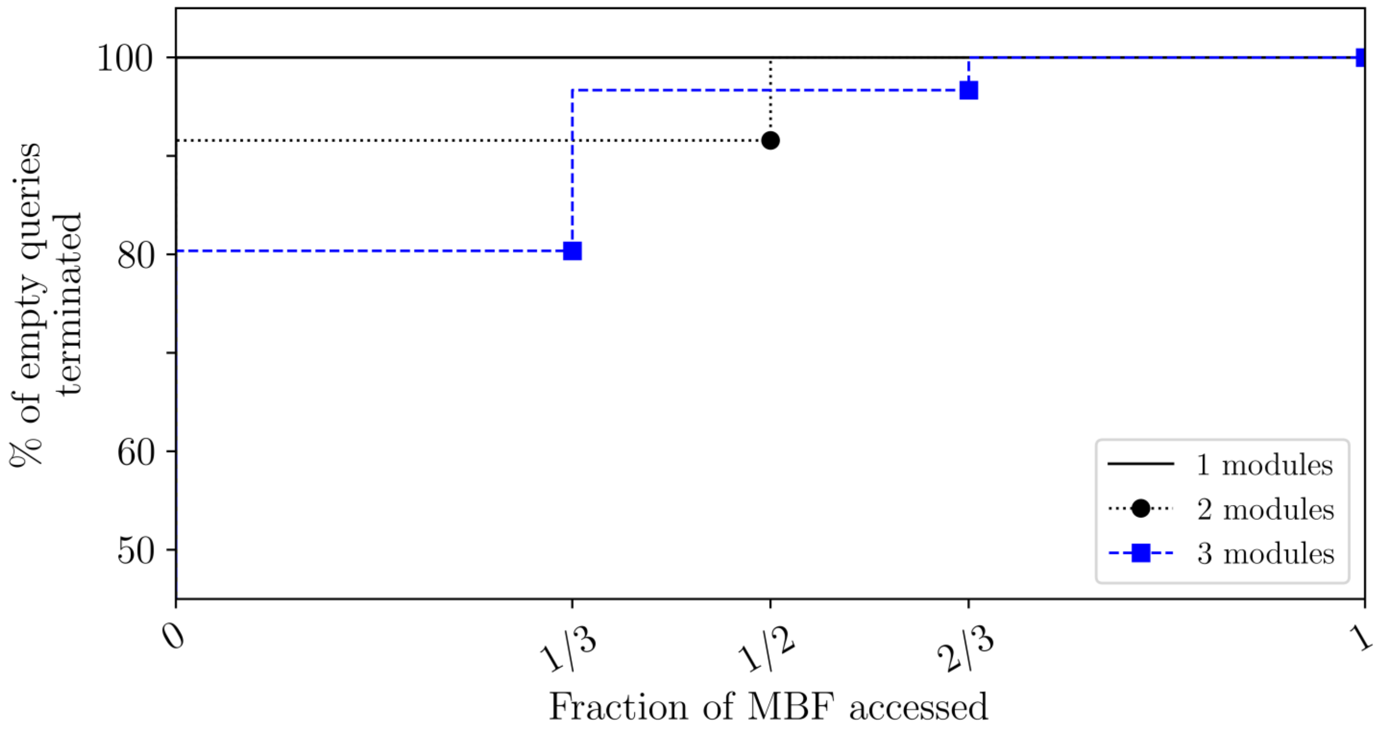


Impact of number of modules



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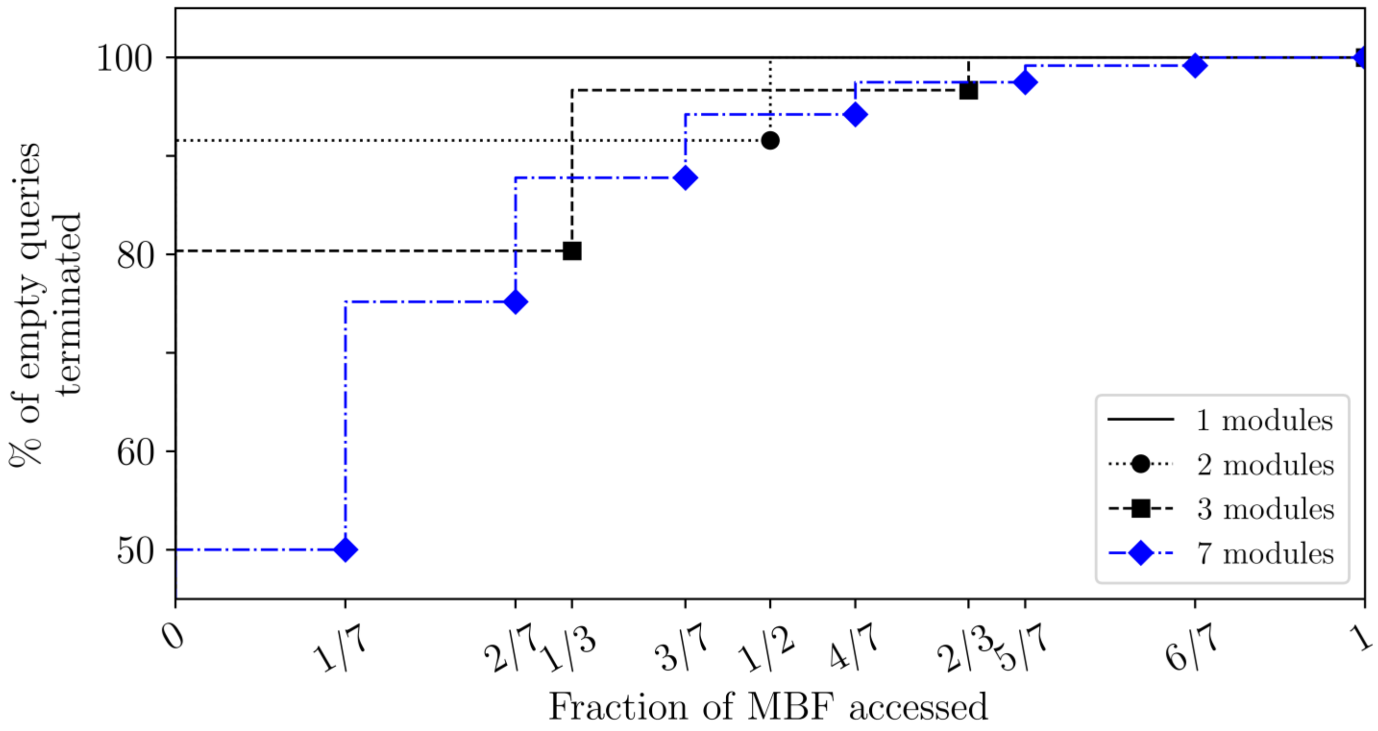
Impact of number of modules



More queries can be terminated earlier with less memory.

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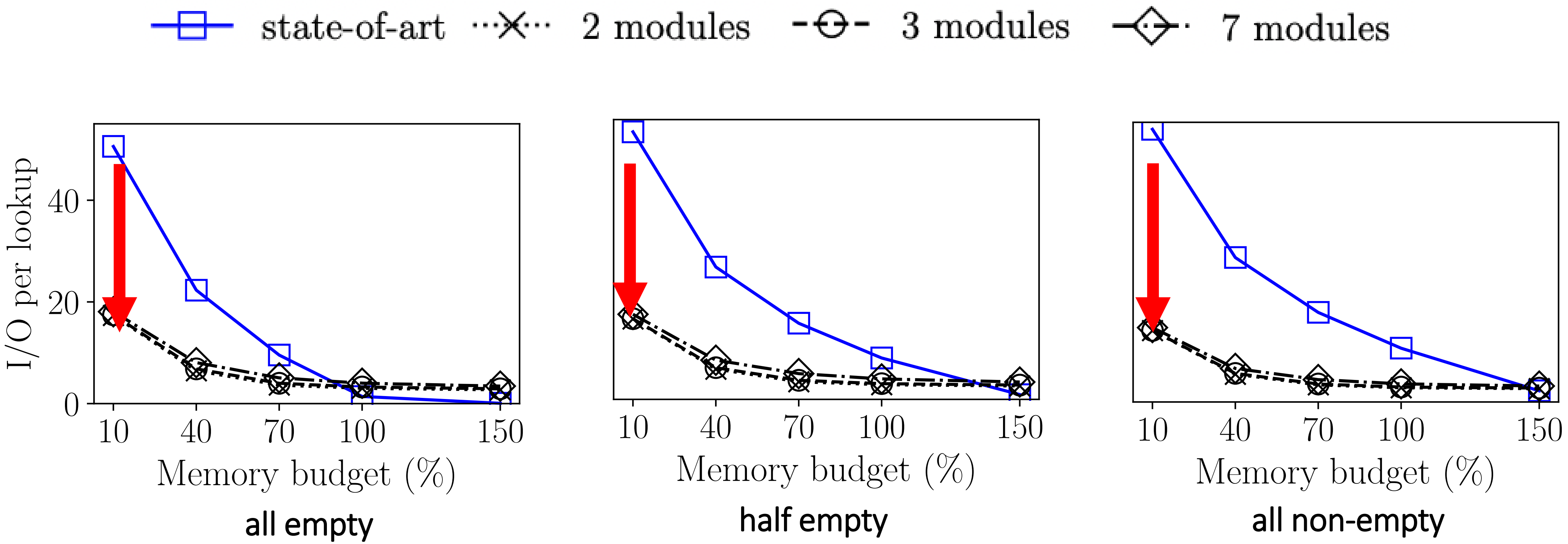
Impact of number of modules

Workload: Uniform, Entry size: 64B, #Entries: 30K
Tuning: full skipping algorithm, equal sized modules



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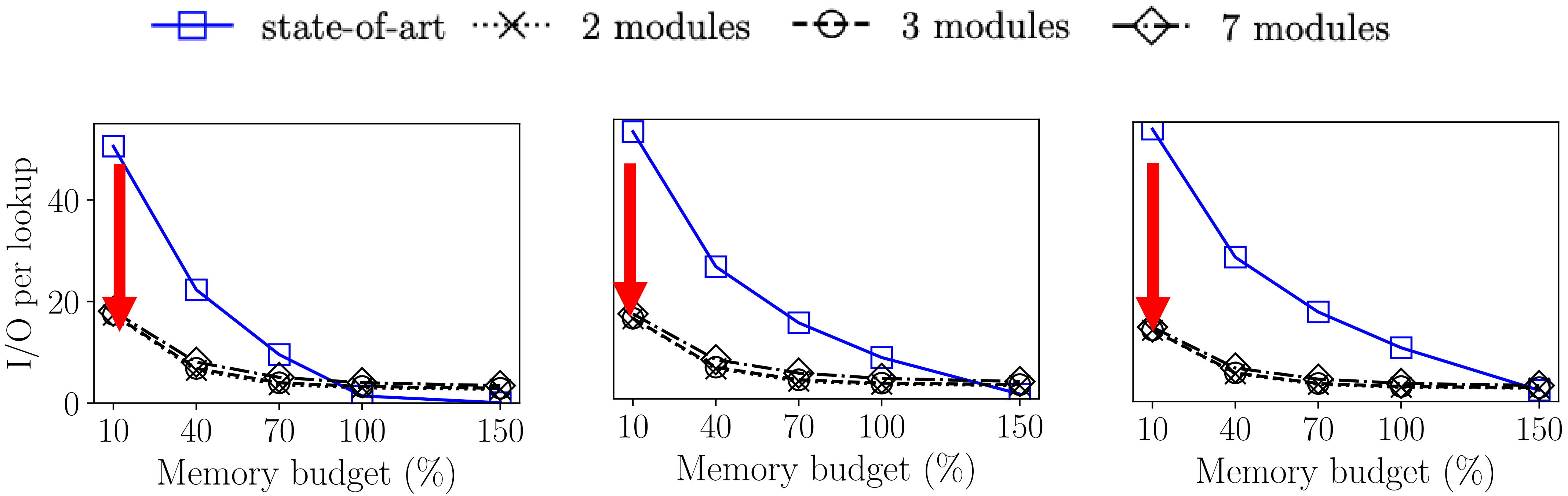

all empty

half empty

all non-empty

Skipping modules effectively skips unnecessary filters/modules.

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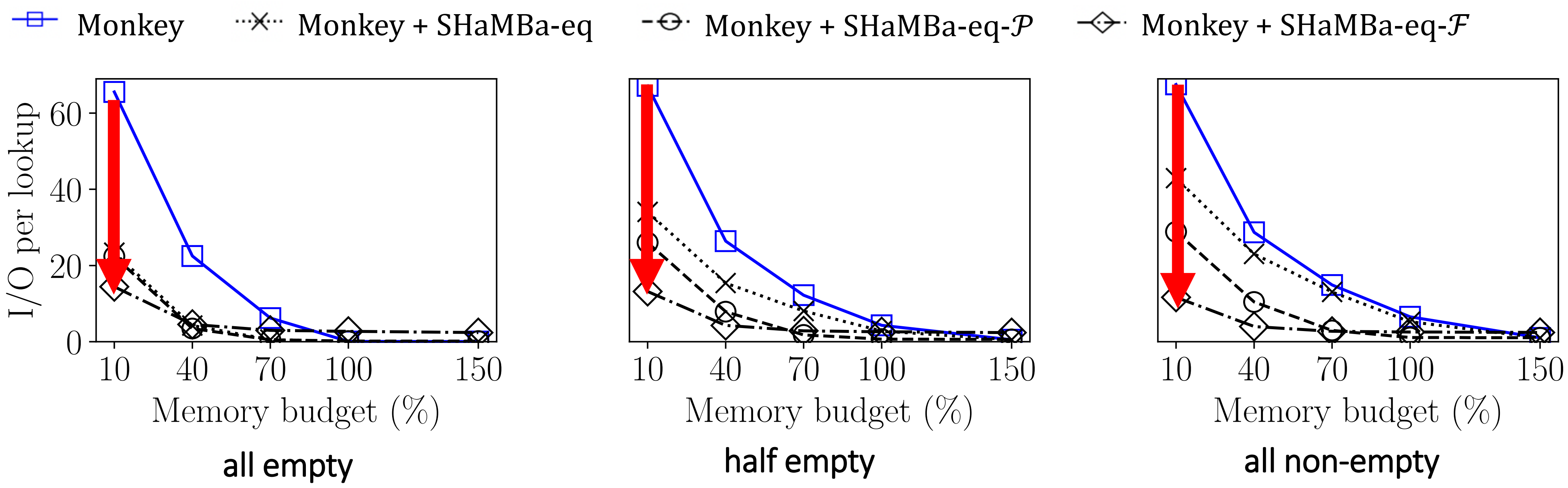
SHaMBa with Monkey

Workload: Uniform, Entry size: 64B, #Entries: 30K
Tuning: 2 equal sized modules

Monkey allocates more bits per element in the shallower levels to aggressively reduce their false positives

Monkey: Optimal Navigable Key-Value Store, ACM SIGMOD 2017



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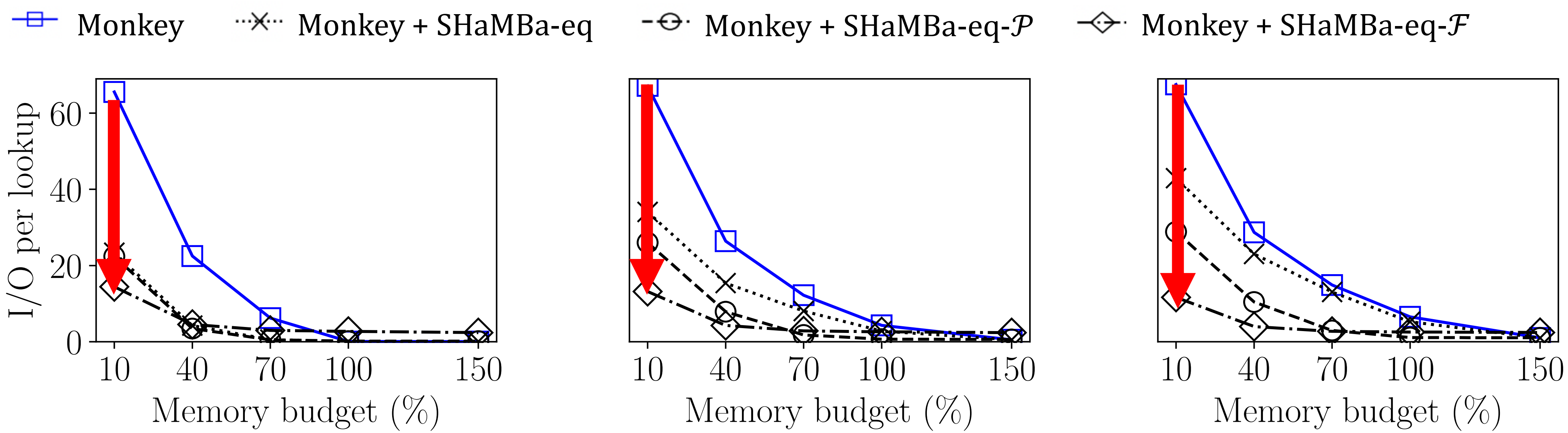

all empty

half empty

all non-empty

SHaMBa further improves performance of Monkey

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Conclusion

- SHaMBa
  - a novel LSM-based key-value engine
  - specifically addresses performance loss due to memory pressure
  - the same average number of I/Os, with 1/3 of the memory by the state of the art
- Modular Bloom filters (MBFs)
  - a BF variant that consists of multiple module
  - enable smooth navigation of the memory vs. performance trade-off

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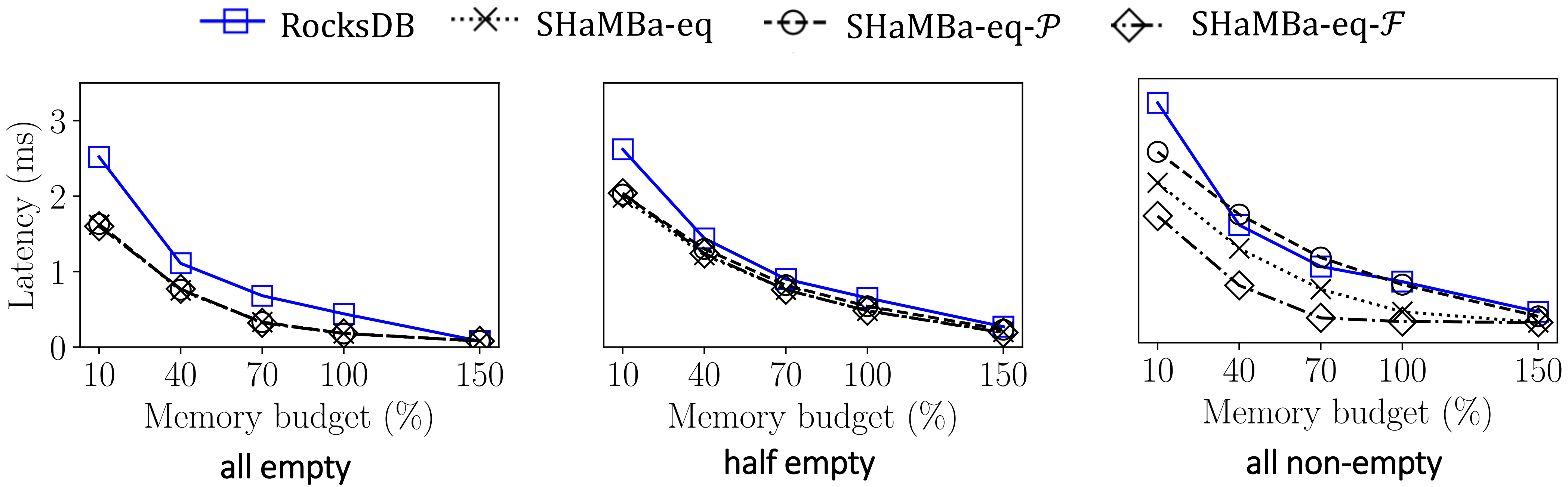
DiSC lab

Q&A

SHaMBa with RocksDB

Workload: Uniform, Entry size: 64B, #Entries: 30K
Tuning: 2 equal sized modules, RocksDB version 6.19.3



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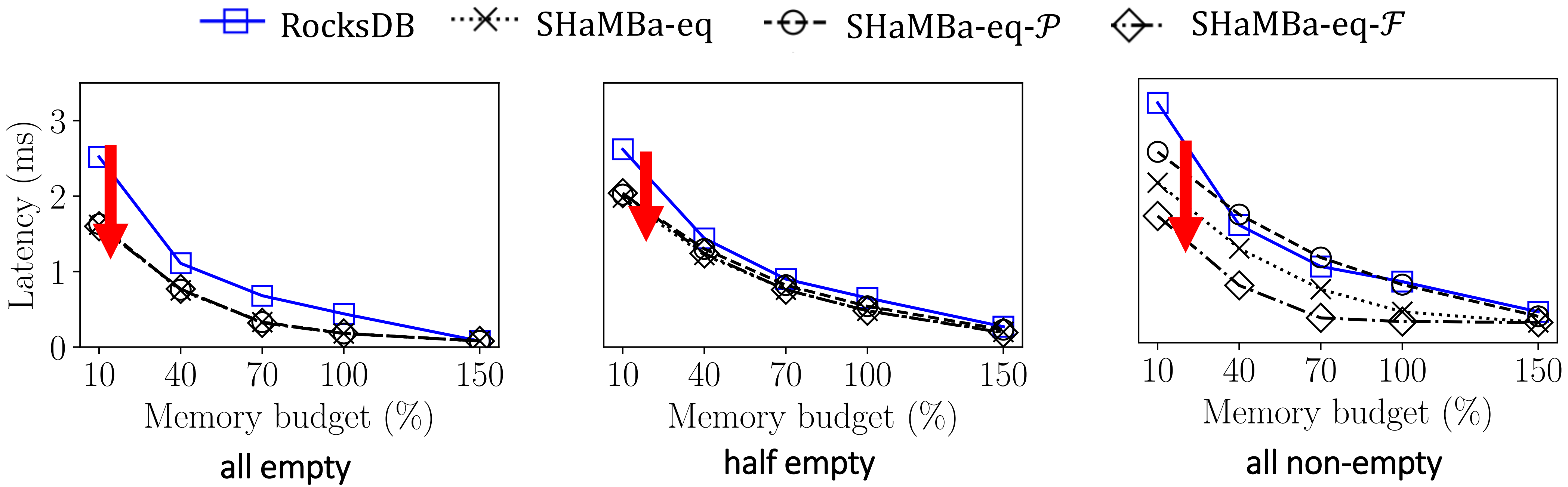
SHaMBa with RocksDB

Workload: Uniform, Entry size: 64B, #Entries: 30K
Tuning: 2 equal sized modules, RocksDB version 6.19.3



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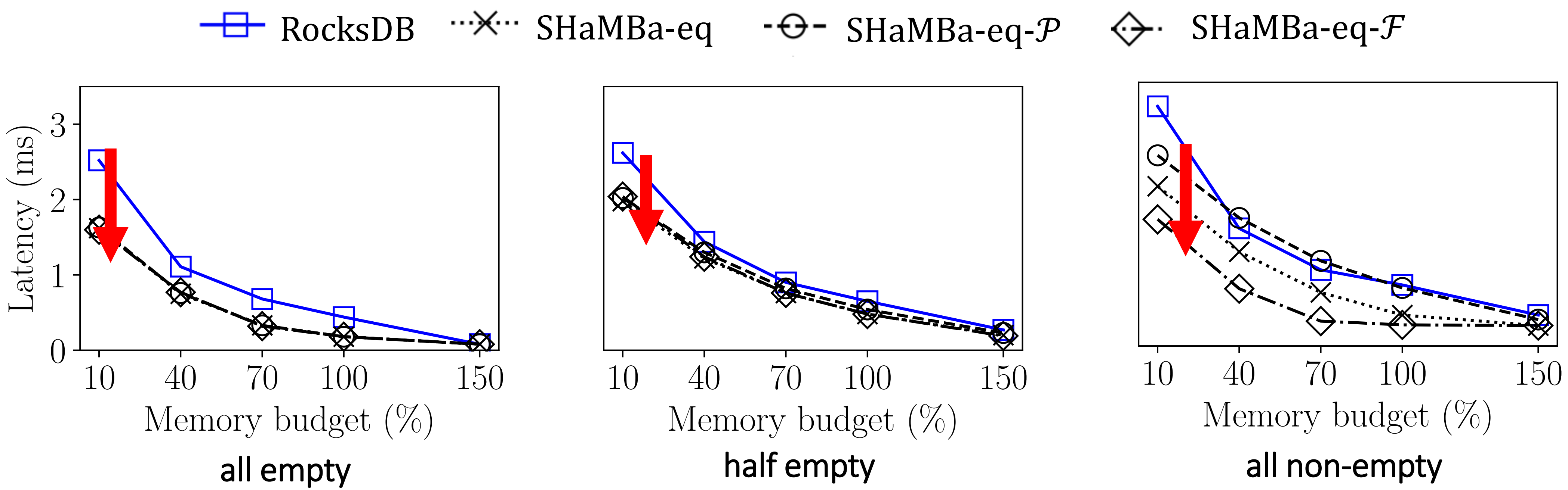
SHaMBa with RocksDB

Workload: Uniform, Entry size: 64B, #Entries: 30K
Tuning: 2 equal sized modules, RocksDB version 6.19.3



SHaMBa-eq accelerates point lookups

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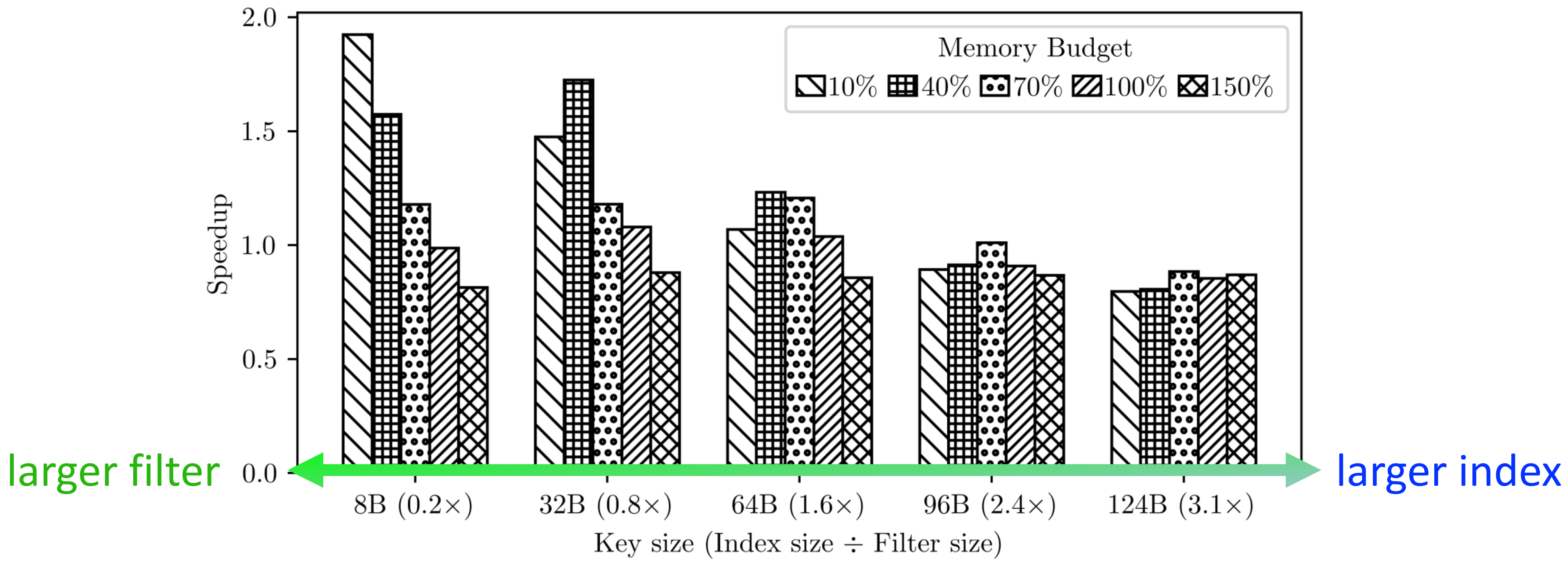
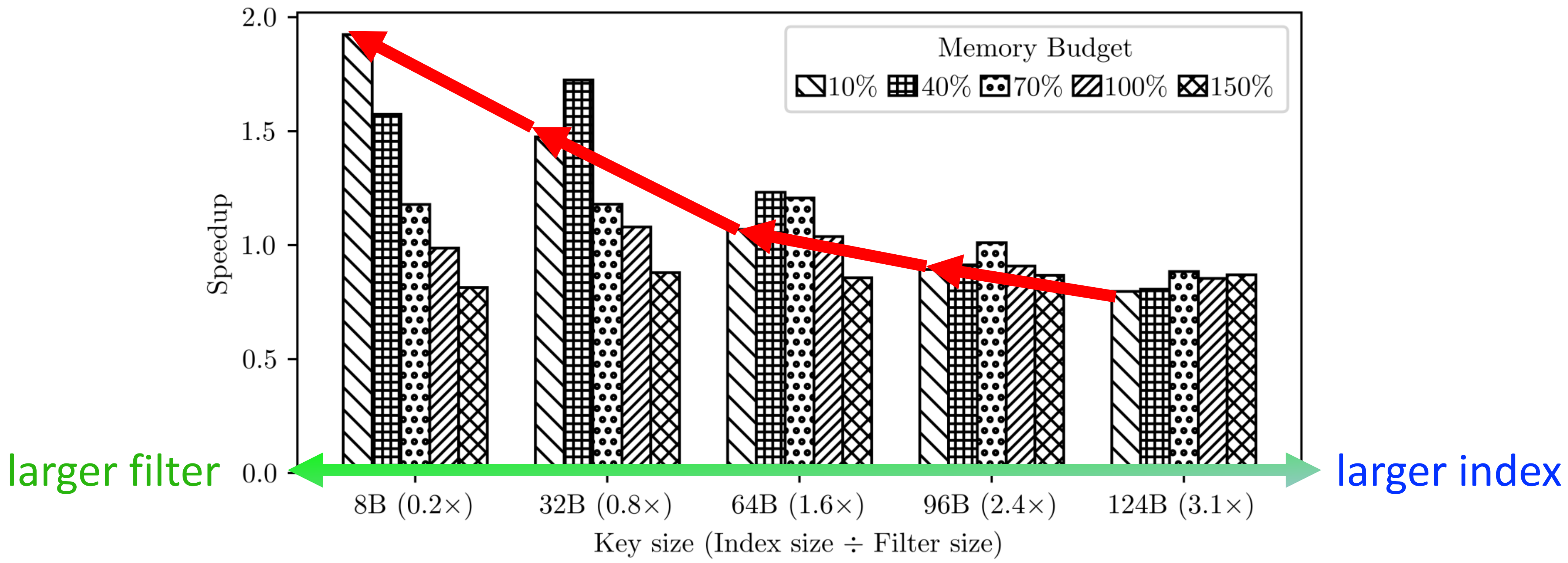
SHaMBa with larger index

Workload: Uniform (all empty), Entry size: 128B, #Entries: 30K
Tuning: 2 equal sized modules, RocksDB version 6.19.3



SHaMBa with larger index

Workload: Uniform (all empty), Entry size: 128B, #Entries: 30K
Tuning: 2 equal sized modules, RocksDB version 6.19.3



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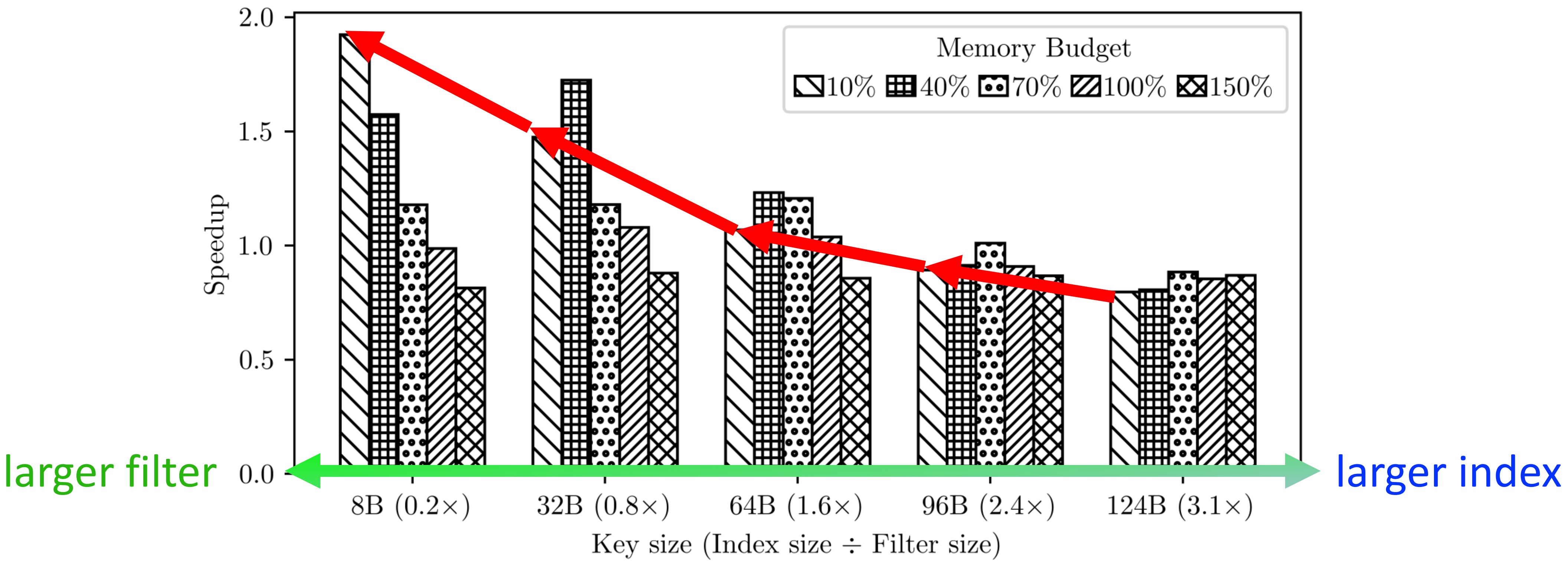
SHaMBa with larger index

Workload: Uniform (all empty), Entry size: 128B, #Entries: 30K
Tuning: 2 equal sized modules, RocksDB version 6.19.3



SHaMBa performs best when filters are larger than indexes

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