BOSTON UNIVERSITY

CS 561: Data Systems Architectures

class 6

Log-structured Merge Trees

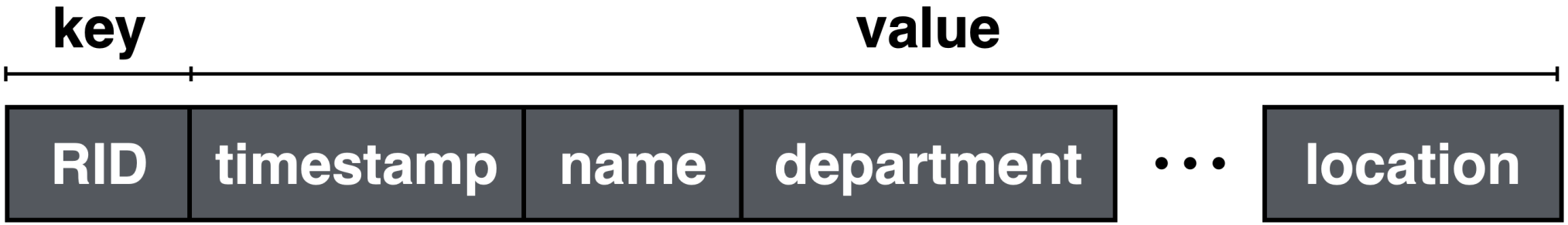
Prof. Manos Athanassoulis

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

Do we have a quiz today … ?

Yes!

Key-Value Stores

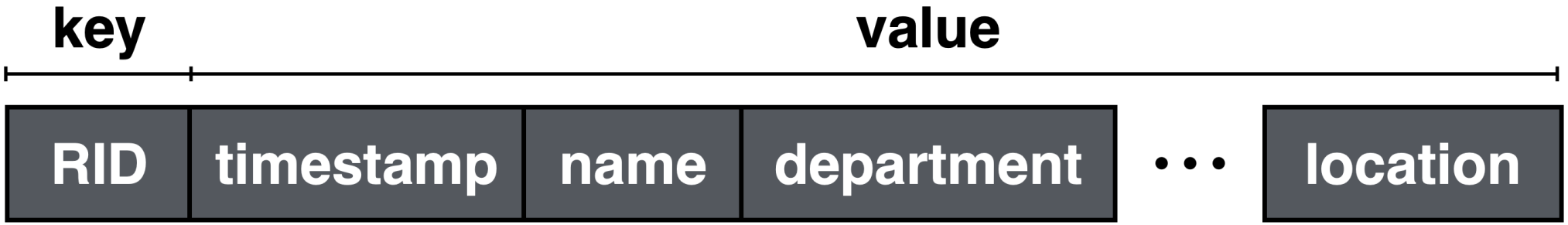


semi-structured data

relational data

document data

LSM-tree based Key-Value Stores



semi-structured data

document data

relational data

Log-**S**tructured **M**erge-tree

LSM-tree

LSM-tree

The Log-Structured Merge-Tree (LSM-Tree)

1996

Patrick O'Neil[1], Edward Cheng[2]
Dieter Gawlick[3], Elizabeth O'Neil[1]
To be published: Acta Informatica

LSM-tree

O'Neil *et al.*

1996

Patrick O'Neil
UMass Boston

LSM-tree

O'Neil *et al.*

1996

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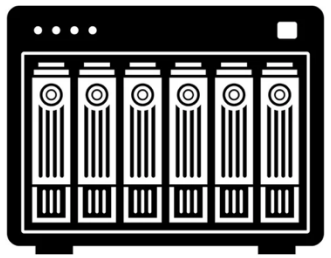
- good random writes
- good reads



array
of discs

how many IOPS?

10KRPM
max seek time 1.5ms
100 disks

10KRPM: 10K rev in 60s
60/10000=6ms per rev
avg. rot. delay: 3ms (6ms/2)
avg. seek time: 0.75ms (1.5ms/2)
1 I/O / 3.75ms: 267 IOPS
100 disks: 26,700 IOPS

why?

RAID, striping ←

✗ LSM not explicitly needed

LSM-tree
O'Neil *et al.*

so, **arrays of disks** were **enough**!

Bigtable

1980s — 1996 — 2006

a decade

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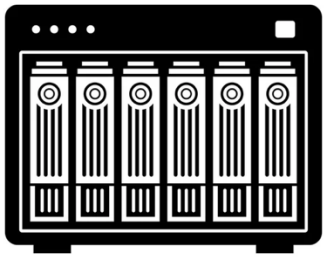
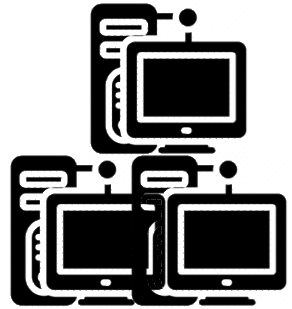
- good random writes
- good reads

- poor ingestion perf.
- poor query perf.



array of discs

what happened in 2006?



commodity hardware

LSM-tree
O'Neil *et al.*

> We set up a Bigtable cluster with N tablet servers to measure the performance and scalability of Bigtable as N is varied. The tablet servers were configured to use 1 GB of memory and to write to a GFS cell consisting of 1786 machines with two 400 GB IDE hard drives each.

Bigtable

1980s — 1996 — 2006

a decade

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- good random writes
- good reads

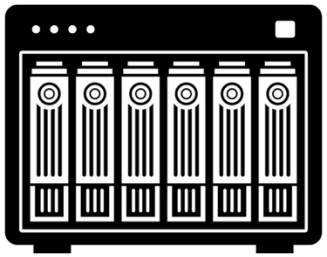
- poor ingestion perf.
- poor query perf.

SSD wear-friendly

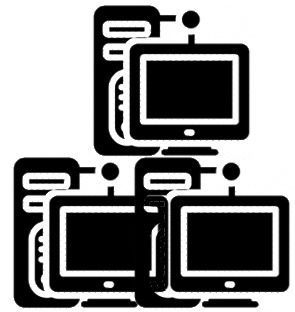
competitive rand. reads

fast ingestion (sequential)

why this is important?



array of discs



commodity hardware

LSM-tree
O'Neil *et al.*

SSDs have dominated storage since!

Bigtable

1980s

1996

2006

a decade

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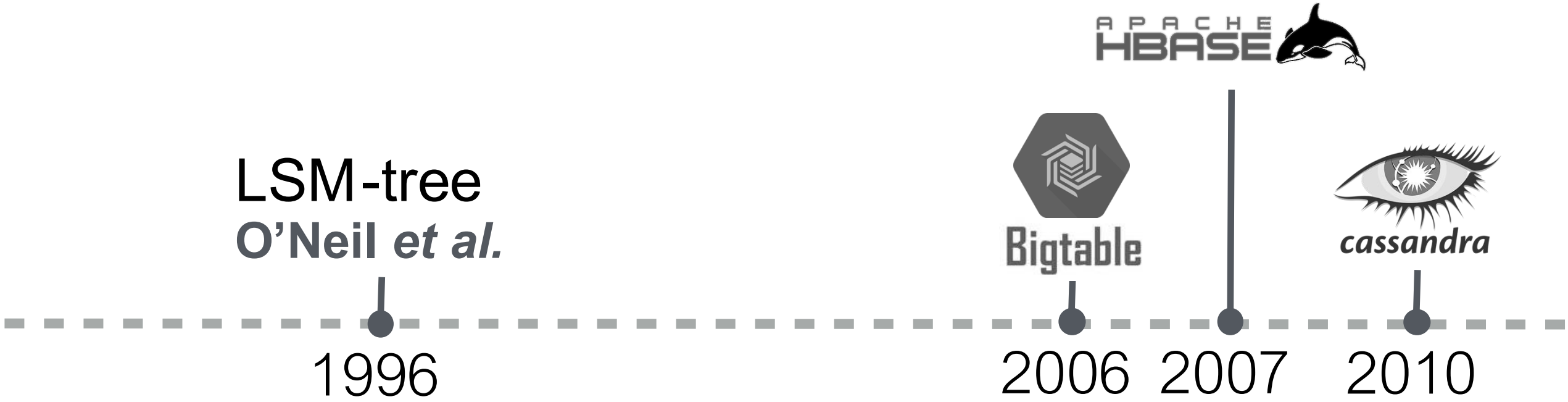
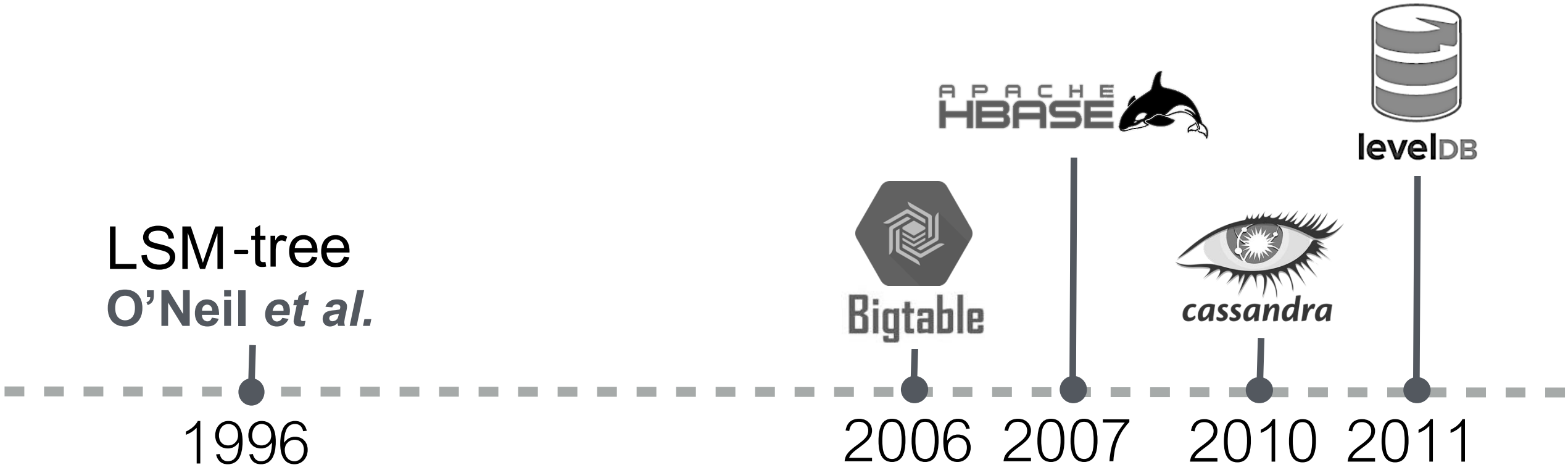
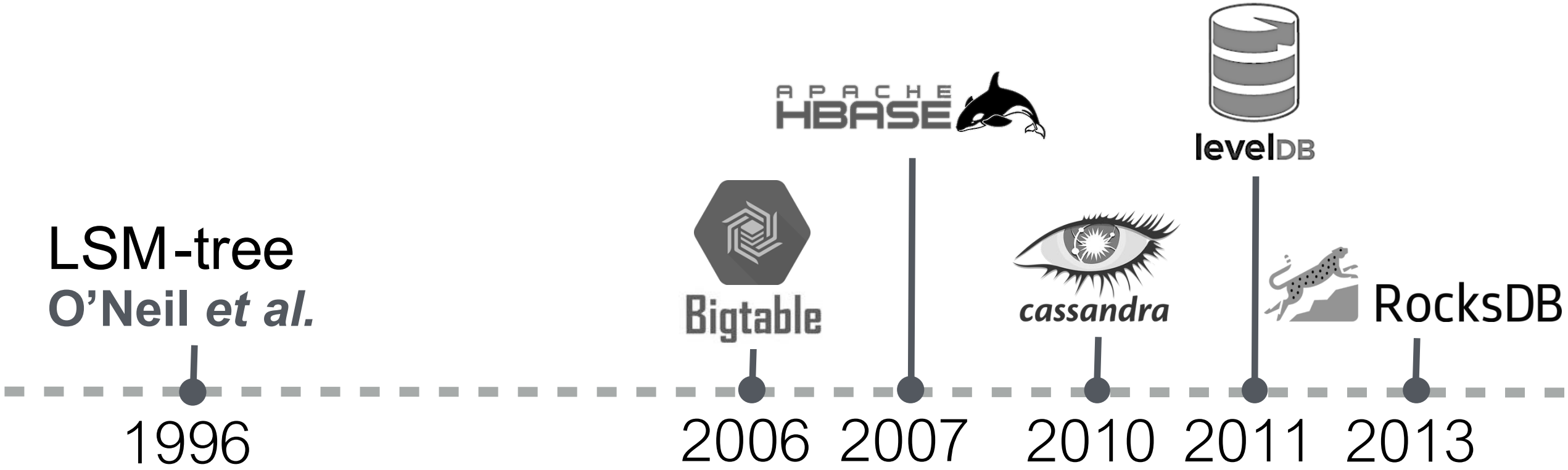
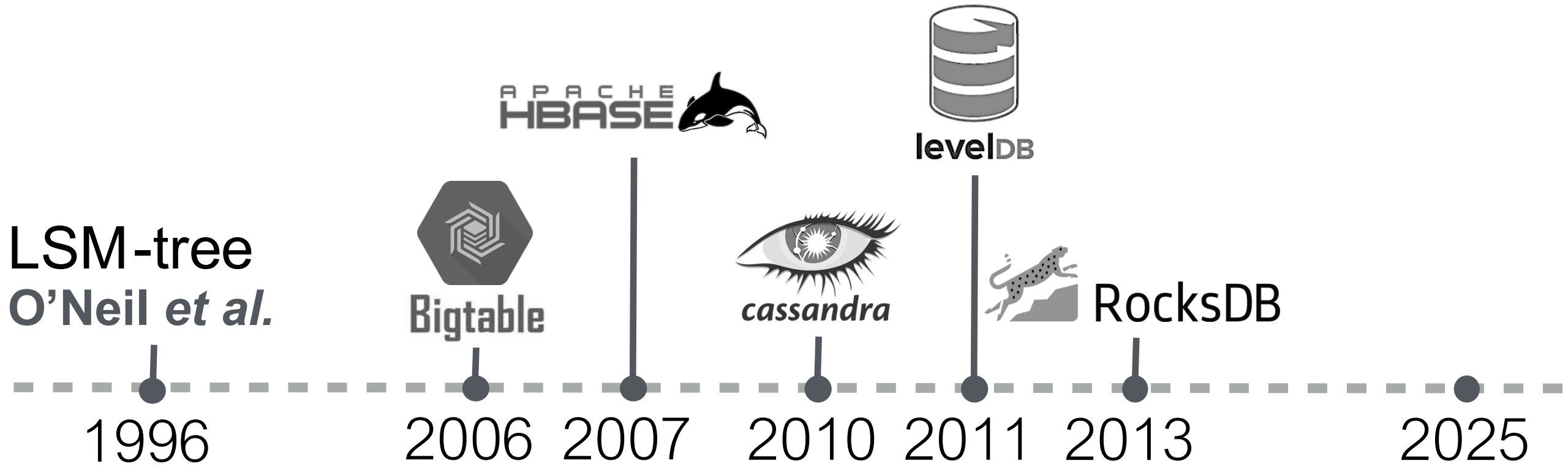
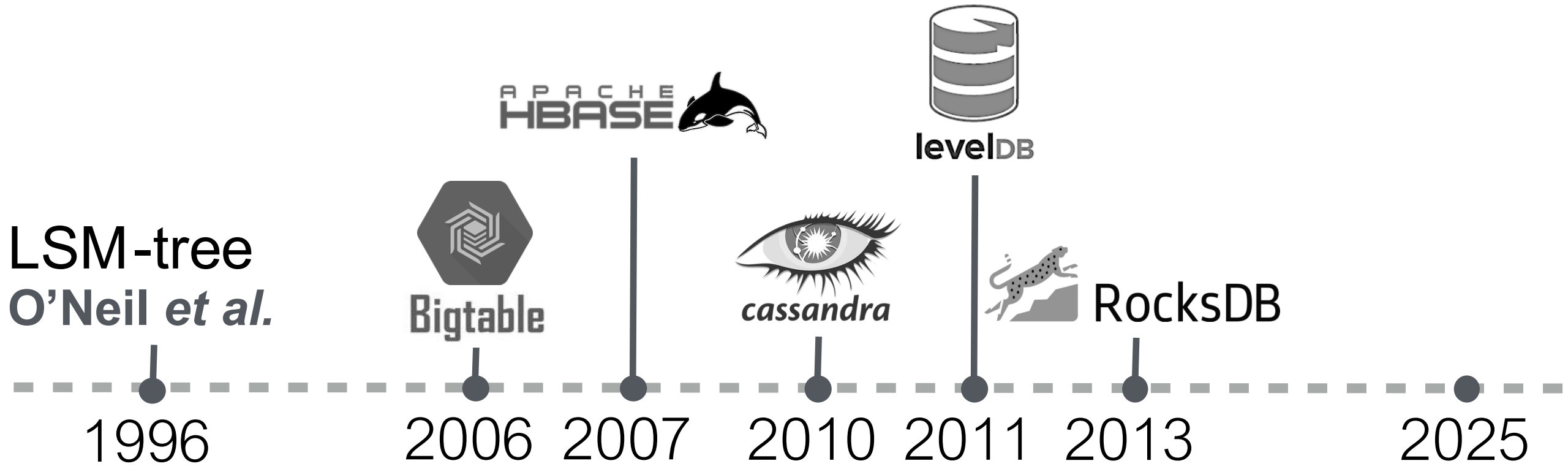
APACHE
HBASE
LSM-tree
O'Neil et al.
Bigtable
1996
2006
2007




LSM-tree
O'Neil *et al.*
1996
Bigtable
2006
APACHE HBASE
2007
cassandra
2010
levelDB
2011


LSM-tree
O'Neil et al.
1996
Bigtable
2006
APACHE HBASE
2007
cassandra
2010
levelDB
2011
RocksDB
2013


LSM-tree
O'Neil et al.
Bigtable
APACHE HBASE
cassandra
levelDB
RocksDB
1996
2006
2007
2010
2011
2013
2025


LSM-tree
O'Neil et al.
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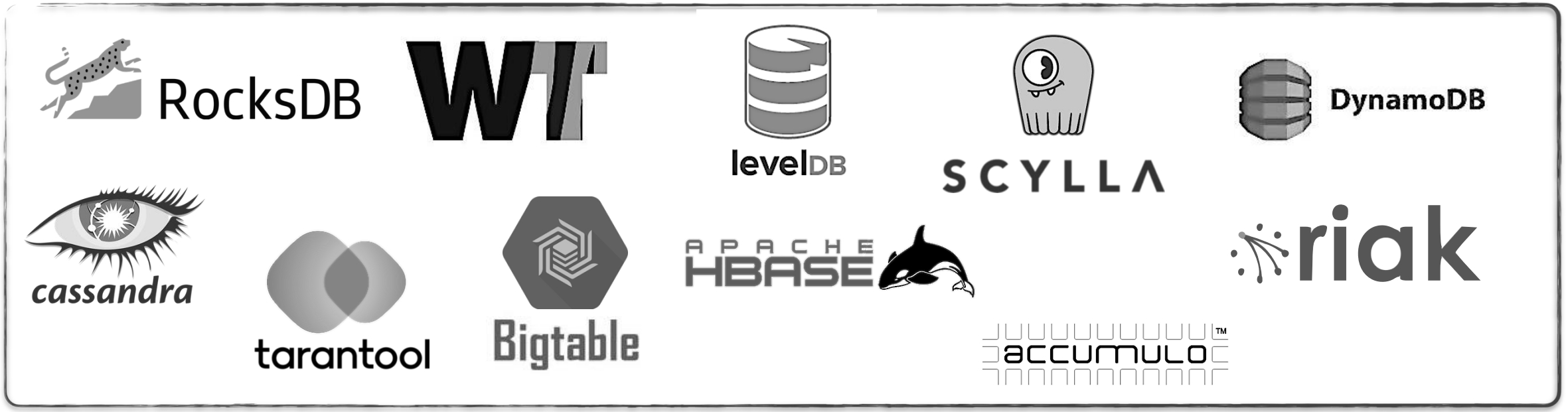
2025

LSM-tree

NoSQL



relational

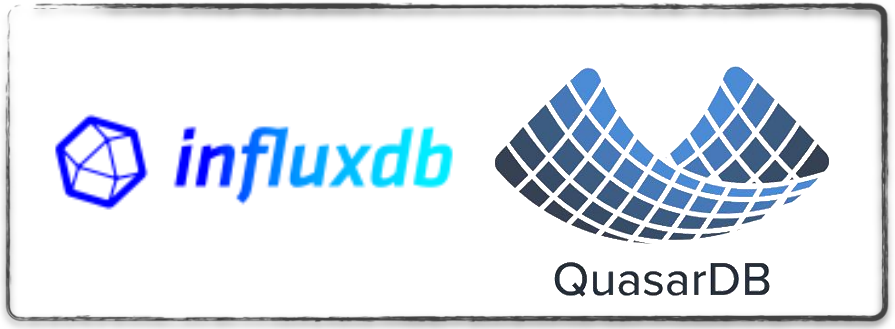
time-series

2025

LSM-tree

NoSQL

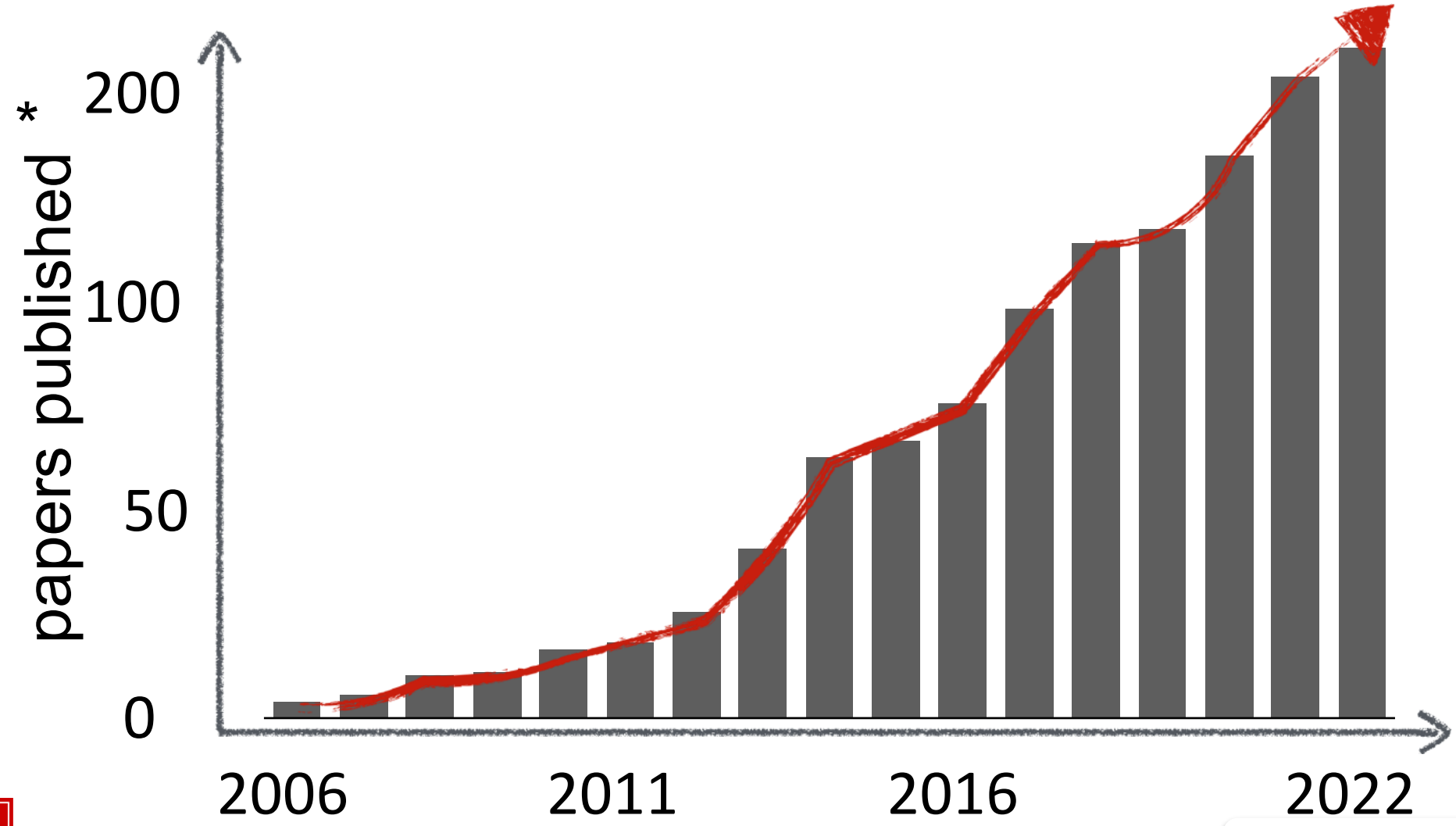
relational



time-series

2025

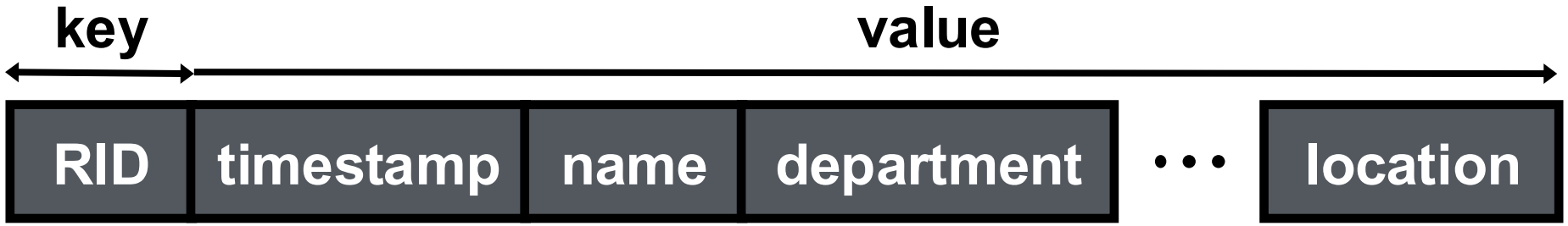
Research Trend



* data from Google scholar

LSM **Basics**

key-value
pairs

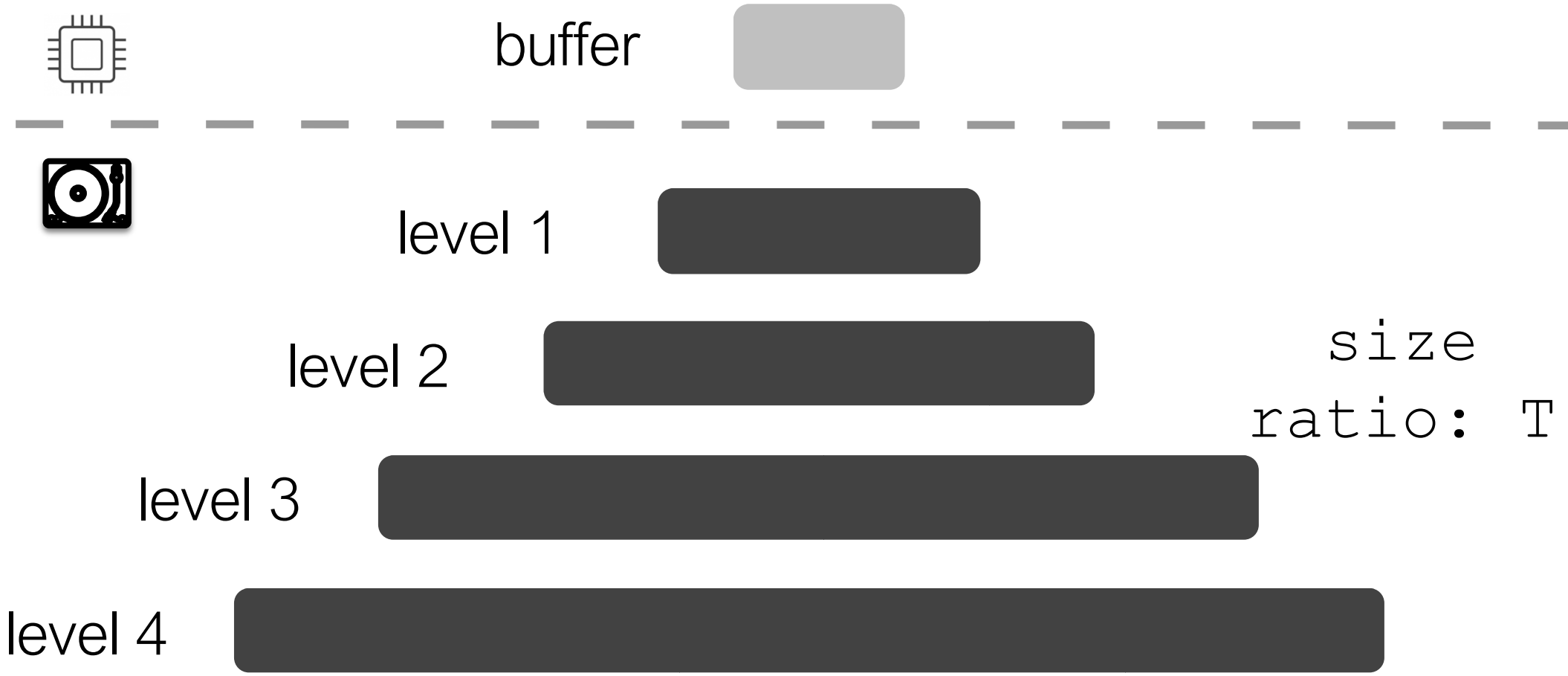


LSM **Basics**

`key-value pairs`

P: pages in buffer
B: entries/page
L: #levels
T: size ratio

LSM **Basics**



LSM Operating **Principles**

Buffering ingestion

Immutable files on storage

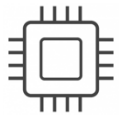
Out-of-place updates & deletes

Periodic data layout reorganization

Buffering ingestion

put(6)

put(2)

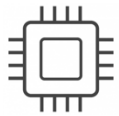


buffer

Buffering ingestion

put(1)

put(6)

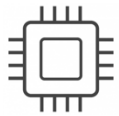


buffer 2

Buffering ingestion

put(4)

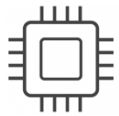
put(1)



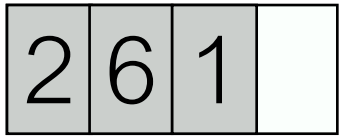
buffer 2 6

Buffering ingestion

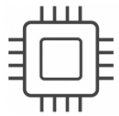
put(4)



buffer

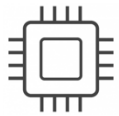


Buffering ingestion



buffer | 2 | 6 | 1 | 4 |

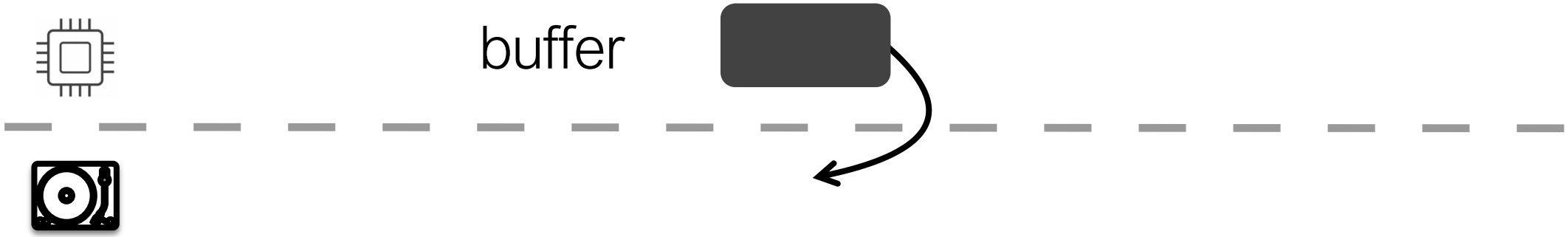
Buffering ingestion



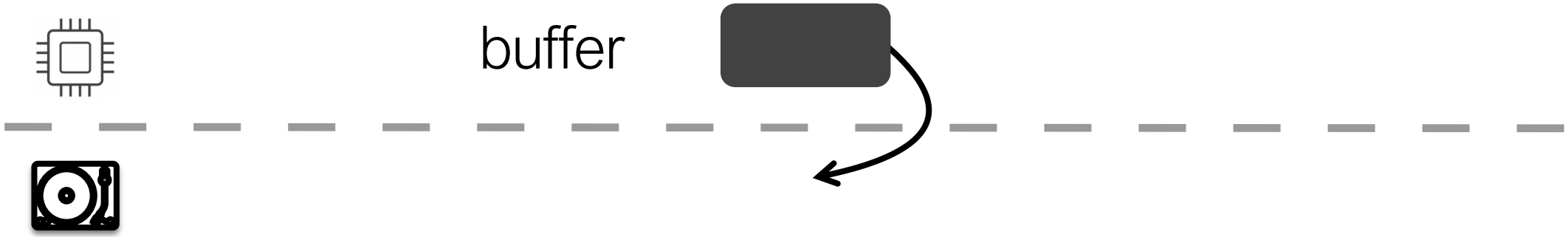
buffer

1	2	4	6

Buffering ingestion

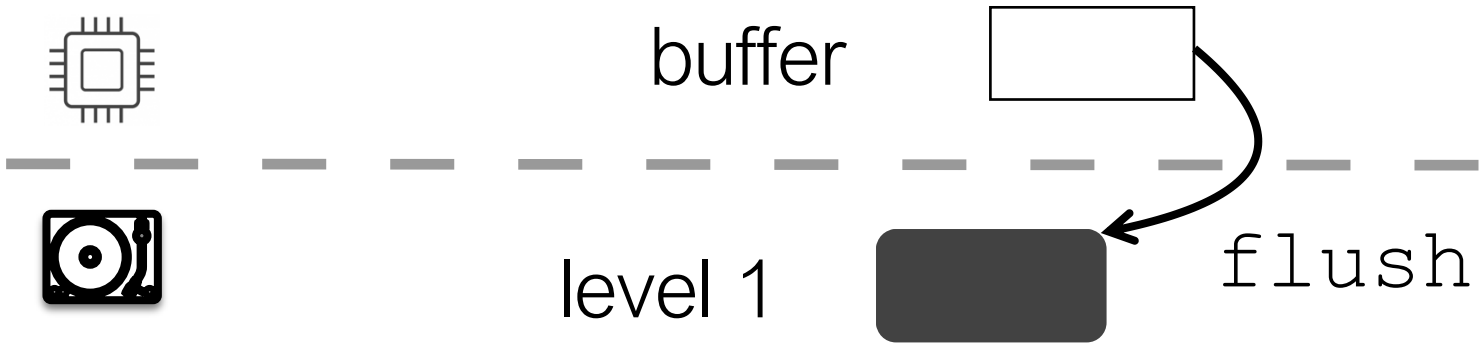


Buffering ingestion



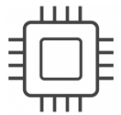
Buffering ingestion

- low ingestion cost
- fast temporal reads

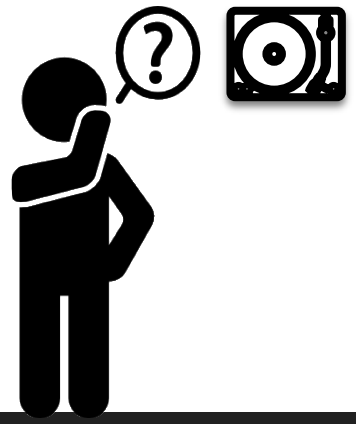


Immutable files on storage

- compact storage
- good ingestion throughput



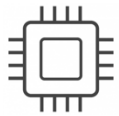
buffer



level 1

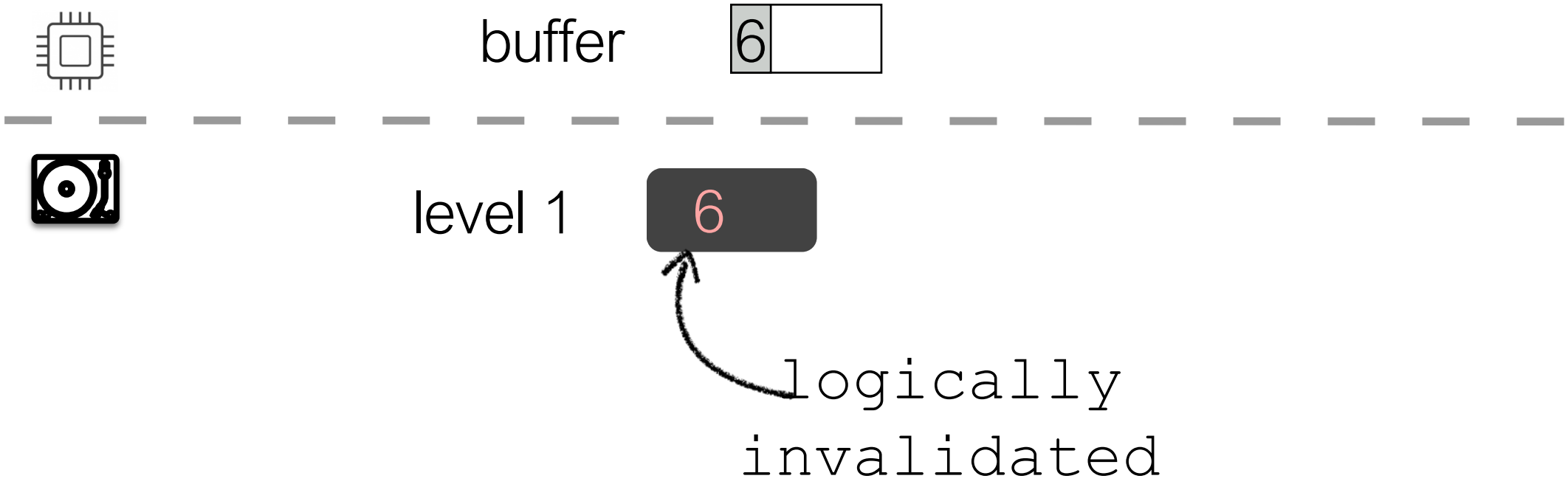
How do we update data?

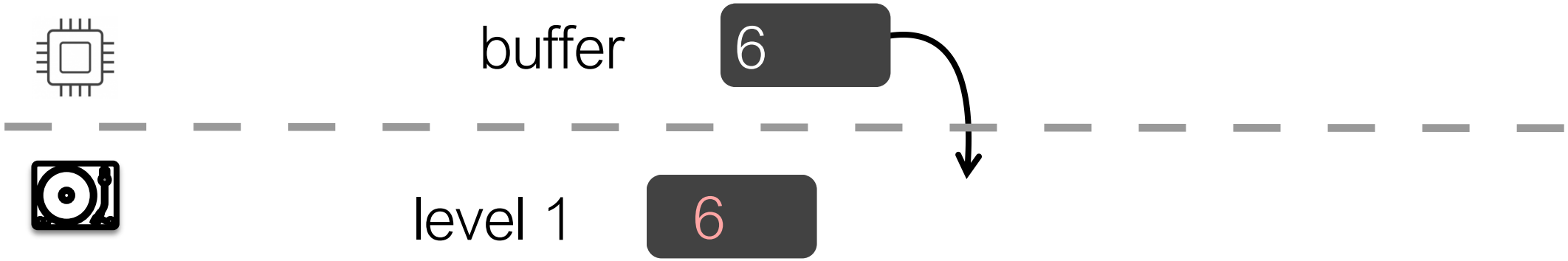
put(6)

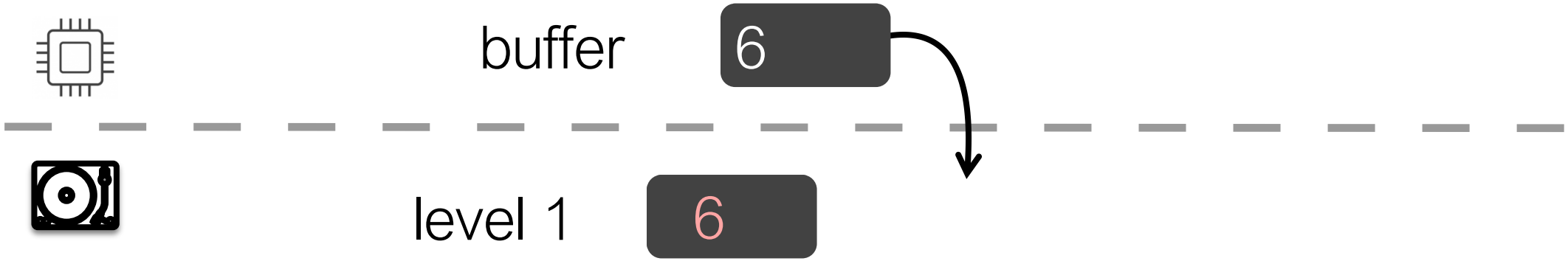


buffer

level 1 6

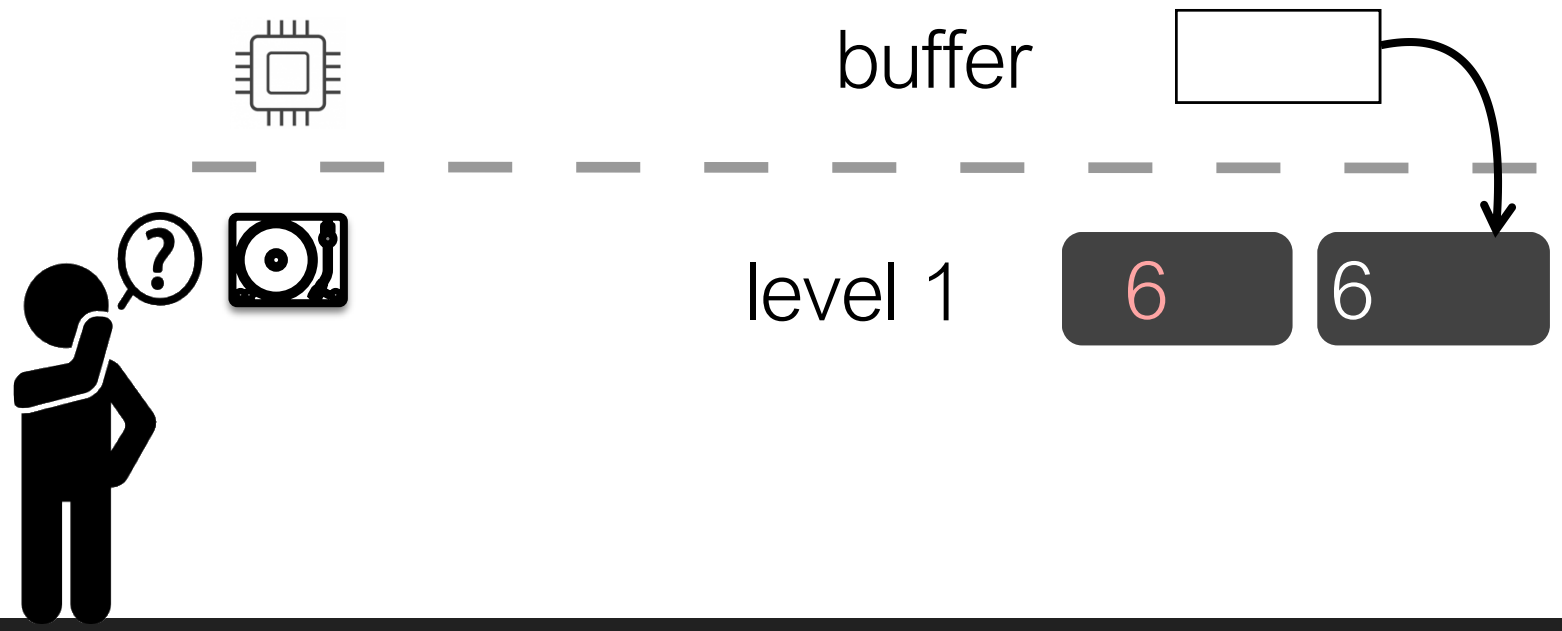




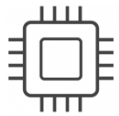


Out-of-place updates

- fast ingestion
- space amplification
- slow reads



How do we reduce this space amplification?

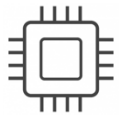


buffer

level 1

6

6

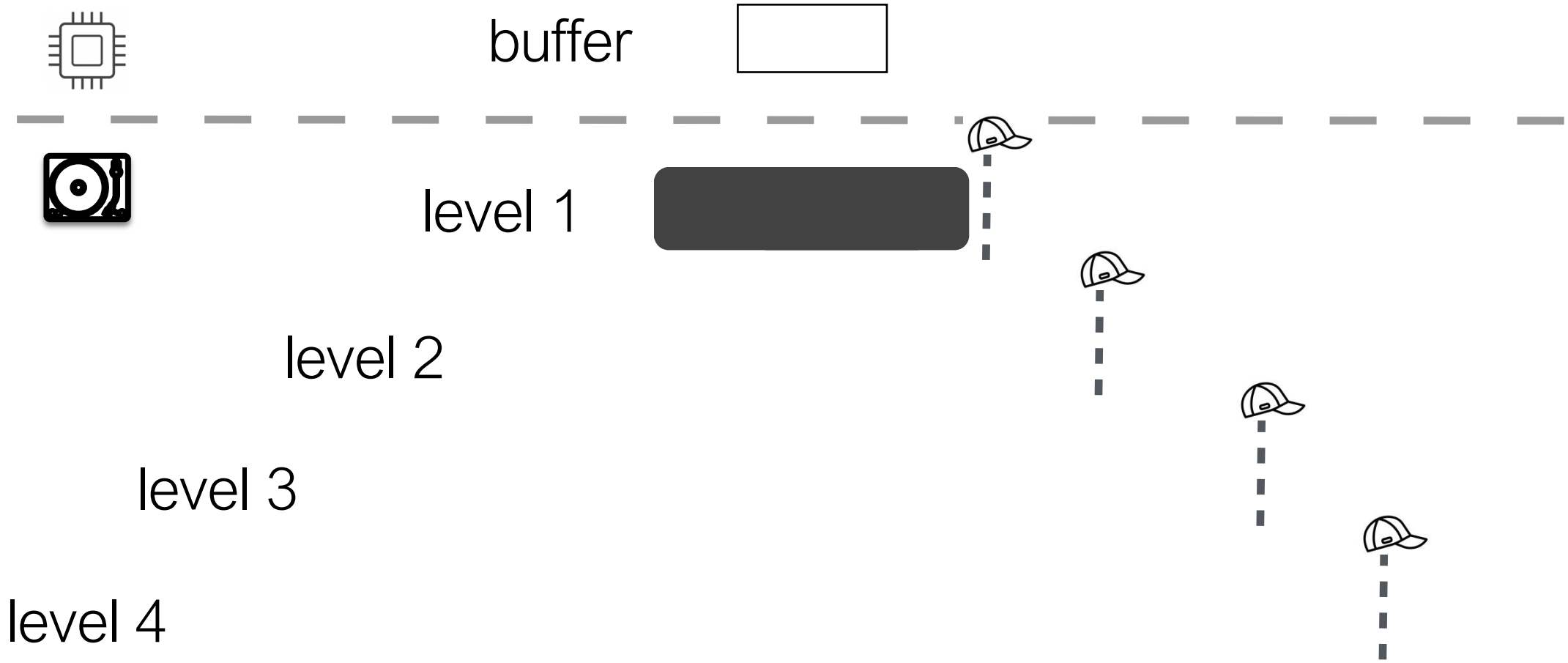


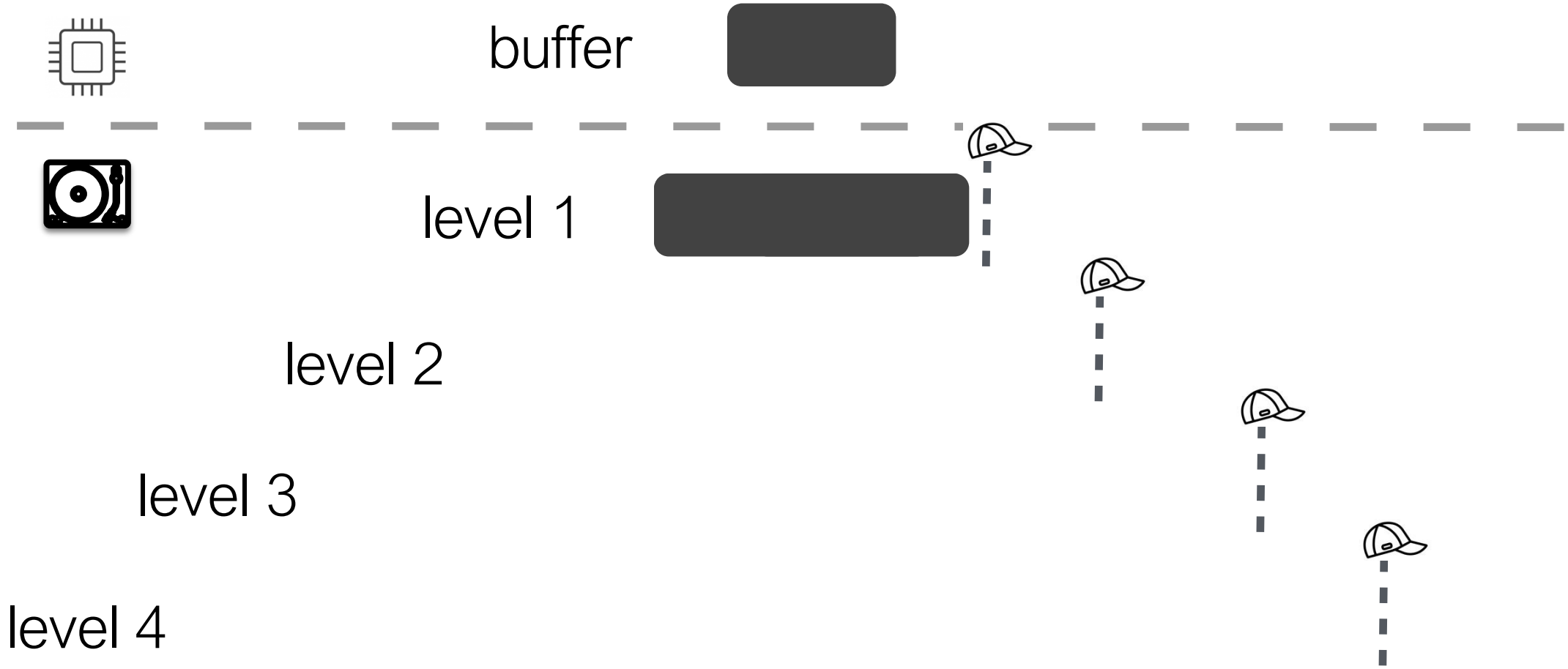
buffer

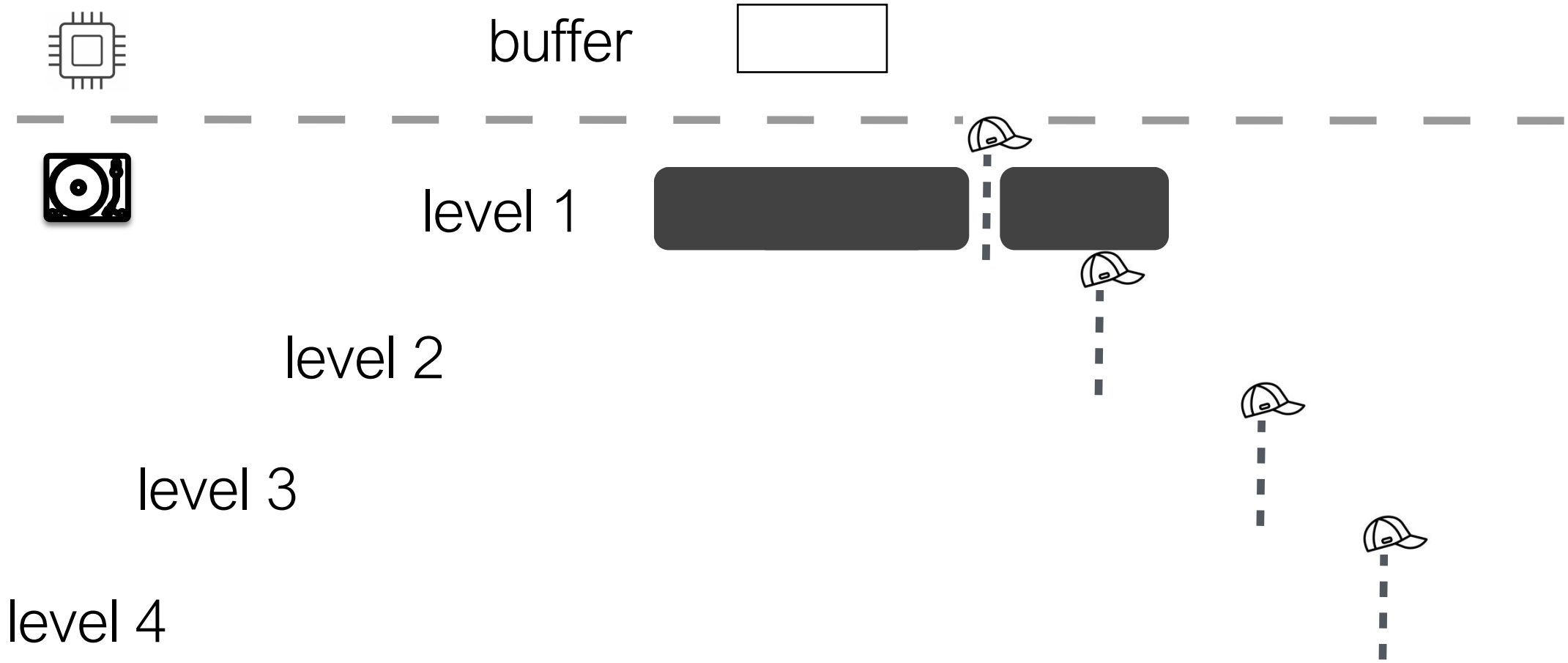
level 1

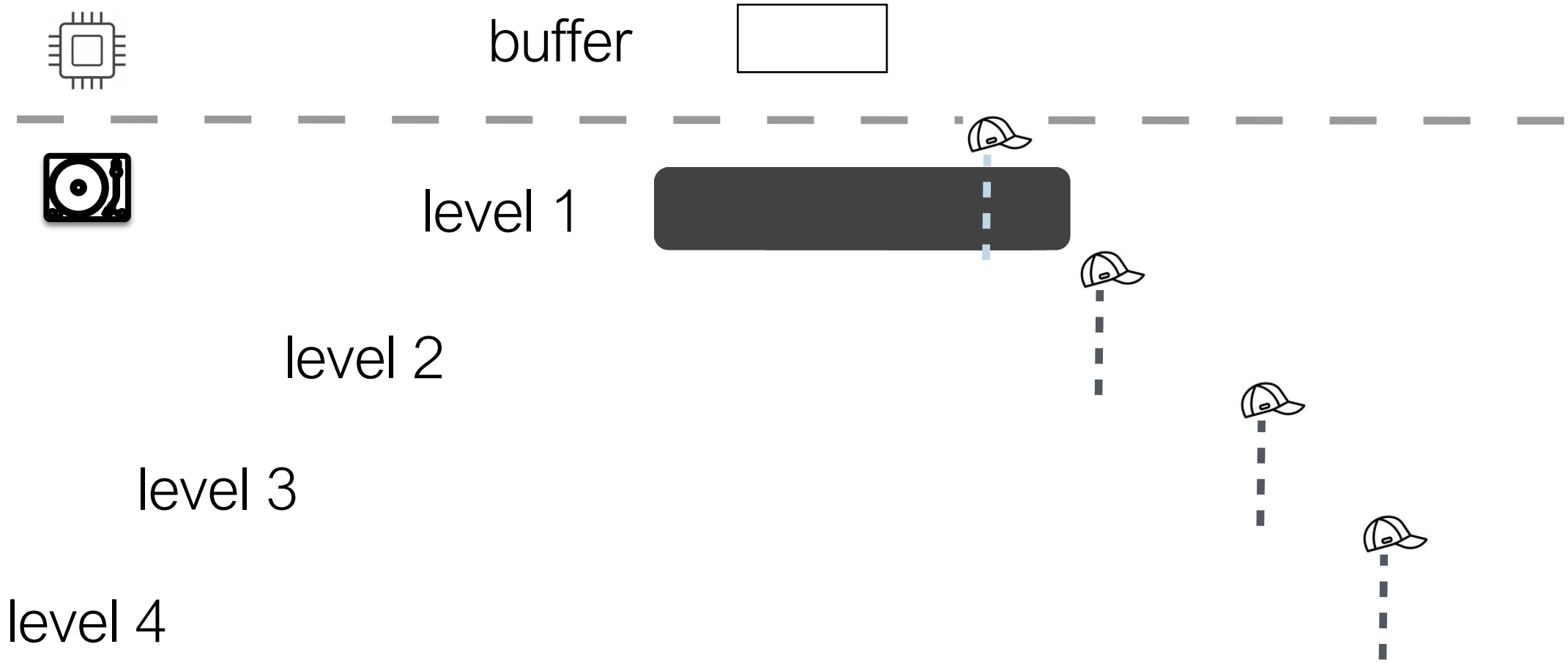
6

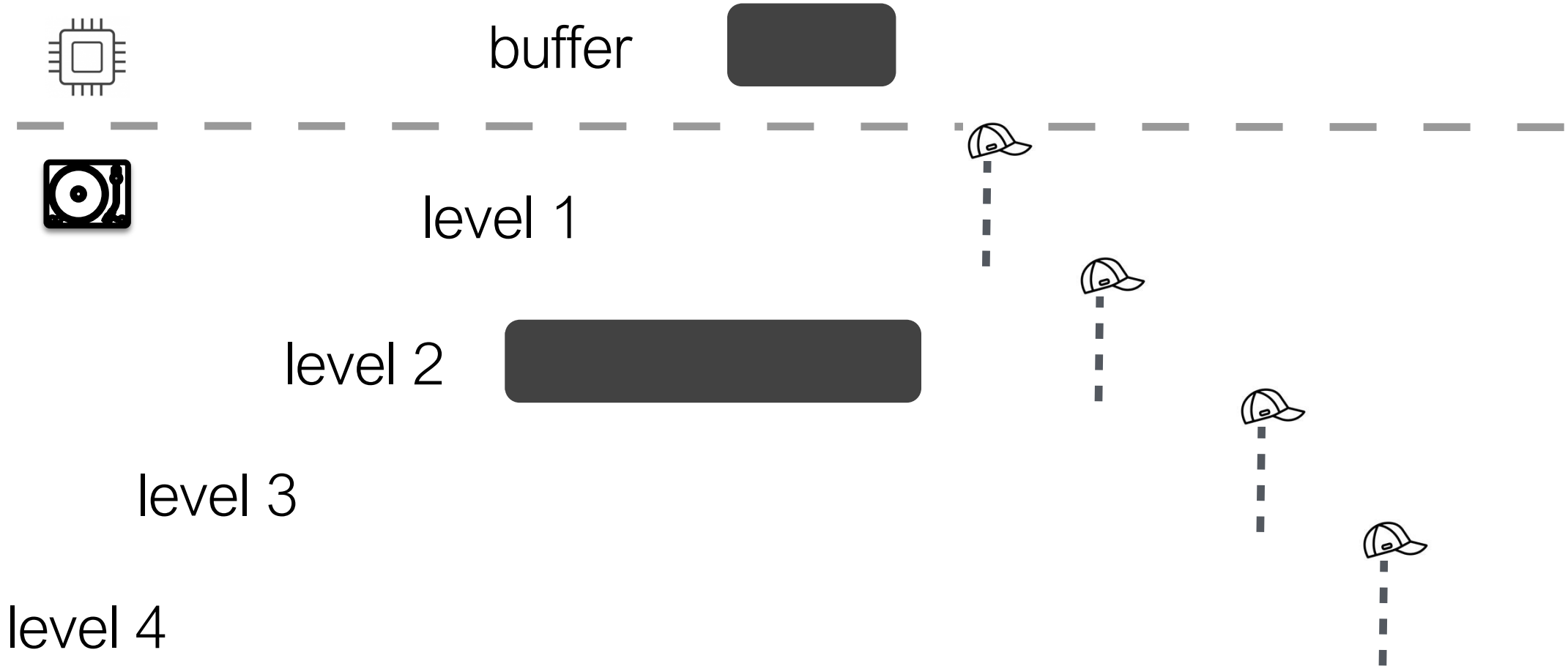
compaction

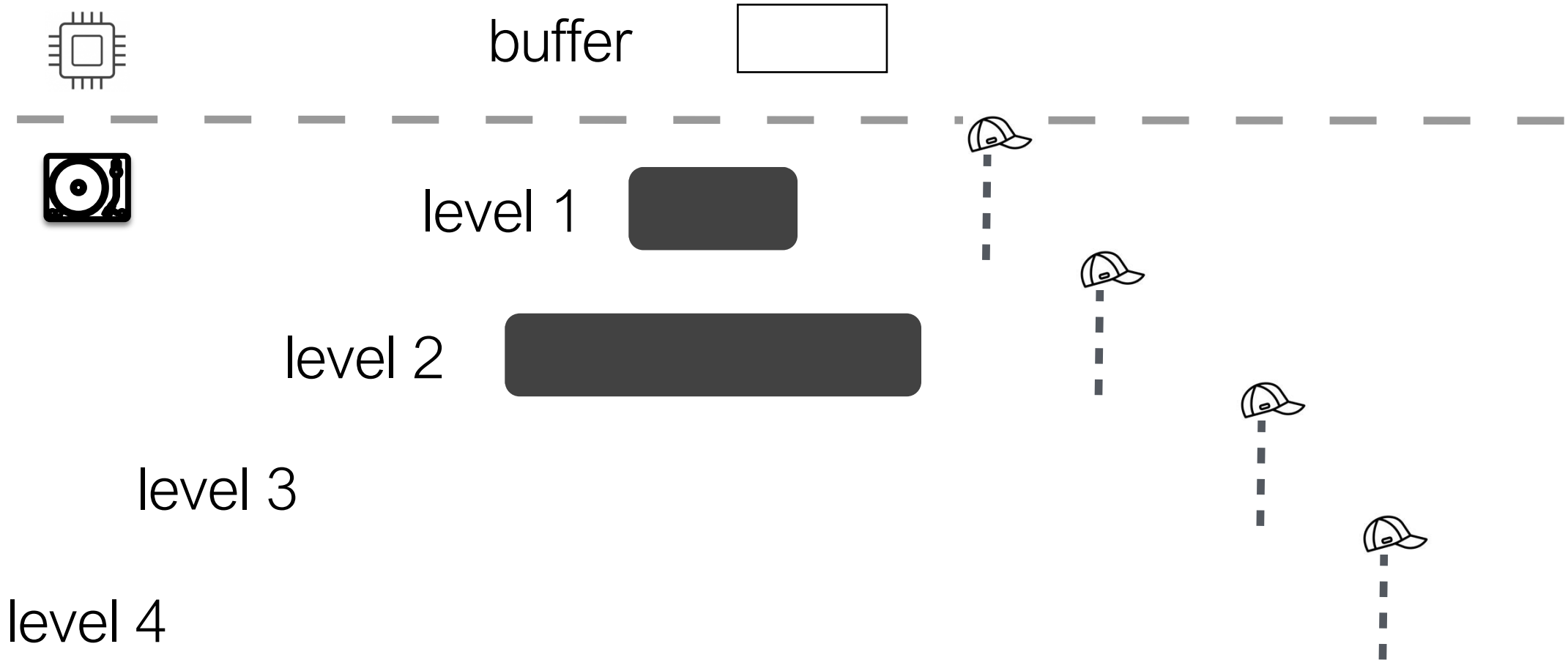


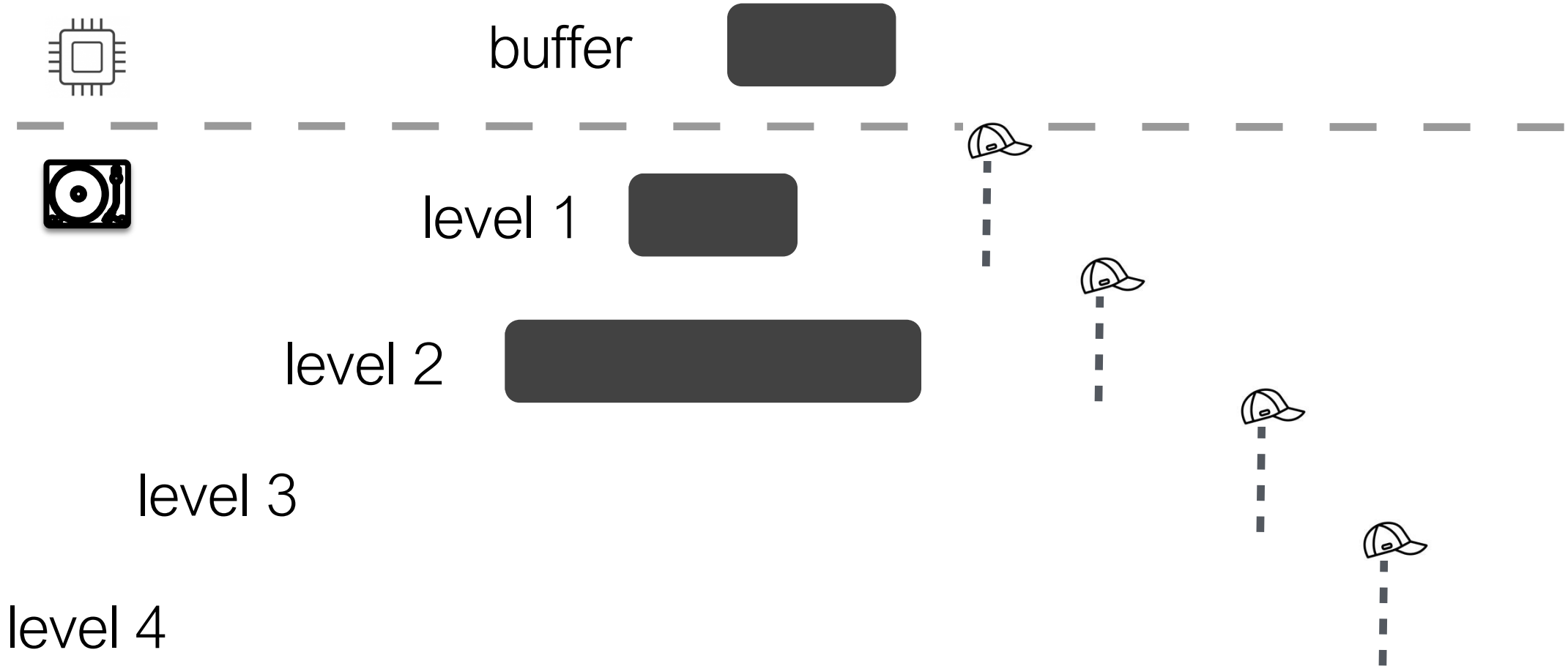


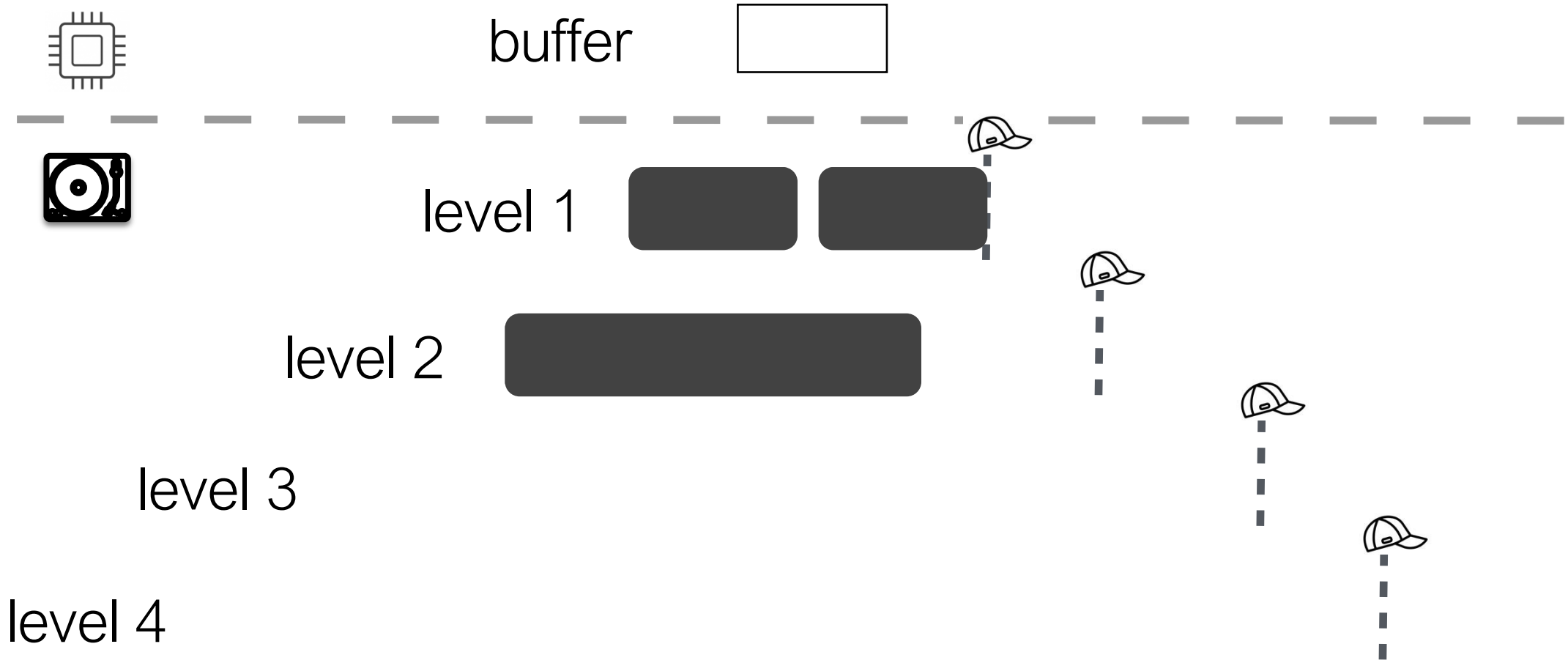


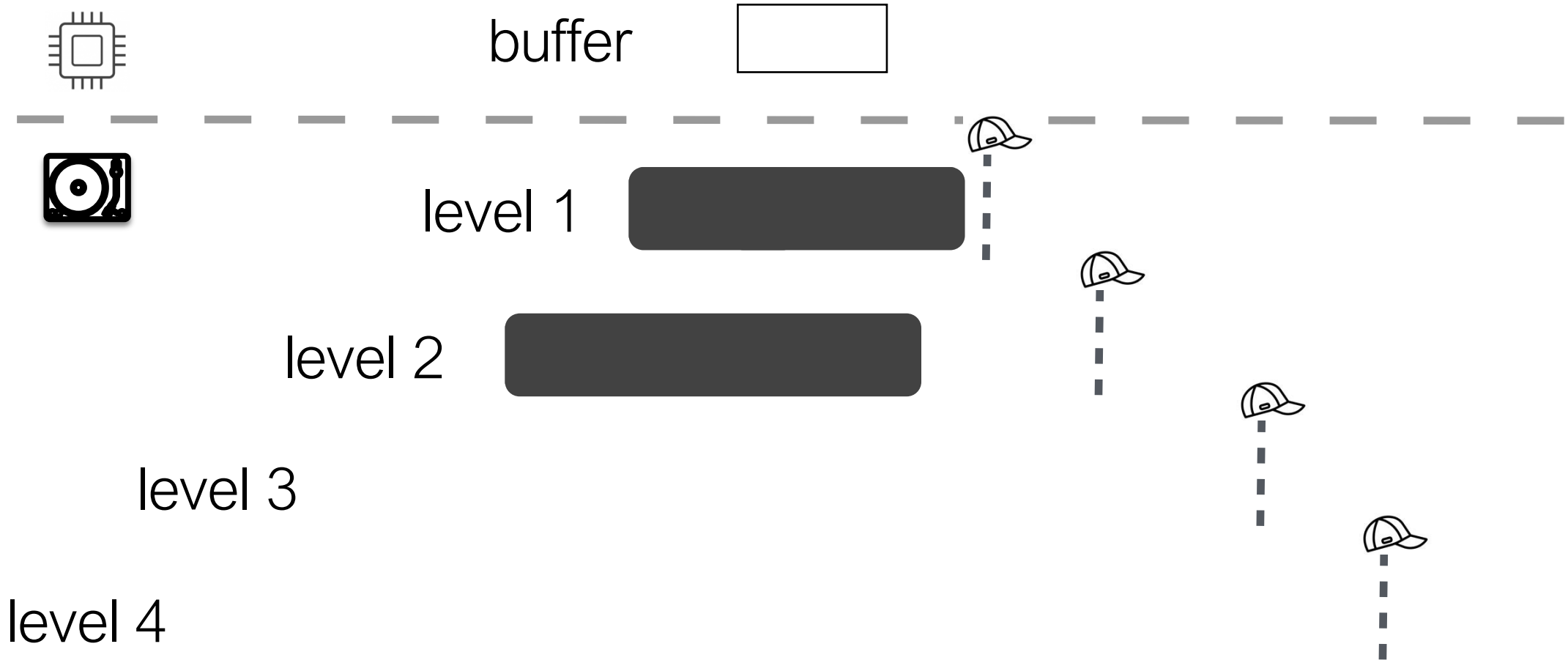


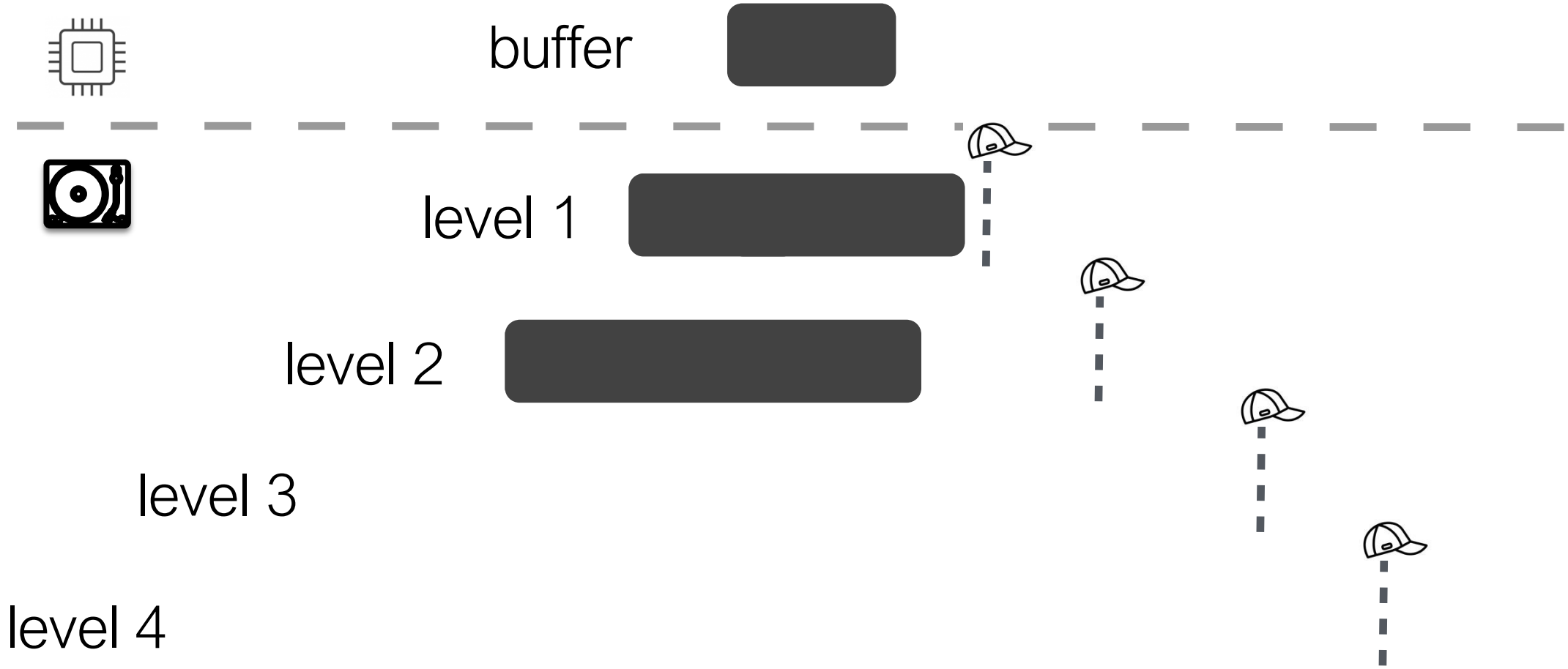


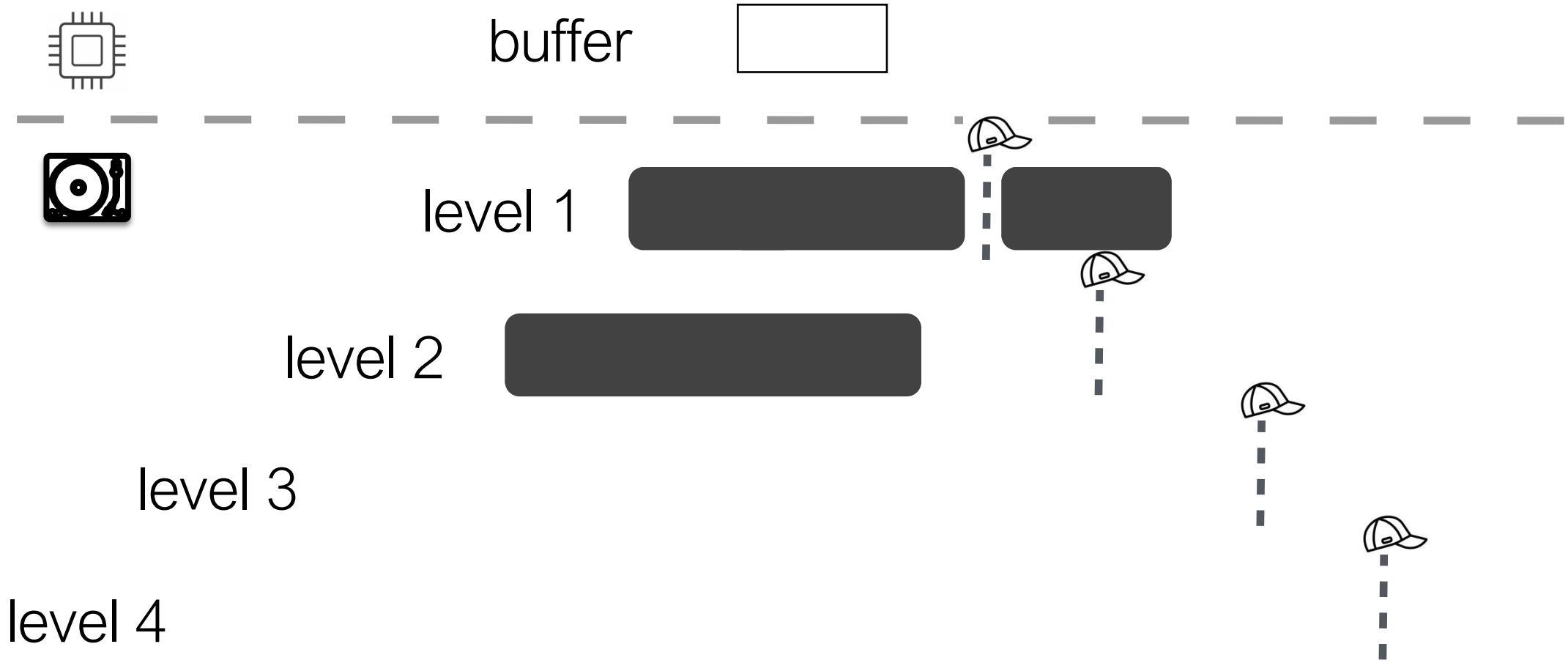


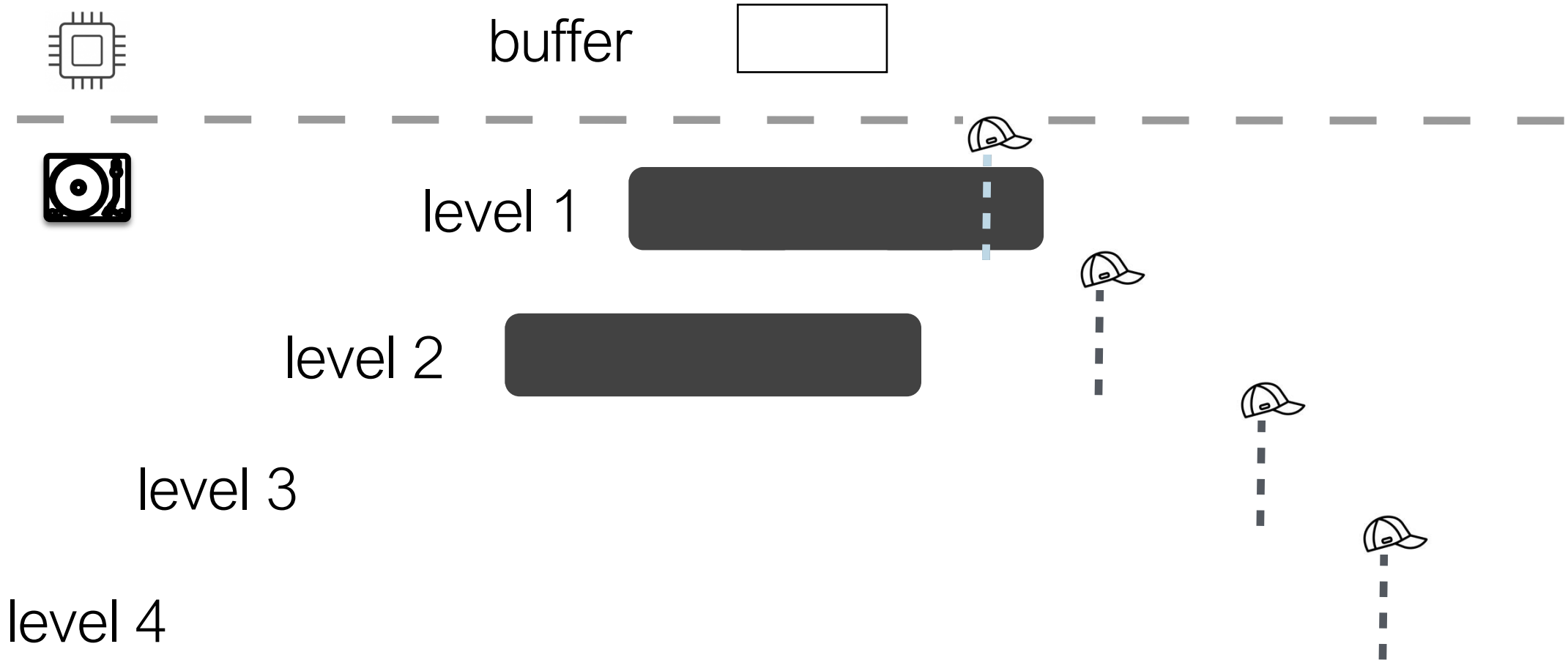


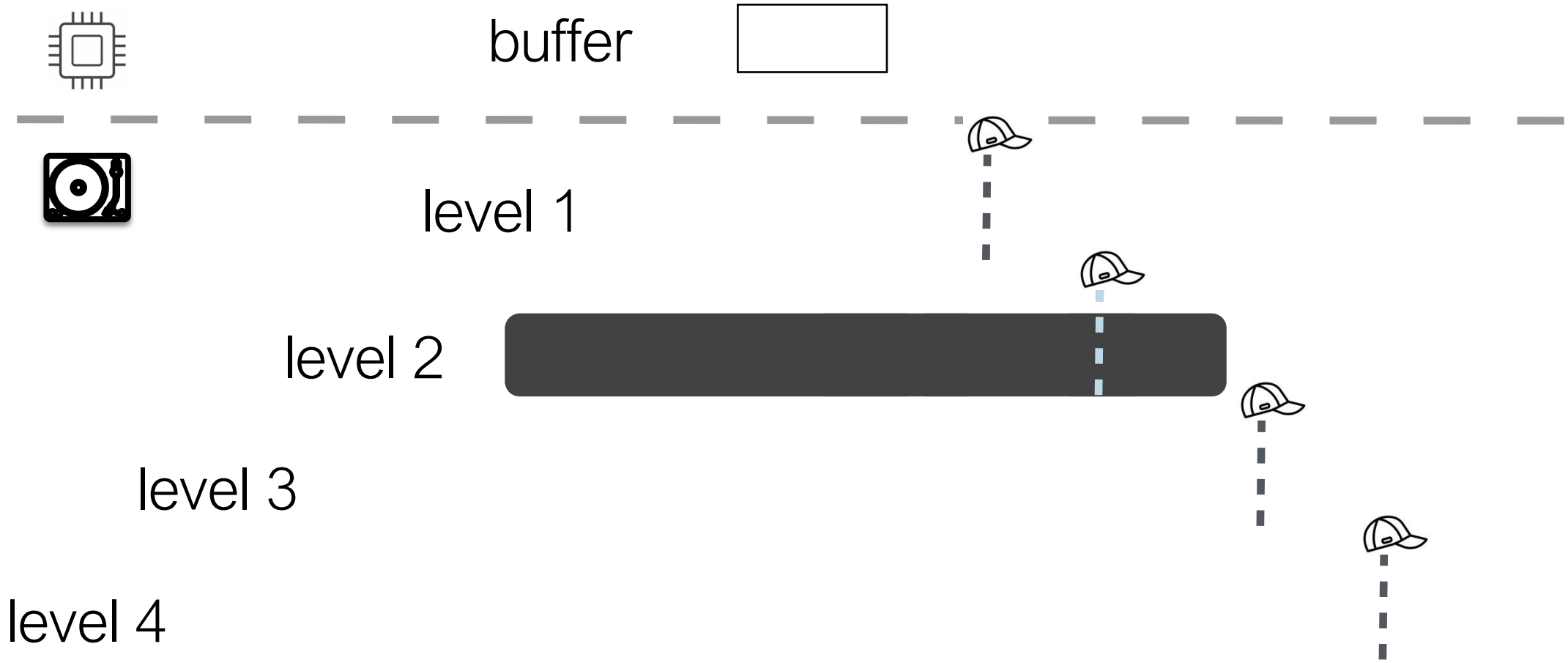


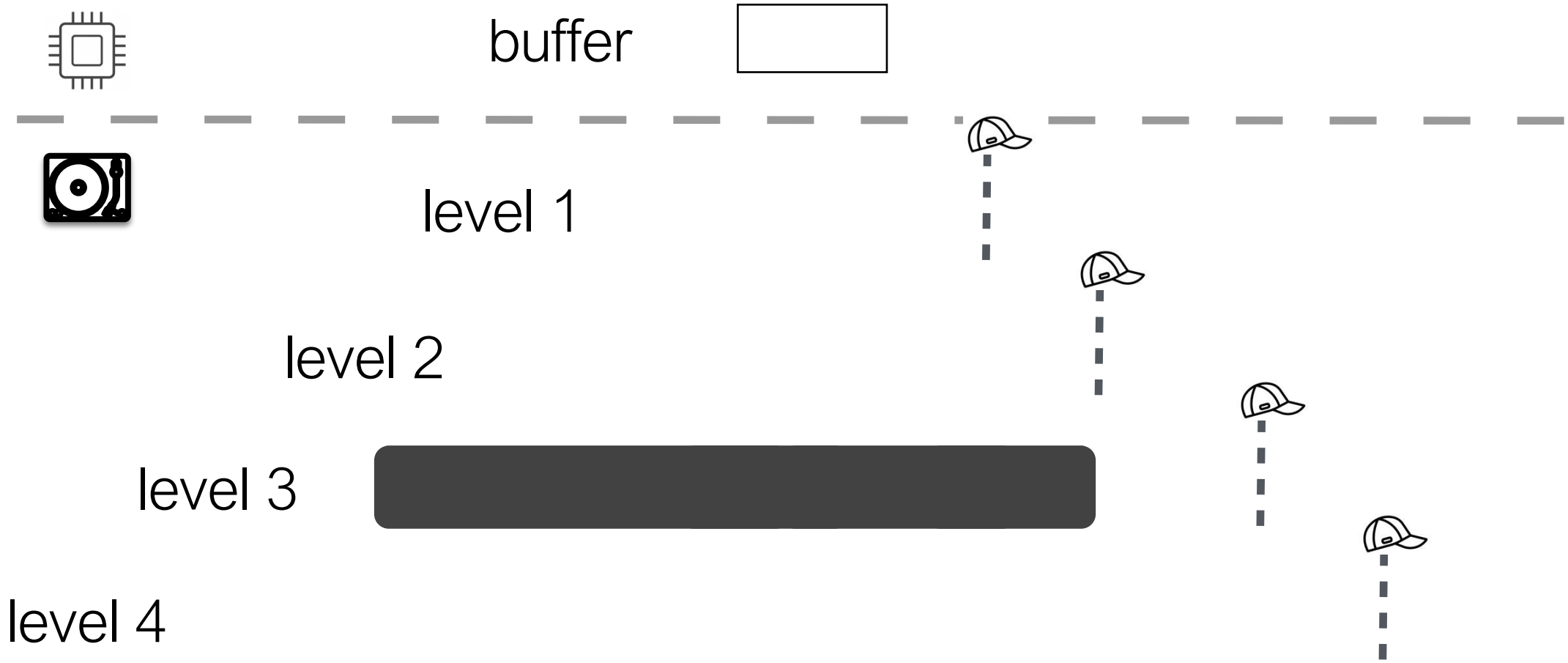








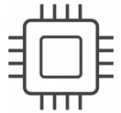




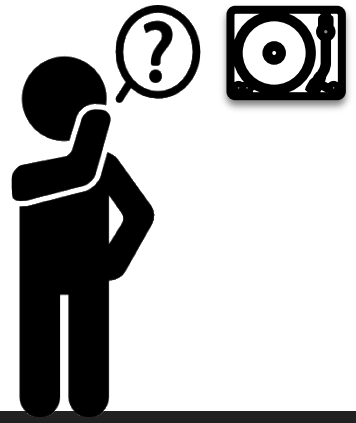
P: pages in buffer
B: entries/page
L: #levels
T: size ratio

Periodic compactions

- low space amplification
- makes reads better
- adds write amplification



buffer $P \cdot B$



level 1

$P \cdot B \cdot T$

level 2

$P \cdot B \cdot T^2$

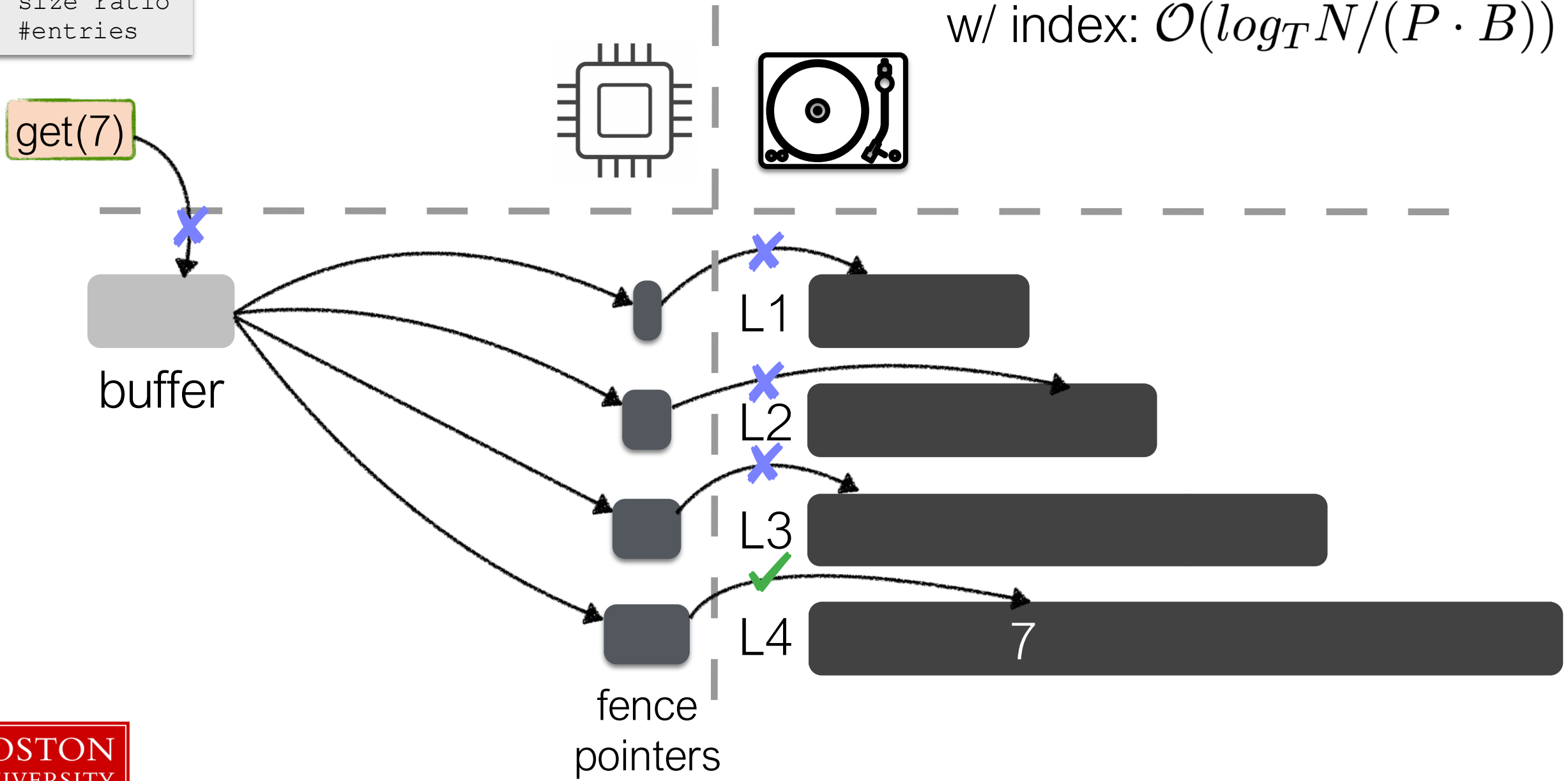
How about queries?

capacity (entries)

P: pages in buffer
B: entries/page
L: #levels
T: size ratio
N: #entries

Cost analysis

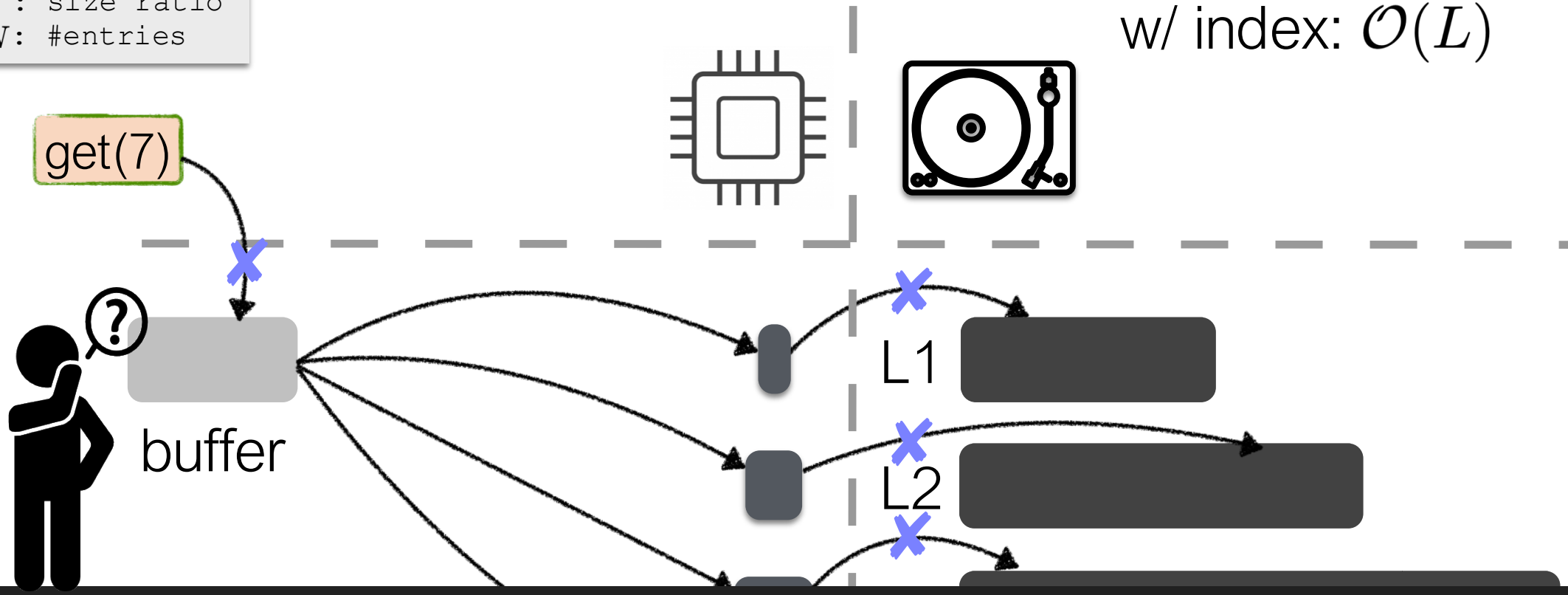
w/ index: $\mathcal{O}(log_T N/(P \cdot B))$



Cost analysis

P: pages in buffer
B: entries/page
L: #levels
T: size ratio
N: #entries

w/ index: $\mathcal{O}(L)$



How to avoid unnecessary I/Os?

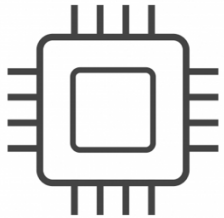
pointers

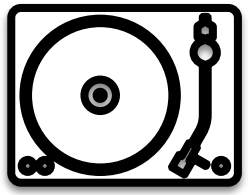
Cost analysis

P: pages in buffer
B: entries/page
L: #levels
T: size ratio
N: #entries
ϕ: FPR of BF

w/ index: $\mathcal{O}(L)$

w F&I: $\mathcal{O}(\phi \cdot L)$





get(7)

buffer

L1

L2

L3

L4

7

$$\phi = e^{-\frac{m_{BF}}{N} \cdot ln2^2}$$

Bloom filters

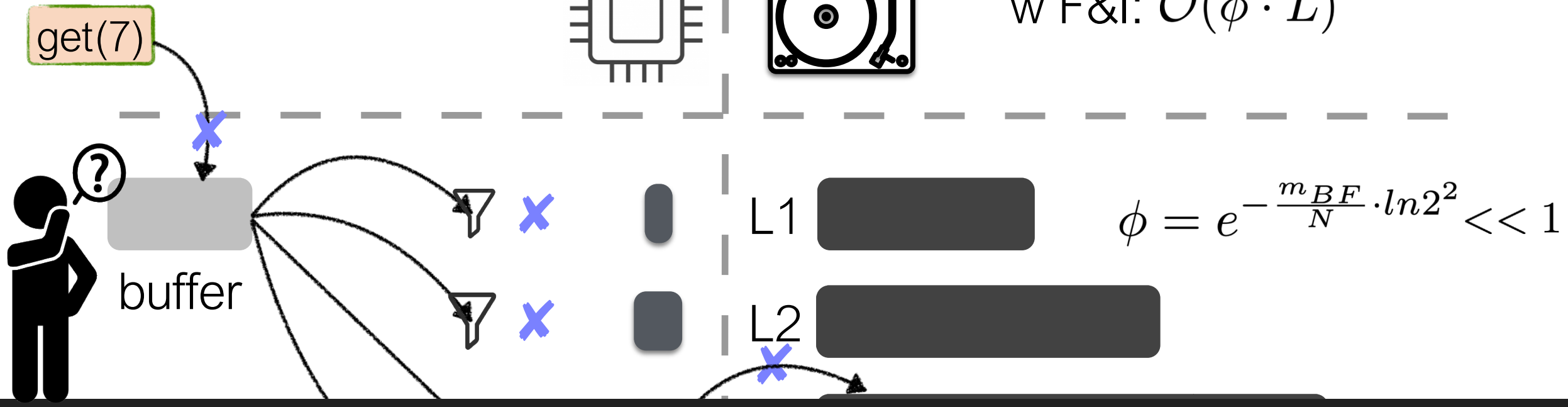
fence pointers

Cost analysis

P: pages in buffer
B: entries/page
L: #levels
T: size ratio
N: #entries
ϕ: FPR of BF

w/ index: $\mathcal{O}(L)$

w F&I: $\mathcal{O}(\phi \cdot L)$



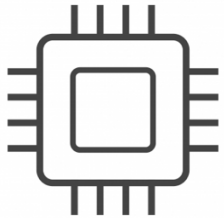
How to manage memory?

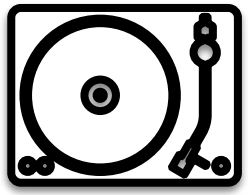
Bloom filters

fence pointers

P: pages in buffer
B: entries/page
L: #levels
T: size ratio
N: #entries
ϕ: FPR of BF

Cost analysis



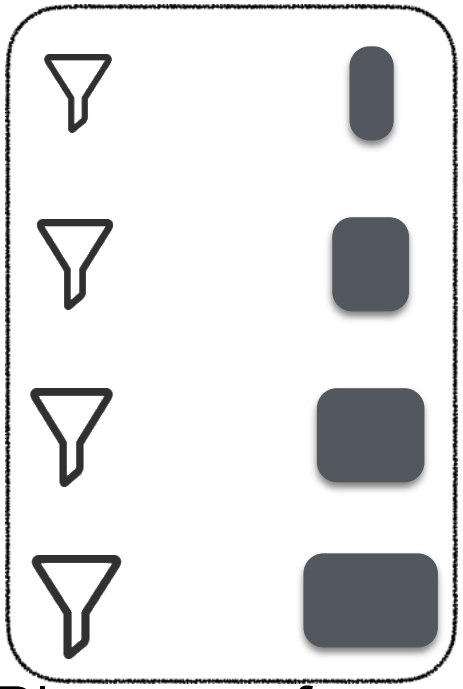


w/ index: $\mathcal{O}(L)$

w F&I: $\mathcal{O}(\phi \cdot L)$

buffer

block cache



Bloom filters

fence pointers

L1

L2

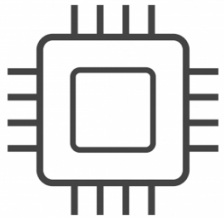
L3

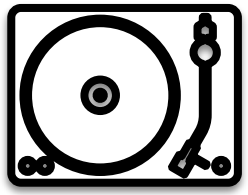
L4

$$\phi = e^{-\frac{m_{BF}}{N} \cdot ln2^2} << 1$$

P: pages in buffer
B: entries/page
L: #levels
T: size ratio
N: #entries
ϕ: FPR of BF

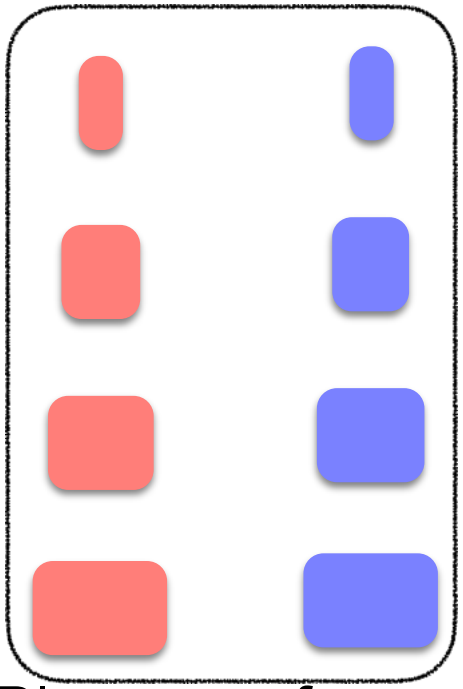
Block Cache





buffer

block cache



Bloom filters

fence pointers

L1

L2

L3

L4

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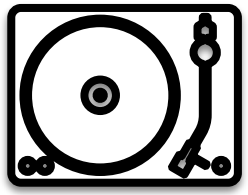
P: pages in buffer
B: entries/page
L: #levels
T: size ratio
N: #entries
ϕ: FPR of BF

Block Cache



Bloom filters

fence pointers

get(7)

buffer

L1

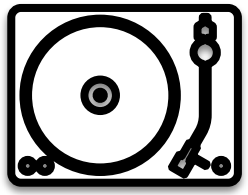
L2

L3

L4

P: pages in buffer
B: entries/page
L: #levels
T: size ratio
N: #entries
ϕ: FPR of BF

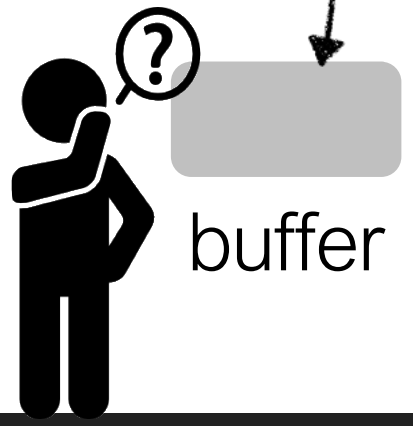
Block Cache



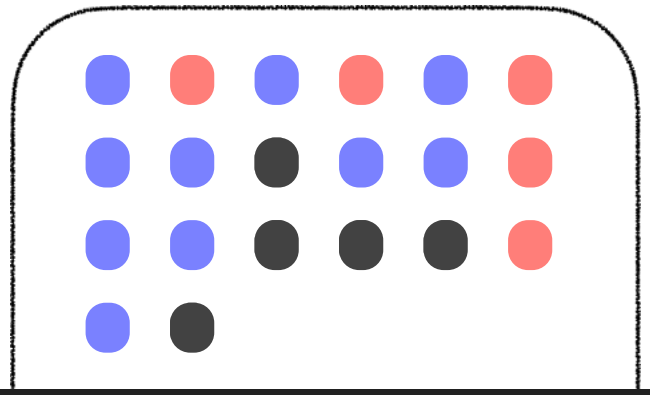
Bloom filters

fence pointers

get(7)



buffer



L1

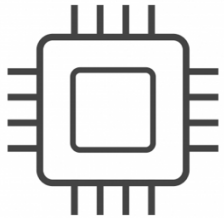
L2

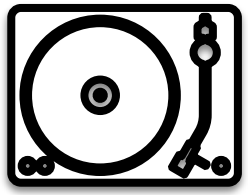
What about range queries?

P: pages in buffer
B: entries/page
L: #levels
T: size ratio
N: #entries
ϕ: FPR of BF

s selectivity
LRQ

Range Queries





buffer

Bloom filters

fence pointers

L1

L2

L3

L4

P: pages in buffer
B: entries/page
L: #levels
T: size ratio
N: #entries
ϕ: FPR of BF

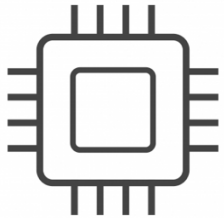
s selectivity

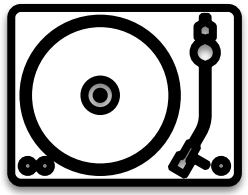
LRQ

Range Queries Cost analysis

long range: $\mathcal{O}(s \cdot N/B)$

get(9,90)





buffer

Bloom filters

fence pointers

L1

L2

L3

L4

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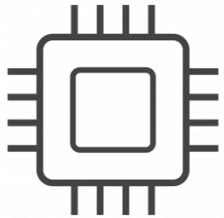
P: pages in buffer
B: entries/page
L: #levels
T: size ratio
N: #entries
ϕ: FPR of BF

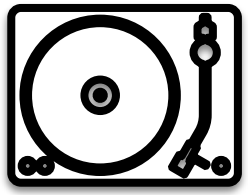
s selectivity
SRQ

Range Queries Cost analysis

long range: $\mathcal{O}(s \cdot N/B)$
short range: $\mathcal{O}(L)$

get(9,15)





buffer

L1

L2

L3

L4

Bloom filters

fence pointers

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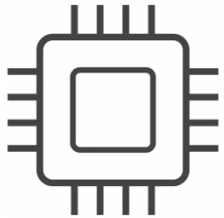
P: pages in buffer
B: entries/page
L: #levels
T: size ratio
N: #entries
ϕ: FPR of BF

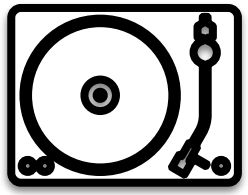
Going back to point queries

Cost analysis

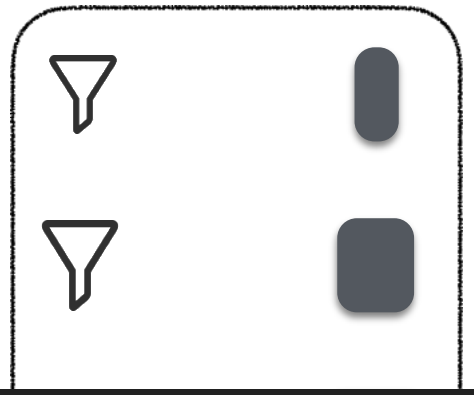
w/ index: $\mathcal{O}(L)$

w F&I: $\mathcal{O}(\phi \cdot L)$





buffer



L1

L2

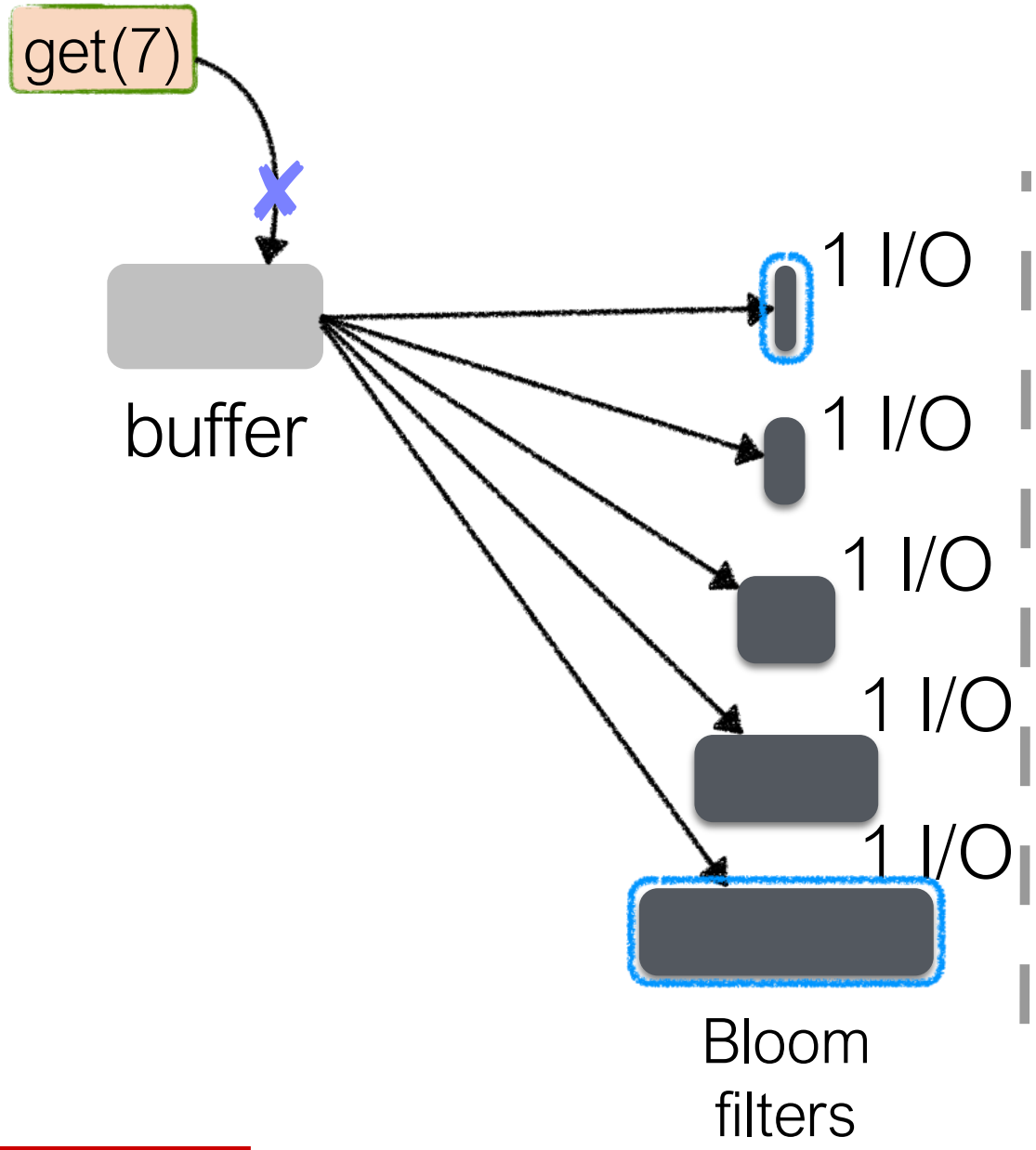
$$\phi = e^{-\frac{m_{BF}}{N} \cdot ln2^2} << 1$$

Should all BFs be equally accurate?

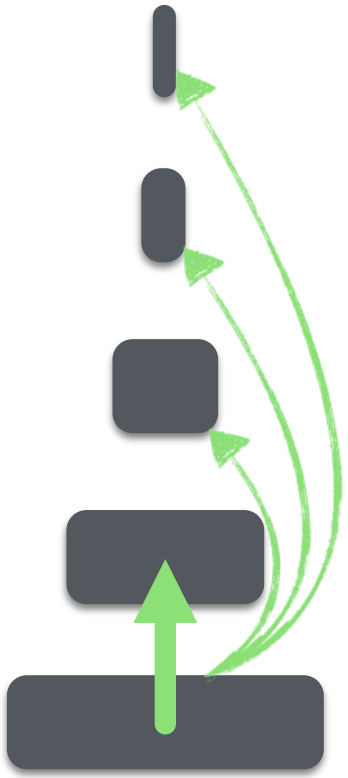
Bloom filters

fence pointers

Insight: most of the memory allocated to BFs is helping us save only 1 I/O (90% for T=10)



Bloom filters



FPR

Monkey FPR

$$\phi > \phi_1 = \phi_0/T^4$$

$$\phi > \phi_2 = \phi_0/T^3$$

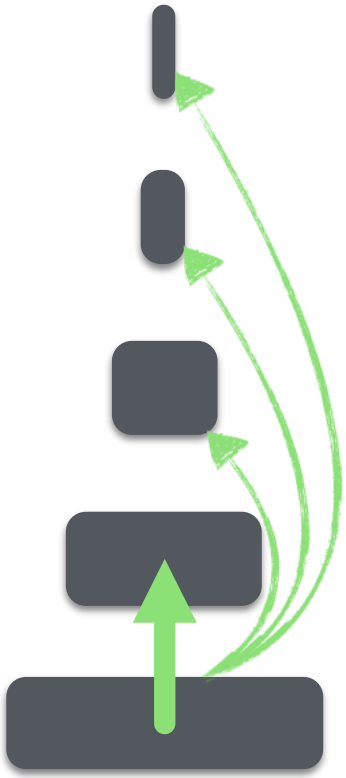
$$\phi > \phi_3 = \phi_0/T^2$$

$$\phi > \phi_4 = \phi_0/T$$

$$\phi < \phi_5 = \phi_0$$

exponentially decreasing

Bloom filters



FPR		Monkey FPR
ϕ	$>$	$\phi_1 = \phi_0/T^4$
ϕ	$>$	$\phi_2 = \phi_0/T^3$
ϕ	$>$	$\phi_3 = \phi_0/T^2$
ϕ	$>$	$\phi_4 = \phi_0/T$
ϕ	$<$	$\phi_5 = \phi_0$

exponentially decreasing

$$L \cdot \phi \qquad \sum_i \phi_i = c \cdot \phi_0$$

point lookup cost

$$\mathcal{O}(L \cdot \phi)$$

$$\vee$$

$$\mathcal{O}(c \cdot \phi_0)$$

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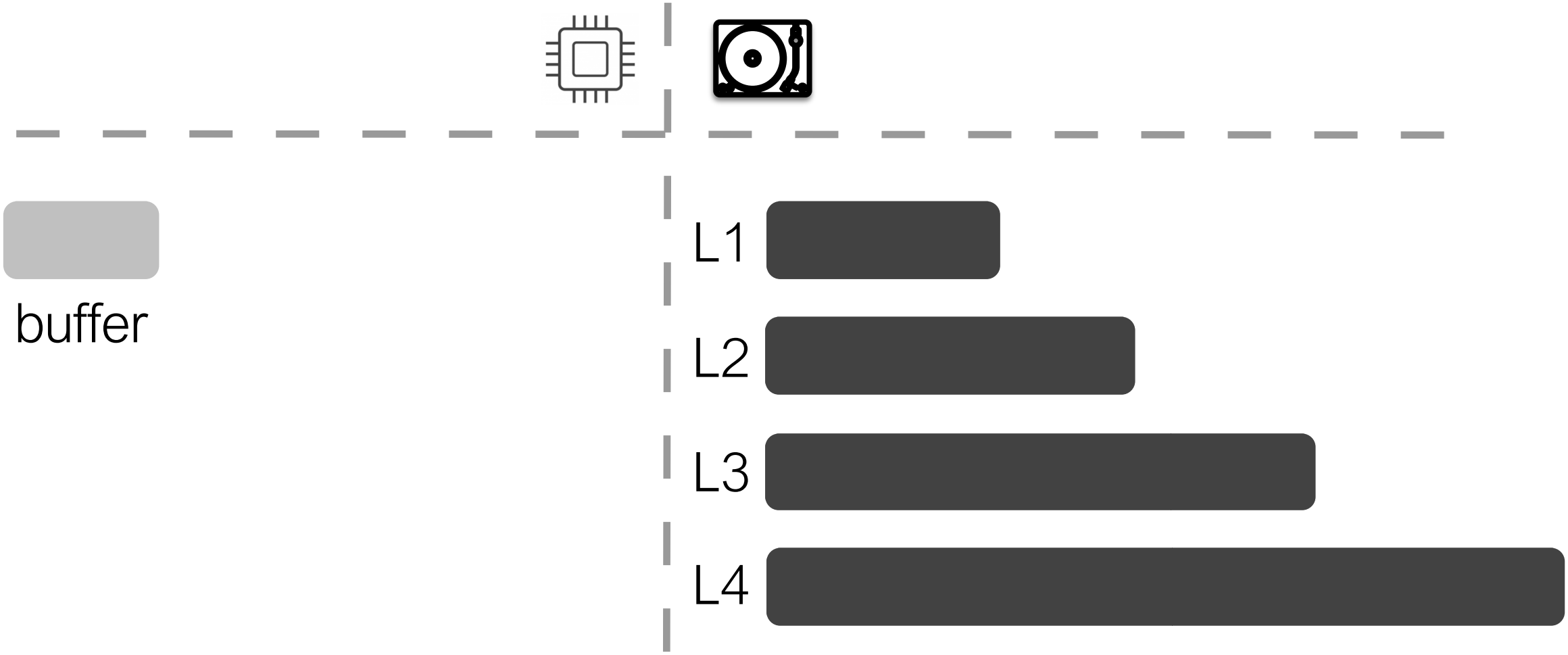
DayanSIGMOD17

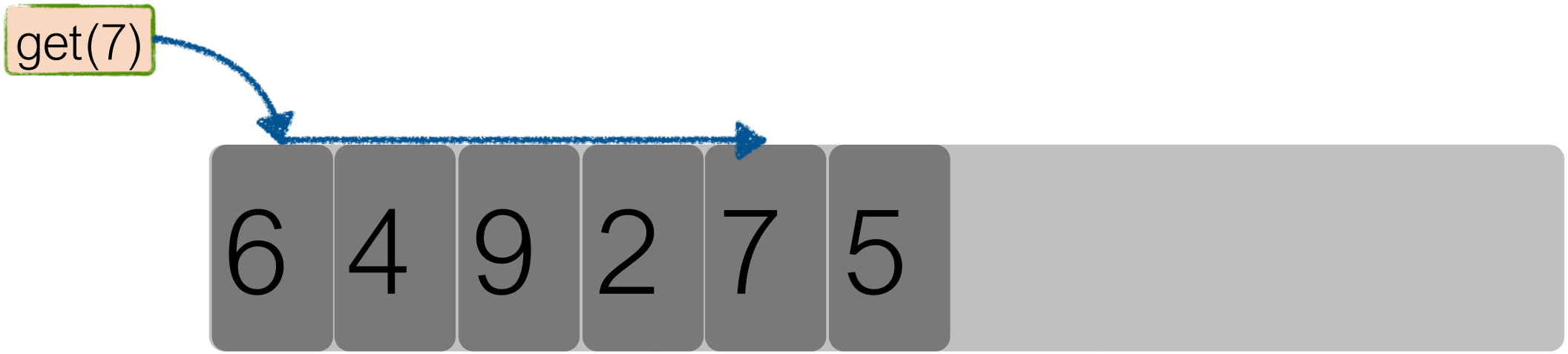
Buffer Optimizations

Buffer Optimizations



P: pages in buffer
B: entries/page

Buffer Implementation: **vector**



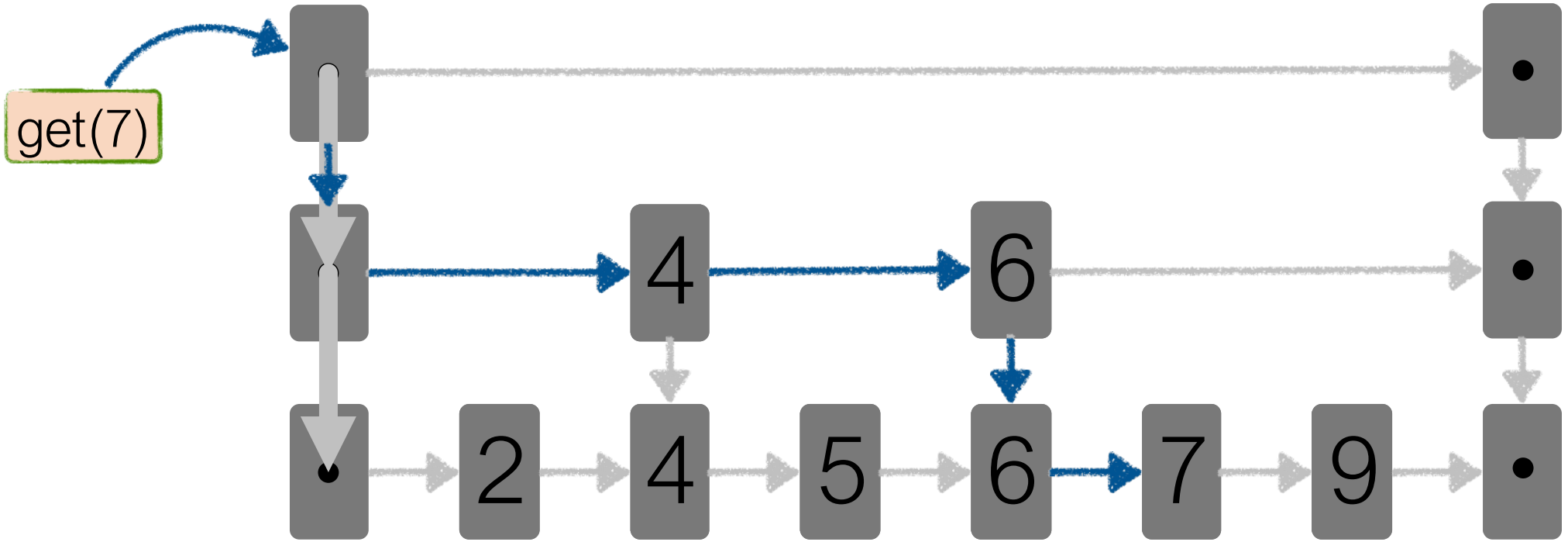
- great for ingestion-heavy w/l
- no extra space needed
- expensive points queries

ingestion cost: $\mathcal{O}(1)$

space complexity: $\mathcal{O}(P \cdot B)$

point query cost: $\mathcal{O}(P \cdot B)$

Buffer Implementation: **skiplist**



- great for mixed w/I
- some extra space needed
- good for points queries

P: pages in buffer
B: entries/page

Buffer Implementation

	vector	skiplist	hashmap
ingestion cost	$\mathcal{O}(1)$	$\mathcal{O}(log(P \cdot B))$	$\mathcal{O}(1)$
space complexity	$\mathcal{O}(P \cdot B)$	$\mathcal{O}(P \cdot B)$	$\mathcal{O}(P \cdot B)$
point query cost	$\mathcal{O}(P \cdot B)$	$\mathcal{O}(log(P \cdot B))$	$\mathcal{O}(1)$

Ingestion-only workloads

Mixed workloads

I/O-bound workloads

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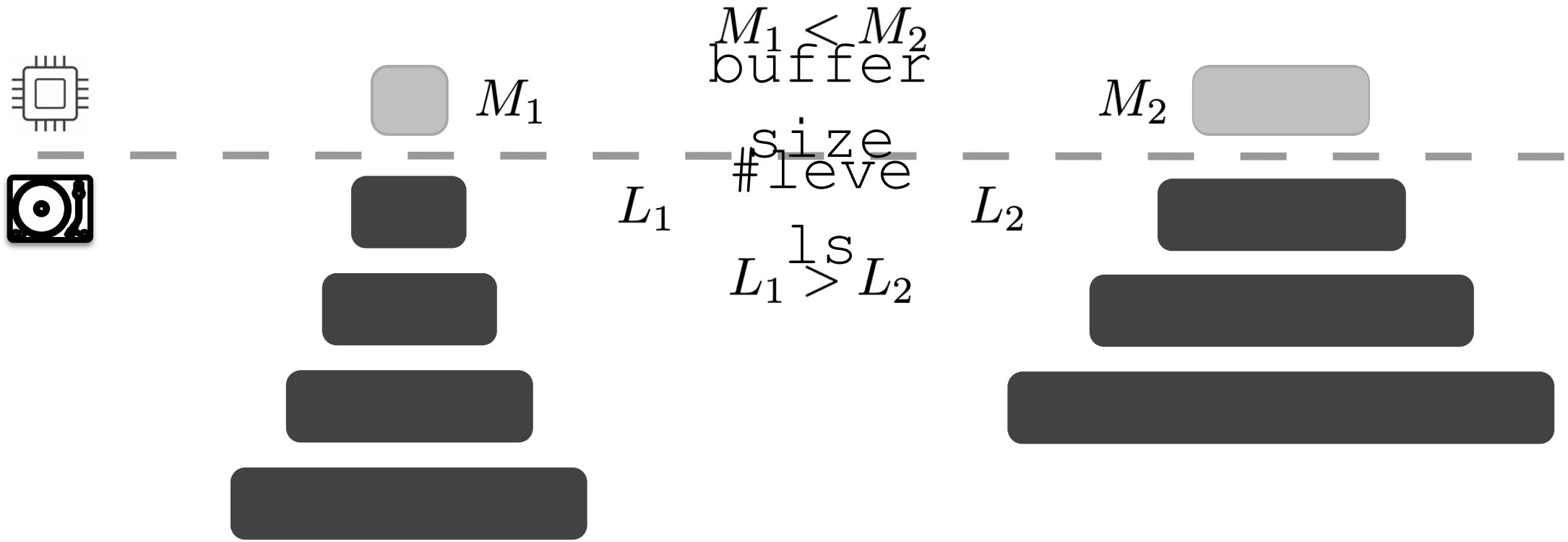
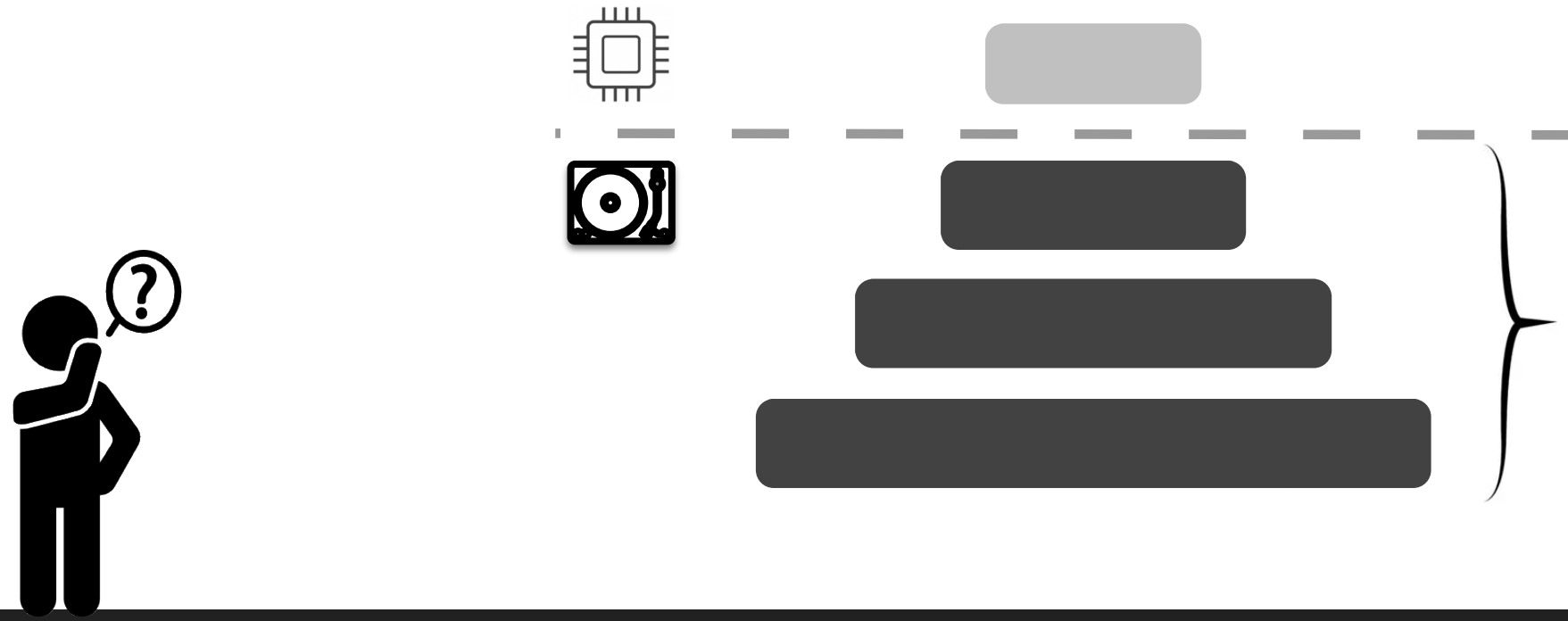
Size of the Buffer

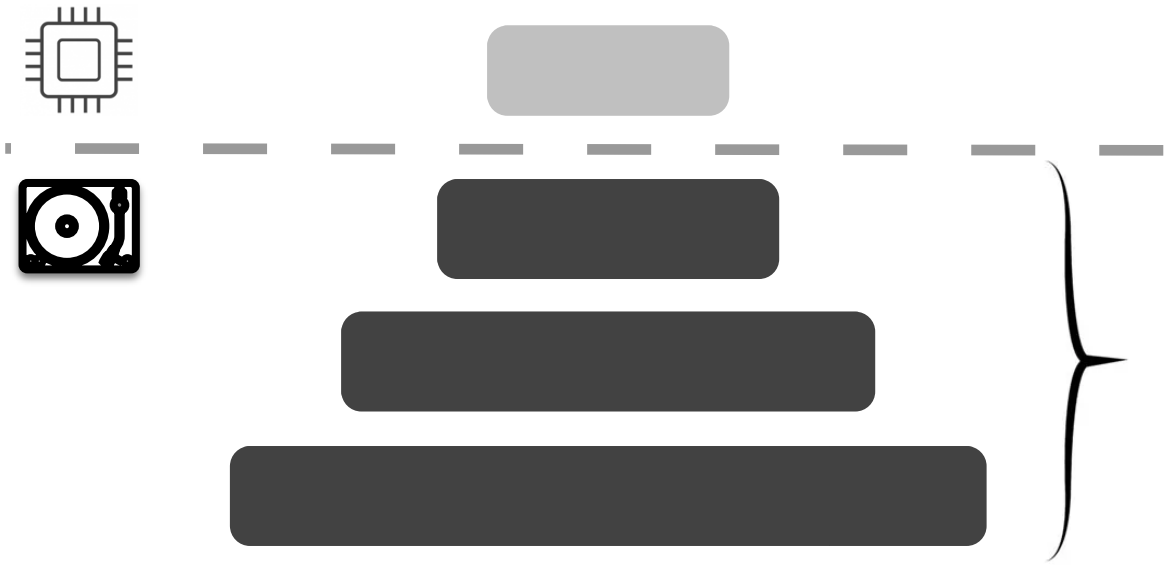


- frequent flushes
- smaller but more levels
- poor read performance
- fewer larger levels
- good for reads
- high tail latency



How does the storage layer affect ingestion?

L: #levels
T: size ratio



most data on storage if $T = 10$ & $L = 4$

99.9% on storage

How does the storage layer affect ingestion?

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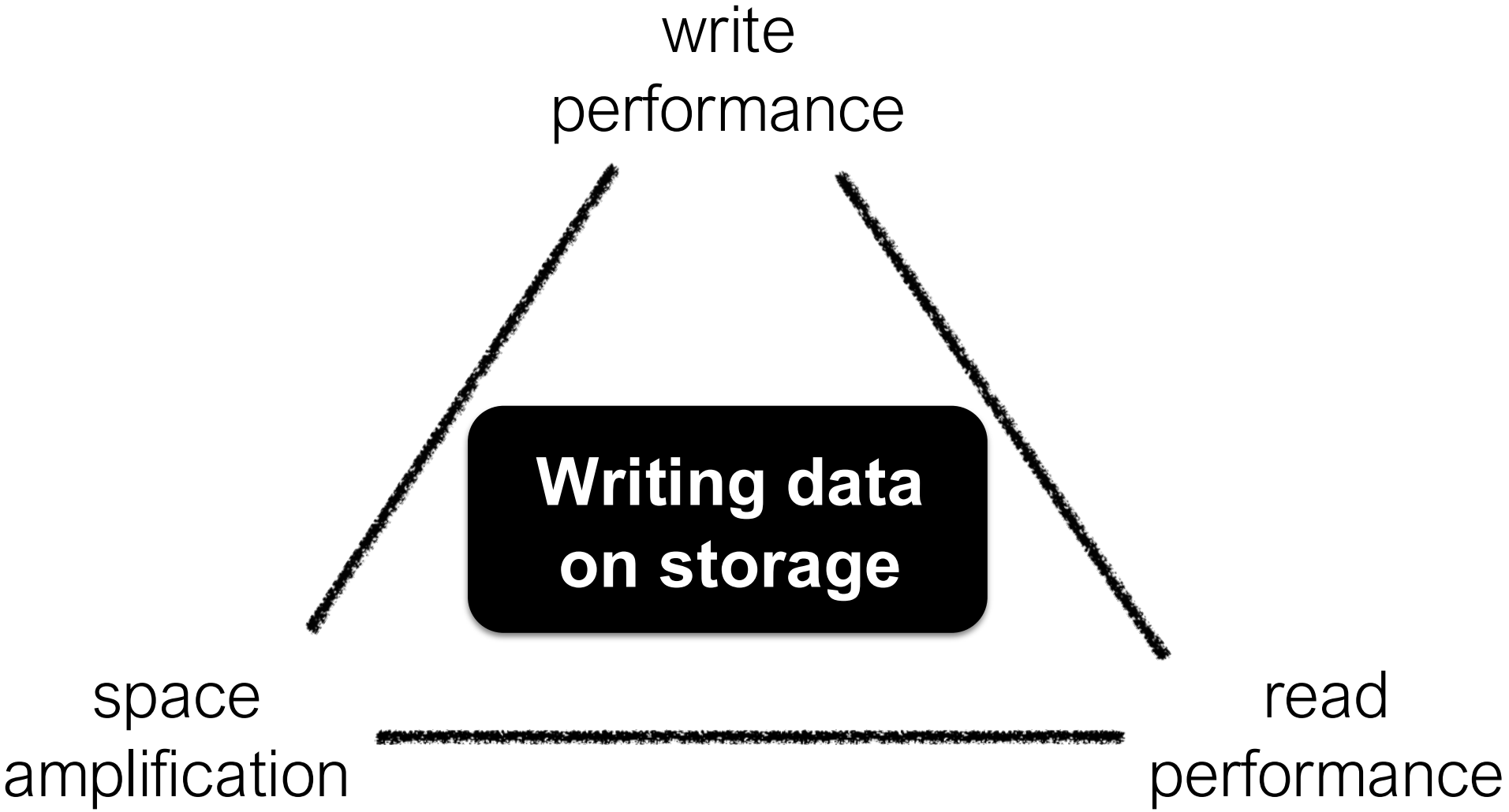
Storage Optimizations



Data **Layout**

Classical LSM design: `levelin g` [eager merging]

Data **Layout**

leveling [eager]

Data **Layout**

leveling [eager]

Data **Layout**

leveling [eager]

Data **Layout**

leveling [eager]

Data **Layout**

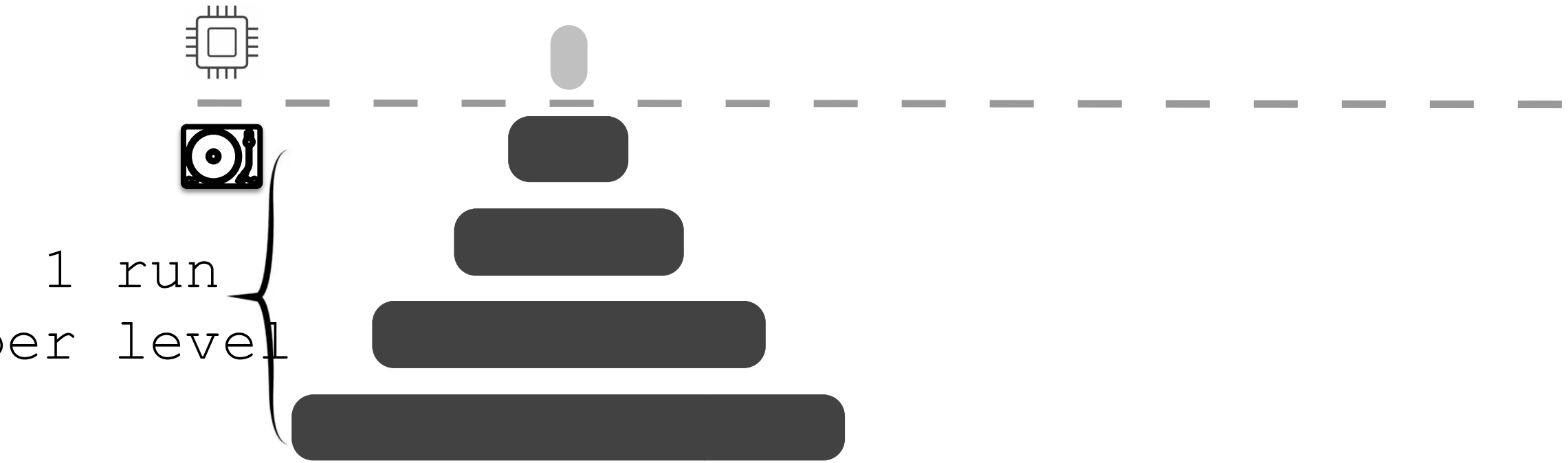
leveling [eager]

Data **Layout**

leveling [eager]

Data **Layout**

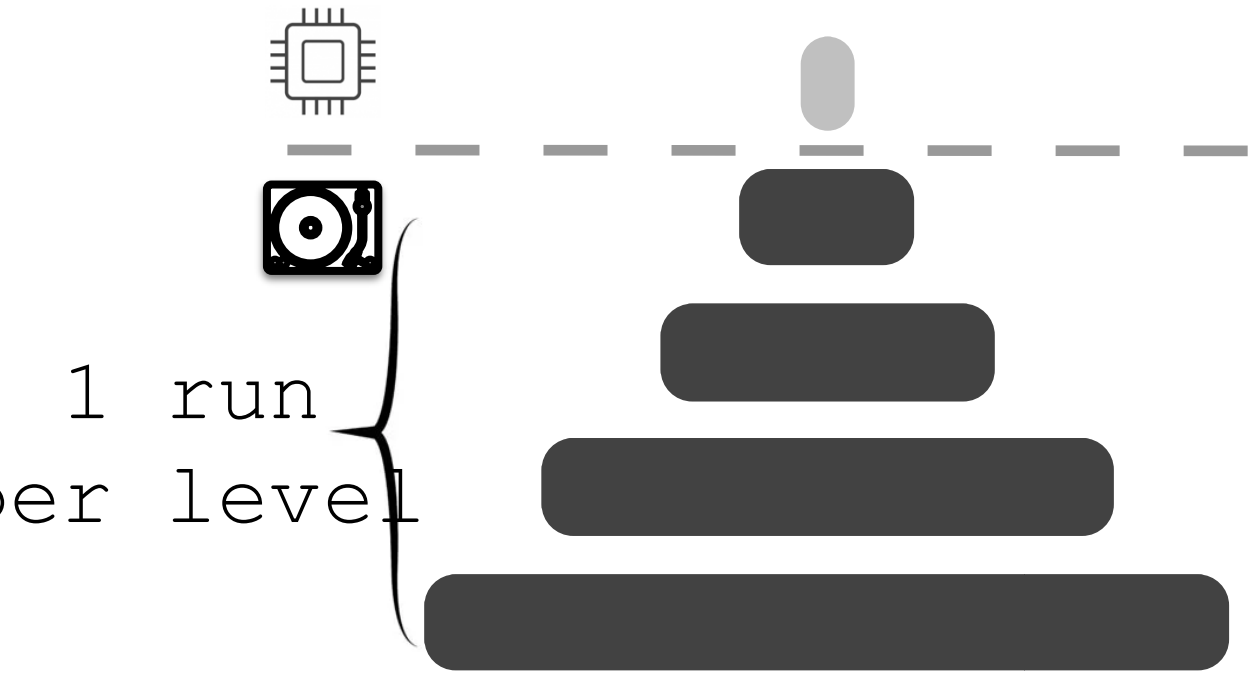
leveling [eager]



- good read performance
- good space amplification
- high write amplification

Data **Layout**

leveling [eager] **tiering** [lazy]

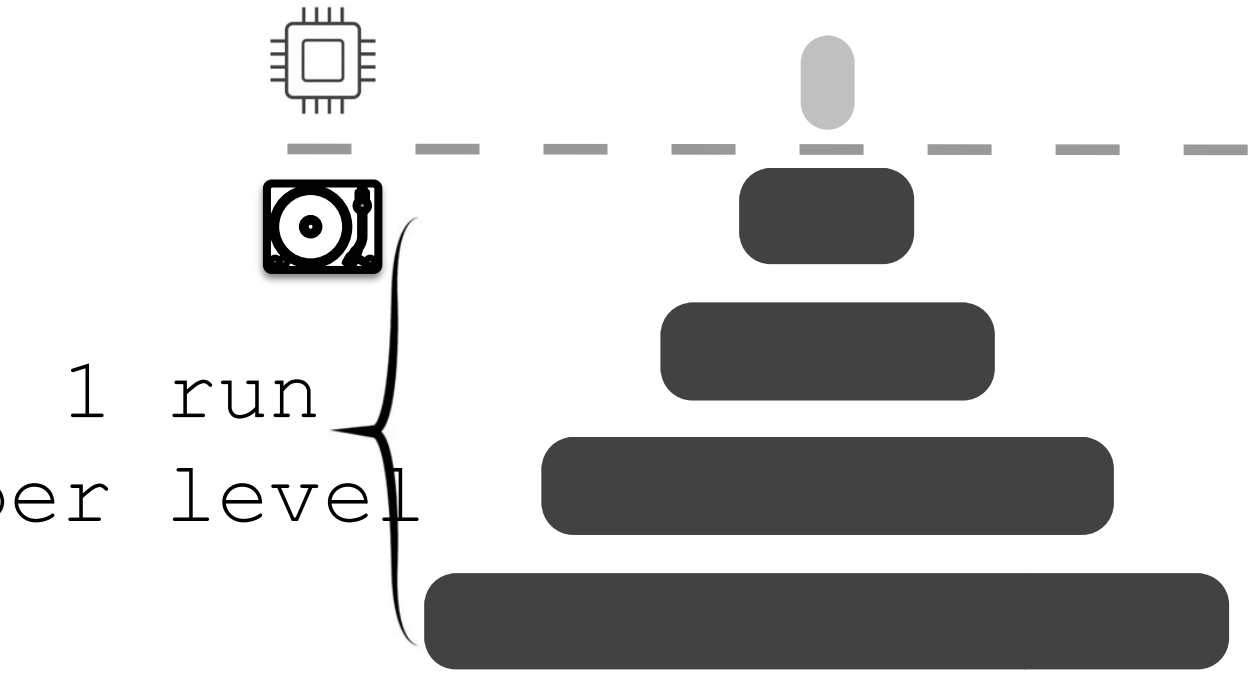


- good read performance
- good space amplification
- high write amplification

Data **Layout**

leveling [eager]

tiering [lazy]

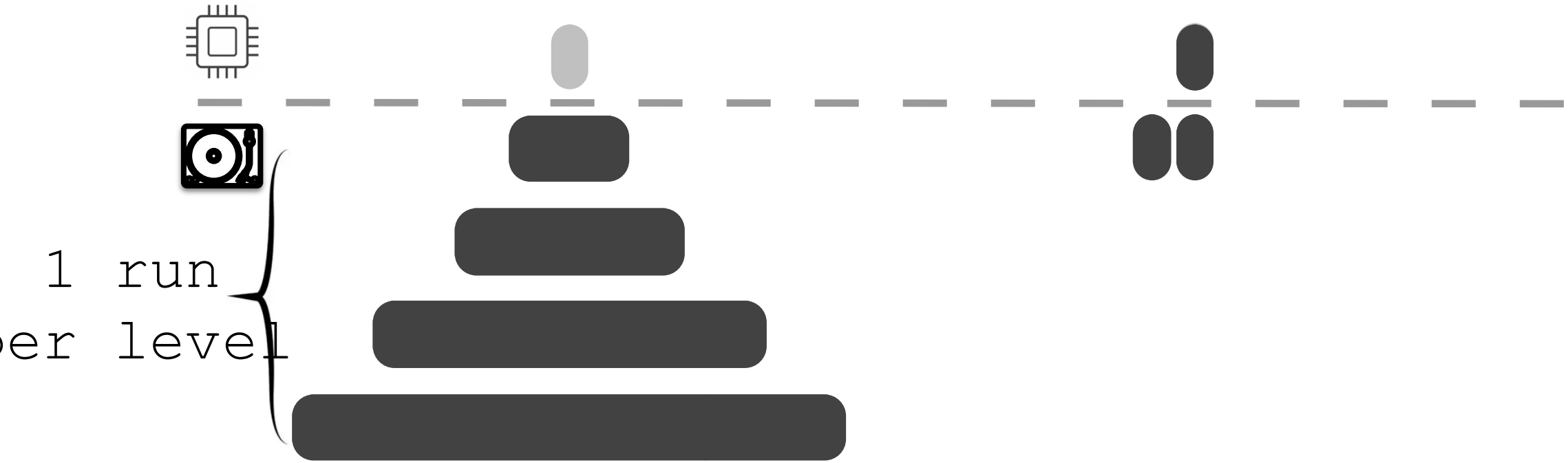


- good read performance
- good space amplification
- high write amplification

Data **Layout**

leveling [eager]

tiering [lazy]

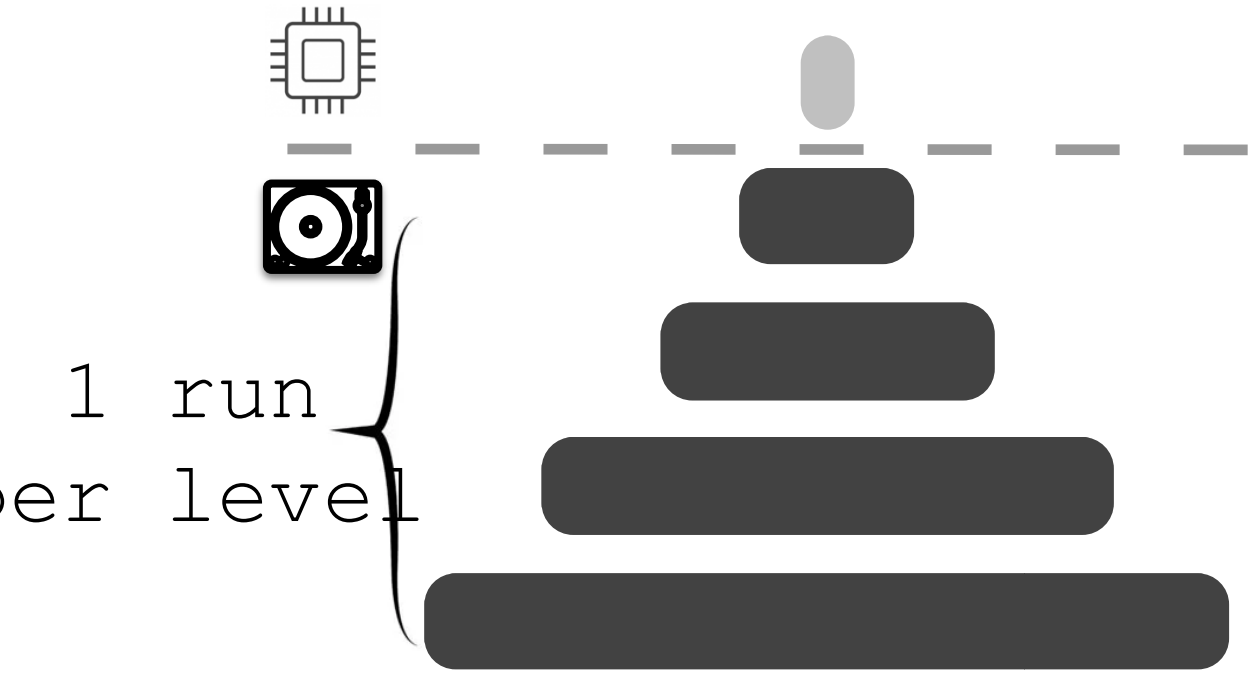


- good read performance
- good space amplification
- high write amplification

Data **Layout**

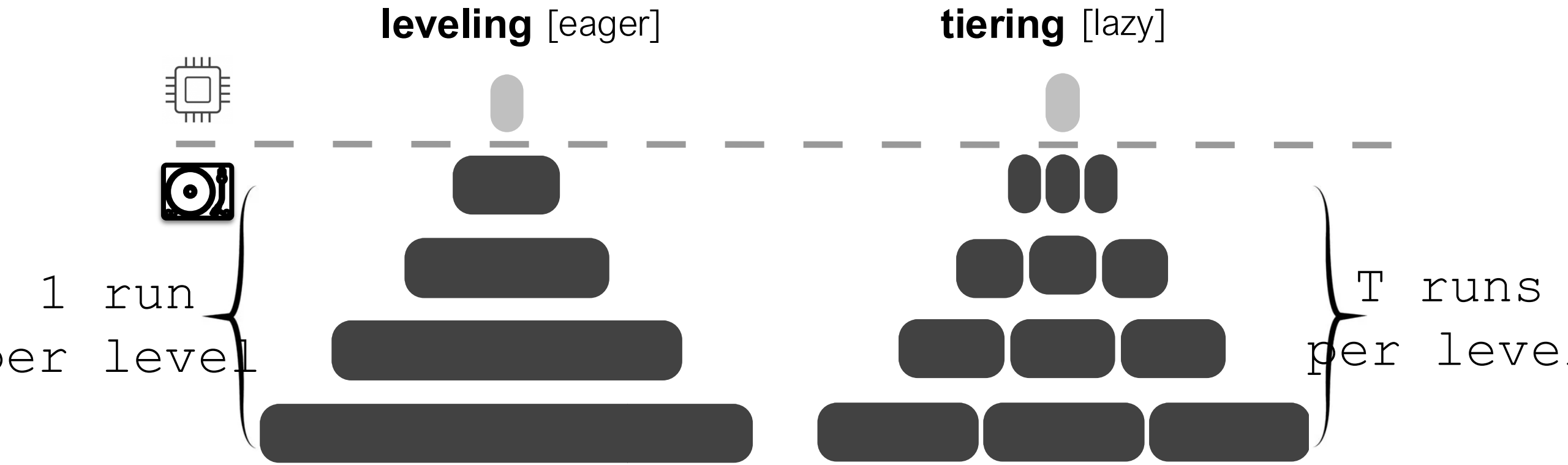
leveling [eager]

tiering [lazy]



- good read performance
- good space amplification
- high write amplification

Data **Layout**

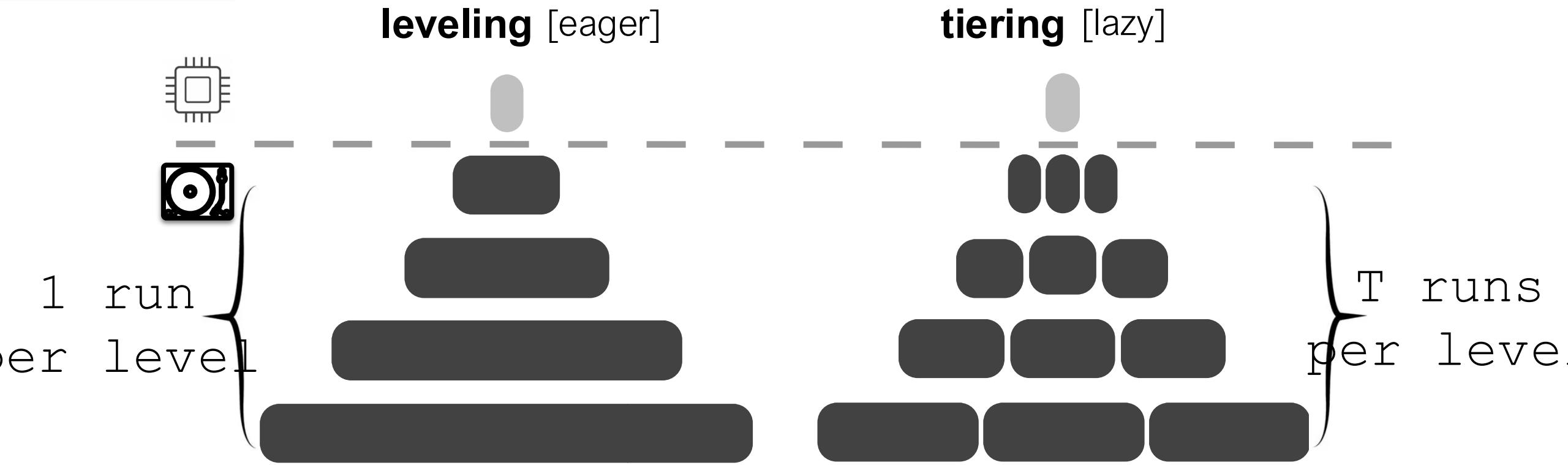


- good read performance
- good space amplification
- high write amplification

- poor read performance
- poor space amplification
- good ingestion performance

P: pages in buffer
B: entries/page
L: #levels
T: size ratio
N: #entries
ϕ: FPR of BF

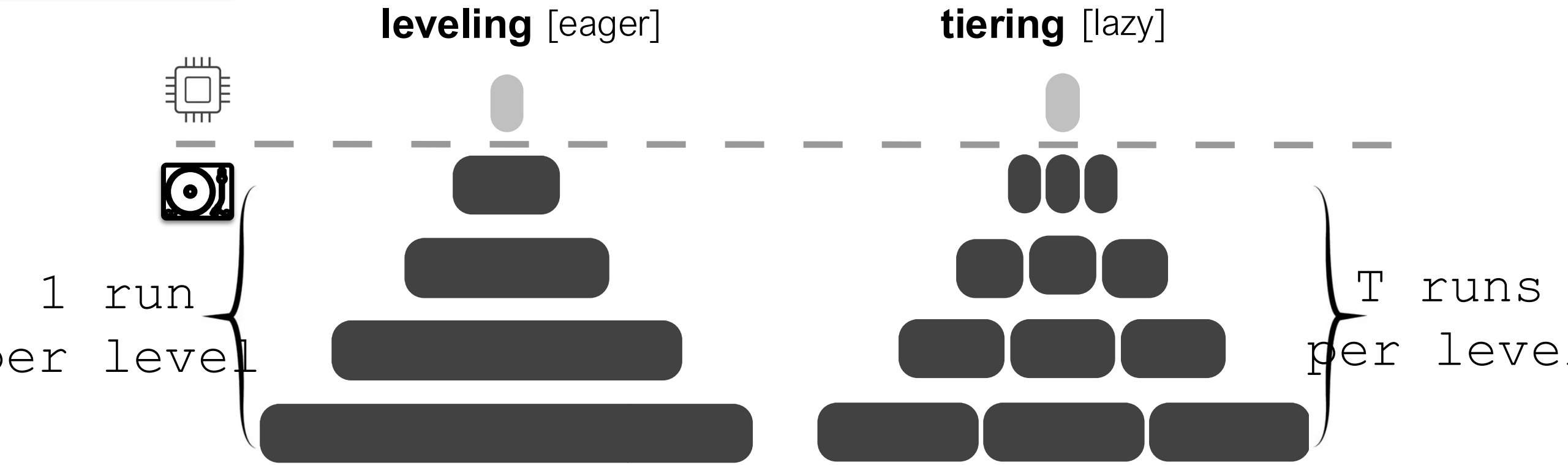
Data **Layout**



	leveling	tiering
Read cost:	$\mathcal{O}(L \cdot \phi)$	$\mathcal{O}(T \cdot L \cdot \phi)$
Write cost:	$\mathcal{O}(T \cdot L/B)$	$\mathcal{O}(L/B)$
SA:	$\mathcal{O}(1/T)$	$\mathcal{O}(T)$

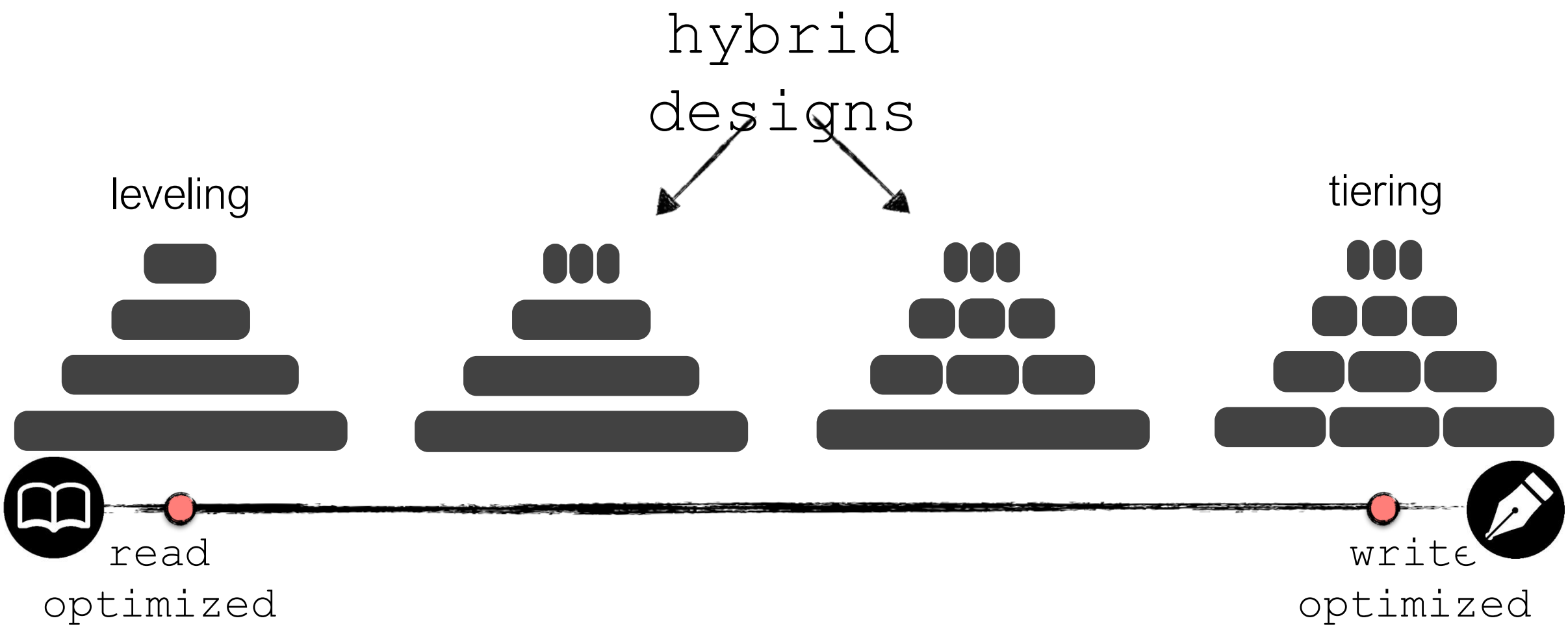
P: pages in buffer
B: entries/page
L: #levels
T: size ratio
N: #entries
ϕ: FPR of BF

Data **Layout**



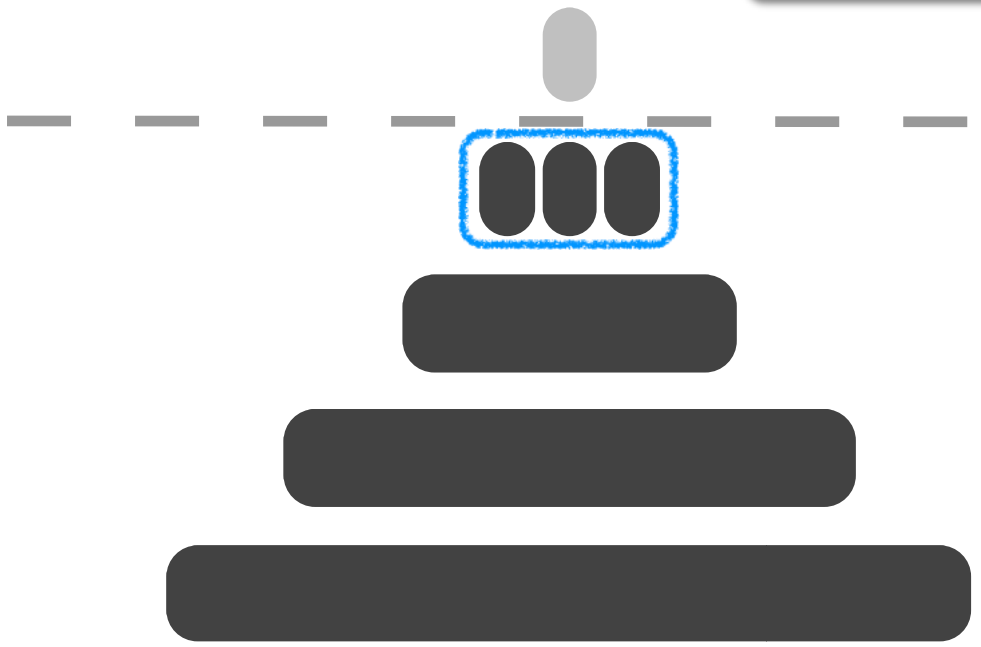
	leveling	tiering
Read cost:	$\mathcal{O}(L \cdot \phi)$	$\mathcal{O}(T \cdot L \cdot \phi)$
Write cost:	$\mathcal{O}(T \cdot L/B)$	$\mathcal{O}(L/B)$
SA:	$\mathcal{O}(1/T)$	$\mathcal{O}(T)$

Data **Layout**



Data **Layout**

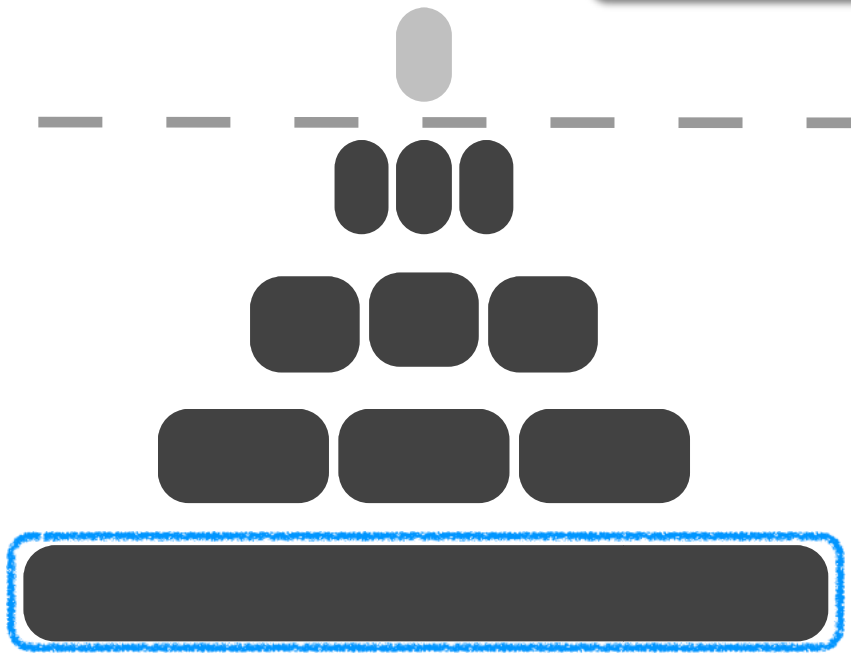
1-leveling RocksDB20



- fewer write stalls
- increased block cache hits

compared to leveling!

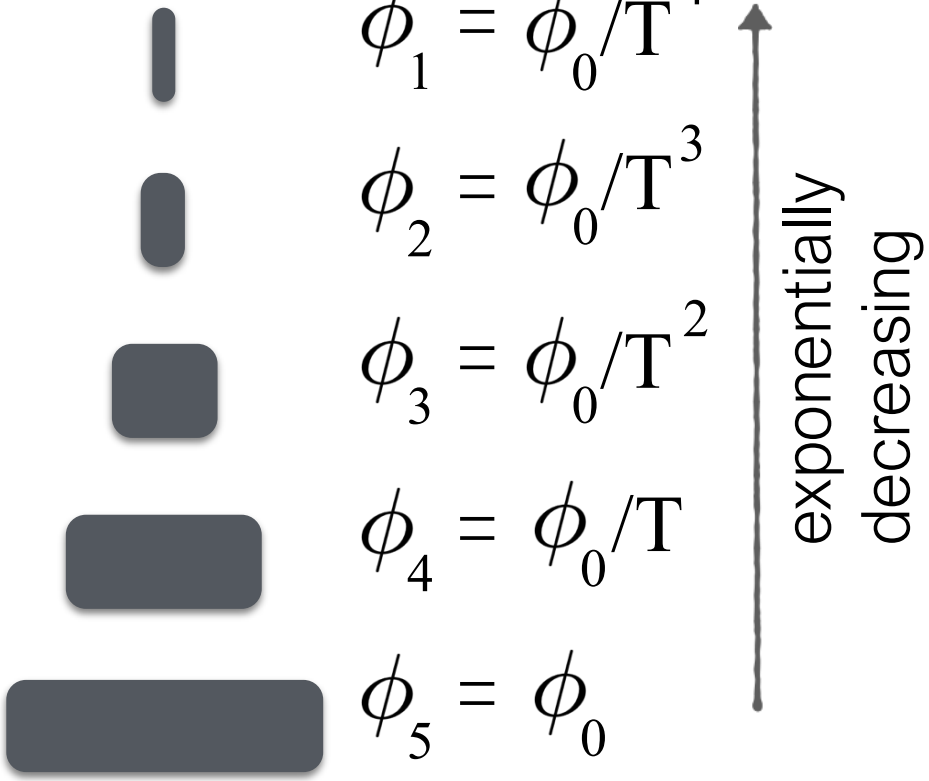
L-leveling DayanSIGMOD18



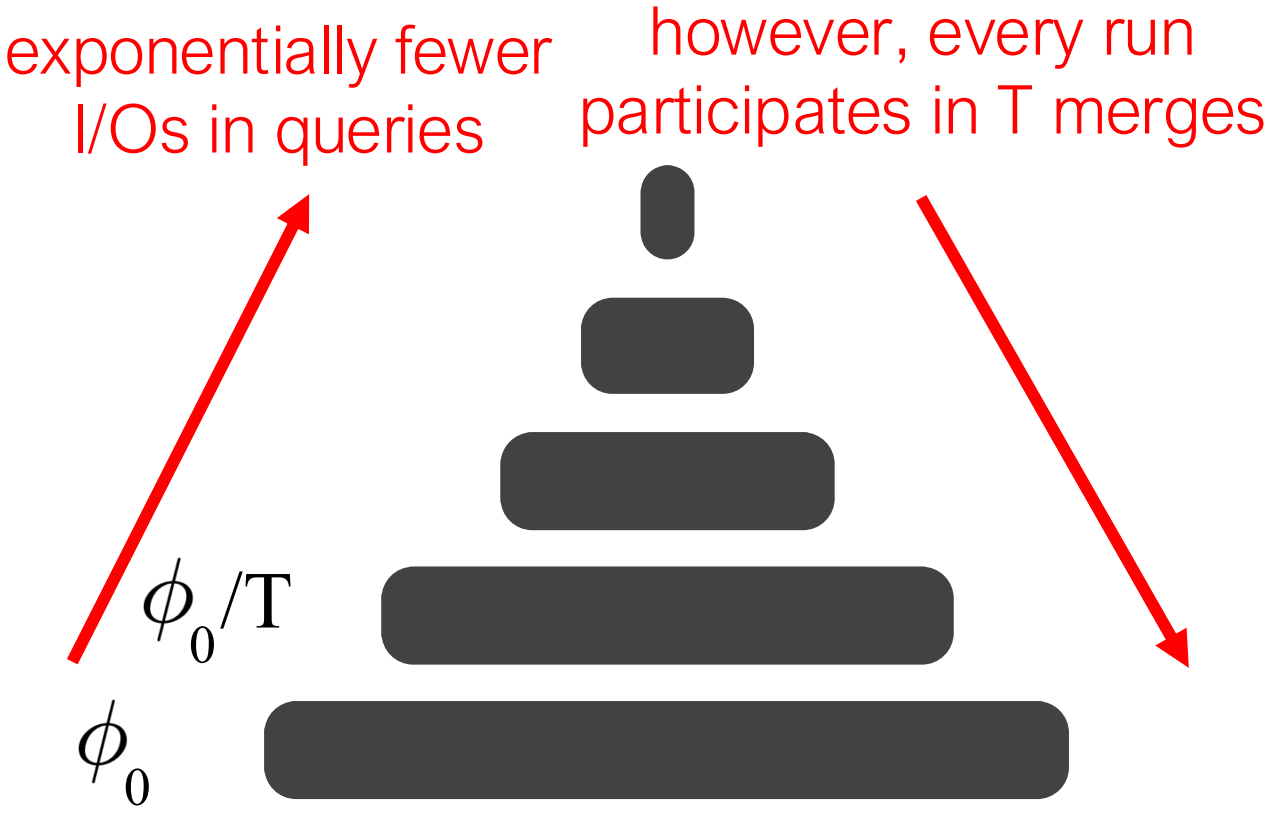
- low write amplification
- better read performance

compared to tiering!

Bloom filters

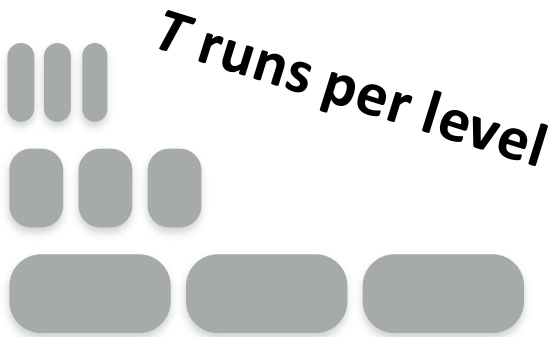


LSM-tree

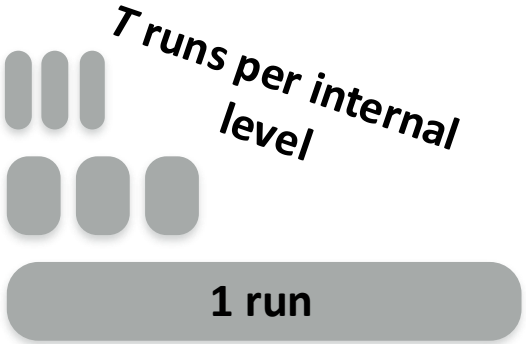


Insight: merging in top levels can become lazy (tiering)!

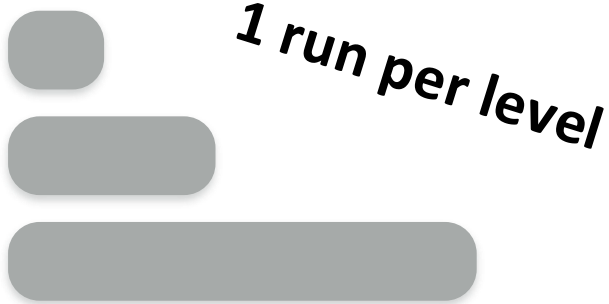
Tiering
write-optimized



Lazy Leveling
hybrid



Leveling
read-optimized



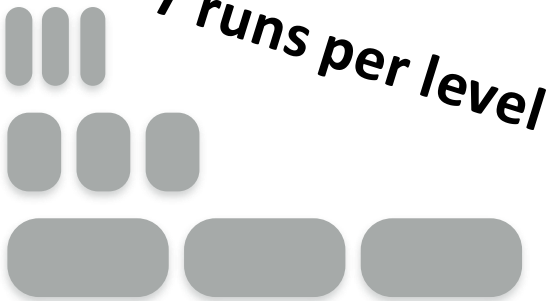
lookup: $O\left(T \cdot log_T(N) \cdot e^{-M/N}\right)$

runs per level — levels — false positive rate

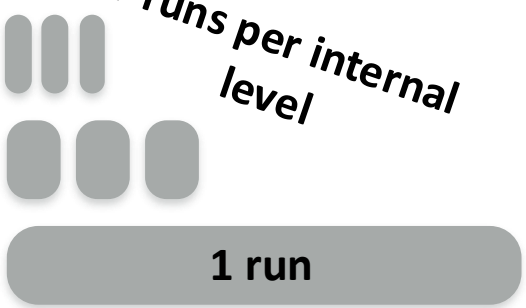
$O\left(log_T(N) \cdot e^{-M/N}\right)$

levels — false positive rate

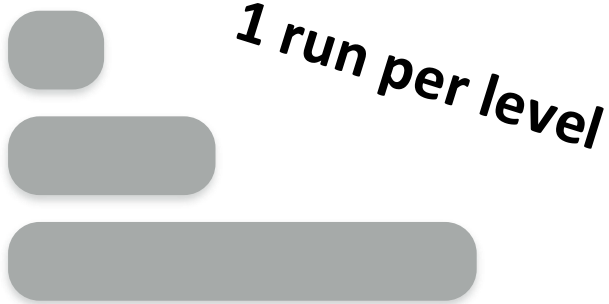
Tiering
write-optimized



Lazy Leveling
hybrid



Leveling
read-optimized



lookup: $O\left(T \cdot log_T(N) \cdot e^{-M/N}\right)$

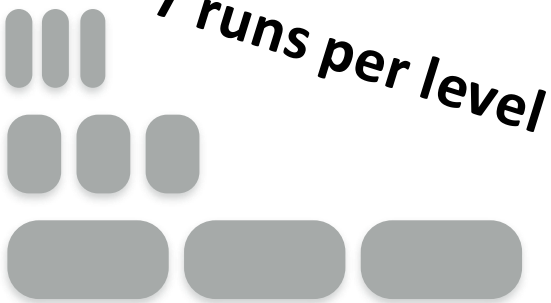
runs per level — levels — false positive rate

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

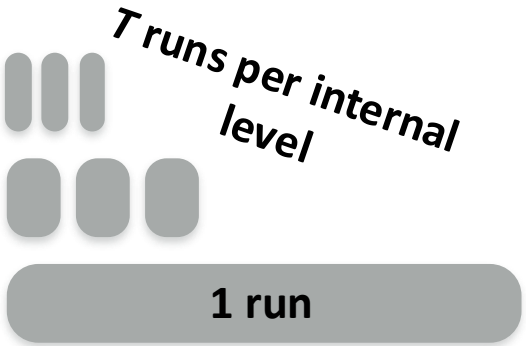
levels — false positive rate

Tiering
write-optimized

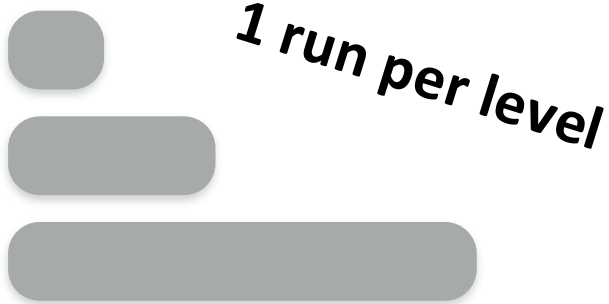
DayanSIGMOD17



Lazy Leveling
hybrid



Leveling
read-optimized



lookup: $O(T \cdot e^{-M/N})$

runs per level

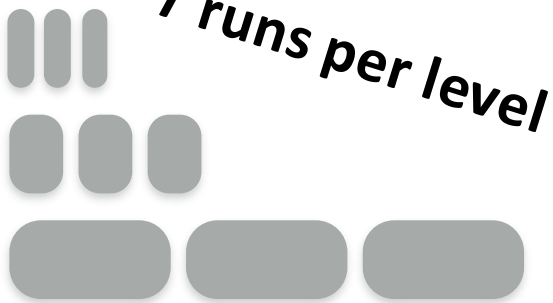
false positive rate

$O(e^{-M/N})$

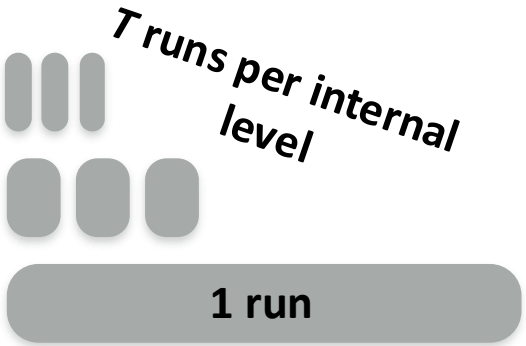
false positive rate

Tiering
write-optimized

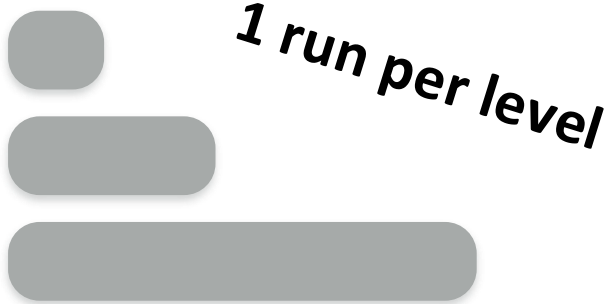
DayanSIGMOD18



Lazy Leveling
hybrid



Leveling
read-optimized



lookup:

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

runs per level

false positive rate

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

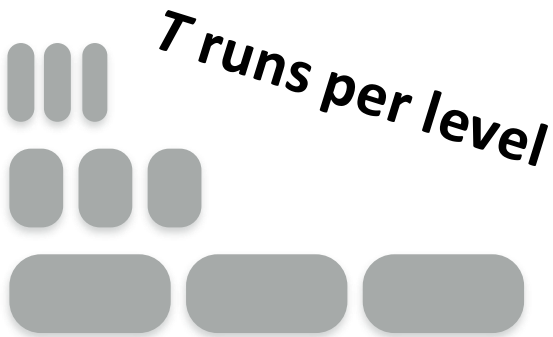
there is a slightly higher constant factor than leveling

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

false positive rate

Tiering
write-optimized

DayanSIGMOD18

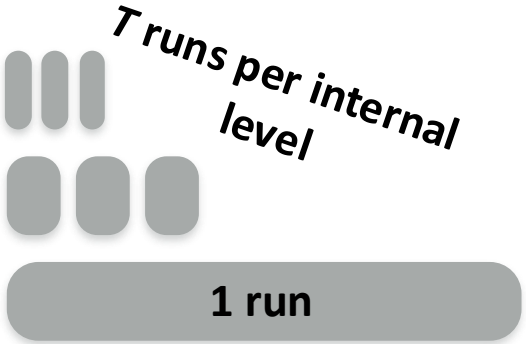


lookup: $O(T \cdot e^{-M/N})$

update cost: $\boldsymbol{O(log_T(N))}$

levels

Lazy Leveling
hybrid



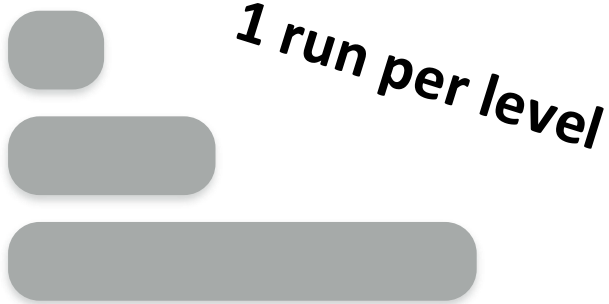
$O(e^{-M/N})$

$\boldsymbol{O(T + log_T(N))}$

T merges for the last level

1 merge for all internal levels

Leveling
read-optimized



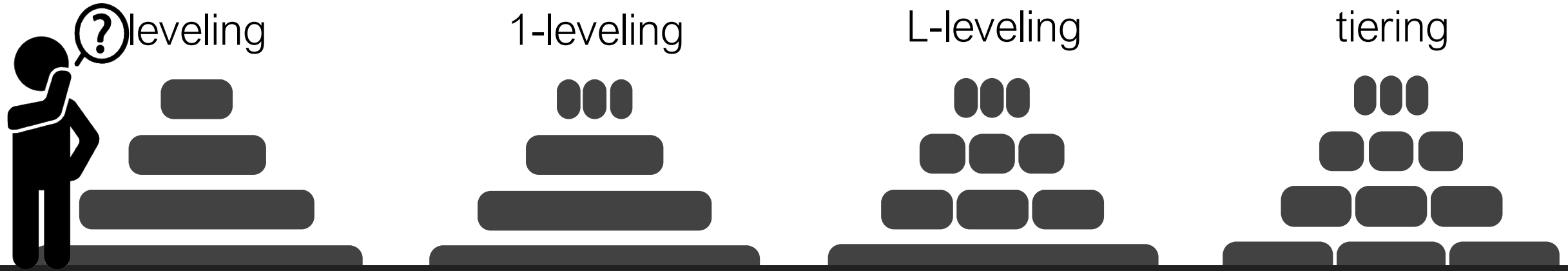
$O(e^{-M/N})$

$\boldsymbol{O(T \cdot log_T(N))}$

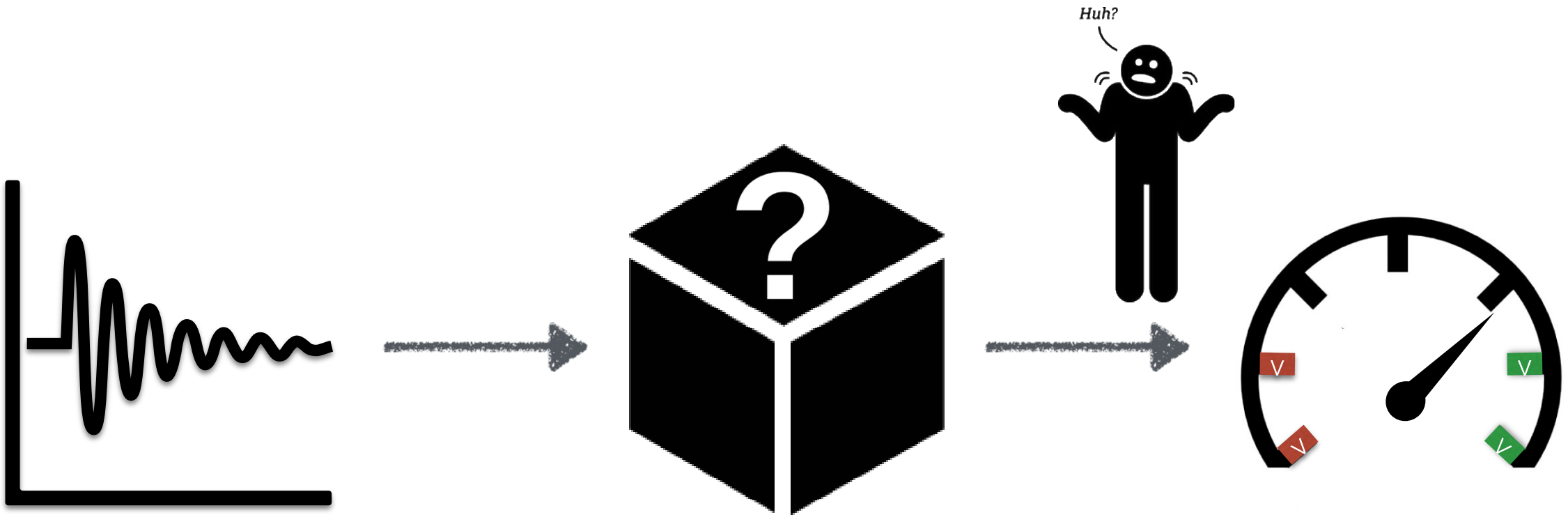
merges per level

levels

Data **Layout**



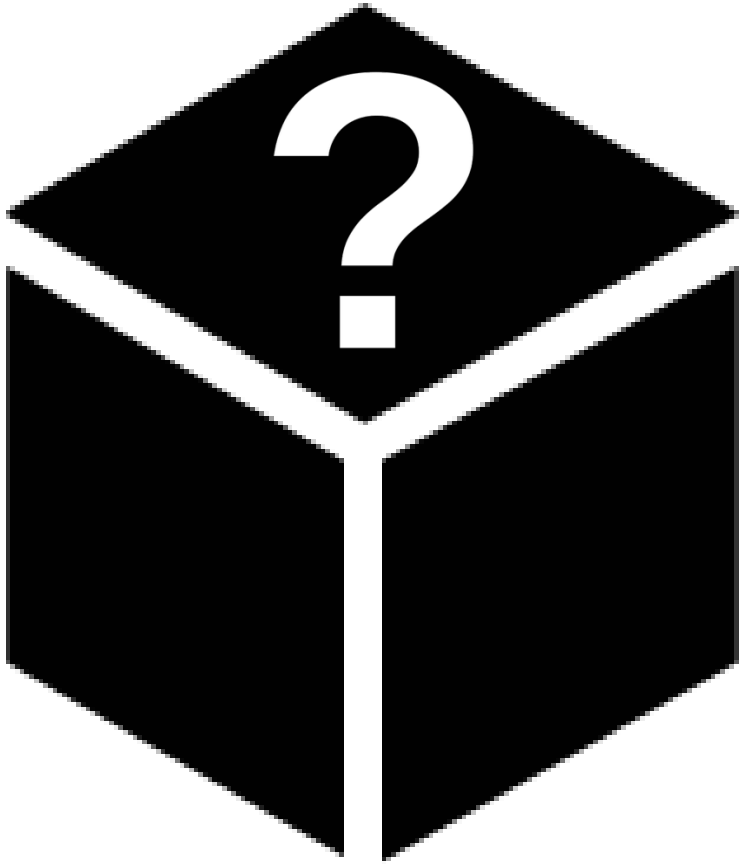
So, how do we reason about the data layout?



workload

data layout

performance



Compaction

black box




How to organize the data on device?

How much data to move at-a-time?

Which block of data to be moved?

When to re-organize the data layout?

SarkarVLDB21

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Data Layout

n Granulari

Data Movement Policy

Compaction Trigger

How to organize the data on device? ✓

How much data to move at-a-time?

Which block of data to be moved?

When to re-organize the data layout?

SarkarVLDB21

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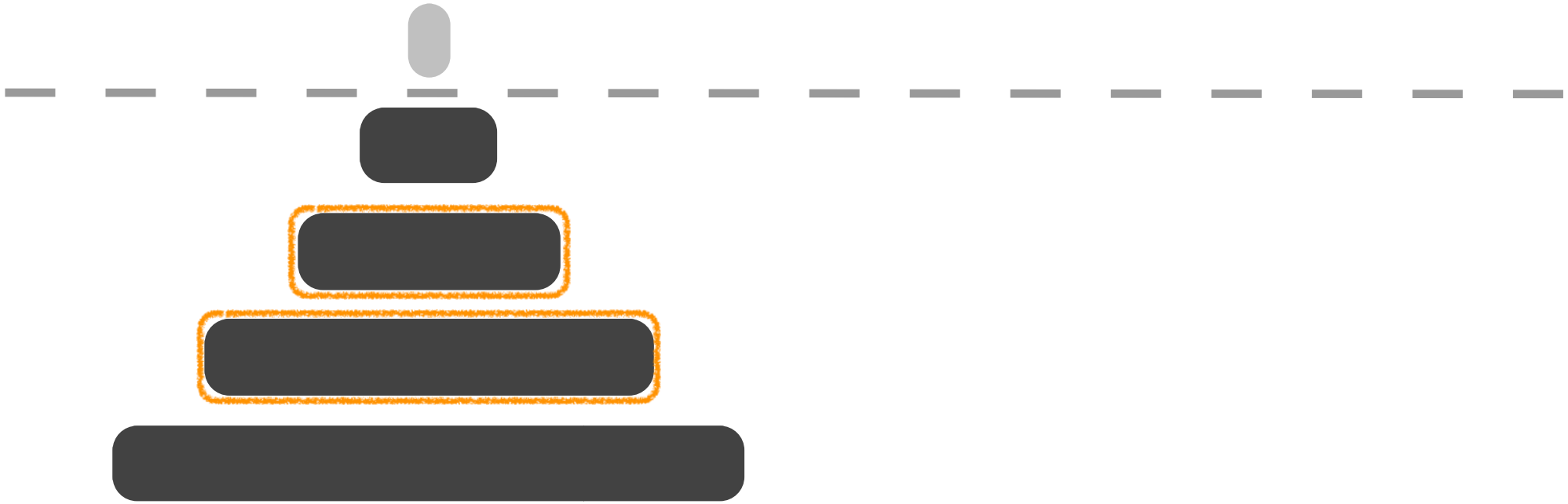
Compaction **Granularity**

data moved per compaction

Compaction **Granularity**

data moved per compaction

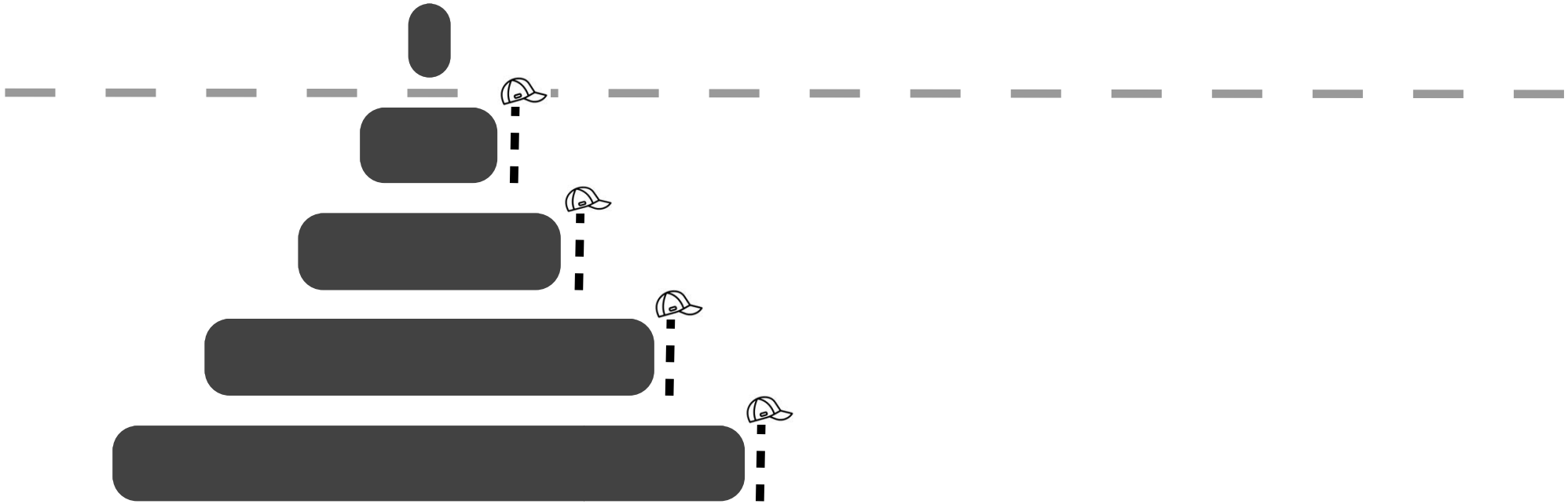


consecutiv
e level

AsterixDB

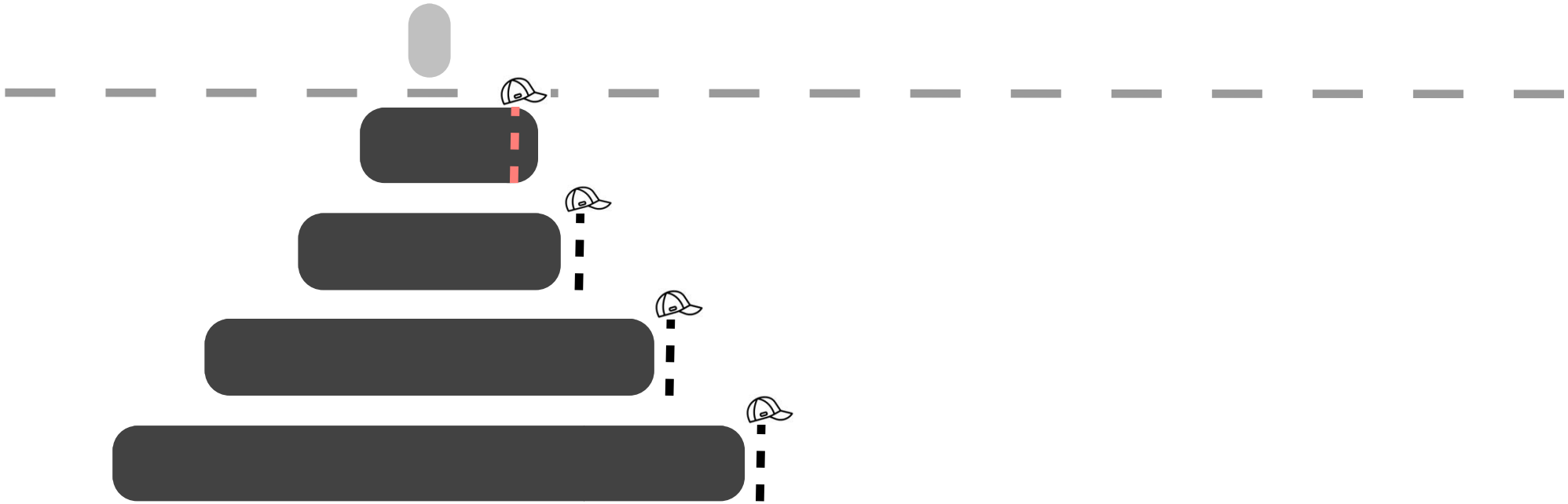
Compaction **Granularity**

data moved per compaction



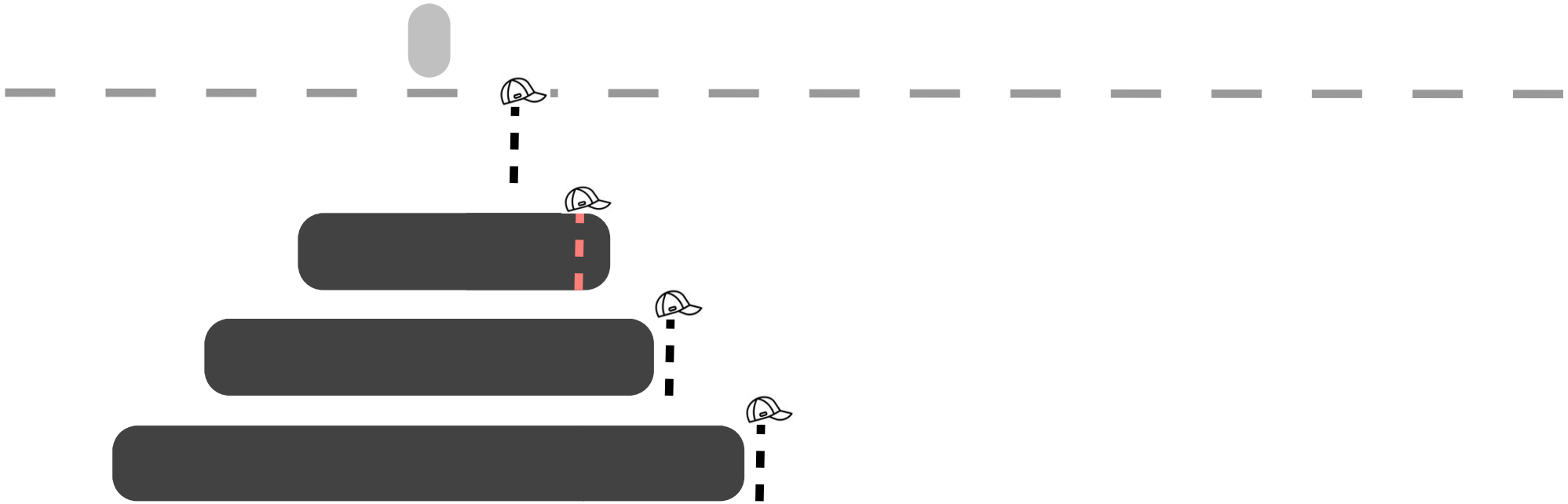
Compaction **Granularity**

data moved per compaction



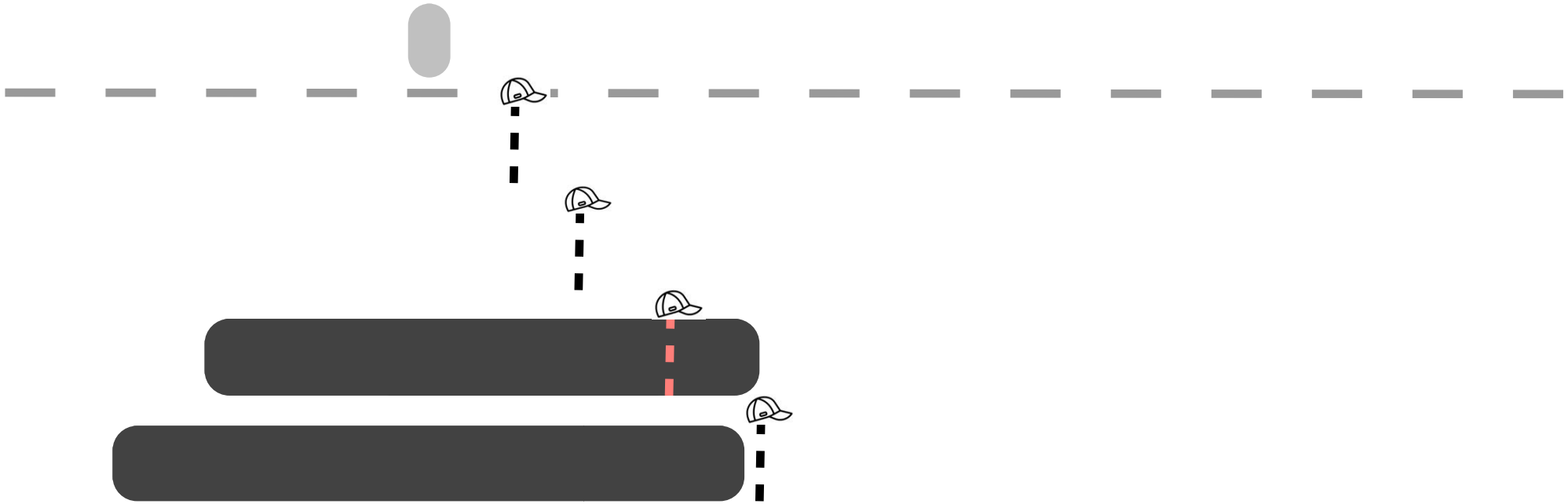
Compaction **Granularity**

data moved per compaction



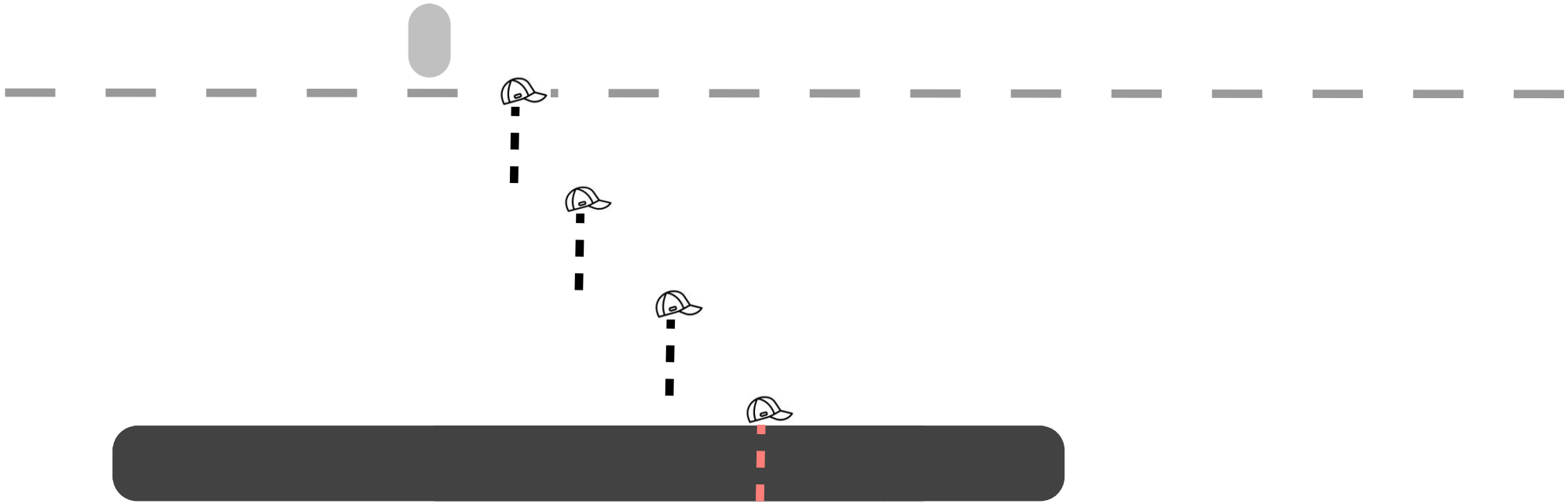
Compaction **Granularity**

data moved per compaction



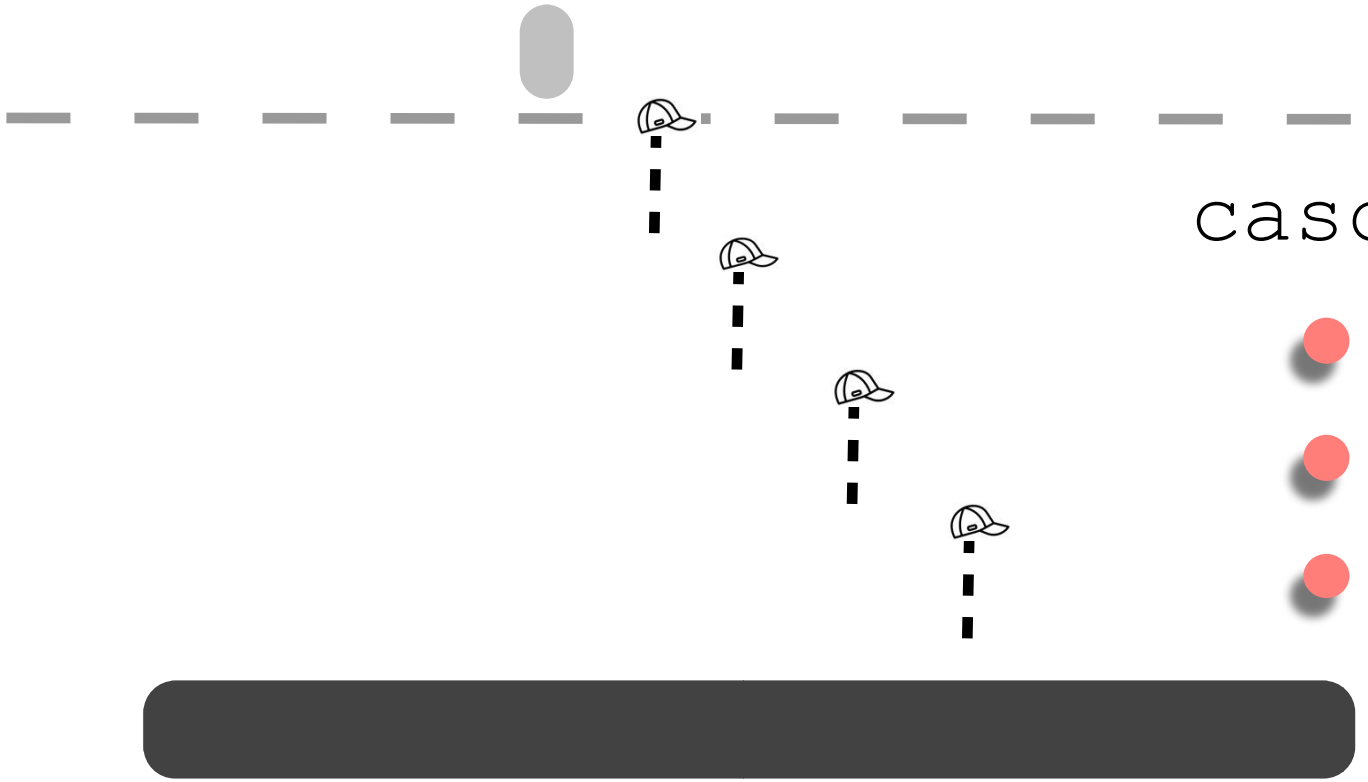
Compaction **Granularity**

data moved per compaction



Compaction **Granularity**

data moved per compaction



`cascading compactions`

- high latency spikes
- write stalls
- unpredictable perf.

Compaction **Granularity**

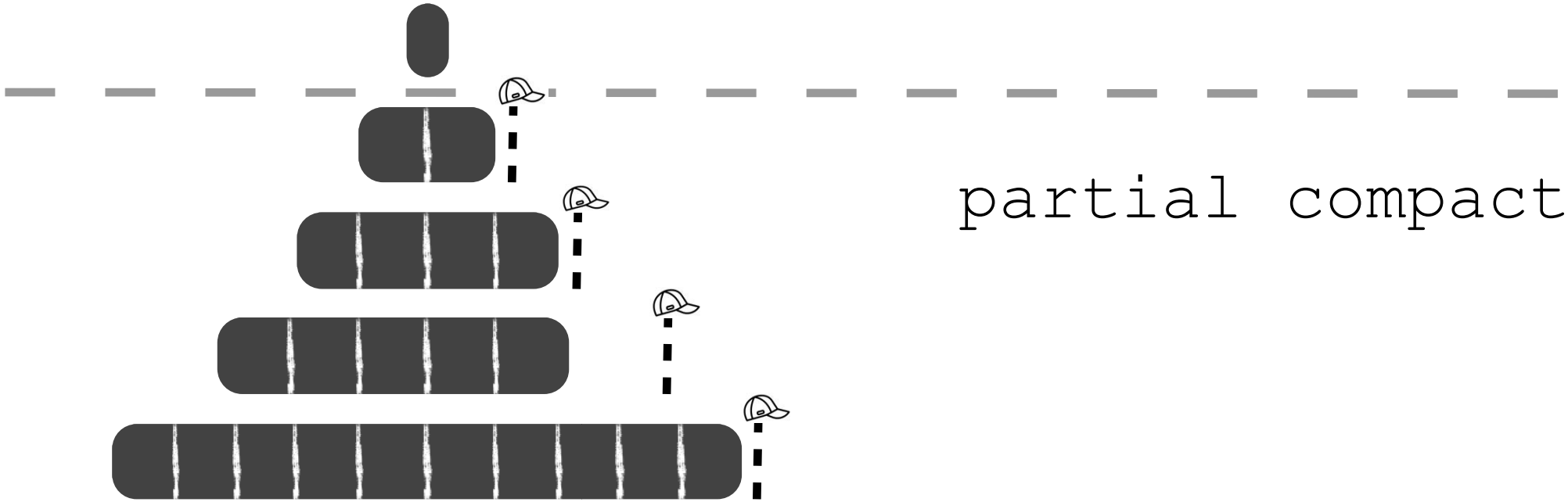
data moved per compaction

`partial compaction`

granularity:`files`

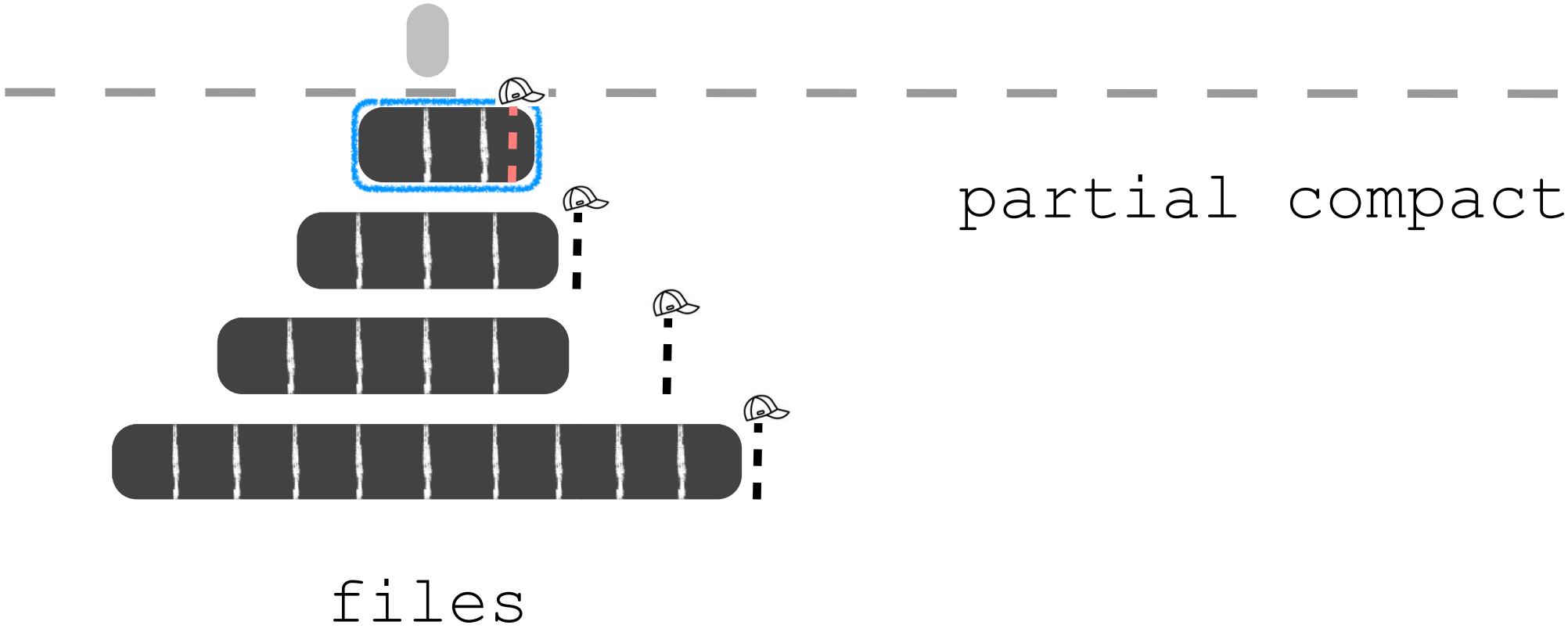
Compaction **Granularity**

data moved per compaction



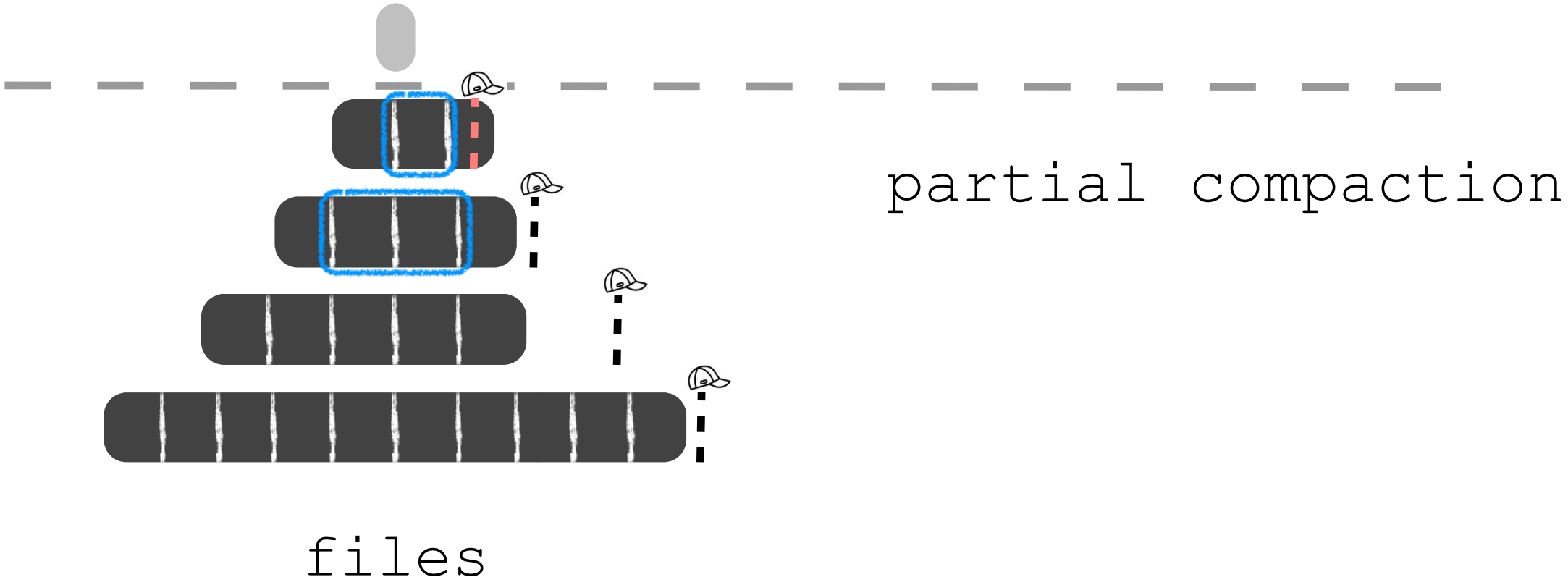
Compaction **Granularity**

data moved per compaction



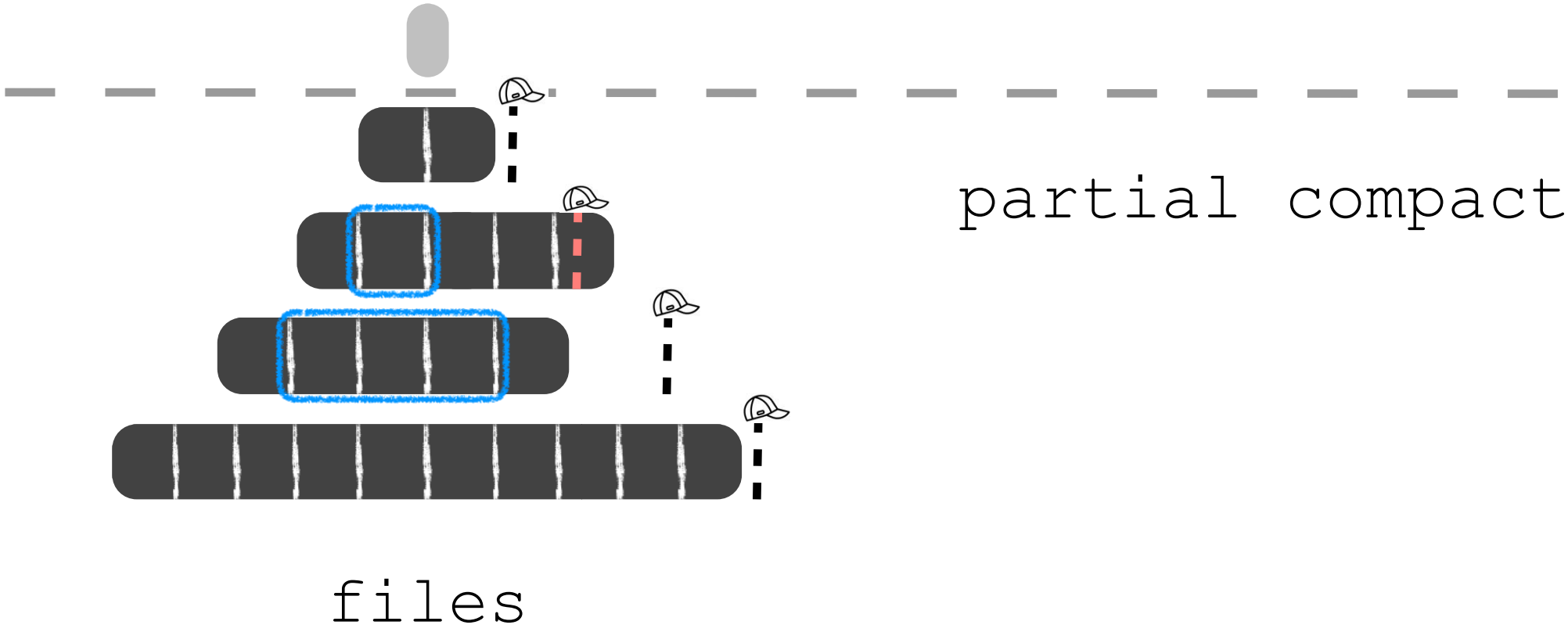
2 Compaction **Granularity**

data moved per compaction



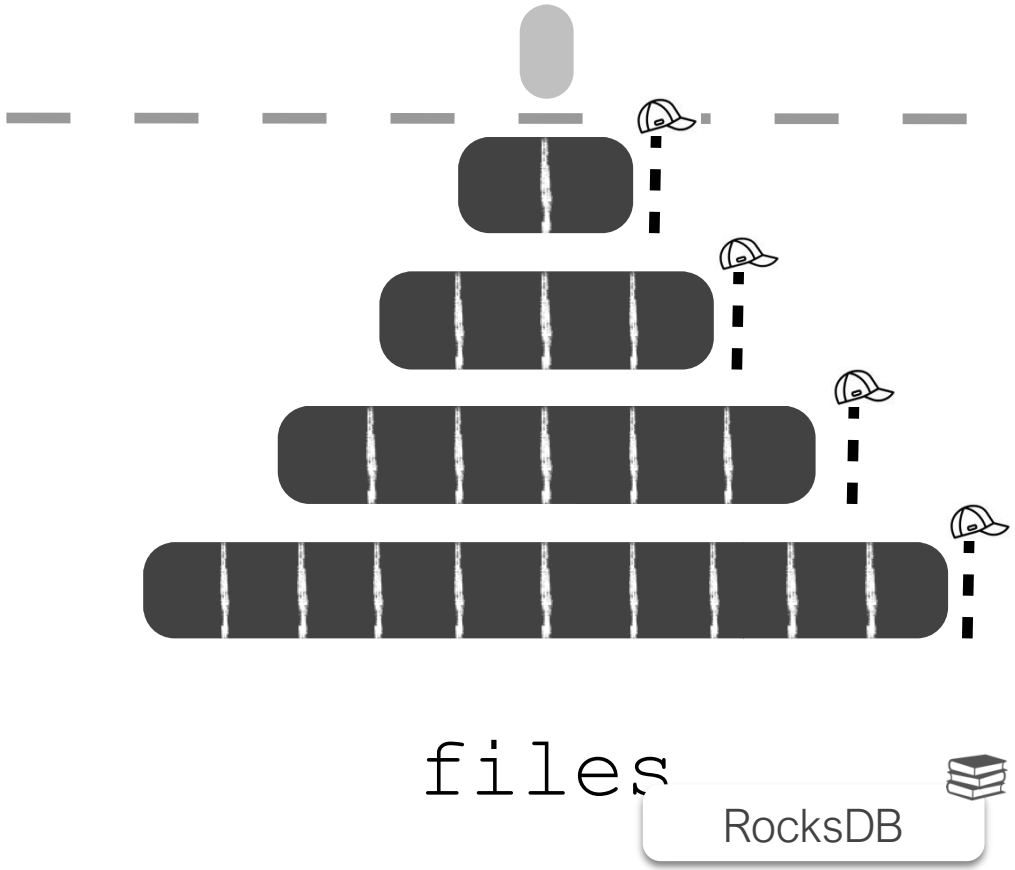
Compaction **Granularity**

data moved per compaction



2 Compaction **Granularity**

data moved per compaction



`partial compaction`

- ~same data movement
- amortized cost for compactions
- predictable perf.

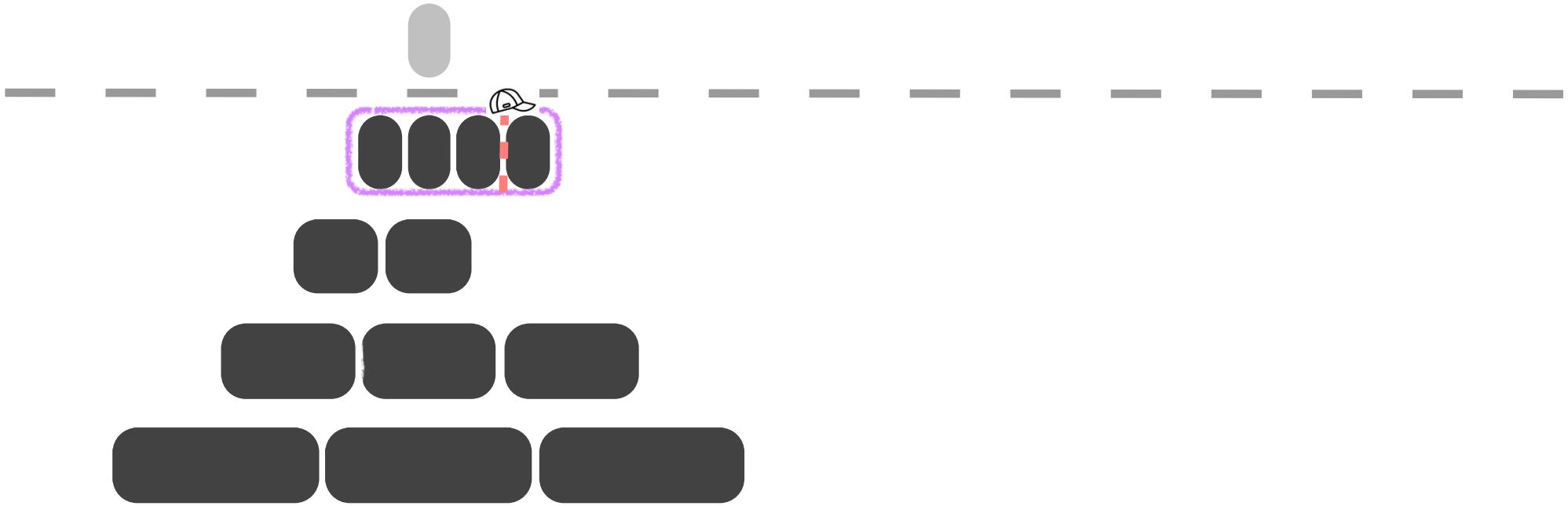
Compaction **Granularity**

data moved per compaction

sorted runs in a level

Compaction **Granularity**

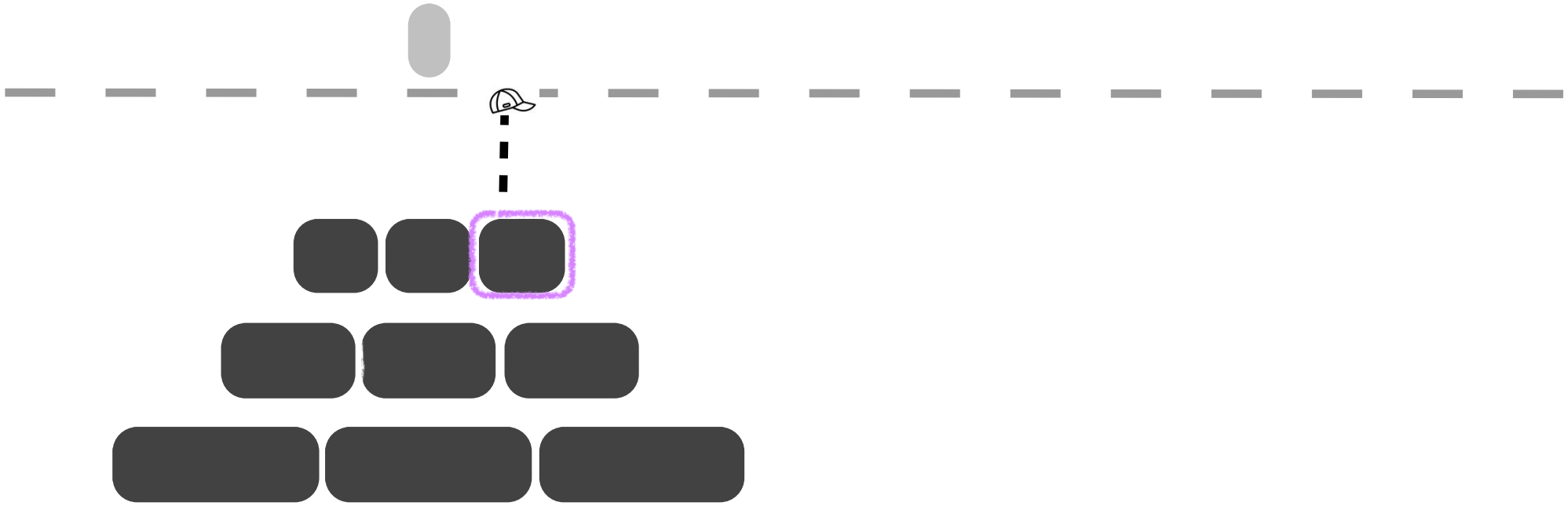
data moved per compaction



sorted runs in a level

2 Compaction **Granularity**

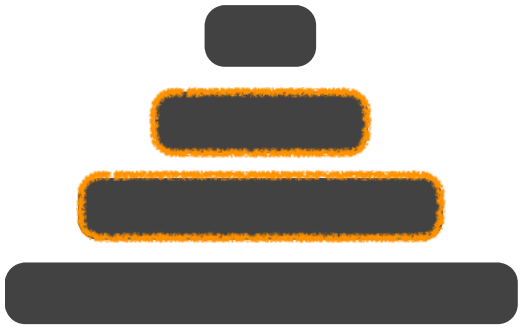
data moved per compaction



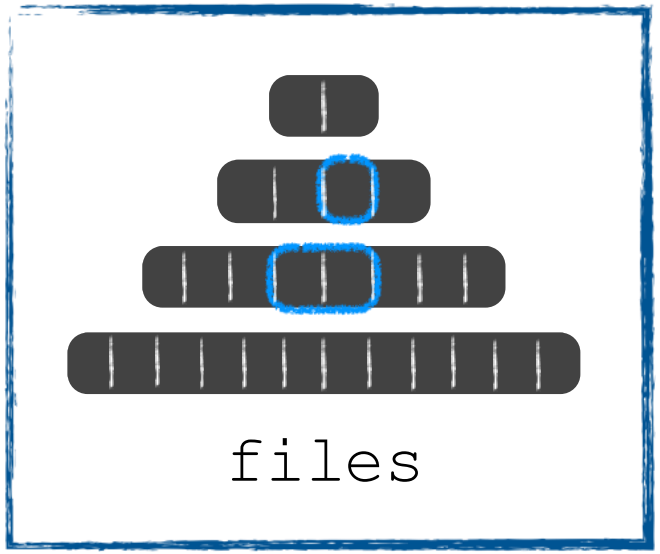
sorted runs in a level

Compaction **Granularity**

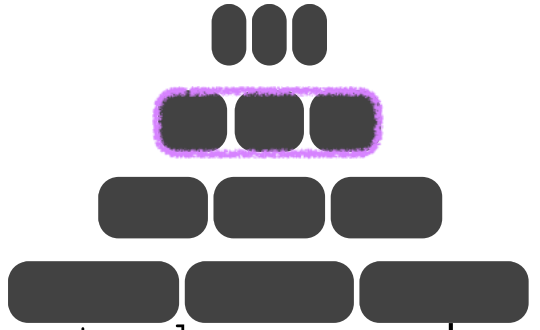
data moved per compaction



levels



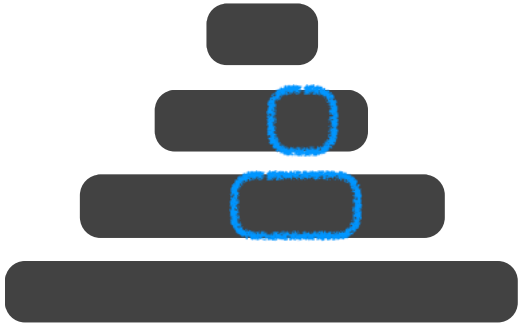
files



sorted runs in a level

Data Movement Policy

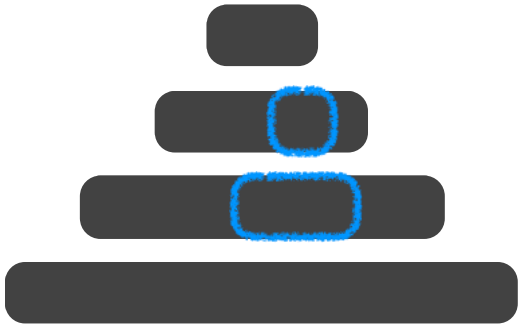
which data to compact



files

Data Movement Policy

which data to compact



files

round-robin !

minimum **overlap with parent** level WA

file with most **tombstones** SA

coldest file PQ

Compaction **Trigger**

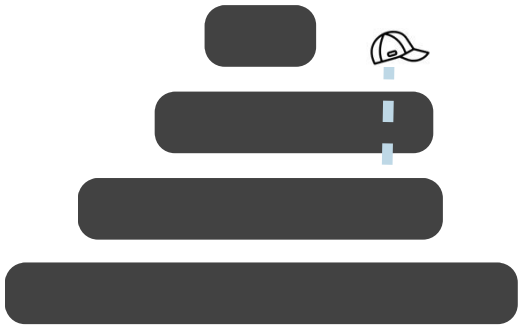
invoking the compaction routine

level **saturation**

Compaction **Trigger**

invoking the compaction routine

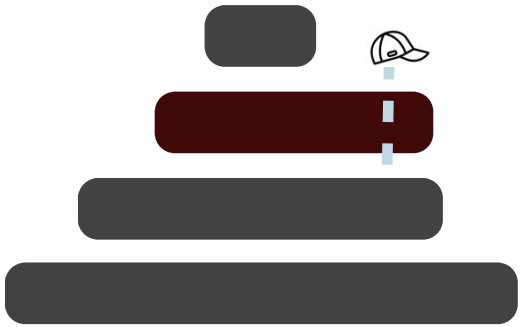
level **saturation**



Compaction **Trigger**

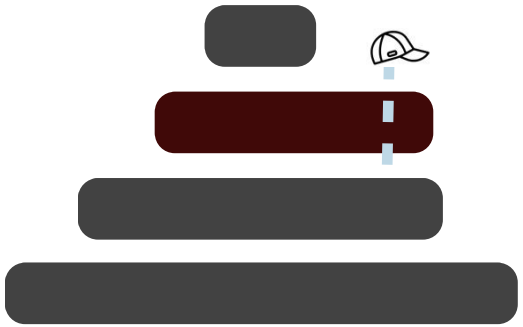
invoking the compaction routine

level **saturation**



Compaction **Trigger**

invoking the compaction routine



level **saturation**

number of **sorted runs**

space amplification SA

age of a file De

Data Layout

Compaction Granularity

Data Movement Policy

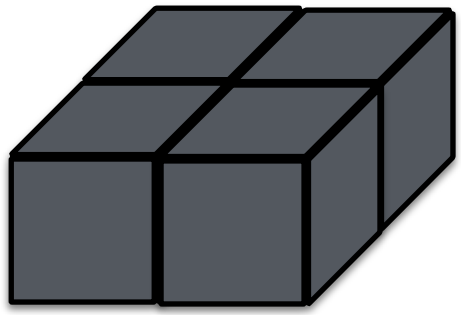
Compaction Trigger

Data Layout

Compaction Granularity

Data Movement Policy

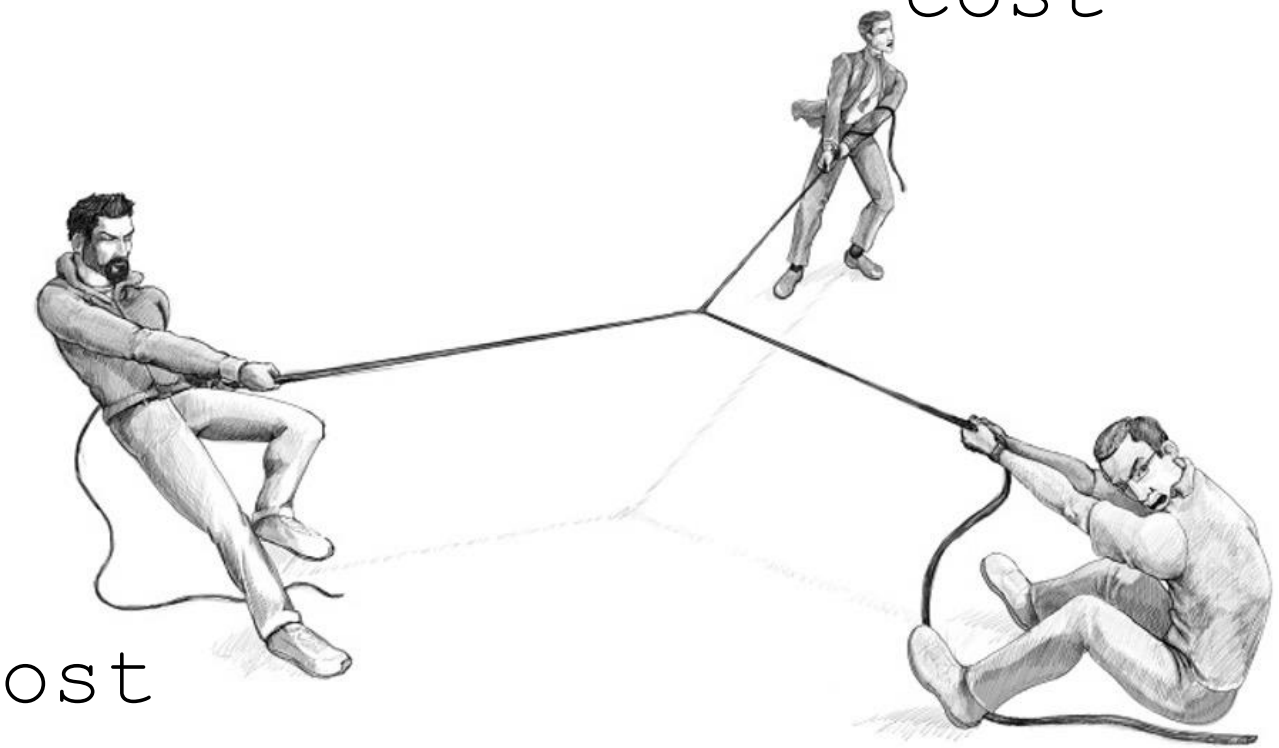
Compaction Trigger



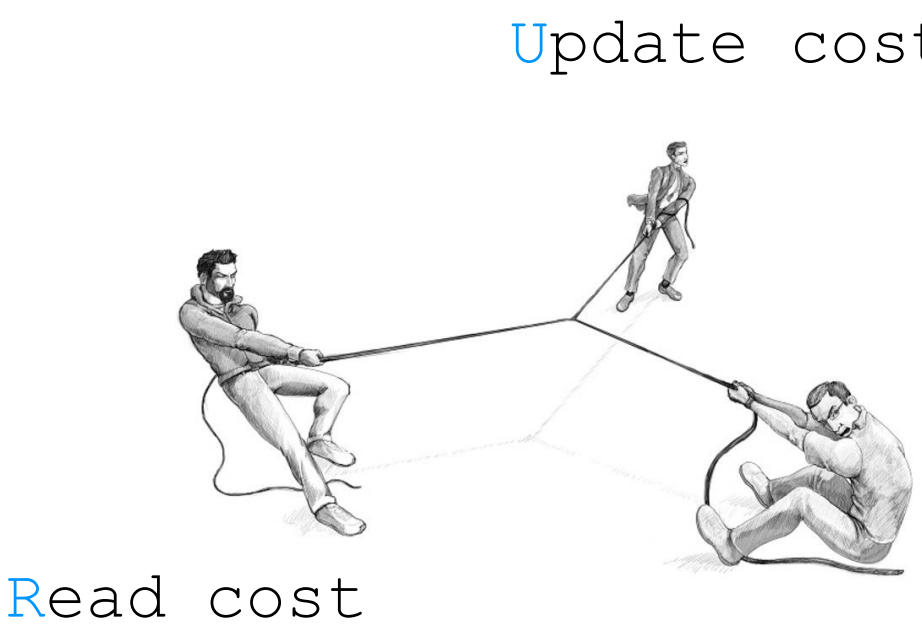
***Any* Compaction Algorithm**

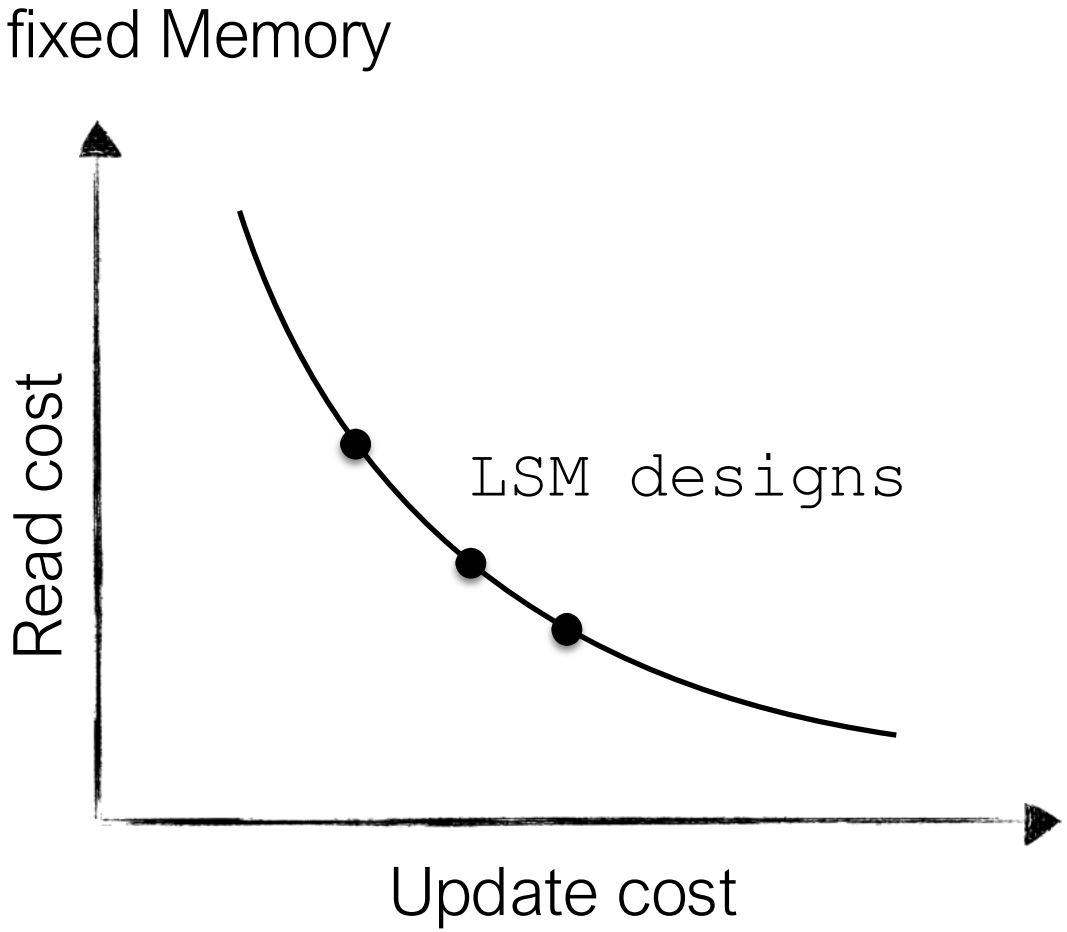
LSM **Design Space**

LSM **Design Space**

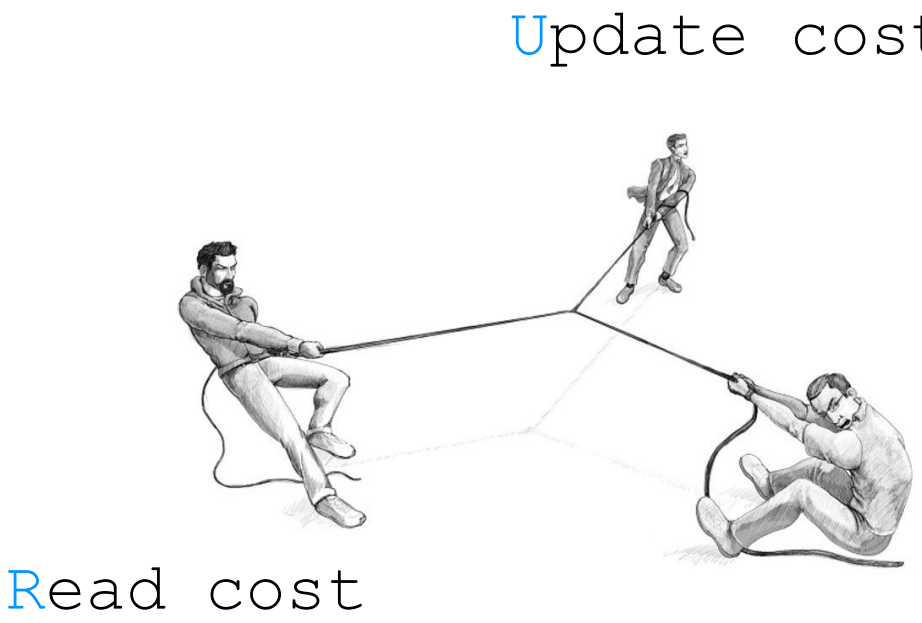


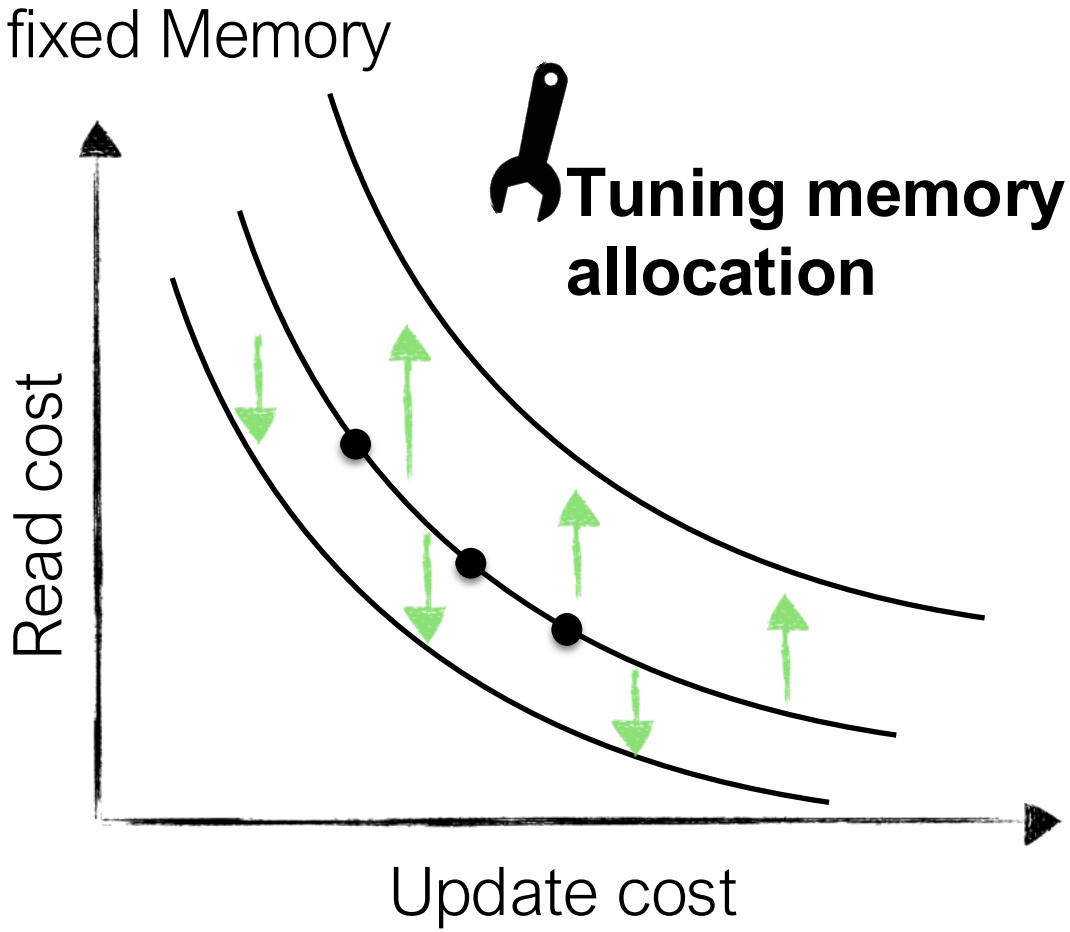
LSM **Design Space**



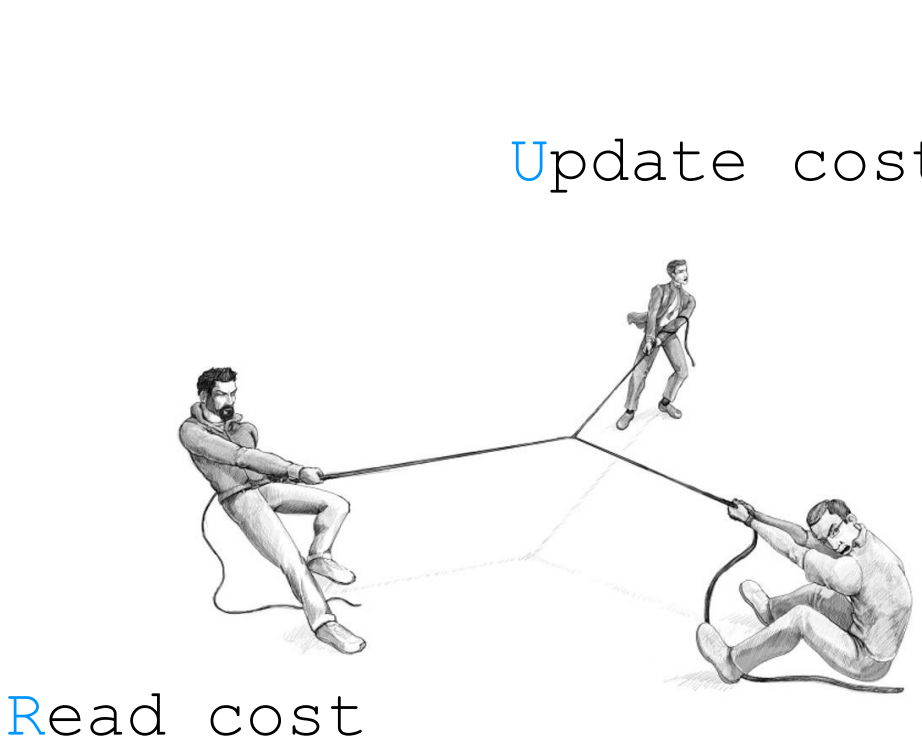


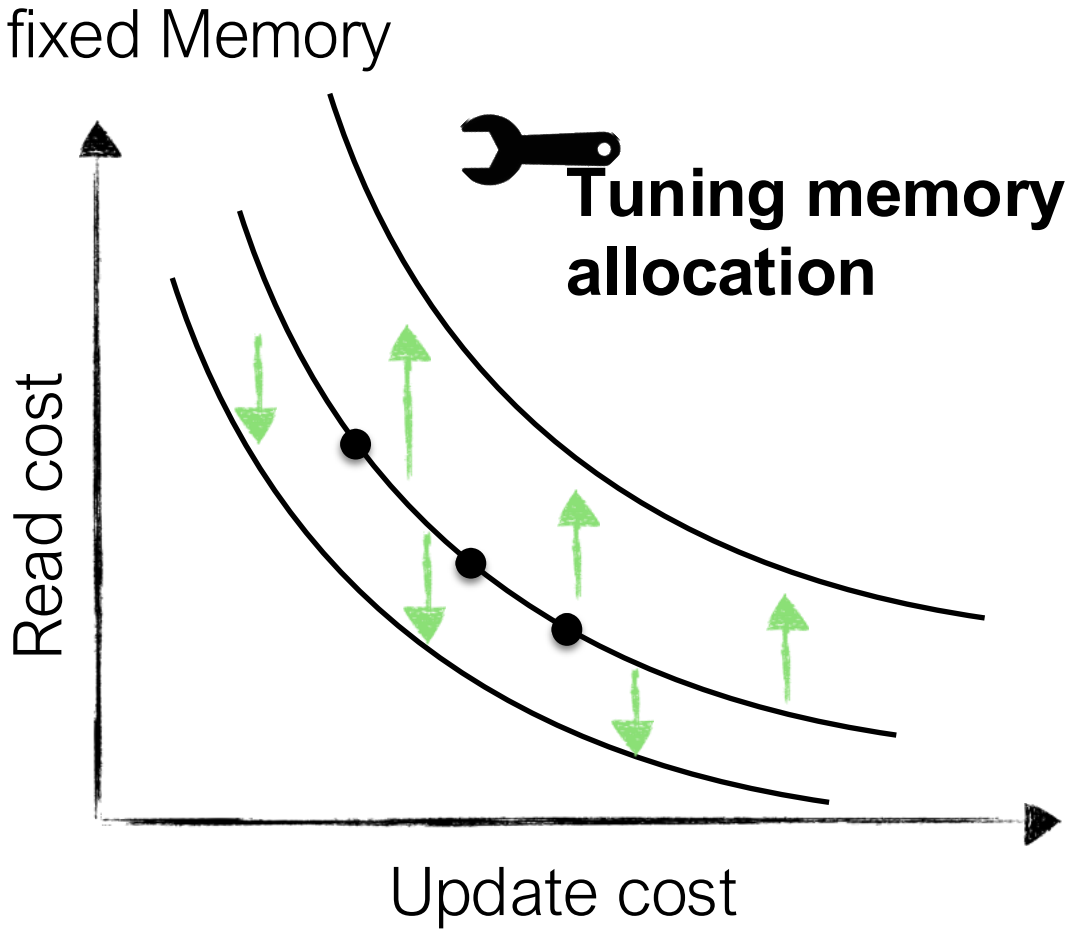
LSM **Design Space**



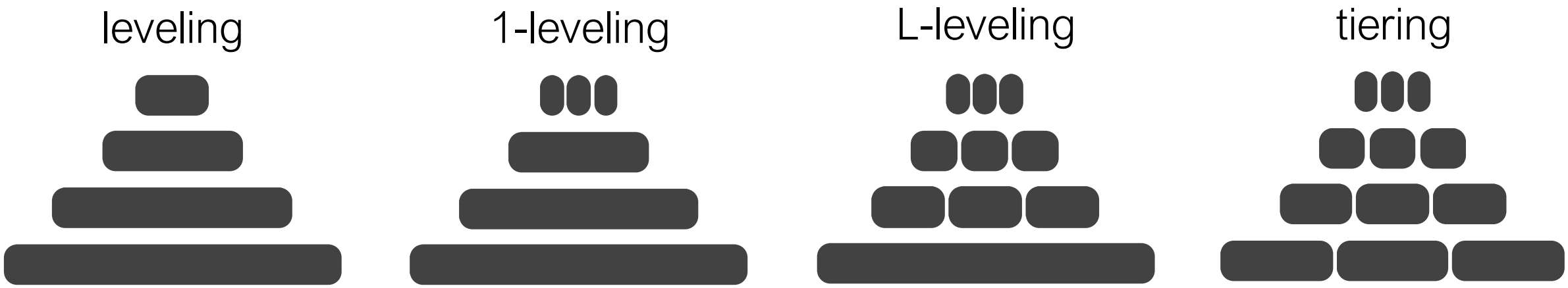


LSM **Design Space**





Storage Layer **Design Continuum**



Any design can be defined by the tuple-set: (T, i)

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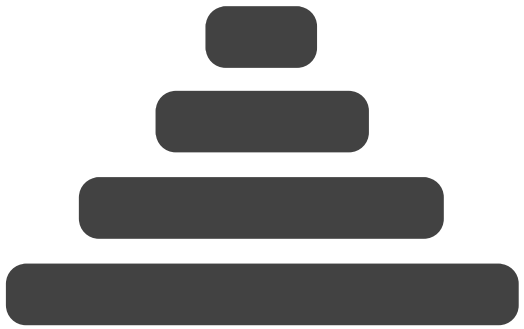
Storage Layer **Design Continuum**

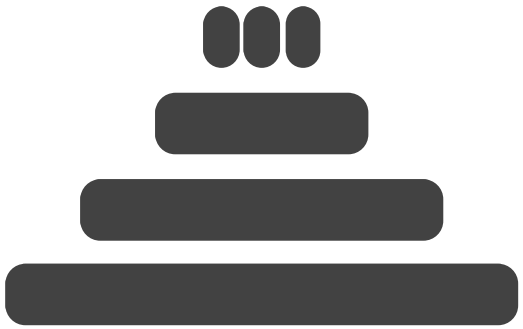
leveling

(T, 0)



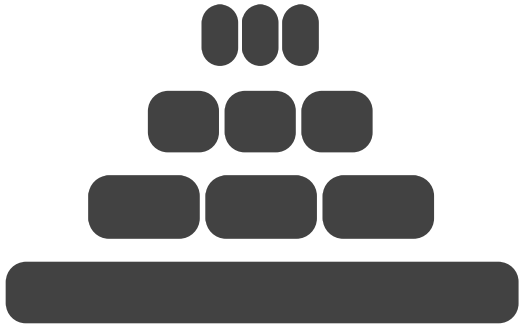
1-leveling

(T, 1)



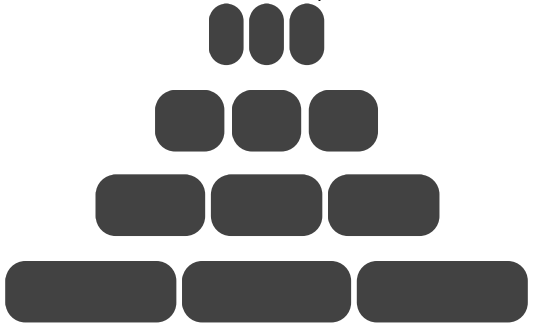
L-leveling

(T, L)



tiering

(T, L+1)



Any design can be defined by the tuple-set: (T, i)

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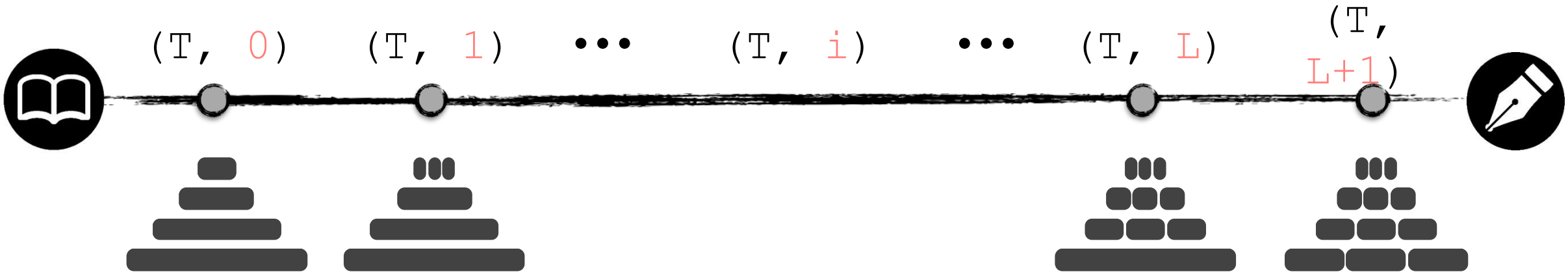
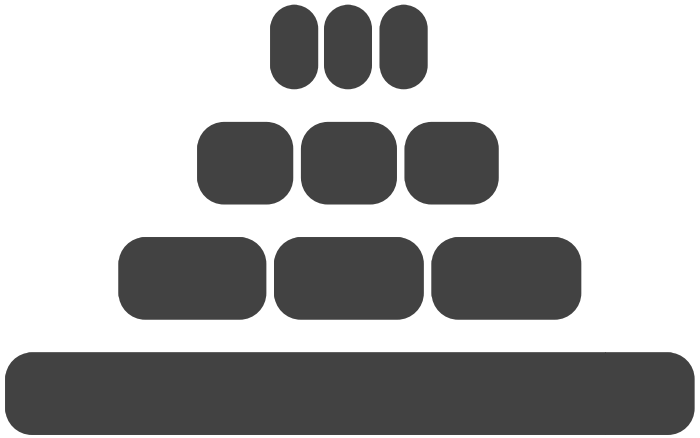
Storage Layer **Design Continuum**



Storage Layer **Design Continuum**

Storage Layer **Design Continuum**



size ratio

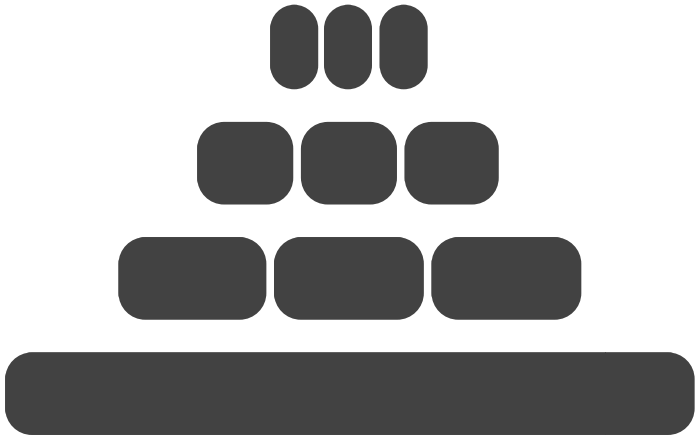
T

T

T

T

Storage Layer **Design Continuum**



size ratio

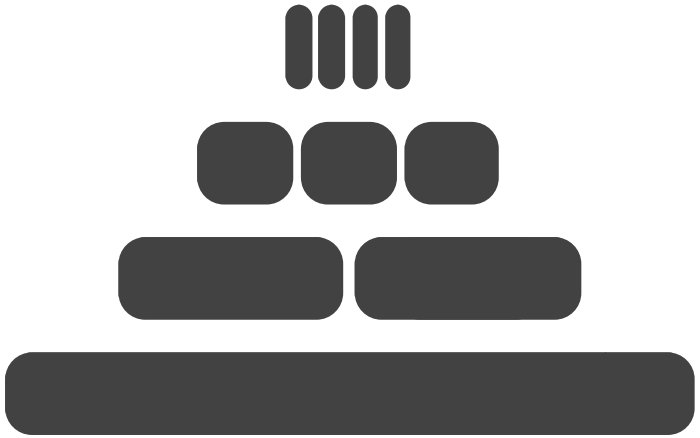
T

T

T

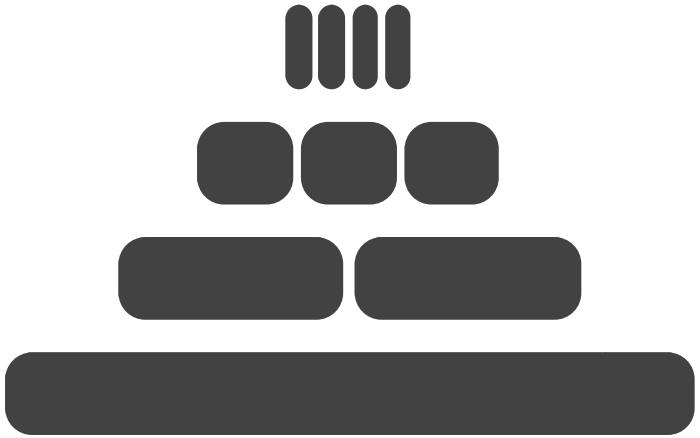
T

Storage Layer **Design Continuum**



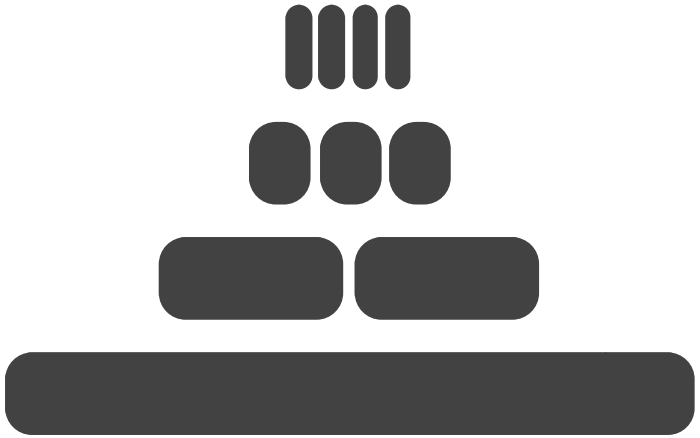
size ratio	#runs
T	4
T	3
T	2
T	1

Storage Layer **Design Continuum**



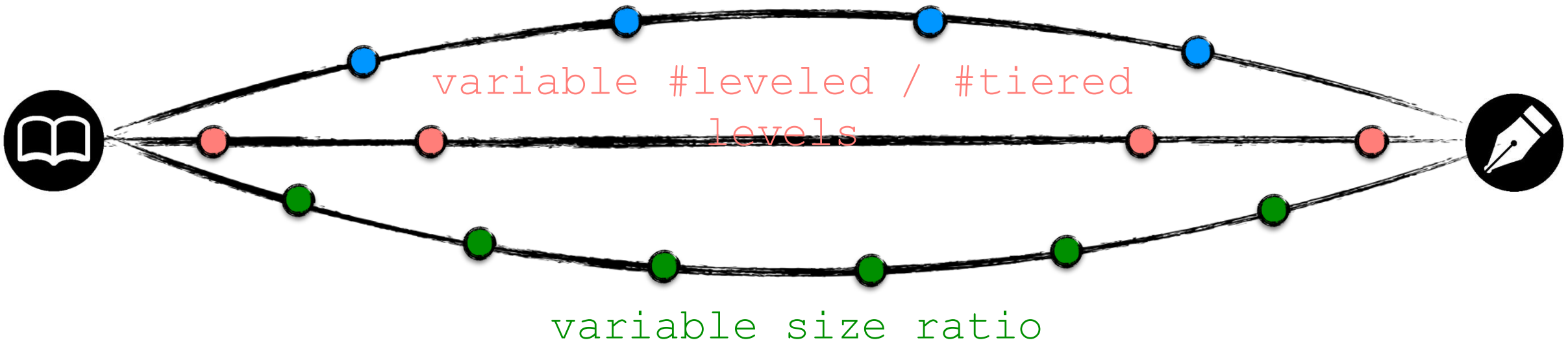
size ratio	#runs
T	4
T	3
T	2
T	1

Storage Layer **Design Continuum**



size ratio	#runs
2	4
2.5	3
3	2
4	1

Storage Layer **Design Continuum**



The LSM storage layer design continuum

BOSTON UNIVERSITY

CS 561: Data Systems Architectures

class 6

Log-structured Merge Trees

Prof. Manos Athanassoulis

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