

Dissecting, Designing, and Optimizing **LSM-Based Data Stores**

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DiSC lab

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

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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

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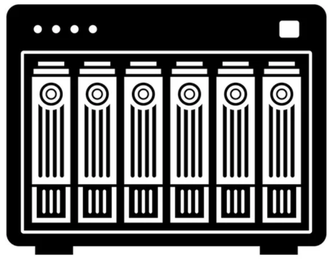
- good random writes
- good reads



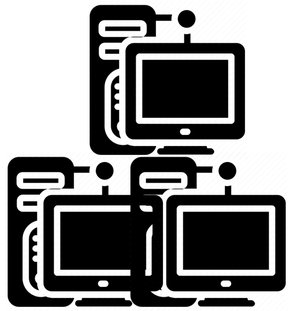
array
of discs

SSD wear-friendly

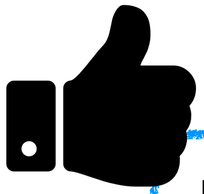
competitive rand. reads

fast ingestion

- poor ingestion perf.
- poor query perf.



commodity
hardware



LSM-tree
O'Neil *et al.*

Bigtable

1980s

1996

2006

a decade

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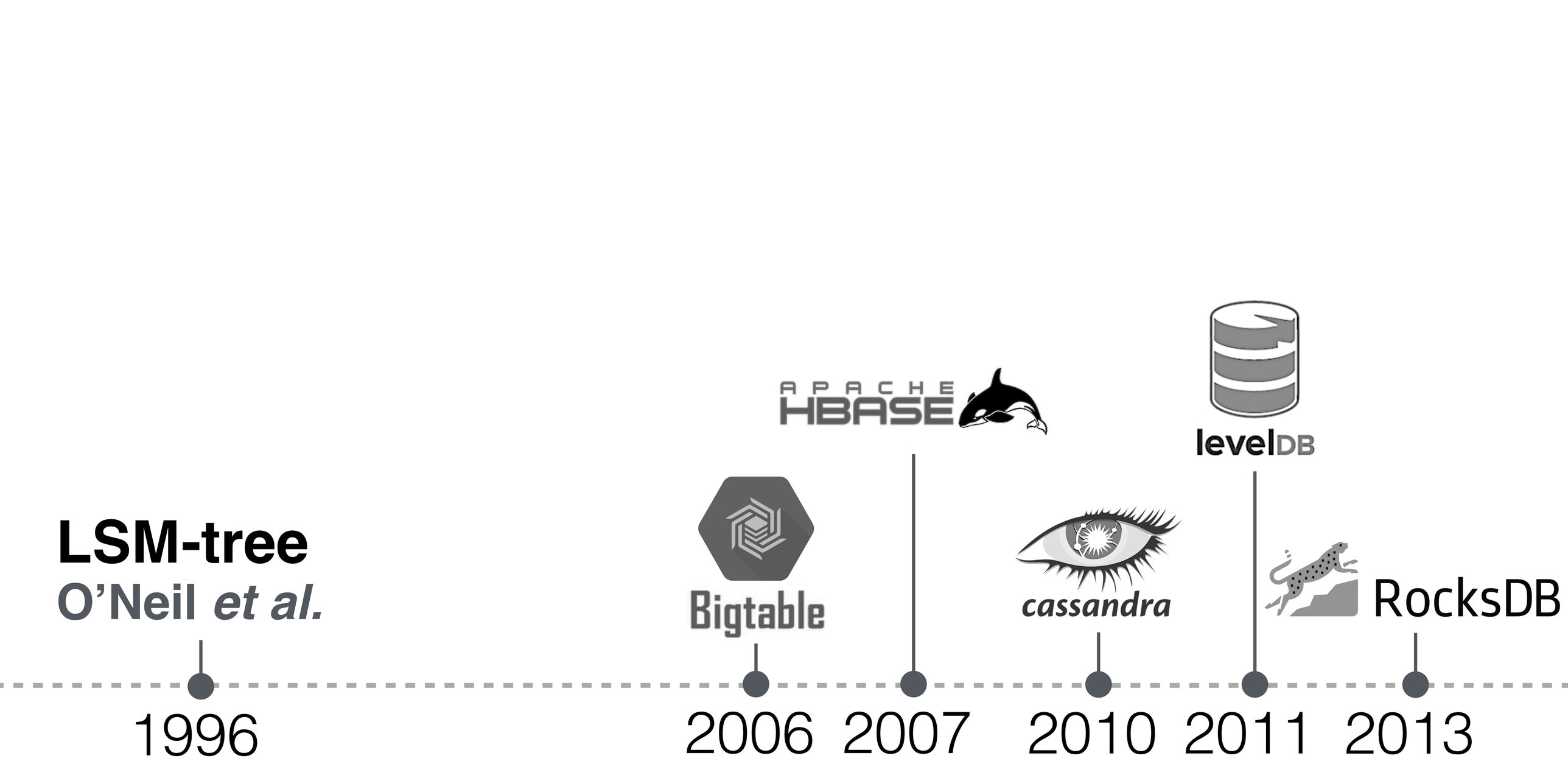

LSM-tree
O'Neil et al.
1996
Bigtable
2006
APACHE HBASE
2007
cassandra
2010
levelDB
2011
RocksDB
2013

LSM-tree

NoSQL

relational

time-series

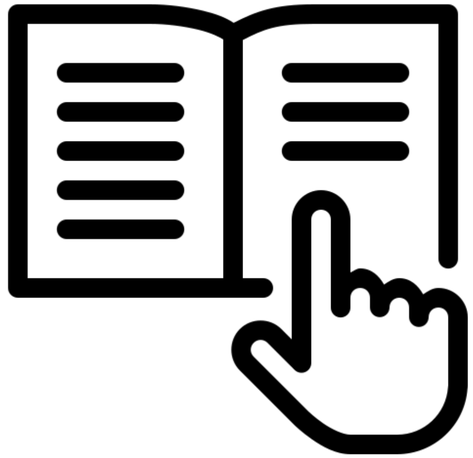
2022

Why **LSM** ?

fast ingestion

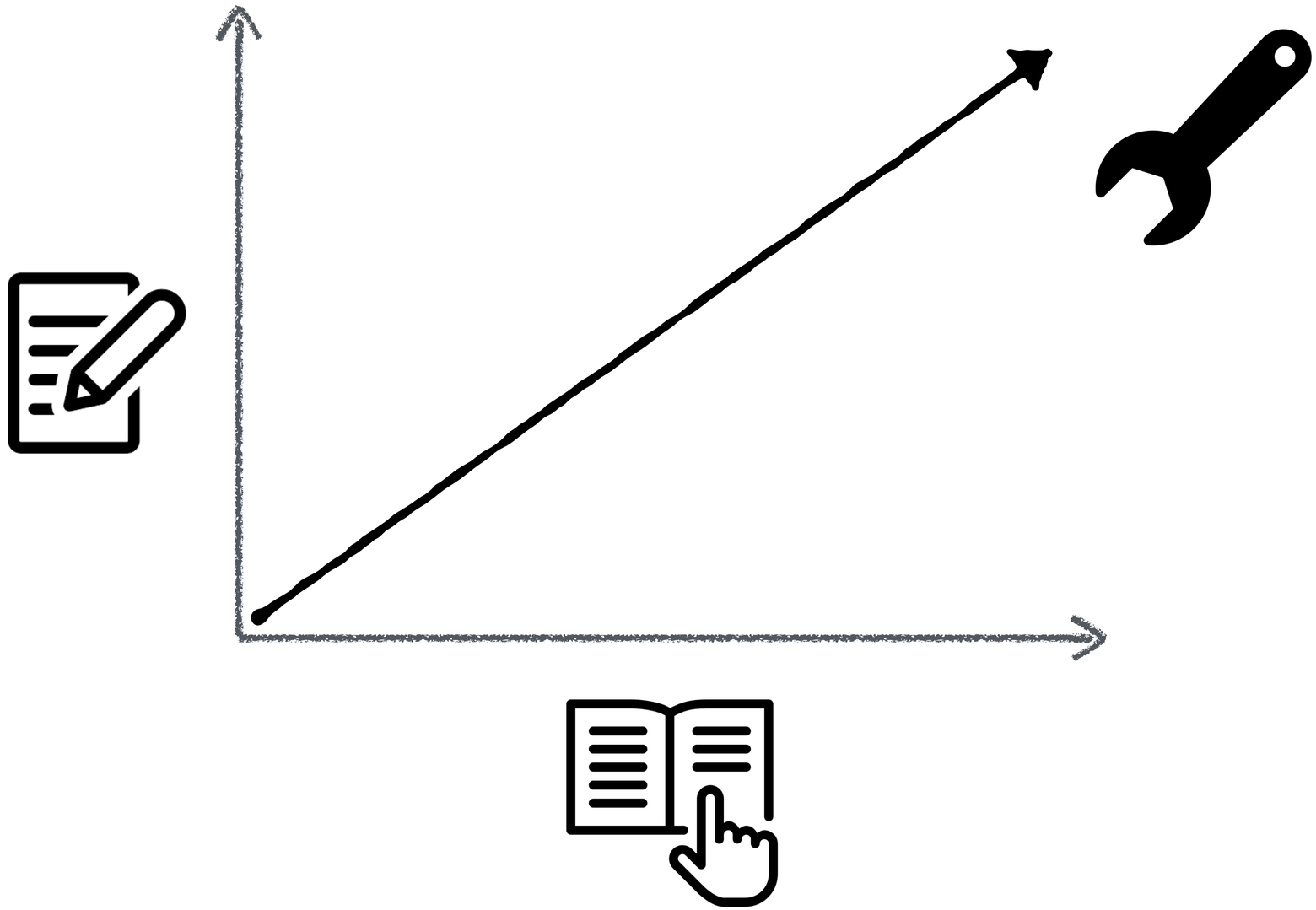
Why **LSM** ?

fast ingestion

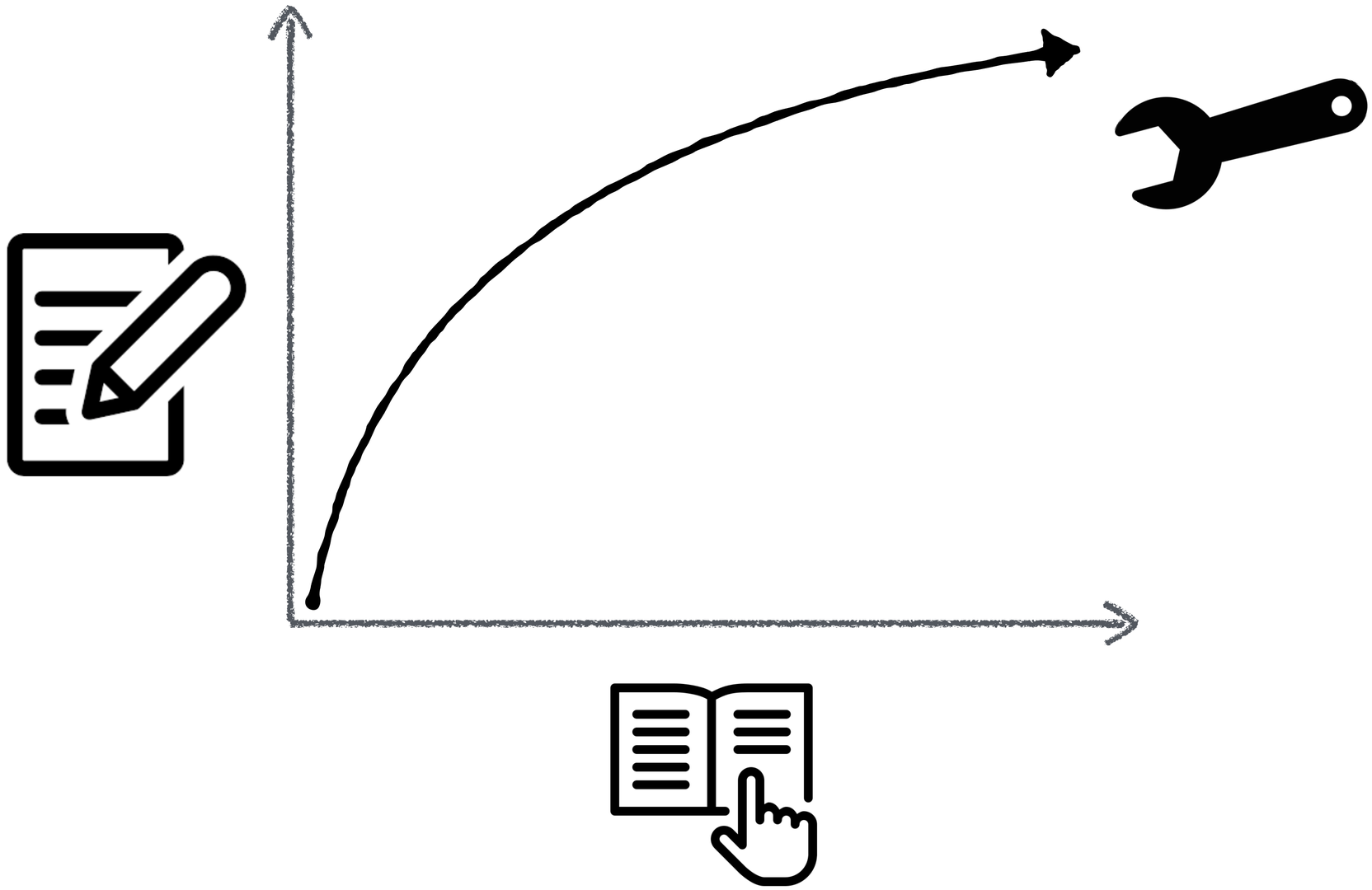


competitive reads

Why **LSM** ?



Why **LSM** ?



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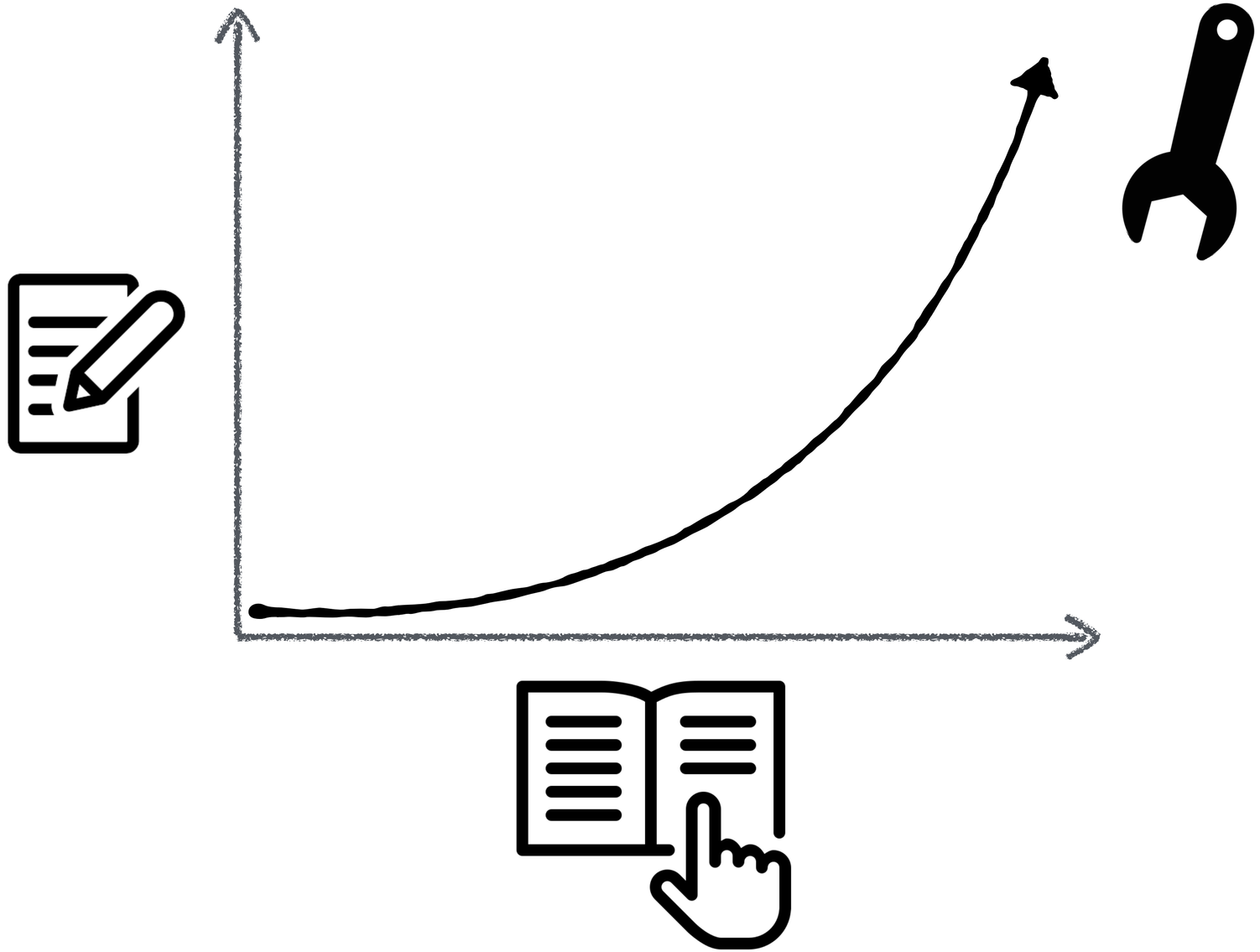
Why **LSM** ?



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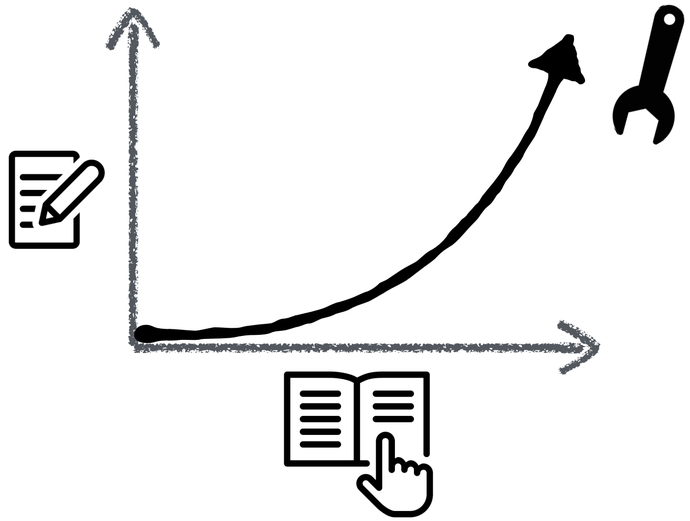
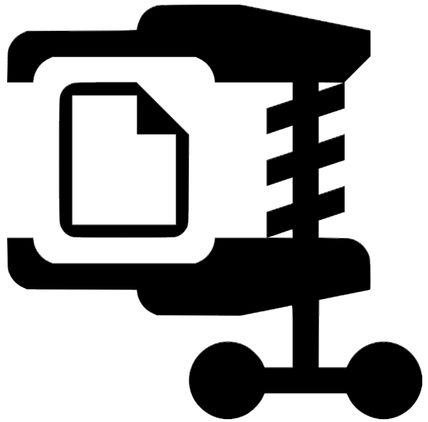
Why **LSM** ?

fast writes



tunable read-write performance



good space utilization

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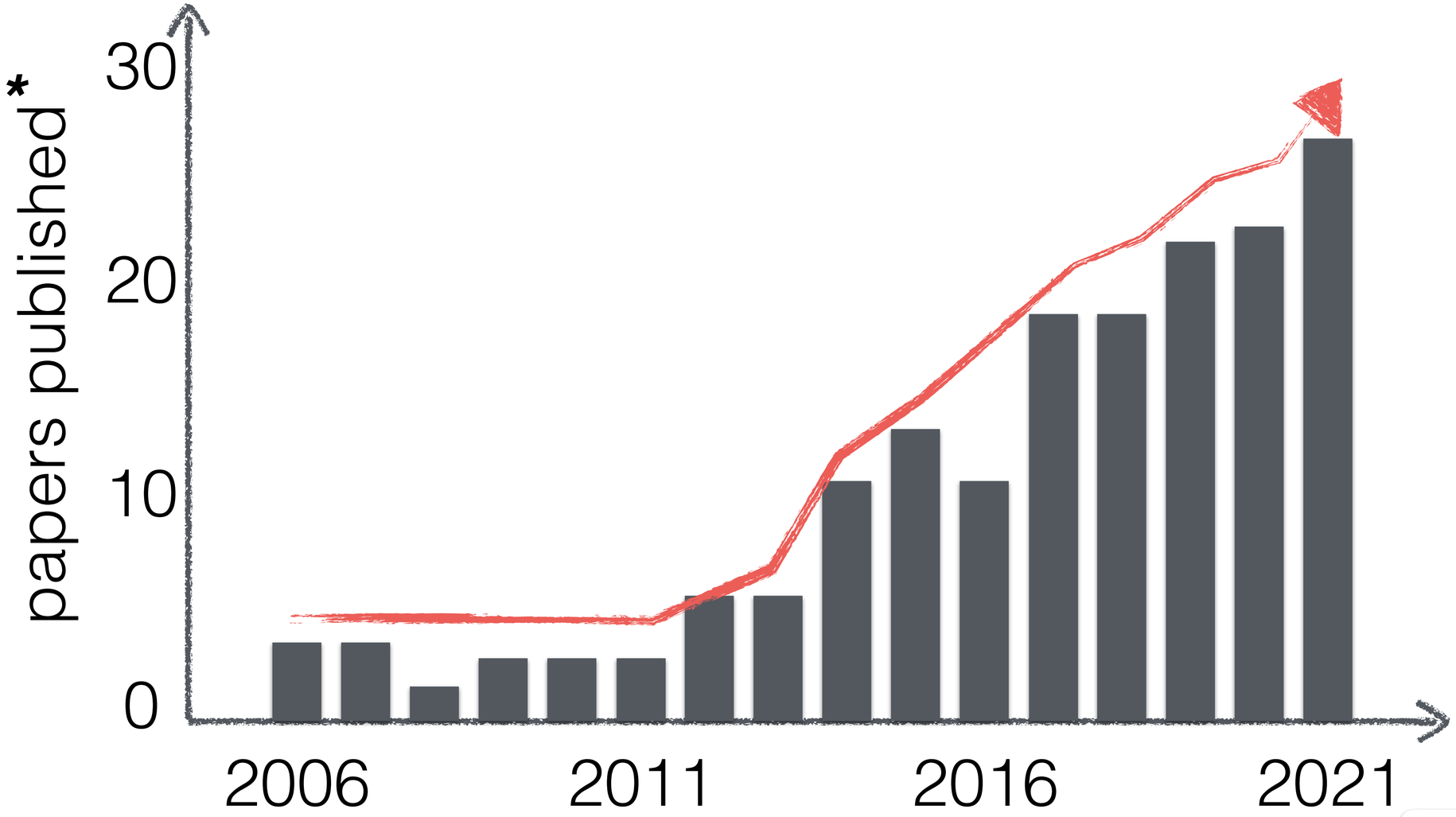
Research Trend



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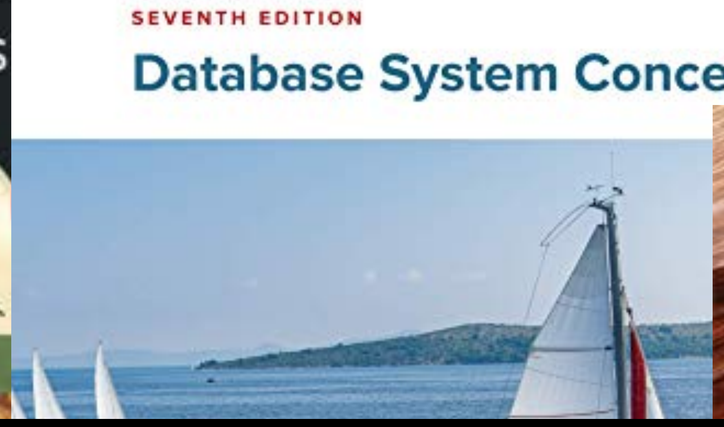
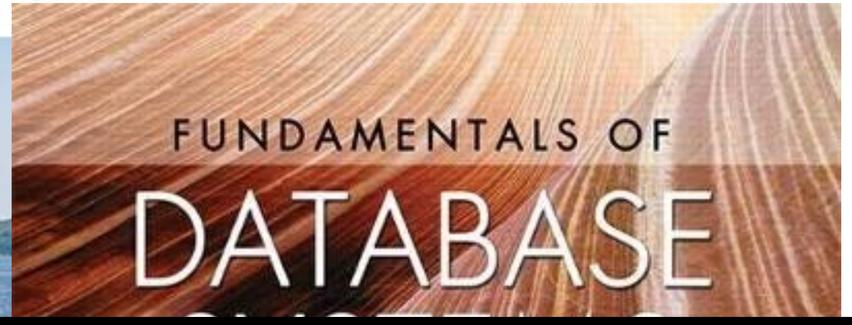
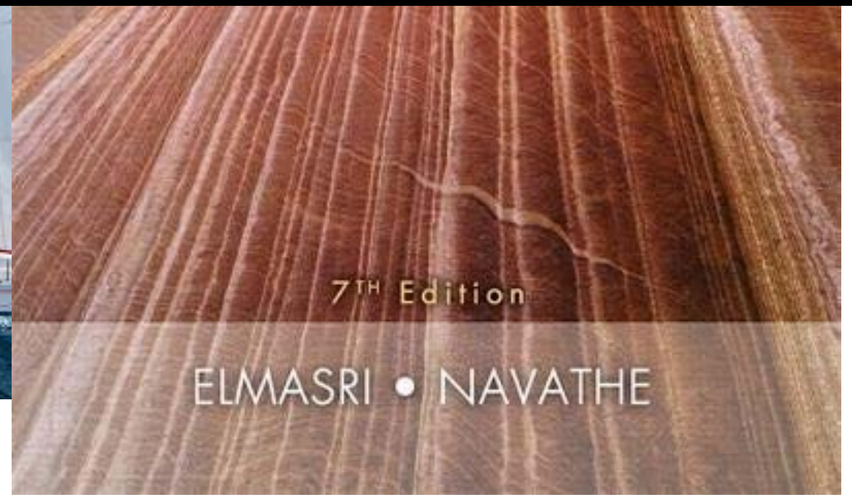
* data from DBLP





No Textbook on LSMs !!



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No Textbook on LSMs !!

explore the LSM paradigm

construct LSM design space

provide useful **insights**

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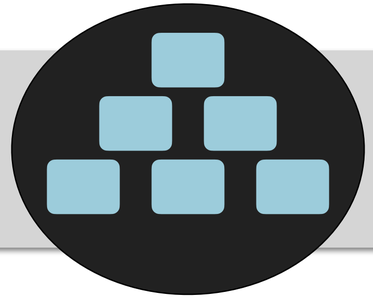
Outline

Part 1: **LSM Basics**

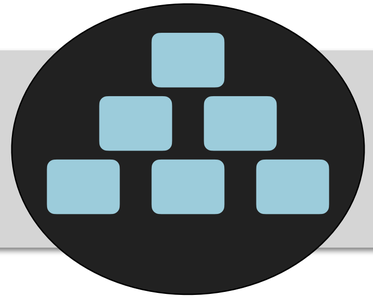


Part 2: **Optimizing Ingestion in LSMs**

Part 3: **Navigating the LSM Design Space**

Outline

Part 1: **LSM Basics**

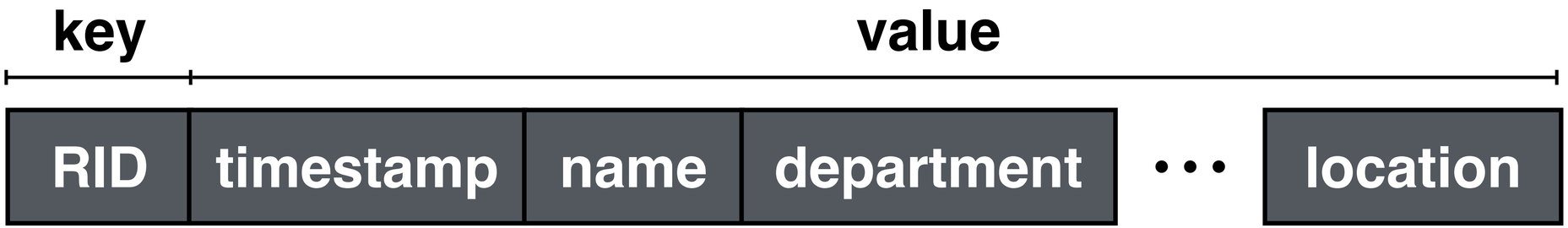


Part 2: **Optimizing Ingestion in LSMs**

Part 3: **Navigating the LSM Design Space**

LSM **Basics**

key-value pairs

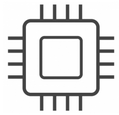


LSM **Basics**

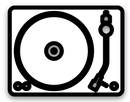
key-value pairs

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

LSM **Basics**



buffer



level 1

level 2

level 3

level 4

size ratio: T

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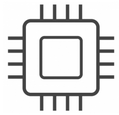
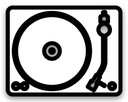
Buffering ingestion

put(6)

put(2)



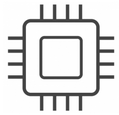
buffer



Buffering ingestion

put(1)

put(6)



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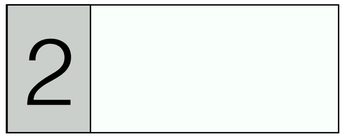

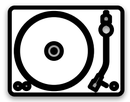

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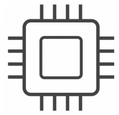
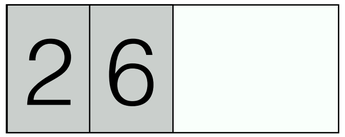
Buffering ingestion

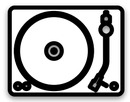
put(4)

put(1)



buffer





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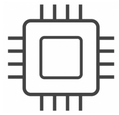
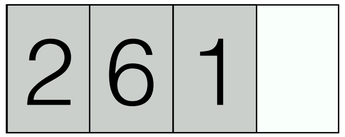
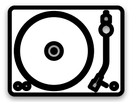
Buffering ingestion

put(4)

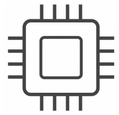


buffer

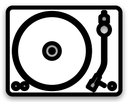




Buffering ingestion



buffer | 2 | 6 | 1 | 4 |



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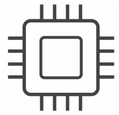
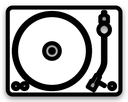
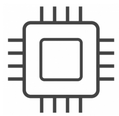
Buffering ingestion



buffer | 1 | 2 | 4 | 6 |



Buffering ingestion



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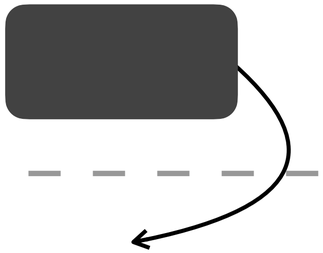
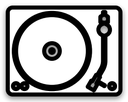
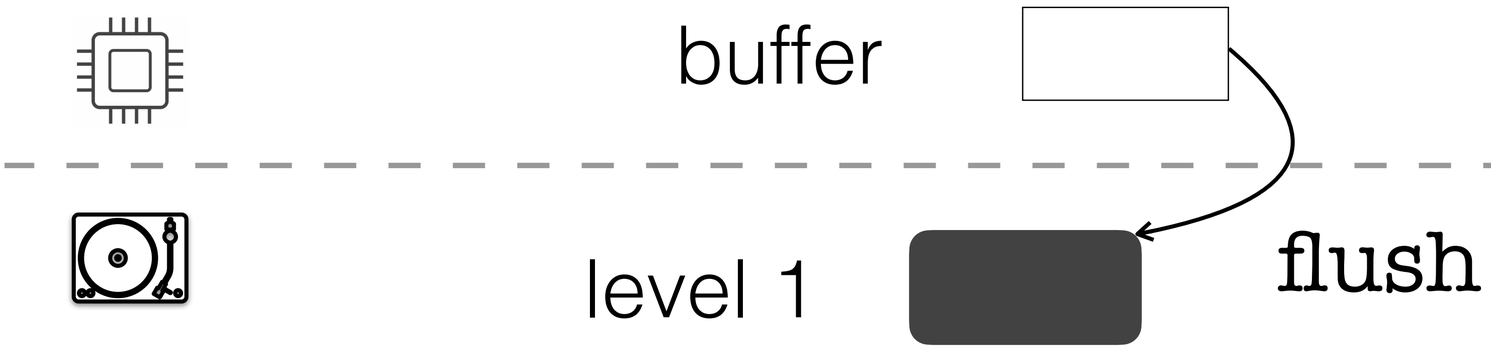




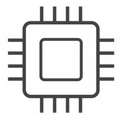
Buffering ingestion

- low ingestion cost
- fast temporal reads

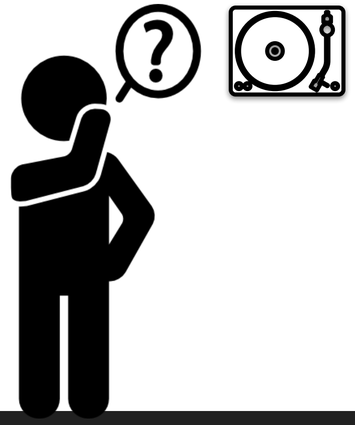


Immutable files on storage

- compact storage
- good ingestion throughput



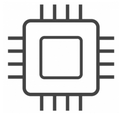
buffer



level 1

How do we update data?

put(6)



buffer

level 1 6

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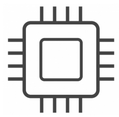

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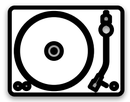
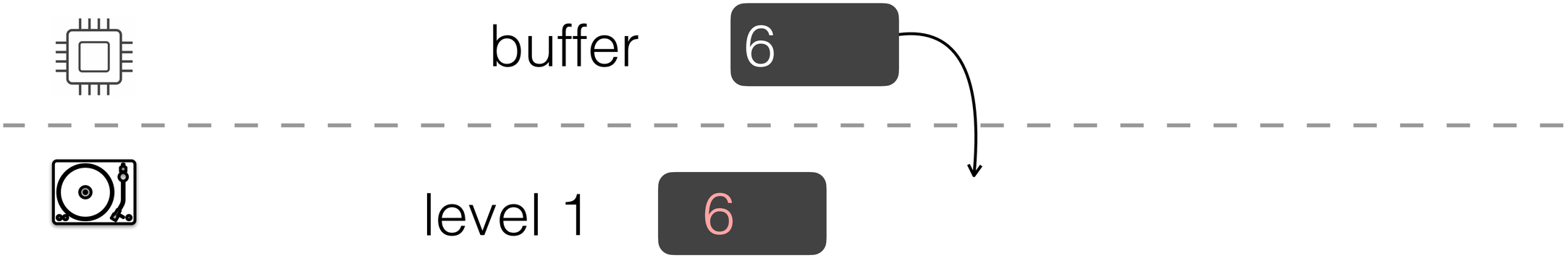
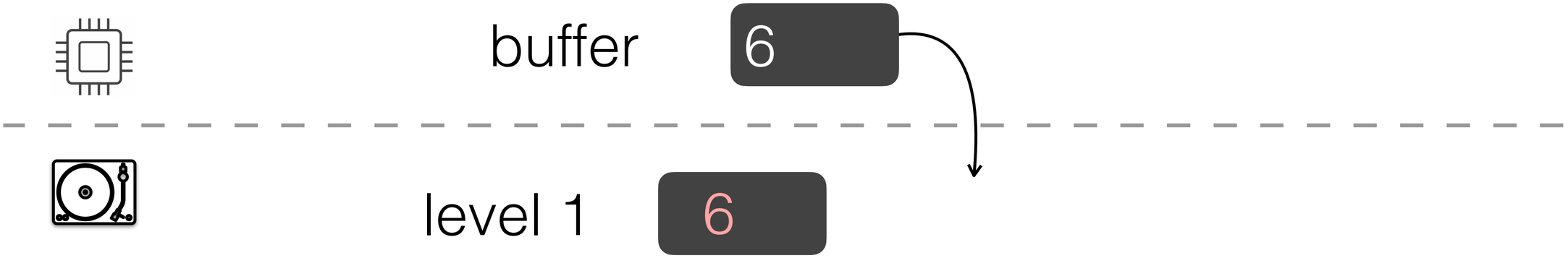


level 1

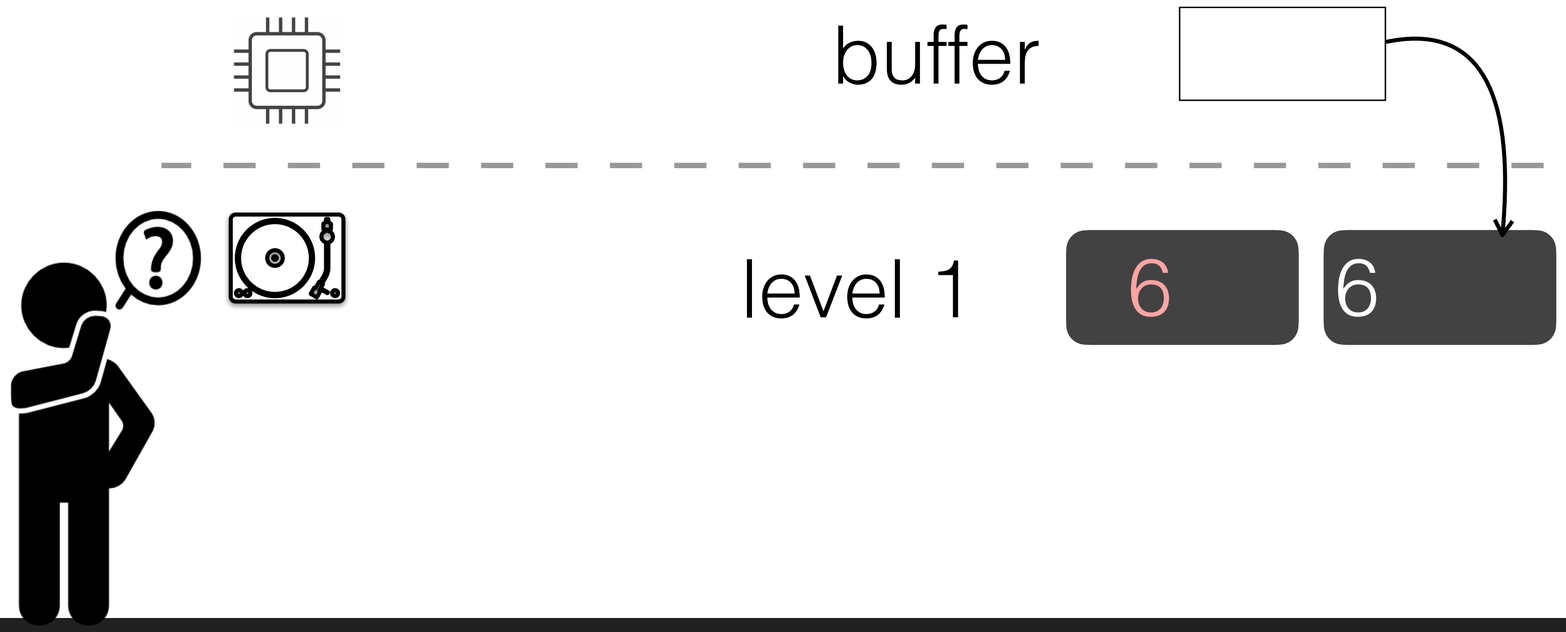
logically
invalidated



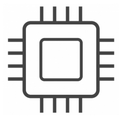


Out-of-place updates

- fast ingestion
- space amplification
- slow reads



How do we reduce this space amplification?



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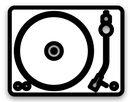
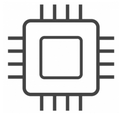


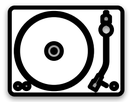
level 1

6

6



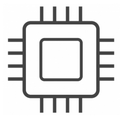
buffer



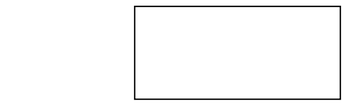
level 1

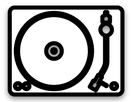
6

compaction



buffer





level 1

level 2

level 3

level 4

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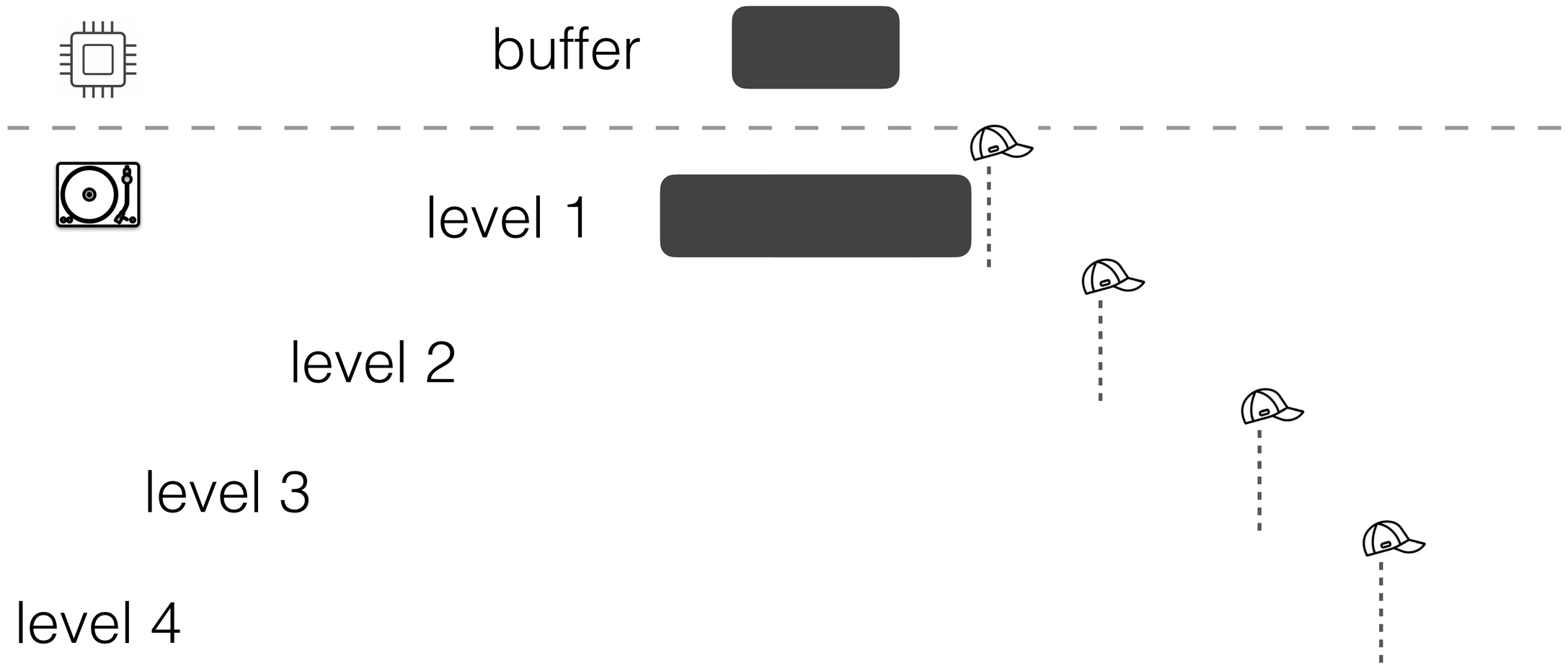
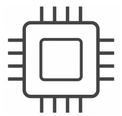
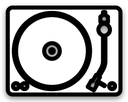
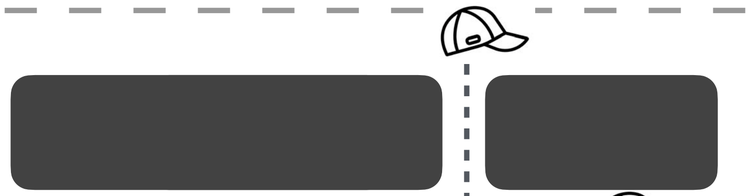




buffer



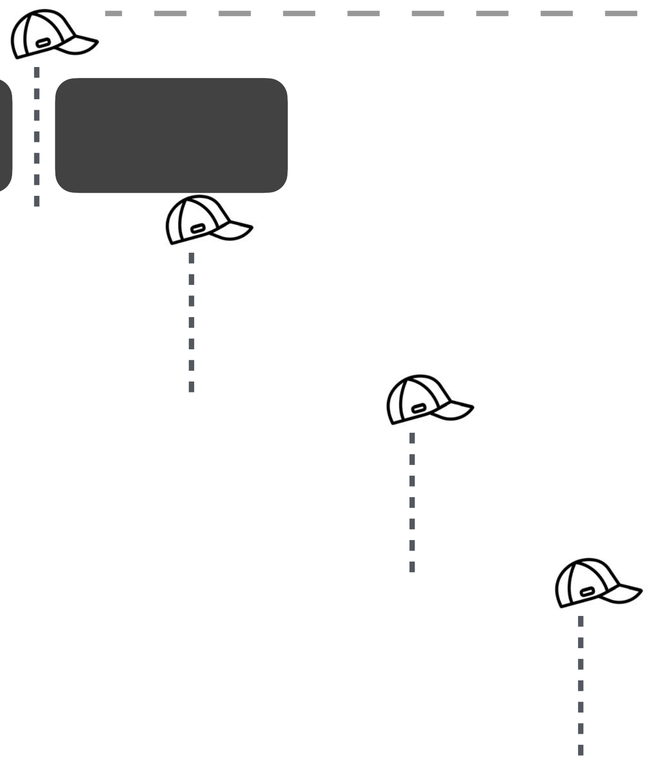
level 1



level 2

level 3

level 4



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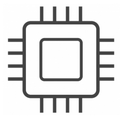
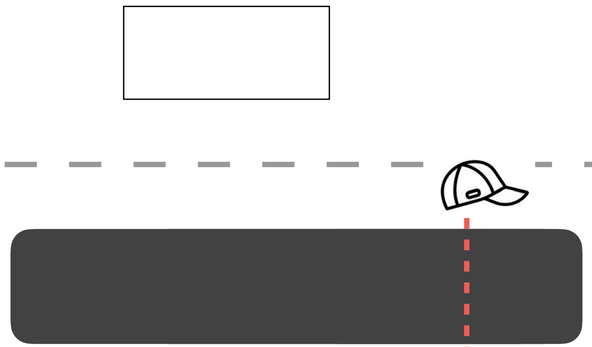
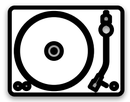


buffer



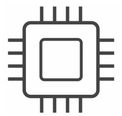


level 1

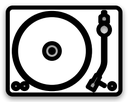
level 2

level 3

level 4



buffer



level 1

level 2

level 3

level 4

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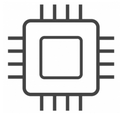
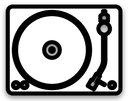
P: pages in buffer
B: entries/page
L: #levels
T: size ratio

Periodic compactions

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



buffer $P \cdot B$



level 1 $P \cdot B \cdot T$

level 2 $P \cdot B \cdot T^2$

level 3 $P \cdot B \cdot T^3$

level 4 $P \cdot B \cdot T^4$

capacity (entries)

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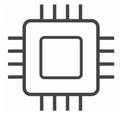
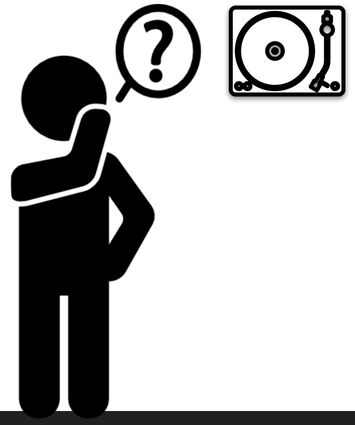
P: pages in buffer
B: entries/page
L: #levels
T: size ratio

Periodic compactions

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



buffer $P \cdot B$

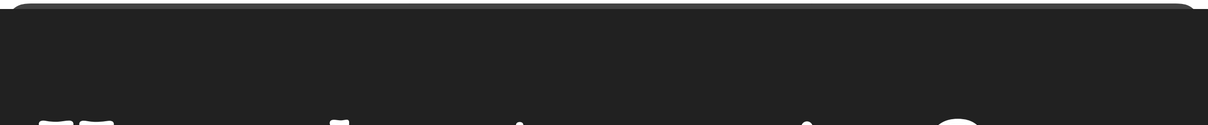


level 1

$P \cdot B \cdot T$

level 2

$P \cdot B \cdot T^2$



capacity
(entries)

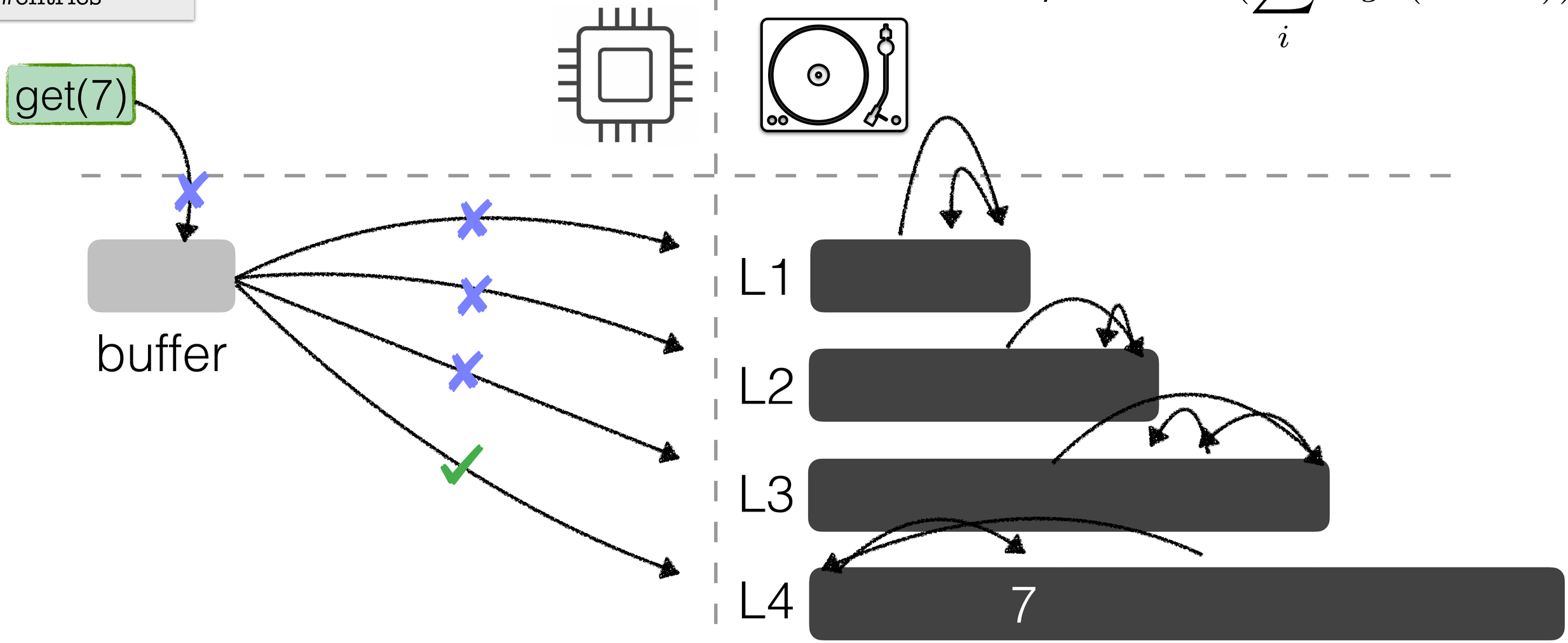
How about queries?

BOSTON UNIVERSITY

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

Cost analysis

w/o F&I: $\mathcal{O}(\sum_i log_2(P \cdot T^i))$

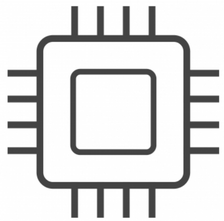


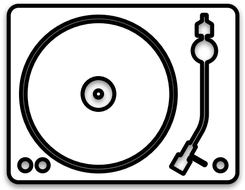
P: pages in buffer
B: entries/page
L: #levels
T: size ratio
N: #entries

Cost analysis

w/o F&I: $\mathcal{O}(\sum_i log_2(P \cdot T^i))$

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





get(7)

buffer

L1

L2

L3

L4

7

fence pointers

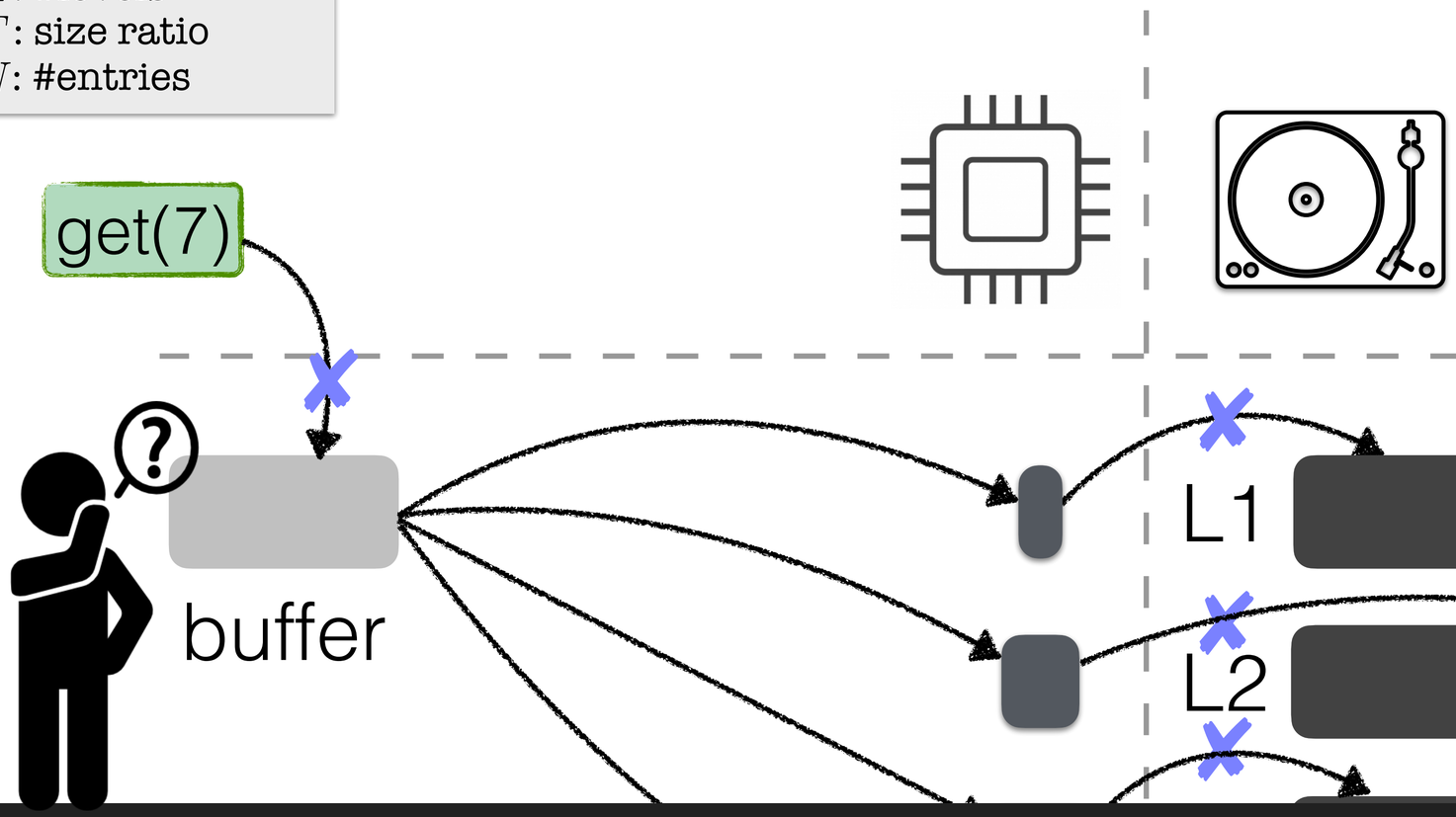
BOSTON UNIVERSITY

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

Cost analysis

w/o F&I: $\mathcal{O}(\sum_{i} log_2(P \cdot T^i))$

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



How to avoid unnecessary I/Os?

fence pointers

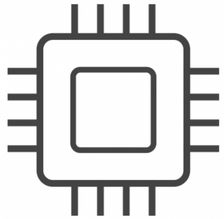
P: pages in buffer
B: entries/page
L: #levels
T: size ratio
N: #entries
ϕ : FPR of BF

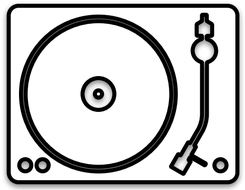
Cost analysis

w/o F&I: $\mathcal{O}(\sum_{i} log_2(P \cdot T^i))$

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

BOSTON UNIVERSITY

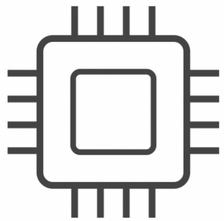
P: pages in buffer
B: entries/page
L: #levels
T: size ratio
N: #entries
ϕ : FPR of BF

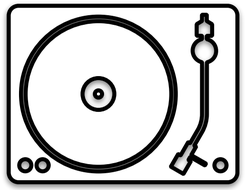
Cost analysis

w/o F&I: $\mathcal{O}(\sum_{i} log_2(P \cdot T^i))$

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

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





get(7)

buffer

L1

L2

L3

L4

7

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

Bloom filters

fence pointers

BOSTON UNIVERSITY

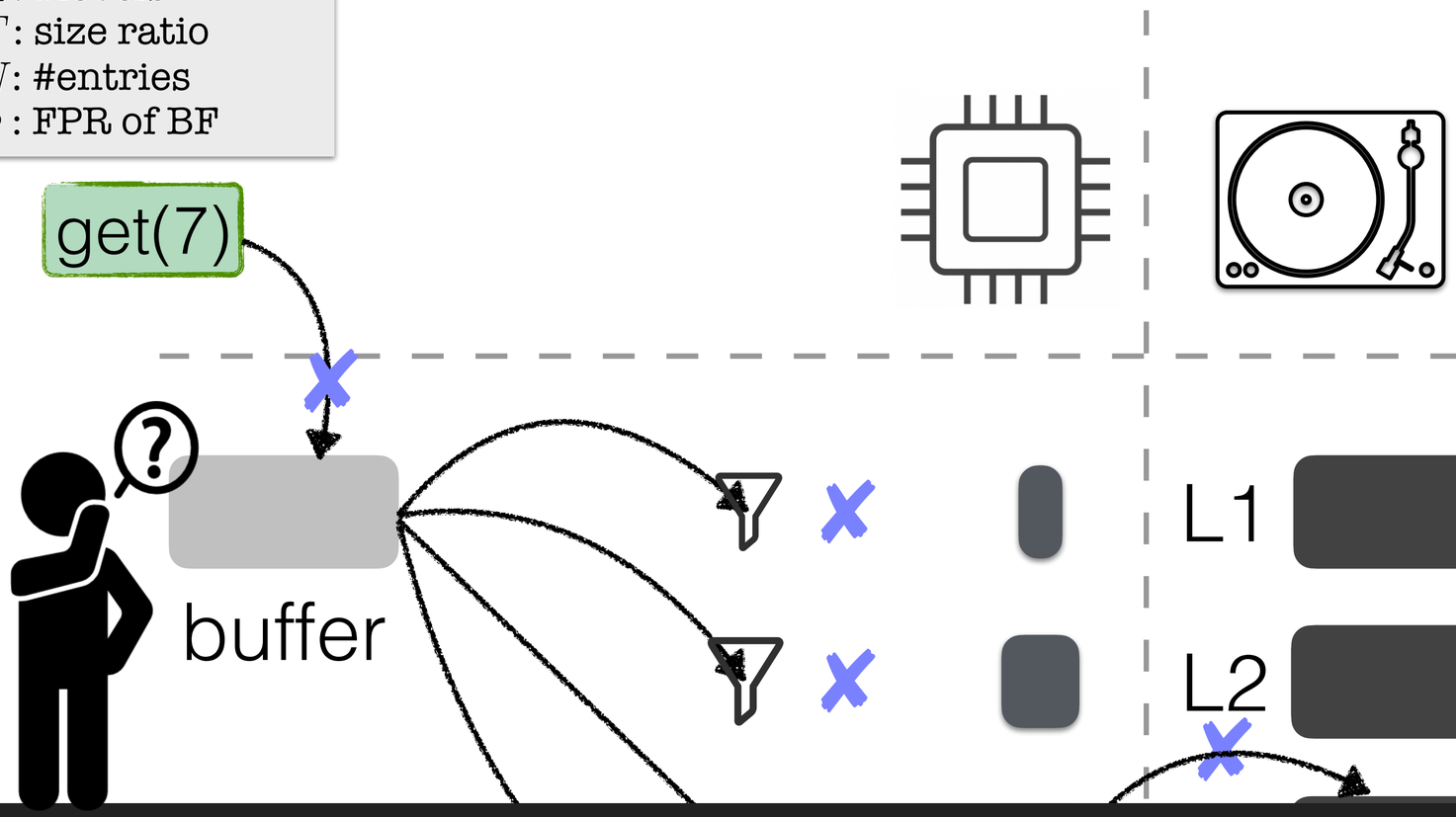
P: pages in buffer
B: entries/page
L: #levels
T: size ratio
N: #entries
ϕ : FPR of BF

Cost analysis

w/o F&I: $\mathcal{O}(\sum_{i} log_2(P \cdot T^i))$

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

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



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

How to manage memory?

Bloom filters

fence pointers

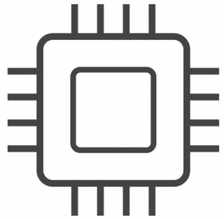
P: pages in buffer
B: entries/page
L: #levels
T: size ratio
N: #entries
ϕ : FPR of BF

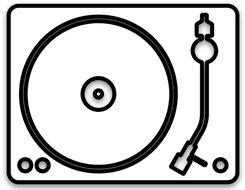
Cost analysis

w/o F&I: $\mathcal{O}(\sum_{i} log_2(P \cdot T^i))$

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

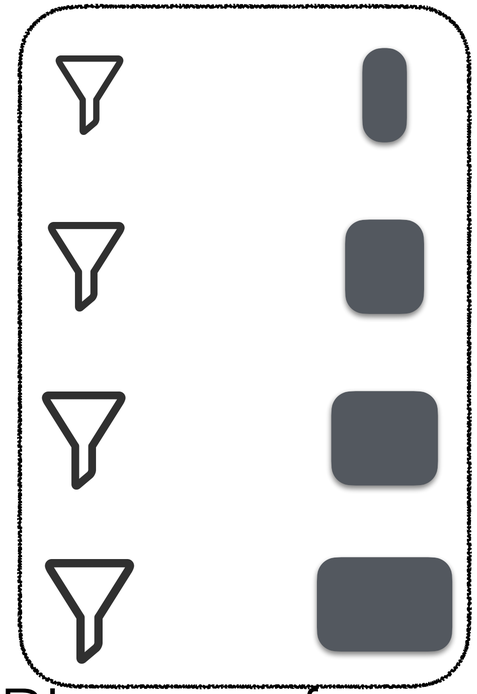
w F&I: $\mathcal{O}(\phi \cdot L)$





buffer

block cache



Bloom filters

fence pointers

L1

L2

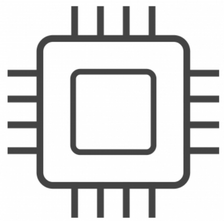
L3

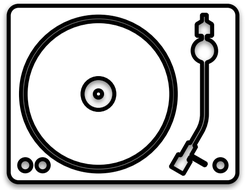
L4

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

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

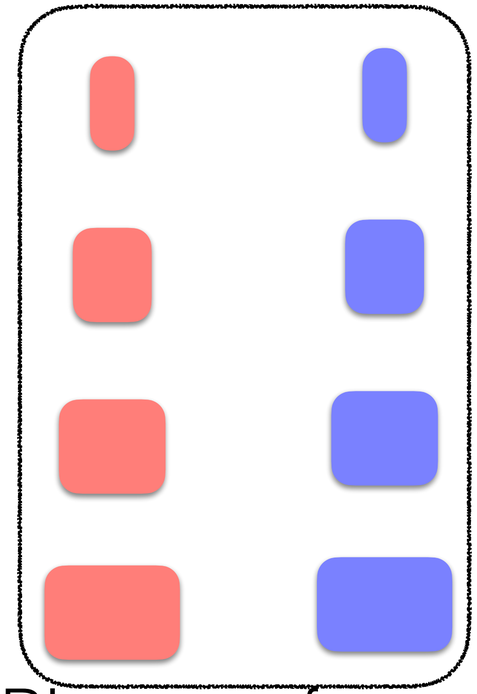
Block Cache





buffer

block cache



Bloom filters

fence pointers

L1

L2

L3

L4

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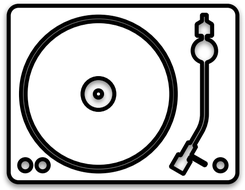
P: pages in buffer
B: entries/page
L: #levels
T: size ratio
N: #entries
ϕ: FPR of BF

Block Cache

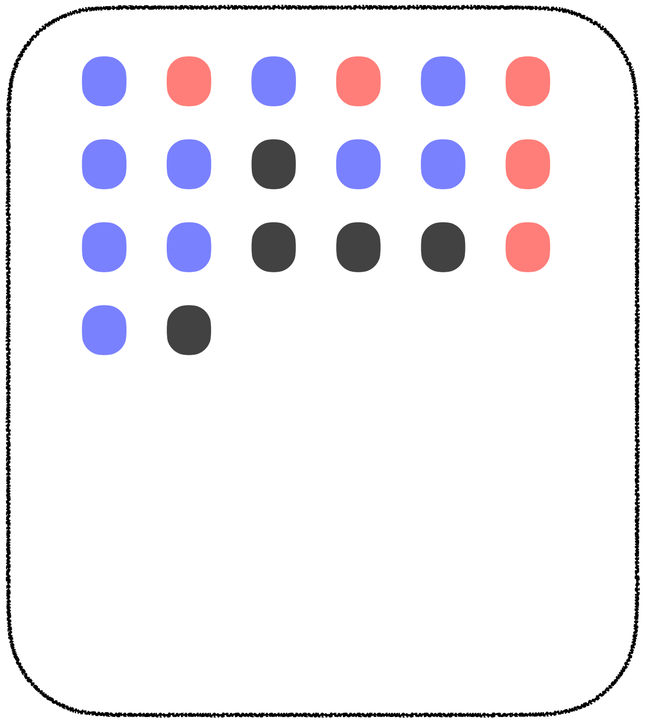


Bloom filters

fence pointers

get(7)

buffer



L1

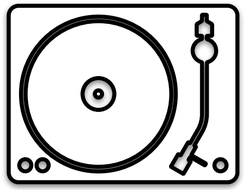
L2

L3

L4

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

Block Cache

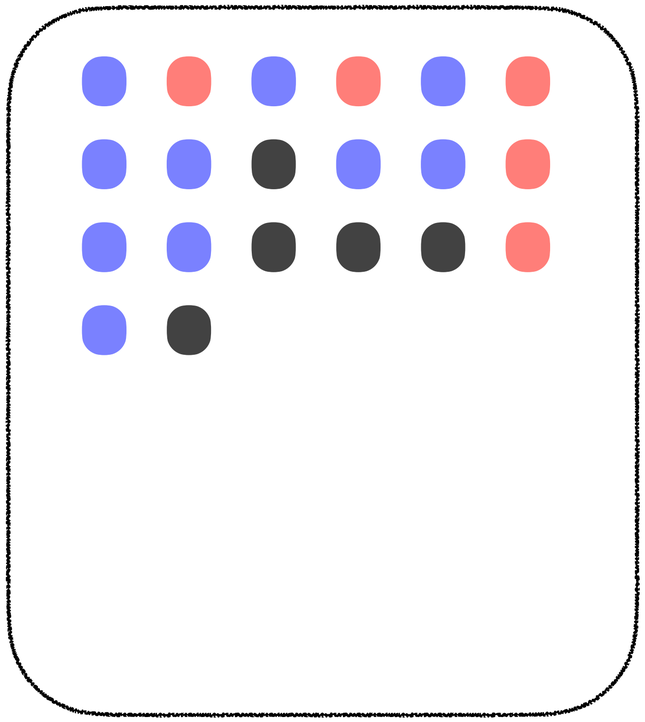


Bloom filters

fence pointers

get(7)

buffer



L1

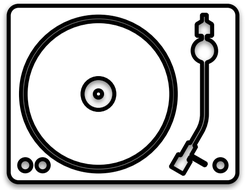
L2

L3

L4

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

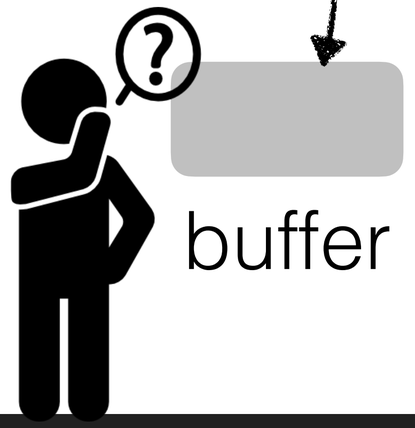
Block Cache



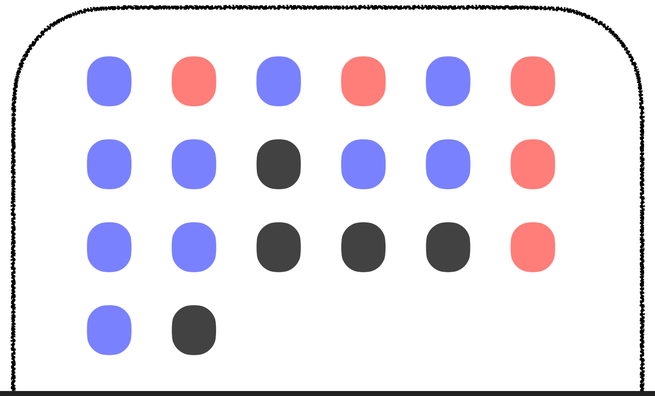
Bloom filters

fence pointers

get(7)



buffer



L1

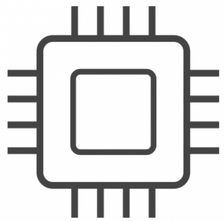
L2

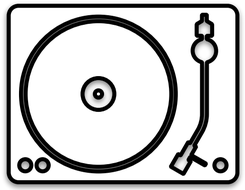
What about range queries?

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

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

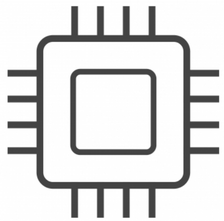
s : selectivity LRQ

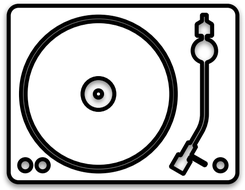
Range Queries

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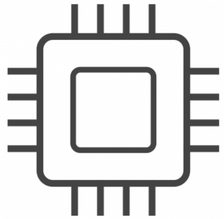
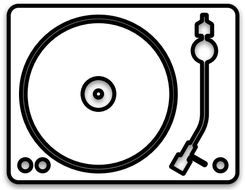
P: pages in buffer
B: entries/page
L: #levels
T: size ratio
N: #entries
ϕ: FPR of BF

s : selectivity SRQ

get(9,15)

Range Queries





Cost analysis

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

short range: $\mathcal{O}(L)$

buffer

Bloom filters

fence pointers

L1

L2

L3

L4

More **Read Optimizations**

filter structures

Better performance

Chucky — DayanSIGMOD21

Less memory usage

Ribbon filter — DillingerArxiv21

Less CPU usage

Shared Hashing — ZhuDAMON21

Support range queries

SuRF — ZhangSIGMOD18

Rosetta — LuoSIGMOD20

indexes

Better performance

Learned — DaiOSDI20

Less memory usage

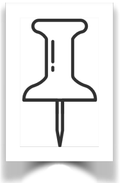
FerraginaVLDB20

block cache

Better performance

Less memory usage

Prefetching — HuangVLDB20



Pinning — CallaghanSD18

Priority — CallaghanSD16

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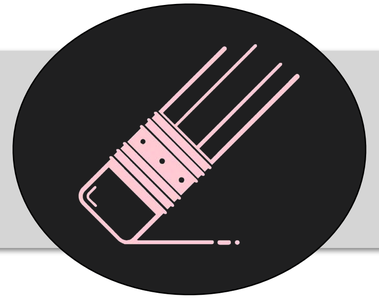
Outline

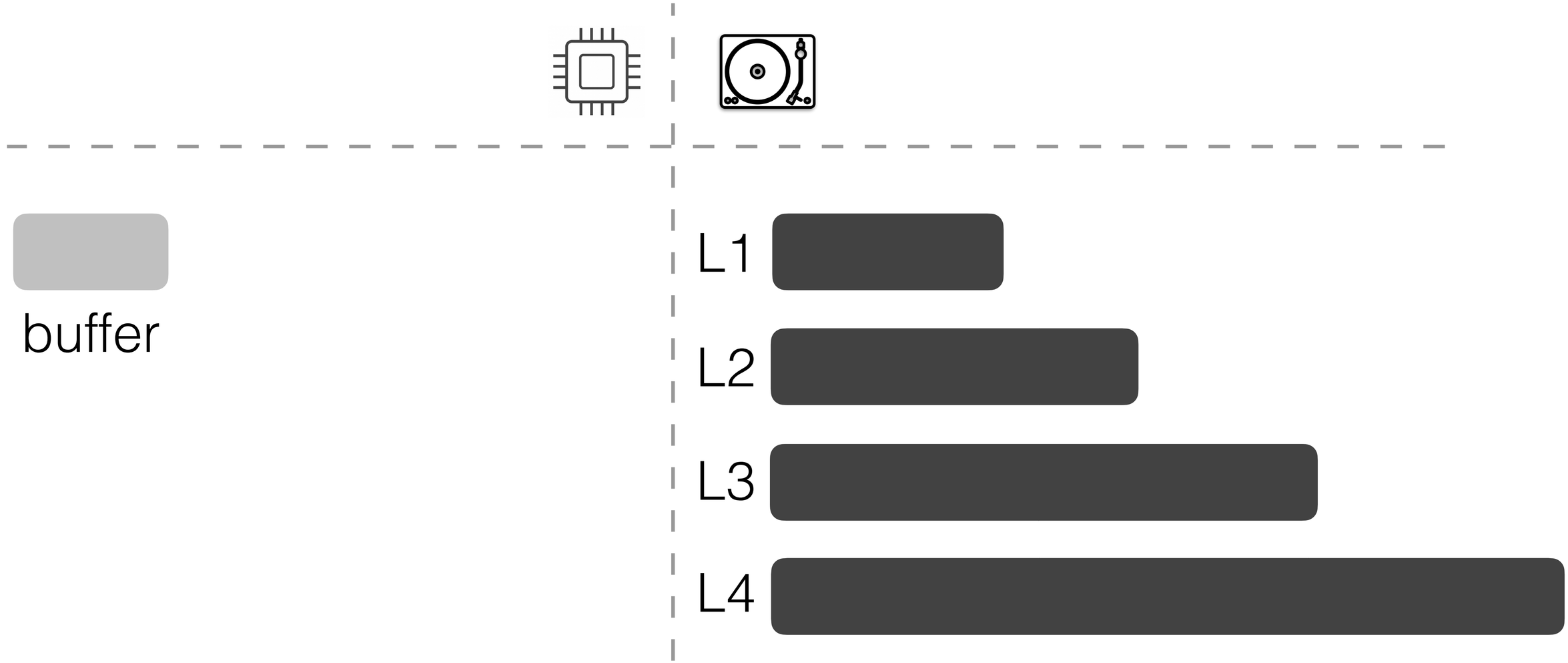
Part 1: **LSM Basics**

Part 2: **Optimizing Ingestion in LSMs**



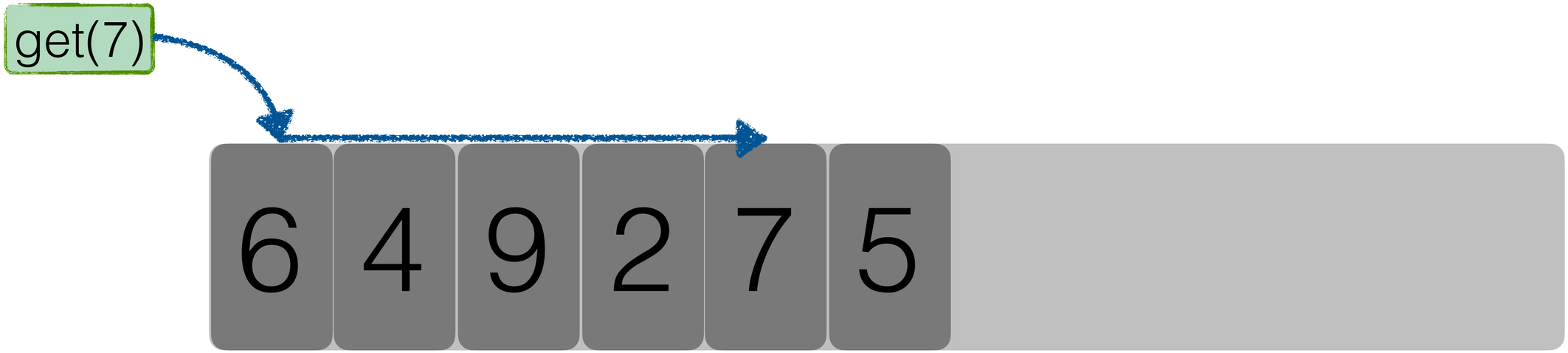
Part 3: **Navigating the LSM Design Space**

Buffer Optimizations



P: pages in buffer
B: entries/page

Buffer Implementation: **vector**



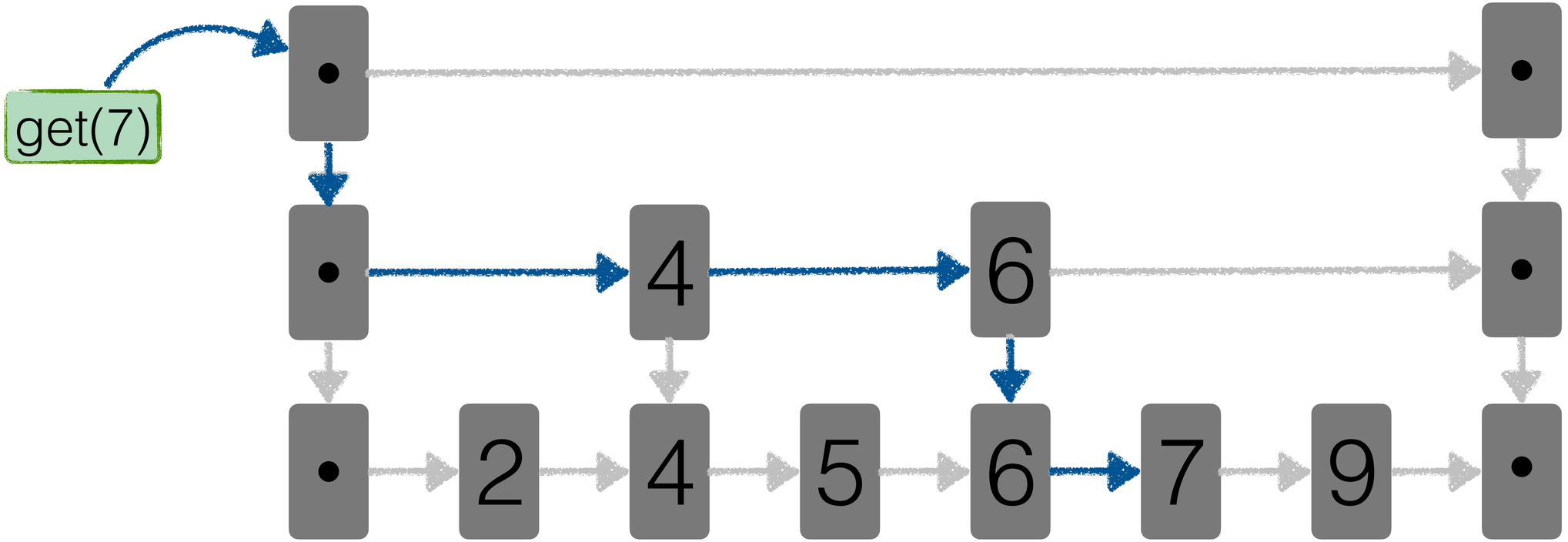
- great for ingestion-heavy w/l
- no extra space needed
- expensive points queries

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/l
- 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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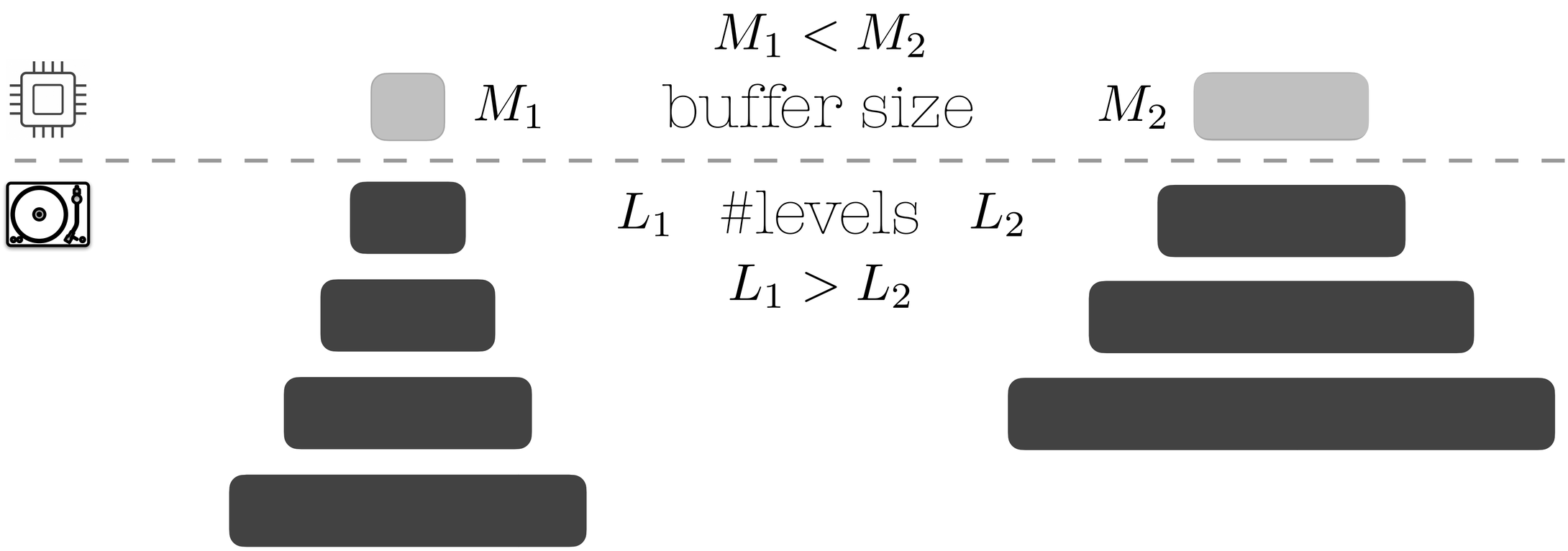
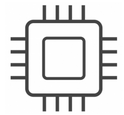
Size of the Buffer

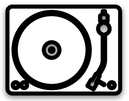


- frequent flushes
- smaller but more levels
- poor read performance

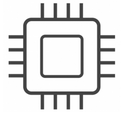
- fewer larger levels
- good for reads
- high tail latency

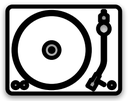
#Buffer Components



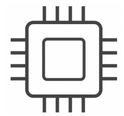


#Buffer Components

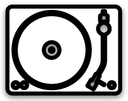




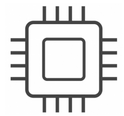
#Buffer Components



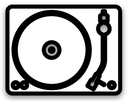
immutable
buffers



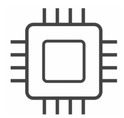
#Buffer Components

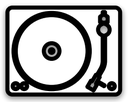


immutable
buffers



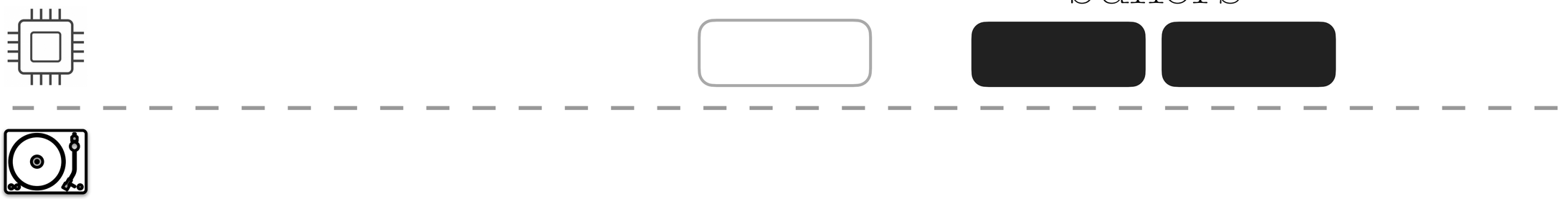
#Buffer Components



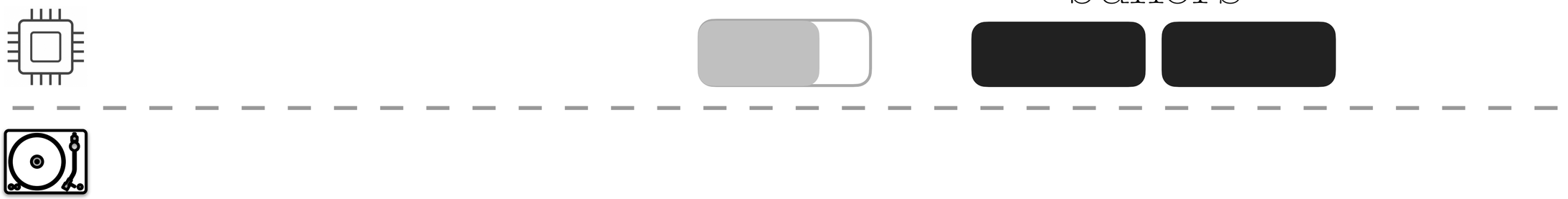


immutable
buffers

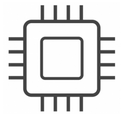
#Buffer Components



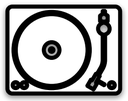
#Buffer Components



#Buffer Components

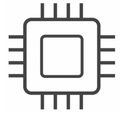


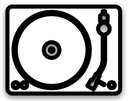
immutable
buffers



#Buffer Components

immutable
buffers





lazy flushing

- avoid write stalls
- improved ingestion throughput
- better bandwidth utilization
- requires more memory

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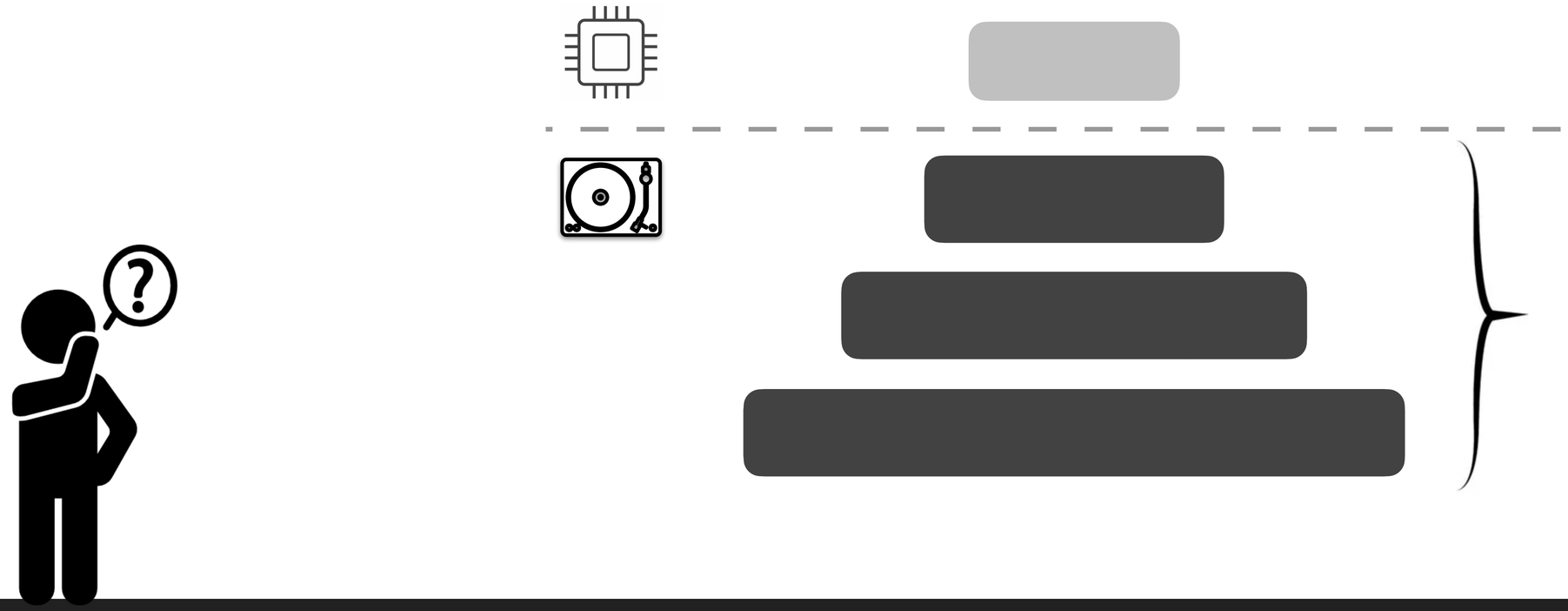
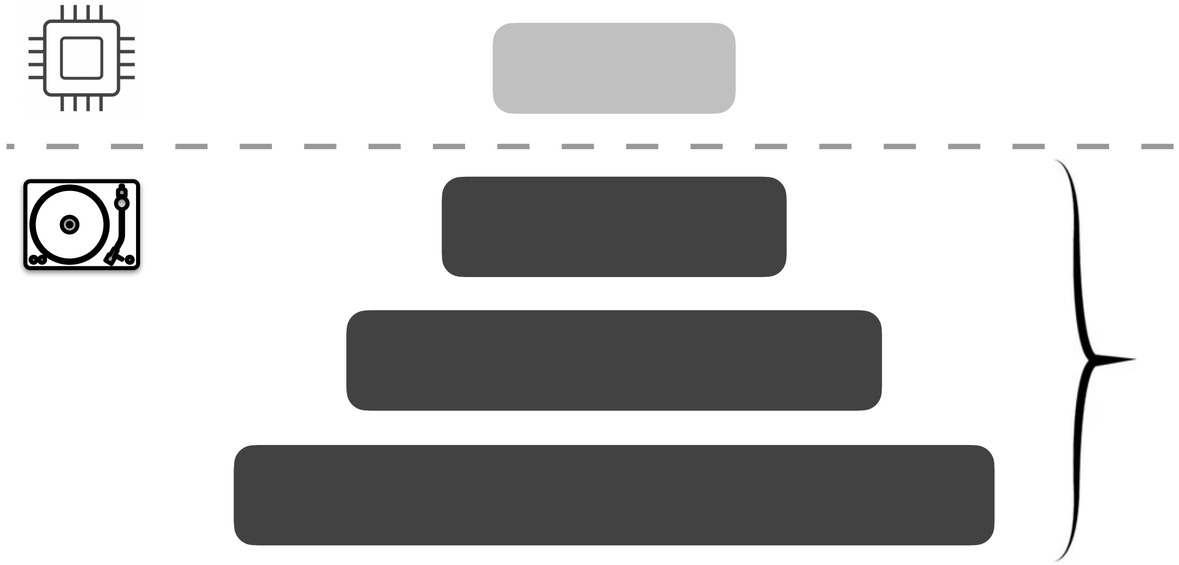


How does the storage layer affect ingestion?

L: #levels
T: size ratio



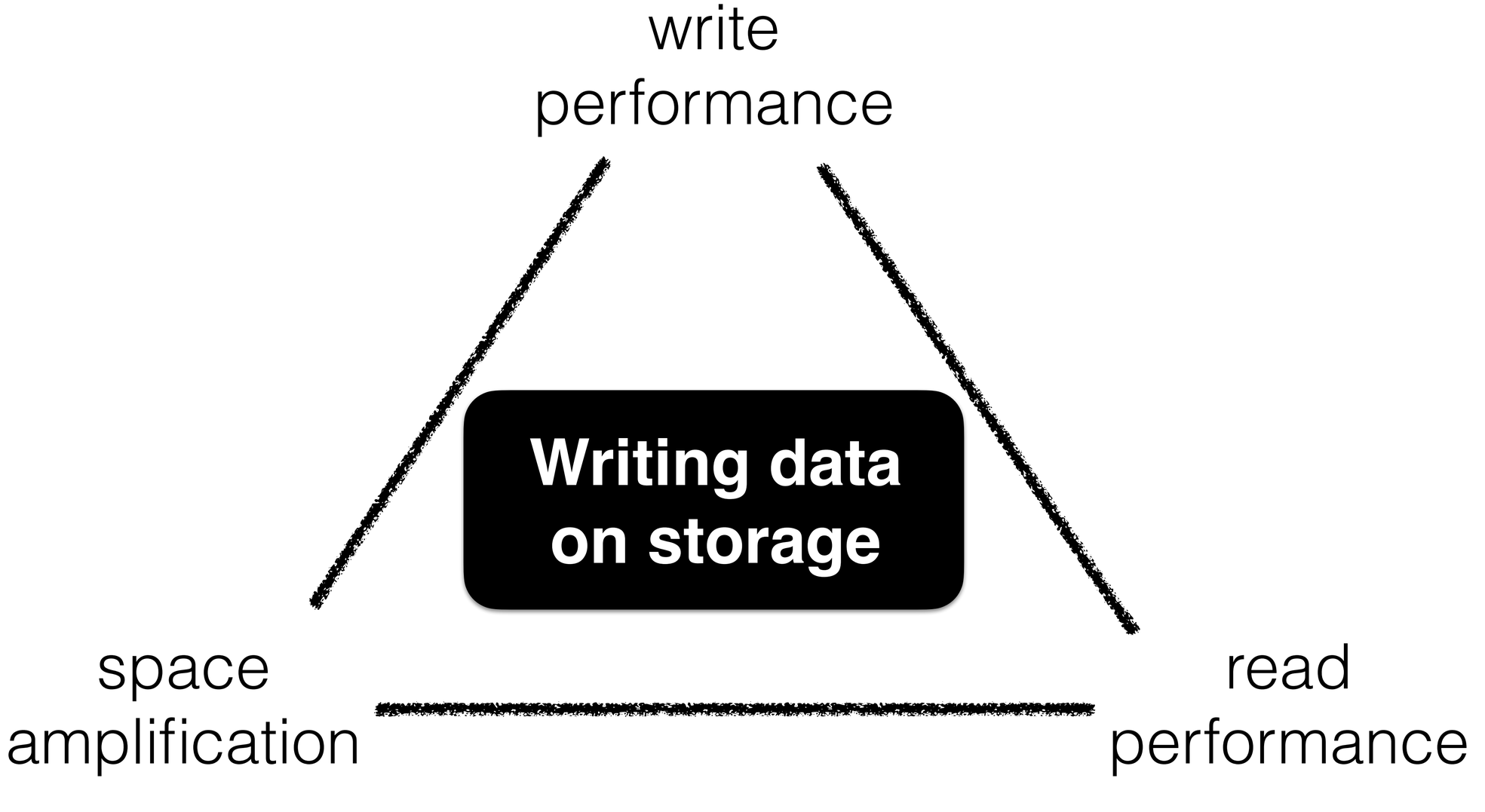
most data
on storage

if $T = 10$ & $L = 4$

99.9% on storage

How does the storage layer affect ingestion?

Storage Optimizations



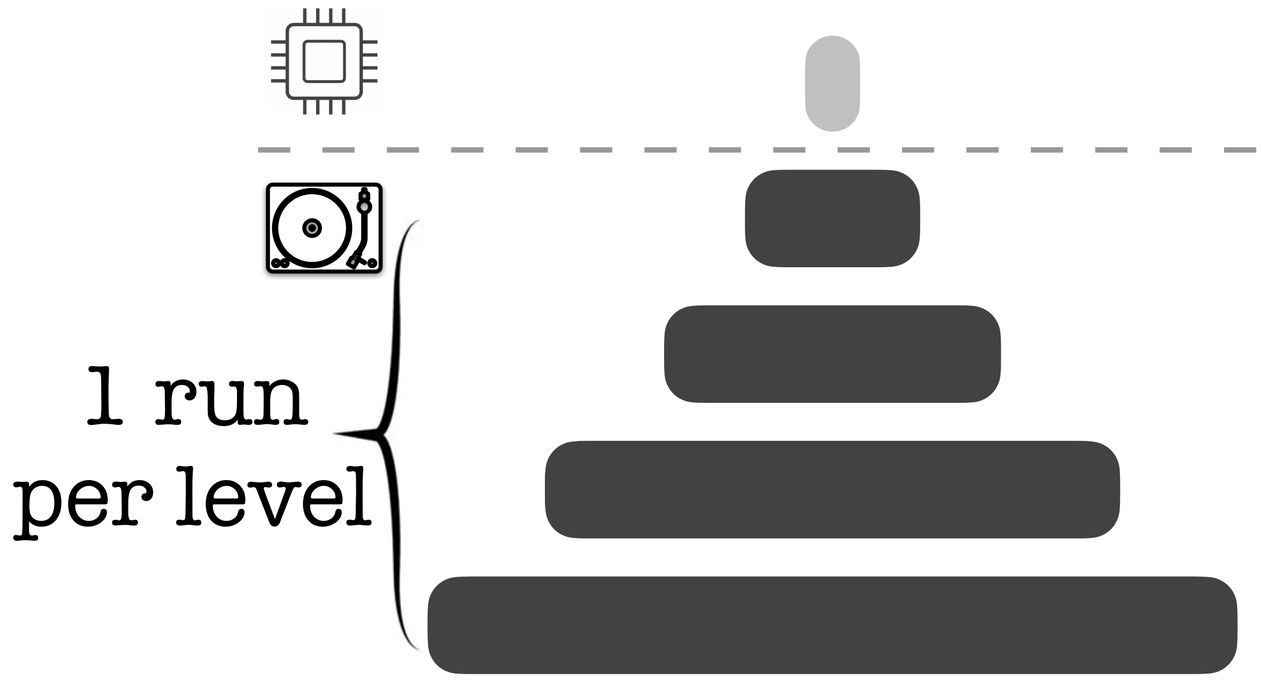
Data **Layout**

Classical LSM design: **leveling**

[eager merging]

Data **Layout**

leveling [eager]



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

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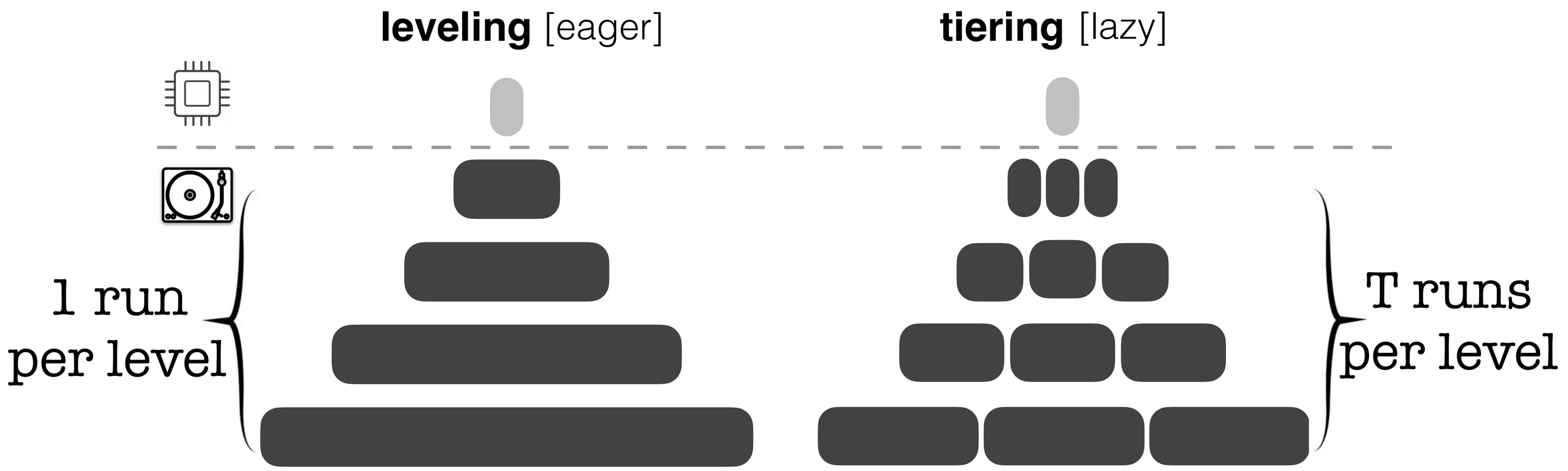
Data **Layout**



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

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

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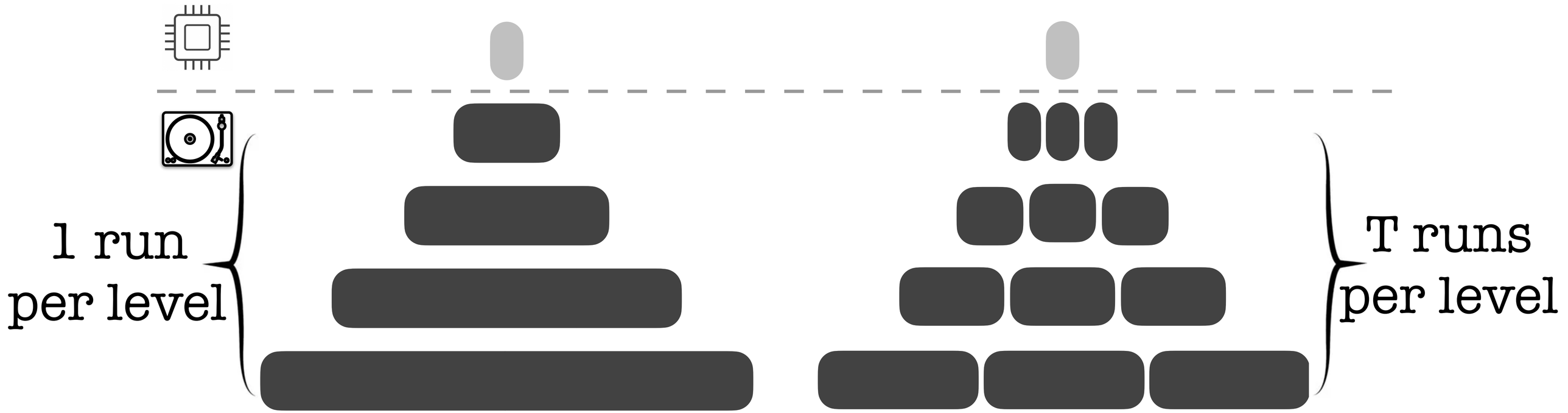
P: pages in buffer
B: entries/page
L: #levels
T: size ratio
N: #entries
ϕ : FPR of BF

Data **Layout**

leveling [eager]

tiering [lazy]



	leveling [eager]	**tiering** [lazy]
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:	$\mathcal{O}(1/T)$	$\mathcal{O}(T)$

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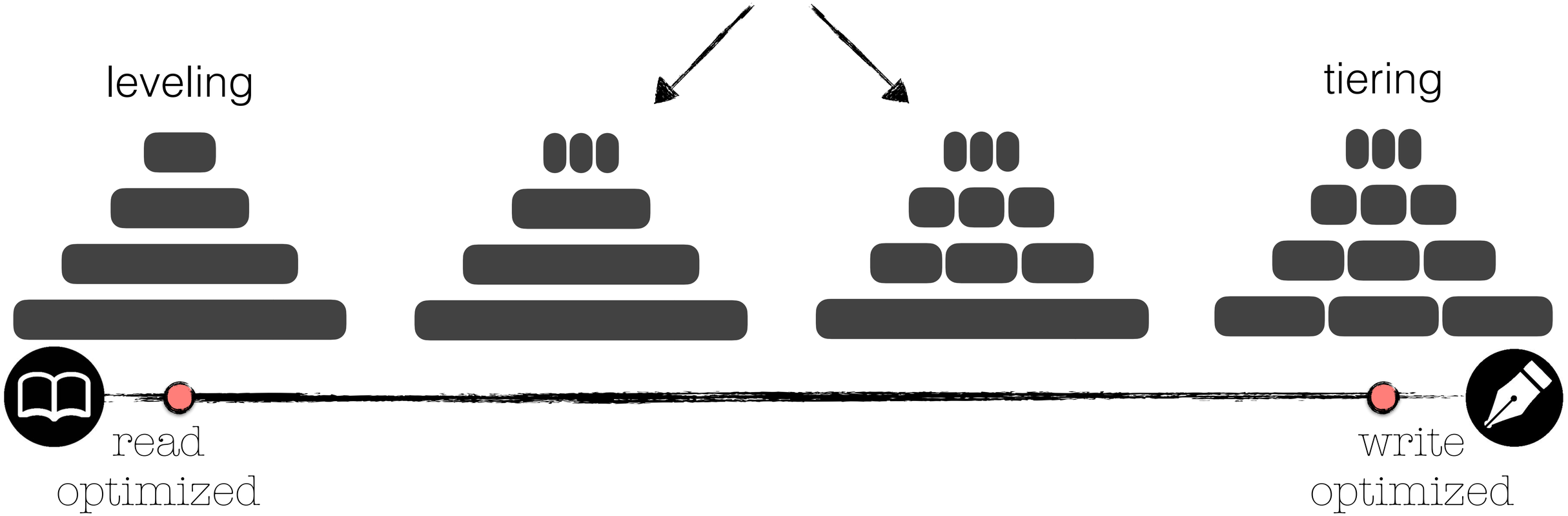
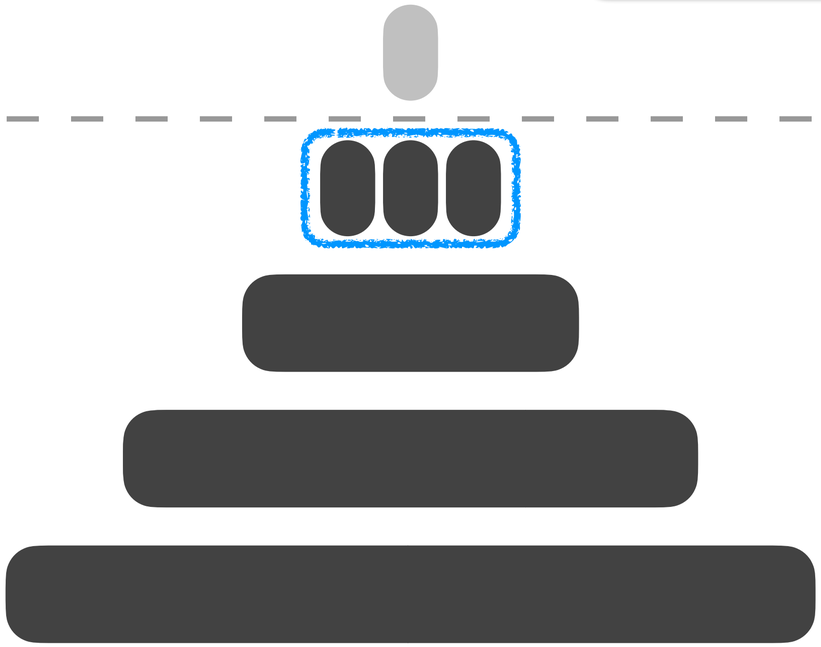
Data **Layout**

hybrid designs



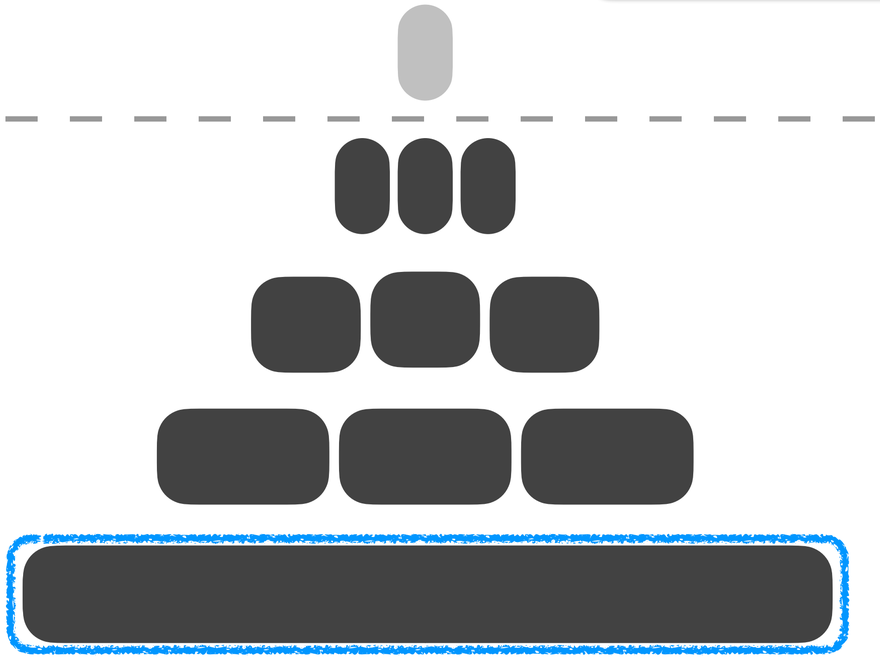
Data **Layout**

1-leveling RocksDB20



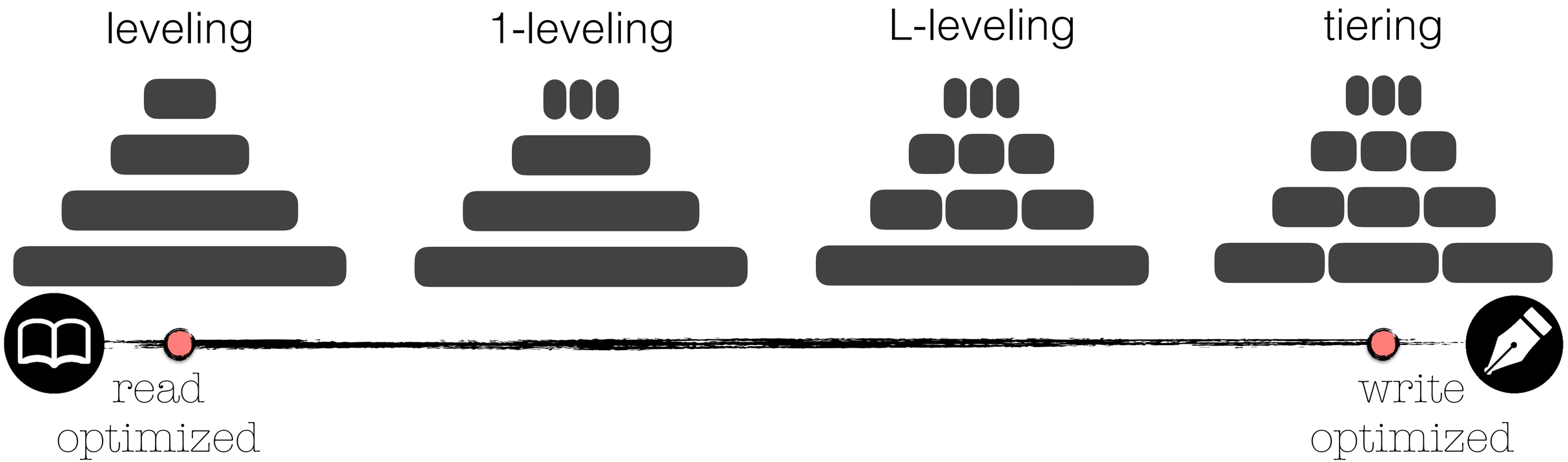
- fewer write stalls
- increased block cache hits

L-leveling DayanSIGMOD18

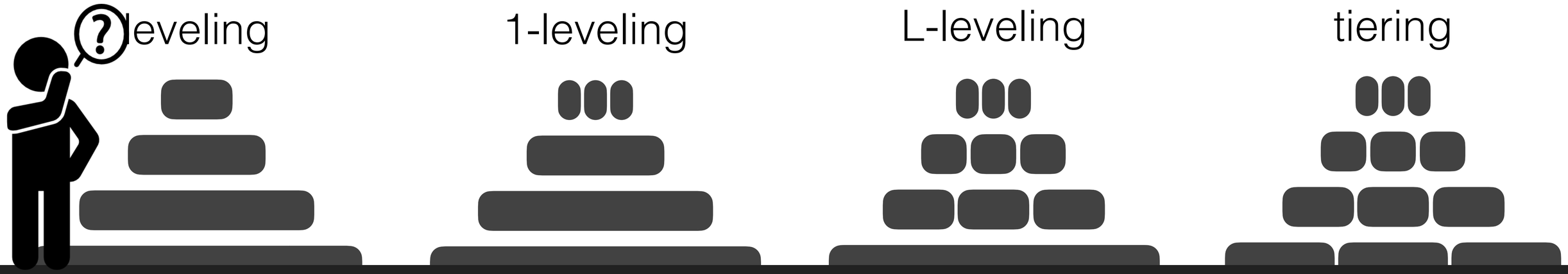


- low write amplification
- better read performance

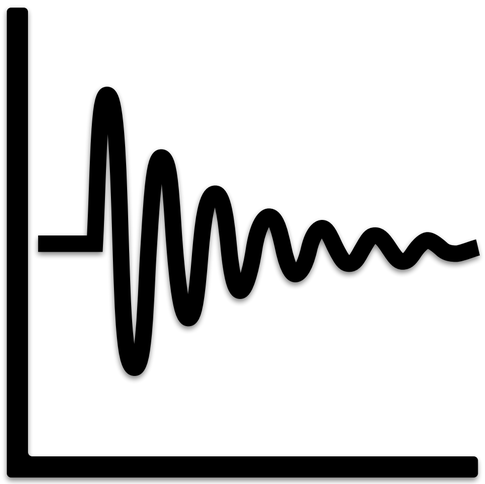
Data **Layout**


leveling
1-leveling
L-leveling
tiering
read
optimized
write
optimized

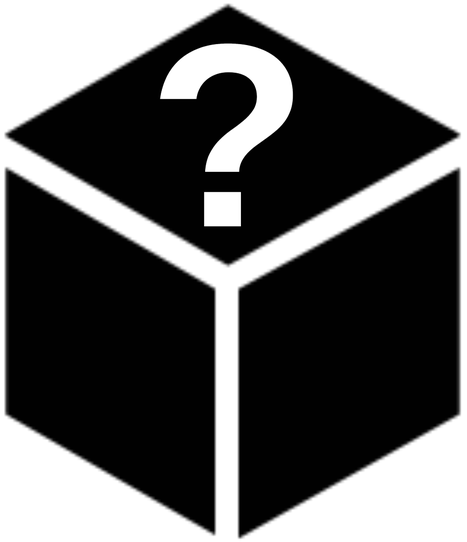
Data **Layout**



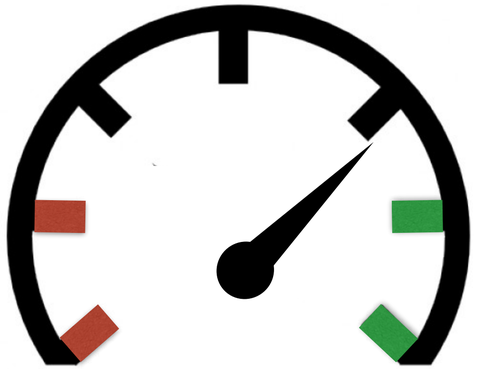
So, how do we reason about the data layout?



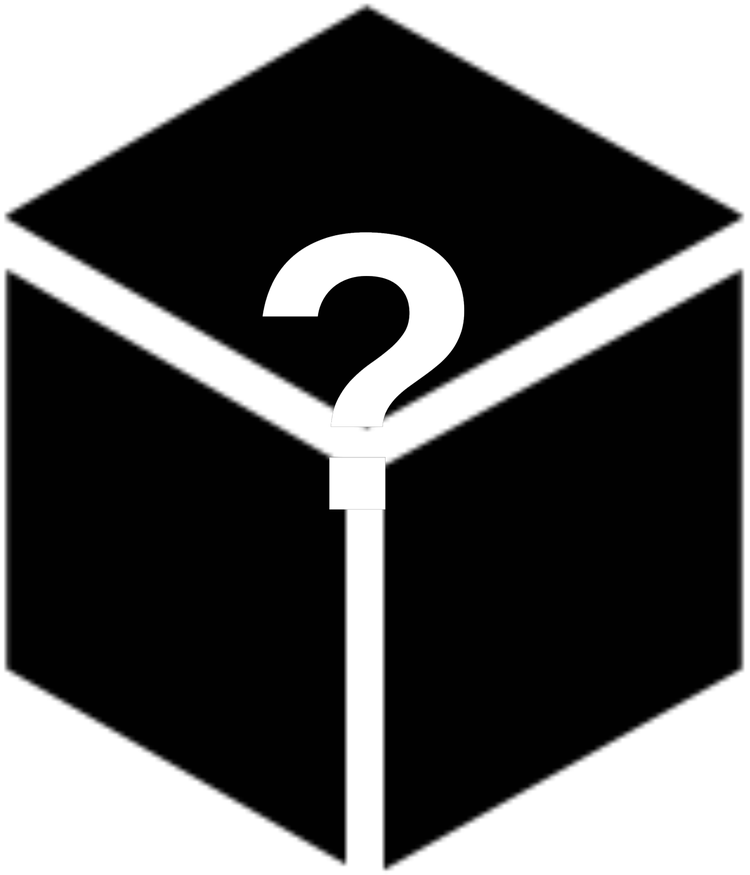
workload



data layout



performance



Compaction

black box

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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

How to organize the data on device? ✓

Compaction Granularity

How much data to move at-a-time?

Data Movement Policy

Which block of data to be moved?

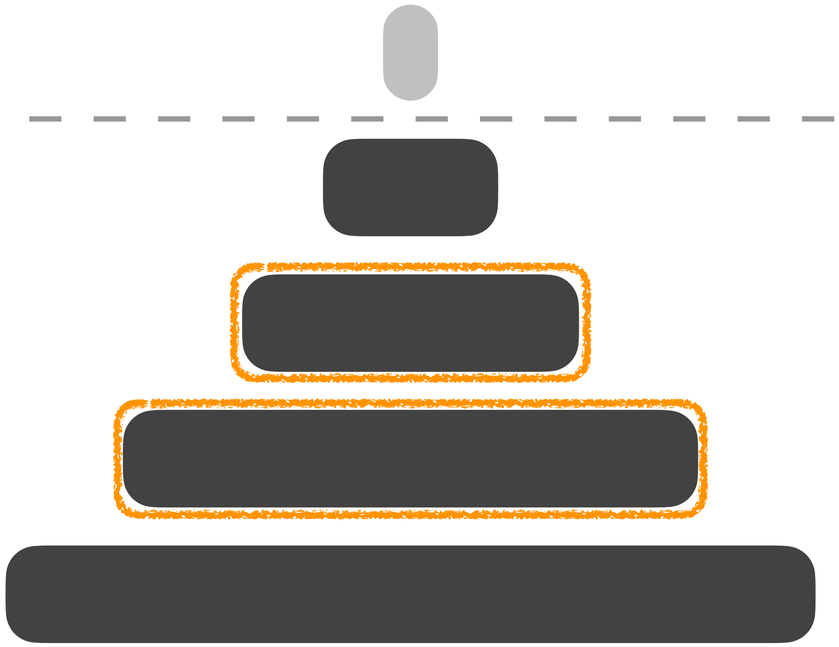
Compaction Trigger

When to re-organize the data layout?

SarkarVLDB21

Compaction **Granularity**

data moved per compaction

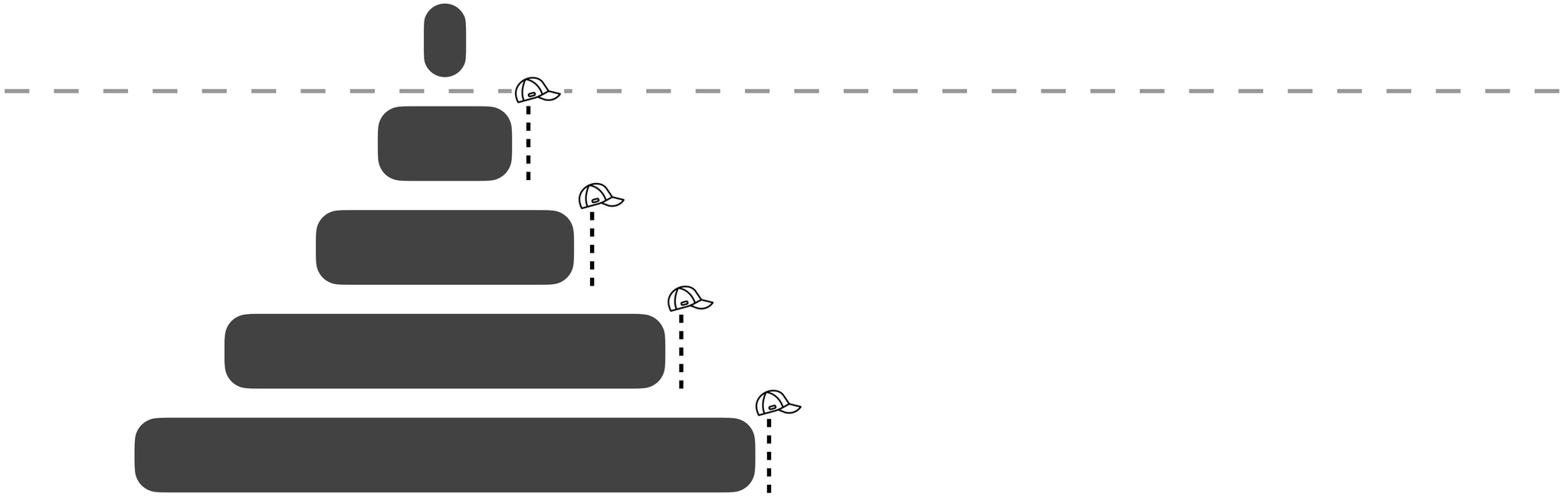


consecutive levels

AsterixDB

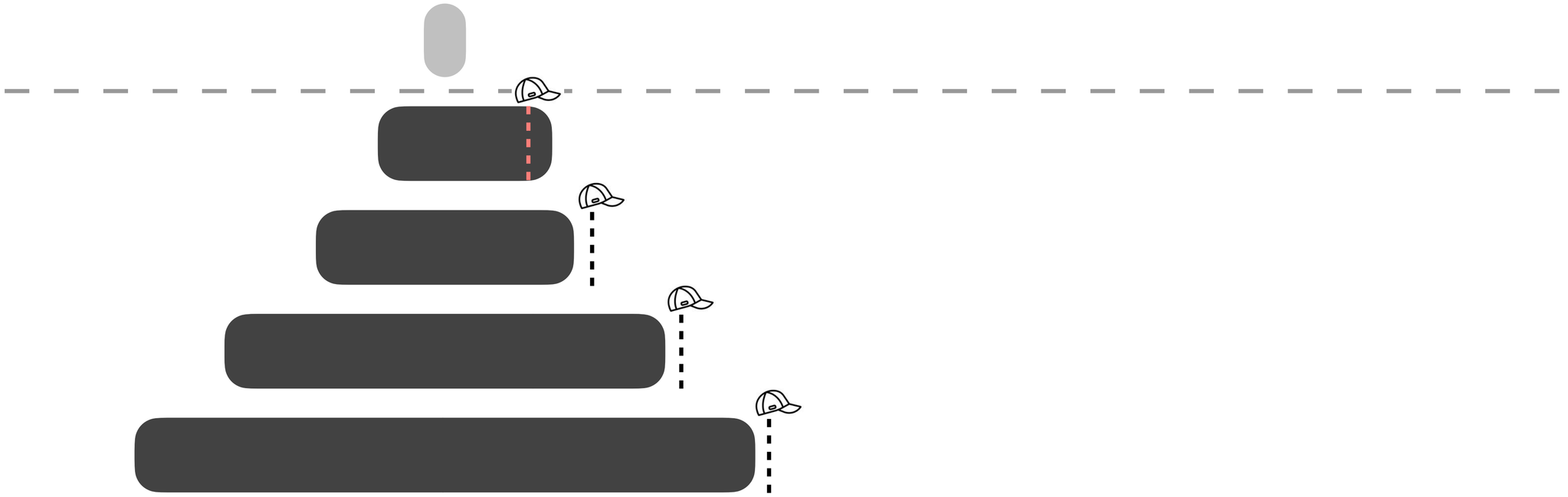
Compaction **Granularity**

data moved per compaction



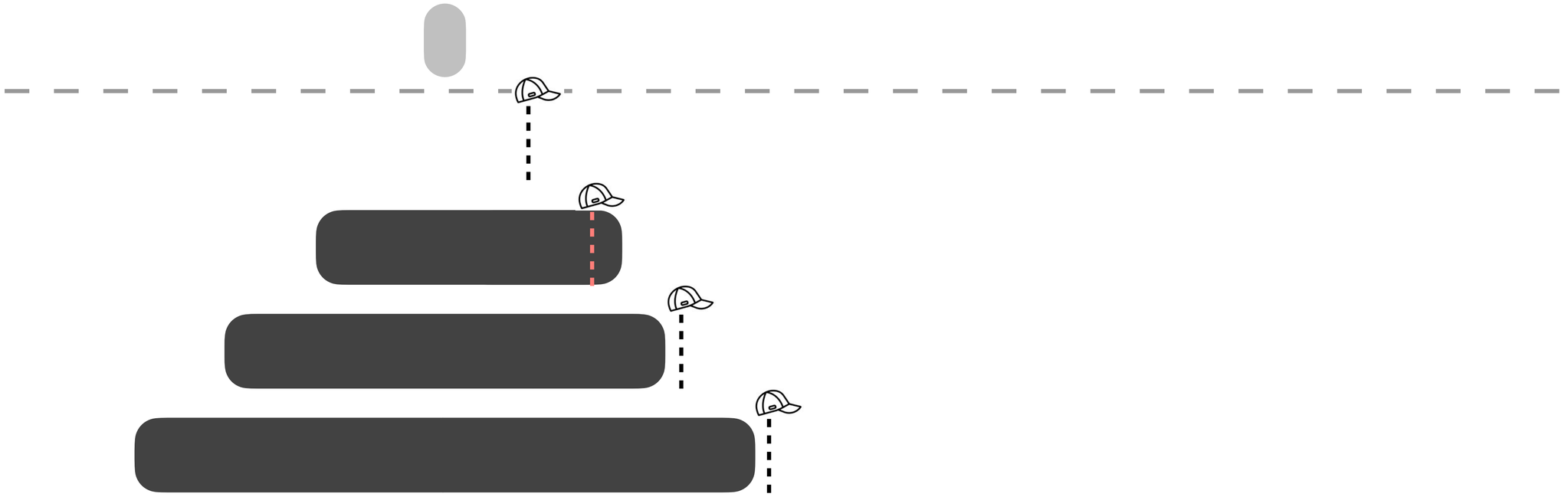
Compaction **Granularity**

data moved per compaction



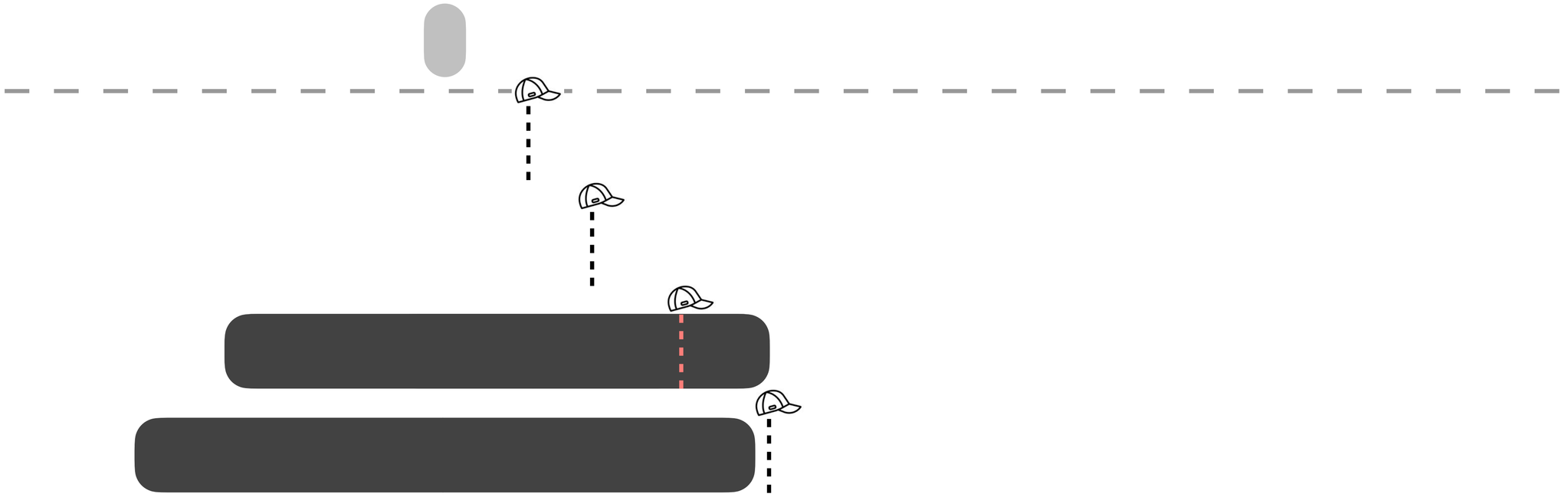
Compaction **Granularity**

data moved per compaction



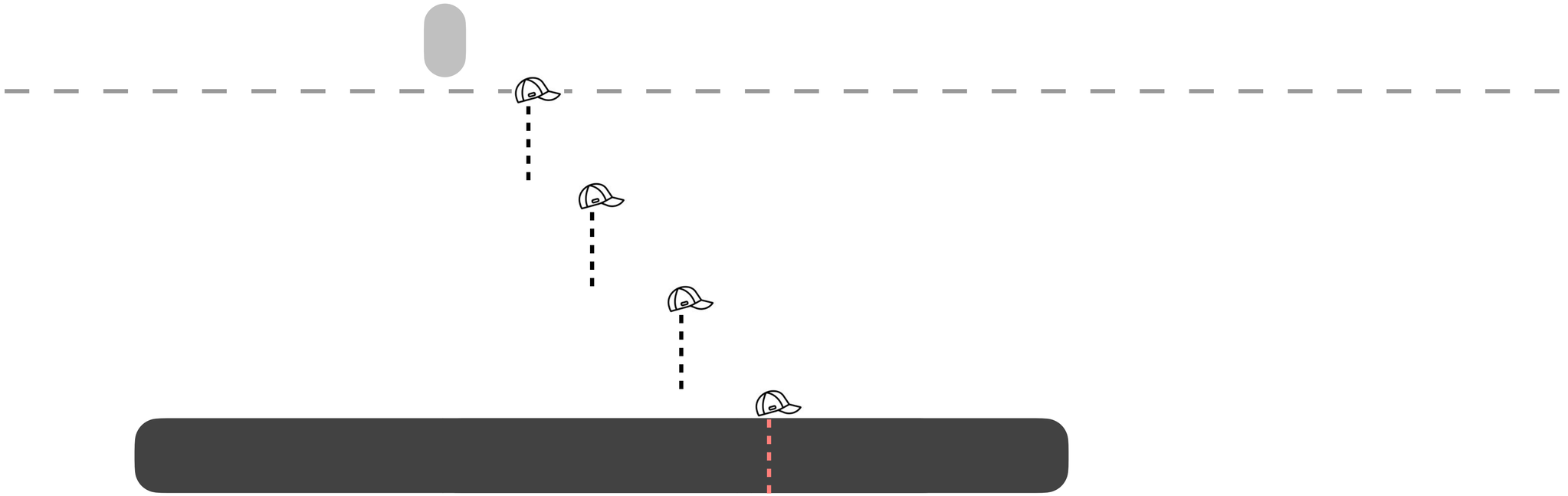
Compaction **Granularity**

data moved per compaction



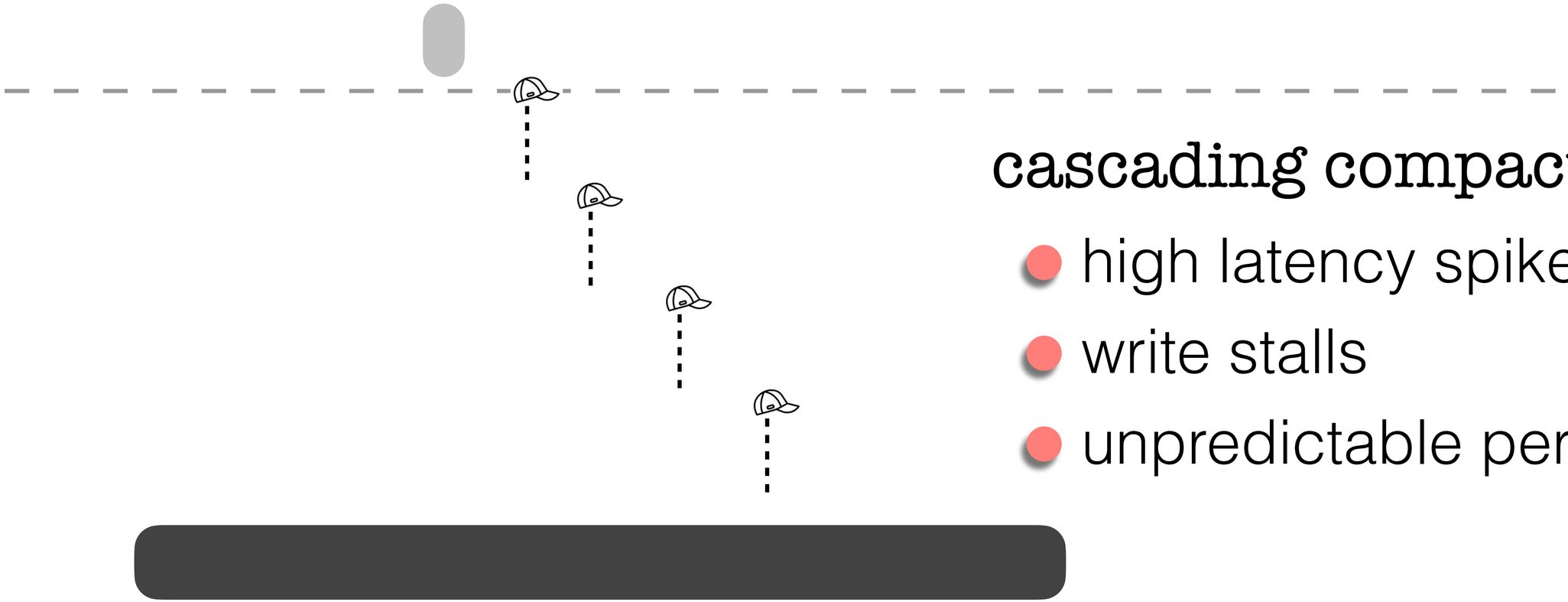
Compaction **Granularity**

data moved per compaction



Compaction **Granularity**

data moved per compaction



cascading compactions

- high latency spikes
- write stalls
- unpredictable perf.

Compaction **Granularity**

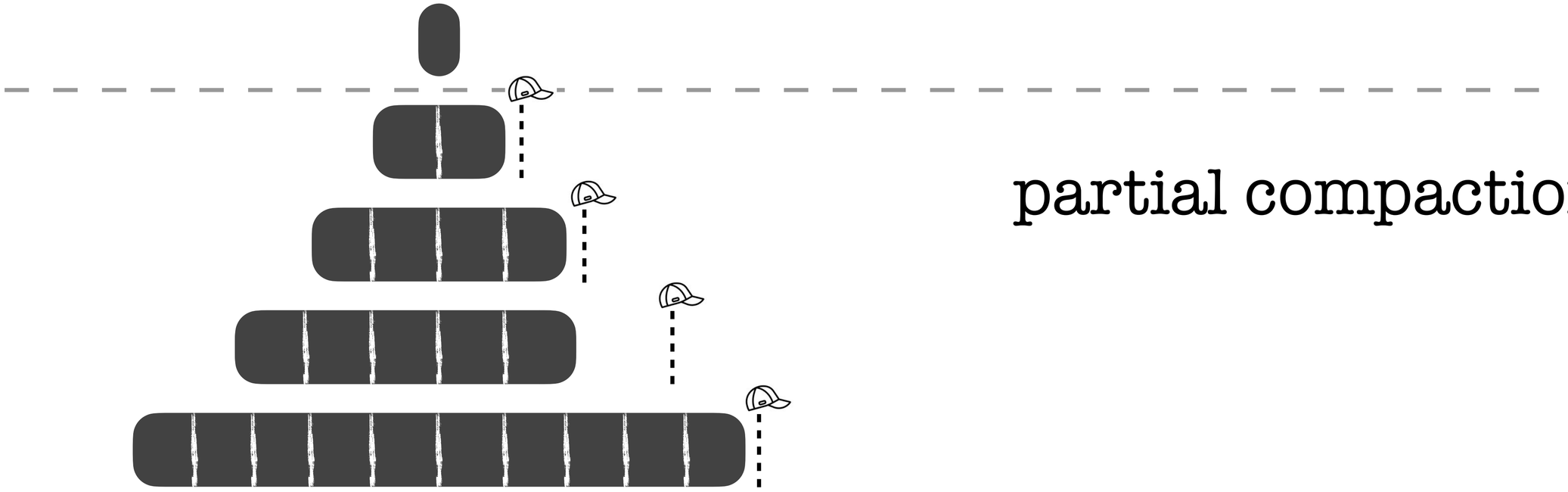
data moved per compaction

partial compaction

granularity: **files**

Compaction **Granularity**

data moved per compaction

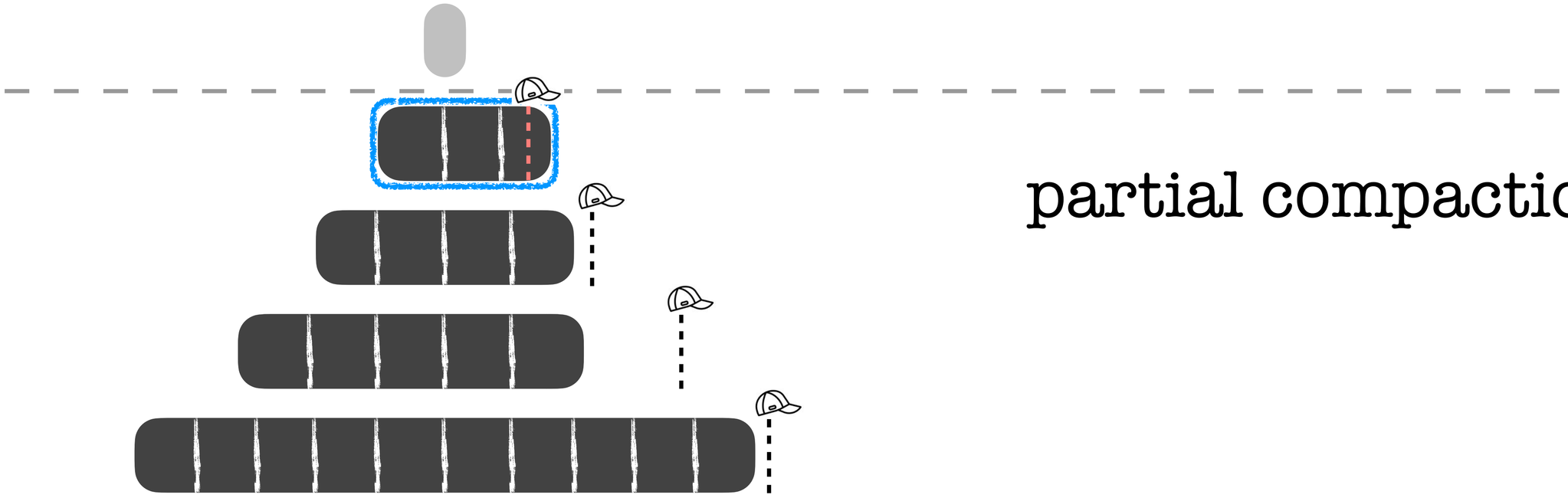


partial compaction

files

Compaction **Granularity**

data moved per compaction

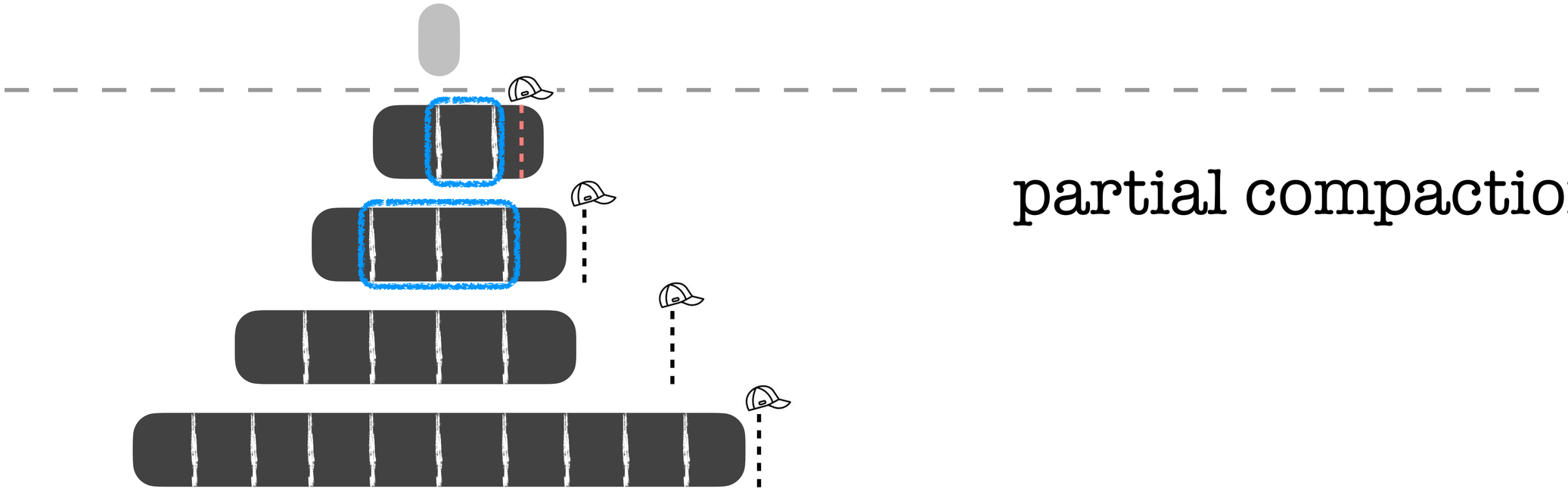


partial compaction

files

Compaction **Granularity**

data moved per compaction

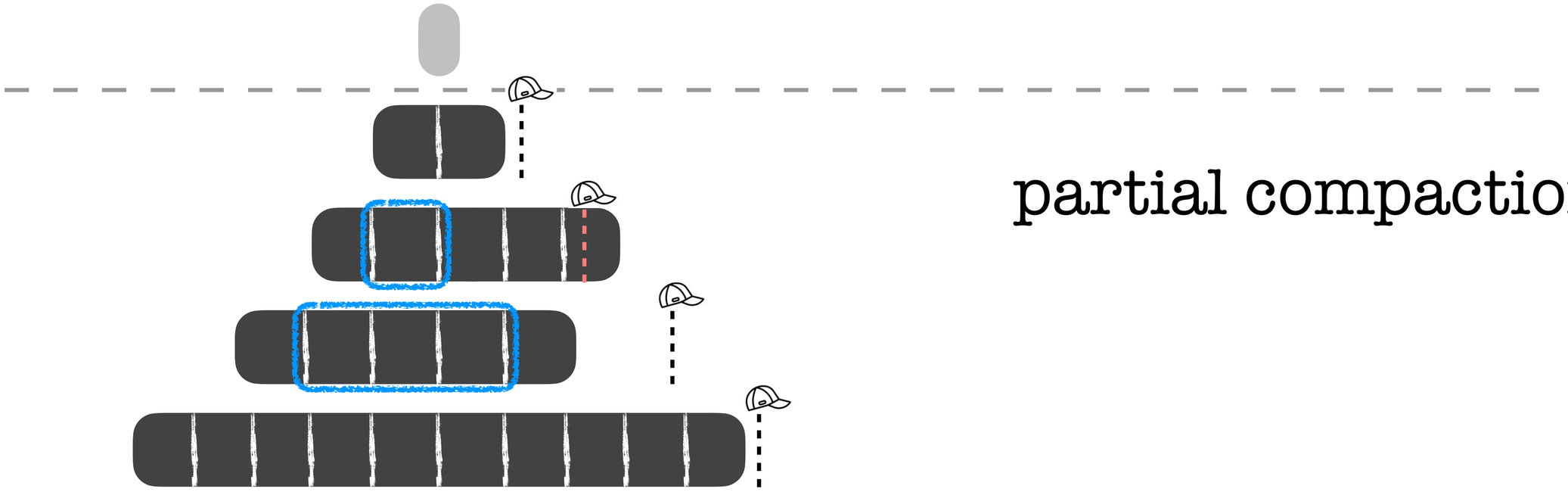


partial compaction

files

Compaction **Granularity**

data moved per compaction

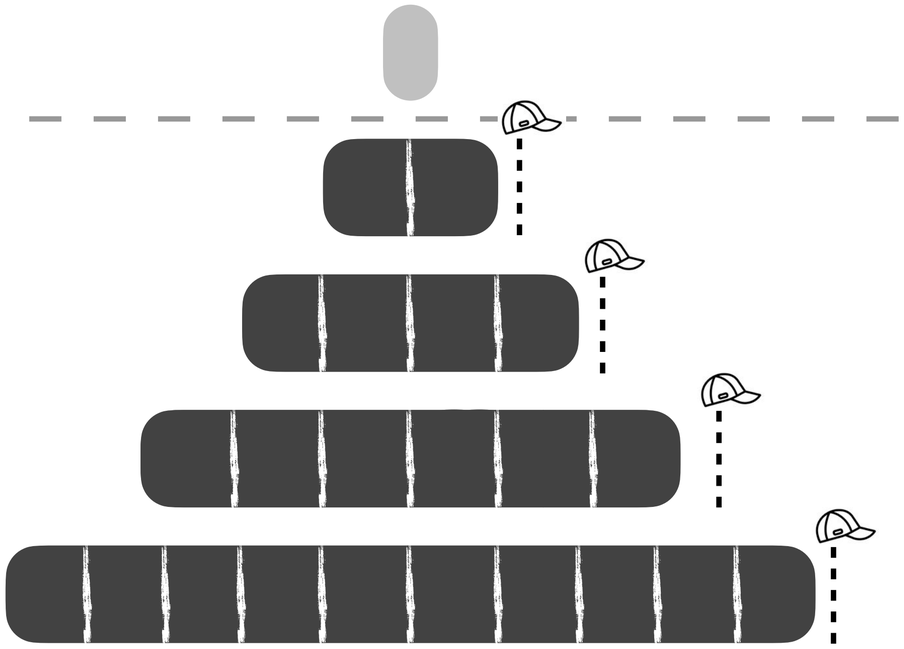


partial compaction

files

2 Compaction **Granularity**

data moved per compaction



files

RocksDB

partial compaction

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

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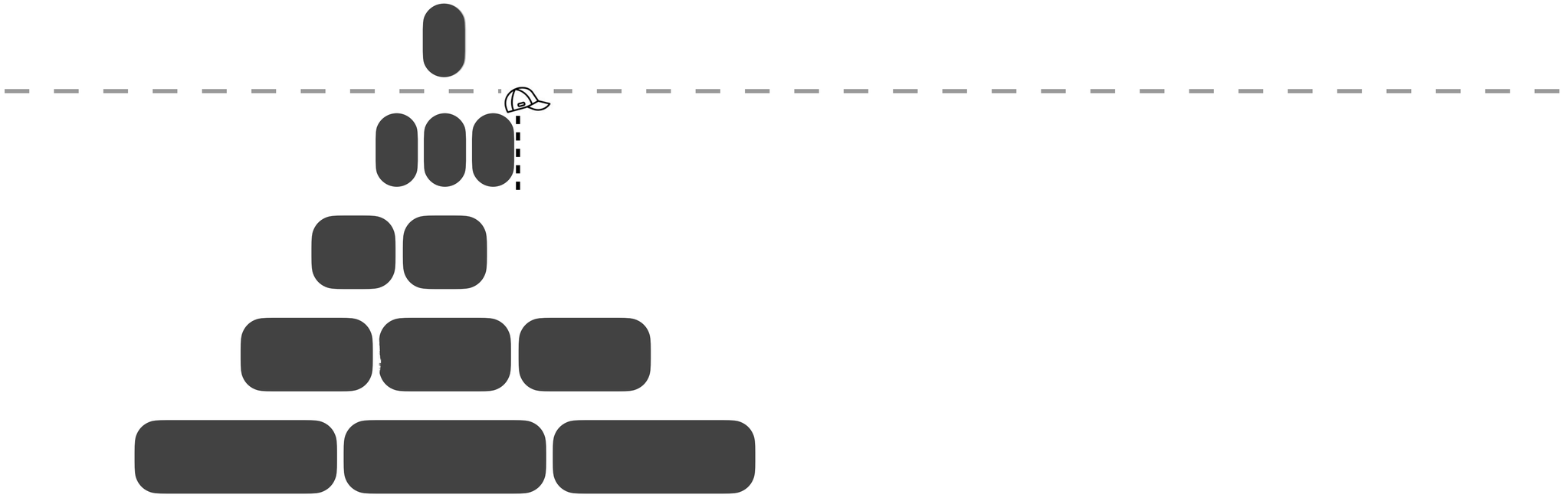
Compaction **Granularity**

data moved per compaction



sorted runs in a level

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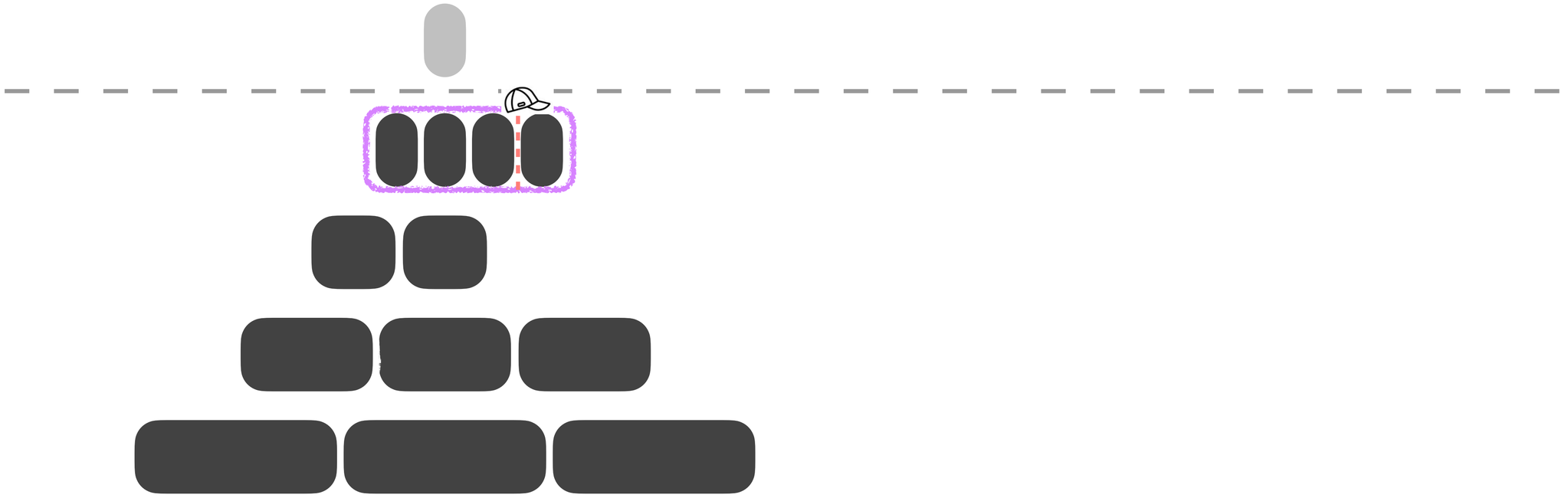
Compaction **Granularity**

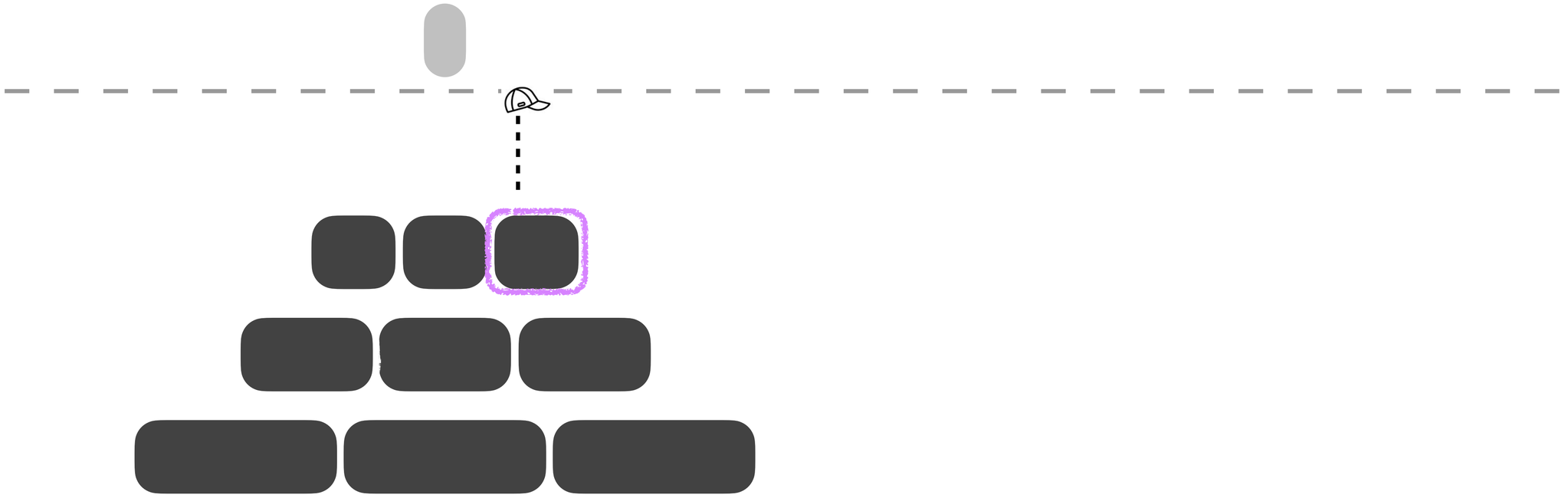
data moved per compaction



sorted runs in a level

Compaction **Granularity**

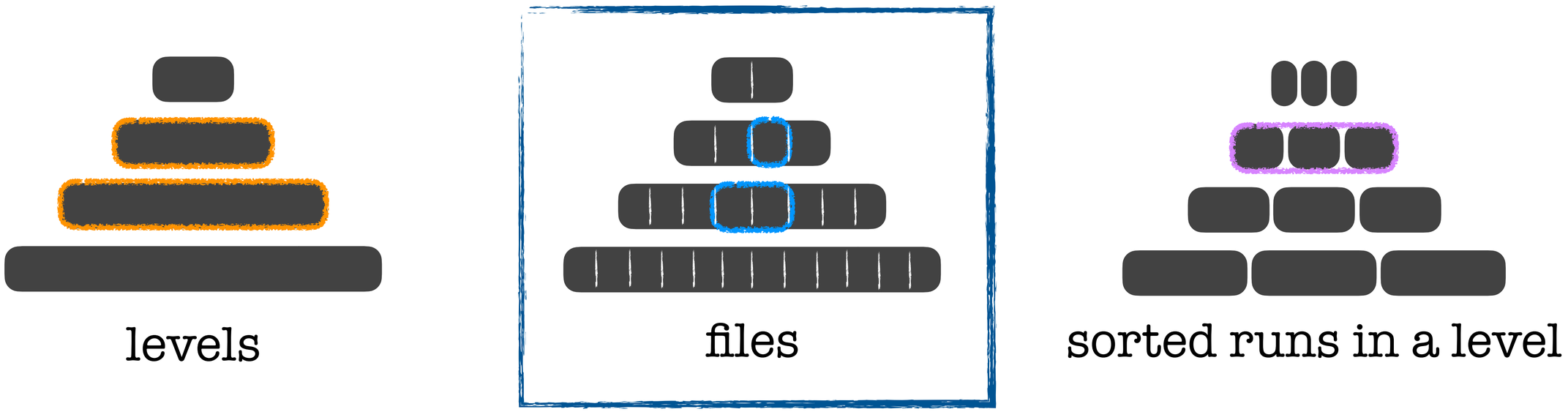
data moved per compaction



sorted runs in a level

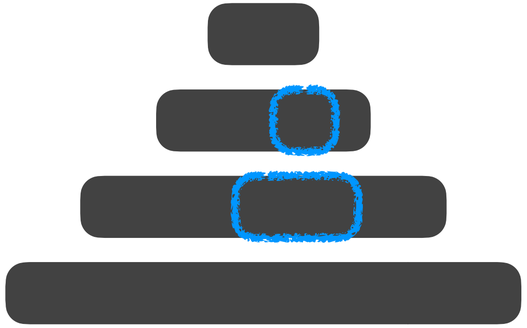
Compaction **Granularity**

data moved per compaction



Data Movement Policy

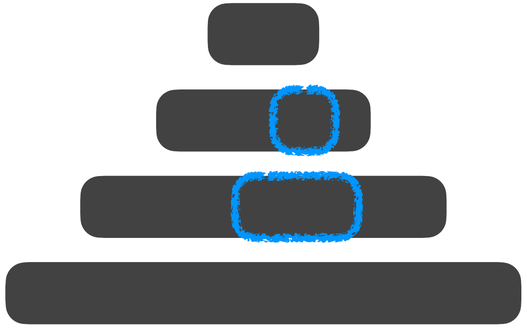
which data to compact



files

Data Movement Policy

which data to compact



files

round-robin !

minimum **overlap with parent** level WA

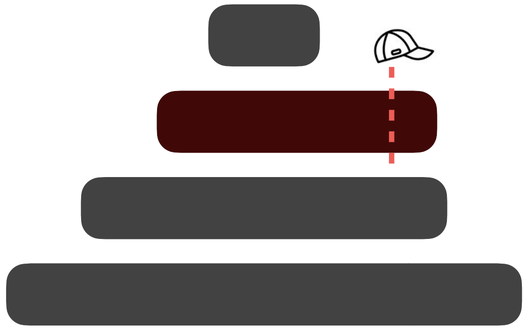
file with most **tombstones** SA

coldest file PQ

Compaction **Trigger**

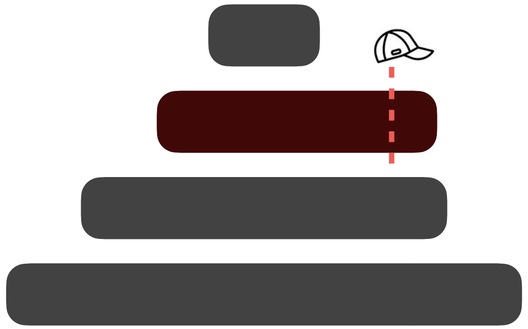
invoking the compaction routine

level **saturation**



Compaction **Trigger**

invoking the compaction routine



level **saturation**

number of **sorted runs**

space amplification

SA

age of a file

De

Data Layout

Compaction Granularity

Data Movement Policy

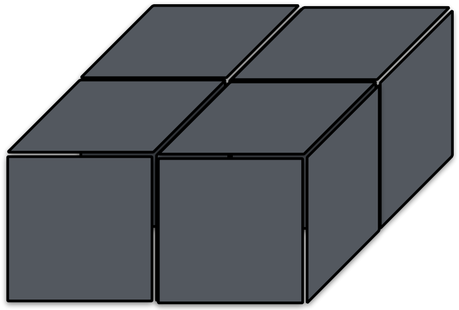
Compaction Trigger

Data Layout

Compaction Granularity

Data Movement Policy

Compaction Trigger



***Any* Compaction Algorithm**

Database	Data layout	Compaction Trigger					Compaction Granularity				Data Movement Policy							
		Level saturation	#Sorted runs	File staleness	Space amp.	Tombstone-TTL	Level	Sorted run	File (single)	File (multiple)	Round-robin	Least overlap (+1)	Least overlap (+2)	Coldest file	Oldest file	Tombstone density	Expired TS-TTL	N/A (entire level)
RocksDB [30], Monkey [22]	Leveling / 1-Leveling	✓		✓					✓	✓		✓		✓	✓	✓		
	Tiering		✓		✓	✓		✓										✓
LevelDB [32], Monkey (J.) [21]	Leveling	✓							✓		✓	✓	✓					
SlimDB [47]	Tiering	✓							✓	✓								✓
Dostoevsky [23]	*L*-leveling	$✓^{L}$	$✓^{T}$				$✓^{L}$	$✓^{T}$				$✓^{L}$						$✓^{T}$
LSM-Bush [24]	Hybrid leveling	$✓^{L}$	$✓^{T}$				$✓^{L}$	$✓^{T}$				$✓^{L}$						$✓^{T}$
Lethe [51]	Leveling	✓				✓			✓	✓		✓					✓	
Silk [11], Silk+ [12]	Leveling	✓							✓	✓	✓							
HyperLevelDB [35]	Leveling	✓							✓		✓	✓	✓					
PebblesDB [46]	Hybrid leveling	✓							✓	✓								✓
Cassandra [8]	Tiering		✓	✓		✓		✓										✓
	Leveling	✓				✓			✓	✓		✓				✓	✓	
WiredTiger [62]	Leveling	✓					✓											✓
X-Engine [34], Leaper [63]	Hybrid leveling	✓							✓	✓		✓				✓		
HBase [7]	Tiering		✓					✓										✓
AsterixDB [3]	Leveling	✓					✓											✓
	Tiering		✓					✓										✓

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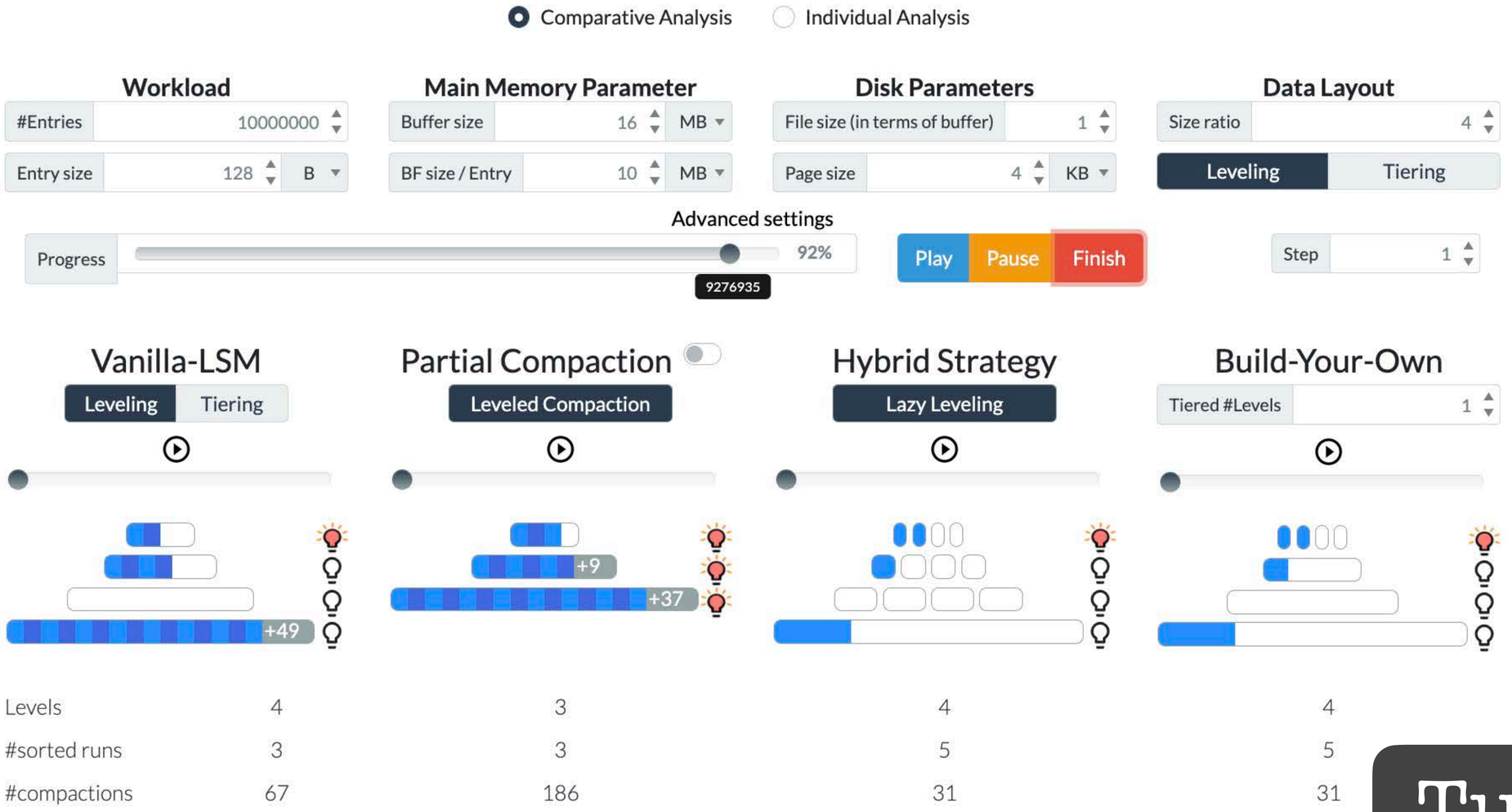
Database	Data layout	Compaction Trigger					Compaction Granularity				Data Movement Policy							
		Level saturation	#Sorted runs	File staleness	Space amp.	Tombstone-TTL	Level	Sorted run	File (single)	File (multiple)	Round-robin	Least overlap (+1)	Least overlap (+2)	Coldest file	Oldest file	Tombstone density	Expired TS-TTL	N/A (entire level)
RocksDB [30], Monkey [22]	Leveling / 1-Leveling	✓		✓					✓	✓		✓		✓	✓	✓		
	Tiering		✓		✓	✓		✓										✓
LevelDB [32], Monkey (J.) [21]	Leveling	✓							✓		✓	✓	✓					
SlimDB [47]	Tiering	✓							✓	✓								✓
Dostoevsky [23]	*L*-leveling	$✓^L$	$✓^T$				$✓^L$	$✓^T$				$✓^L$						$✓^T$
LSM-Bush [24]	Hybrid leveling	$✓^L$	$✓^T$				$✓^L$	$✓^T$				$✓^L$						$✓^T$
Lethe [51]	Leveling	✓				✓			✓	✓		✓					✓	
Silk [11], Silk+ [12]	Leveling	✓							✓	✓	✓							
HyperLevelDB [35]	Leveling	✓							✓		✓	✓	✓					
PebblesDB [46]	Hybrid leveling	✓							✓	✓								✓
Cassandra [8]	Tiering		✓	✓		✓		✓										✓
	Leveling	✓				✓			✓	✓		✓				✓	✓	
WiredTiger [62]	Leveling	✓					✓											✓
X-Engine [34], Leaper [63]	Hybrid leveling	✓							✓	✓		✓				✓		
HBase [7]	Tiering		✓					✓										✓
AsterixDB [3]	Leveling	✓					✓											✓
	Tiering		✓					✓										✓

Database	Data layout	Compaction Trigger					Compaction Granularity				Data Movement Policy							
		Level saturation	#Sorted runs	File staleness	Space amp.	Tombstone-TTL	Level	Sorted run	File (single)	File (multiple)	Round-robin	Least overlap (+1)	Least overlap (+2)	Coldest file	Oldest file	Tombstone density	Expired TS-TTL	N/A (entire level)
RocksDB [30], Monkey [22]	Leveling / 1-Leveling	✓		✓					✓	✓		✓		✓	✓	✓		
	Tiering		✓		✓	✓		✓										✓
LevelDB [32], Monkey (J.) [21]	Leveling	✓							✓		✓	✓	✓					
SlimDB [47]	Tiering	✓							✓	✓								✓
Dostoevsky [23]	*L*-leveling	$✓^L$	$✓^T$				$✓^L$	$✓^T$				$✓^L$						$✓^T$
LSM-Bush [24]	Hybrid leveling	$✓^L$	$✓^T$				$✓^L$	$✓^T$				$✓^L$						$✓^T$
Lethe [51]	Leveling	✓				✓			✓	✓		✓					✓	
Silk [11], Silk+ [12]	Leveling	✓							✓	✓	✓							
HyperLevelDB [35]	Leveling	✓							✓		✓	✓	✓					
PebblesDB [46]	Hybrid leveling	✓							✓	✓								✓
Cassandra [8]	Tiering		✓	✓		✓		✓										✓
	Leveling	✓				✓			✓	✓		✓				✓	✓	
WiredTiger [62]	Leveling	✓					✓											✓
X-Engine [34], Leaper [63]	Hybrid leveling	✓							✓	✓		✓				✓		
HBase [7]	Tiering		✓					✓										✓
AsterixDB [3]	Leveling	✓					✓											✓
	Tiering		✓					✓										✓

Database	Data layout	Compaction Trigger					Compaction Granularity				Data Movement Policy							
		Level saturation	#Sorted runs	File staleness	Space amp.	Tombstone-TTL	Level	Sorted run	File (single)	File (multiple)	Round-robin	Least overlap (+1)	Least overlap (+2)	Coldest file	Oldest file	Tombstone density	Expired TS-TTL	N/A (entire level)
RocksDB [30], Monkey [22]	Leveling / 1-Leveling	✓		✓					✓	✓		✓		✓	✓	✓		
	Tiering		✓		✓	✓		✓										✓
LevelDB [32], Monkey (J.) [21]	Leveling	✓							✓		✓	✓	✓					
SlimDB [47]	Tiering	✓							✓	✓								✓
Dostoevsky [23]	*L*-leveling	$✓^{L}$	$✓^{T}$				$✓^{L}$	$✓^{T}$				$✓^{L}$						$✓^{T}$
LSM-Bush [24]	Hybrid leveling	$✓^{L}$	$✓^{T}$				$✓^{L}$	$✓^{T}$				$✓^{L}$						$✓^{T}$
Lethe [51]	Leveling	✓				✓			✓	✓		✓					✓	
Silk [11], Silk+ [12]	Leveling	✓							✓	✓	✓							
HyperLevelDB [35]	Leveling	✓							✓		✓	✓	✓					
PebblesDB [46]	Hybrid leveling	✓							✓	✓								✓
Cassandra [8]	Tiering		✓	✓		✓		✓										✓
	Leveling	✓				✓			✓	✓		✓				✓	✓	
WiredTiger [62]	Leveling	✓					✓											✓
X-Engine [34], Leaper [63]	Hybrid leveling	✓							✓	✓		✓				✓		
HBase [7]	Tiering		✓					✓										✓
AsterixDB [3]	Leveling	✓					✓											✓
	Tiering		✓					✓										✓

SIGMOD Demo: Compactionary



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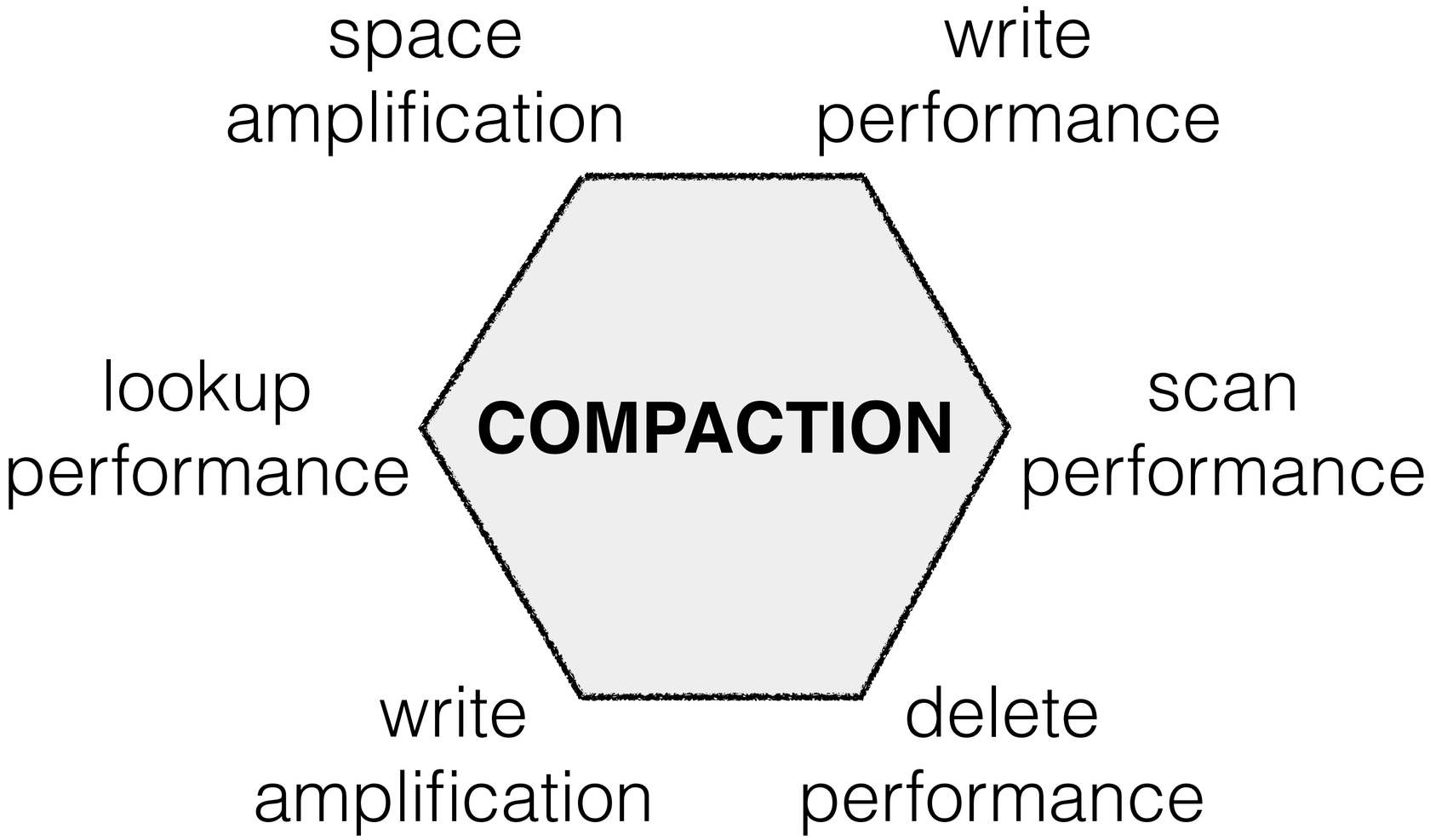
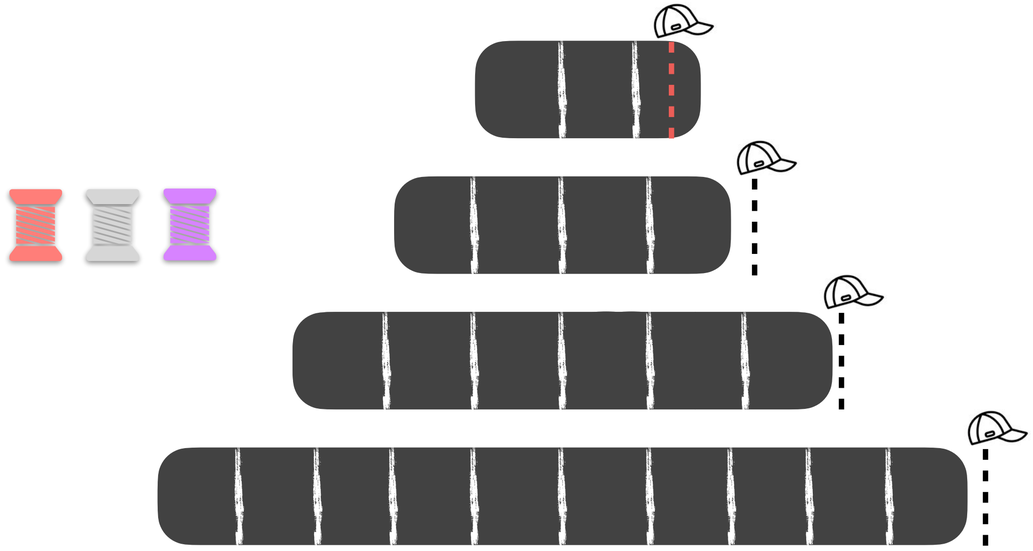
SarkarSIGMOD22

Tuesday 4-6PM


space
amplification
write
performance
lookup
performance
COMPACTION
scan
performance
write
amplification
delete
performance

Optimizing **Compactions**

Background Compactions



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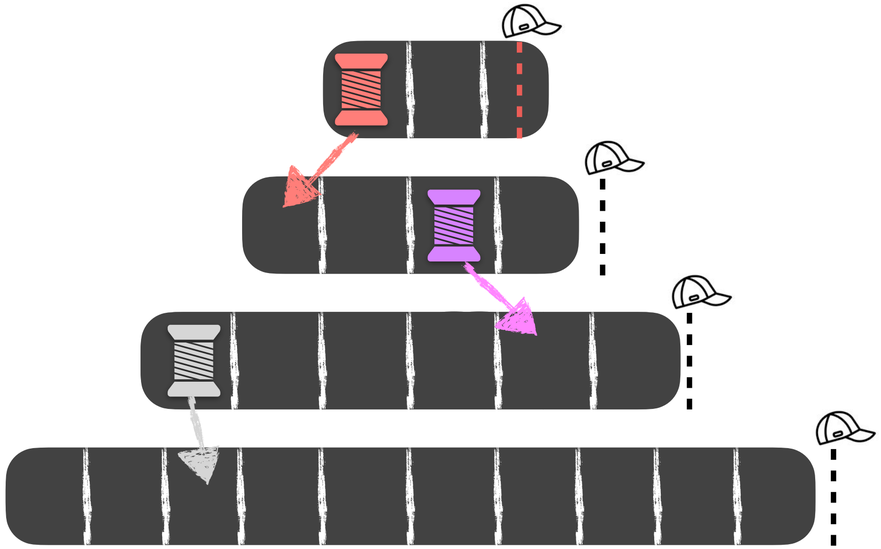
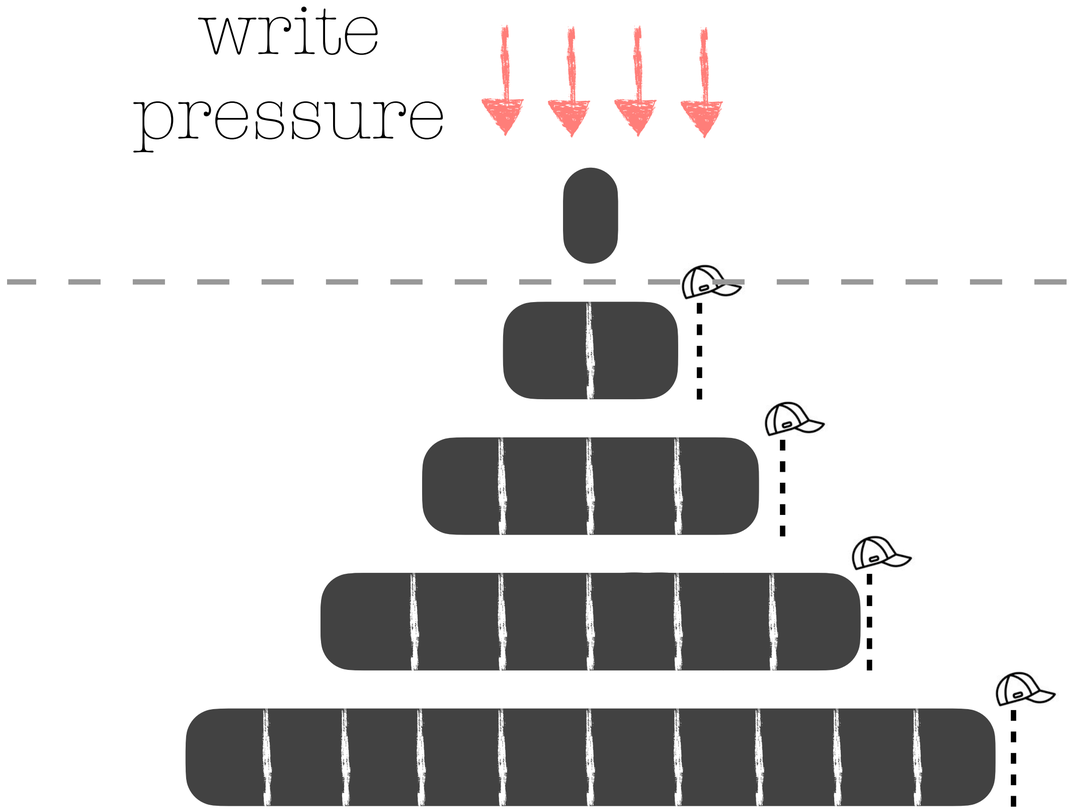
Optimizing **Compactions**

Background Compactions



- non-blocking reads/writes
- improves write throughput

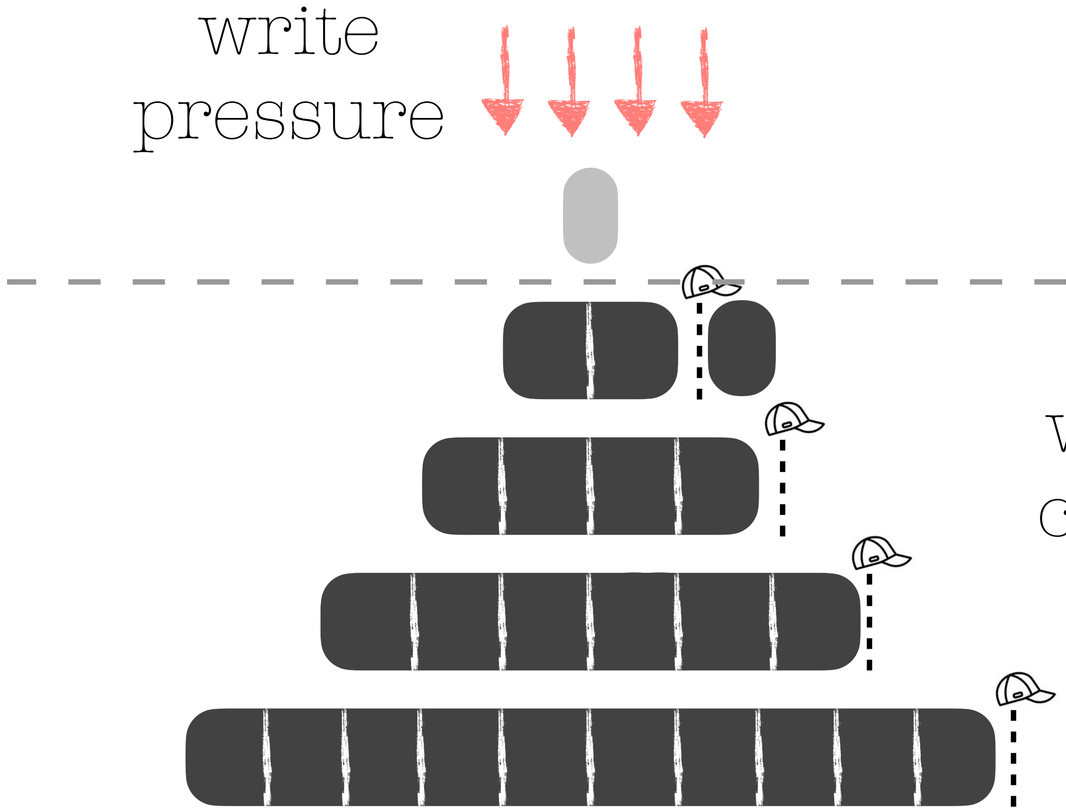
Optimizing **Compactions**



Background Compactions

Compaction Priority

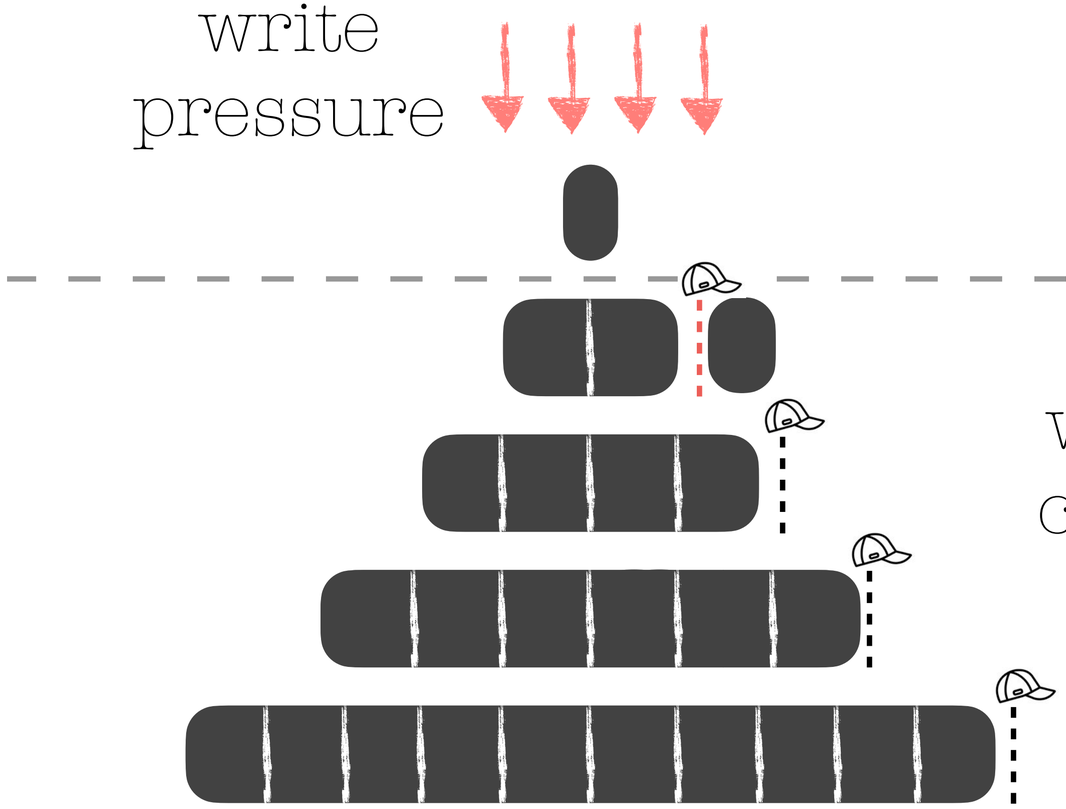
Optimizing **Compactions**



Background Compactions

Compaction Priority

Optimizing **Compactions**

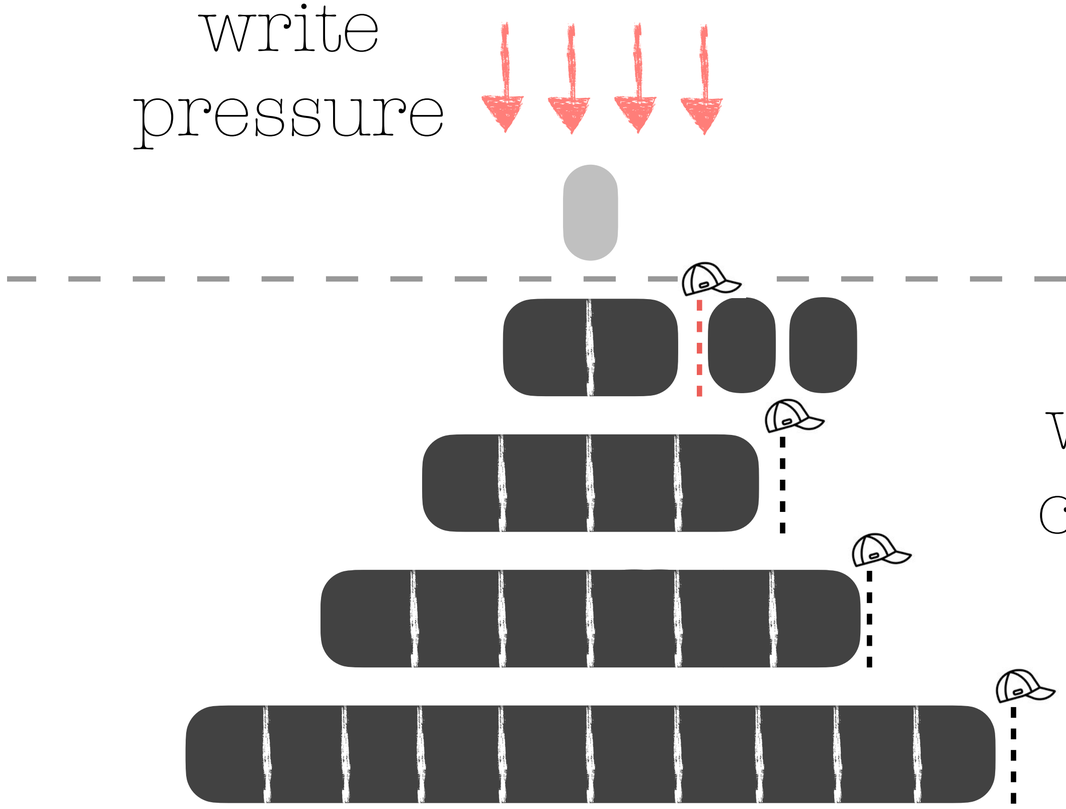


prioritize
writes over
compaction

Background
Compactions

Compaction
Priority

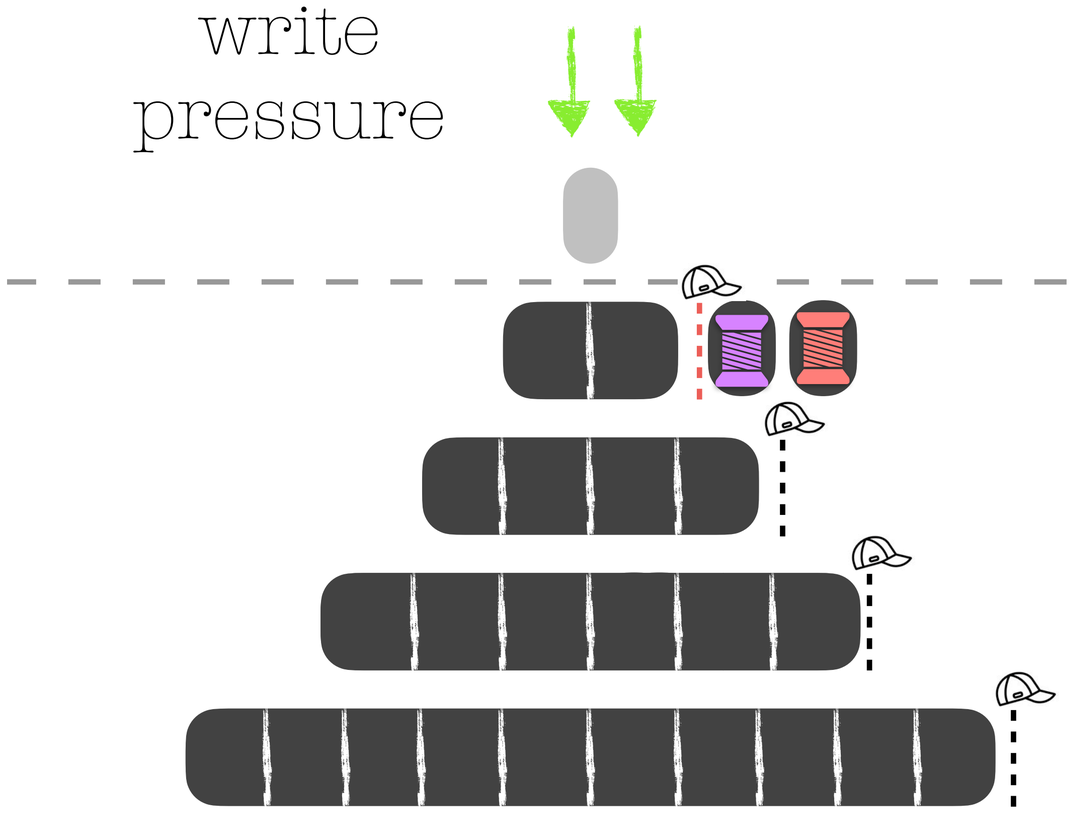
Optimizing **Compactions**



Background Compactions

Compaction Priority

Optimizing **Compactions**

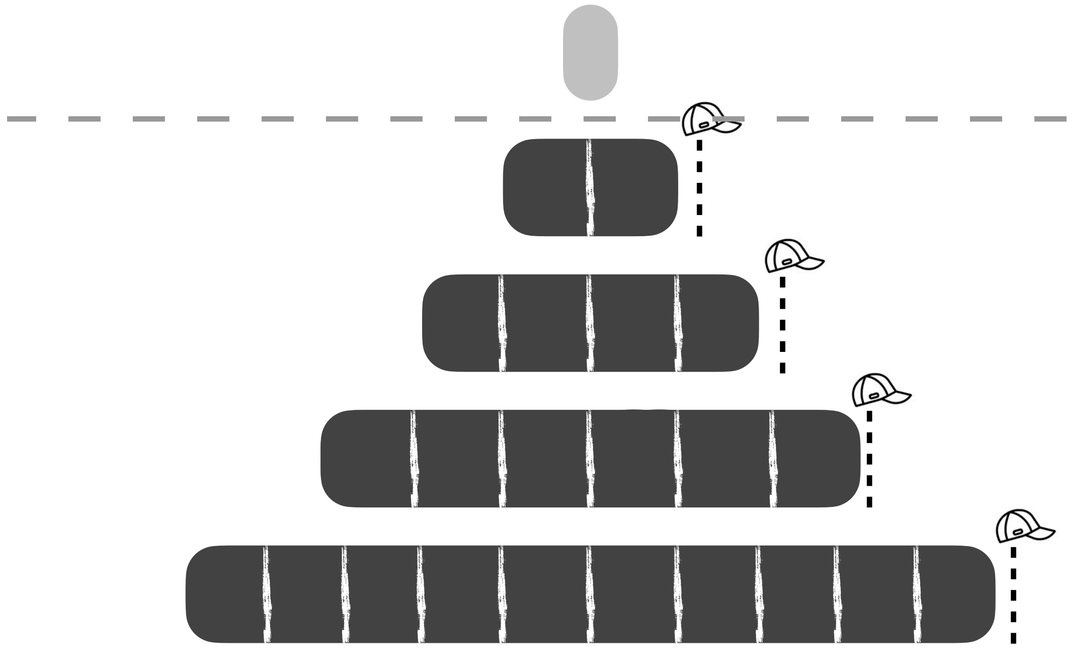


Background Compactions

Compaction Priority

- sustain heavy write bursts
- tree becomes out of shape

Optimizing **Compactions**

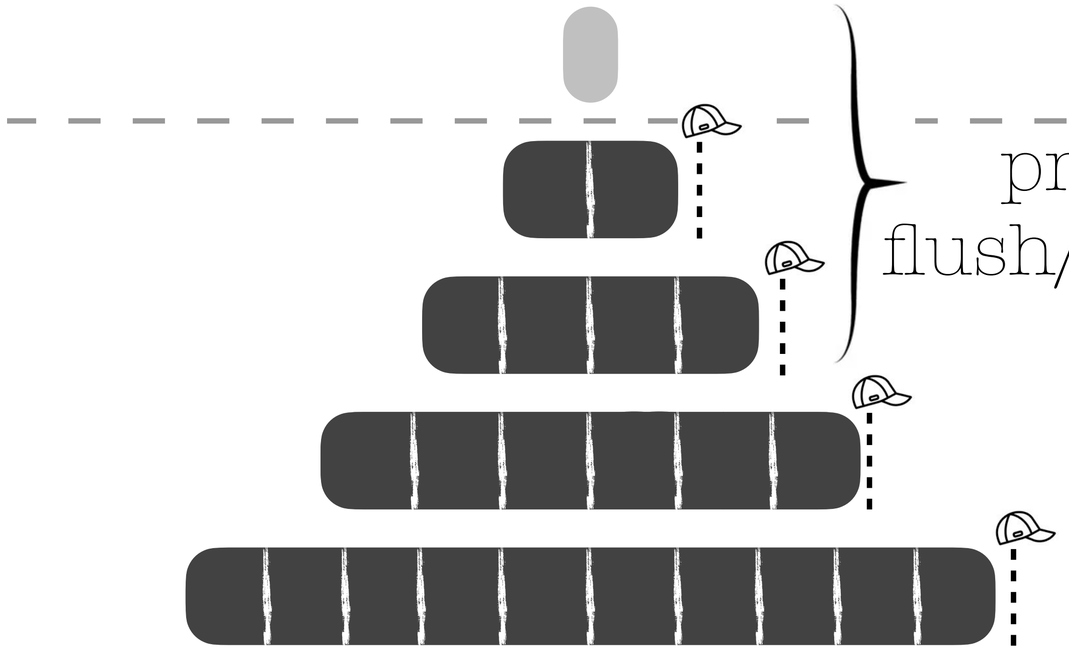


Background Compactions

Compaction Priority

I/O Scheduler

Optimizing **Compactions**



Background Compactions

Compaction Priority

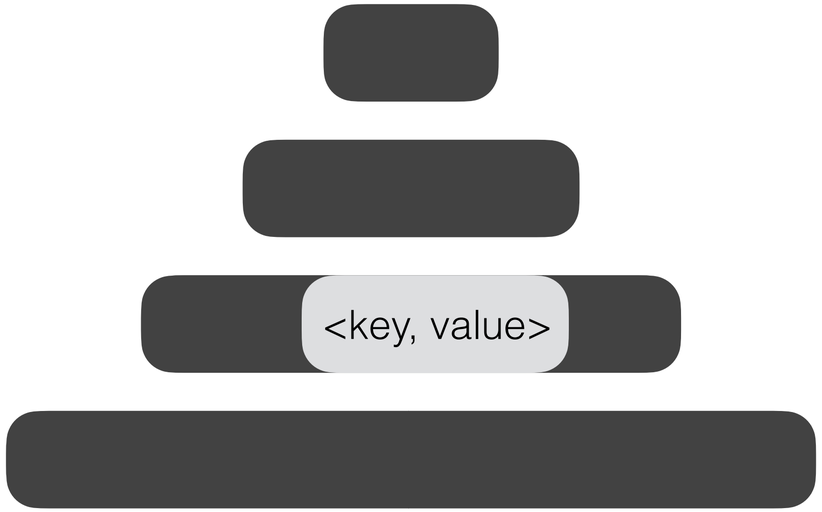
I/O Scheduler

- eliminates write stalls
- no unnecessary high-priority compactions in lower levels

BalmauATC19

BalmauToCS20

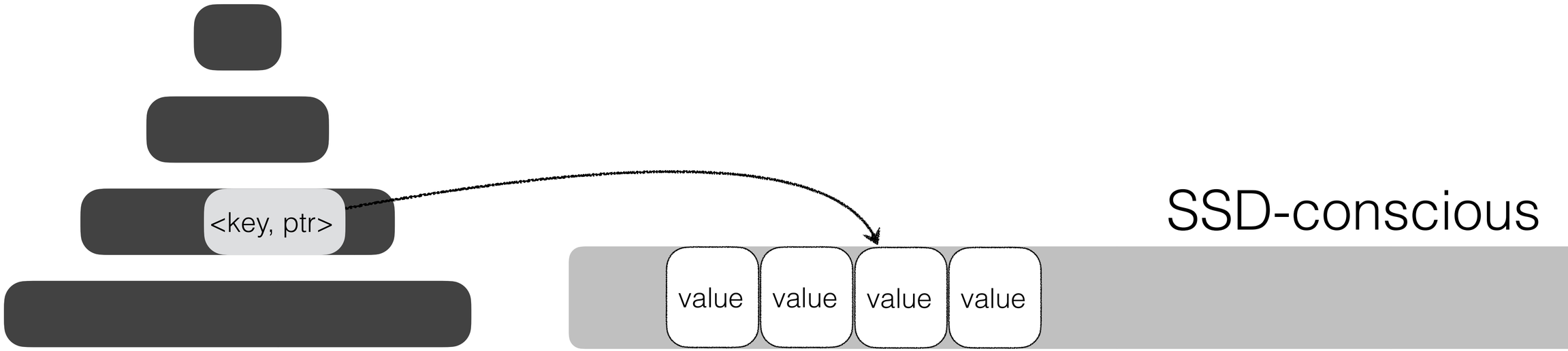
Data Placement Variations



key-value separation

LuFAST16

Data Placement Variations



key-value separation

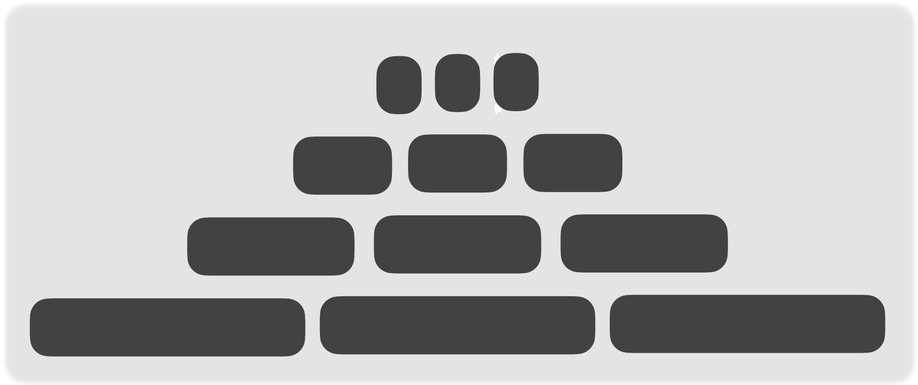
LuFAST16

- reduced write amplification
- better read performance

Data Placement Variations

partitioning / sharding

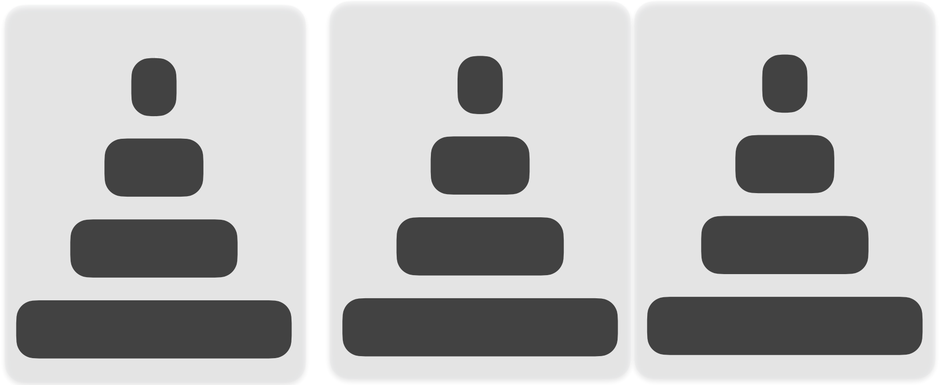
Data Placement Variations



storage

partitioning

RajuSOSP17



storage-1 storage-2 storage-3

sharding

HuangSIGMOD21

- improved ingestion throughput
- reduced write amplification

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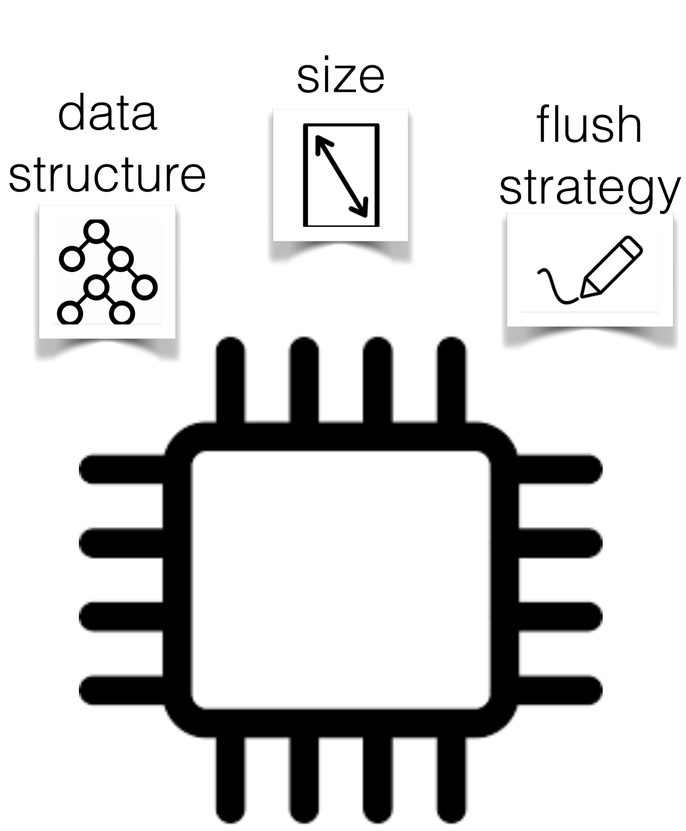
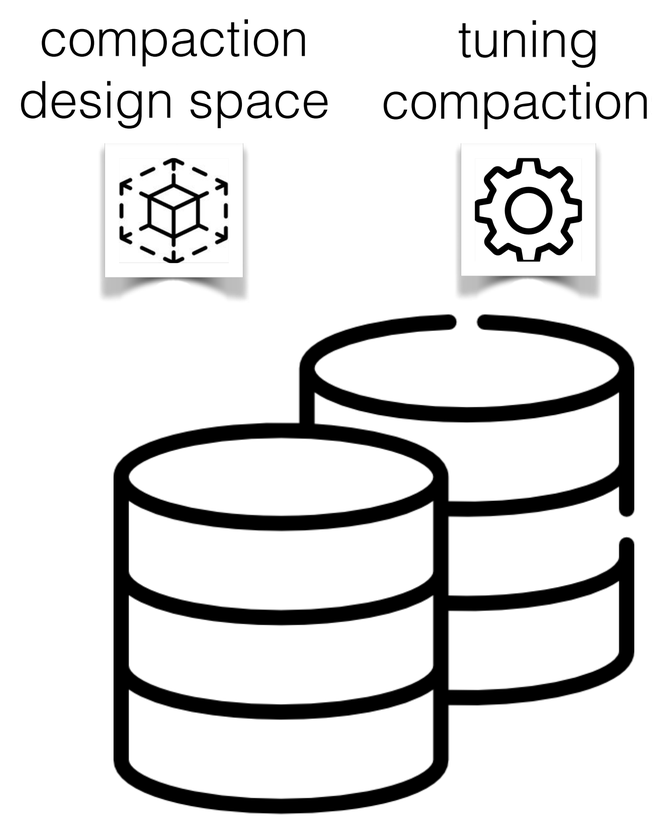
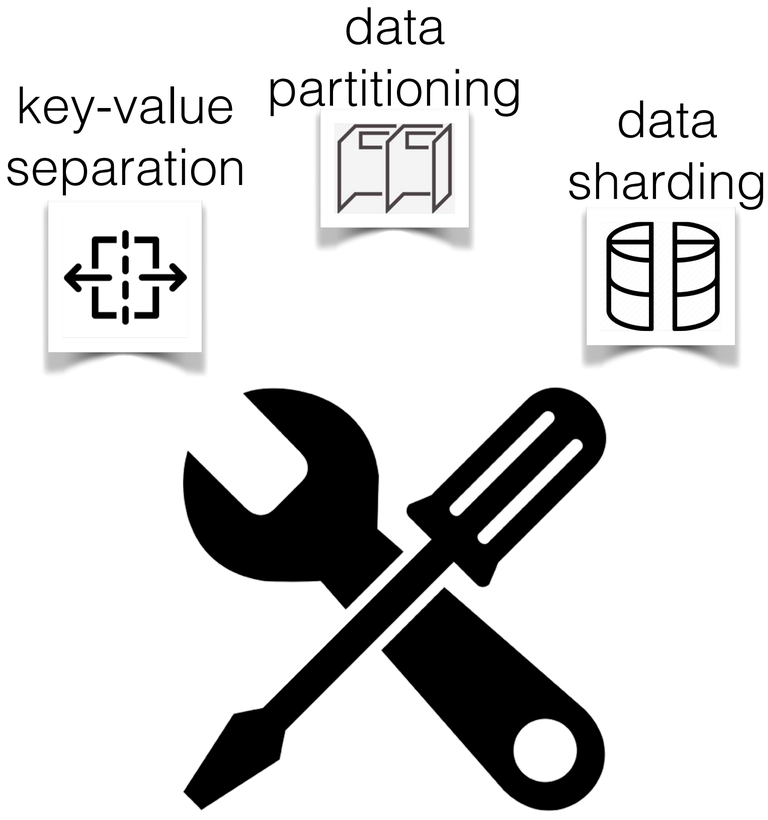
Summary: **Ingestion Optimization**



main memory design elements



data layout on storage



hardware-conscious designs

Outline

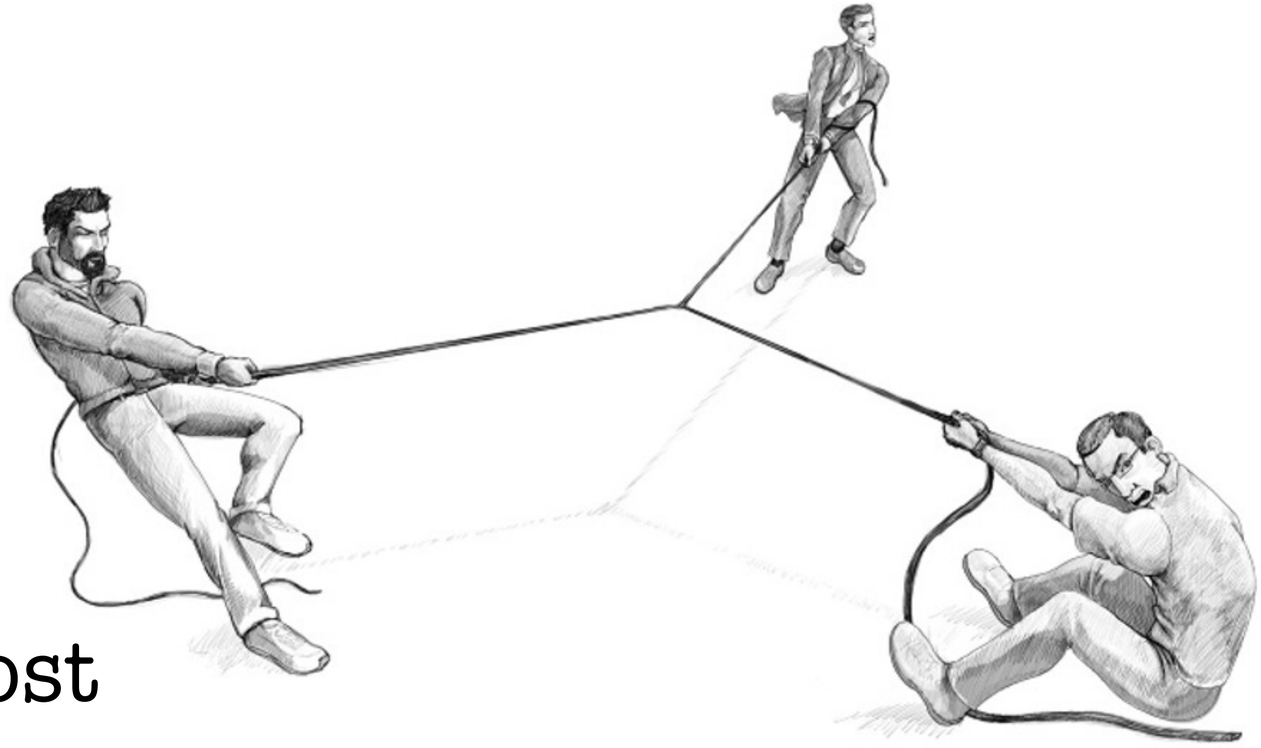
Part 1: **LSM Basics**

Part 2: **Optimizing Ingestion in LSMs**

Part 3: **Navigating the LSM Design Space**

LSM **Design Space**

Update cost



Read cost

Memory/space footprint

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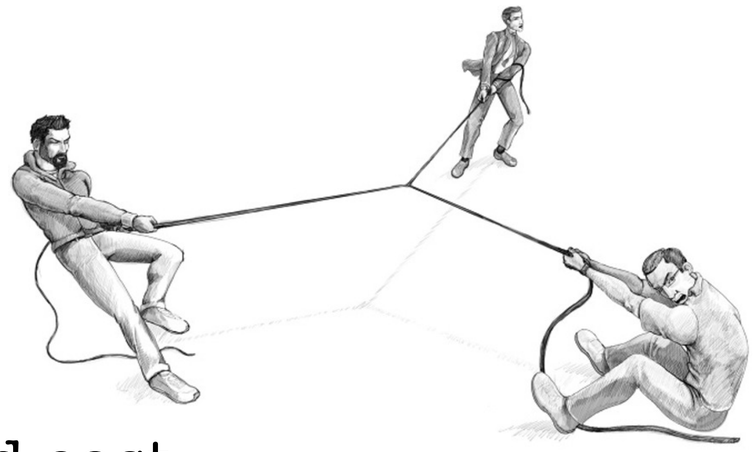
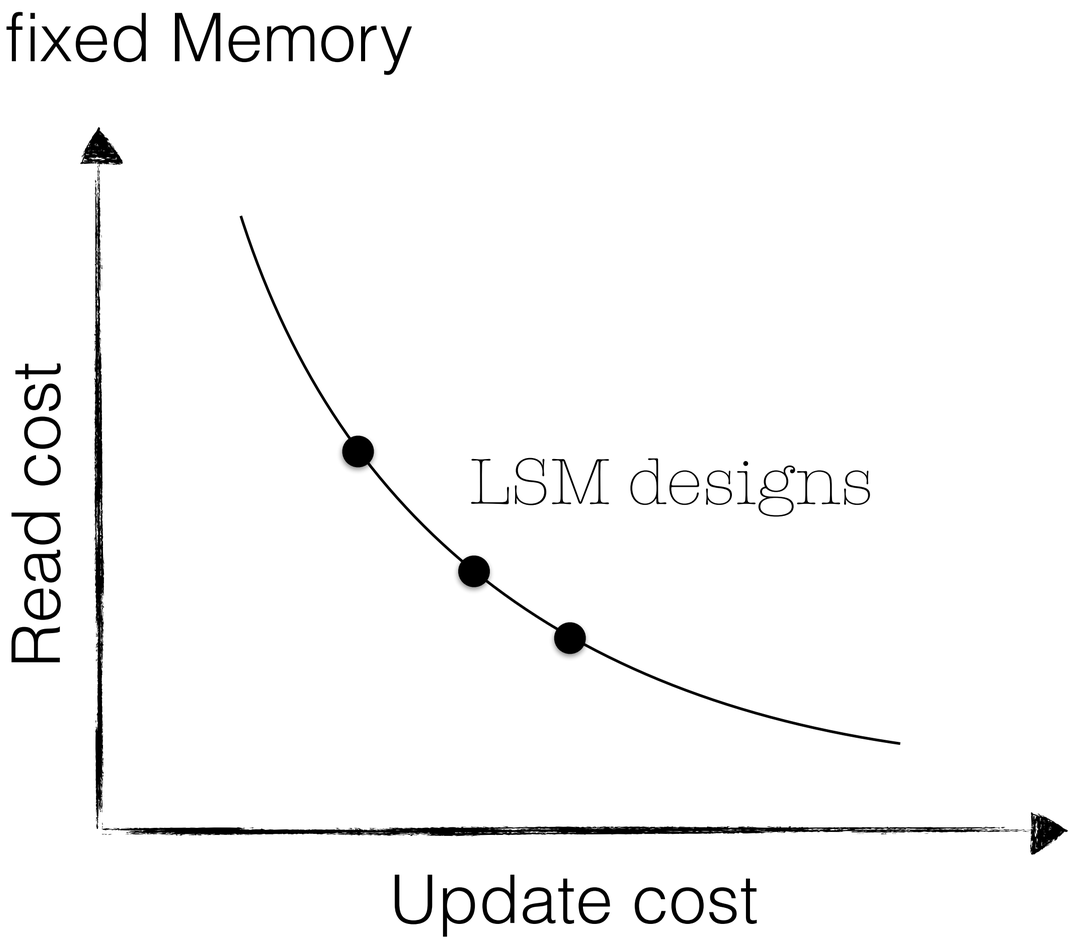
AthanassoulisEDBT16

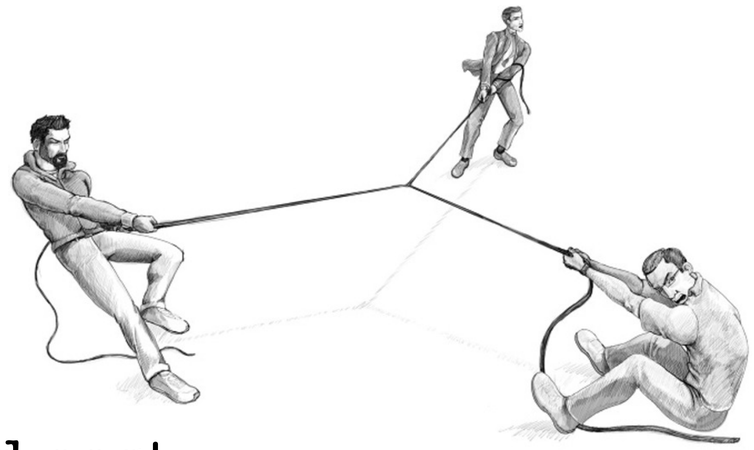
LSM **Design Space**





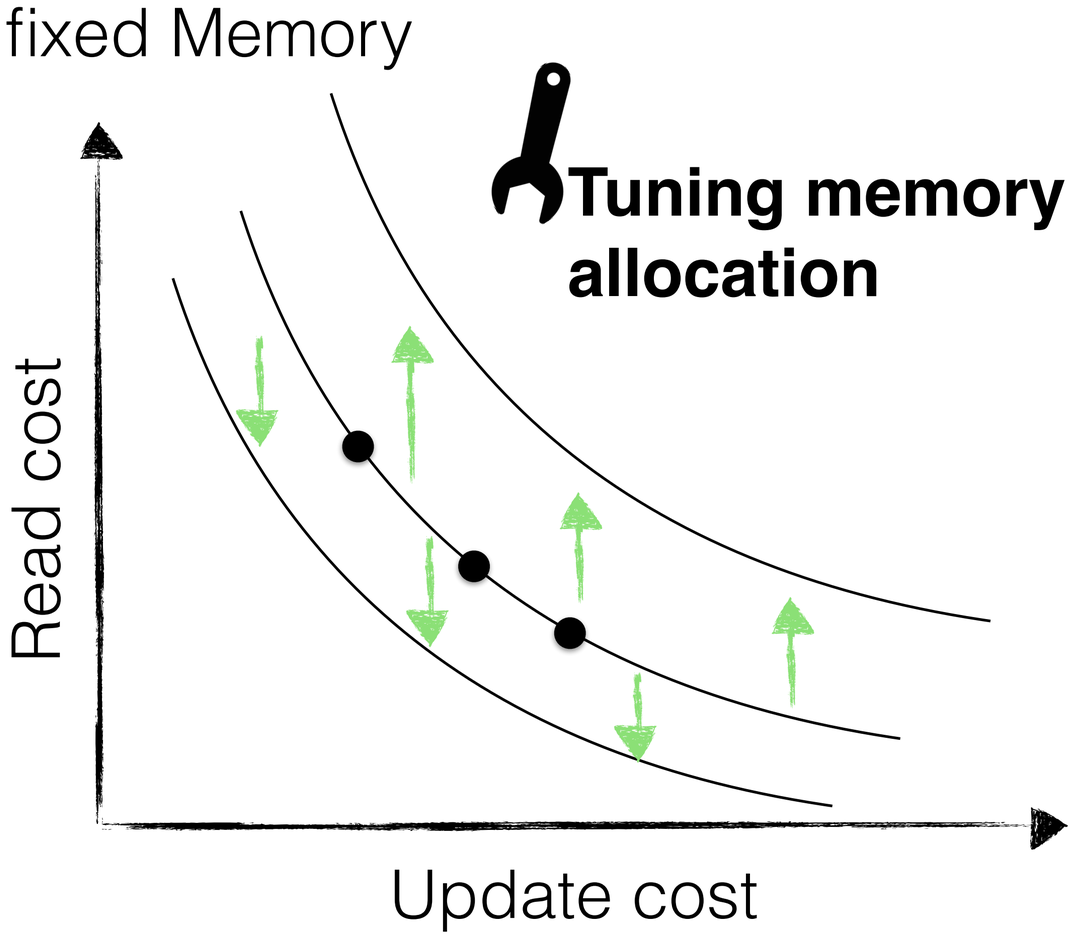
LSM **Design Space**

Update cost

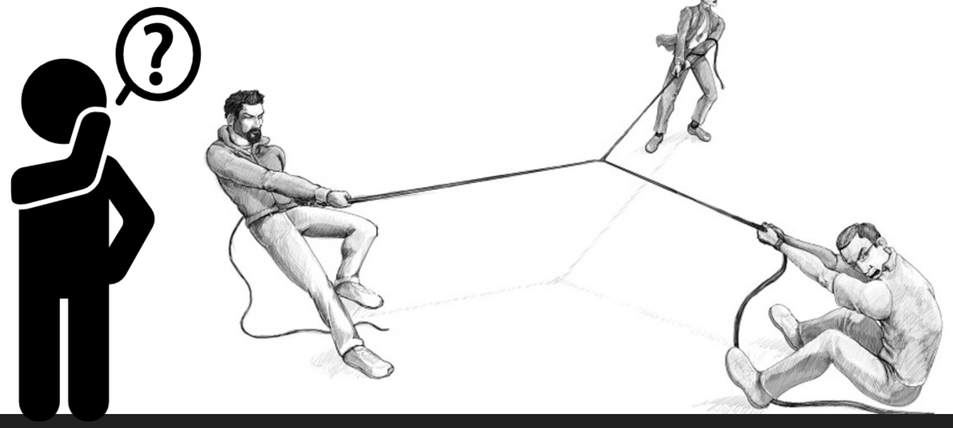


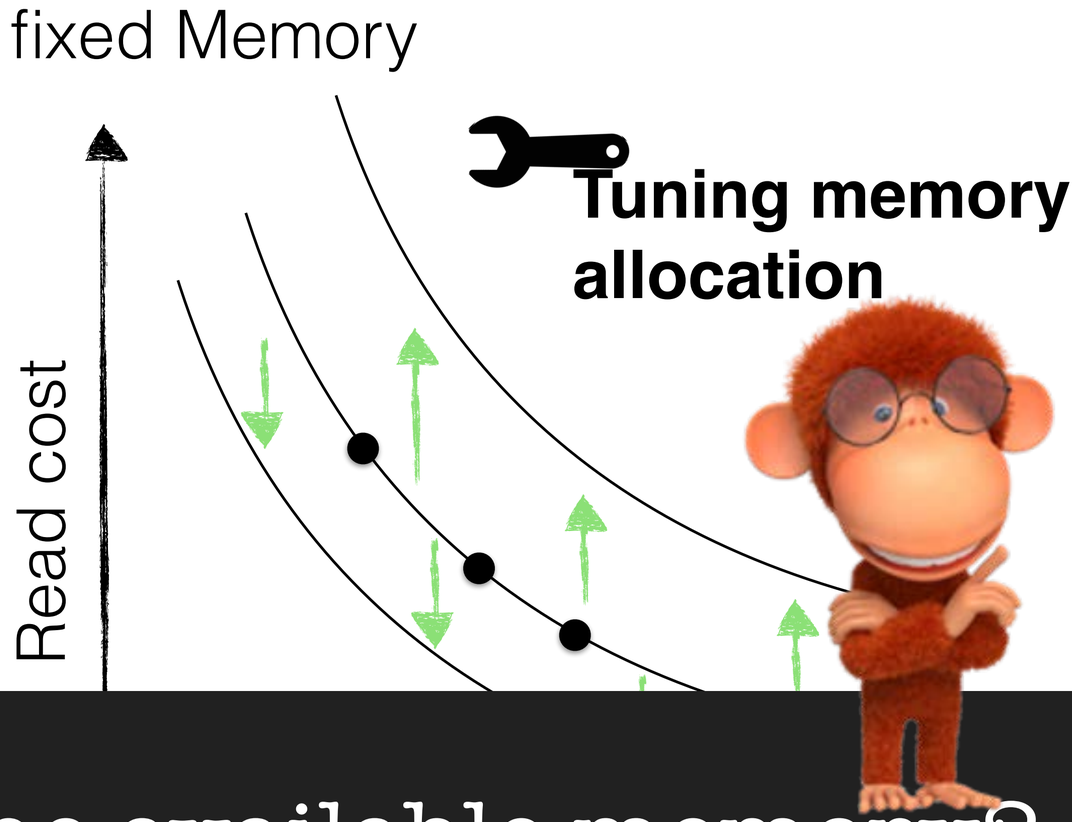
Read cost

Memory/space footprint

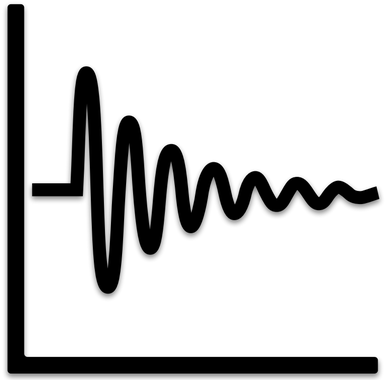


LSM **Design Space**

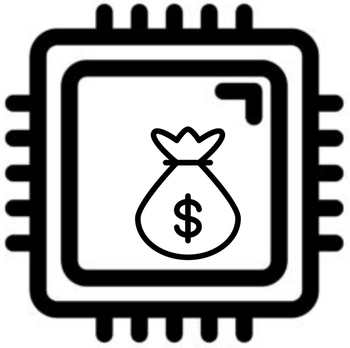




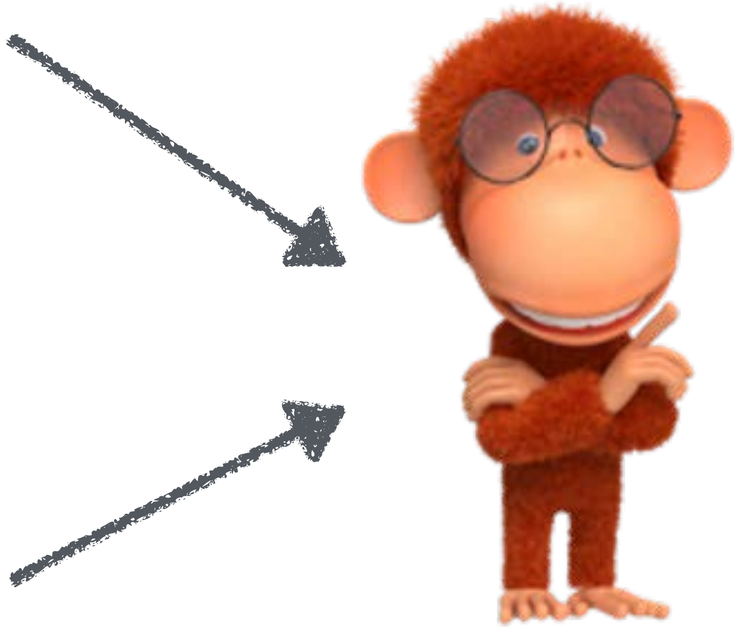
How to optimally allocate the available memory?



workload

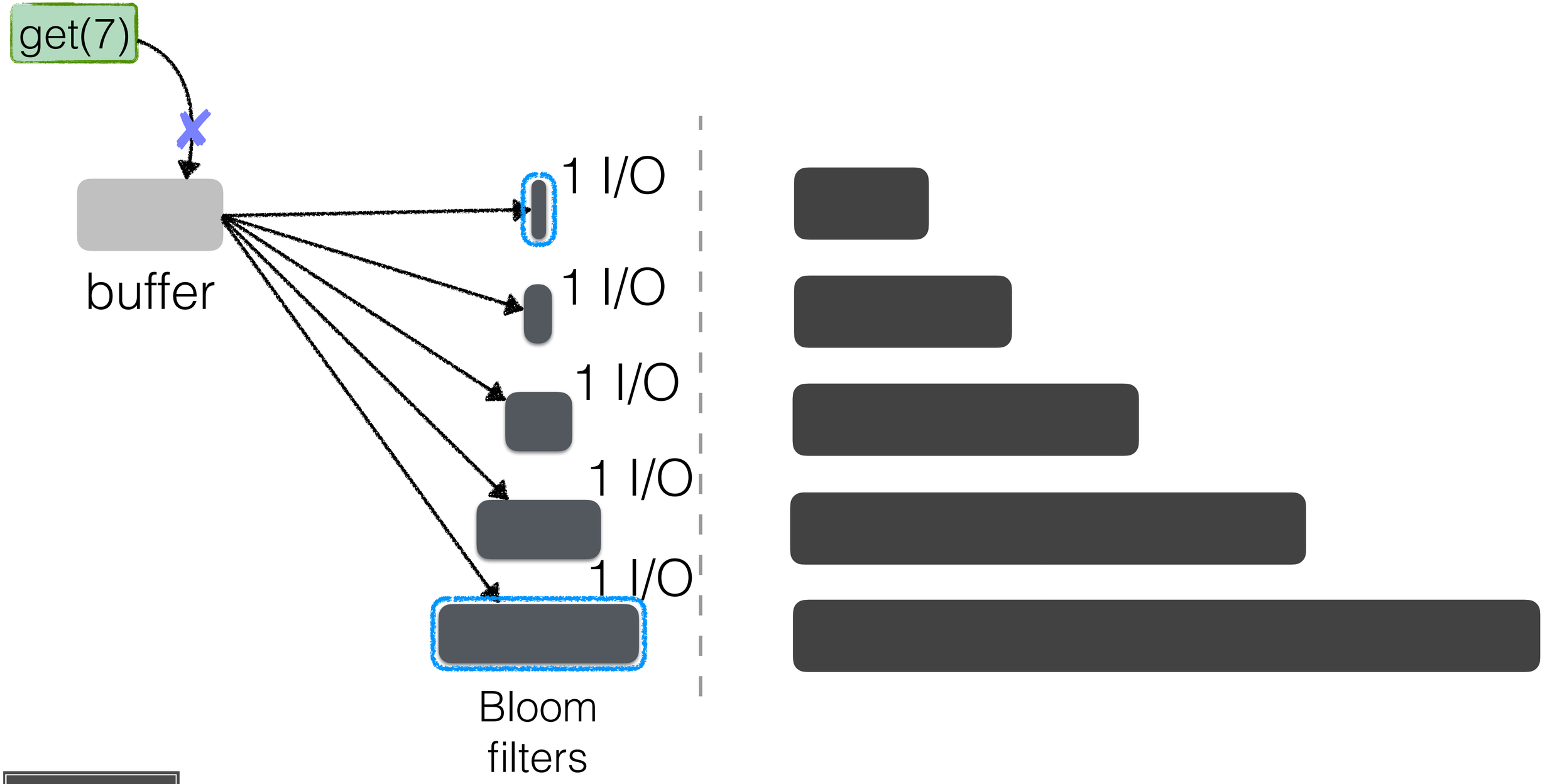


memory budget



How to allocate memory between buffer and BF

How to allocate memory among BFs in LSM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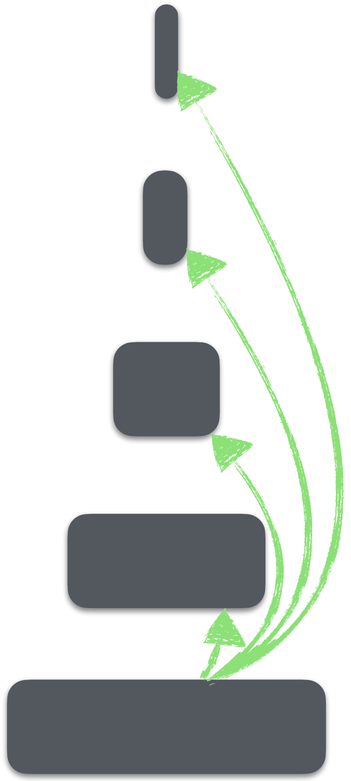
buffer
1 I/O
1 I/O
1 I/O
1 I/O
1 I/O
Bloom
filters

Bloom filters



FPR

Monkey FPR

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

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

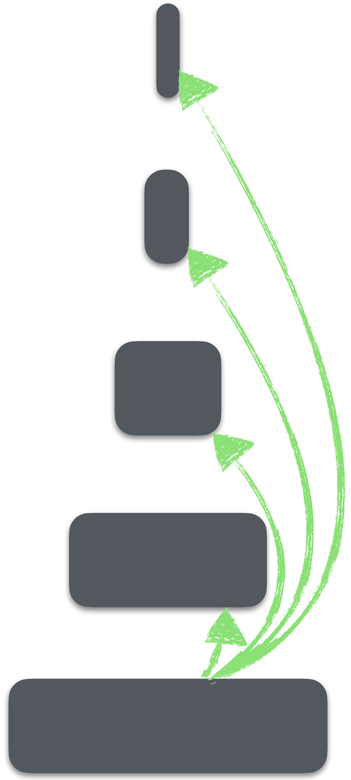
$$\phi > \phi_3 = \phi_0/T^2$$

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

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

exponentially decreasing

Bloom filters



FPR		Monkey FPR
ϕ	$>$	$\phi_1 = \phi_0/\mathrm{T}^4$
ϕ	$>$	$\phi_2 = \phi_0/\mathrm{T}^3$
ϕ	$>$	$\phi_3 = \phi_0/\mathrm{T}^2$
ϕ	$>$	$\phi_4 = \phi_0/\mathrm{T}$
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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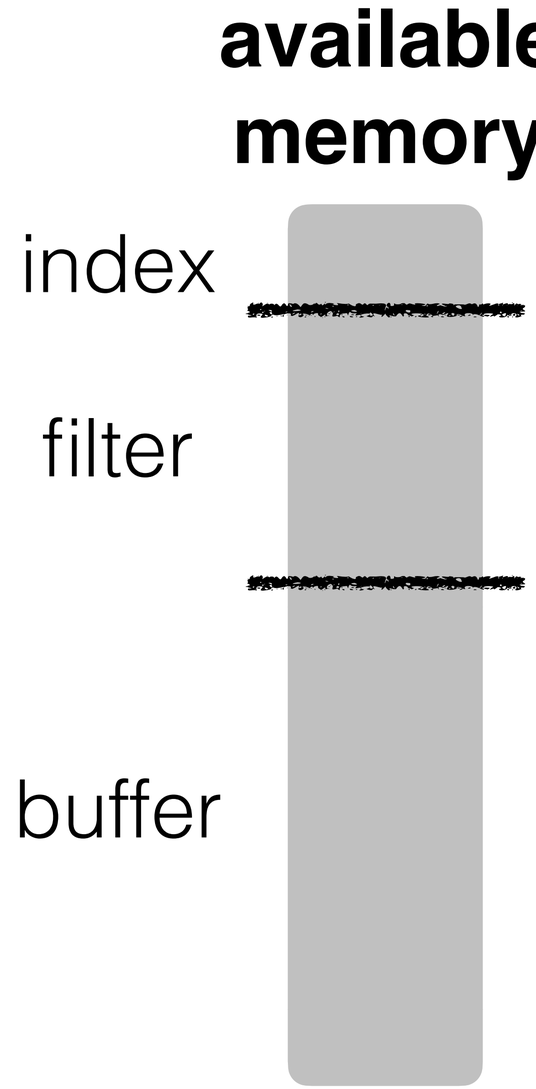
The **Optimal** Memory Allocation

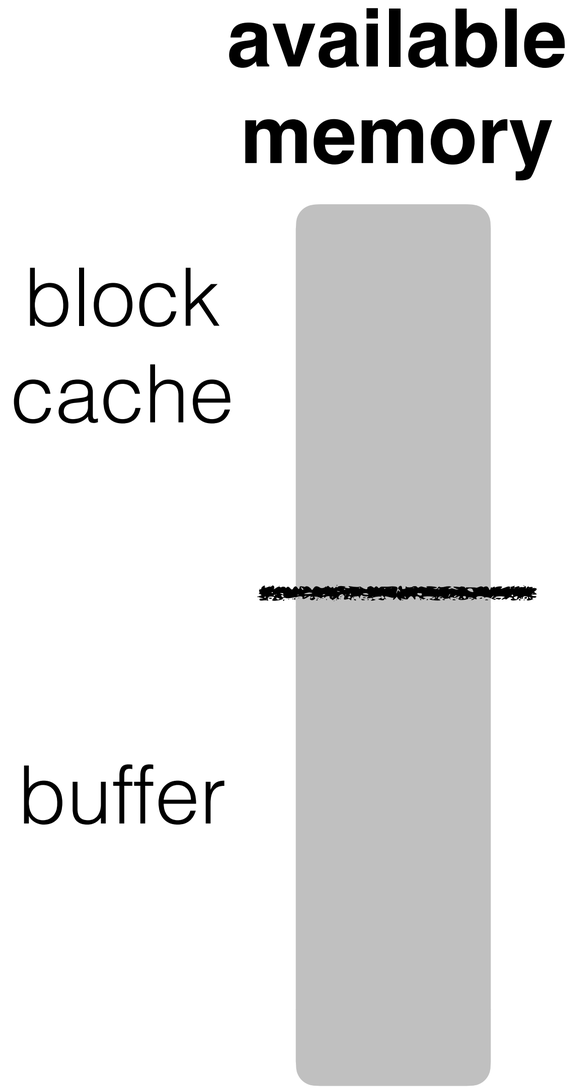


read_cost(N, mem_idx, mem_filt, mem_buf)

write_cost(N, mem_buf)

minimize overall cost given workload
(e.g., read ratio vs. write ratio)

The **Optimal** Memory Allocation



read_cost(N, mem_block_cache)

write_cost(N, mem_buf)

minimize overall cost given workload
(e.g., read ratio vs. write ratio)

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LuoVLDB20

[Open Problem]

The **Optimal** Memory Allocation

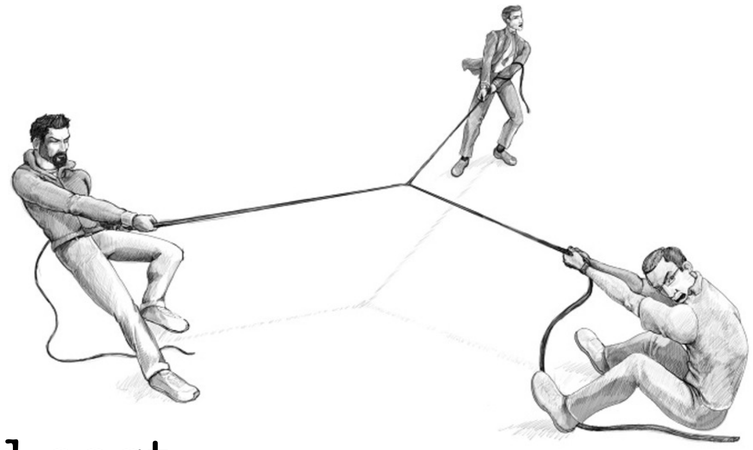
available memory

index

filter

block cache

buffer



Update cost

Read cost

Memory/space footprint

Holistic memory allocation & tuning

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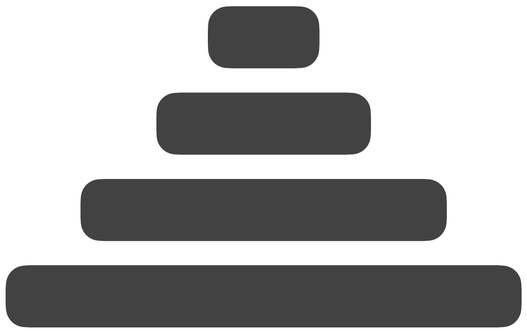
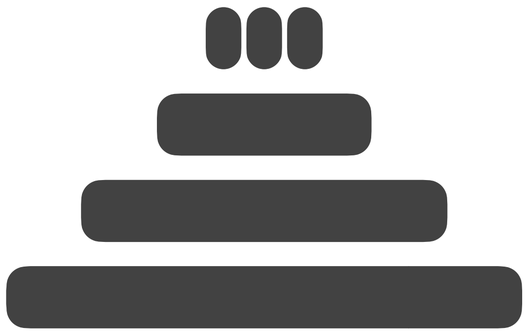
Storage Layer **Design Continuum**

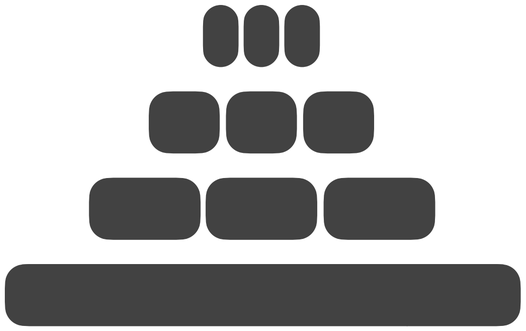
leveling



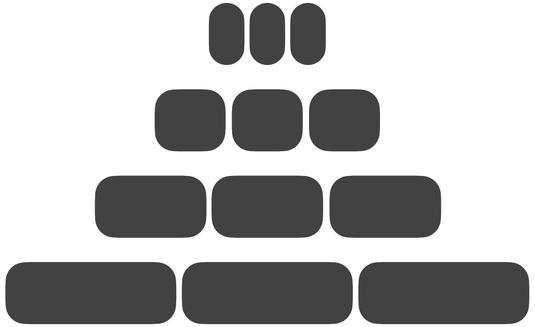
1-leveling



L-leveling



tiering

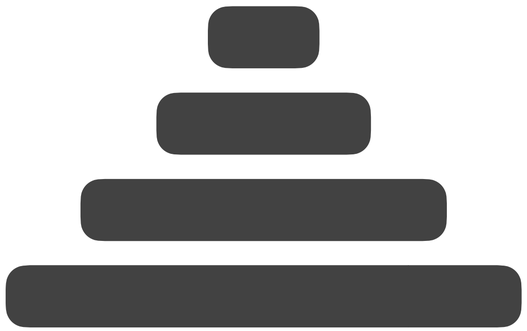


Any design can be defined by the tuple-set: $(\mathtt{T}, \mathtt{i})$

Storage Layer **Design Continuum**

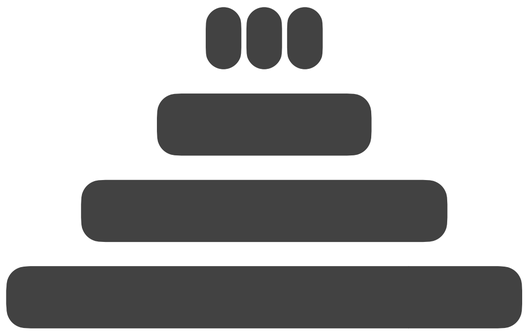
leveling

(T, 0)



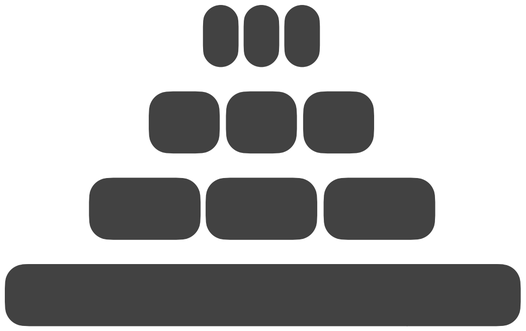
1-leveling

(T, 1)



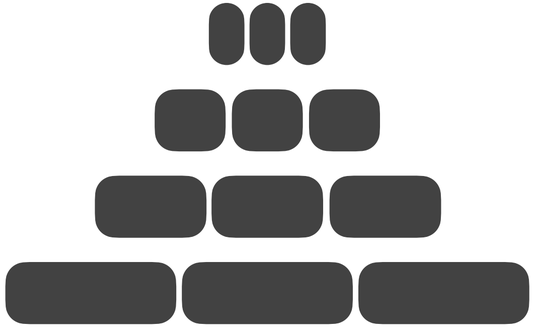
L-leveling

(T, L)



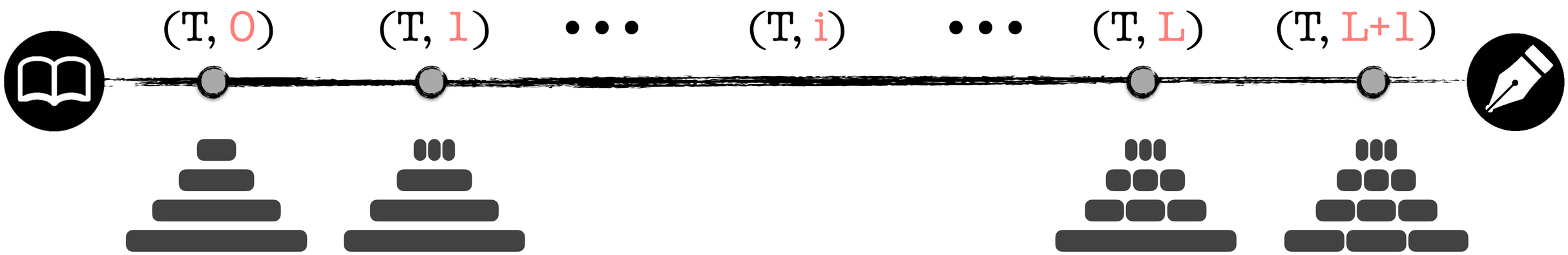
tiering

(T, L+1)

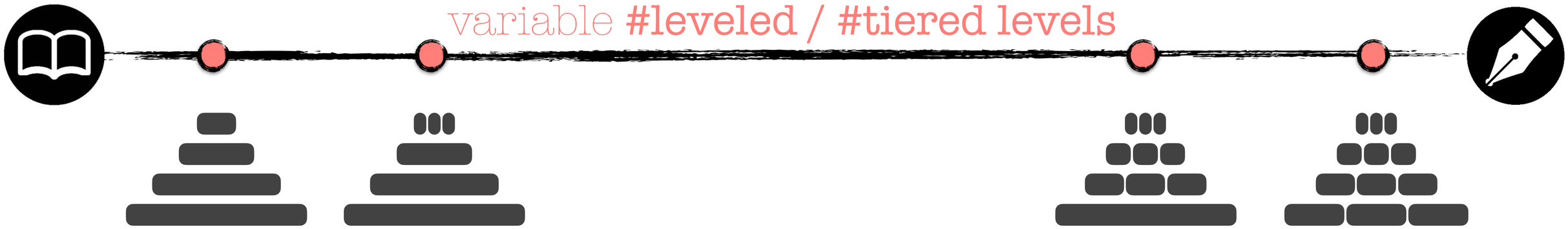


Any design can be defined by the tuple-set: (T, i)

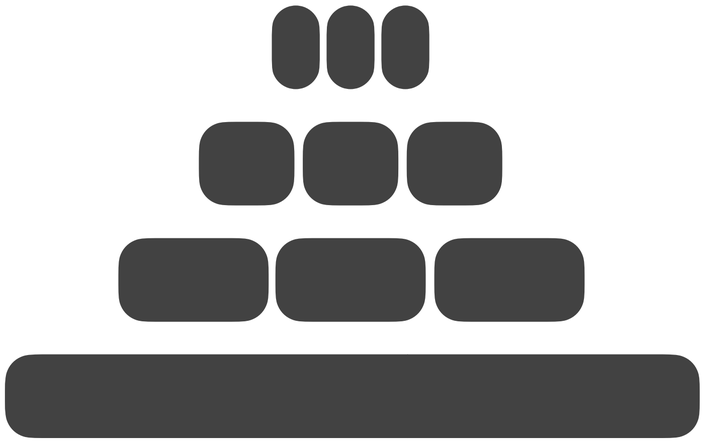
Storage Layer **Design Continuum**



Storage Layer **Design Continuum**



Storage Layer **Design Continuum**



size ratio

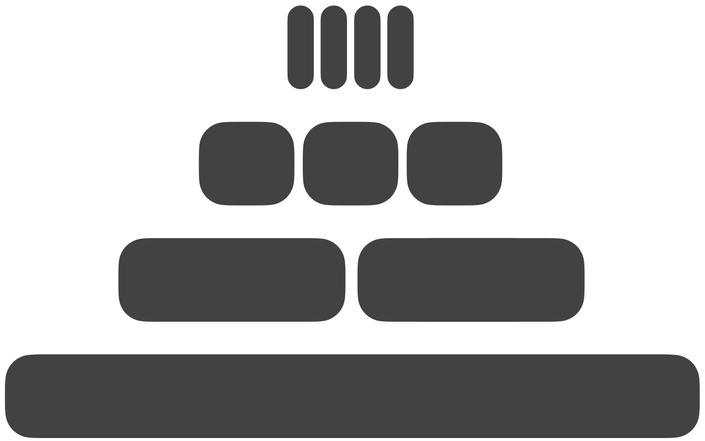
T

T

T

T

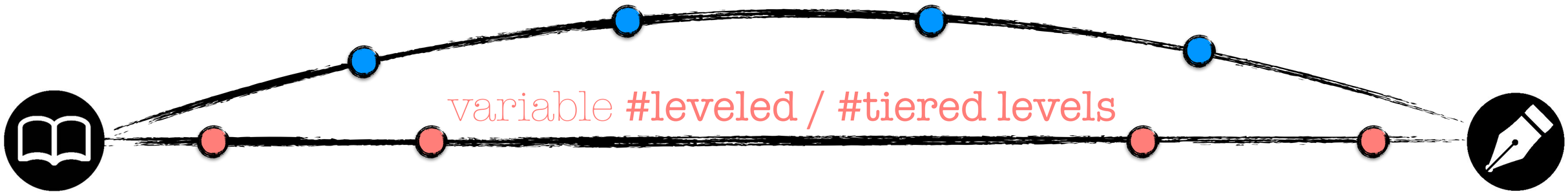
Storage Layer **Design Continuum**



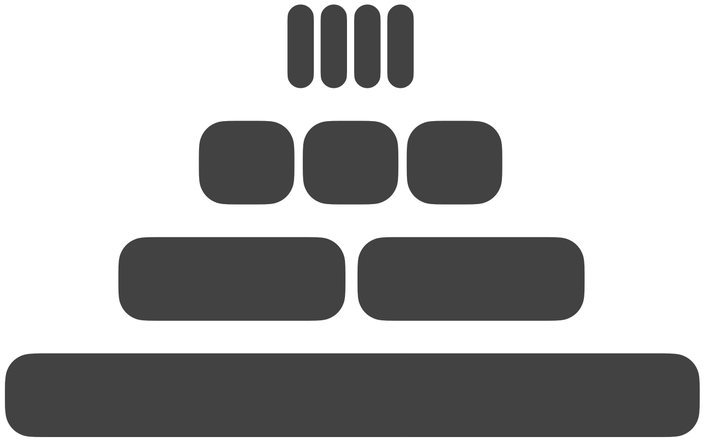
size ratio	#runs
T	4
T	3
T	2
T	1

Storage Layer **Design Continuum**

variable **#runs/level**



variable **#leveled / #tiered levels**



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

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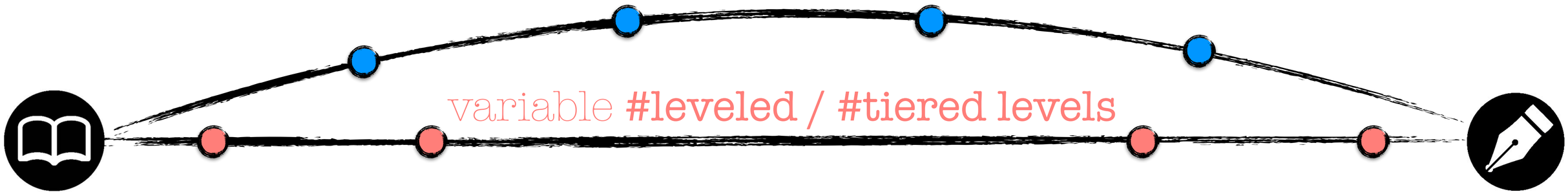
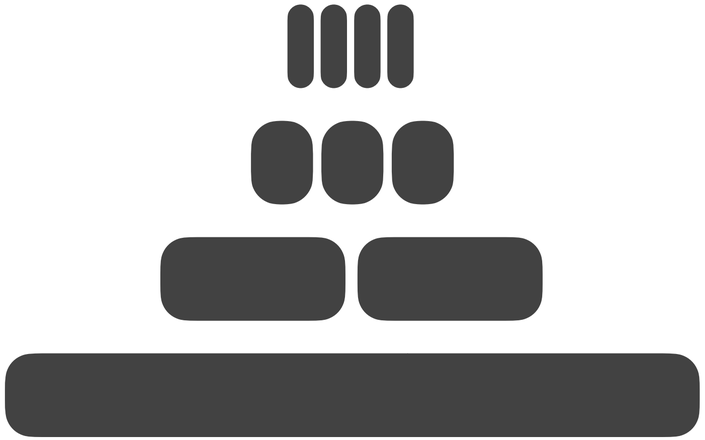
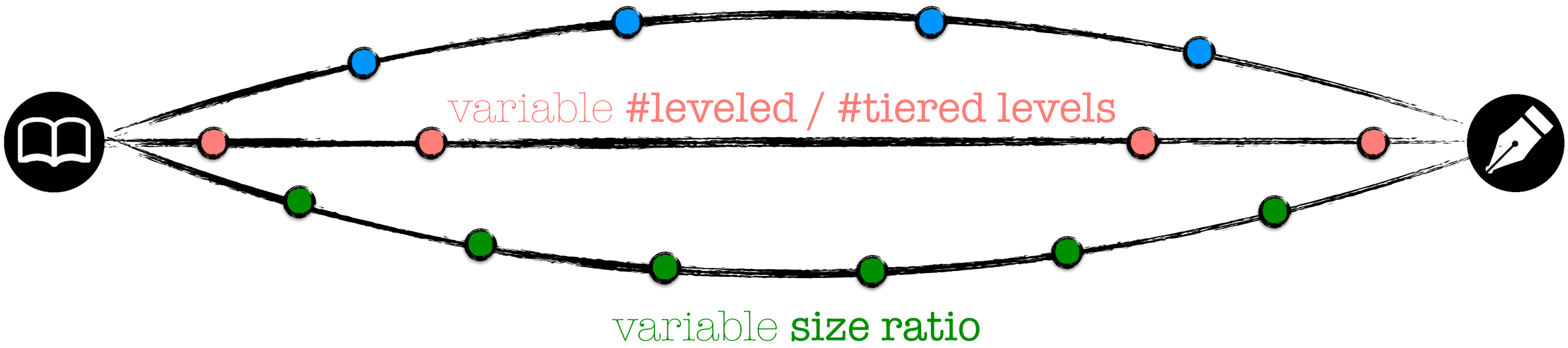
Storage Layer **Design Continuum**



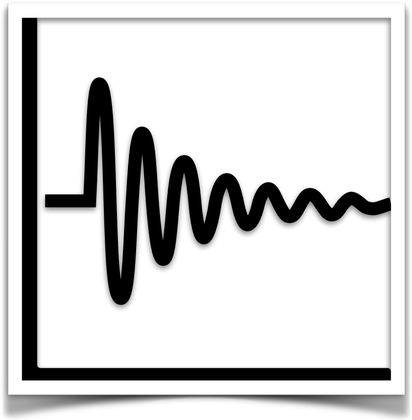


size ratio	#runs
2	4
2.5	3
3	2
4	1

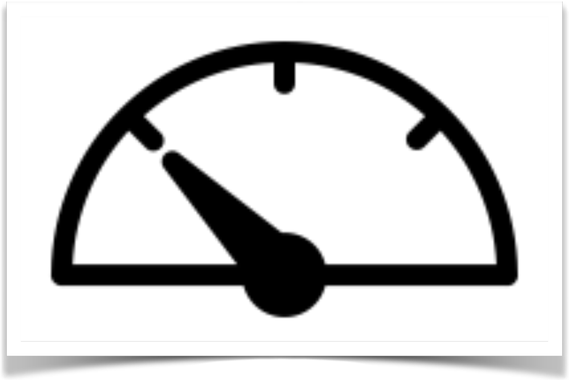
Storage Layer **Design Continuum**



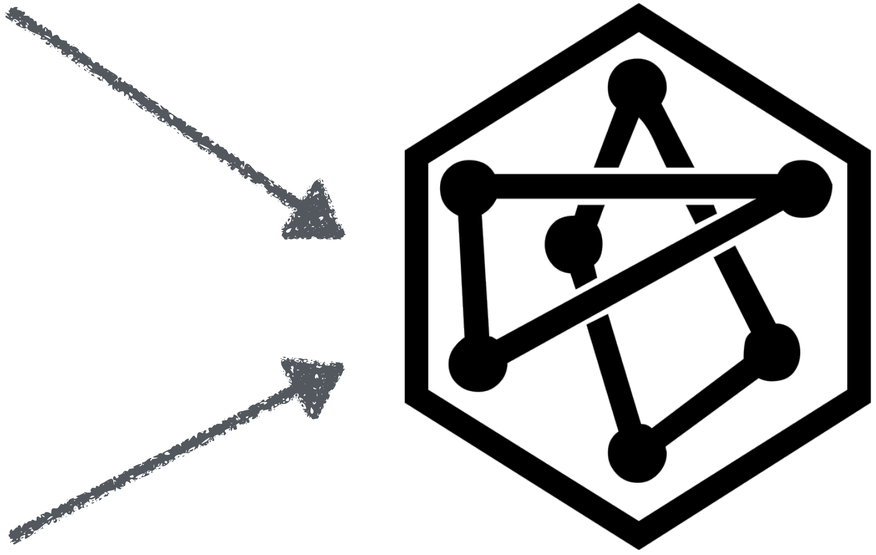
The LSM storage layer design continuum



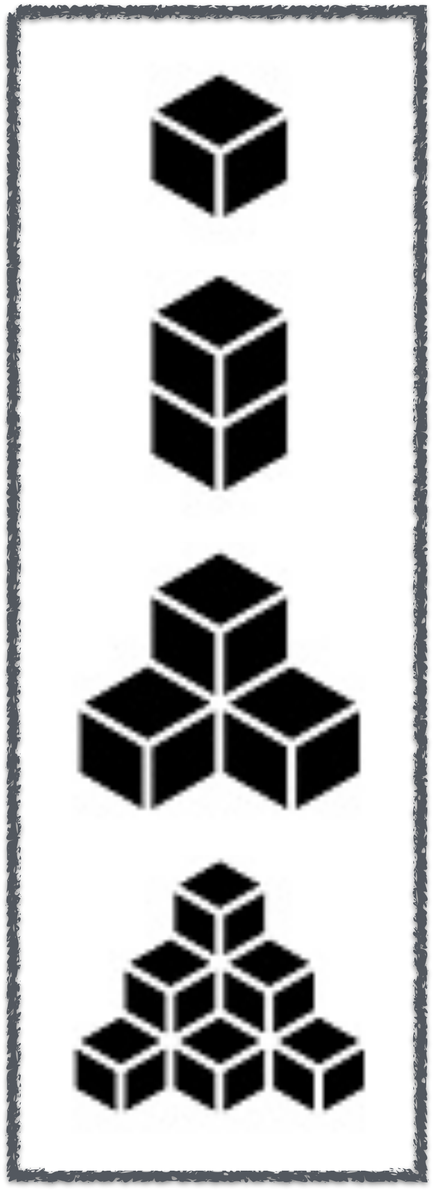
workload



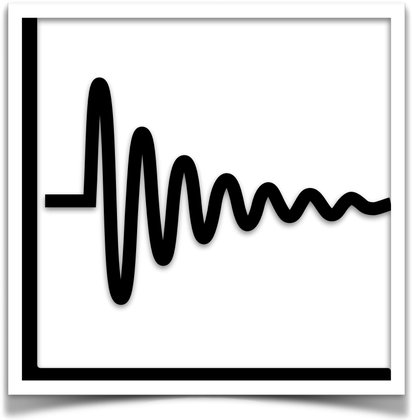
performance target



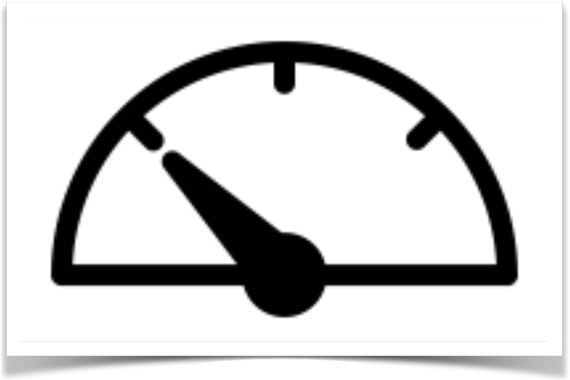
performance modeling



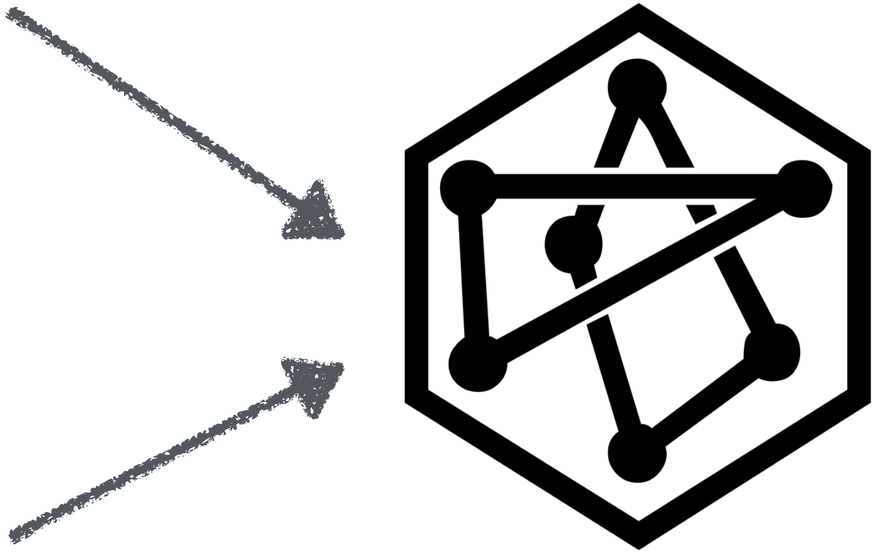
LSM designs



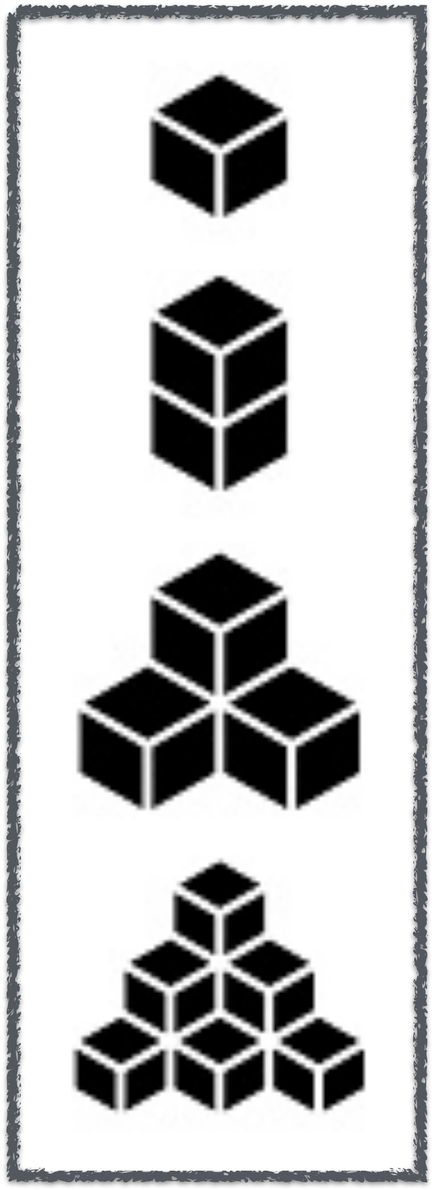
workload



performance target



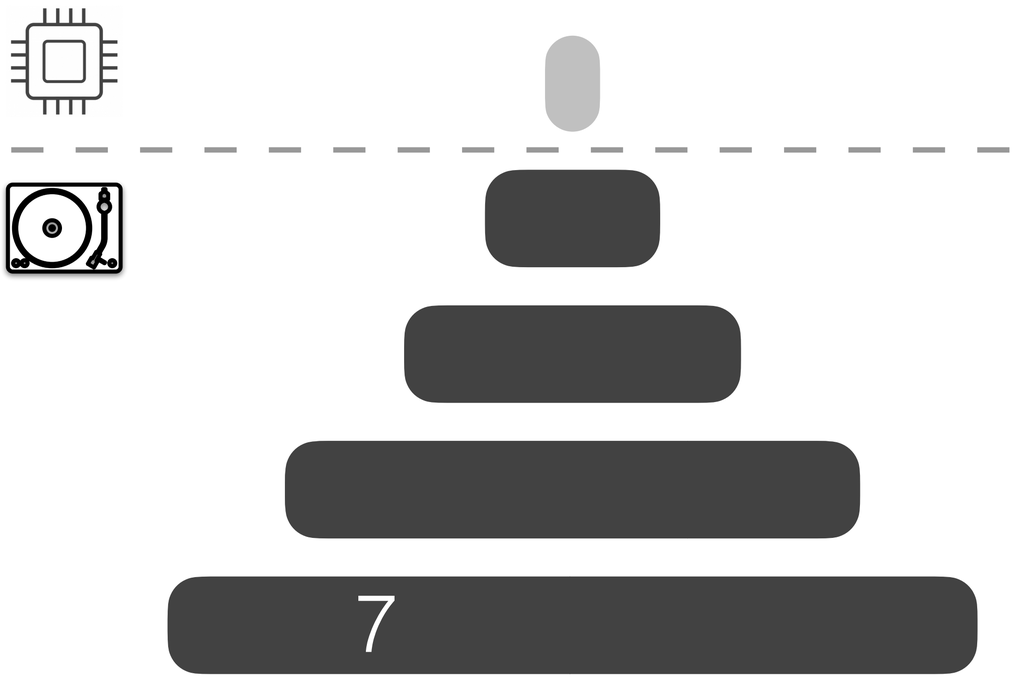
worst-case performance modeling



LSM designs

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

worst-case performance modeling



worst-case read cost: $1 + \sum_{i=1}^{L-1} \phi_i$

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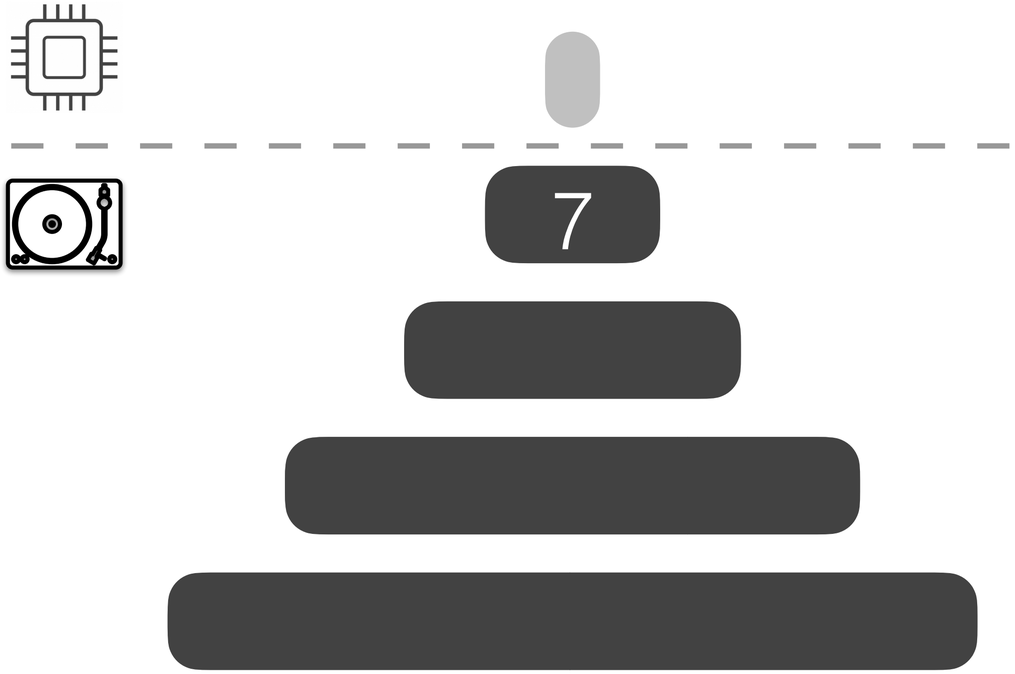
P: pages in buffer
B: entries/page
L: #levels
T: size ratio
N: #entries
ϕ : FPR of BF

worst-case
performance
modeling

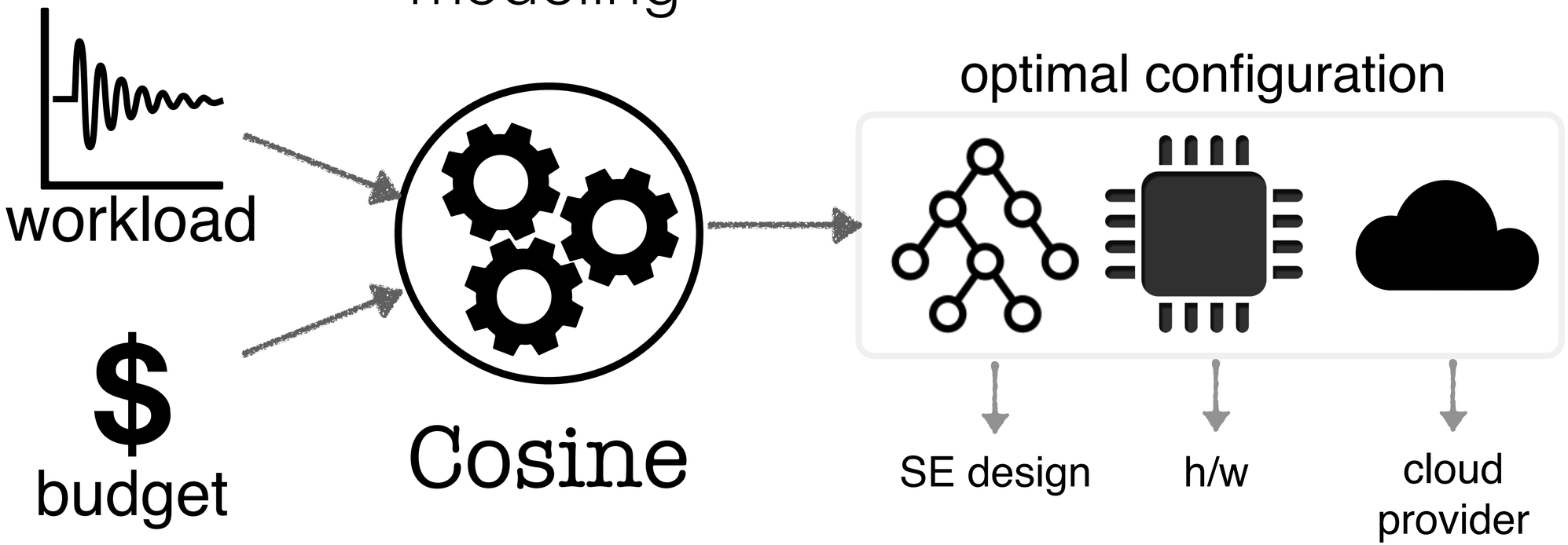


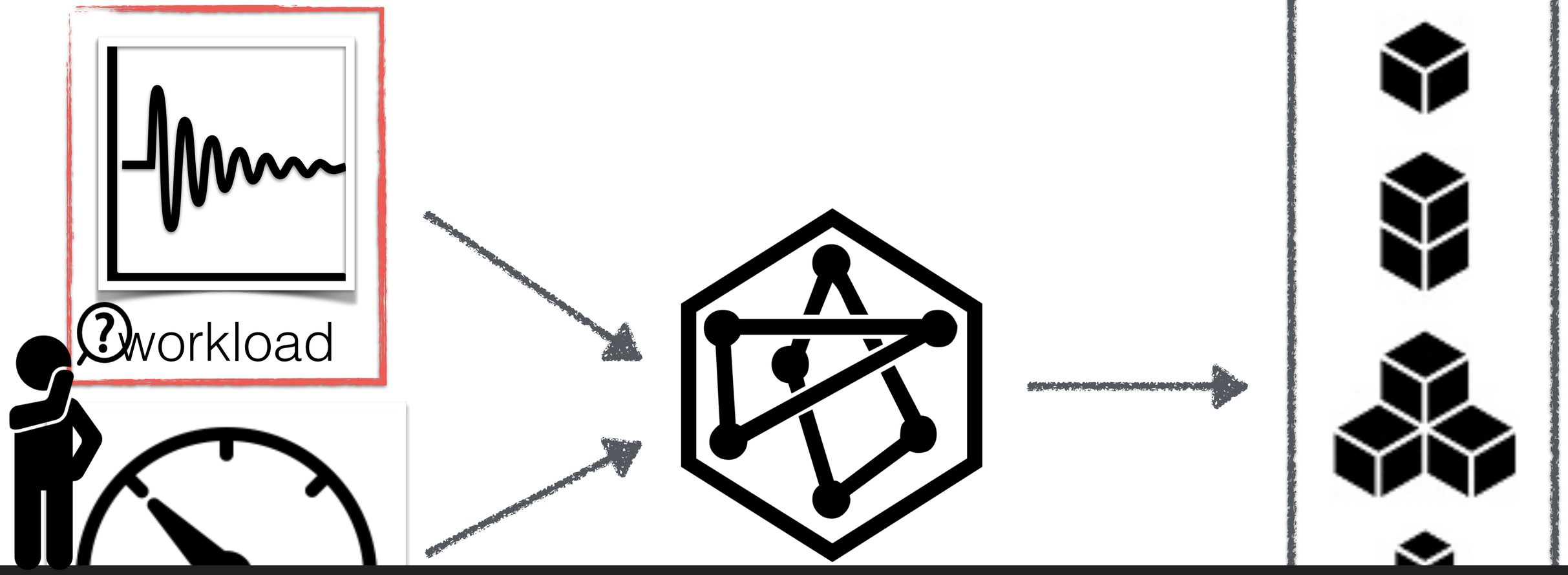
worst-case read cost: $1 + \sum_{i=1}^{L-1} \phi_i$

average-case
performance
modeling

$$\sum_{i=1}^{L} (\mathbb{P}[\text{query in } L_i] \cdot (1 + \sum_{j=1}^{i-1} \phi_i))$$

average-case
performance
modeling

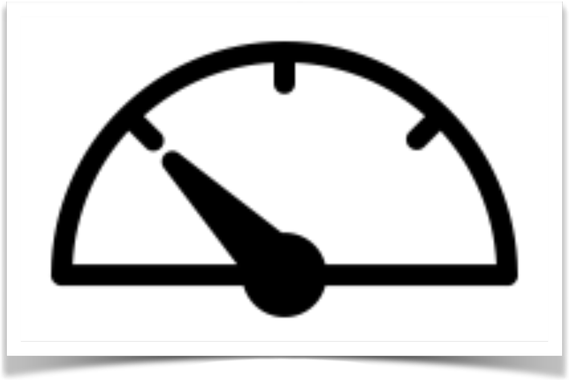




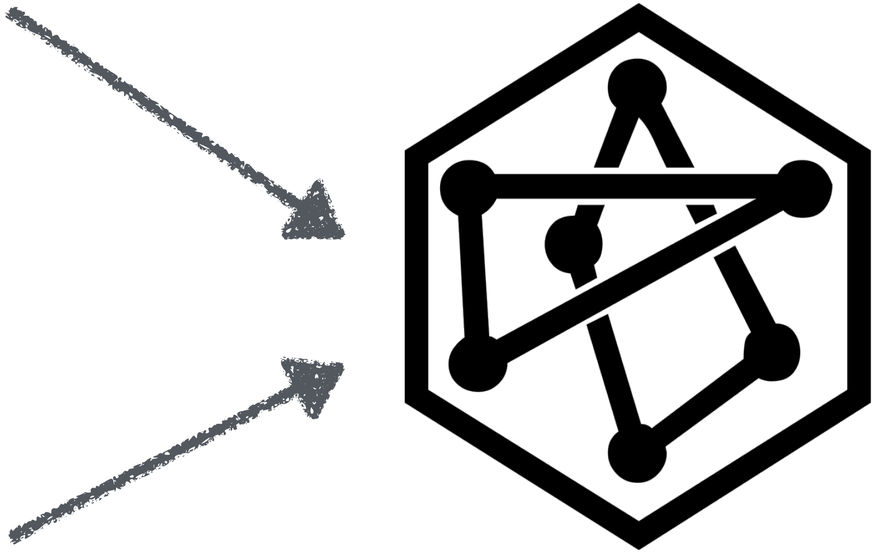
What if the workload changes?

ESM designs

workload

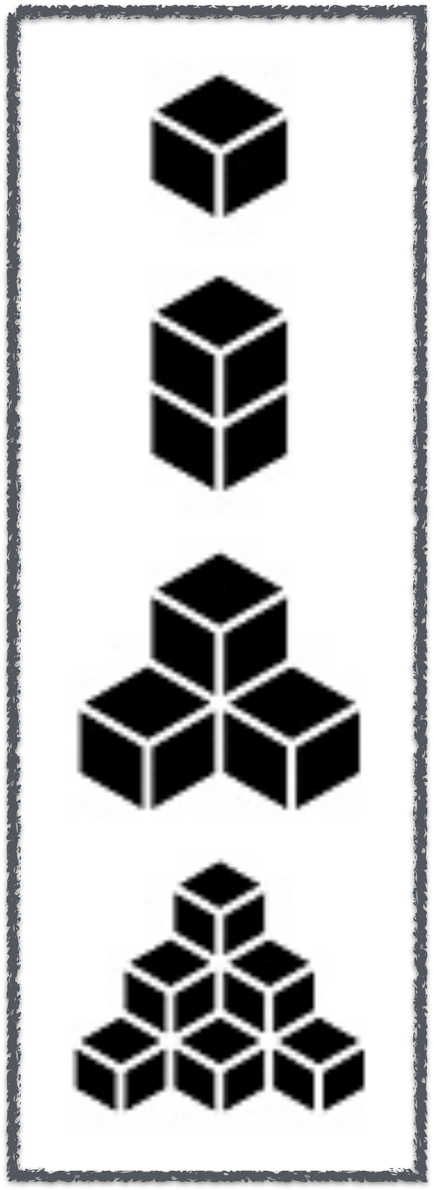


performance target



average-case

performance modeling



LSM designs

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Tuning

workload
hardware
design

optimal
tuning

given workload $\mathcal{W}$, dataset $\mathcal{D}$, find a tuning $\mathcal{T}^{\text{opt}}$:

$$\mathcal{T}^{\text{opt}} = \text{argmin}_{\mathcal{T}}\big(\text{cost}(\mathcal{W}, \mathcal{D}, \mathcal{T})\big)$$

Robust Tuning

unpredictability in

workload
hardware
design

optimal tuning

given workload $\mathcal{W}$, dataset $\mathcal{D}$, and a region $\mathcal{R}(\mathcal{W})$, find a tuning $\mathcal{T}^{rob}$:

$$\mathcal{T}^{\text{rob}} = \text{argmin}_{\mathcal{T}} \text{max}_{\mathcal{W}' \in \mathcal{R}(\mathcal{W})} \big(\text{cost}(\mathcal{W}', \mathcal{D}, \mathcal{T})\big)$$

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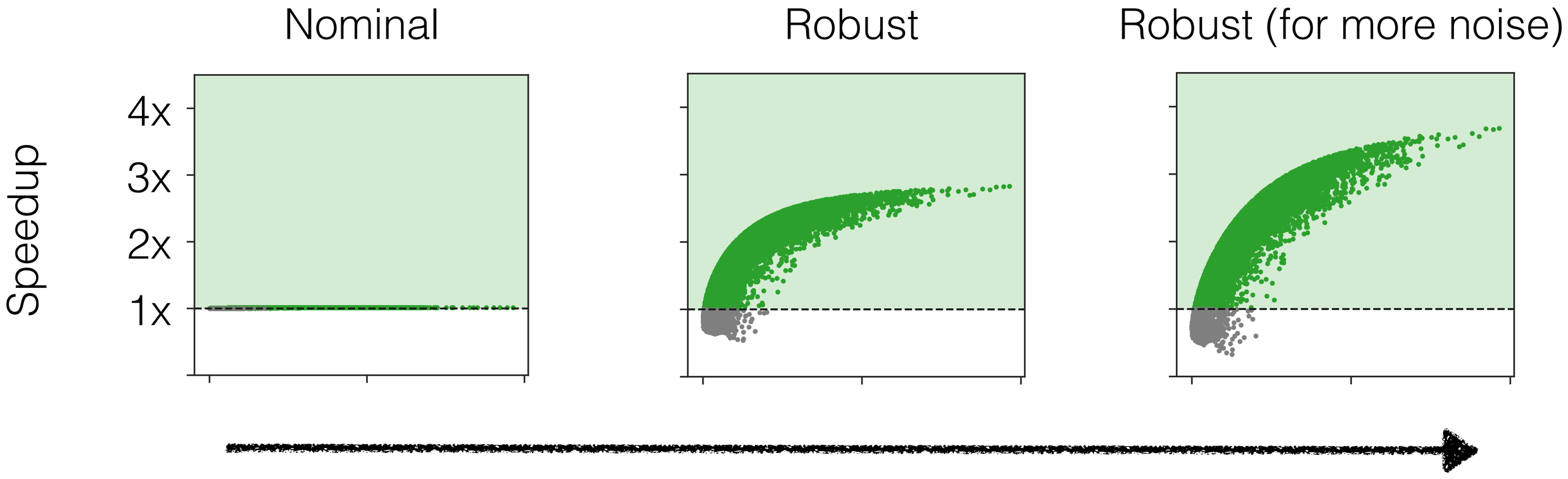
Robust Tuning



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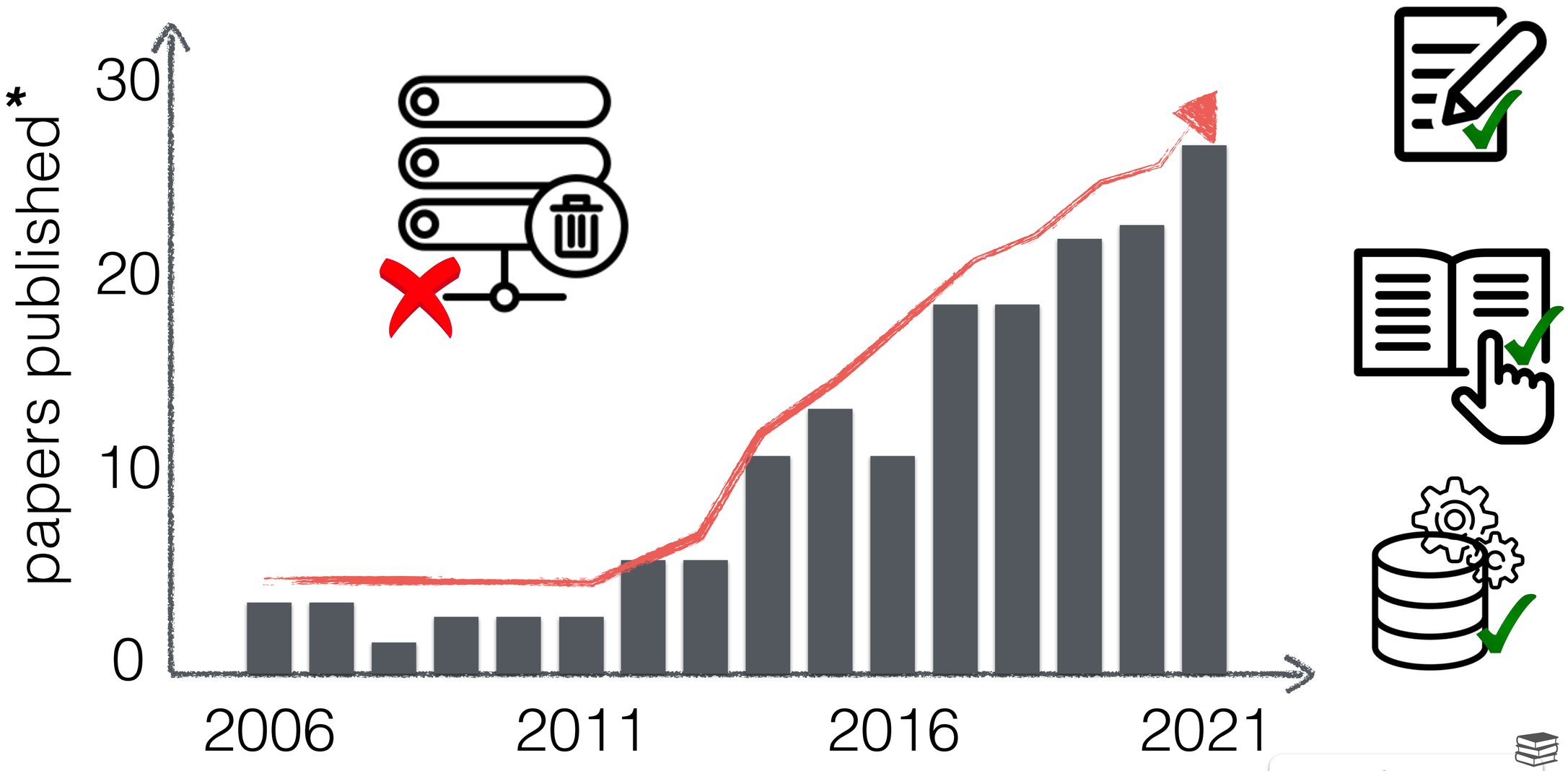
Research Trend: **What about Deletes?**



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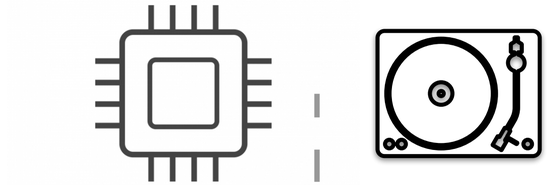
* data from DBLP

deletes in LSM-tree



delete(5)

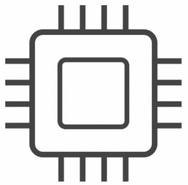
buffer 5

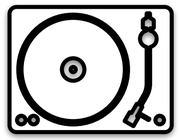
L1

L2 5

L3 5

deletes in LSM-tree





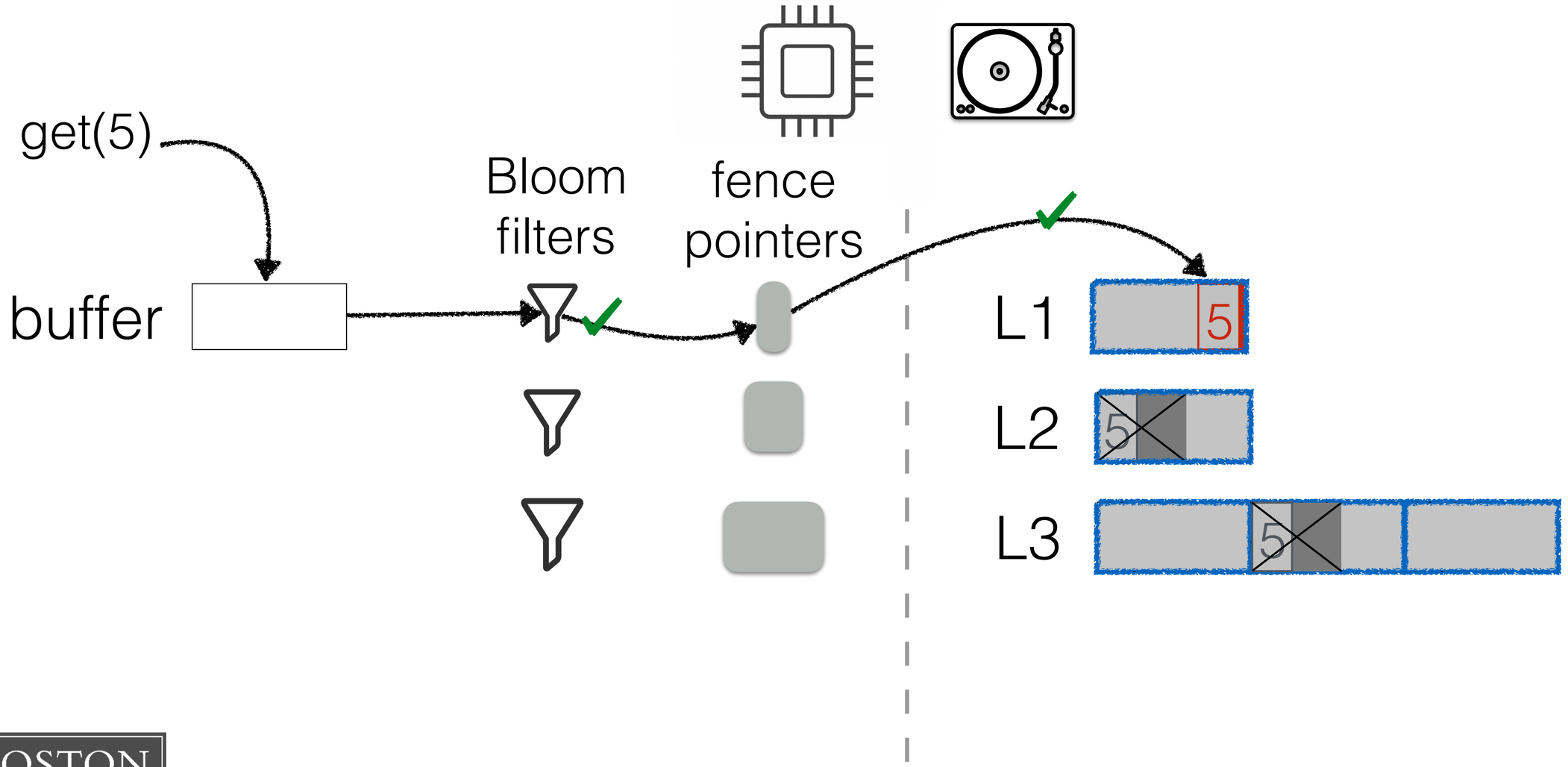
buffer

L1

L2

L3

deletes in LSM-tree



Large-scale production

ZippyDB

25.2M/day

UP2X

92.5% merge through deletes

Internal DB ops

table drop

data migration

periodic cleanup

Privacy

GDPR (EU, UK)

CCPA (California)

VCDPA (Virginia)

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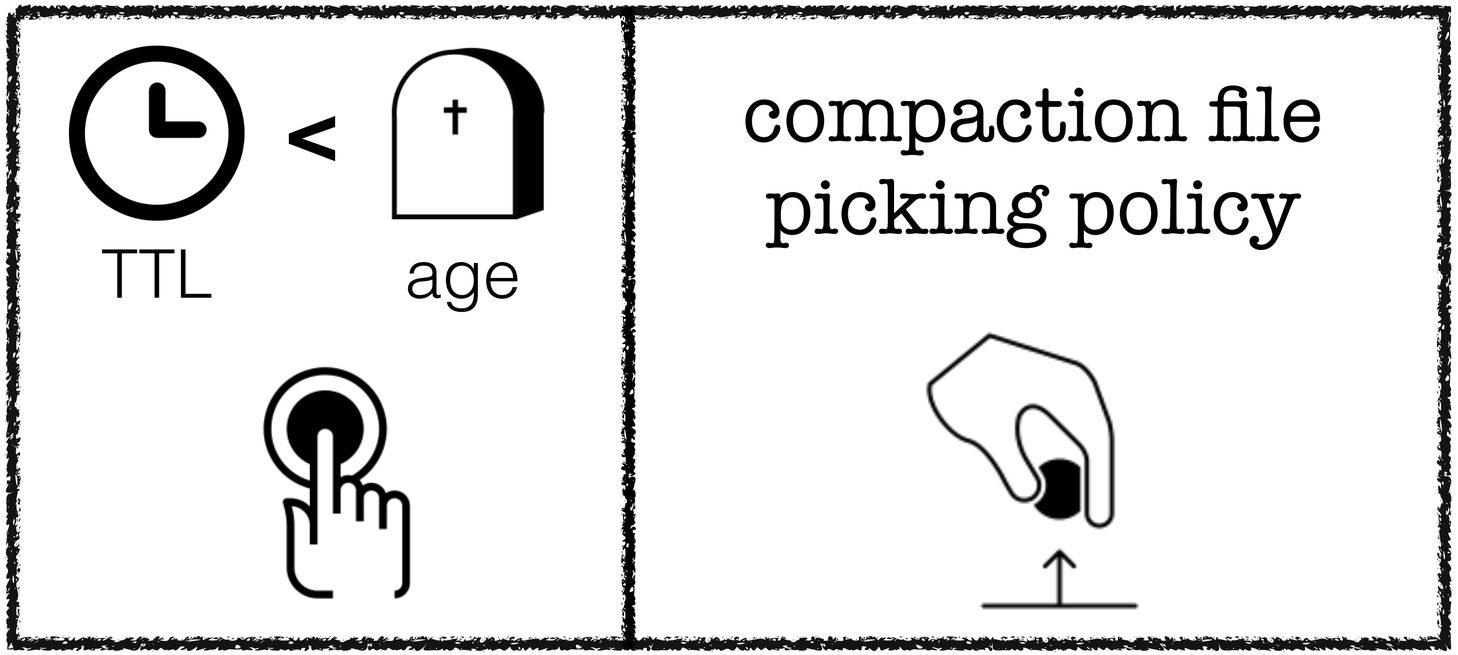
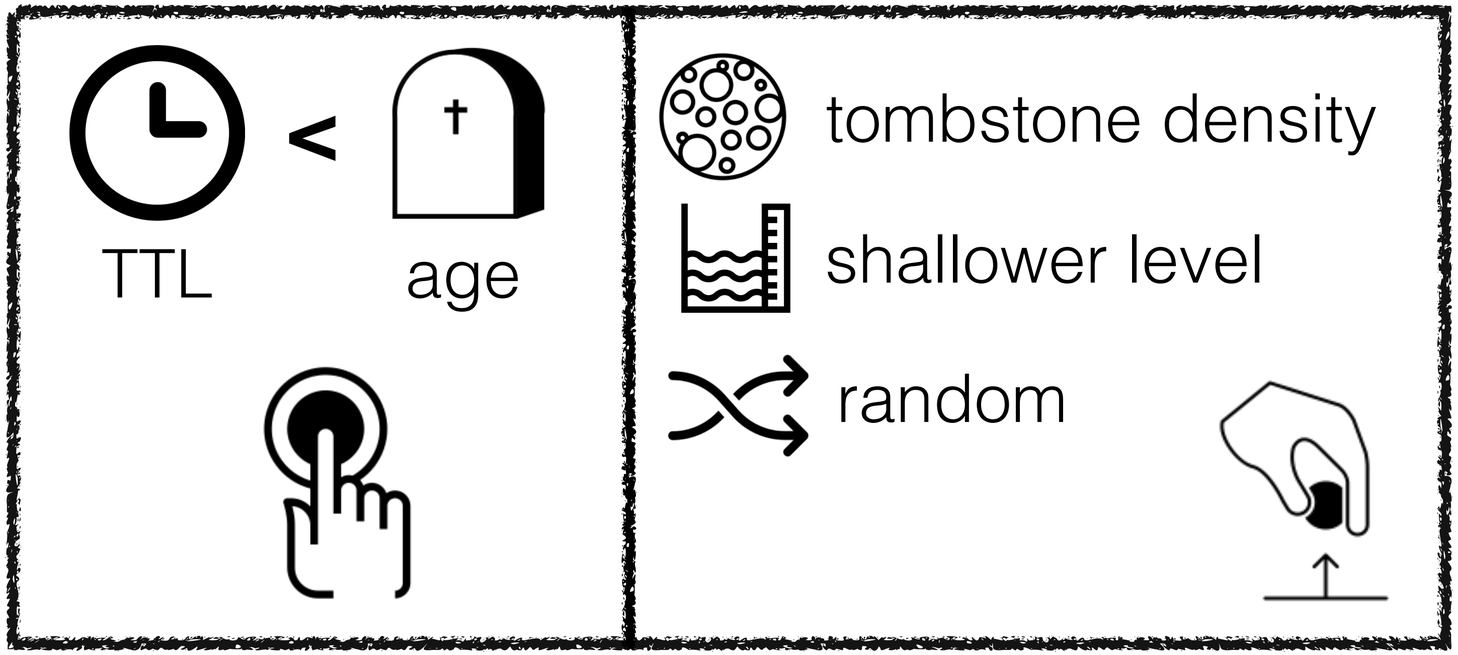
Facilitating **Timely Deletes**

compaction trigger	compaction file picking policy
	

Facilitating **Timely Deletes**

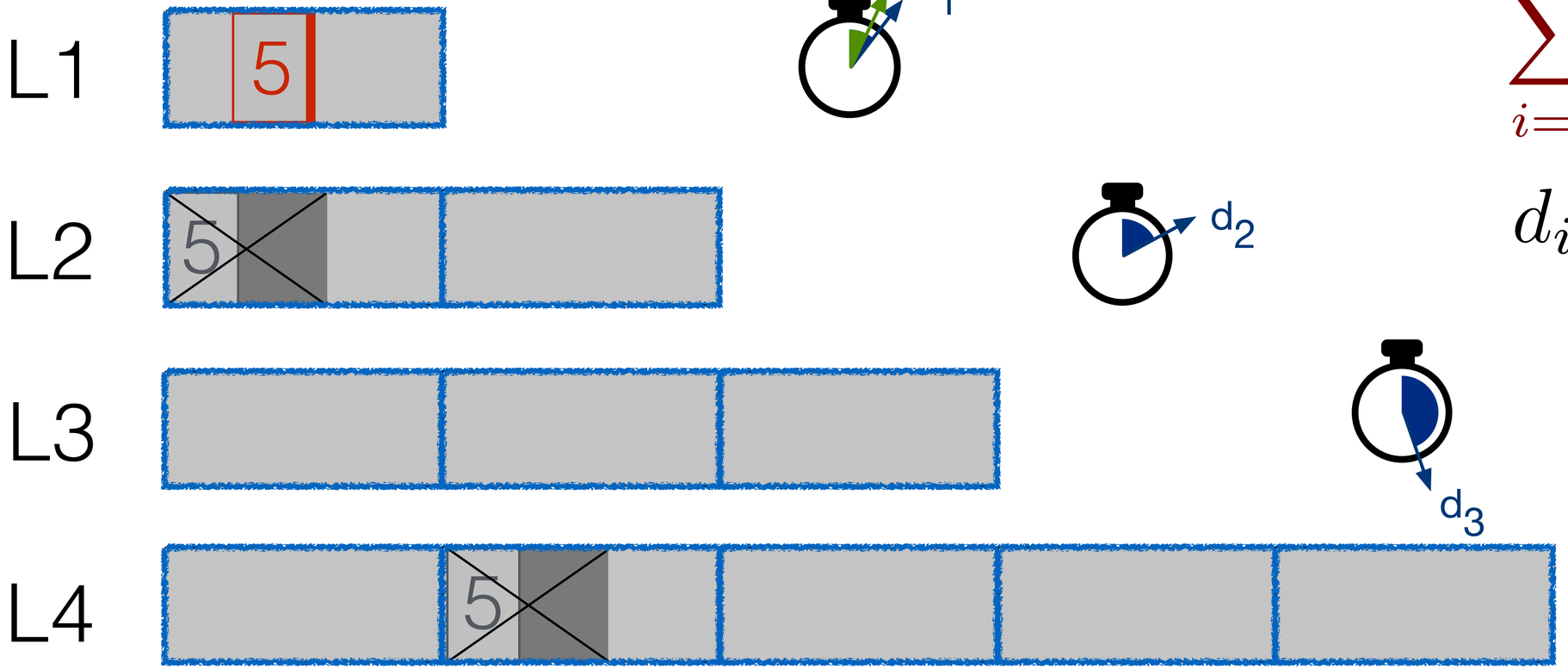


Facilitating **Timely Deletes**



Facilitating **Timely Deletes**

delete(5) within a threshold time: **D_{th}**



$$\sum_{i=1}^{L-1} d_i \leq D_{th}$$

$$d_i = T \cdot d_{i-1}$$

Policy layer

Right to be forgotten

Right to delete

Deletion right

Requirements layer

Retention-based Deletes

On-demand Deletes

AthanassoulisDEBull22

Application layer

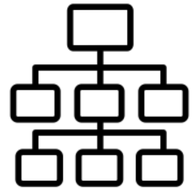
```
CREATE TABLE R (...)
   WITH RET_DUR
   {ARBITRARY | FIXED(...)}
   WITH DPT
   {ARBITRARY | FIXED(...)};
```

```
INSERT INTO R (...)
   WITH RET_DUR {<t>|t<i>};
```

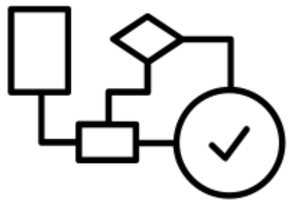
```
DELETE FROM R
   WHERE (...)
      WITH DPT {<d>|d<i>};
```

SarkarEDBT22

System layer



Data layout re-organization



Data deletion algorithms

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Policy layer

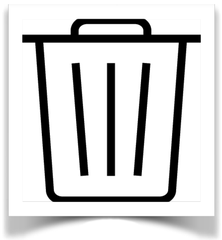
Right to be forgotten

Right to delete

Deletion right

Requirements layer

Retention-based Deletes



On-demand Deletes

AthanassoulisDEBull22

Application layer

```
CREATE TABLE R (...)
  WITH RET_DUR
  {ARBITRARY | FIXED(...)}
  WITH DPT
  {ARBITRARY | FIXED(...)};
```

```
INSERT INTO R (...)
  WITH RET_DUR {<t>|t<i>};
```

```
DELETE FROM R
  WHERE (...)
    WITH DPT {<d>|d<i>};
```

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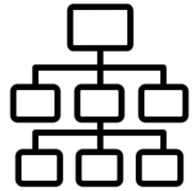
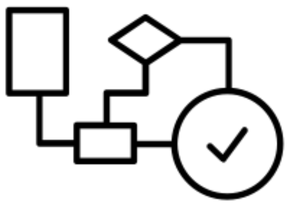
System layer



Data layout re-organization



Data deletion algorithms

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Policy layer

Right to be forgotten

Right to delete

Deletion right

Requirements layer

Retention-based Deletes

On-demand Deletes

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Application layer

```
CREATE TABLE R (...)
   WITH RET_DUR
   {ARBITRARY | FIXED(...)}
   WITH DPT
   {ARBITRARY | FIXED(...)};
```

```
INSERT INTO R (...)
   WITH RET_DUR {<t>|t<i>};
```

```
DELETE FROM R
   WHERE (...)
      WITH DPT {<d>|d<i>};
```

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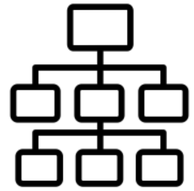
System layer



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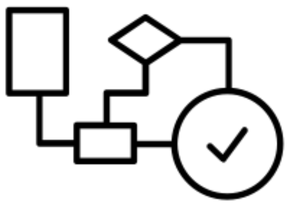

Data deletion algorithms

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The **Key Takeaways**

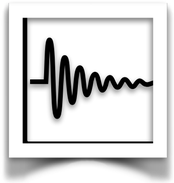
The LSM design space is **vast and complex**.

Compactions are key to building ingestion-friendly systems.

A **tuned LSM** engine can offer superior performance.

Open Research **Challenges**

Reduce write amplification



Workload-aware compactions & layout transformation

Performance Stability & Holistic Tuning

Automatic Tuning & Adaptive Behavior

Privacy-aware LSM designs

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Please see our manuscript for all references!

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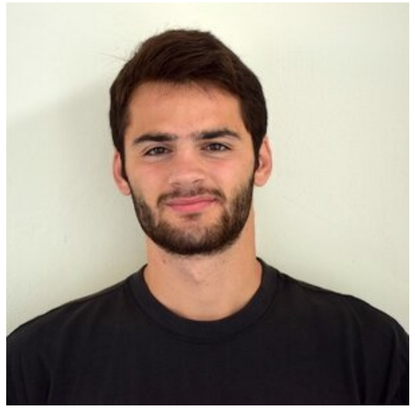
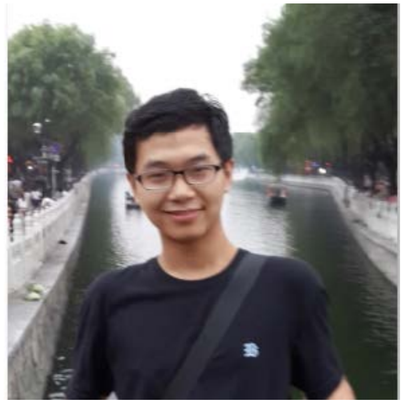
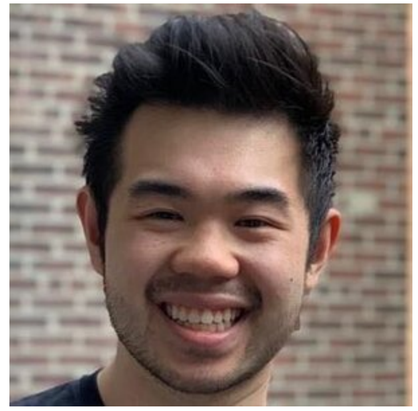



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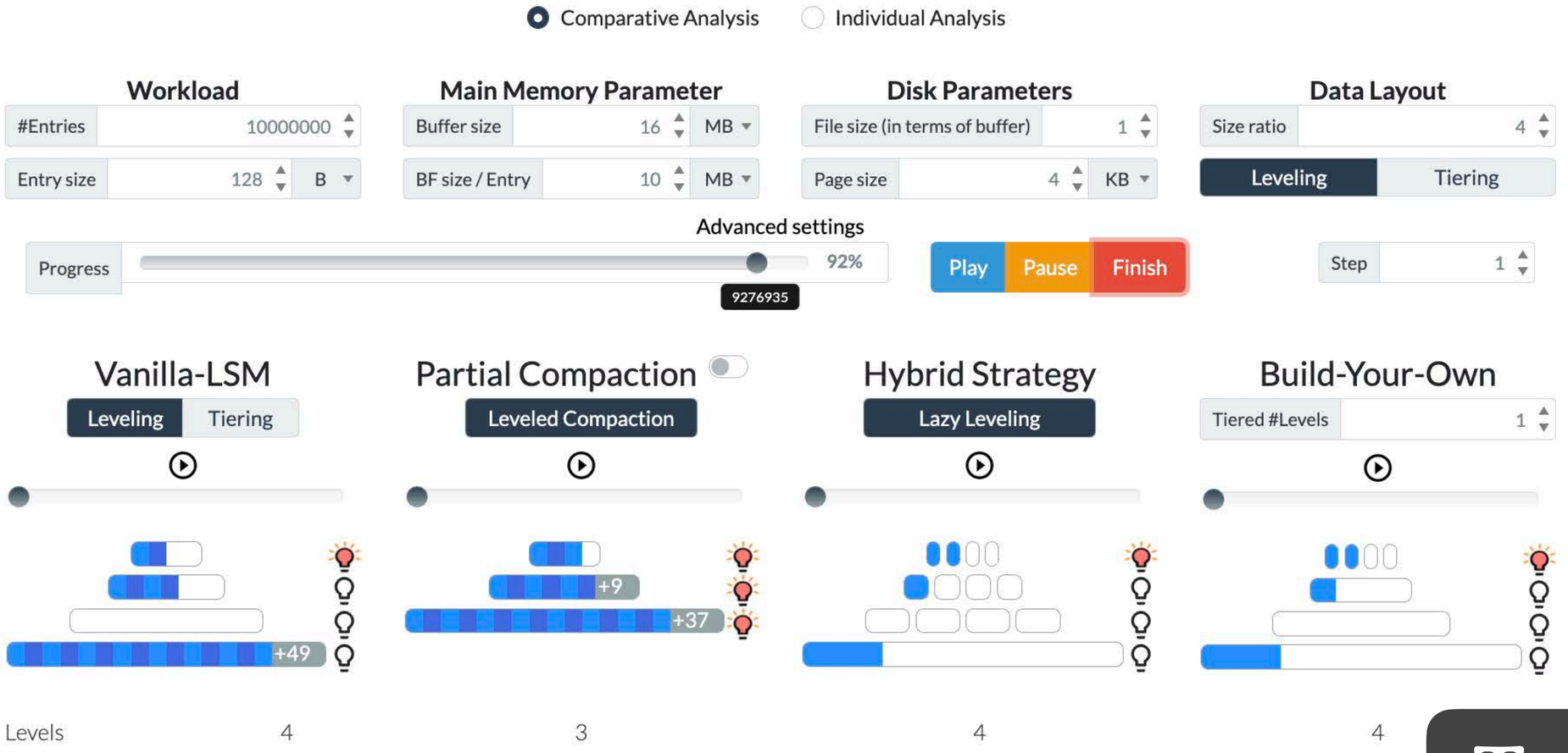
Don’t Miss: Compactionary



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Tuesday 4-6PM

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Dissecting, Designing, and Optimizing **LSM-Based Data Stores**

Subhadeep Sarkar *Manos Athanassoulis*

Thank You!

Questions?

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