

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

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BOSTON UNIVERSITY

DiSC lab

# **L**og-**S**tructured **M**erge-tree

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# LSM-tree

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

1996

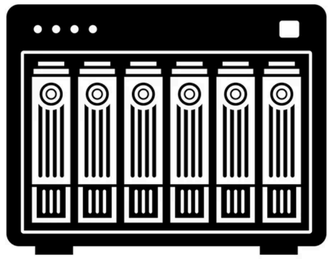
Patrick O'Neil[1], Edward Cheng[2]
Dieter Gawlick[3], Elizabeth O'Neil[1]
To be published: Acta Informatica

**LSM-tree**

**O'Neil *et al.***

1996

- good random writes
- good reads



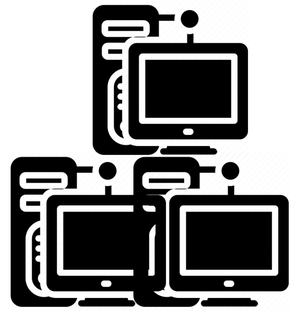
array
of discs

SSD wear-friendly

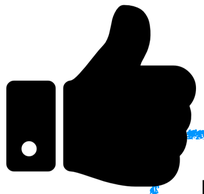
competitive rand. reads

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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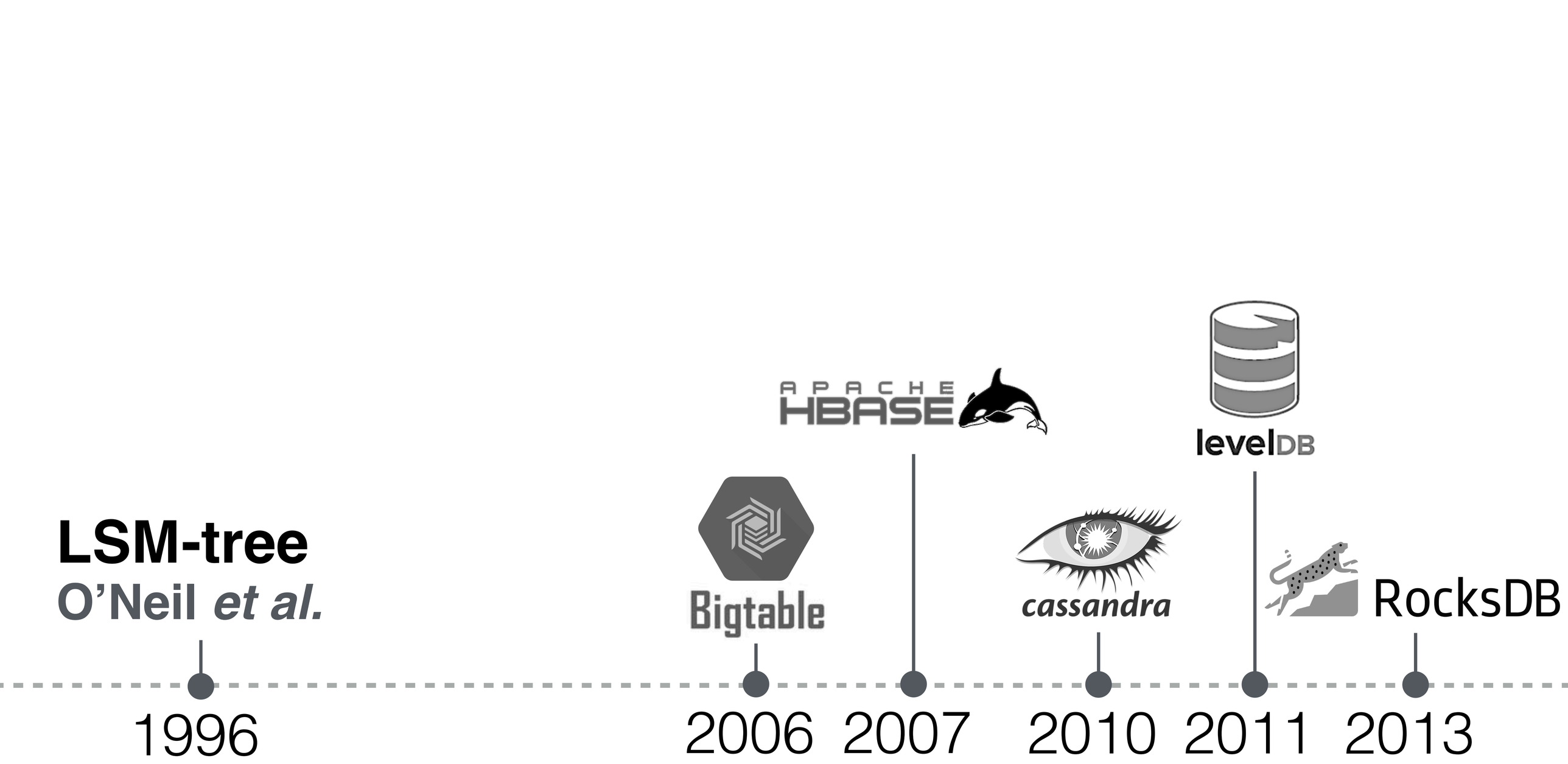

LSM-tree
O'Neil et al.
1996
Bigtable
2006
APACHE HBASE
2007
cassandra
2010
levelDB
2011
RocksDB
2013

# LSM-tree

NoSQL



relational


time-series

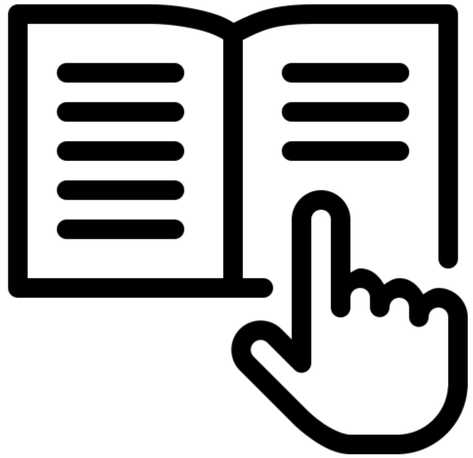
2022

# Why **LSM** ?

fast ingestion

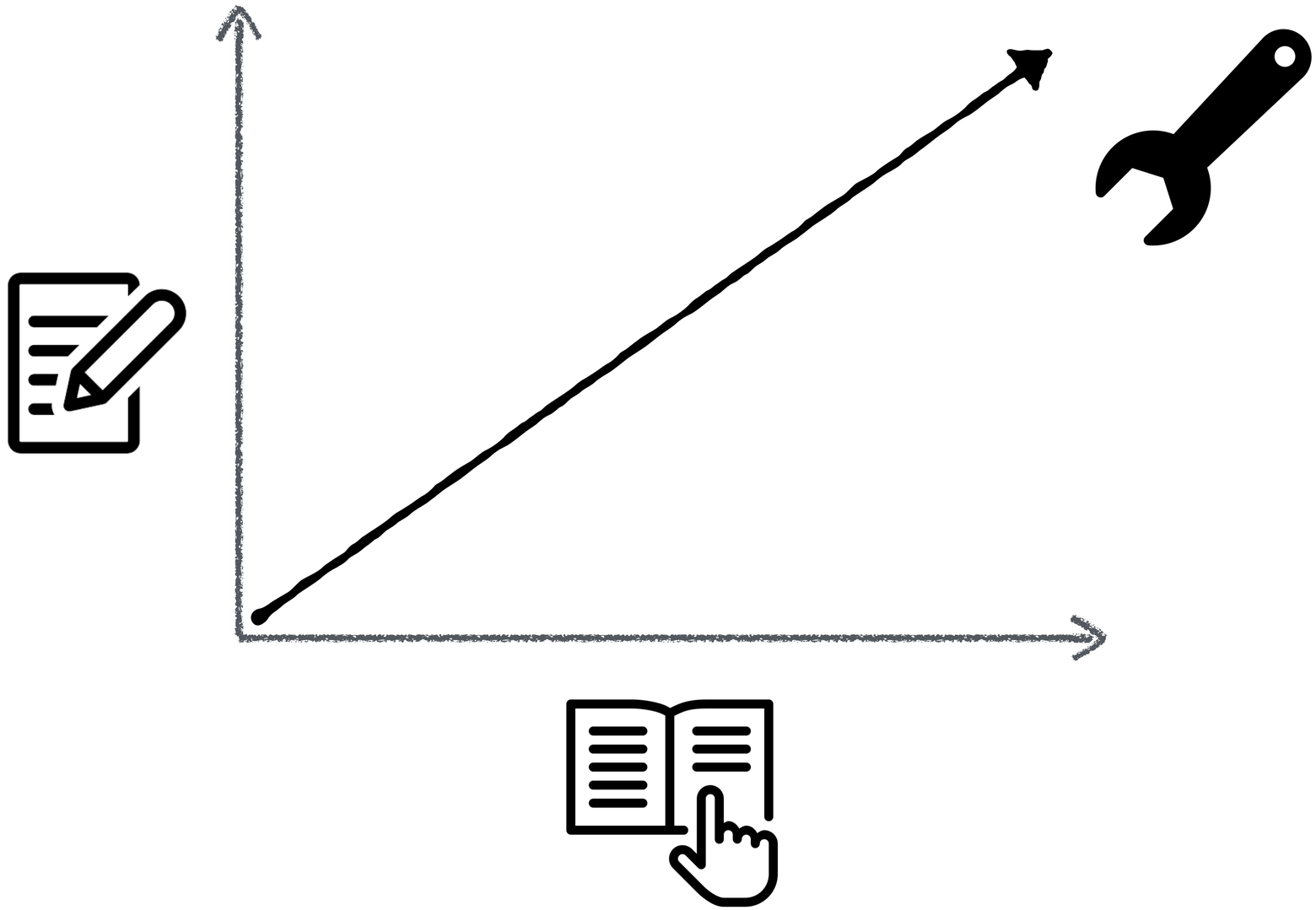
# Why **LSM** ?

fast ingestion



competitive reads

# Why **LSM** ?



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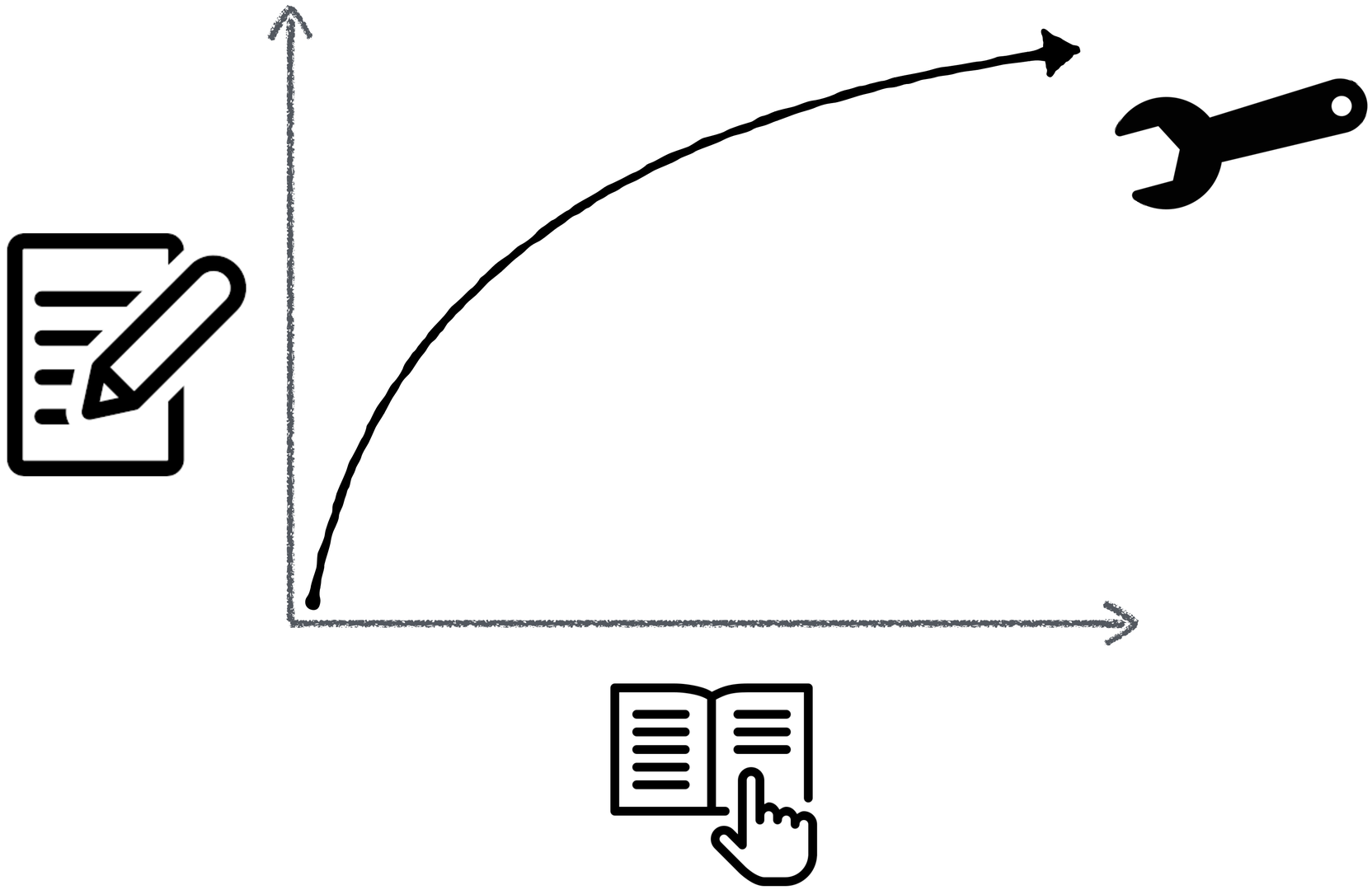
# Why **LSM** ?



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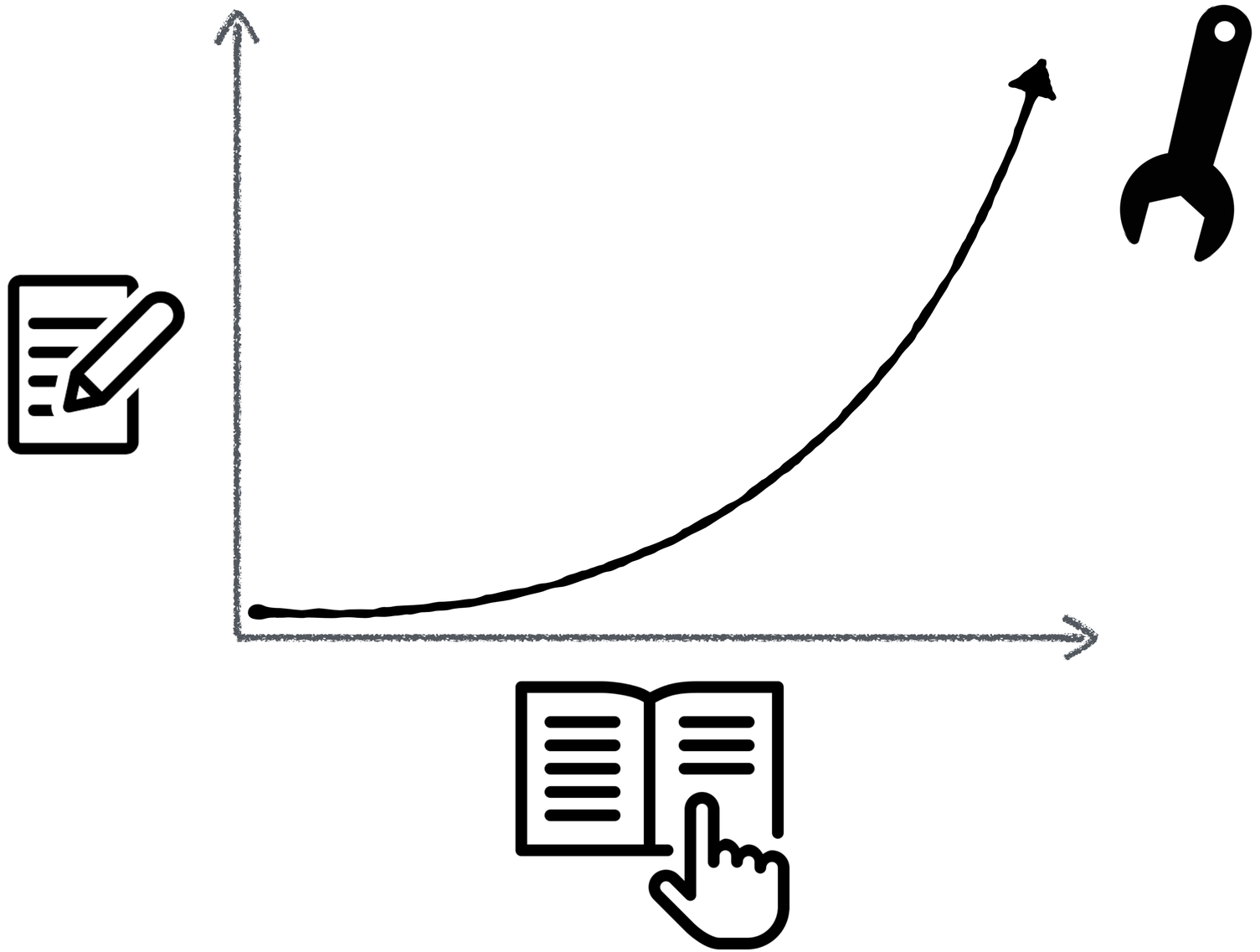
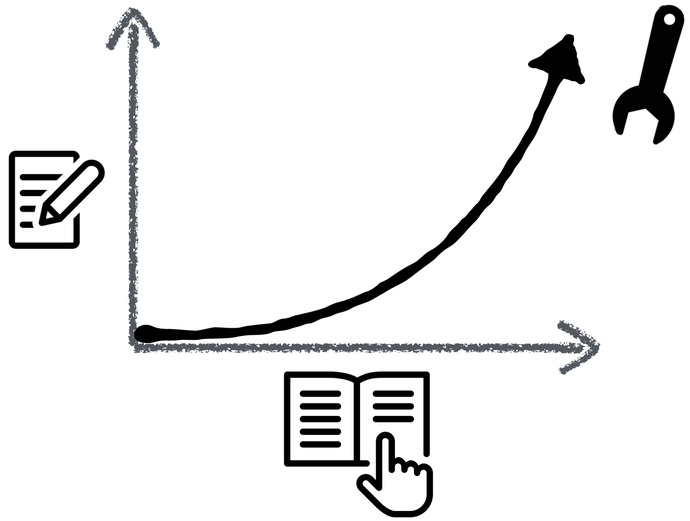
# Why **LSM** ?

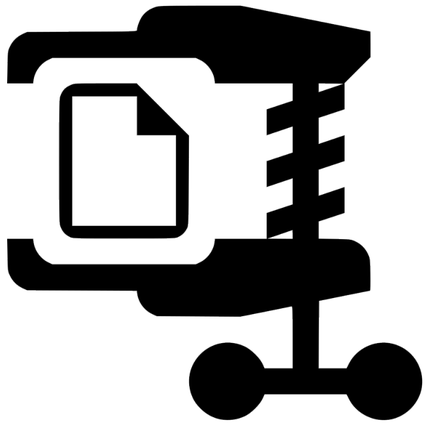


# Why **LSM** ?

fast writes

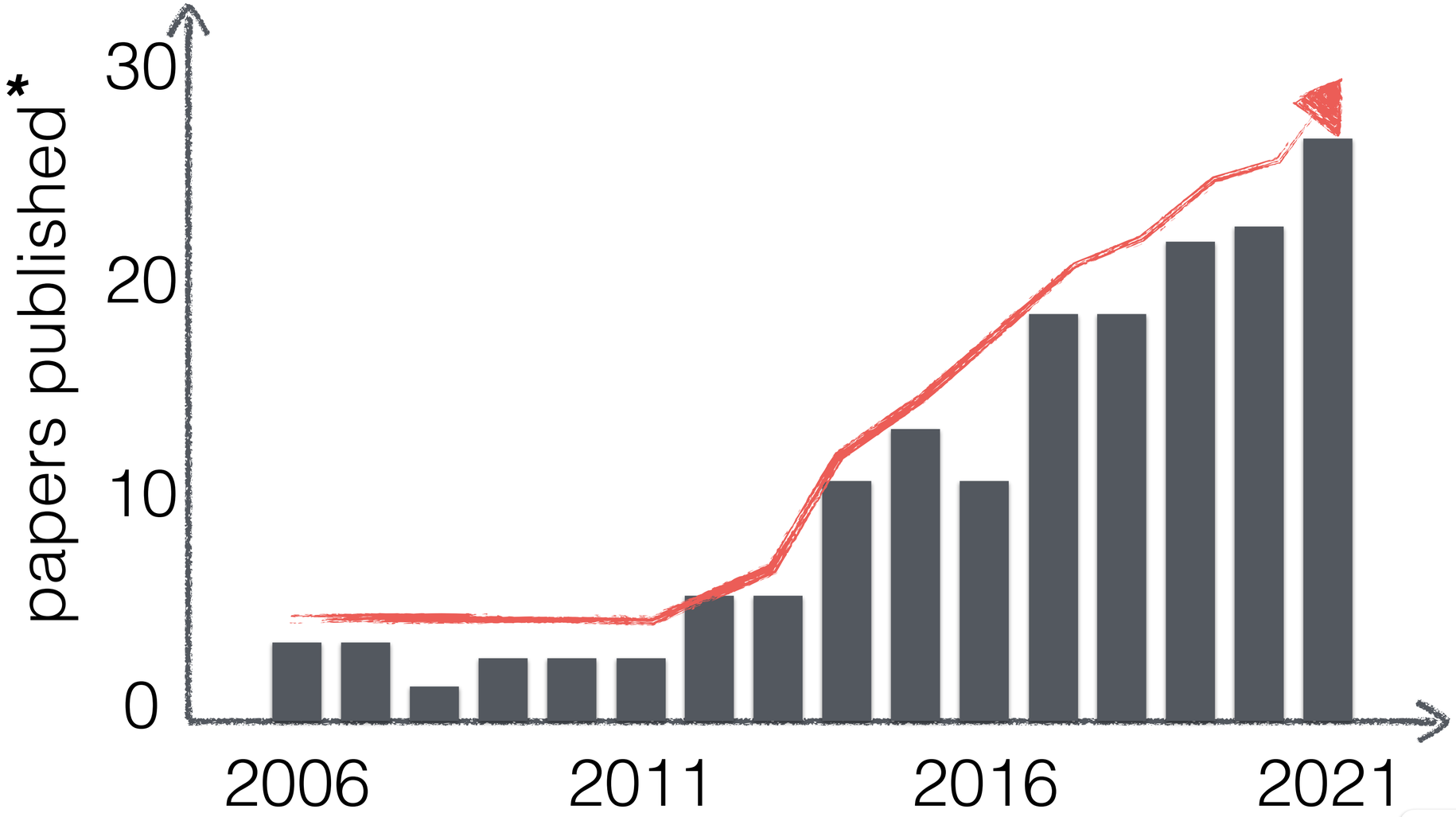


tunable read-write performance



good space utilization

# Research Trend

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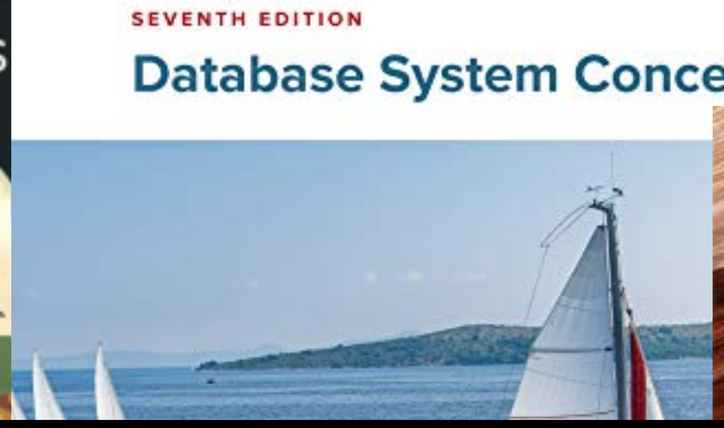
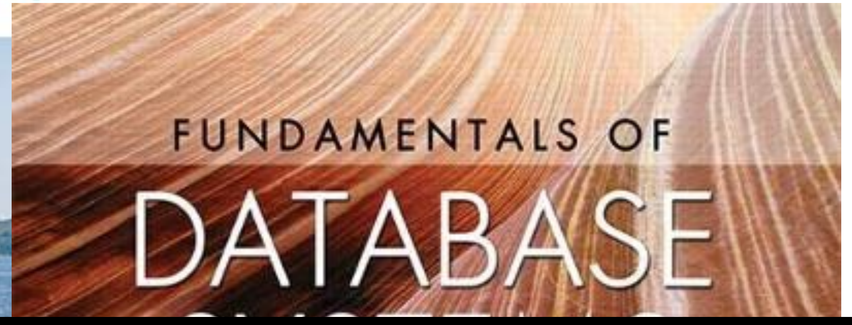
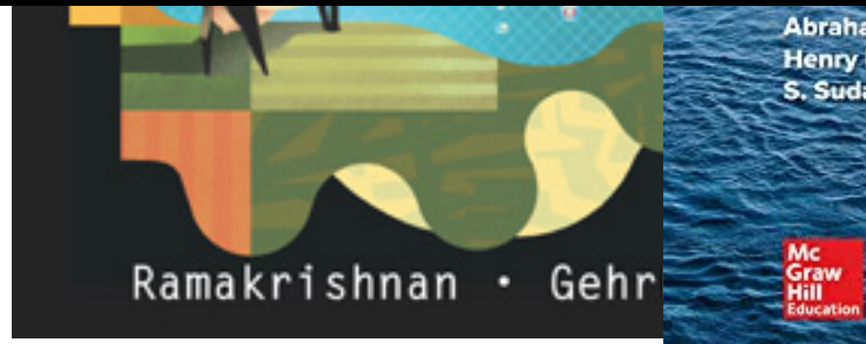
* data from DBLP

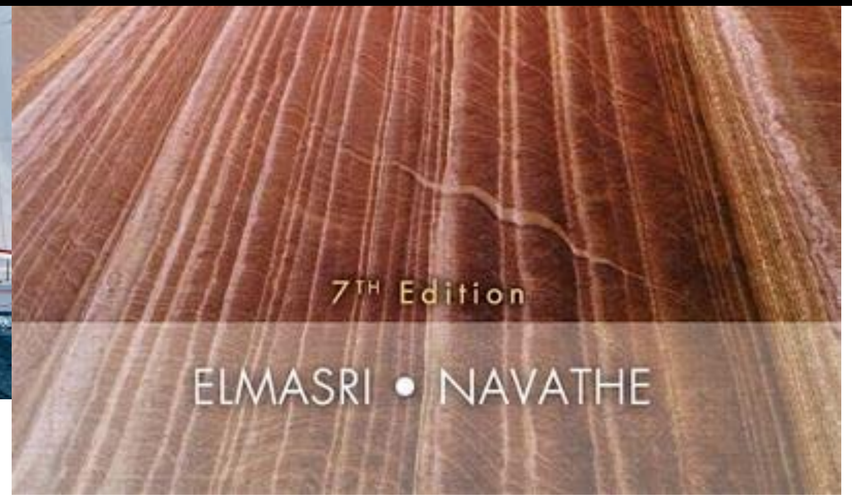




# No Textbook on LSMs !!





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# No Textbook on LSMs !!

**explore** the LSM paradigm

**construct** LSM design space

provide useful **insights**

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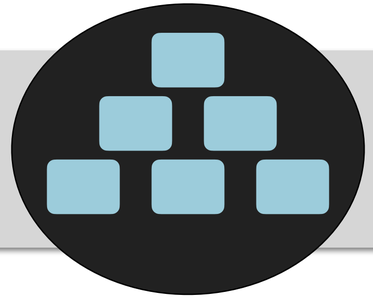
# Outline

Part 1: **LSM Basics**

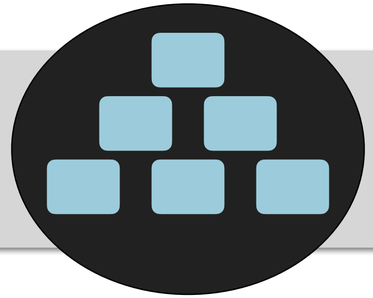


Part 2: **Optimizing Ingestion in LSMs**

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

# Outline

## Part 1: **LSM Basics**



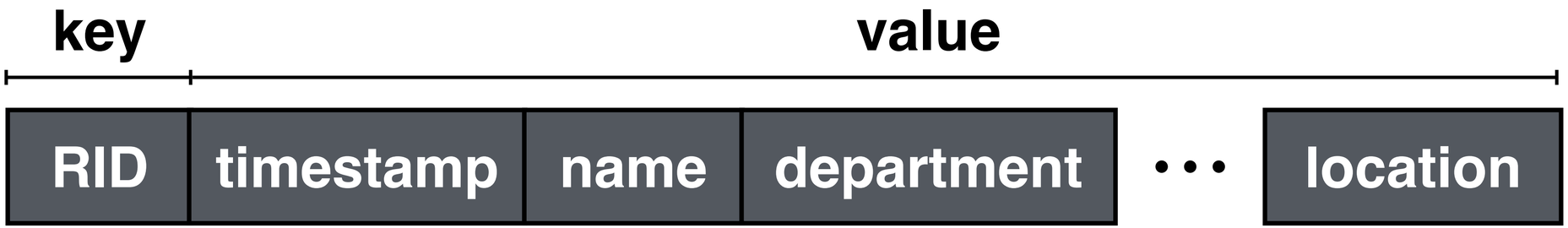
## Part 2: **Optimizing Ingestion in LSMs**



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

# LSM **Basics**

key-value pairs

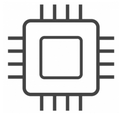


# LSM **Basics**

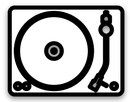
key-value pairs

$P$: 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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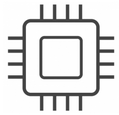
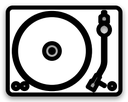
# Buffering ingestion

put(6)

put(2)



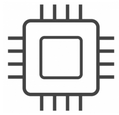
buffer



# Buffering ingestion

put(1)

put(6)



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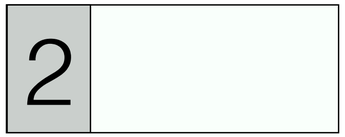


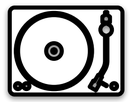

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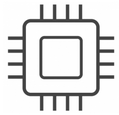
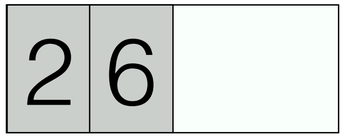
# Buffering ingestion

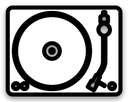
put(4)

put(1)



buffer



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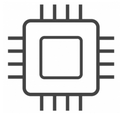
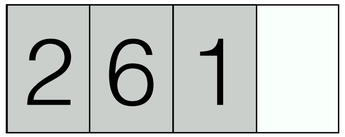
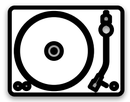
# Buffering ingestion

put(4)

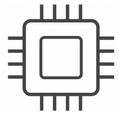


buffer

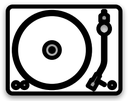


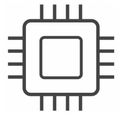
# Buffering ingestion



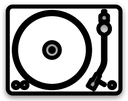
buffer | 2 | 6 | 1 | 4 |



# Buffering ingestion



buffer | 1 | 2 | 4 | 6 |



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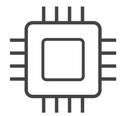

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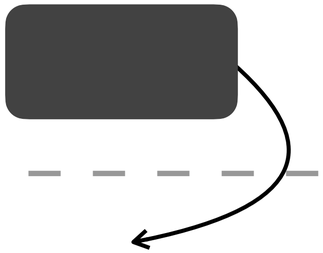
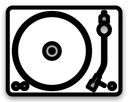
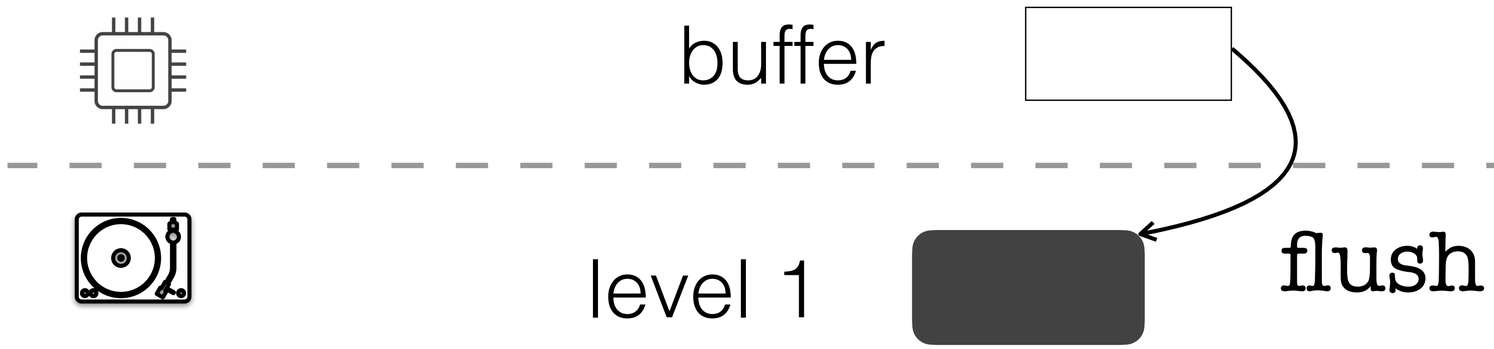




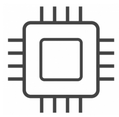
# Buffering ingestion

- low ingestion cost
- fast temporal reads



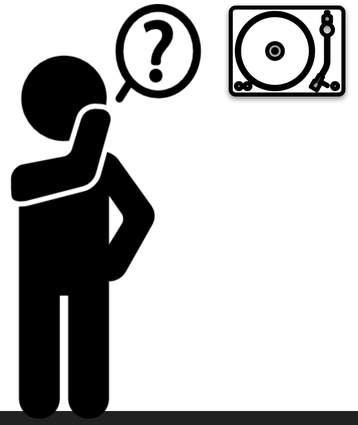
# Immutable files on storage

- compact storage
- good ingestion throughput



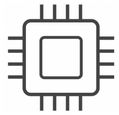
buffer

level 1



How do we update data?

put(6)



buffer

level 1 6

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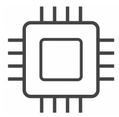

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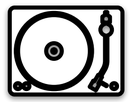
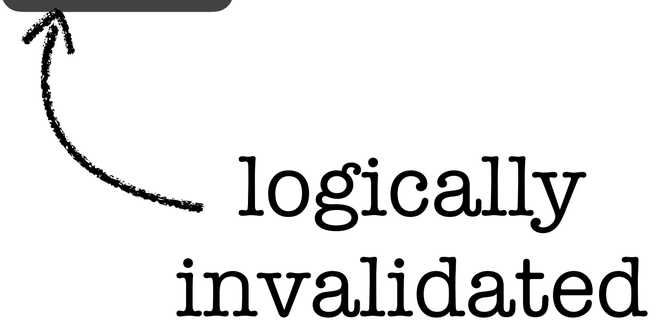
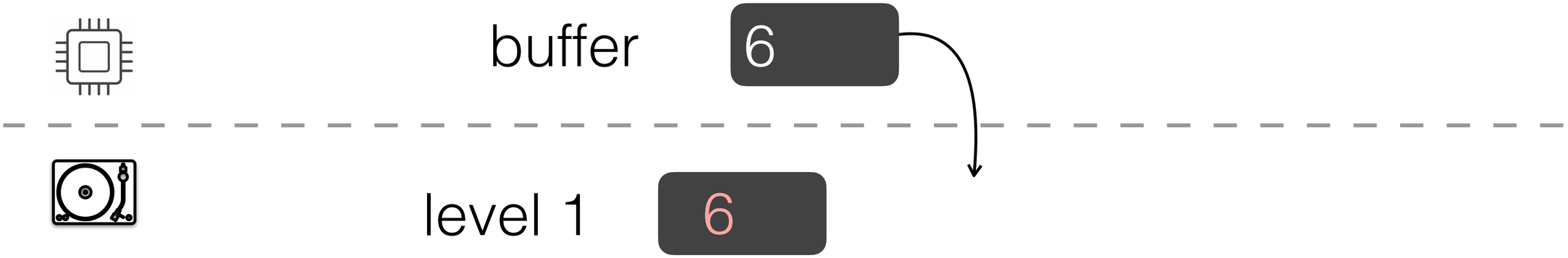
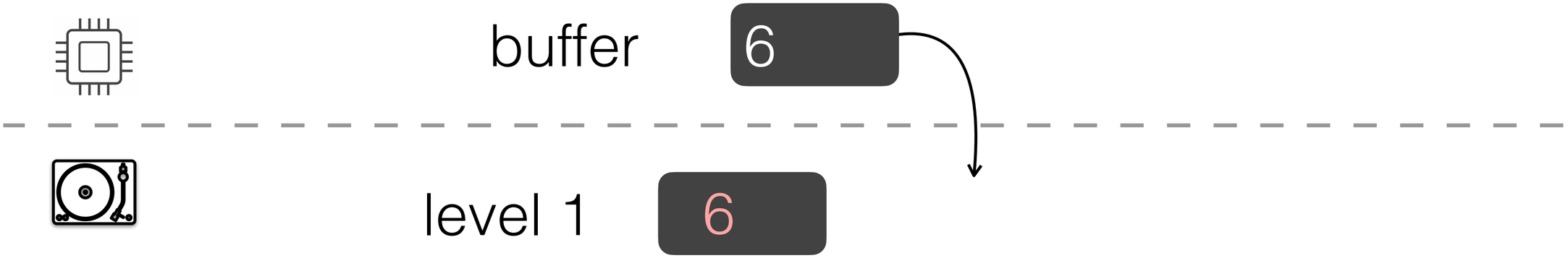


level 1

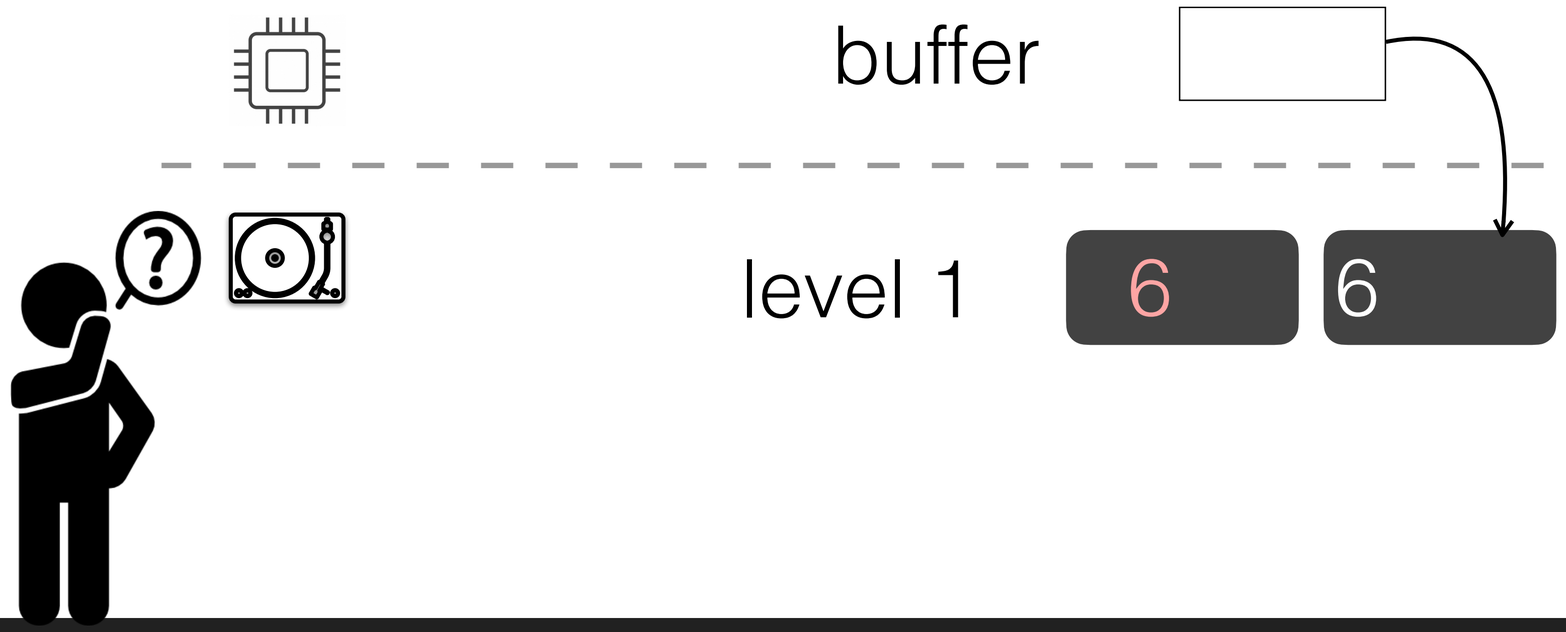





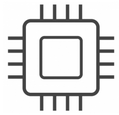


# Out-of-place updates

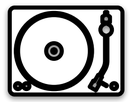
- fast ingestion
- space amplification
- slow reads




How do we reduce this space amplification?



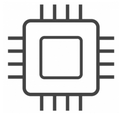
buffer



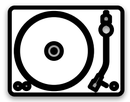
level 1

6

6



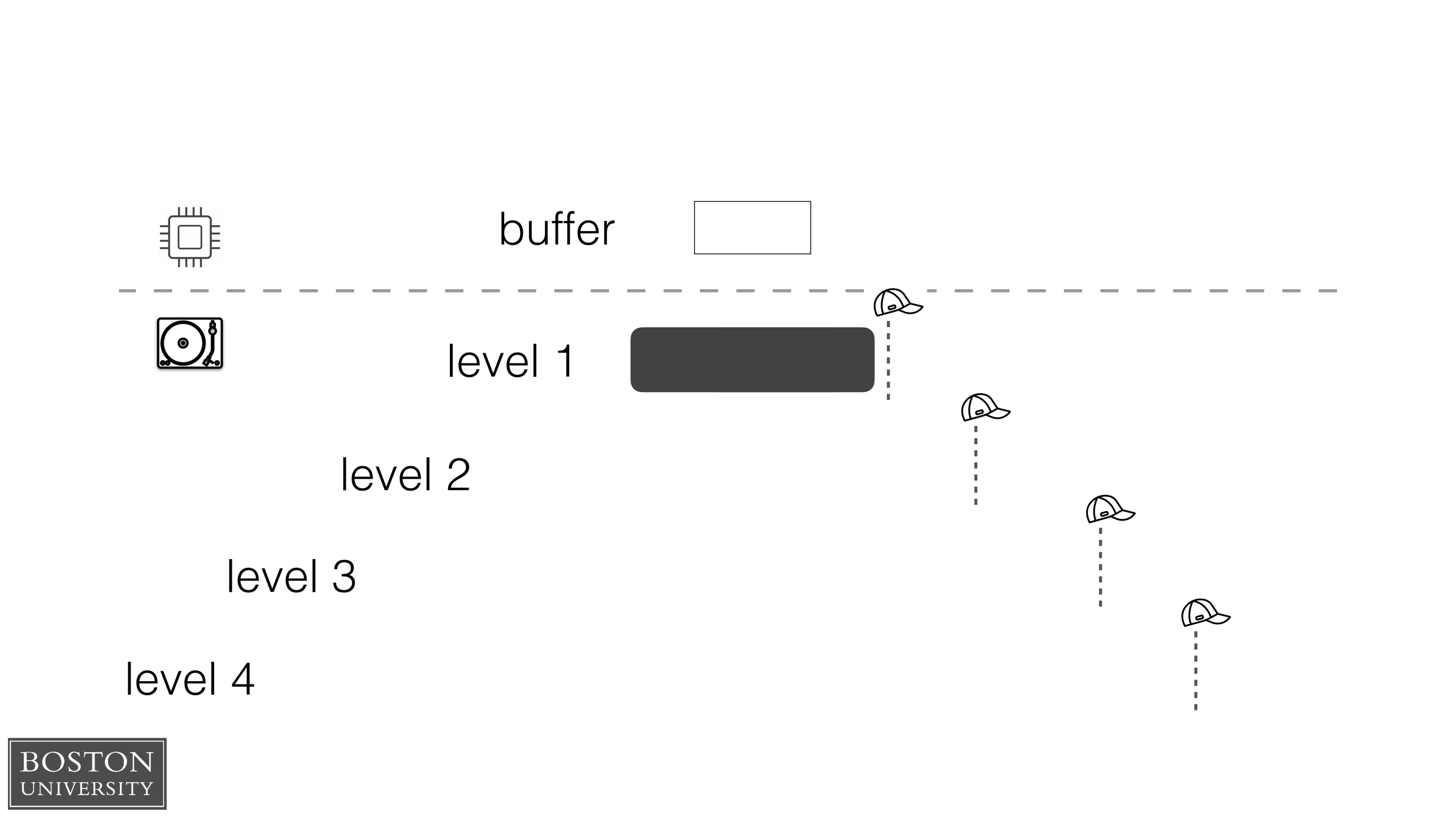
buffer

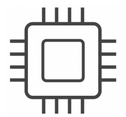


level 1

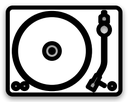
6

compaction

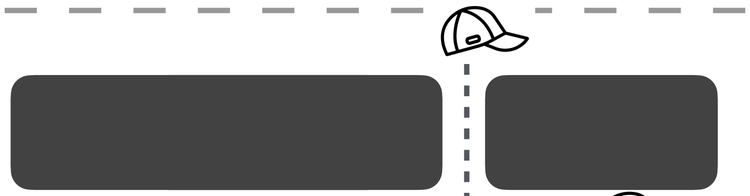




buffer



level 1



level 2

level 3

level 4

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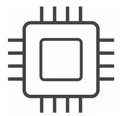
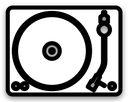
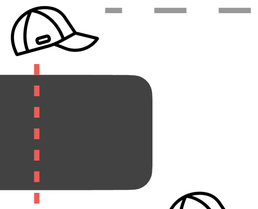


buffer



level 1



level 2

level 3

level 4

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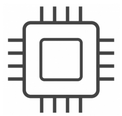
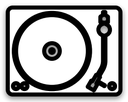


buffer



level 1

level 2

level 3

level 4

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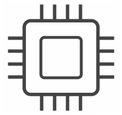
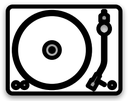
$P$: pages in buffer
$B$: entries/page
$L$: #levels
$T$: size ratio

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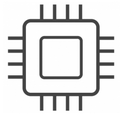
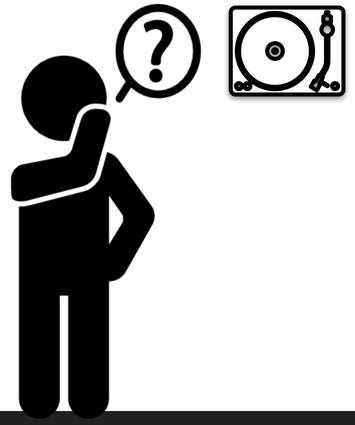
$P$: pages in buffer
$B$: entries/page
$L$: #levels
$T$: size ratio

# Periodic compactions

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



buffer $P \cdot B$



level 1

$P \cdot B \cdot T$

level 2

$P \cdot B \cdot T^2$

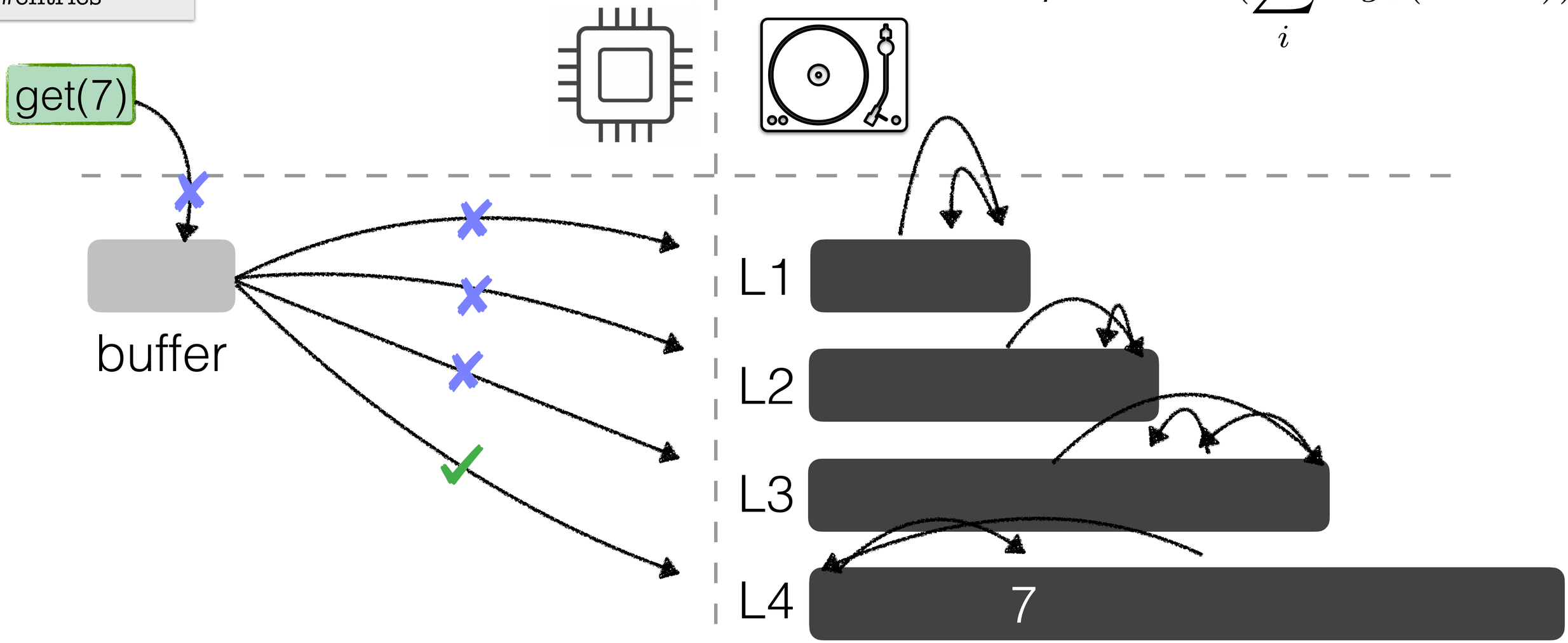
capacity
(entries)

## How about queries?

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

# Cost analysis

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

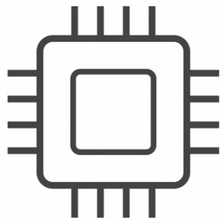


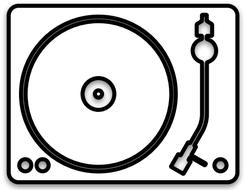
$P$: pages in buffer
$B$: entries/page
$L$: #levels
$T$: size ratio
$N$: #entries

# 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

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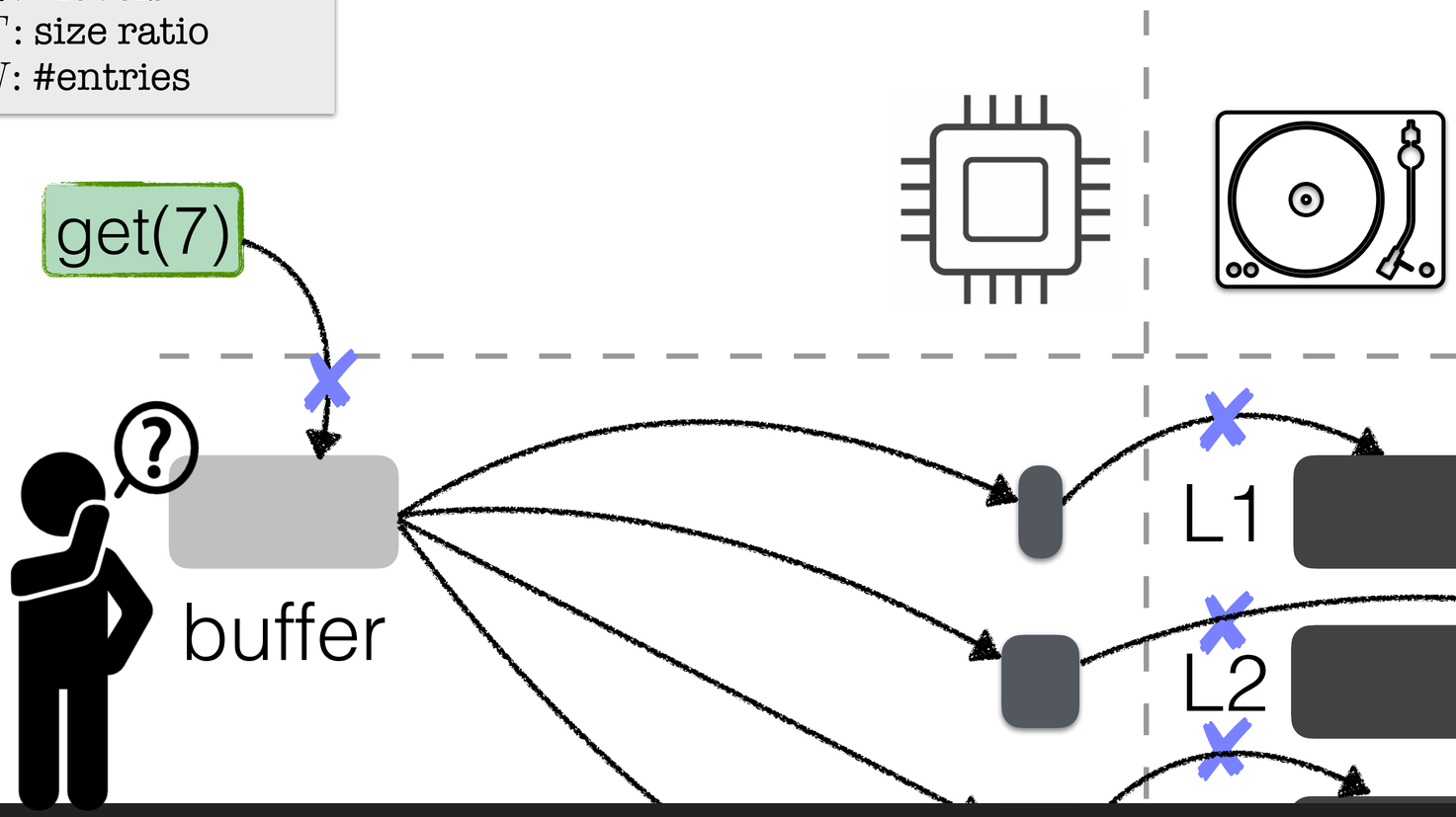
$P$: pages in buffer
$B$: entries/page
$L$: #levels
$T$: size ratio
$N$: #entries

# 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

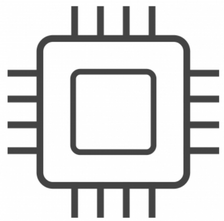
$P$: pages in buffer
$B$: entries/page
$L$: #levels
$T$: size ratio
$N$: #entries
$\phi$ : FPR of BF

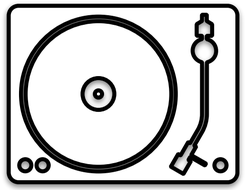
# Cost analysis

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

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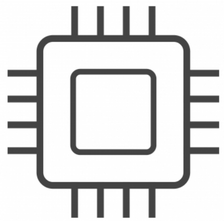
$P$: pages in buffer
$B$: entries/page
$L$: #levels
$T$: size ratio
$N$: #entries
$\phi$ : FPR of BF

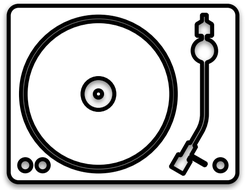
# Cost analysis

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

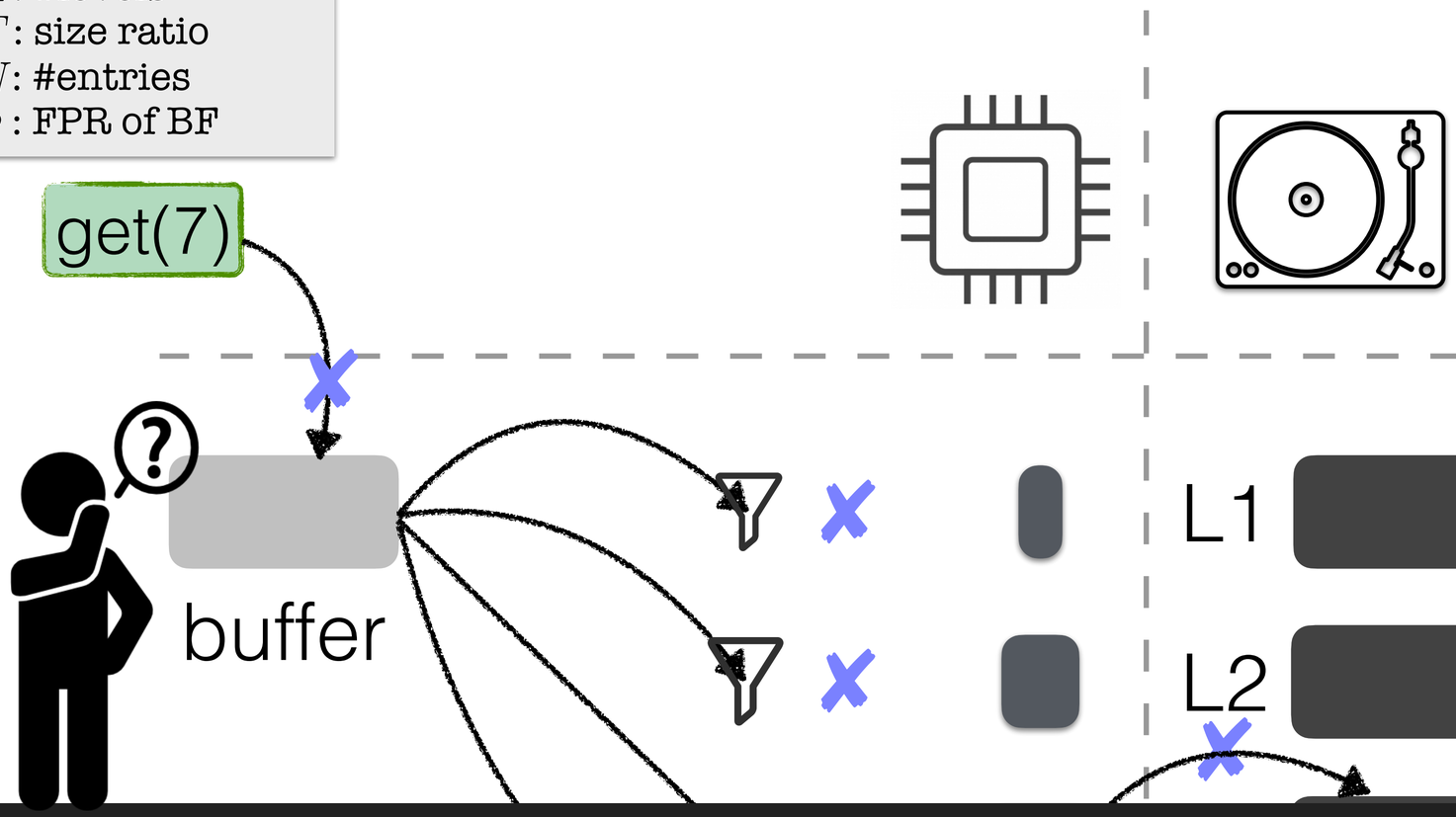
$P$: pages in buffer
$B$: entries/page
$L$: #levels
$T$: size ratio
$N$: #entries
$\phi$ : FPR of BF

# 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

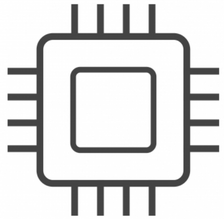
$P$: pages in buffer
$B$: entries/page
$L$: #levels
$T$: size ratio
$N$: #entries
$\phi$ : FPR of BF

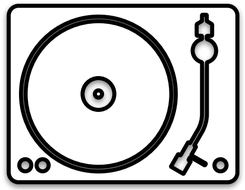
# Cost analysis

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

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

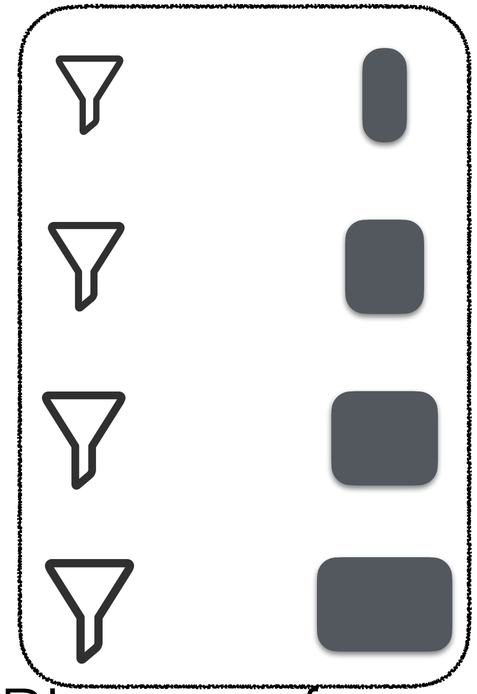
w F&I: $\mathcal{O}(\phi \cdot L)$





buffer

block cache



Bloom filters

fence pointers

L1

L2

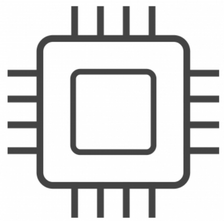
L3

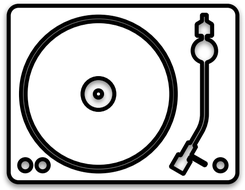
L4

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

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

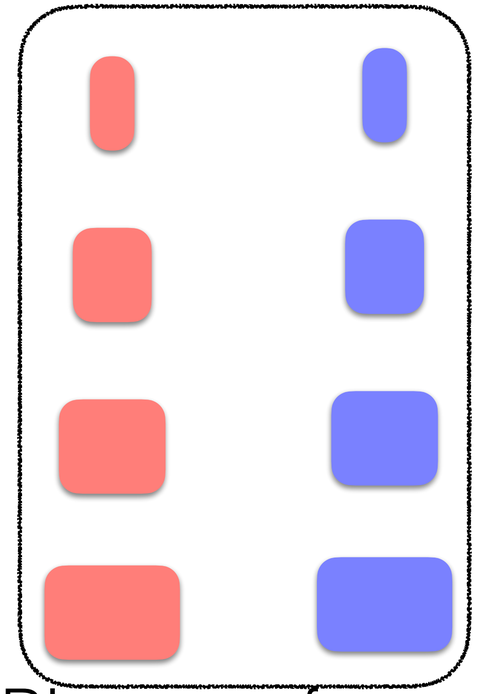
# Block Cache





buffer

block cache



Bloom filters

fence pointers

L1

L2

L3

L4

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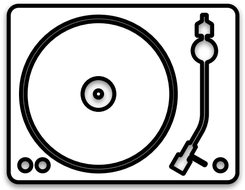
$P$: pages in buffer
$B$: entries/page
$L$: #levels
$T$: size ratio
$N$: #entries
$\phi$: FPR of BF

# Block Cache

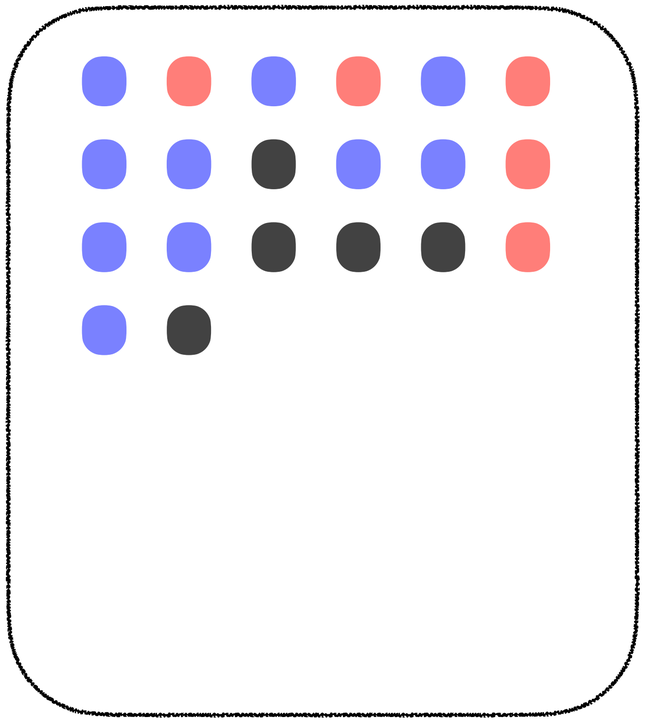


Bloom filters

fence pointers

get(7)

buffer



L1

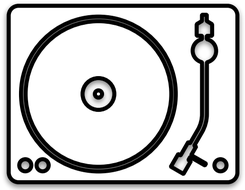
L2

L3

L4

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

# Block Cache

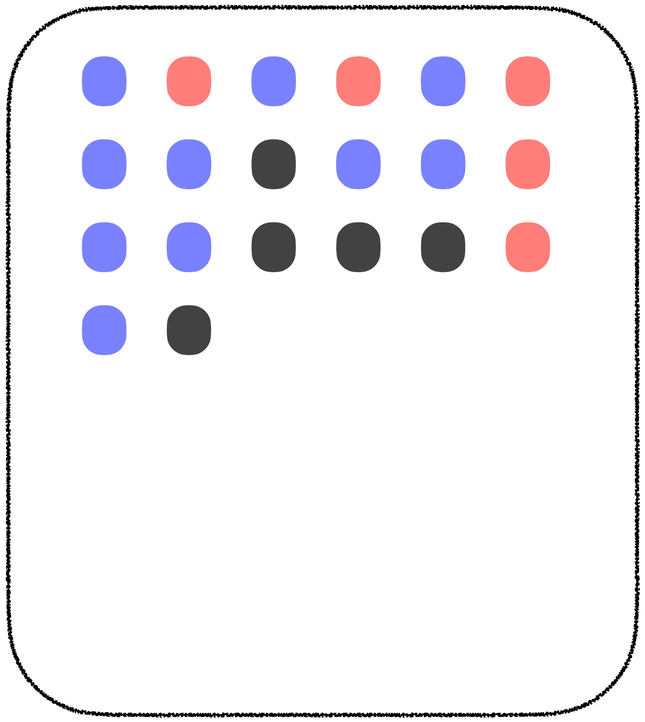


Bloom filters

fence pointers

get(7)

buffer



L1

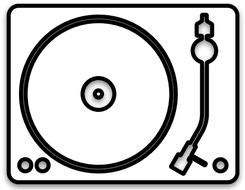
L2

L3

L4

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

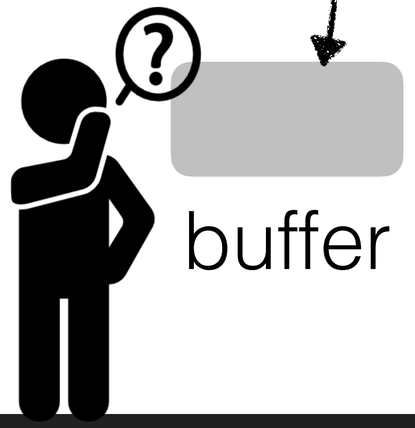
# Block Cache



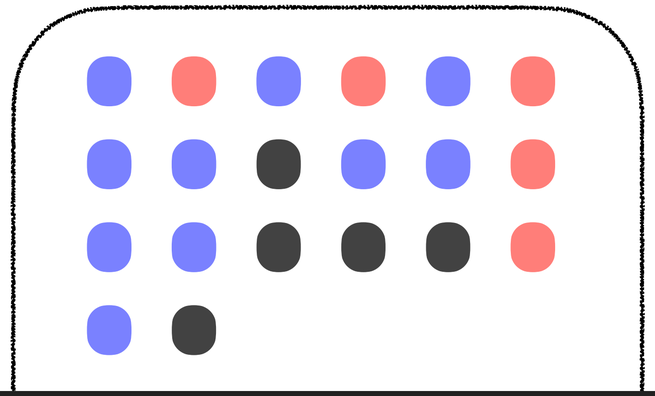
Bloom filters

fence pointers

get(7)



buffer



L1

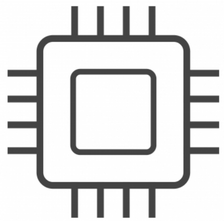
L2

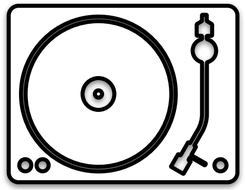
What about range queries?

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

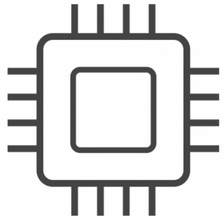
$s$ : selectivity LRQ

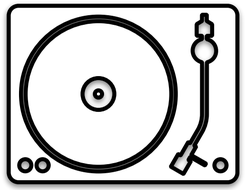
# Range Queries

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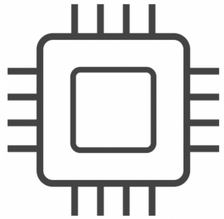
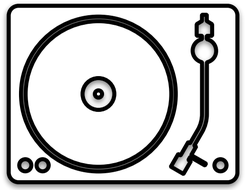
$P$: pages in buffer
$B$: entries/page
$L$: #levels
$T$: size ratio
$N$: #entries
$\phi$: FPR of BF

$s$ : selectivity SRQ

get(9,15)

# Range Queries





# Cost analysis

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

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

buffer

L1

L2

L3

L4

Bloom filters

fence pointers

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# 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

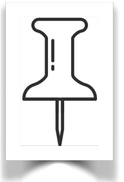
FerraginaVLDB20

## block cache

Better performance

Less memory usage

Prefetching — HuangVLDB20



Pinning — CallaghanSD18

Priority — CallaghanSD16

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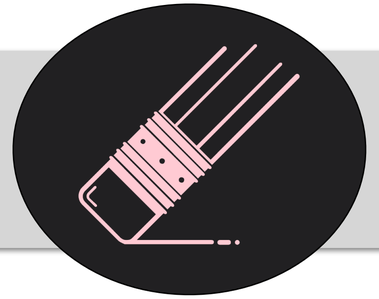
# Outline

Part 1: **LSM Basics**

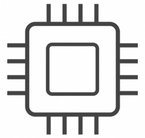


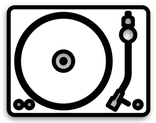
Part 2: **Optimizing Ingestion in LSMs**



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

# **Buffer** Optimizations





buffer

L1

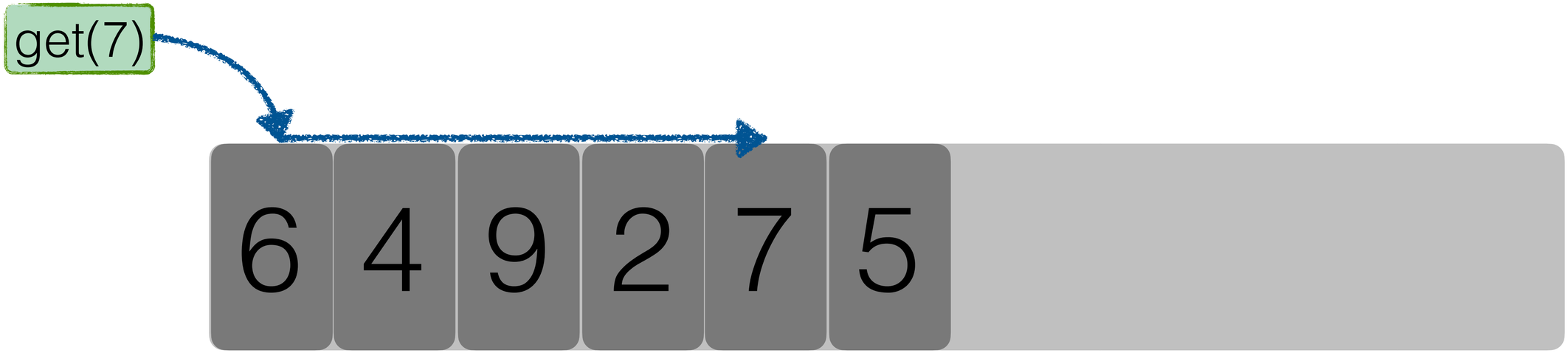
L2

L3

L4

$P$: pages in buffer
$B$: entries/page

# Buffer Implementation: **vector**



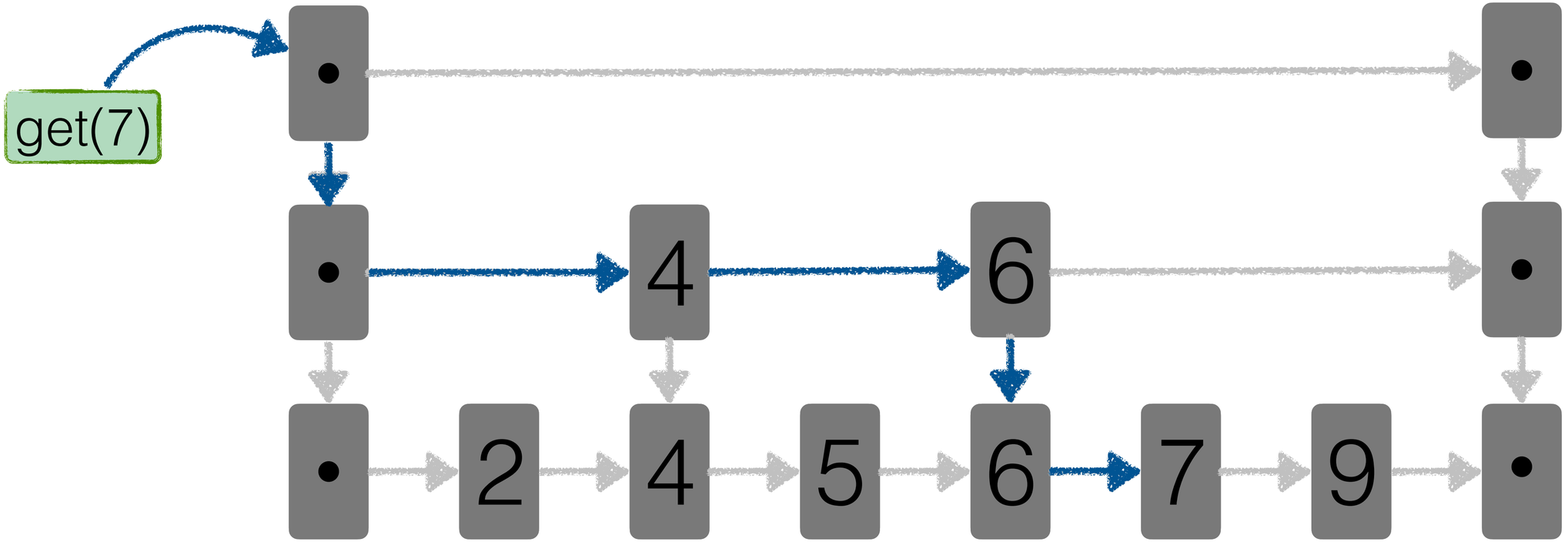

- great for ingestion-heavy w/l
- no extra space needed
- expensive points queries

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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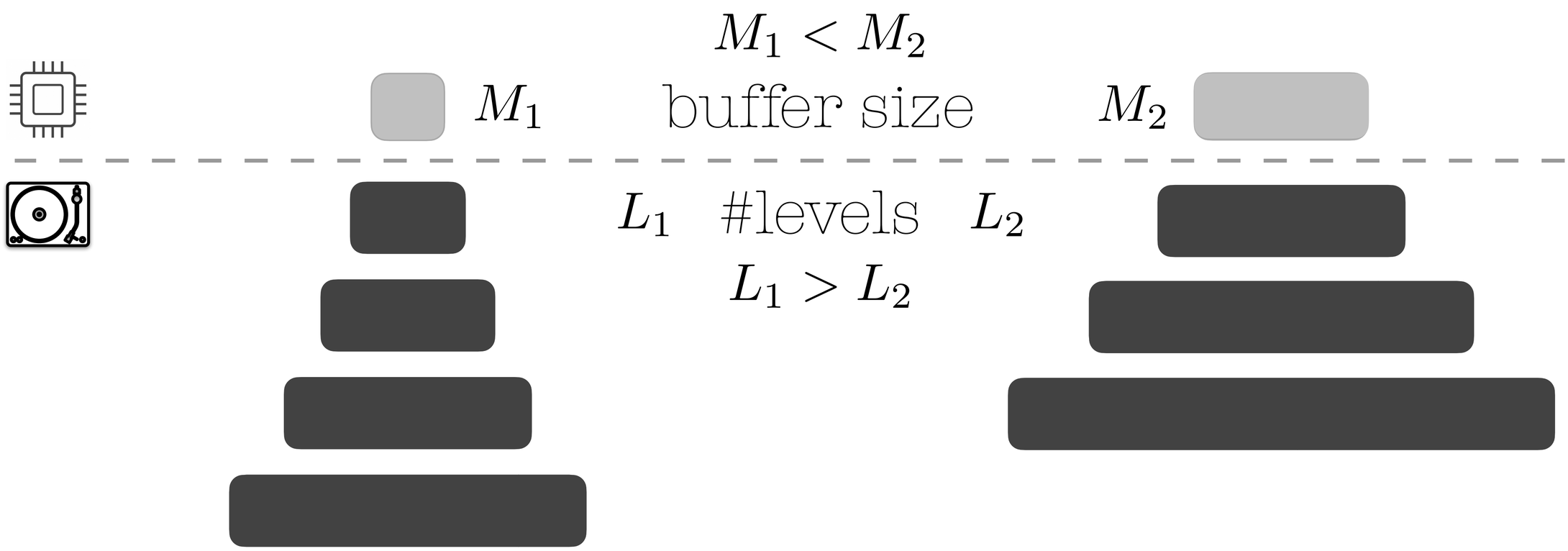
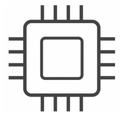
# Size of the Buffer

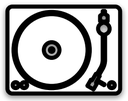



- frequent flushes
- smaller but more levels
- poor read performance

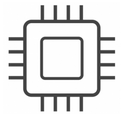
- fewer larger levels
- good for reads
- high tail latency

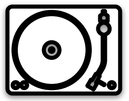
# #Buffer Components



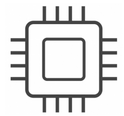


# #Buffer Components

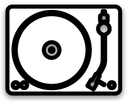




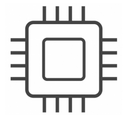
# #Buffer Components



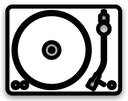
immutable
buffers



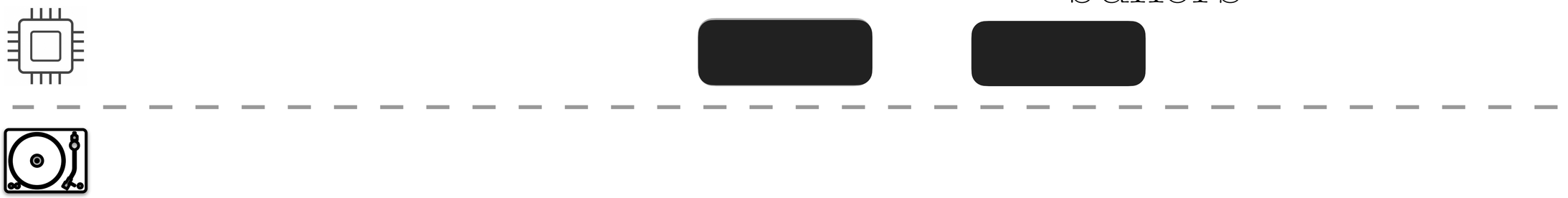
# #Buffer Components



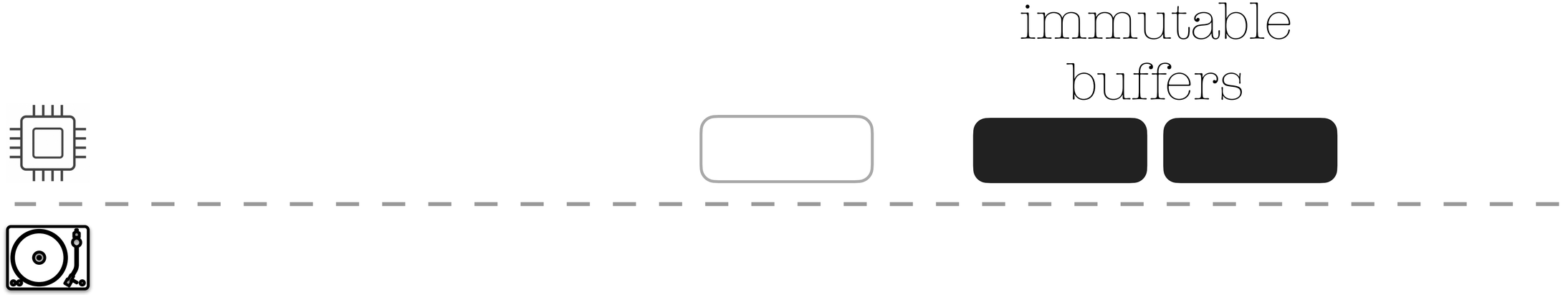
immutable
buffers



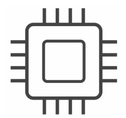
# #Buffer Components



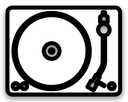
# #Buffer Components



# #Buffer Components



immutable
buffers



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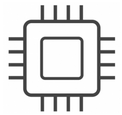
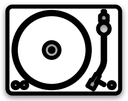
# #Buffer Components

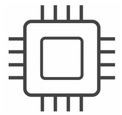


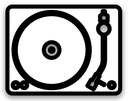
immutable
buffers



# #Buffer Components

immutable
buffers





lazy flushing

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

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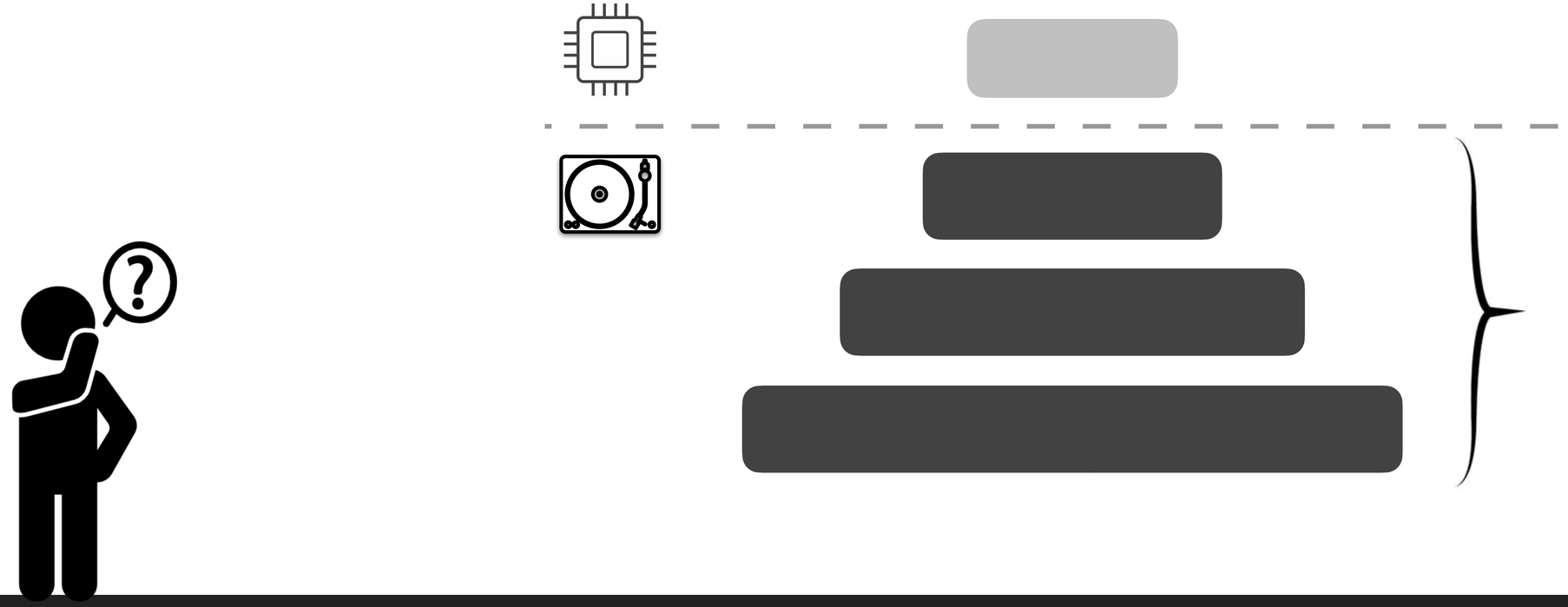
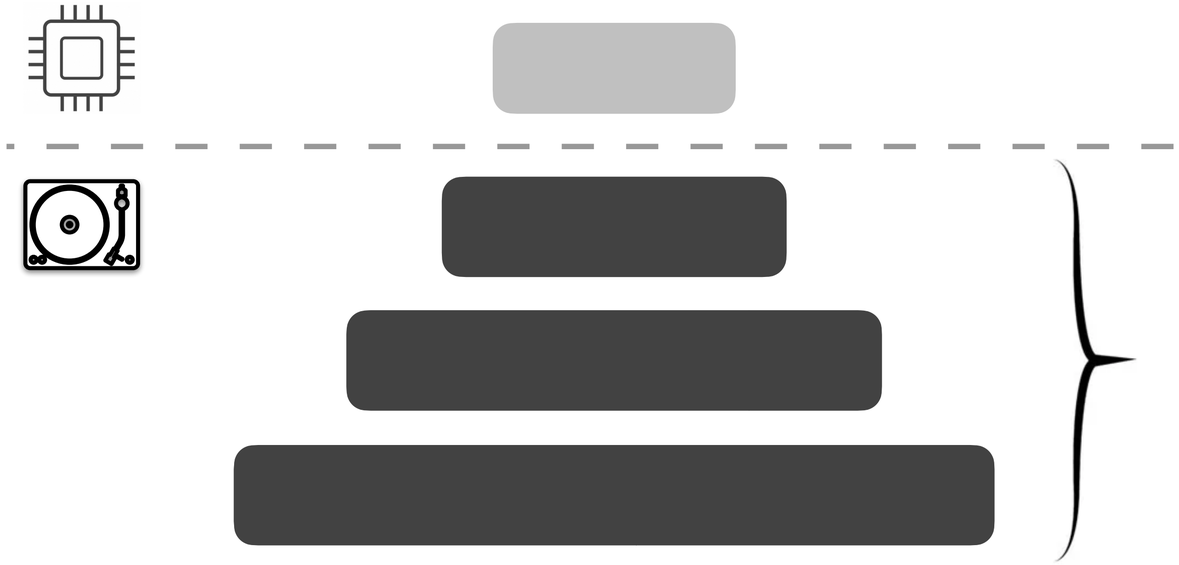



# How does the storage layer affect ingestion?

$L$: #levels
$T$: size ratio



most data
on storage

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

99.9% on storage

How does the storage layer affect ingestion?

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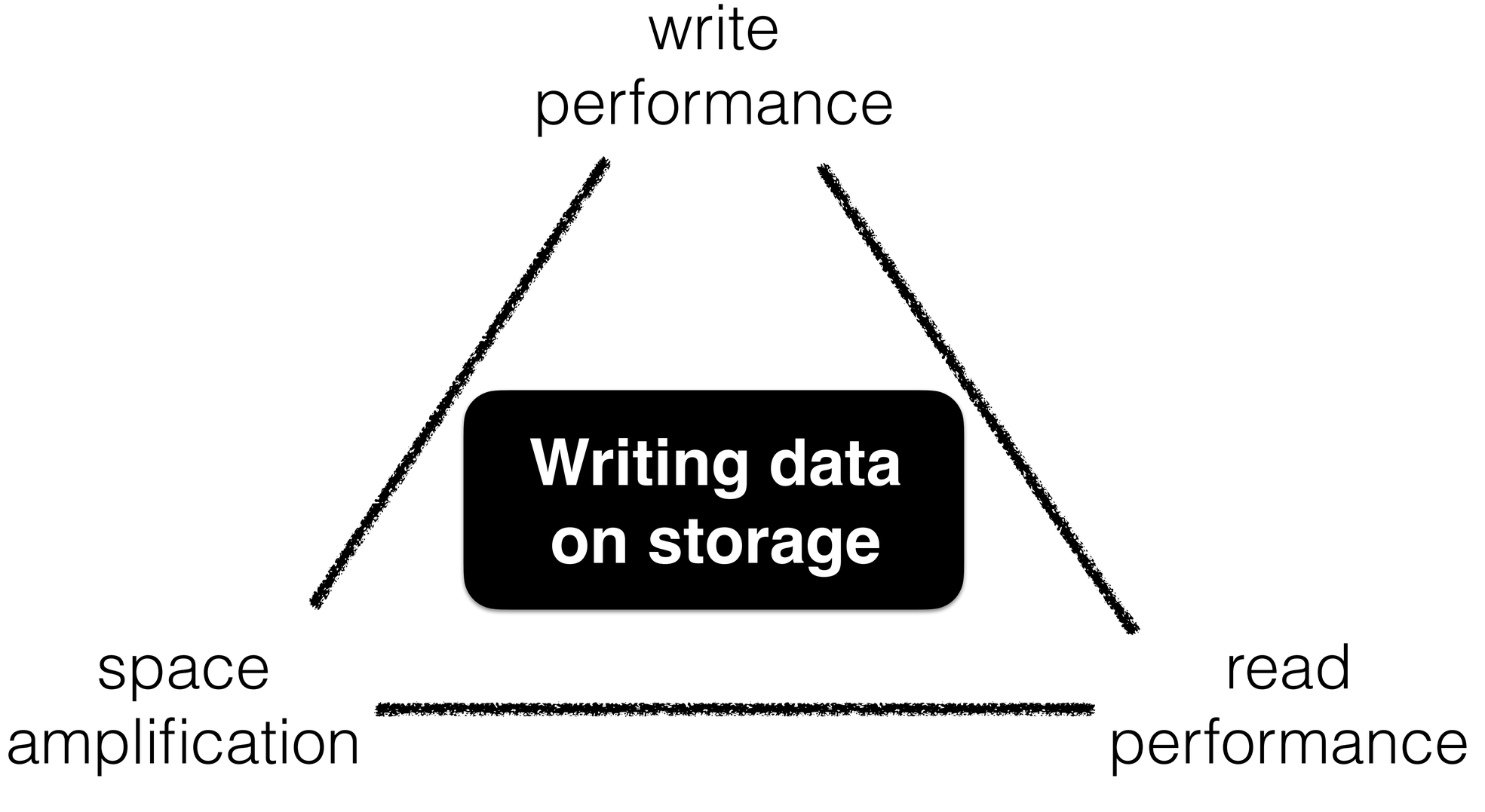
# **Storage** Optimizations



# Data **Layout**

Classical LSM design: **leveling**

[eager merging]



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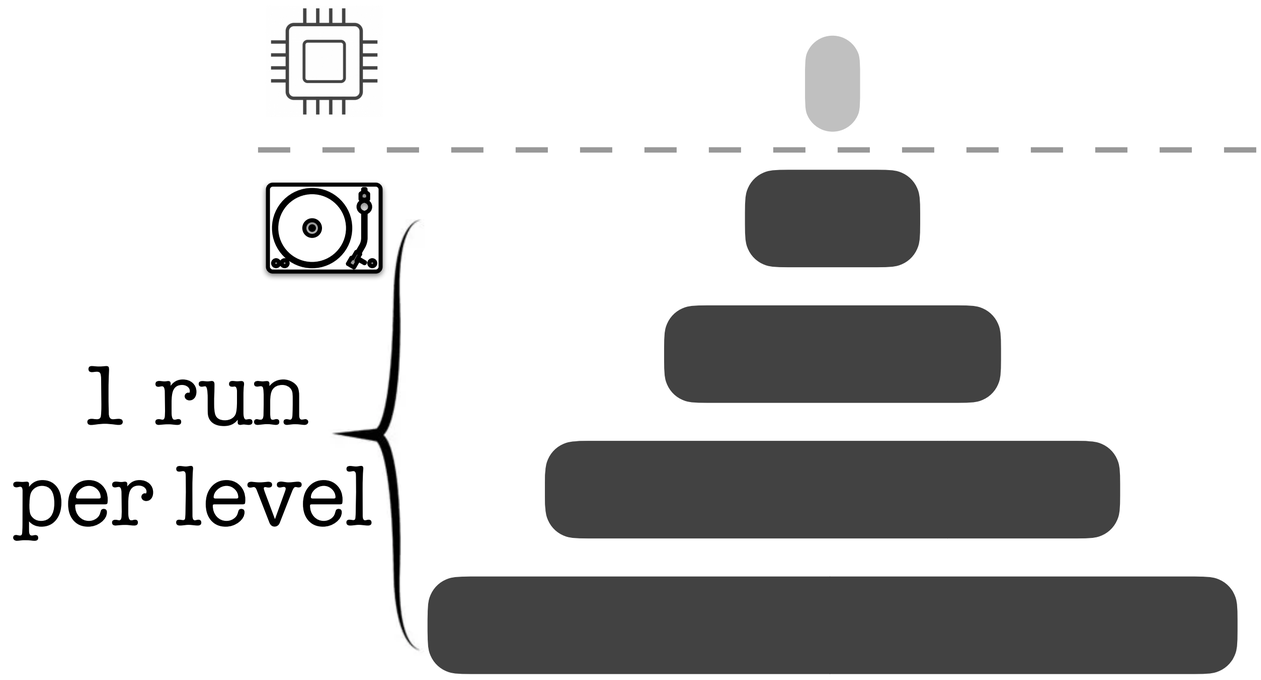
# Data **Layout**

**leveling** [eager]




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

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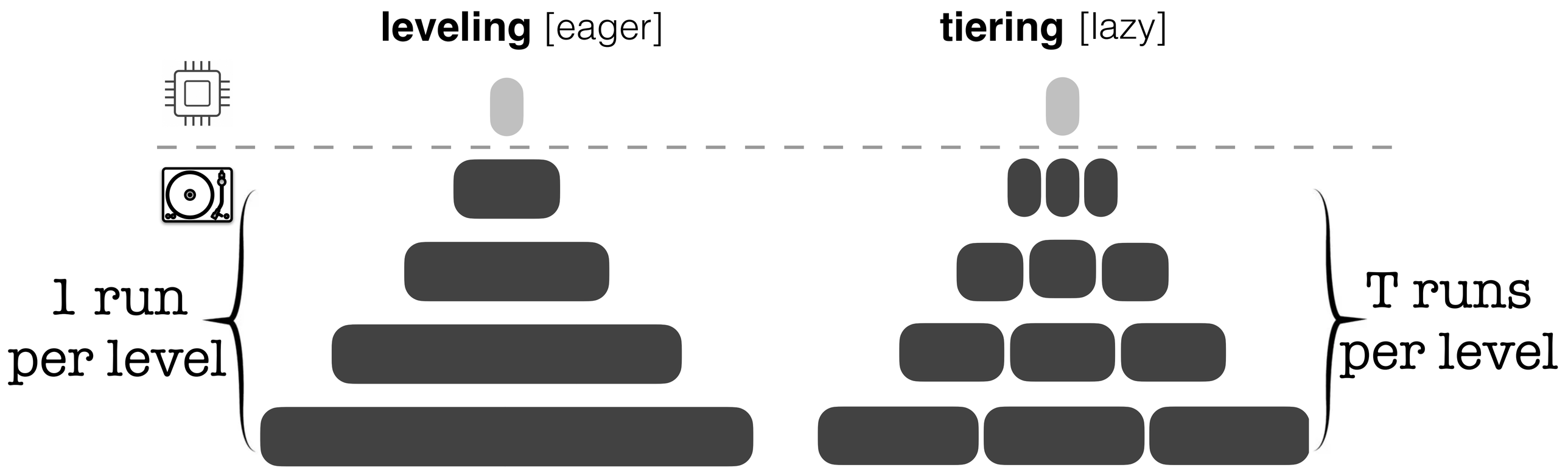
# Data **Layout**




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

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

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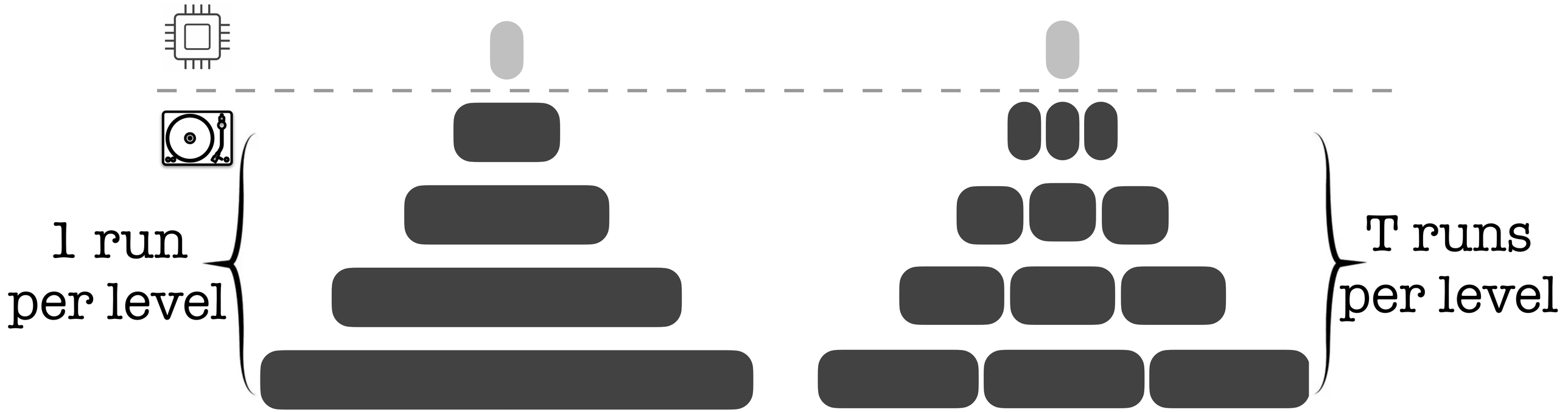
$P$: pages in buffer
$B$: entries/page
$L$: #levels
$T$: size ratio
$N$: #entries
$\phi$ : FPR of BF

# 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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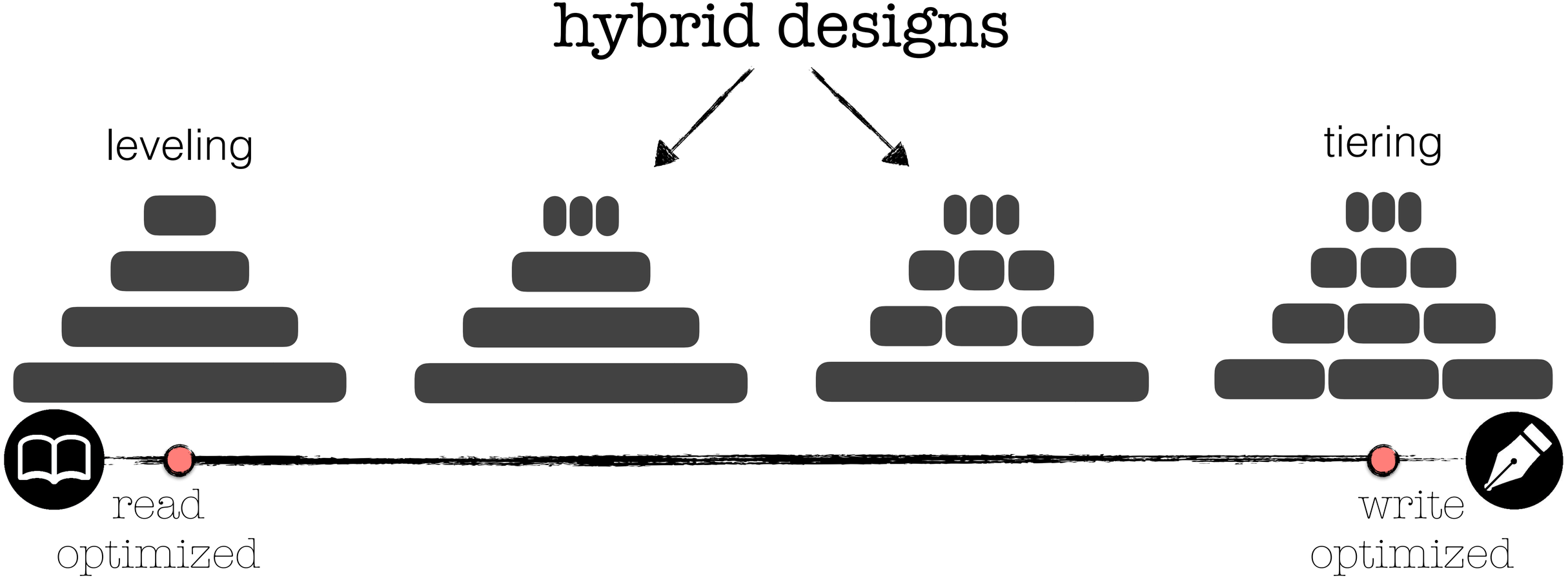
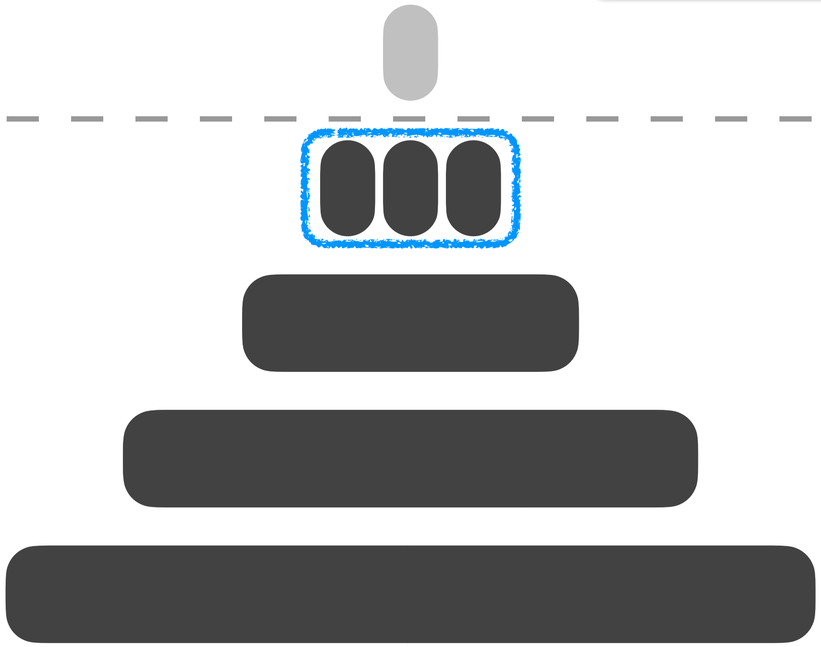
# Data **Layout**


hybrid designs
leveling
tiering
read
optimized
write
optimized

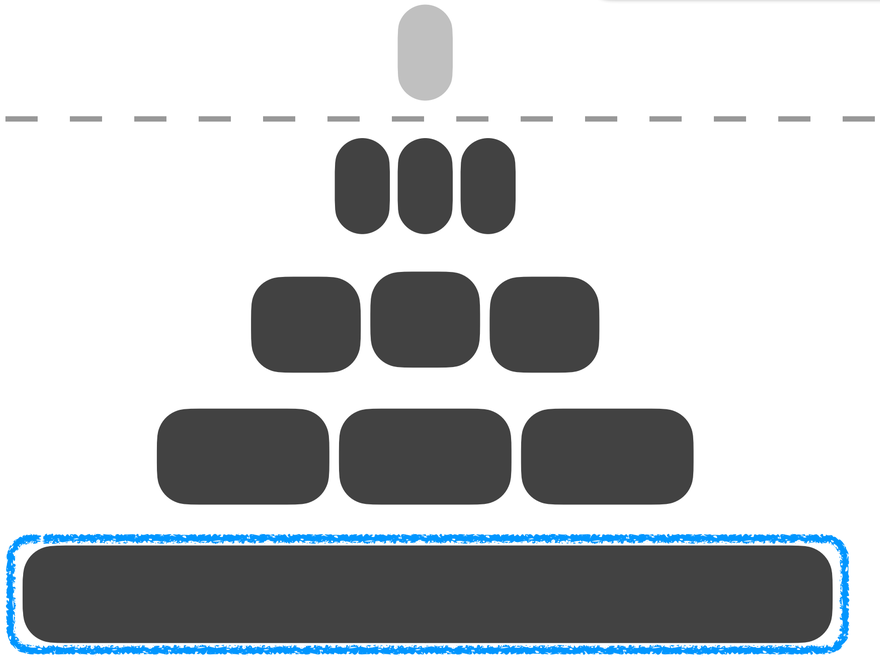
# Data **Layout**

**1-leveling** RocksDB20



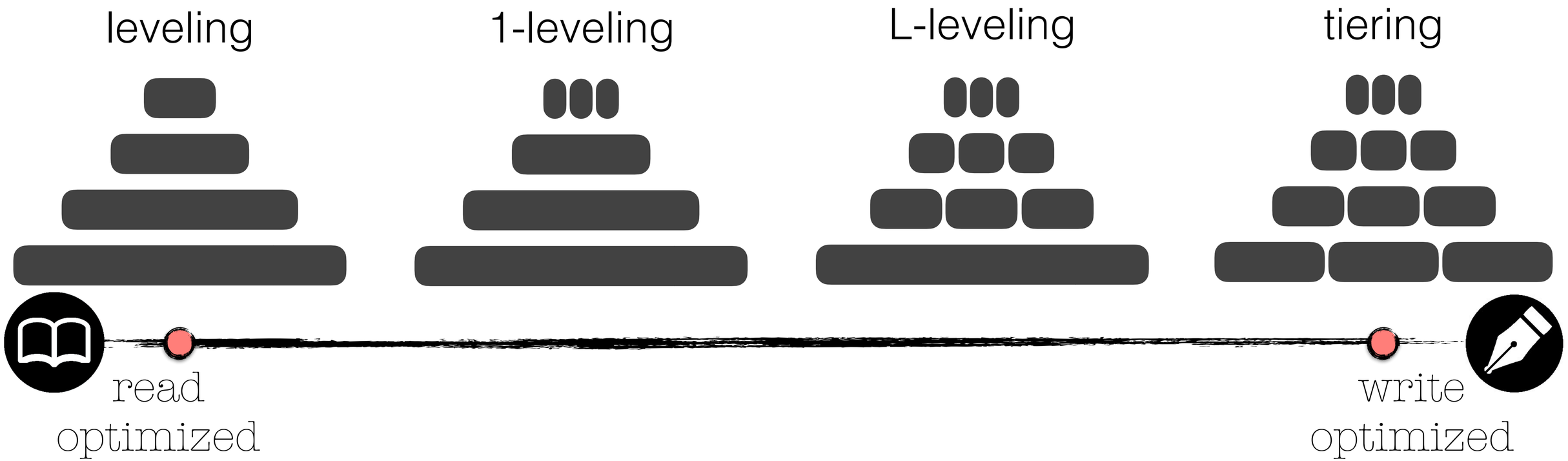
- fewer write stalls
- increased block cache hits

**L-leveling** DayanSIGMOD18

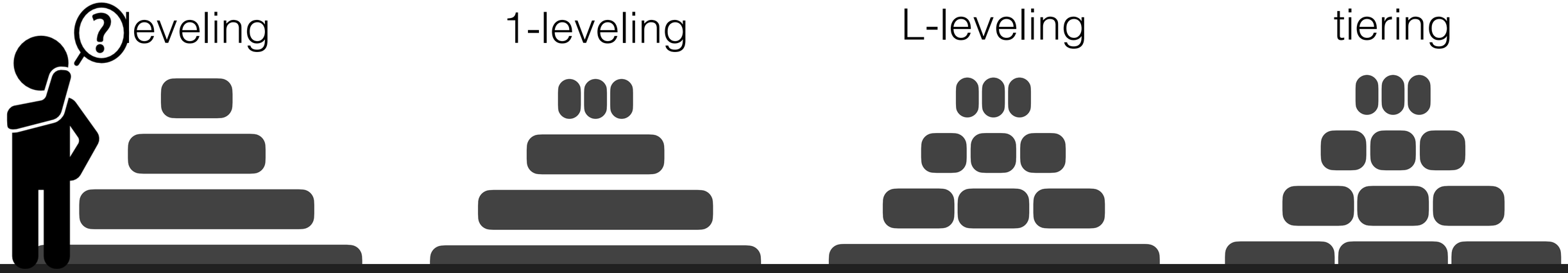


- low write amplification
- better read performance

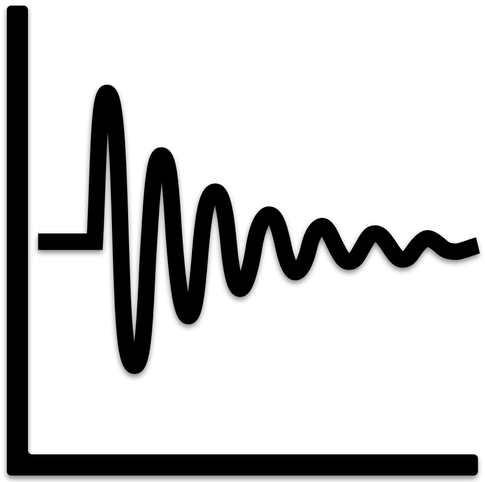
# Data **Layout**


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

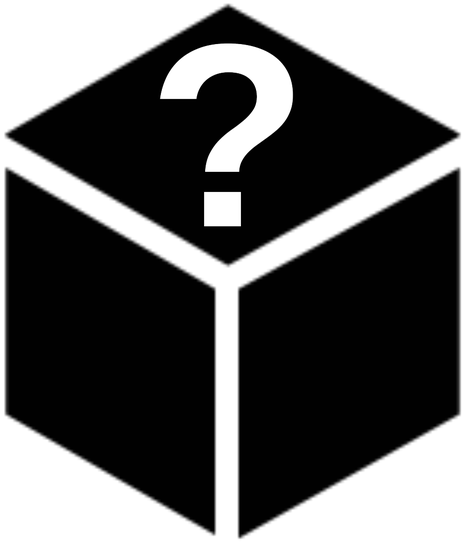
# Data **Layout**



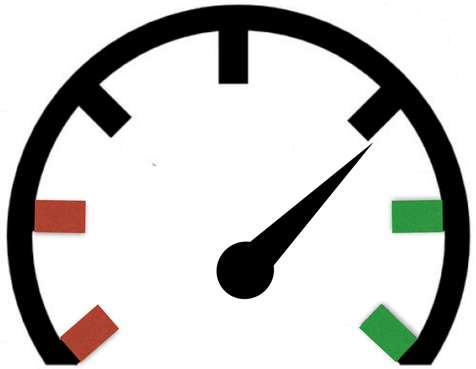

So, how do we reason about the data layout?



workload




**data layout**

performance

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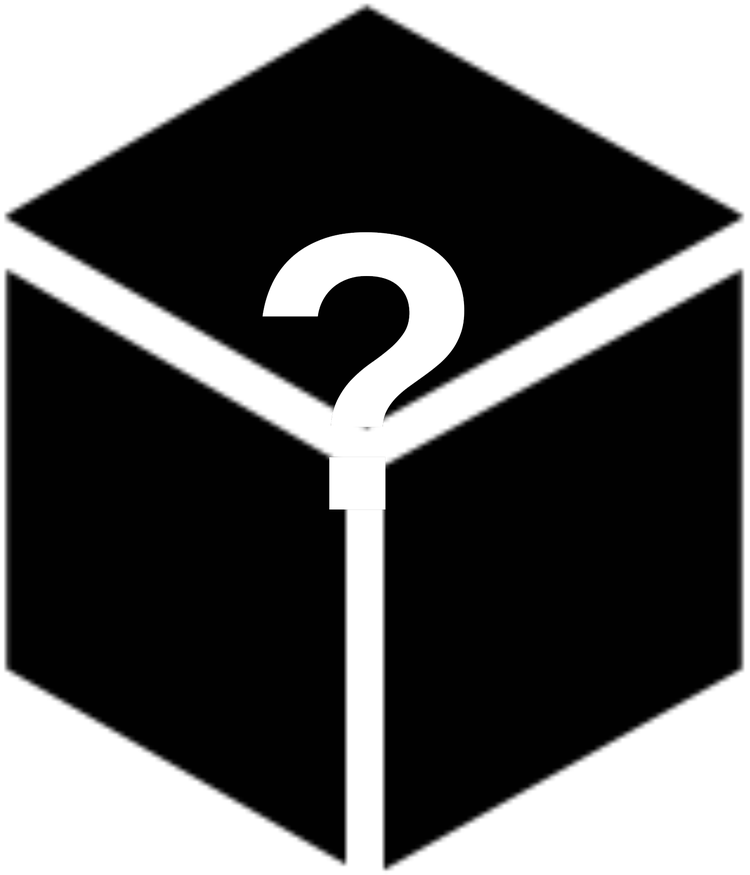

# Compaction

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


**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**

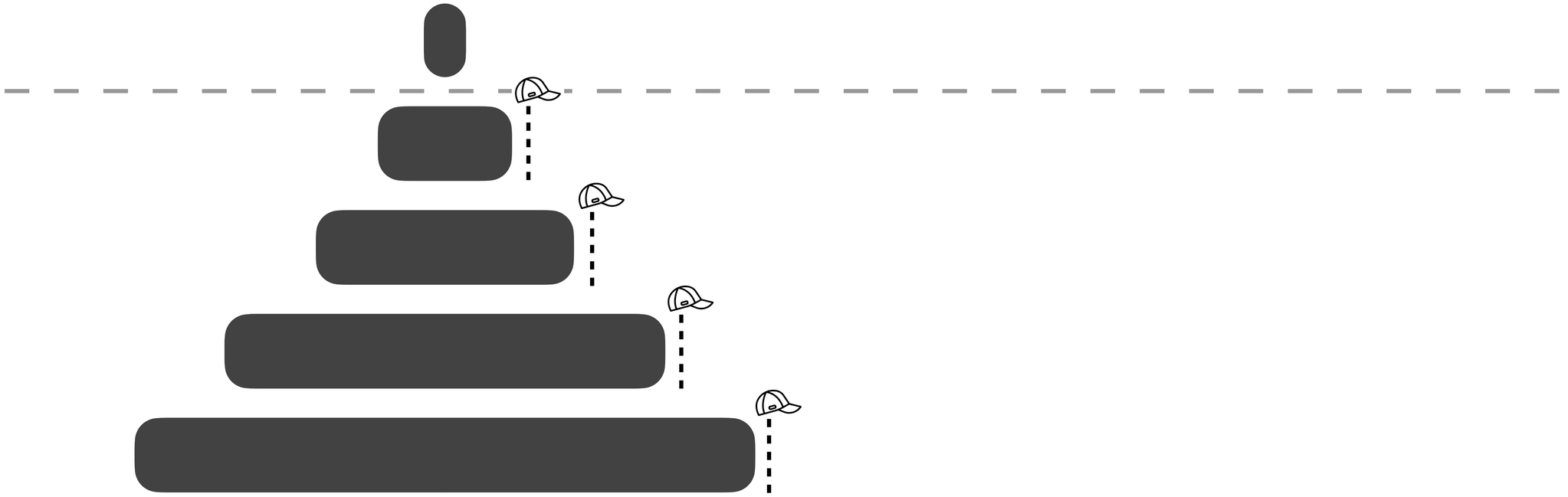
*data moved per compaction*

consecutive levels

AsterixDB

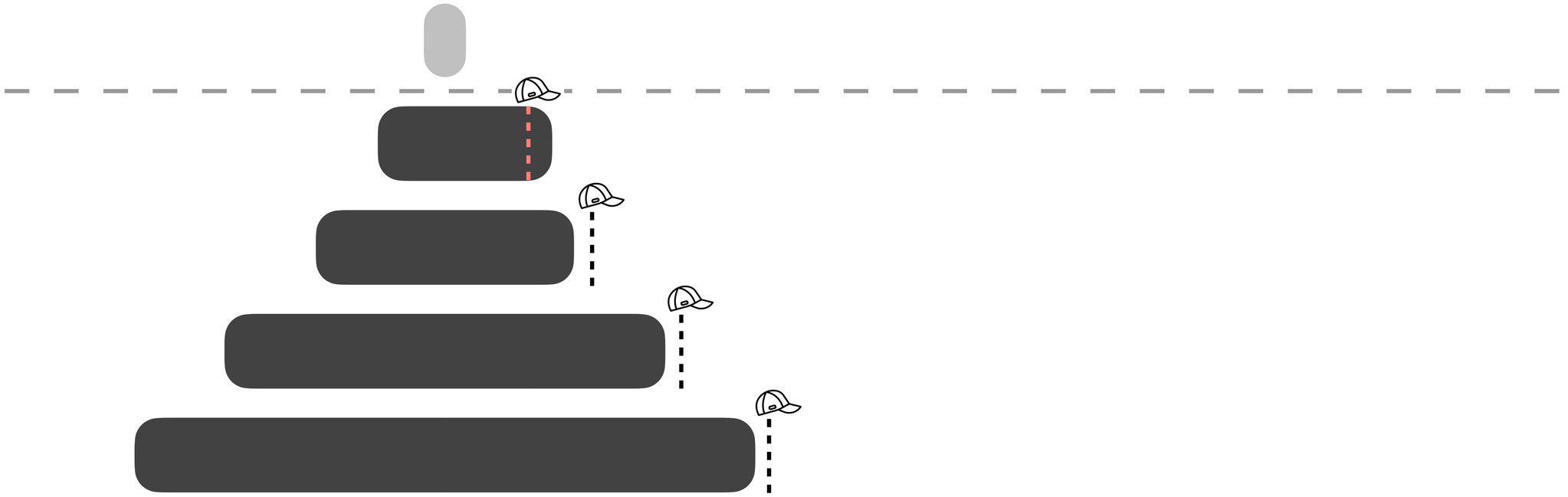

# Compaction **Granularity**

*data moved per compaction*



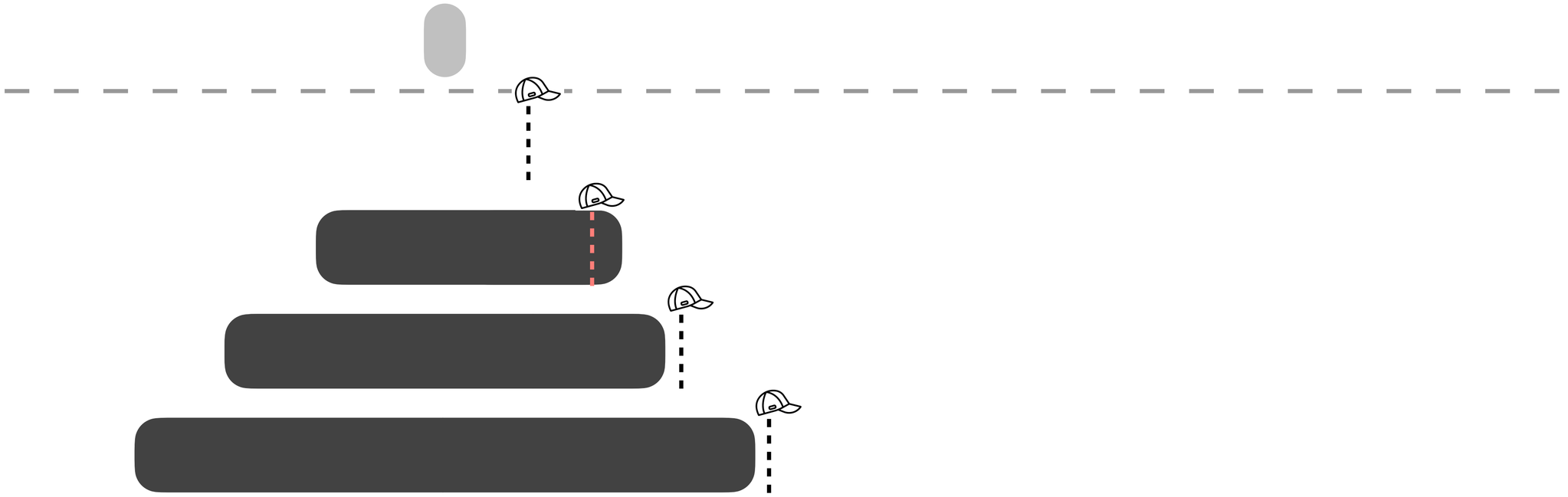

# Compaction **Granularity**

*data moved per compaction*



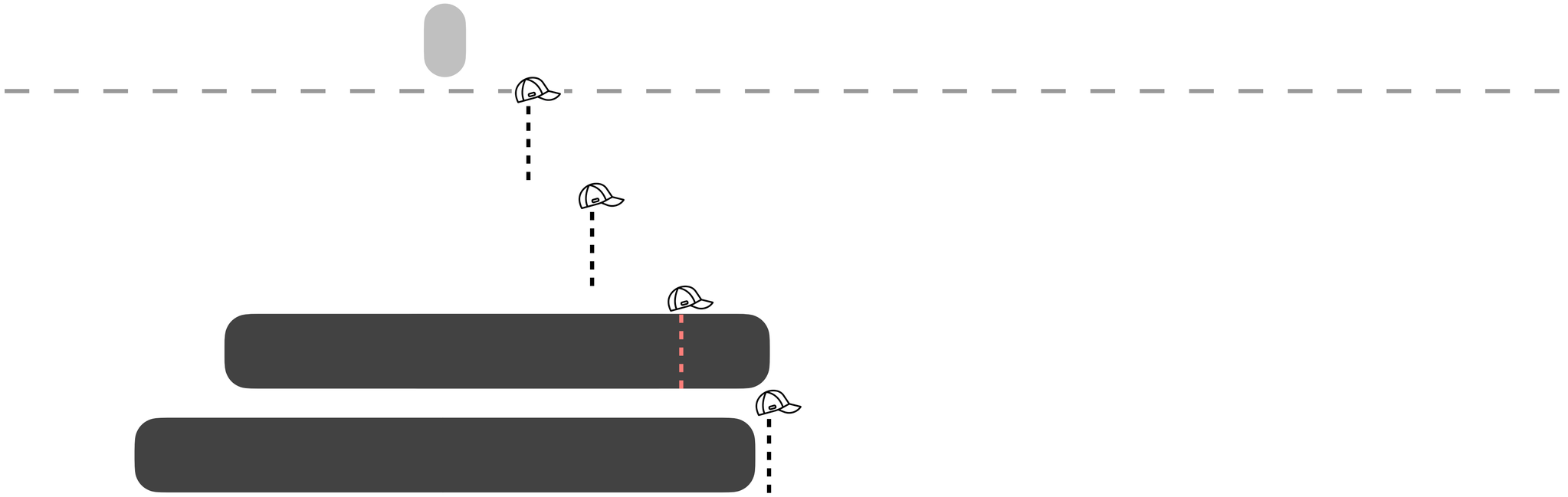

# Compaction **Granularity**

*data moved per compaction*



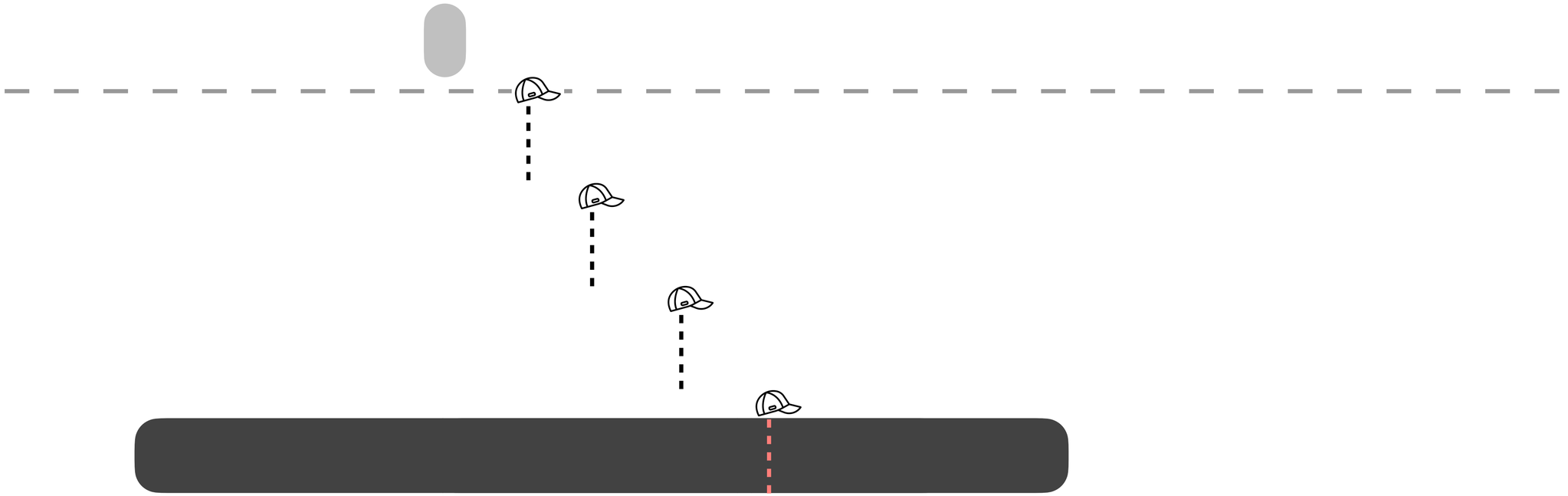

# Compaction **Granularity**

*data moved per compaction*



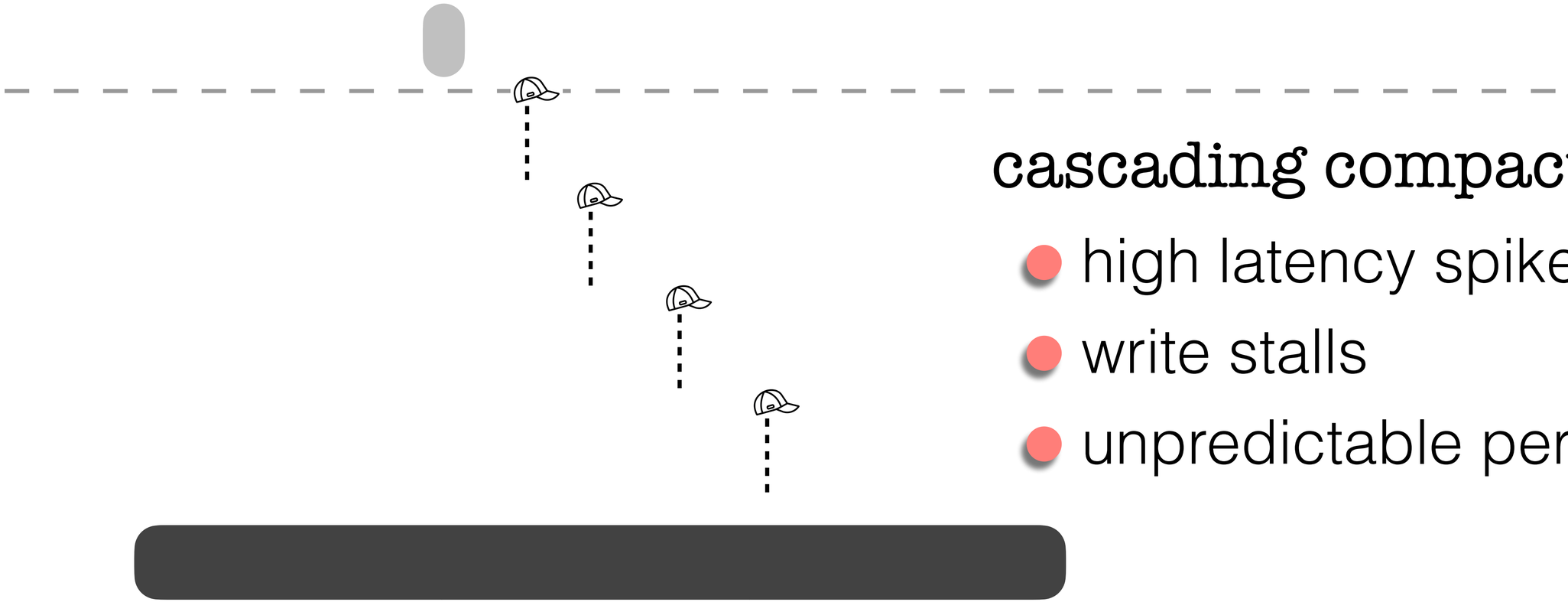

# Compaction **Granularity**

*data moved per compaction*




# Compaction **Granularity**

*data moved per compaction*



cascading compactions

- high latency spikes
- write stalls
- unpredictable perf.


# Compaction **Granularity**

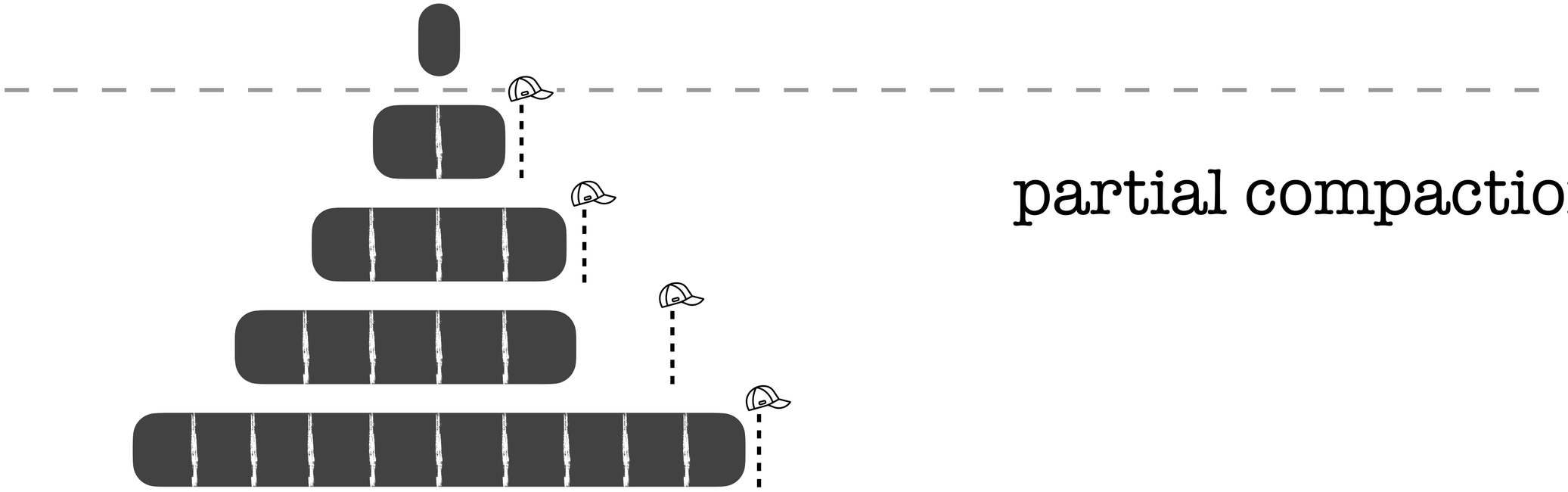
*data moved per compaction*

## partial compaction

granularity: **files**


# Compaction **Granularity**

*data moved per compaction*

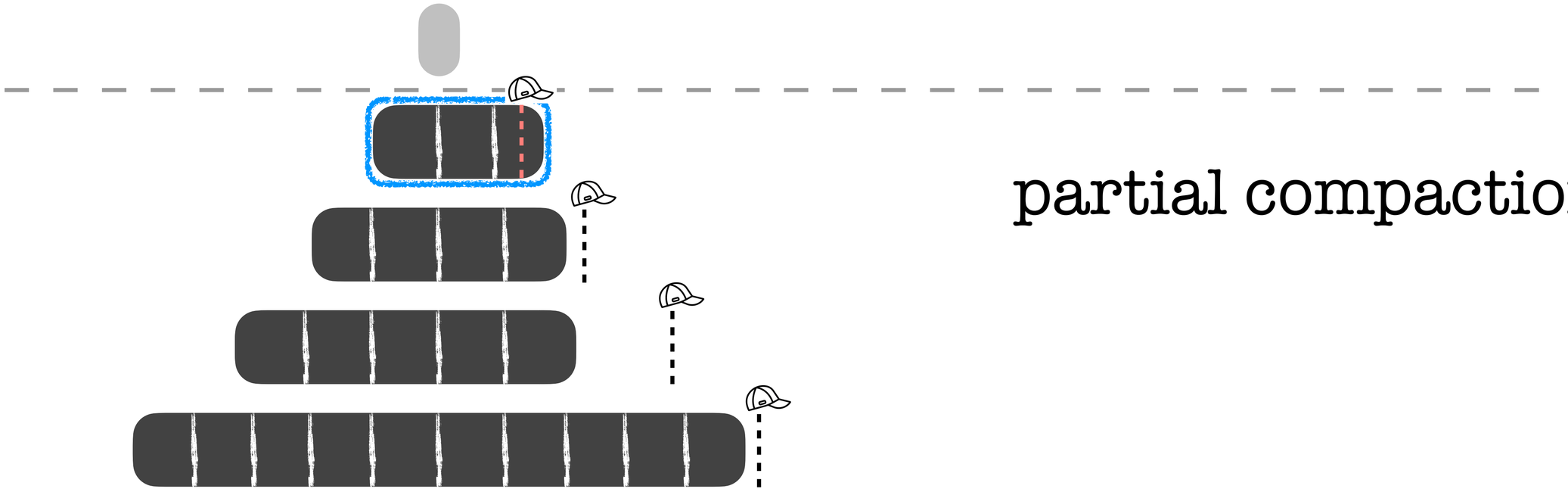


partial compaction

files


# Compaction **Granularity**

*data moved per compaction*

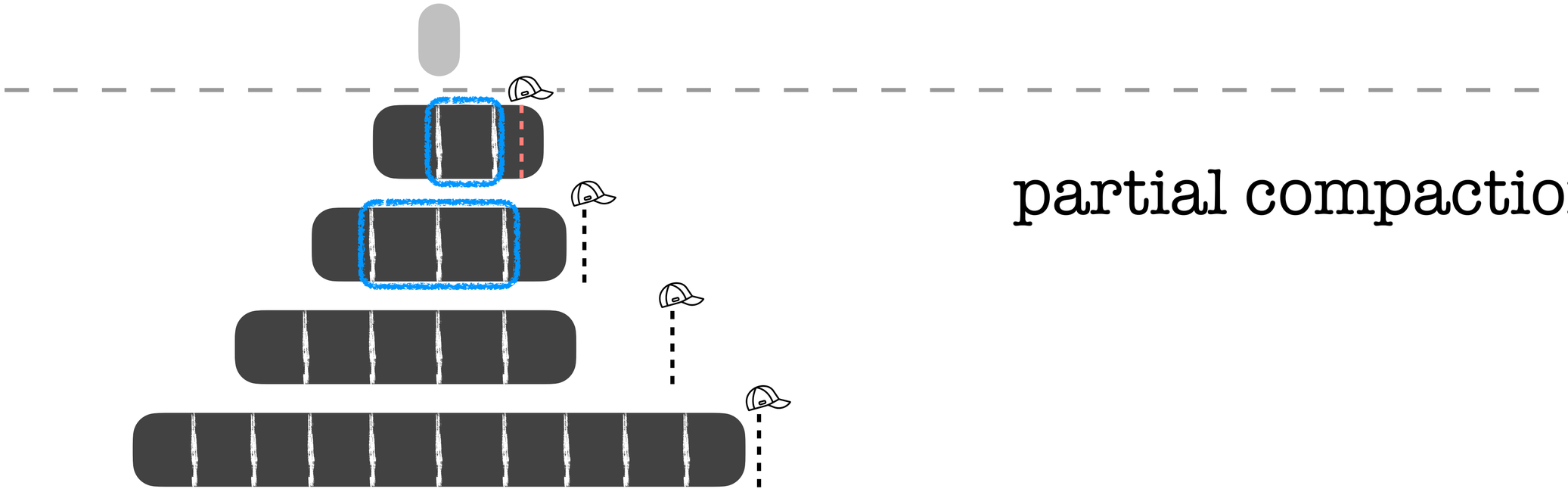


partial compaction

files


# Compaction **Granularity**

*data moved per compaction*

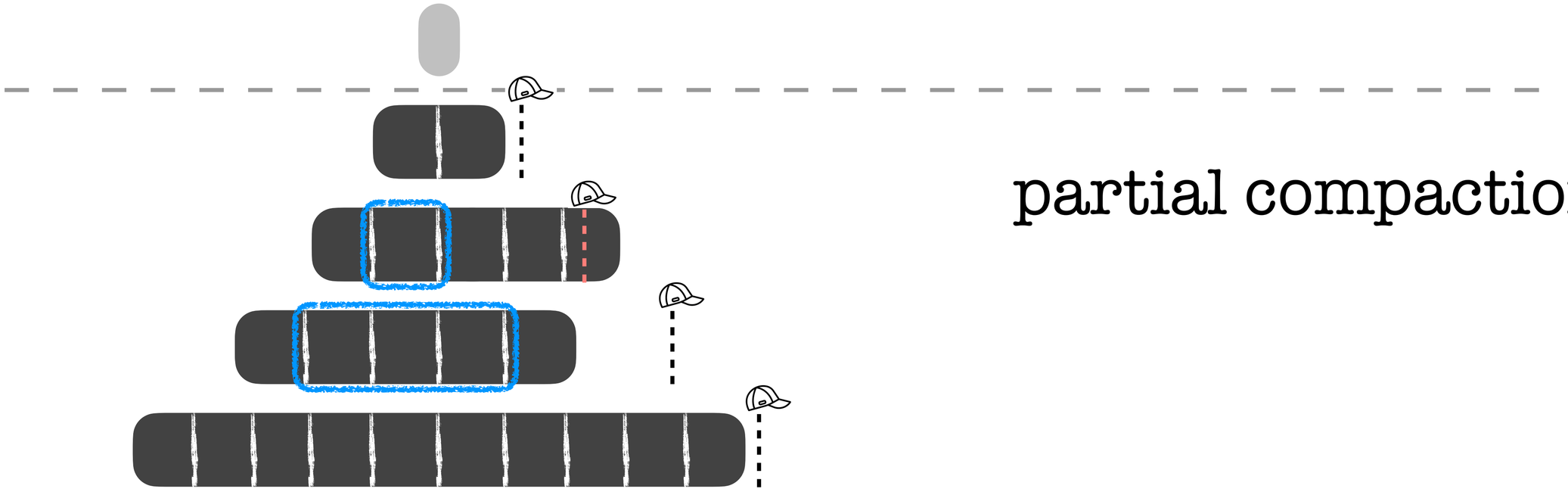


partial compaction

files


# Compaction **Granularity**

*data moved per compaction*

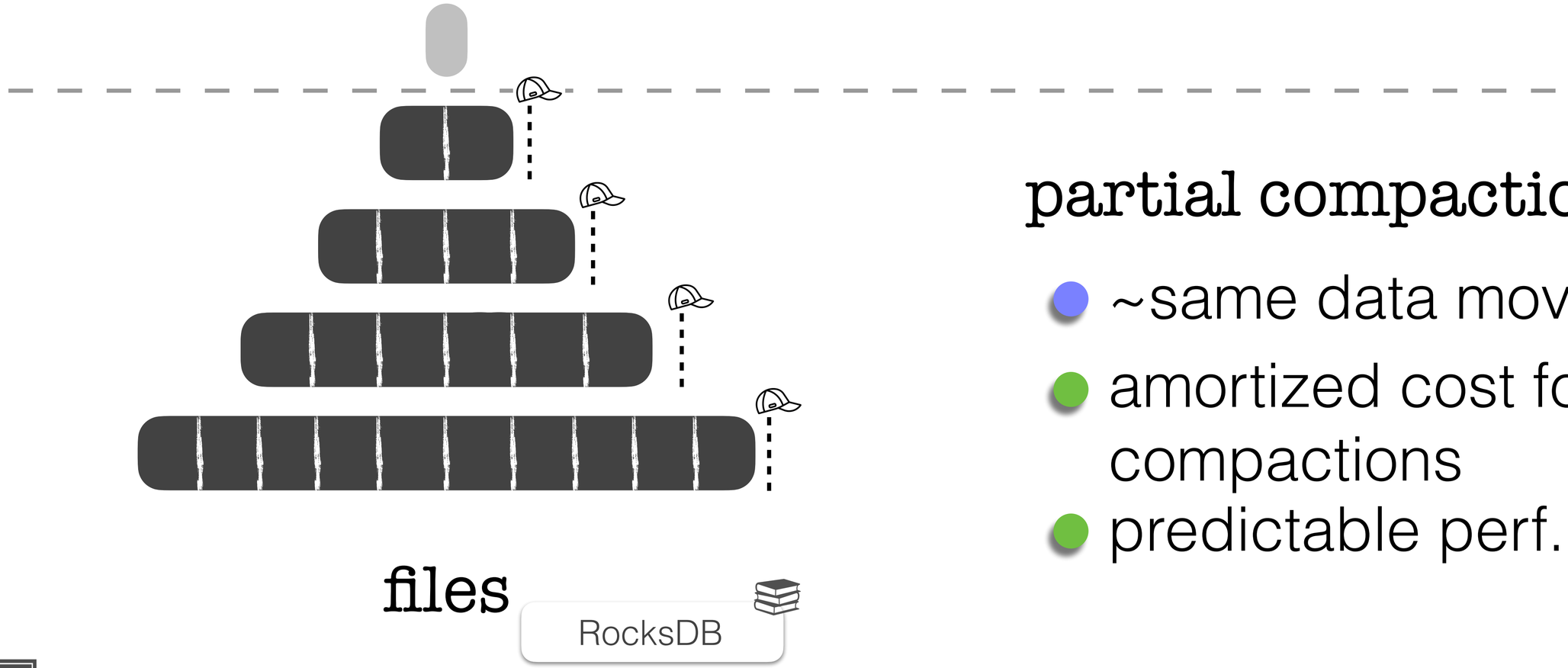


partial compaction

files


# Compaction **Granularity**

*data moved per compaction*

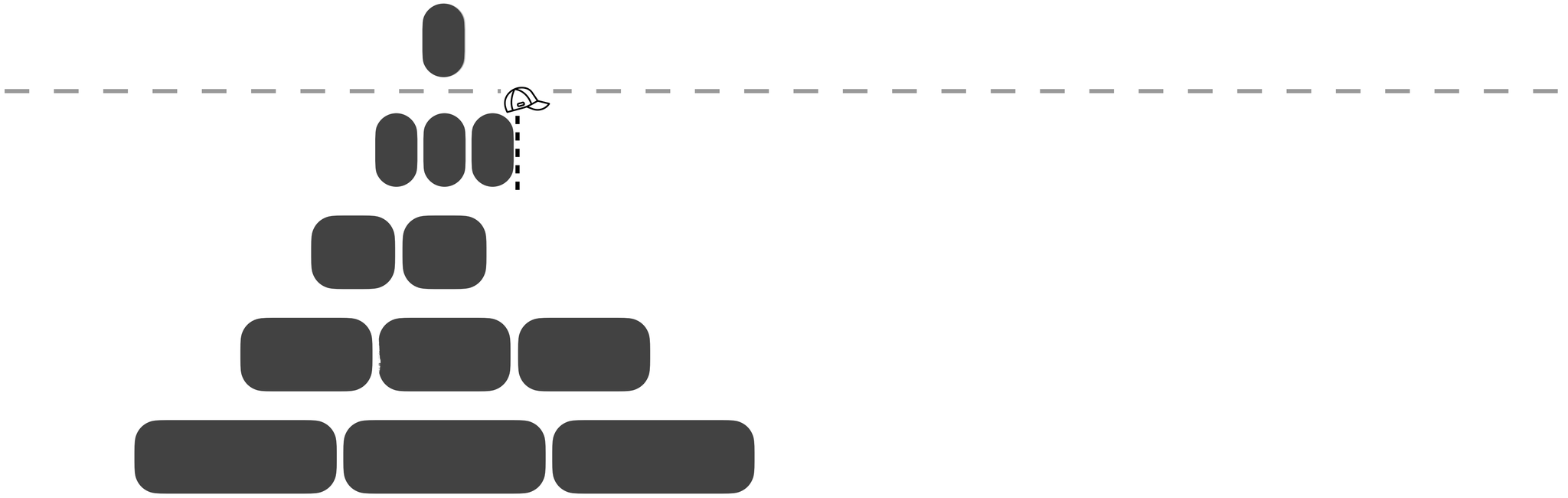



partial compaction

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


# Compaction **Granularity**

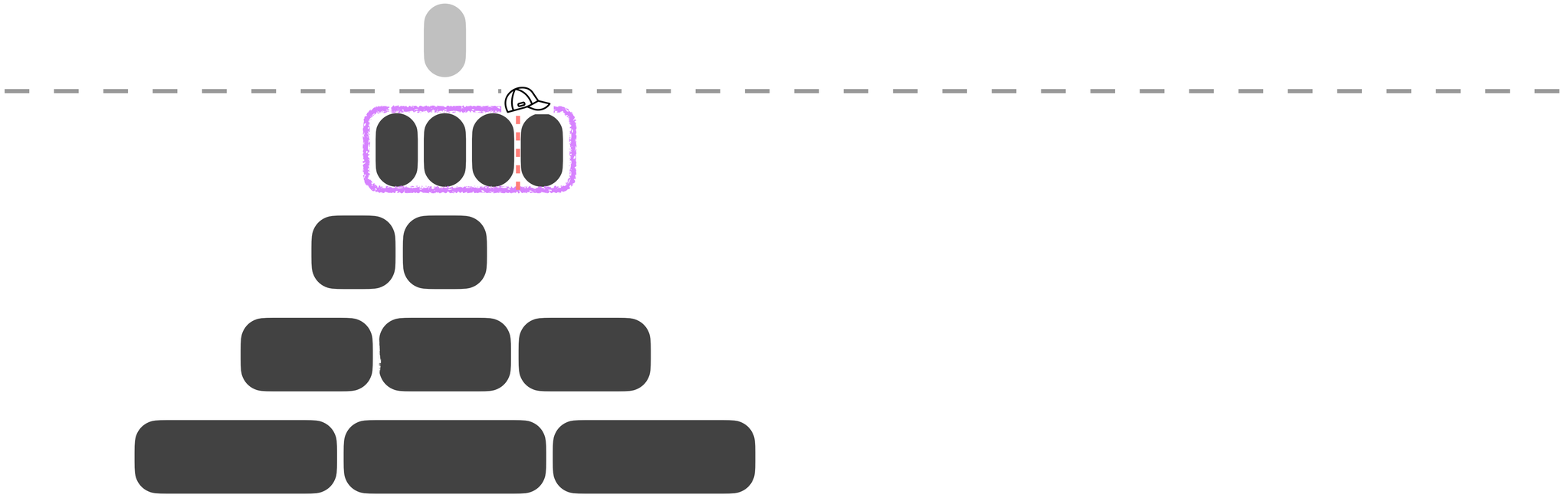
*data moved per compaction*



sorted runs in a level


# Compaction **Granularity**

*data moved per compaction*



sorted runs in a level

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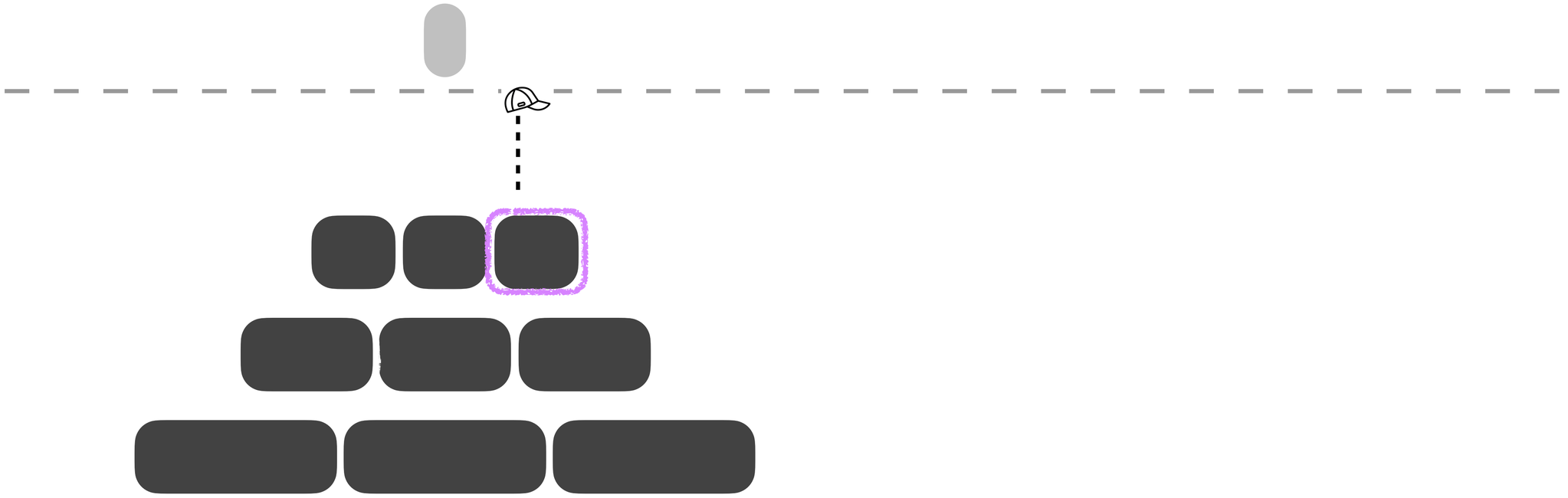
# Compaction **Granularity**

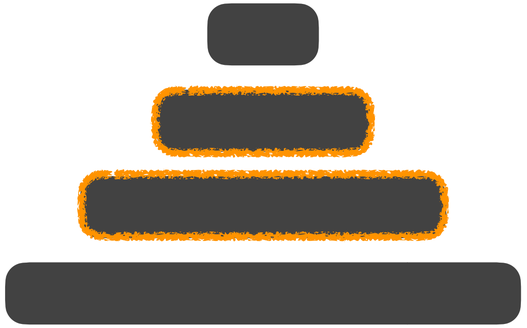
*data moved per compaction*



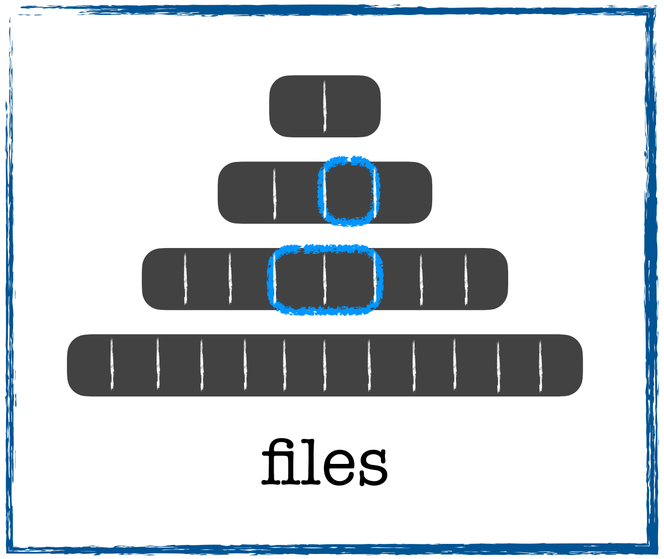
sorted runs in a level


# Compaction **Granularity**

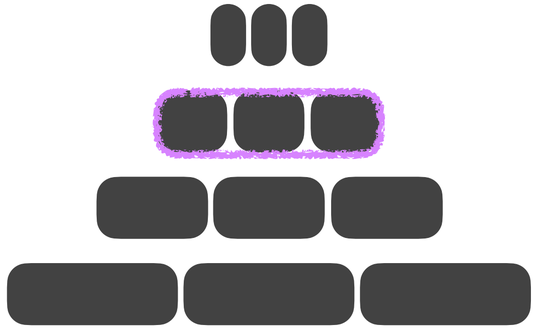
*data moved per compaction*



levels



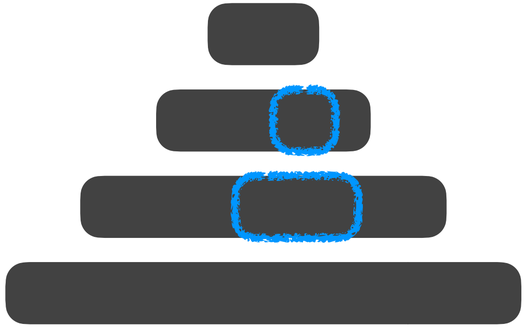
files



sorted runs in a level


# **Data Movement** Policy

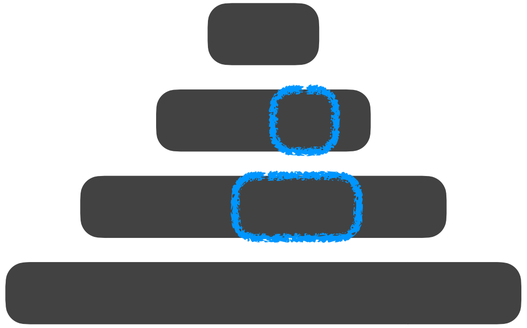
*which data to compact*



files


# **Data Movement** Policy

*which data to compact*



files

**round-robin** !

minimum **overlap with parent** level WA

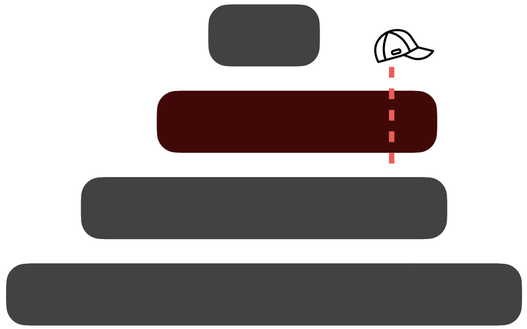
file with most **tombstones** SA

**coldest** file PQ


# Compaction **Trigger**

*invoking the compaction routine*

level **saturation**



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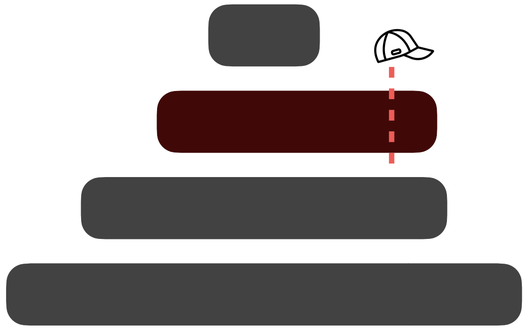
# Compaction **Trigger**

*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

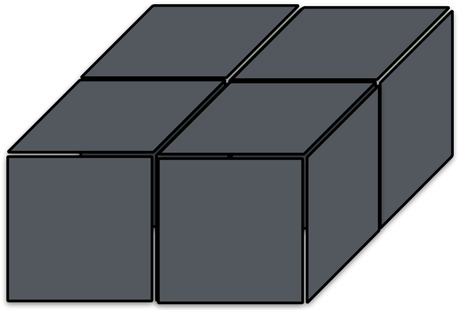

Compaction Trigger

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) |
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| | Tiering | | ✓ | | ✓ | ✓ | | ✓ | | | | | | | | | | ✓ |
| LevelDB [32], Monkey (J.) [21] | Leveling | ✓ | | | | | | | ✓ | | ✓ | ✓ | ✓ | | | | | |
| SlimDB [47] | Tiering | ✓ | | | | | | | ✓ | ✓ | | | | | | | | ✓ |
| Dostoevsky [23] | *L*-leveling | $✓^{L}$ | $✓^{T}$ | | | | $✓^{L}$ | $✓^{T}$ | | | | $✓^{L}$ | | | | | | $✓^{T}$ |
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| Lethe [51] | Leveling | ✓ | | | | ✓ | | | ✓ | ✓ | | ✓ | | | | | ✓ | |
| Silk [11], Silk+ [12] | Leveling | ✓ | | | | | | | ✓ | ✓ | ✓ | | | | | | | |
| HyperLevelDB [35] | Leveling | ✓ | | | | | | | ✓ | | ✓ | ✓ | ✓ | | | | | |
| PebblesDB [46] | Hybrid leveling | ✓ | | | | | | | ✓ | ✓ | | | | | | | | ✓ |
| Cassandra [8] | Tiering | | ✓ | ✓ | | ✓ | | ✓ | | | | | | | | | | ✓ |
| | Leveling | ✓ | | | | ✓ | | | ✓ | ✓ | | ✓ | | | | ✓ | ✓ | |
| WiredTiger [62] | Leveling | ✓ | | | | | ✓ | | | | | | | | | | | ✓ |
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| HBase [7] | Tiering | | ✓ | | | | | ✓ | | | | | | | | | | ✓ |
| AsterixDB [3] | Leveling | ✓ | | | | | ✓ | | | | | | | | | | | ✓ |
| | Tiering | | ✓ | | | | | ✓ | | | | | | | | | | ✓ |

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| Database | Data layout | Compaction Trigger | | | | | Compaction Granularity | | | | Data Movement Policy | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
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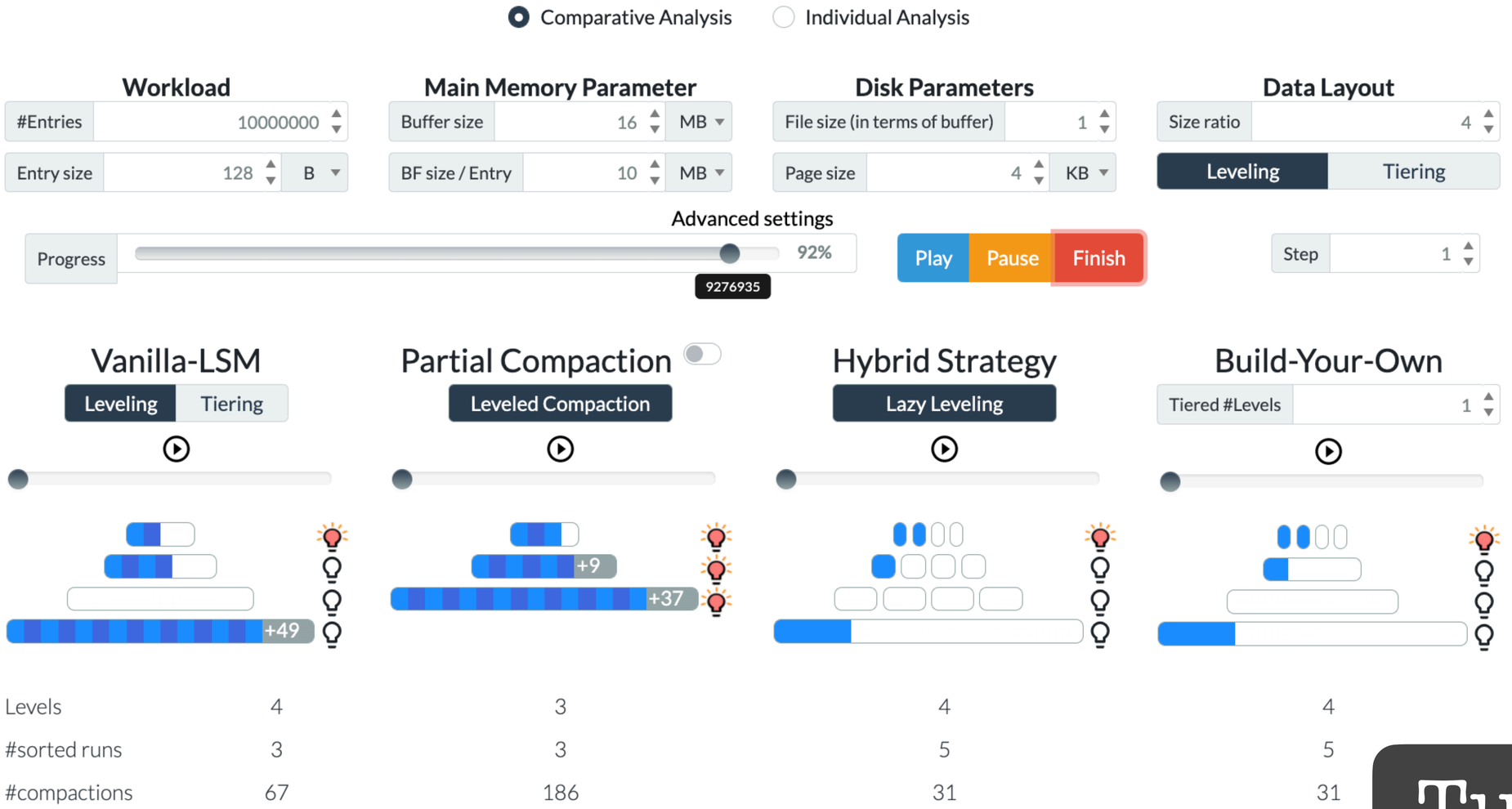
| | Tiering | | ✓ | | | | | ✓ | | | | | | | | | | ✓ |

# SIGMOD Demo: Compactionary

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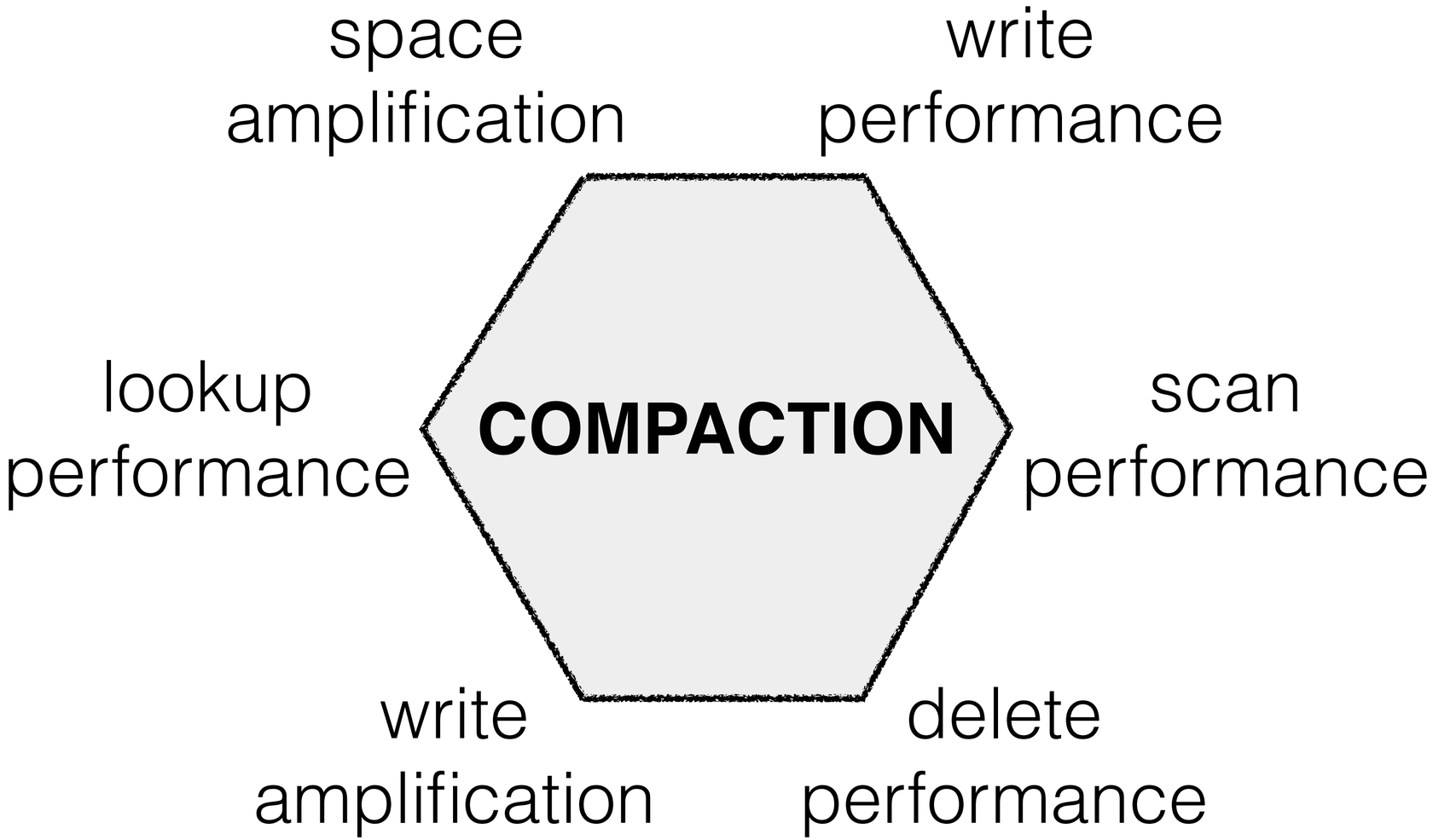
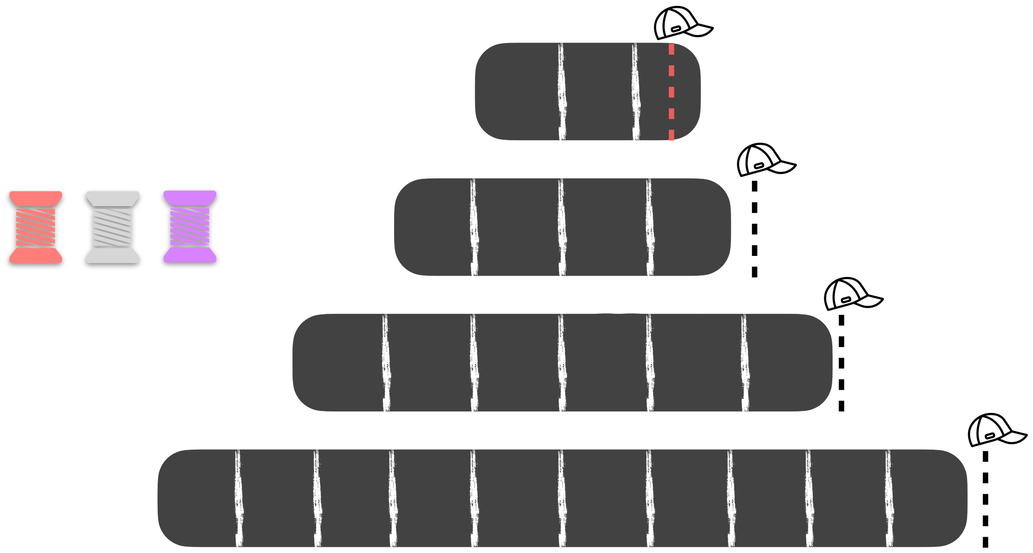
SarkarSIGMOD22

Tuesday 4-6PM


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

# Optimizing **Compactions**

Background Compactions



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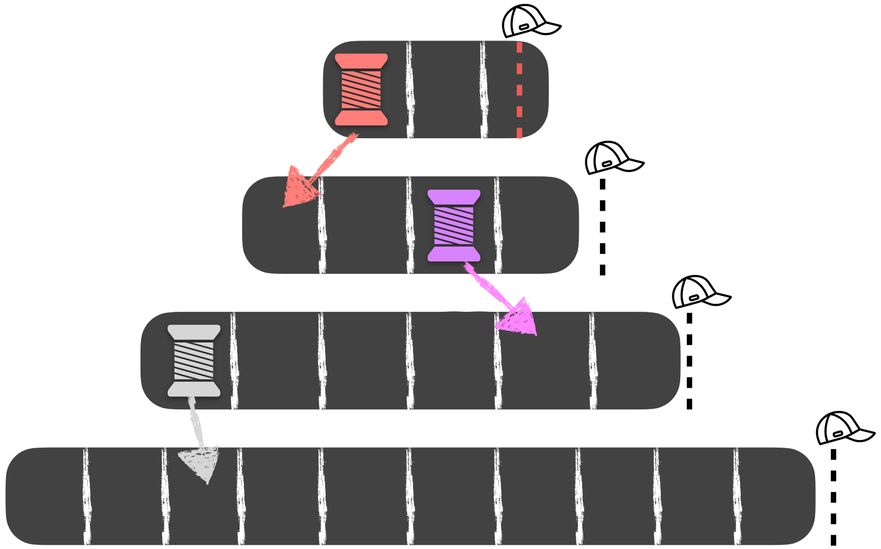
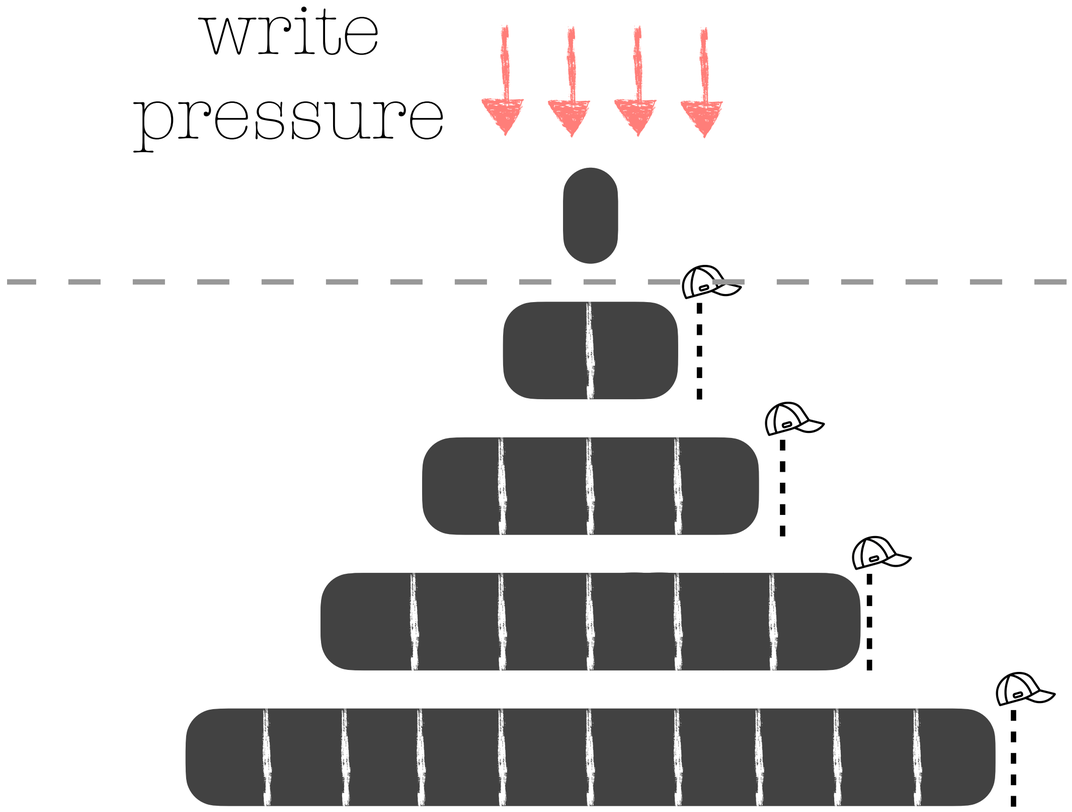
# Optimizing **Compactions**

Background Compactions



- non-blocking reads/writes
- improves write throughput

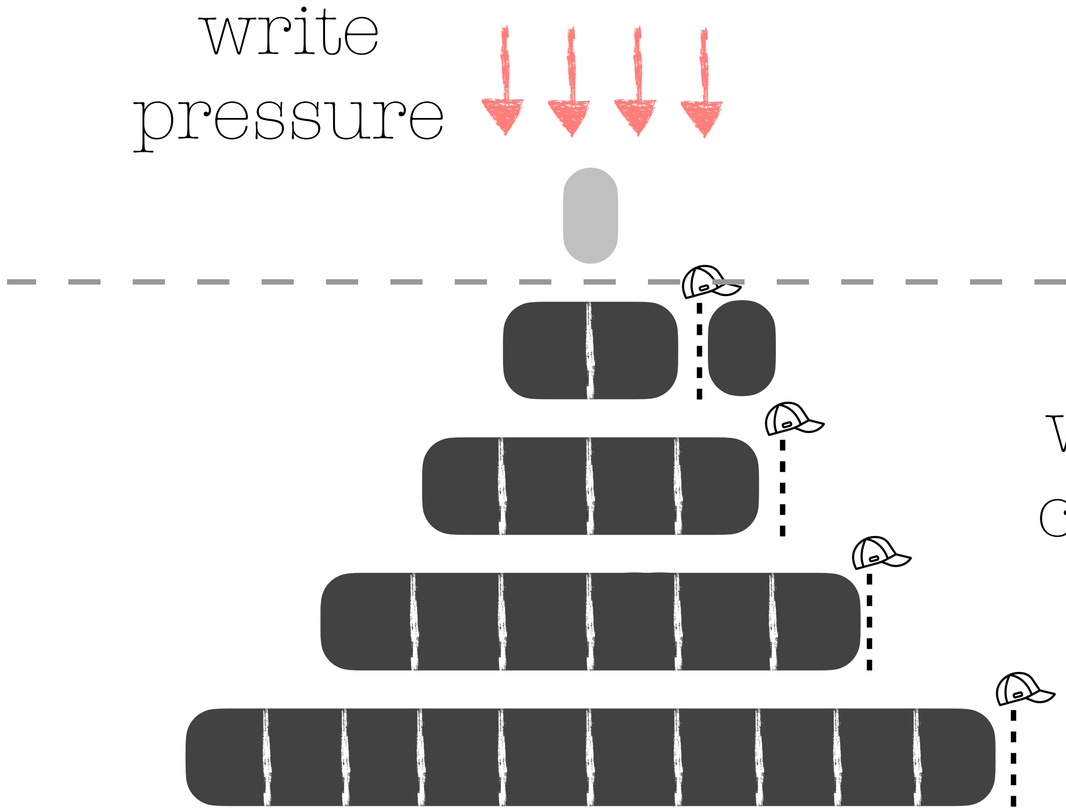
# Optimizing **Compactions**




Background Compactions

Compaction Priority

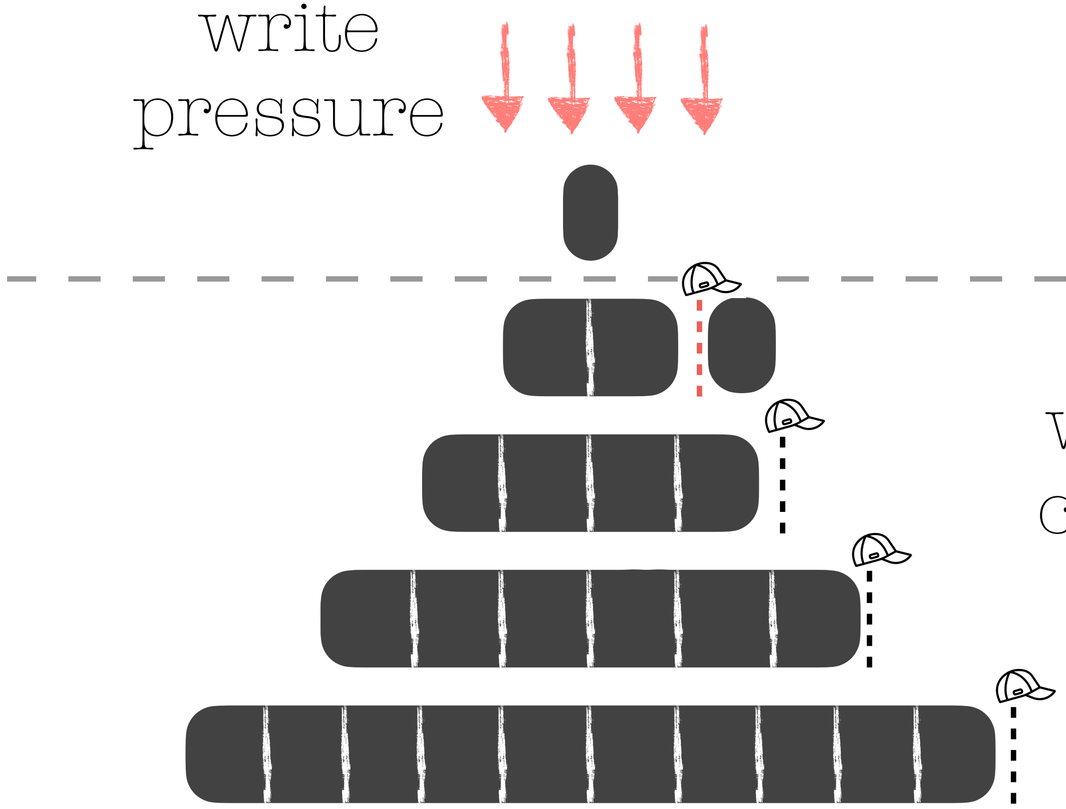
# Optimizing **Compactions**




Background Compactions

Compaction Priority

# Optimizing **Compactions**

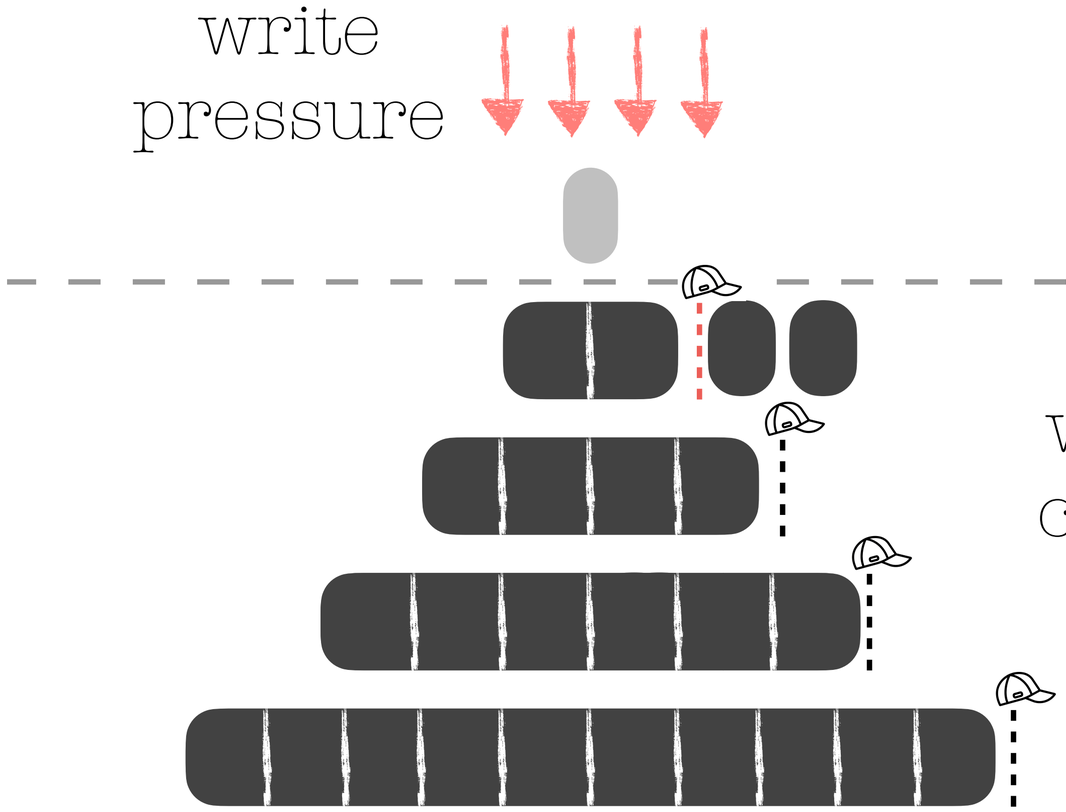



prioritize
writes over
compaction

Background
Compactions

Compaction
Priority

# Optimizing **Compactions**

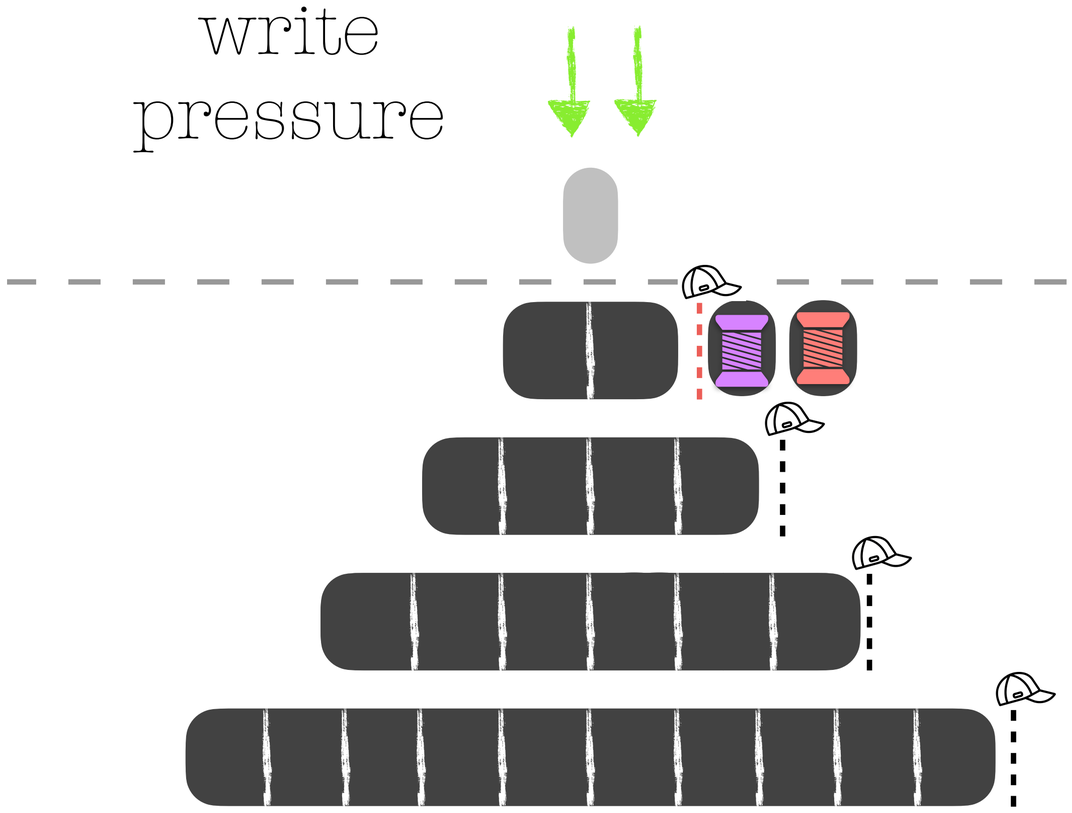



prioritize
writes over
compaction

Background
Compactions

Compaction
Priority

# Optimizing **Compactions**

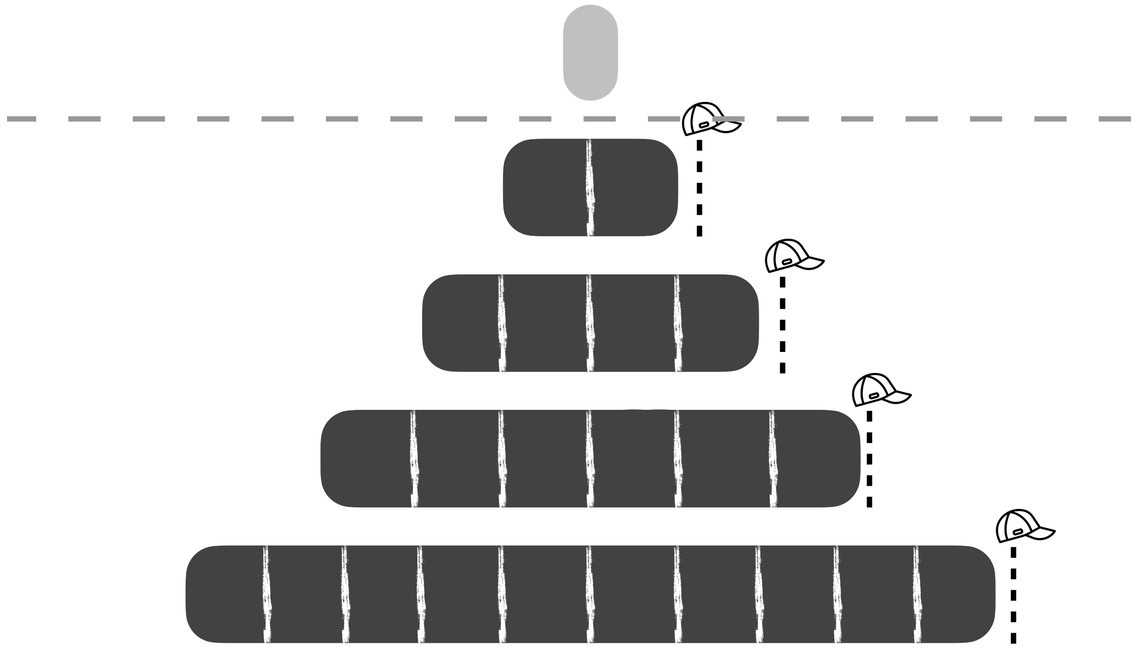



Background Compactions

Compaction Priority

- sustain heavy write bursts
- tree becomes out of shape

# Optimizing **Compactions**

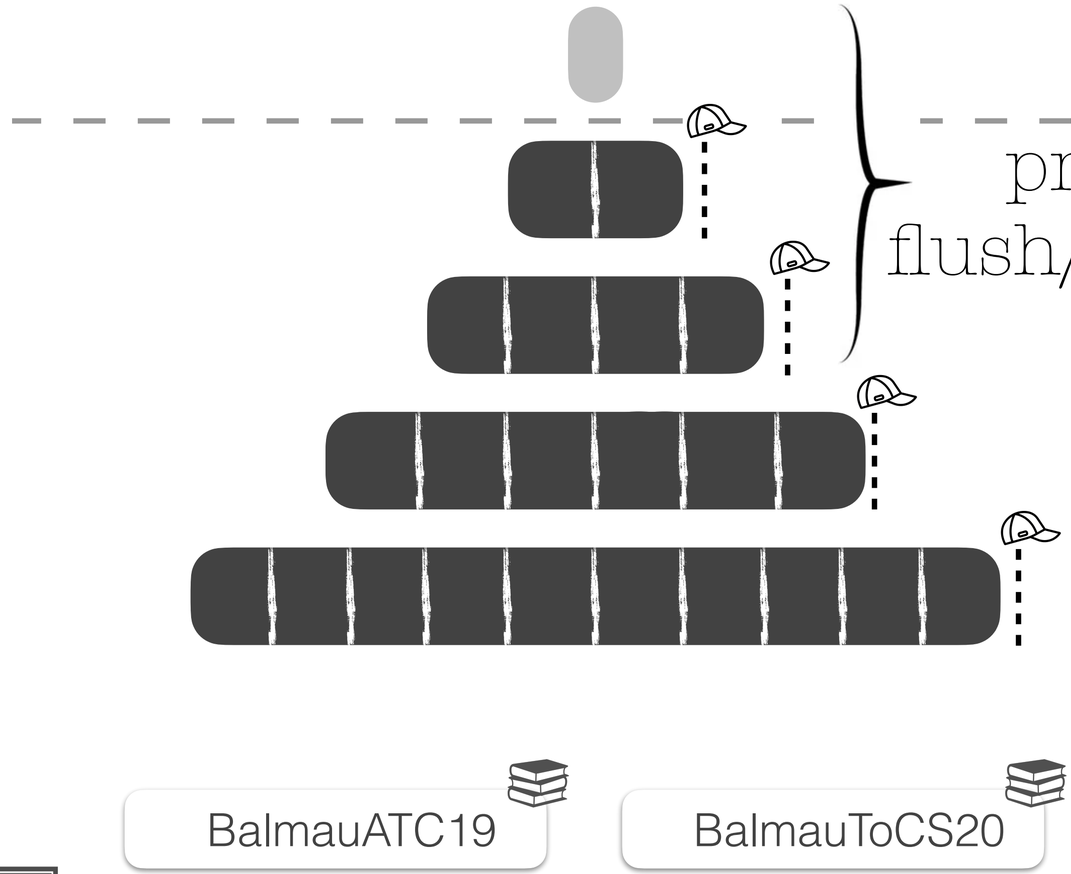


Background Compactions

Compaction Priority

I/O Scheduler

# Optimizing **Compactions**




Background Compactions

Compaction Priority

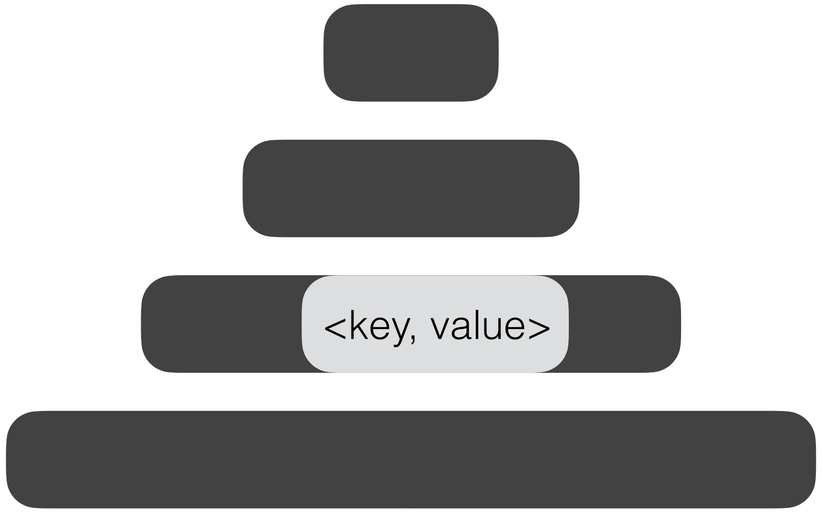
I/O Scheduler

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

BalmauATC19

BalmauToCS20

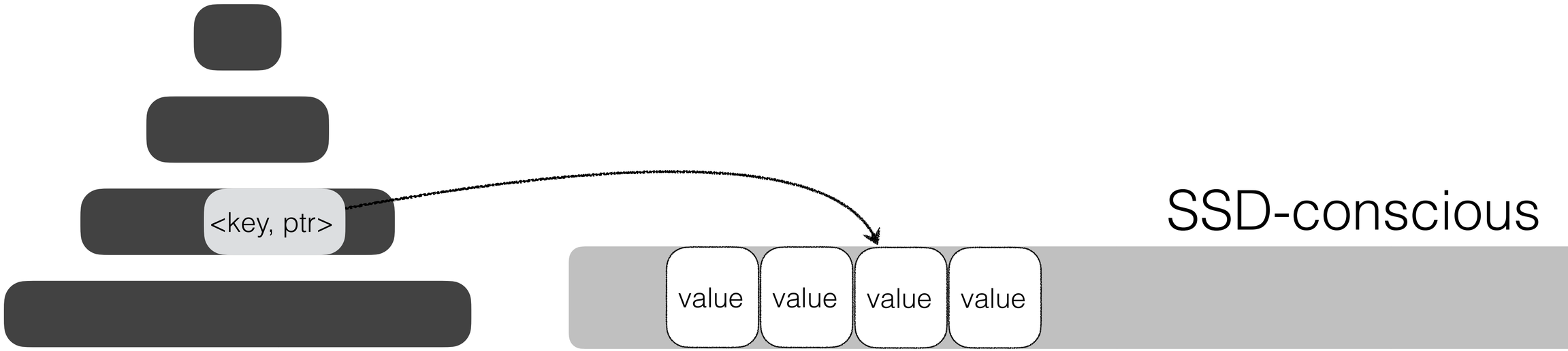
# **Data Placement** Variations




key-value separation

LuFAST16

# **Data Placement** Variations




key-value separation

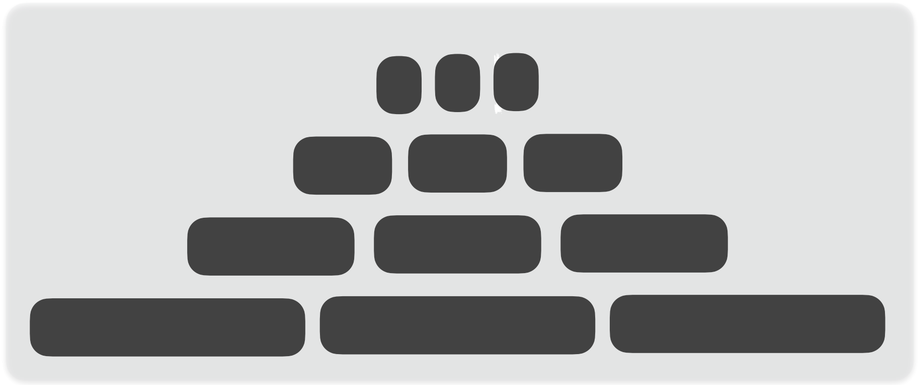
LuFAST16

- reduced write amplification
- better read performance

# **Data Placement** Variations

partitioning / sharding

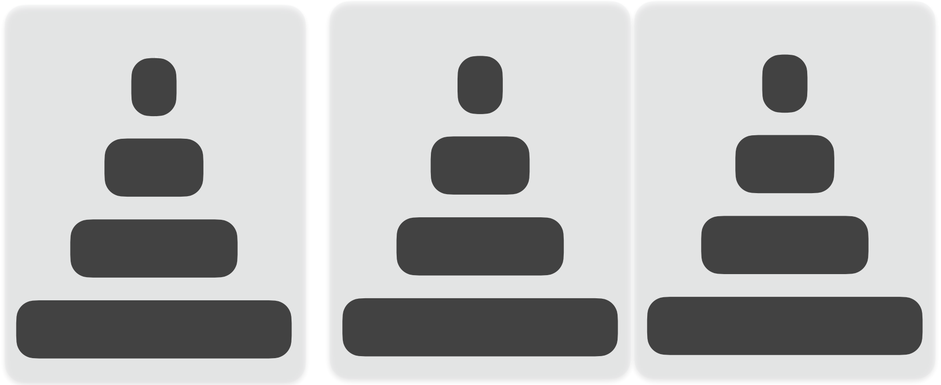
# **Data Placement** Variations



storage

partitioning

RajuSOSP17



storage-1 storage-2 storage-3

sharding

HuangSIGMOD21

- improved ingestion throughput
- reduced write amplification

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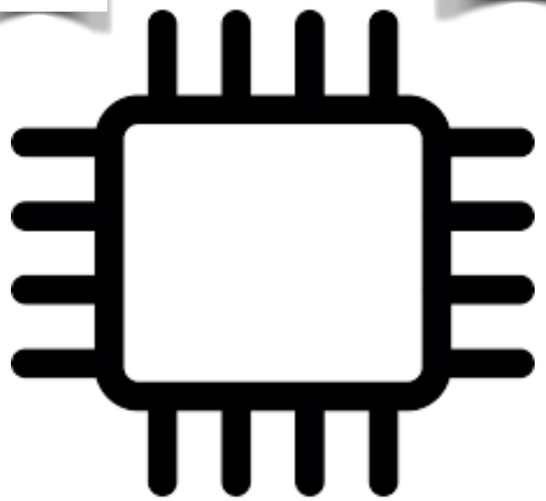
# Summary: **Ingestion Optimization**

data structure

size

flush strategy



main memory design elements

compaction design space

tuning compactions

data layout on storage

key-value separation

data partitioning

data sharding

hardware-conscious designs

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# Outline

Part 1: **LSM Basics**



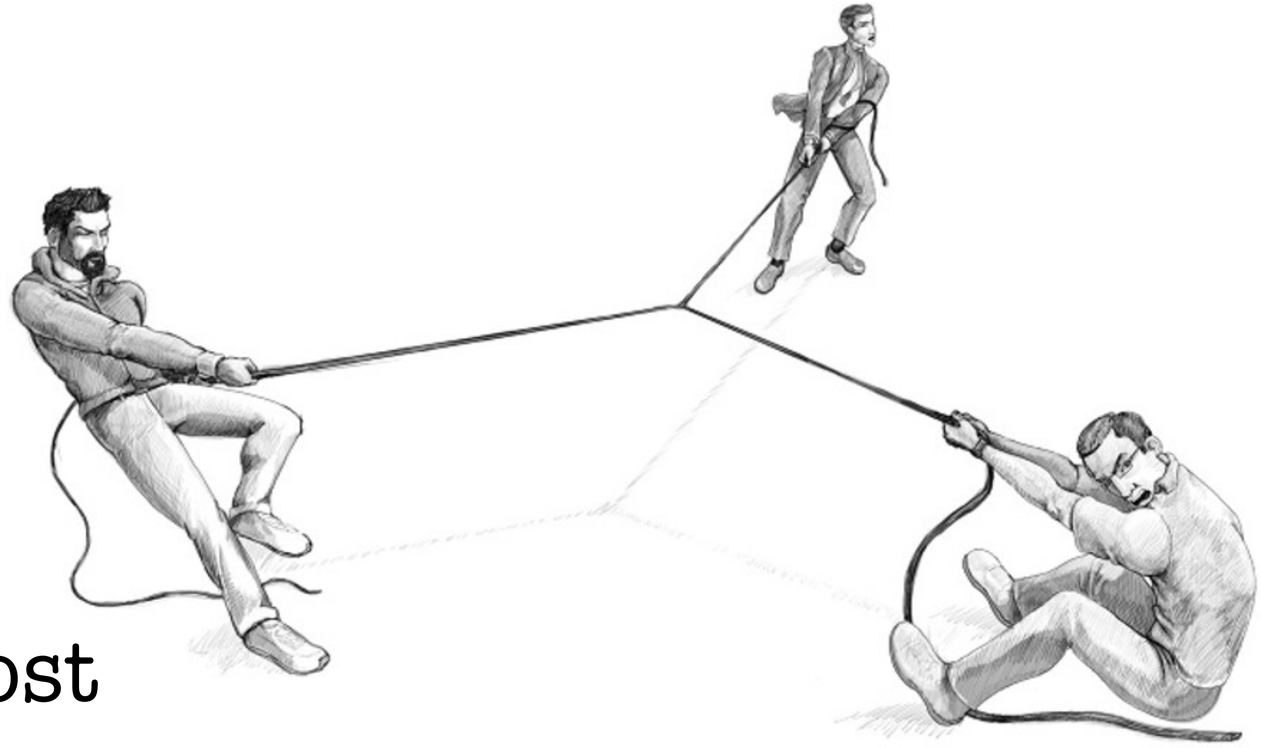
Part 2: **Optimizing Ingestion in LSMs**



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

# LSM **Design Space**

Update cost



Read cost

Memory/space footprint

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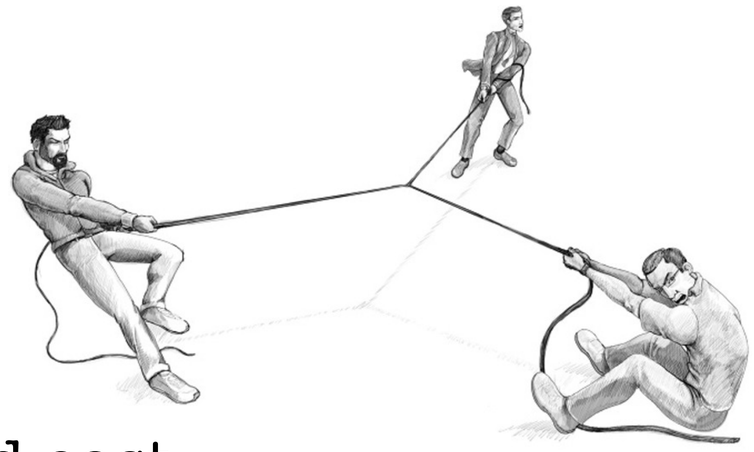
AthanassoulisEDBT16

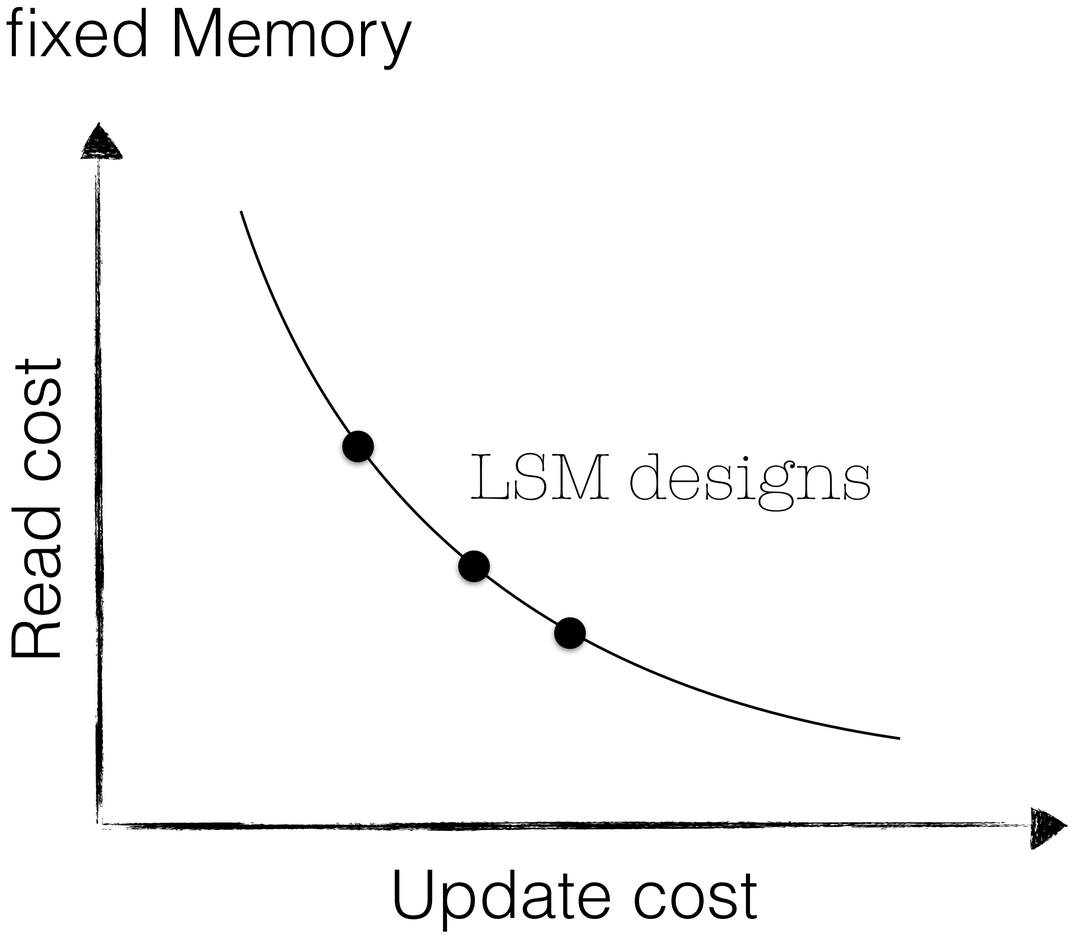
# LSM **Design Space**



Update cost

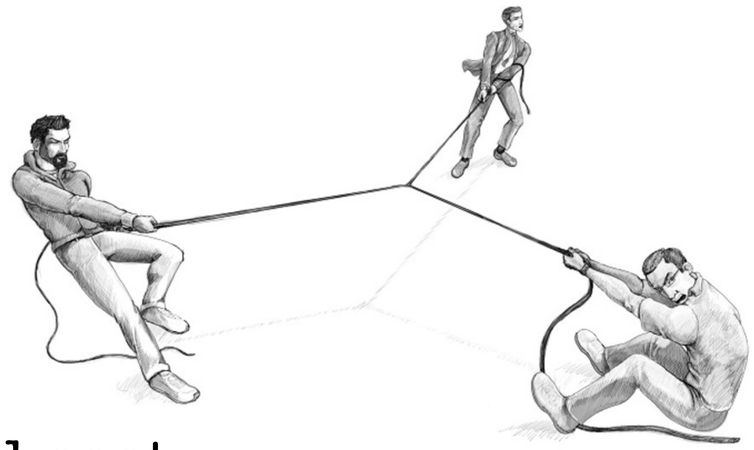
Read cost

Memory/space footprint



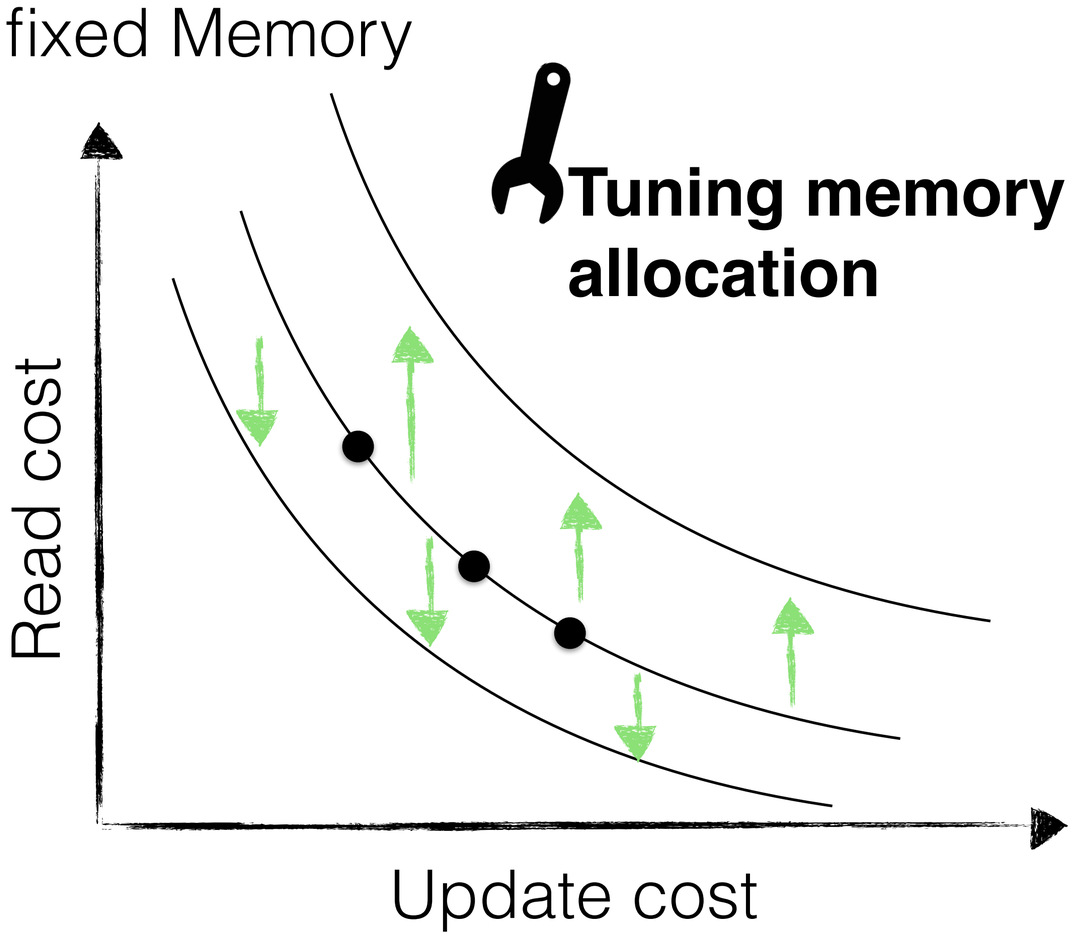
# LSM **Design Space**

Update cost

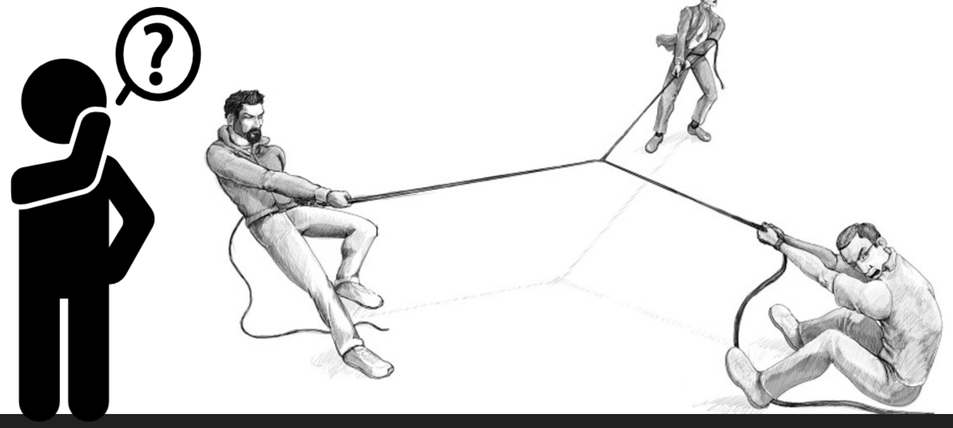


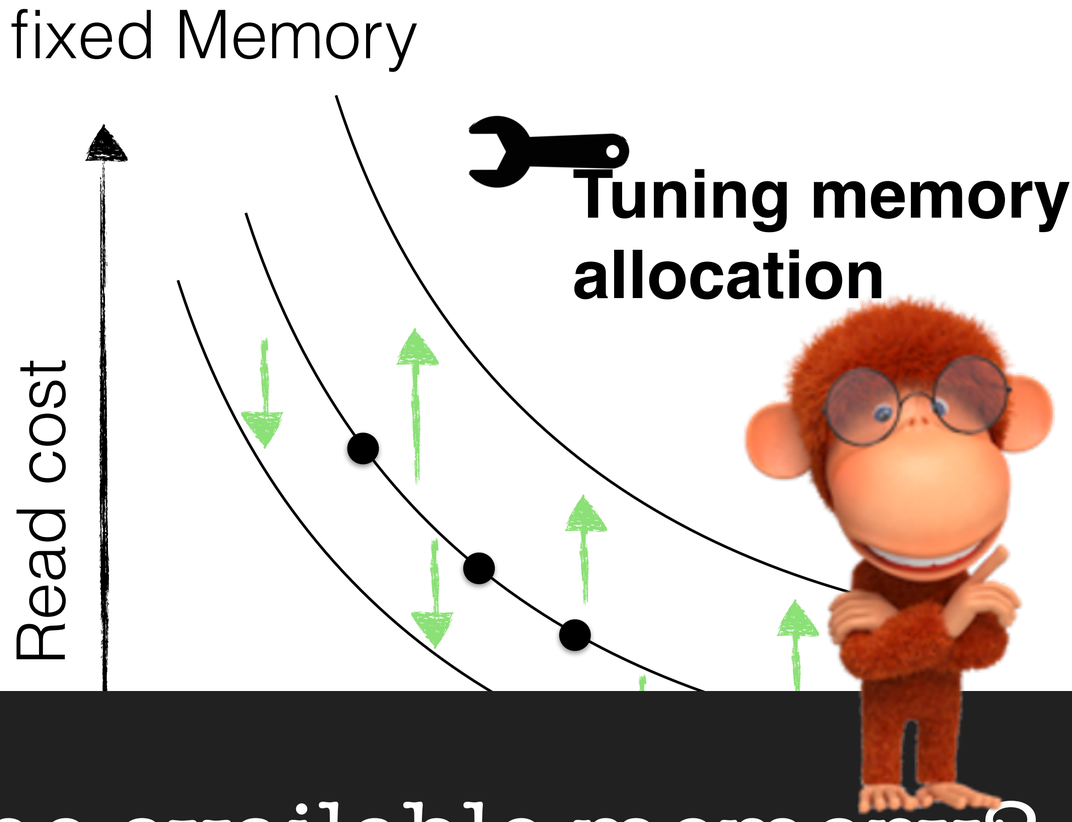
Read cost

Memory/space footprint

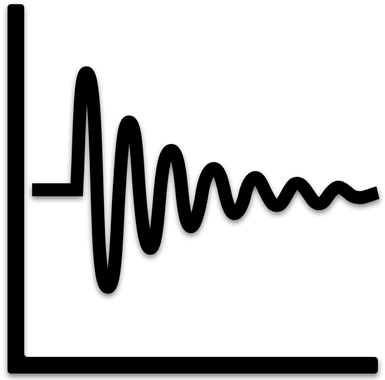


# LSM **Design Space**

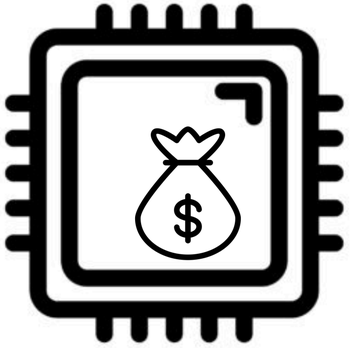


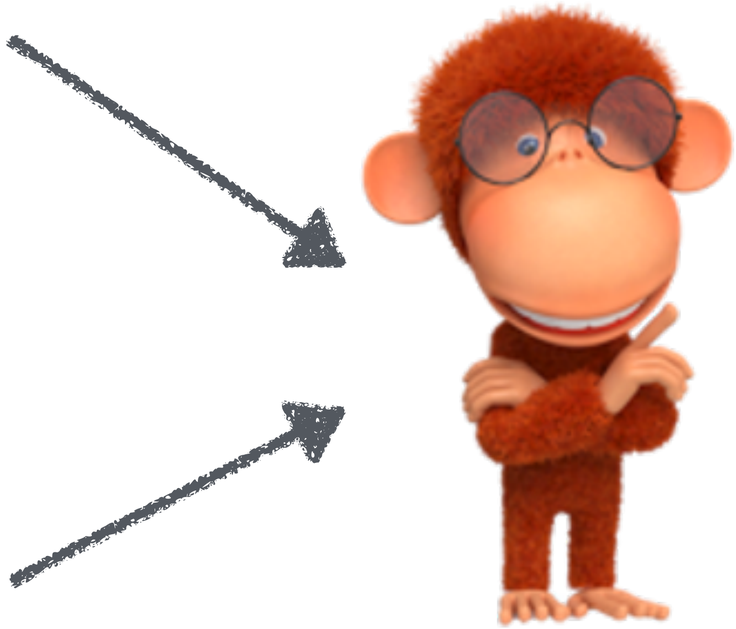

How to optimally allocate the available memory?



workload

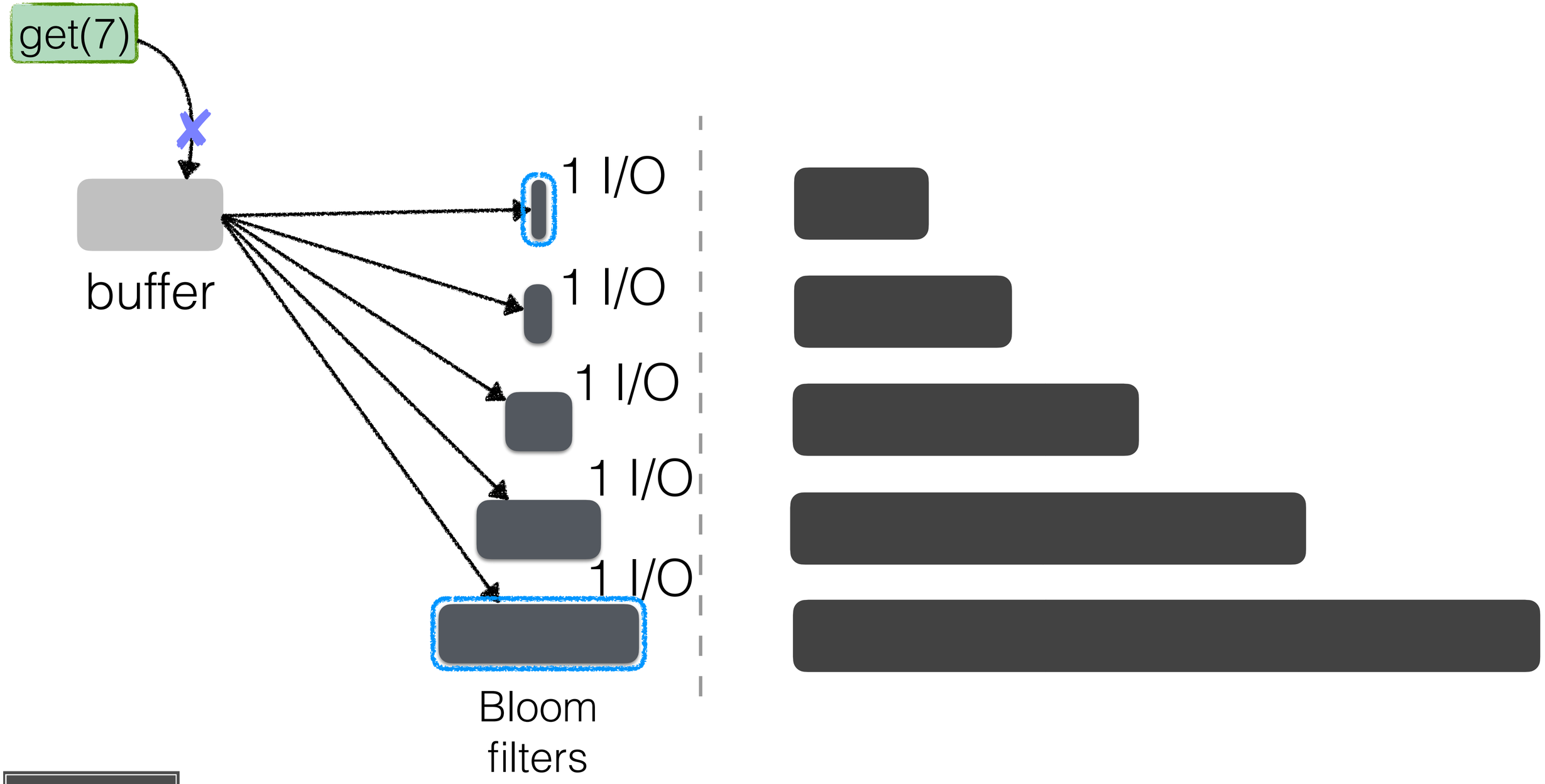


memory budget

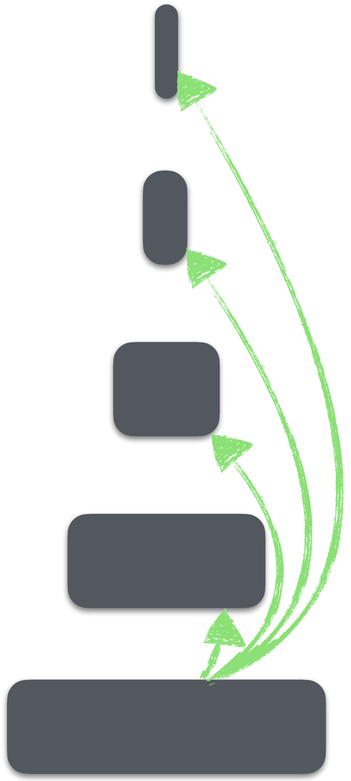


How to allocate memory between buffer and BF

How to allocate memory among BFs in LSM


get(7)
buffer
1 I/O
1 I/O
1 I/O
1 I/O
1 I/O
Bloom
filters

Bloom filters



FPR

Monkey FPR

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

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

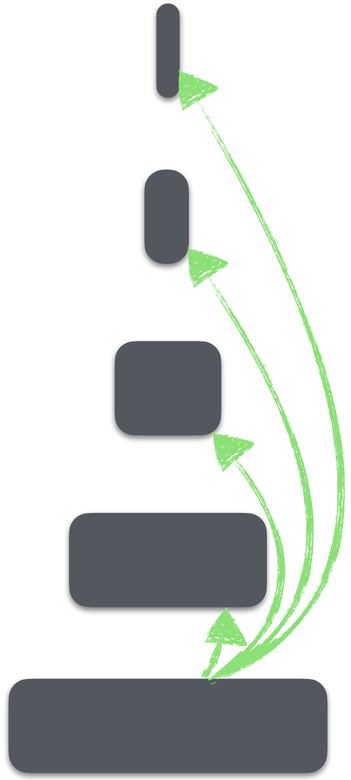
$$\phi > \phi_3 = \phi_0/T^2$$

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

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

exponentially decreasing

Bloom filters



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

exponentially decreasing

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

point lookup cost

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

$$\vee$$

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

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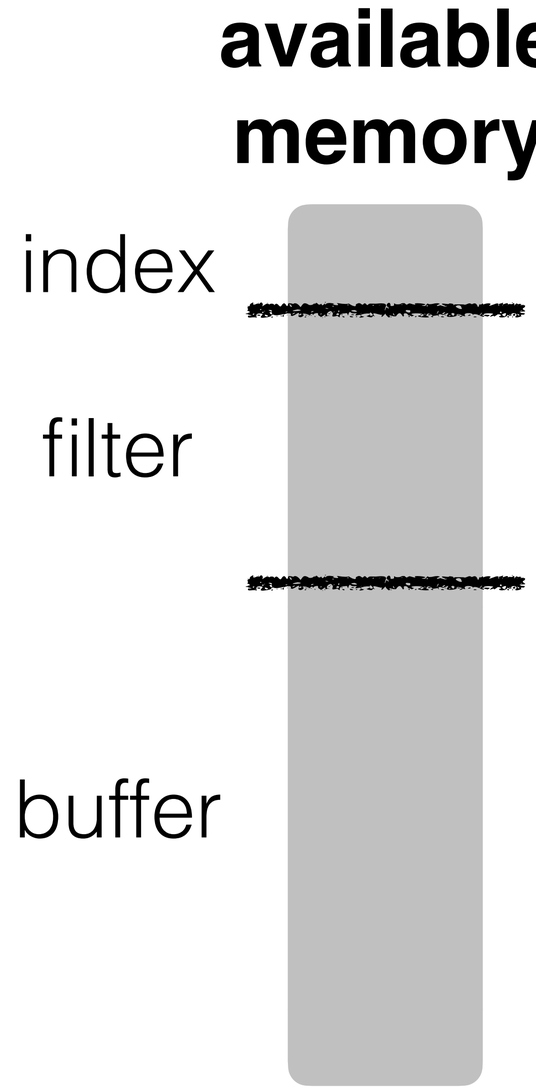
DayanSIGMOD17

# The **Optimal** Memory Allocation

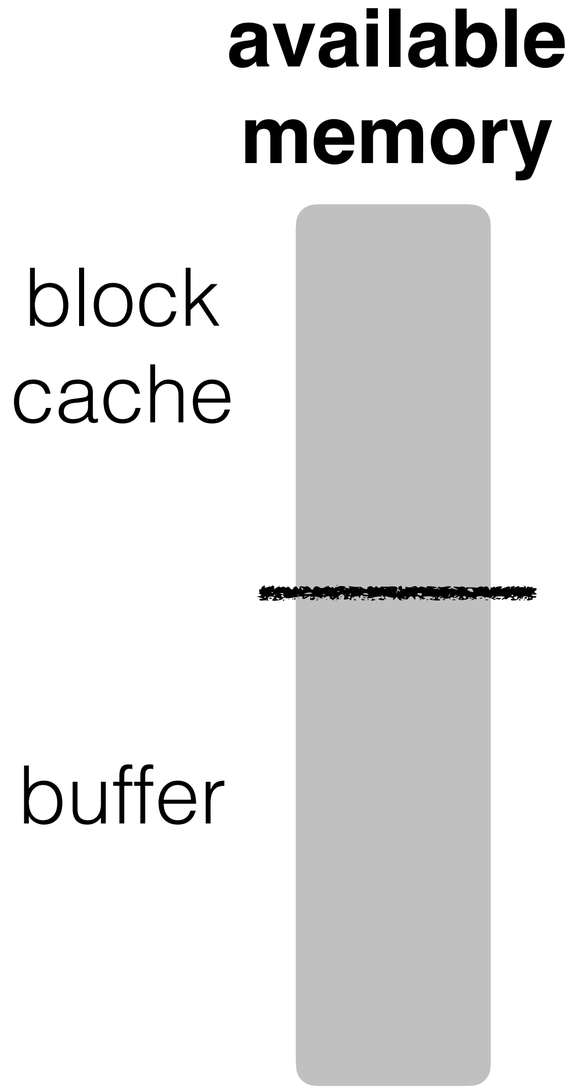



read_cost(N, mem_idx, mem_filt, mem_buf)

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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[Open Problem]

# The **Optimal** Memory Allocation

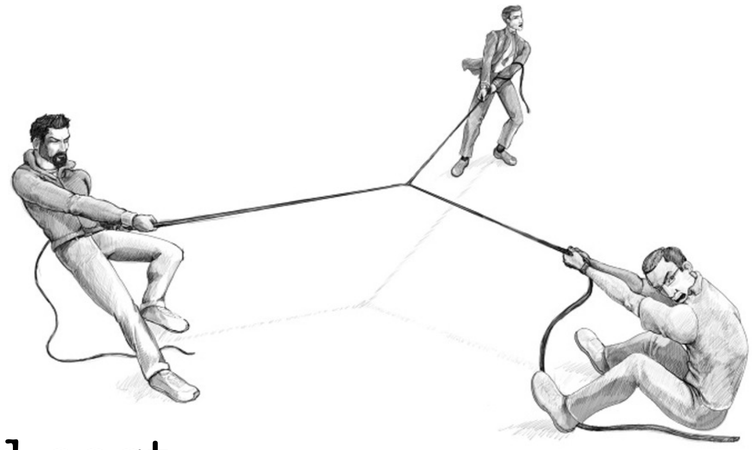
**available memory**

index

filter

block cache

buffer



Update cost

Read cost

Memory/space footprint

Holistic memory allocation & tuning

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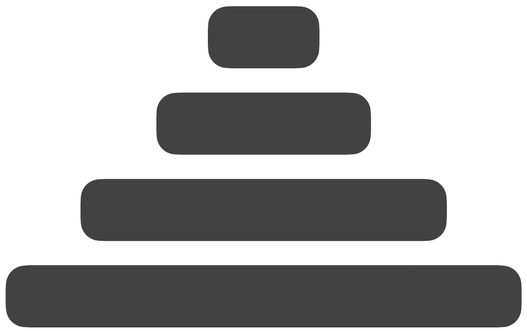
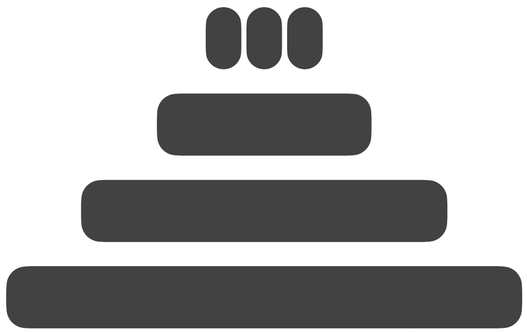
# Storage Layer **Design Continuum**

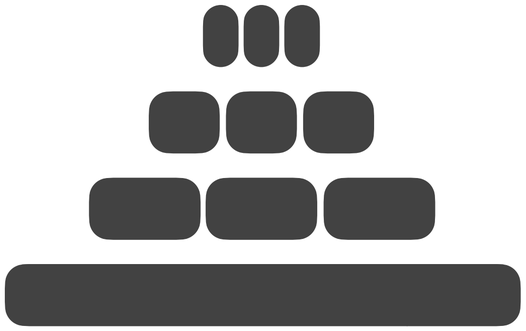
leveling



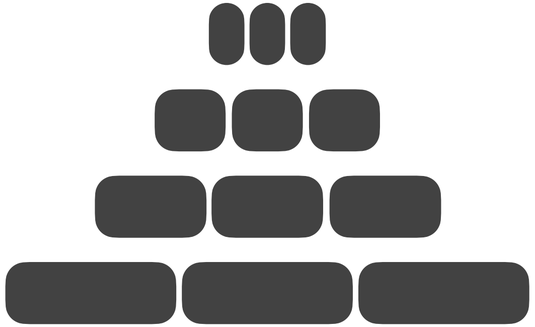
1-leveling



L-leveling



tiering

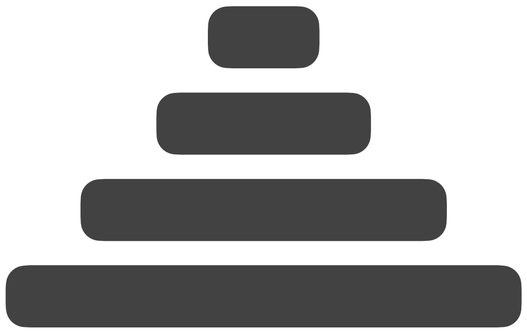


Any design can be defined by the tuple-set: $(\mathtt{T}, \mathtt{i})$

# Storage Layer **Design Continuum**

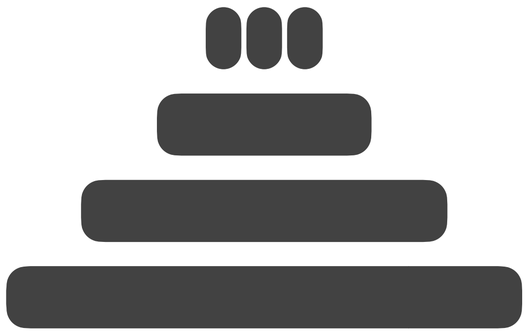
leveling

(T, 0)



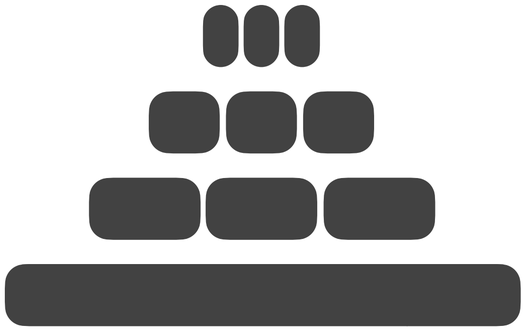
1-leveling

(T, 1)



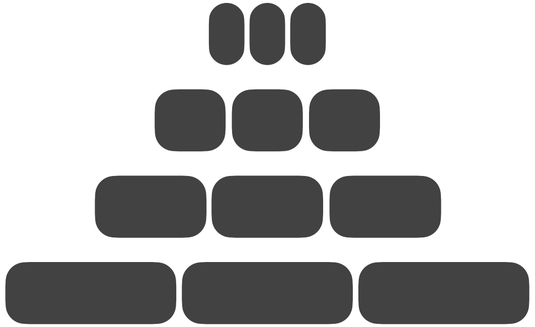
L-leveling

(T, L)



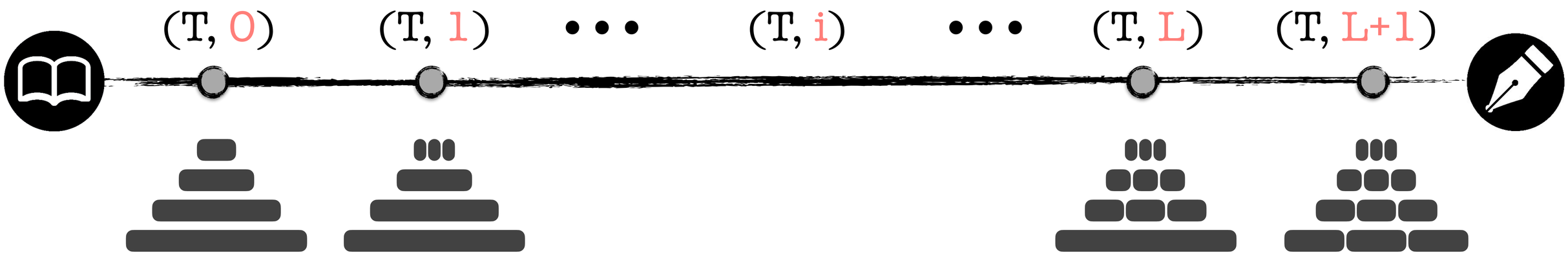
tiering

(T, L+1)

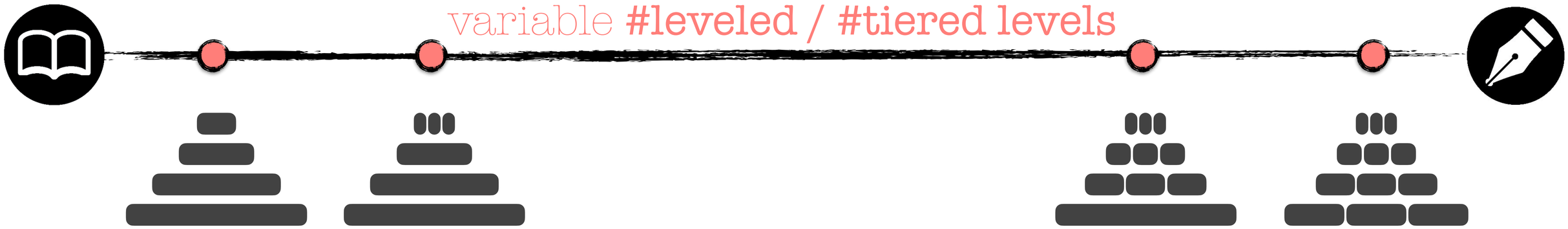


Any design can be defined by the tuple-set: (T, i)

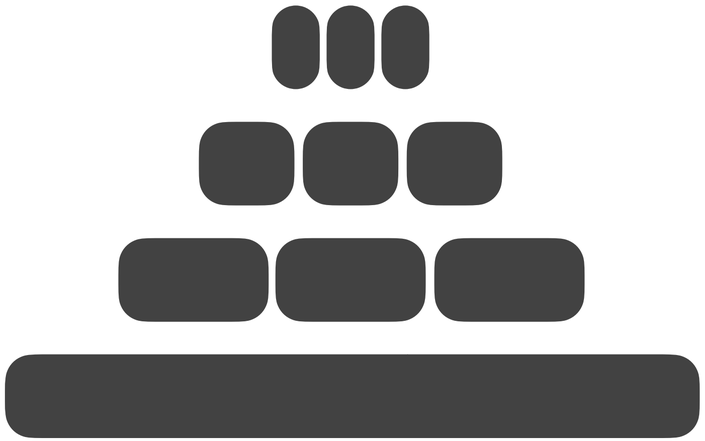
# Storage Layer **Design Continuum**



# Storage Layer **Design Continuum**



# Storage Layer **Design Continuum**

size ratio

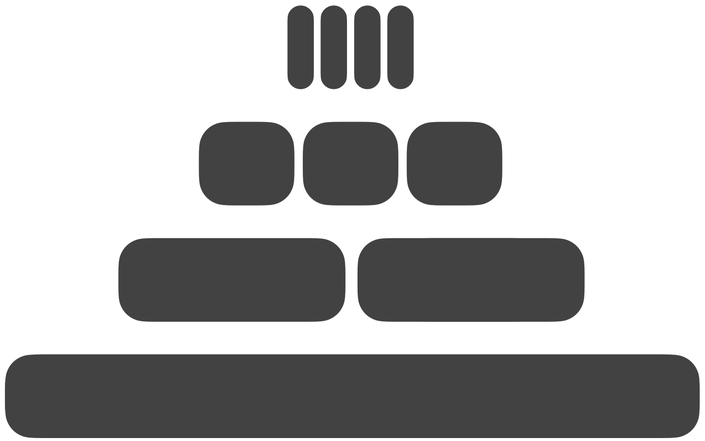
T

T

T

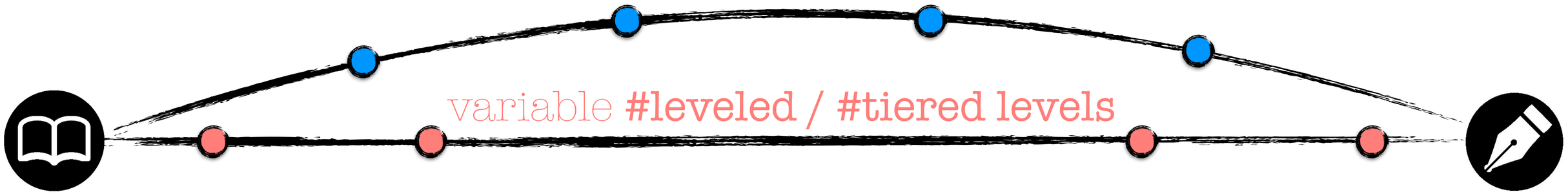
T

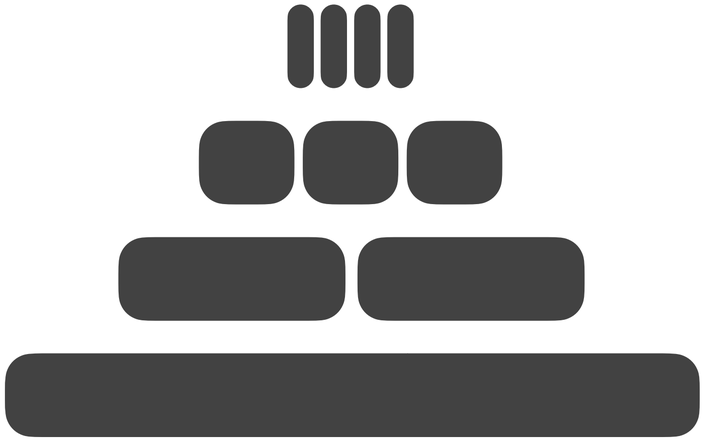
# Storage Layer **Design Continuum**

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

# Storage Layer **Design Continuum**

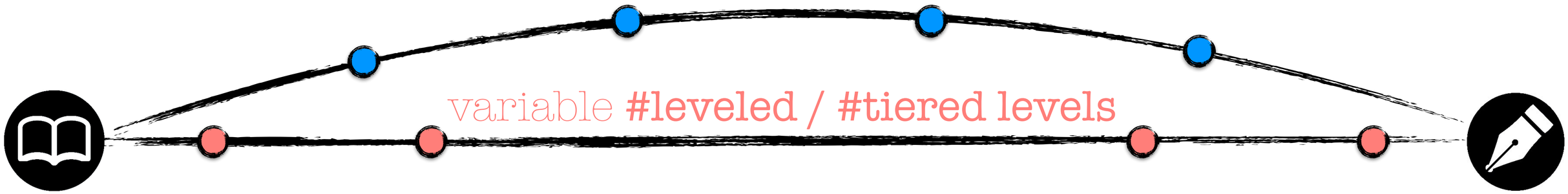


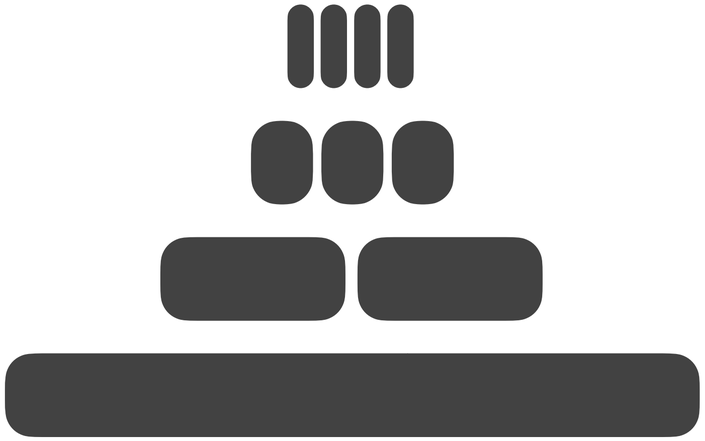
| size ratio | #runs |
|---|---|
| T | 4 |
| T | 3 |
| T | 2 |
| T | 1 |

# Storage Layer **Design Continuum**

variable **#runs/level**

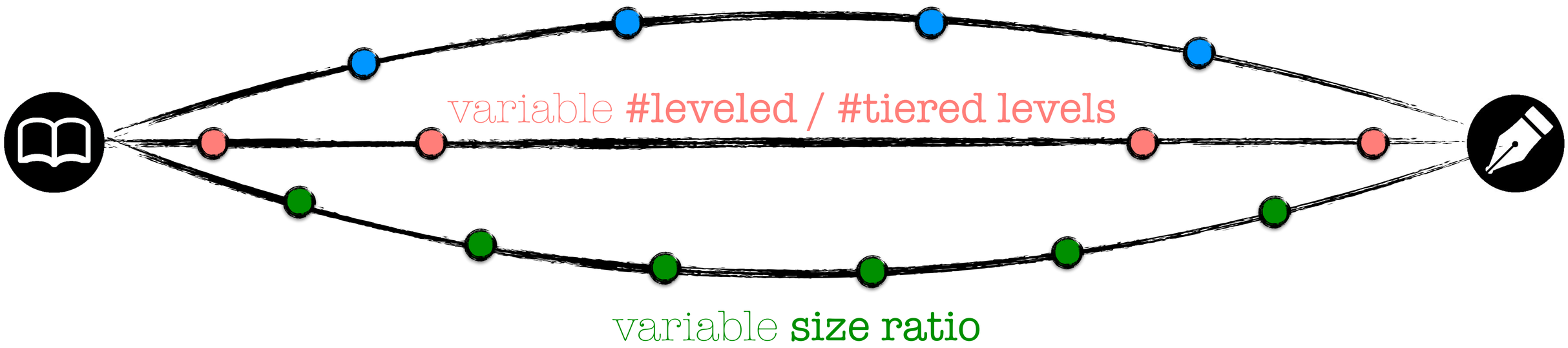


variable **#leveled / #tiered levels**

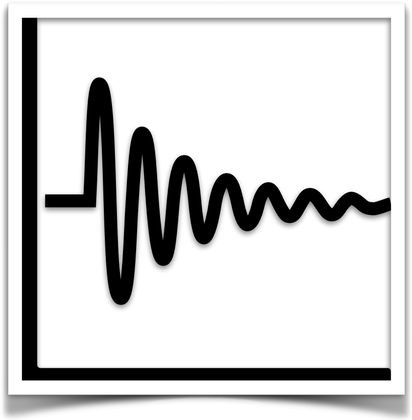


| size ratio | #runs |
|---|---|
| 2 | 4 |
| 2.5 | 3 |
| 3 | 2 |
| 4 | 1 |

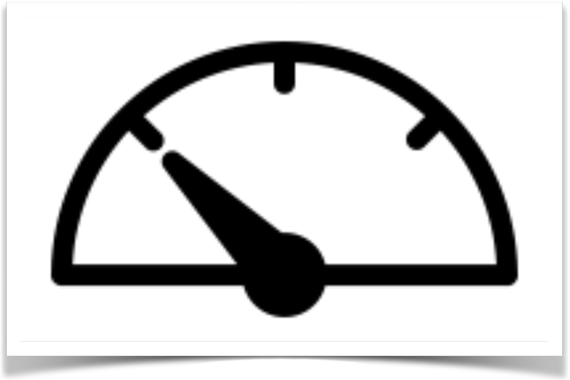
# Storage Layer **Design Continuum**



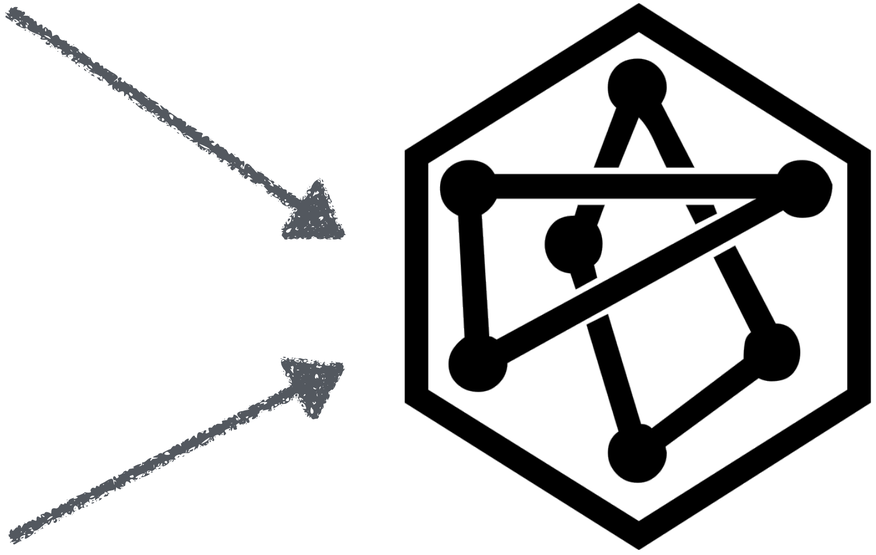

The LSM storage layer design continuum



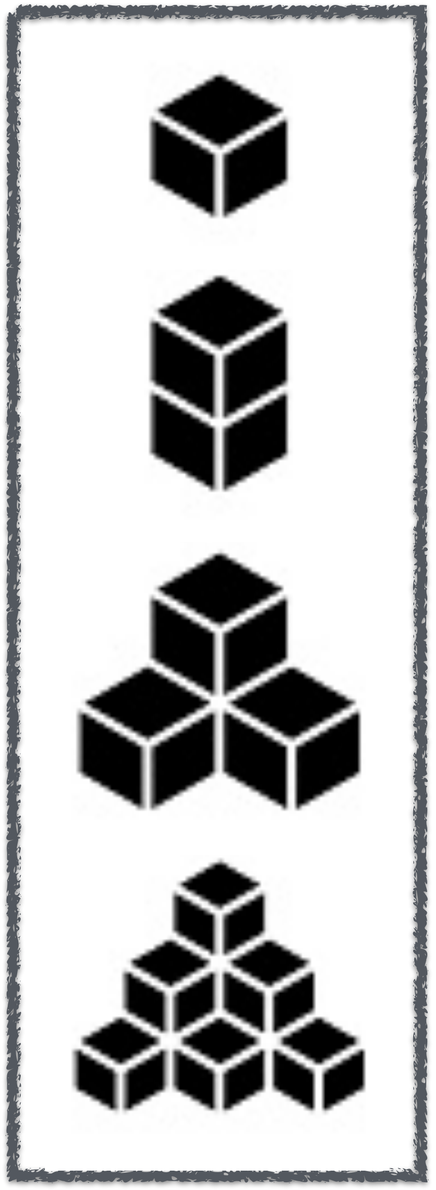
workload



performance target



performance modeling



LSM designs

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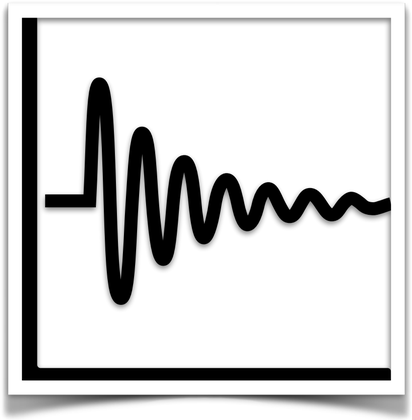
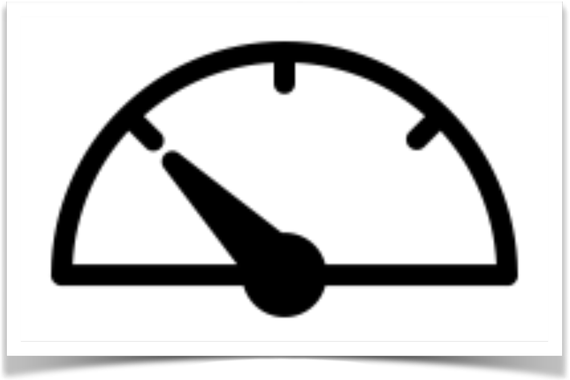
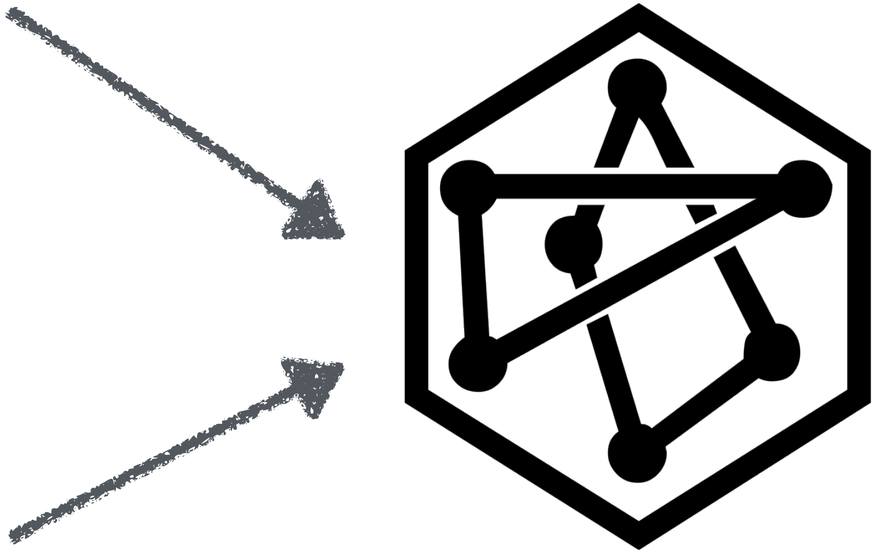


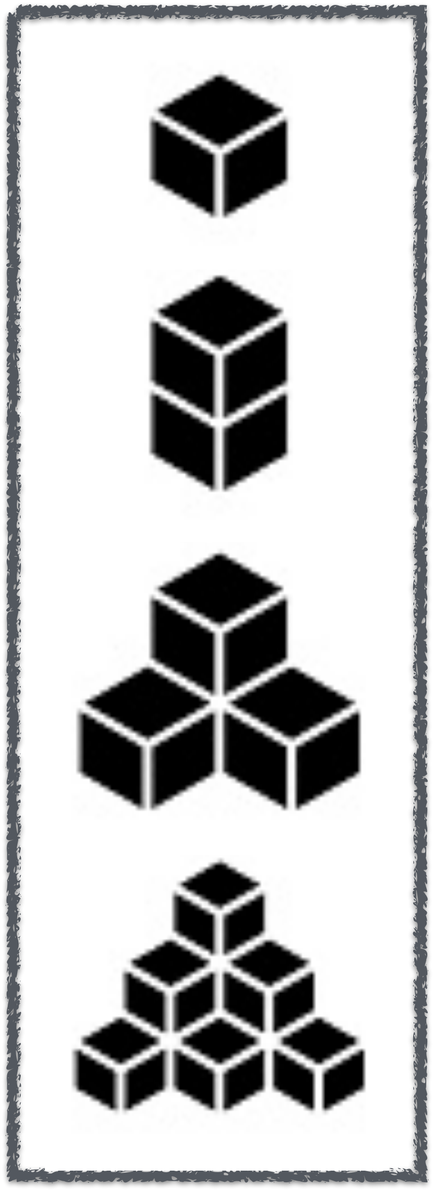
workload



performance target



**worst-case** performance modeling



LSM designs

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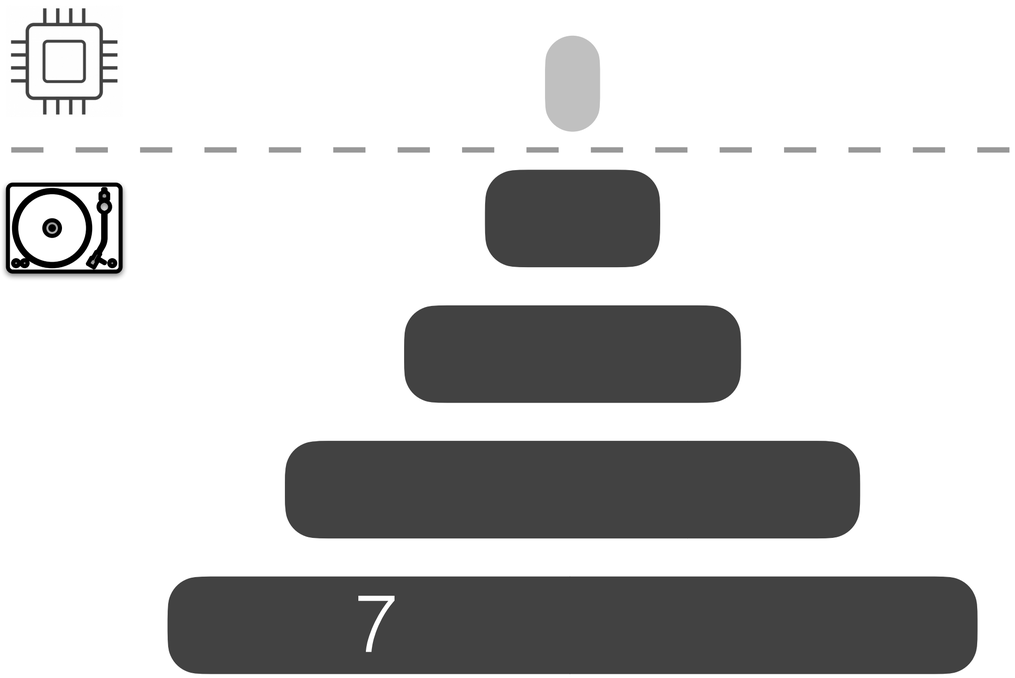
$P$: pages in buffer
$B$: entries/page
$L$: #levels
$T$: size ratio
$N$: #entries
$\phi$ : FPR of BF

# **worst-case** performance modeling




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

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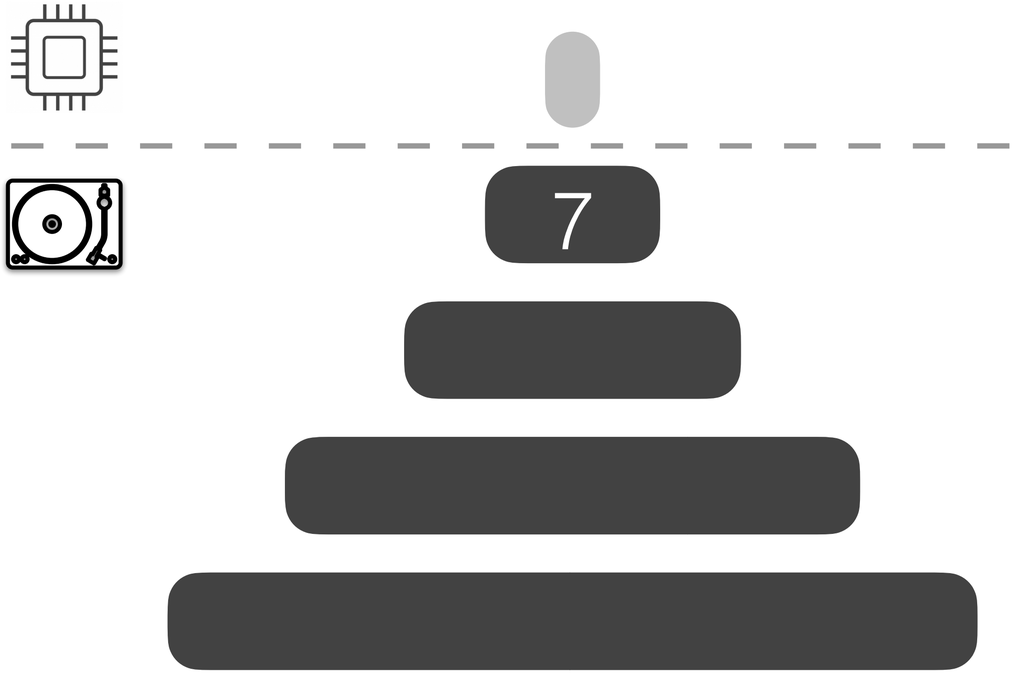
$P$: pages in buffer
$B$: entries/page
$L$: #levels
$T$: size ratio
$N$: #entries
$\phi$ : FPR of BF

**worst-case**
performance
modeling




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

**average-case**
performance
modeling

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

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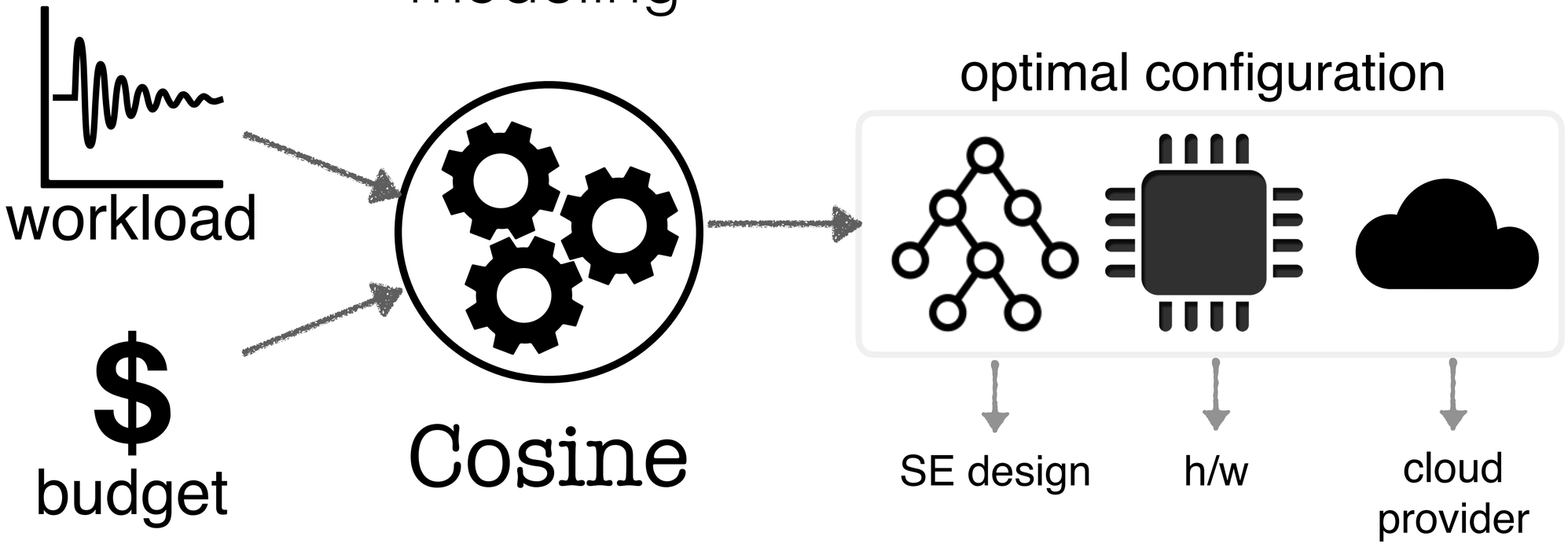
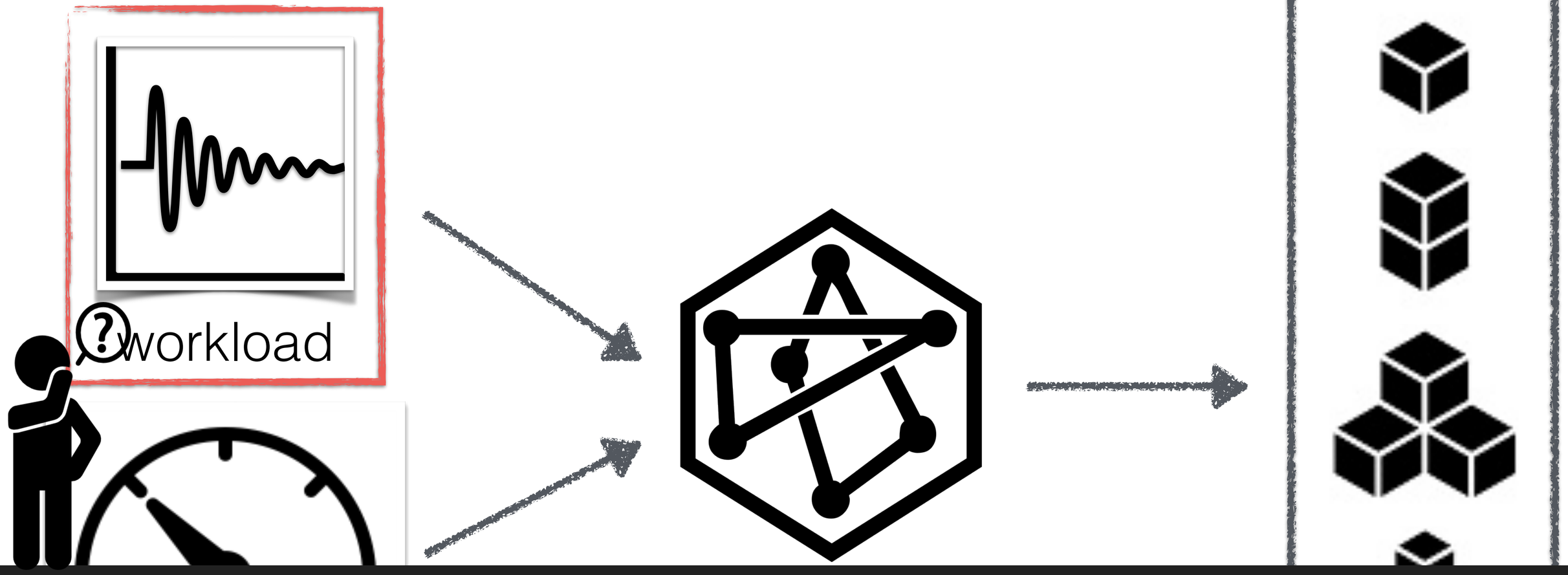
**average-case**
performance
modeling

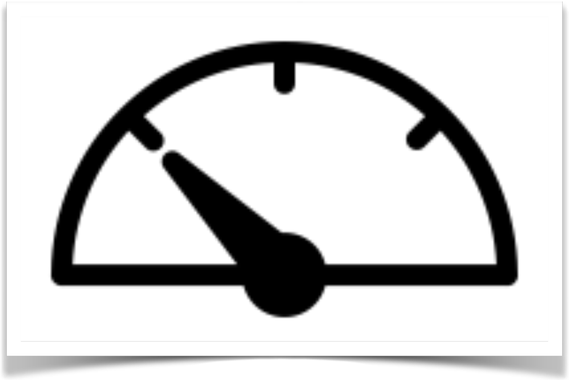




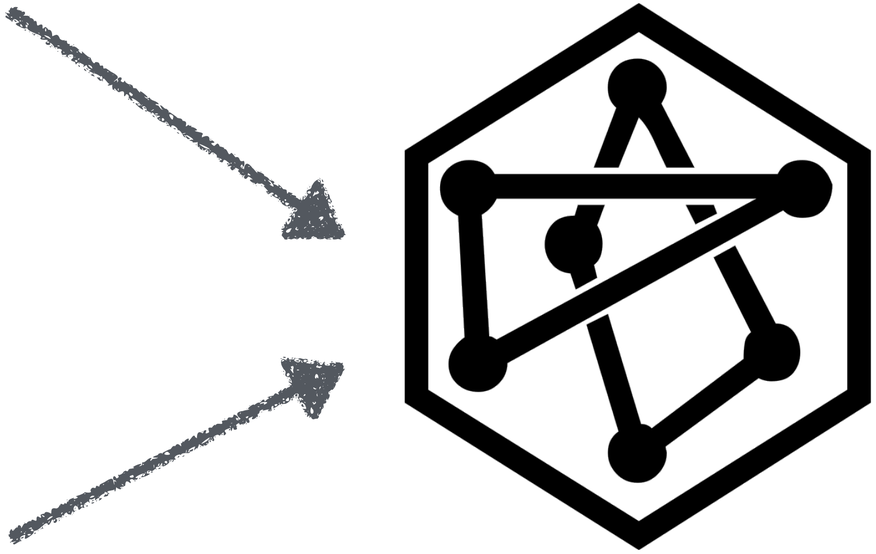

What if the workload changes?

ESM designs

workload

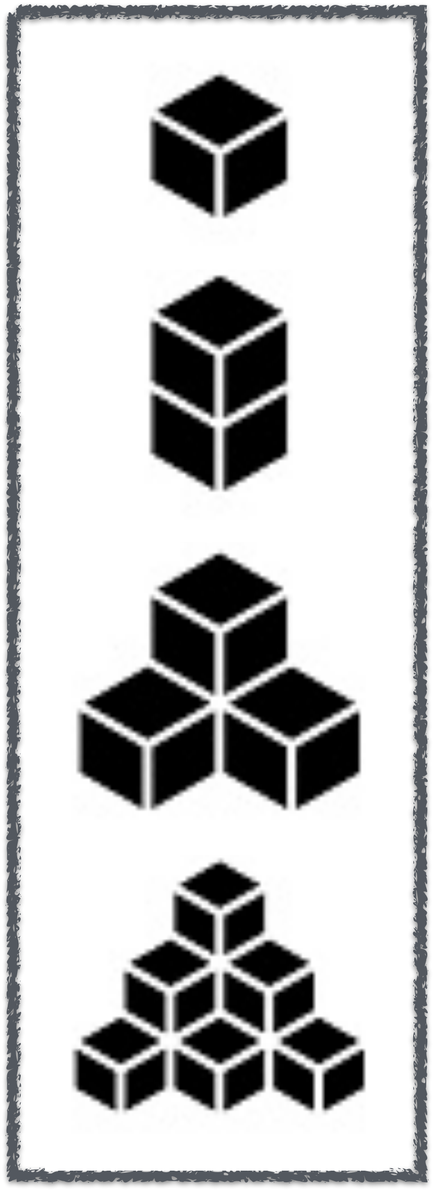


performance target



**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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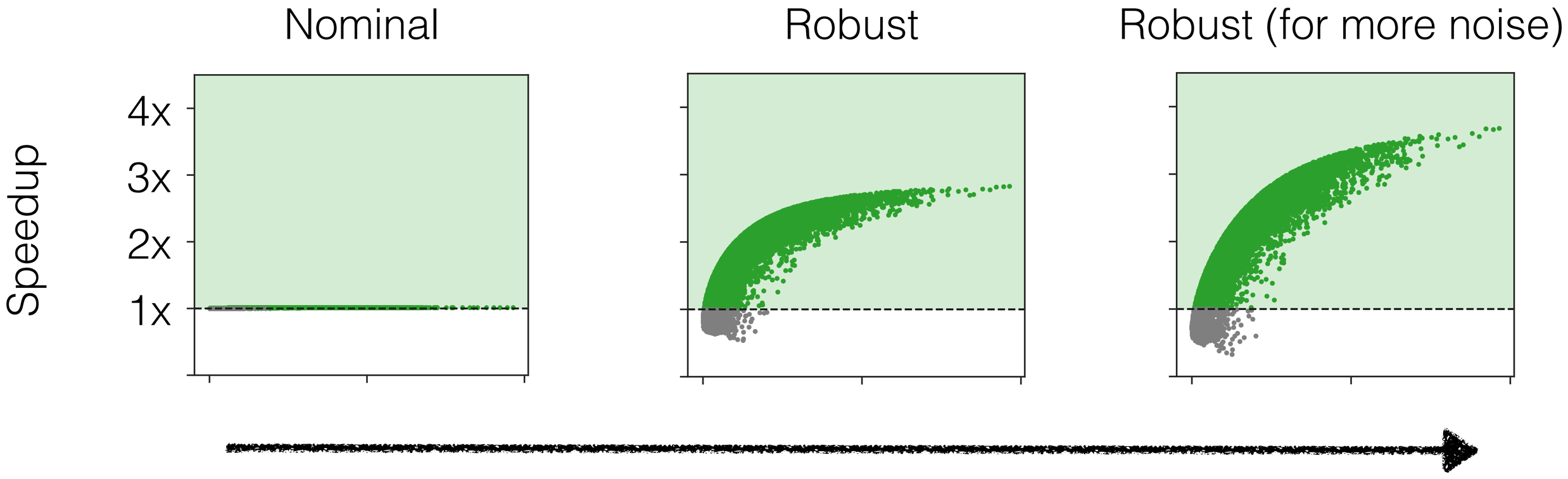
HuynhVLDB22

# **Robust** Tuning

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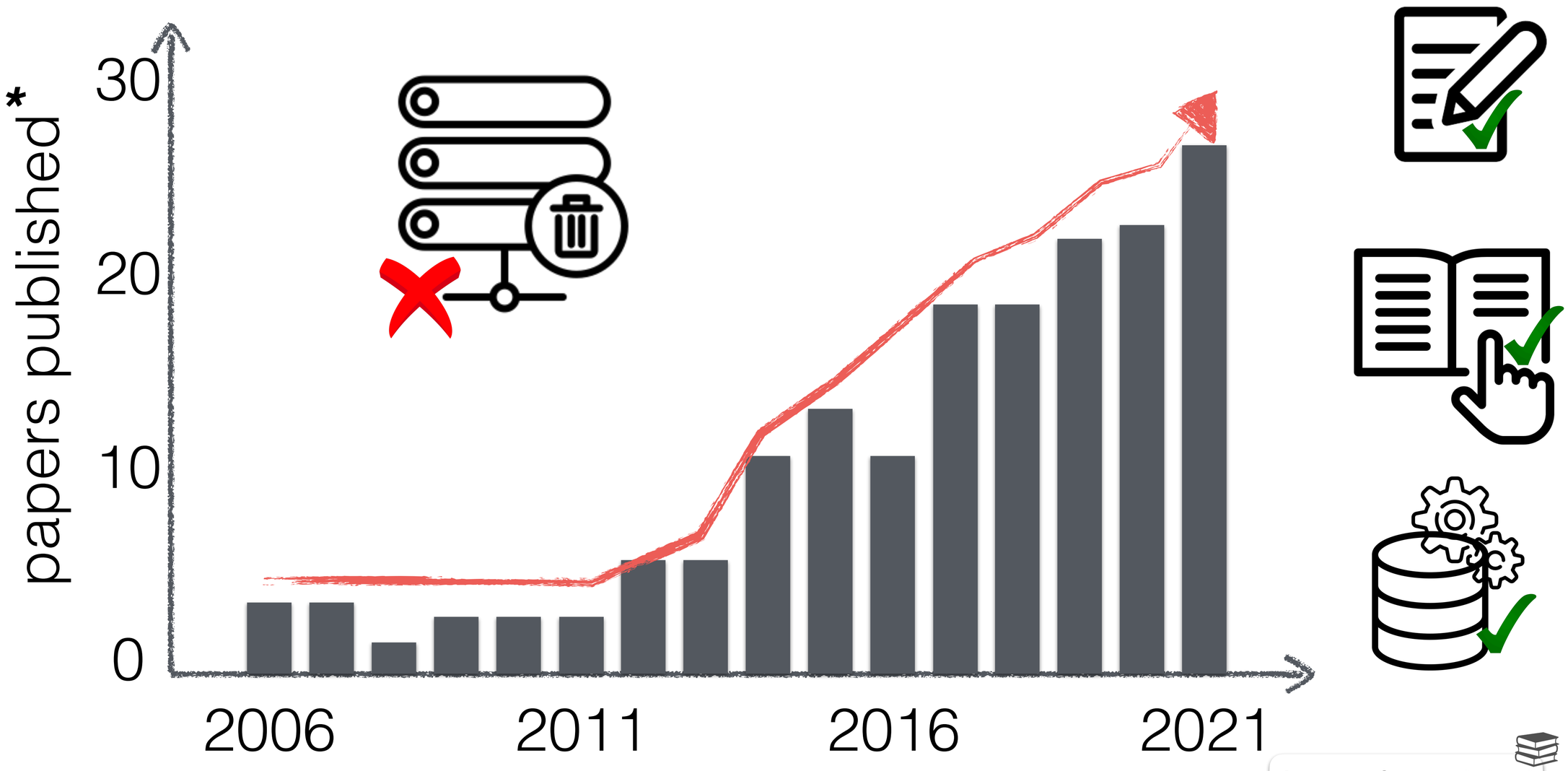
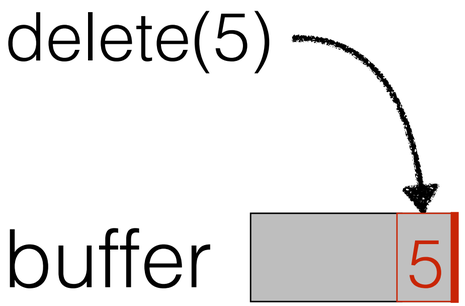
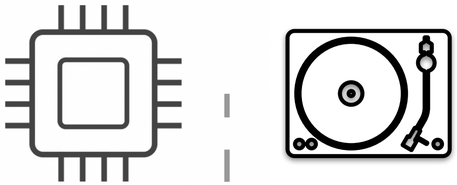
# Research Trend: **What about Deletes?**

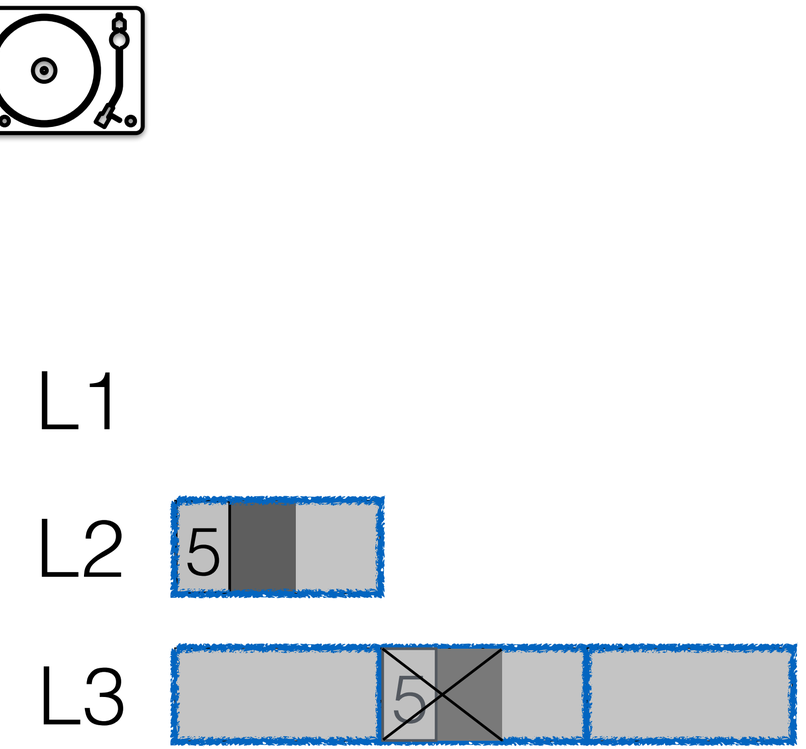



* data from DBLP

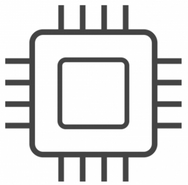
# deletes in LSM-tree

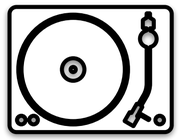




# deletes in LSM-tree





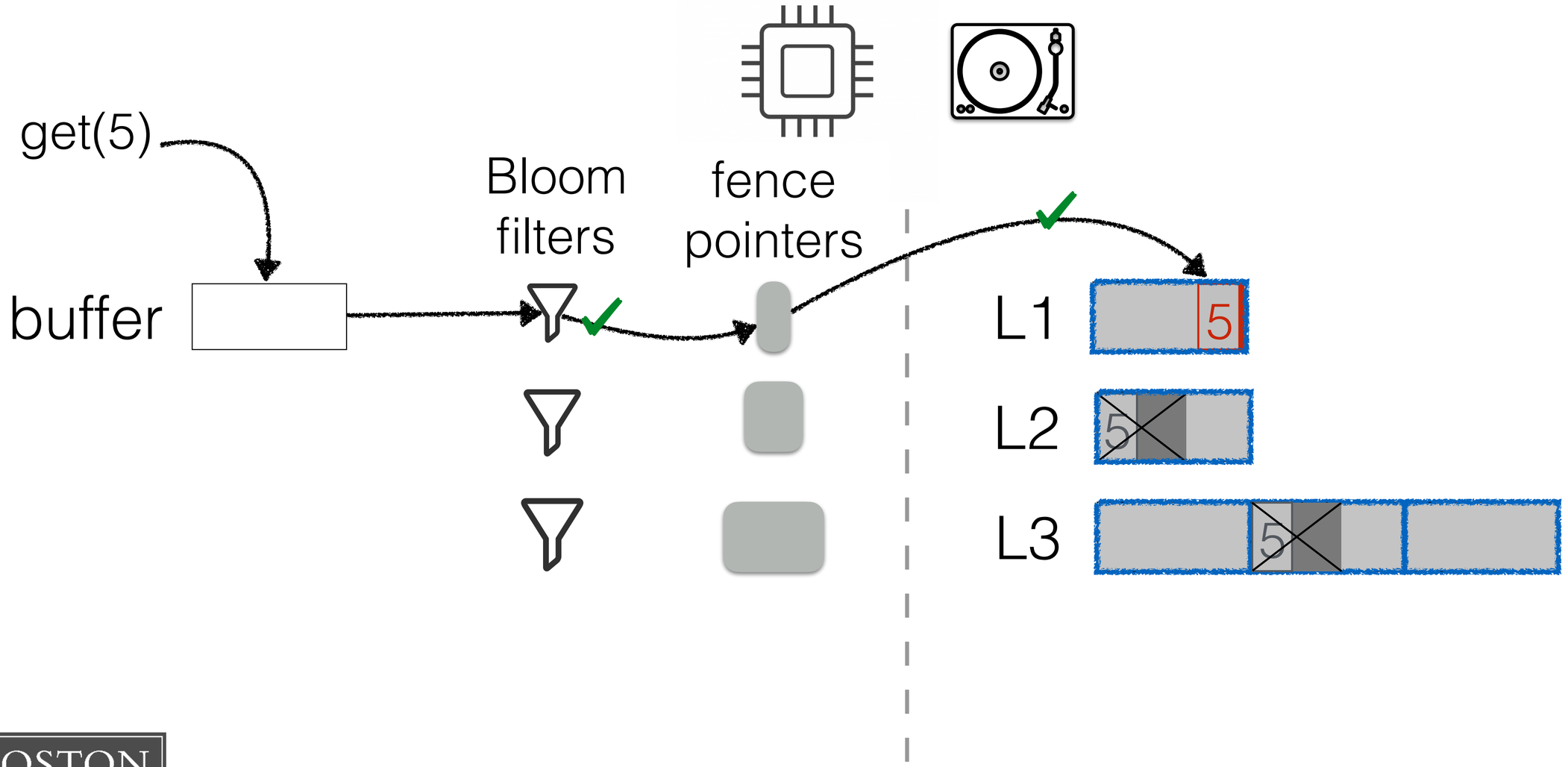
buffer

L1

L2

L3

# deletes in LSM-tree



| Large-scale production | Internal DB ops | Privacy |
| --- | --- | --- |
| ZippyDB<br>**25.2M/day** | table drop | GDPR (EU, UK) |
| UP2X<br>**92.5% merge through deletes** | data migration | CCPA (California) |
| | periodic cleanup | VCDPA (Virginia) |

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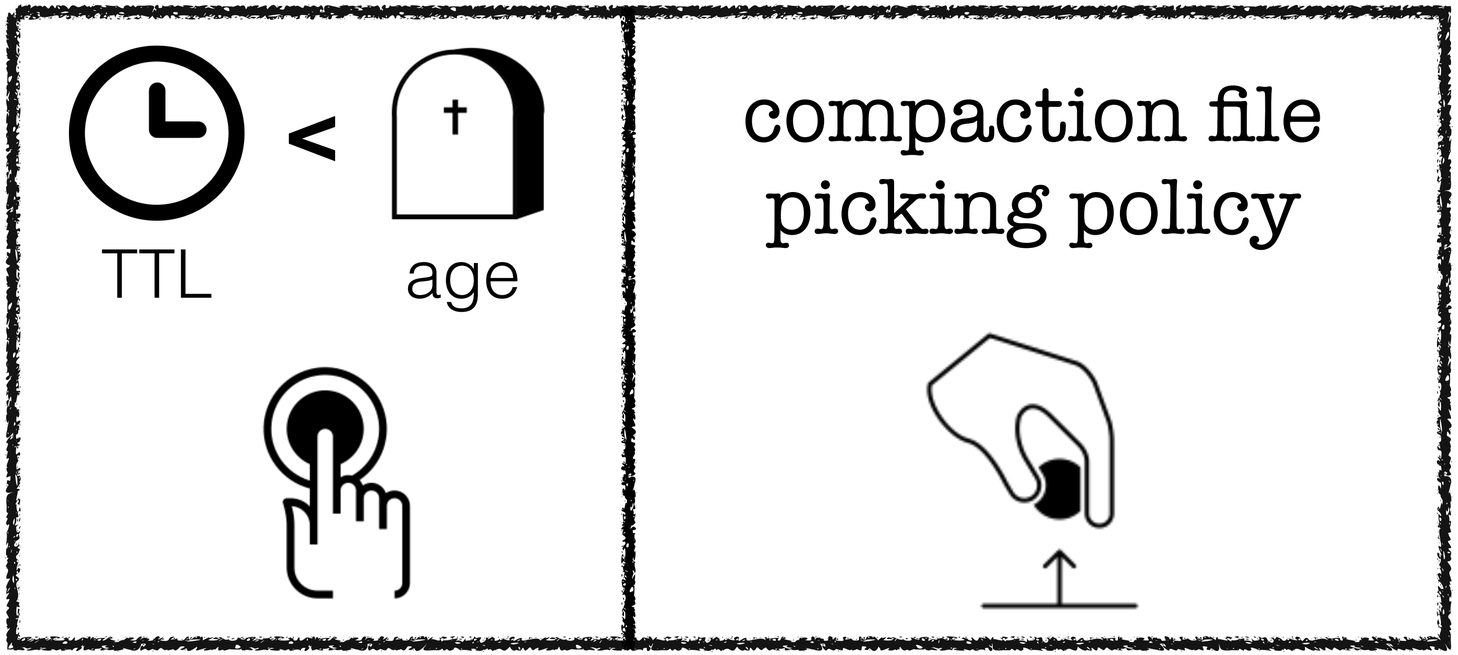
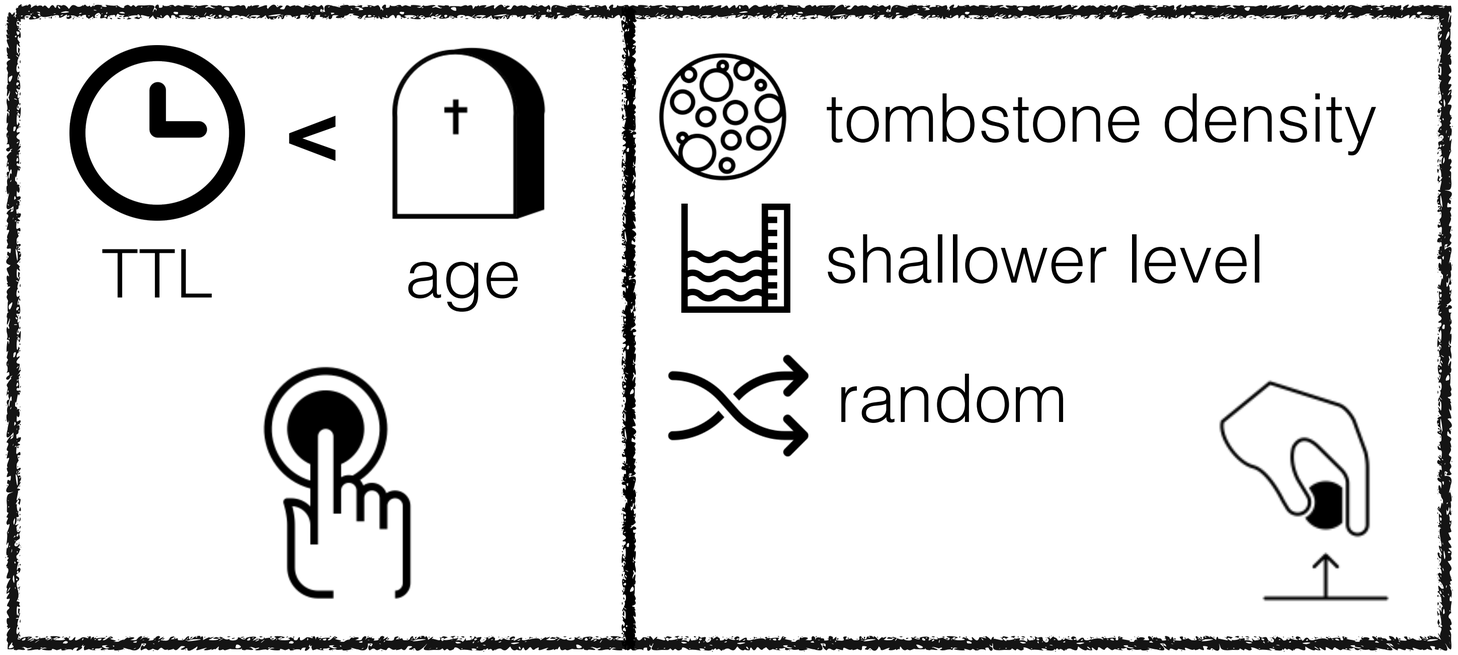
# Facilitating **Timely Deletes**

| compaction trigger | compaction file picking policy |
| --- | --- |
|  |  |

# Facilitating **Timely Deletes**

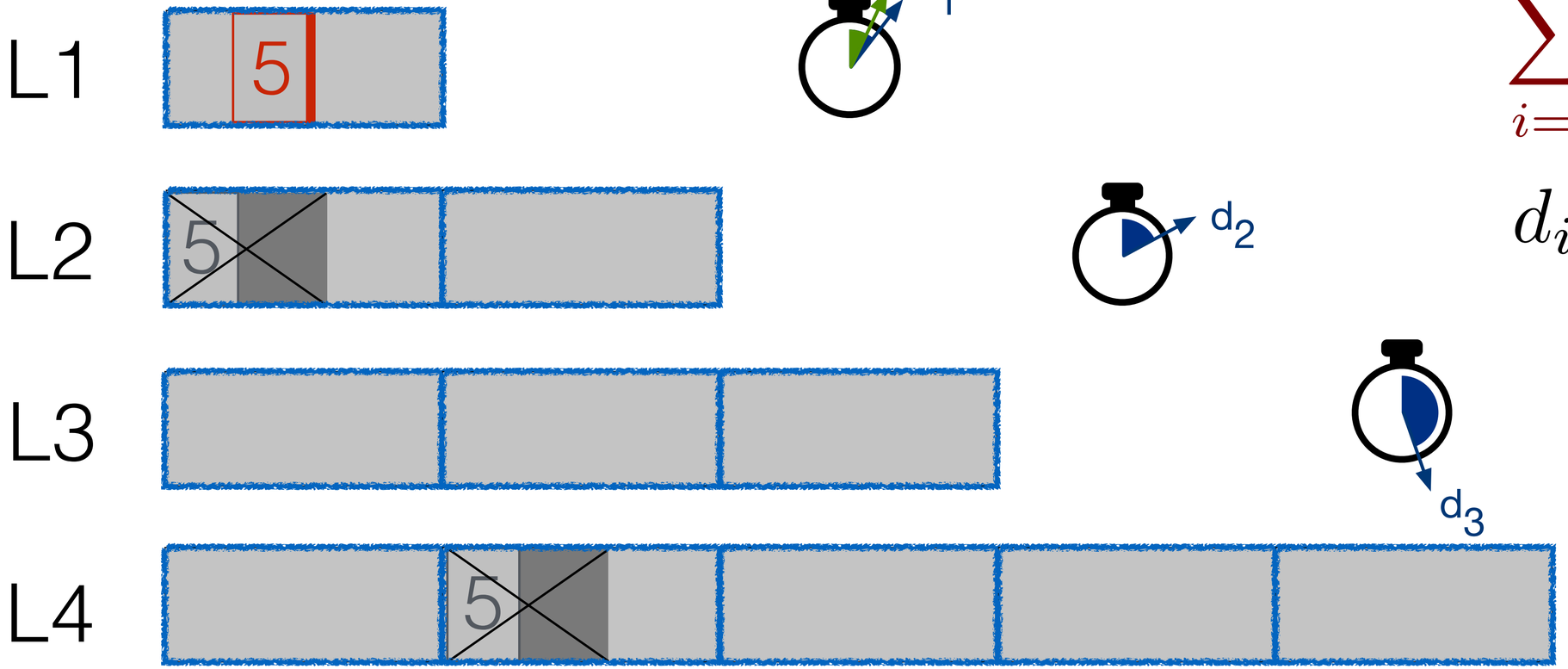


# Facilitating **Timely Deletes**



# 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>};
```

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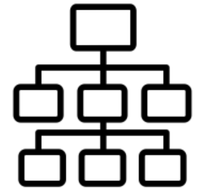
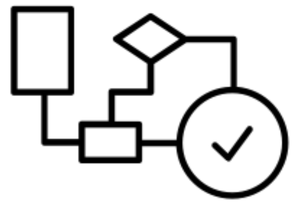
## System layer



Data layout re-organization



Data deletion algorithms

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AthanassoulisDEBull22

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SarkarEDBT22

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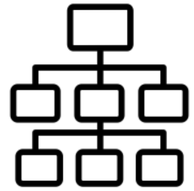
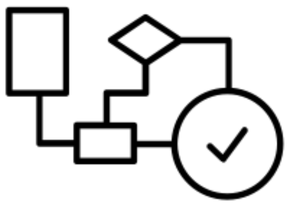


Data layout re-organization



Data deletion algorithms

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SarkarEDBT22

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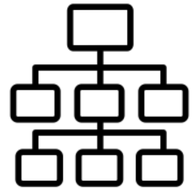

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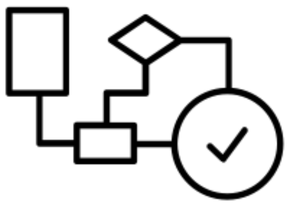

Data deletion algorithms

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# The **Key Takeaways**

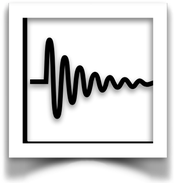
The LSM design space is **vast and complex**.

**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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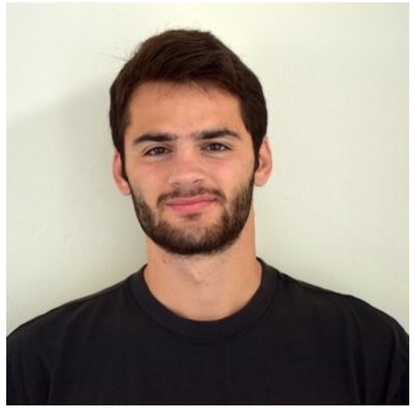
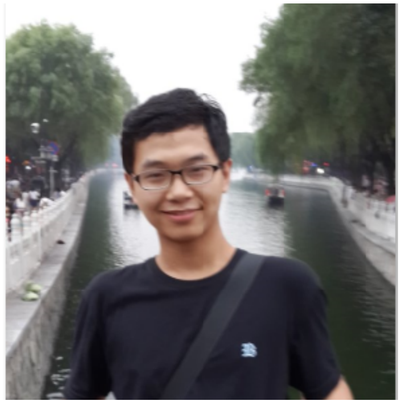
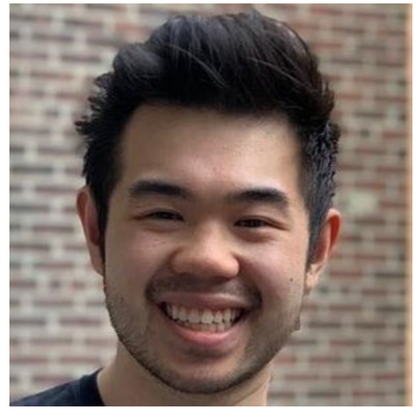



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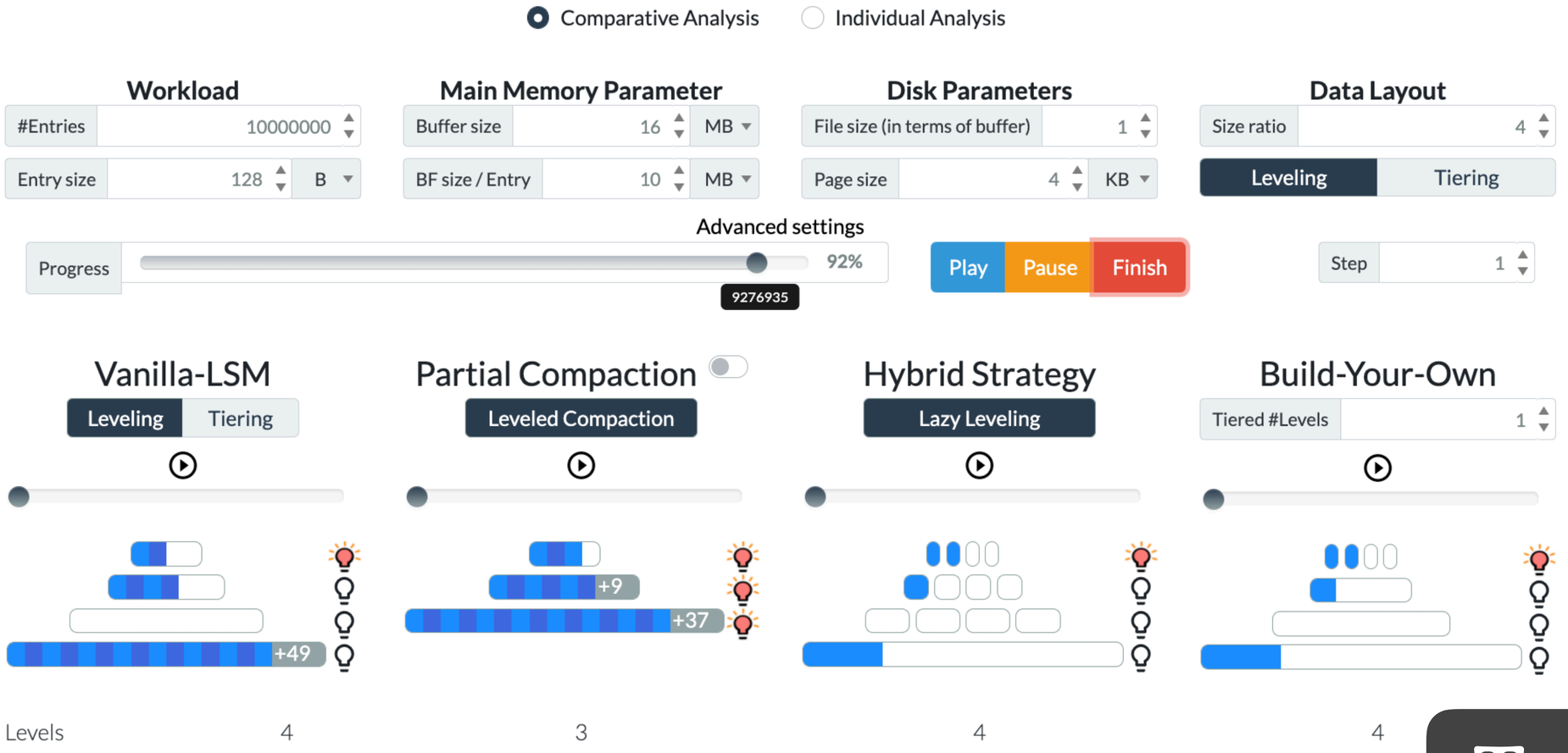
# Don’t Miss: Compactionary




disc-projects.bu.edu/compactionary

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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