BlowFish:
Dynamic Storage-Performance Tradeoff in Data Stores

Anurag Khandelwal, Rachit Agarwal, Ion Stoica


High-Throughput Data Stores

High-Throughput Data Stores

Key-Value Stores

BigTable

amazon DynamoDB

redis

High-Throughput Data Stores

Key-Value Stores

BigTable

amazon DynamoDB

redis

NoSQL Stores

HYPERTABLE

High-Throughput Data Stores

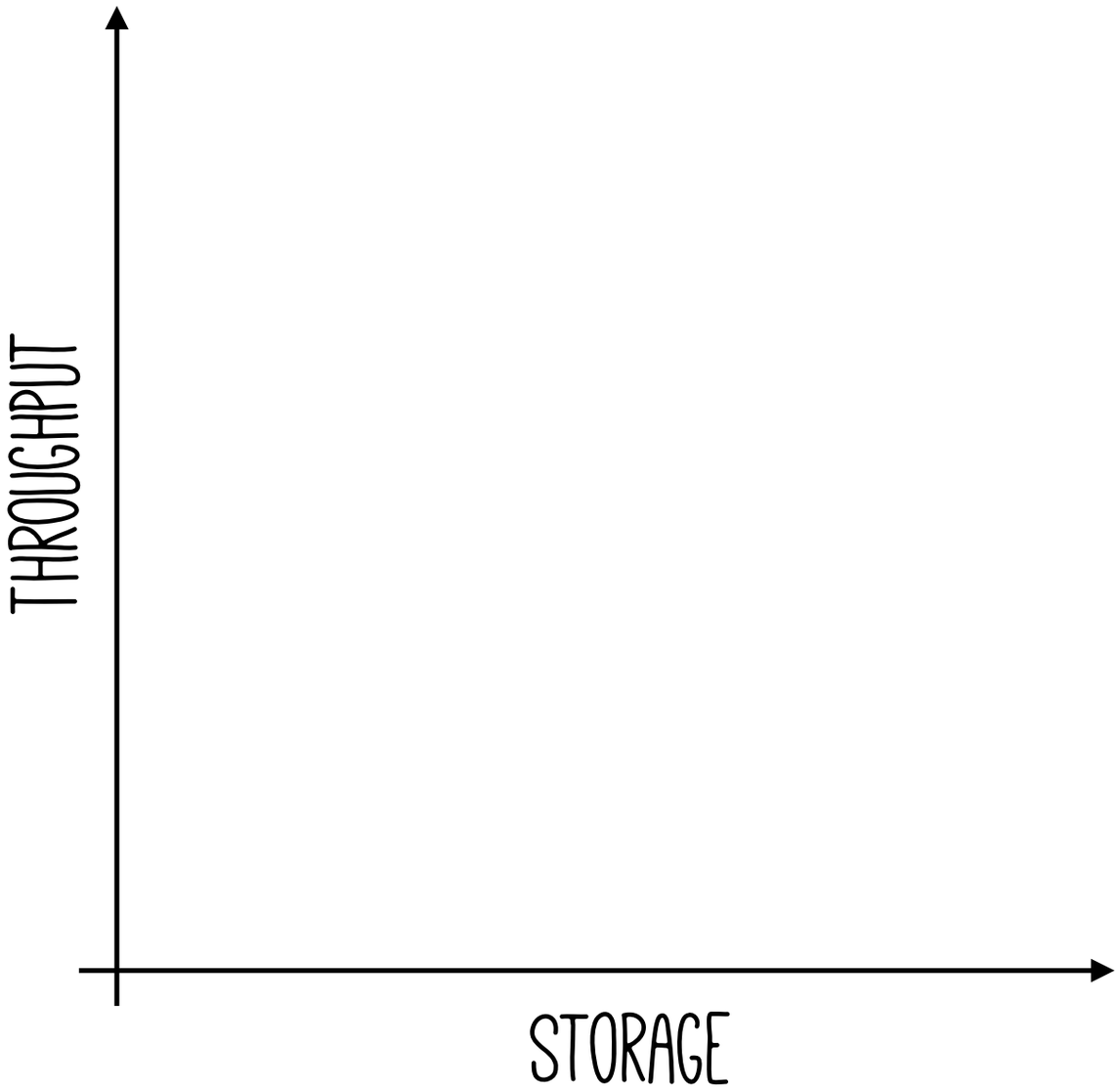
Key-Value Stores

NoSQL Stores

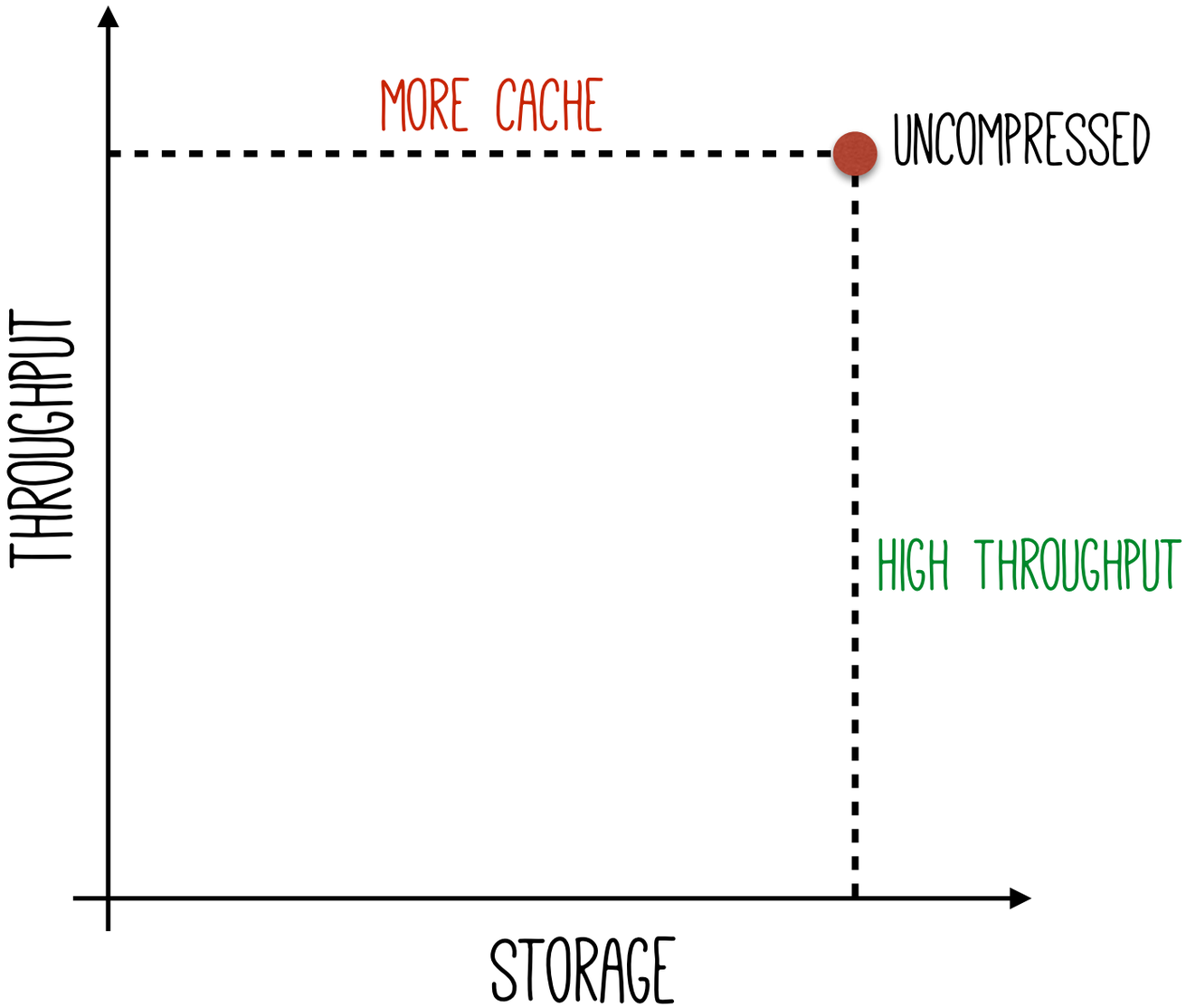
High Throughput: Queries/Second

Existing Data Stores

Existing Data Stores



Existing Data Stores



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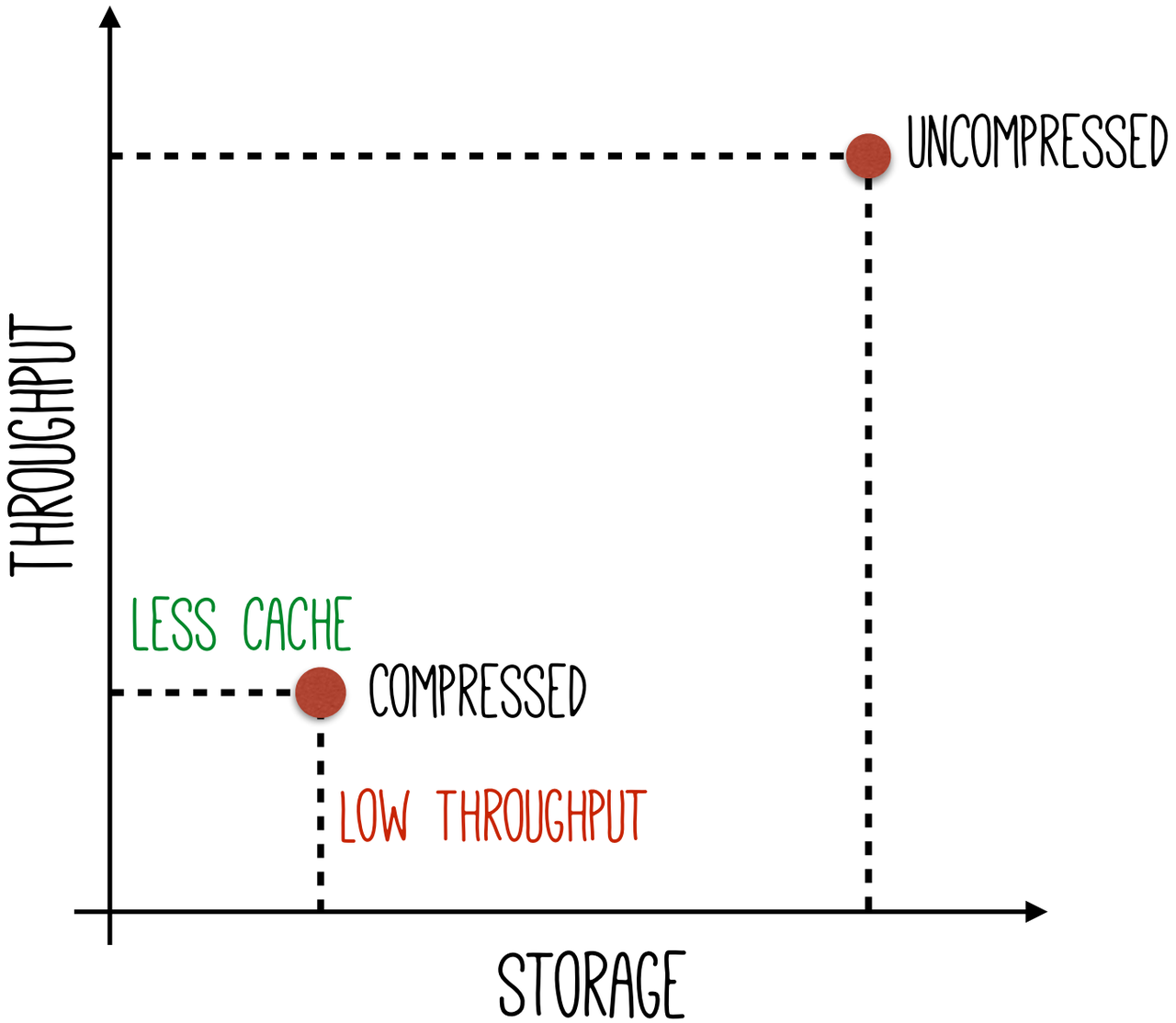

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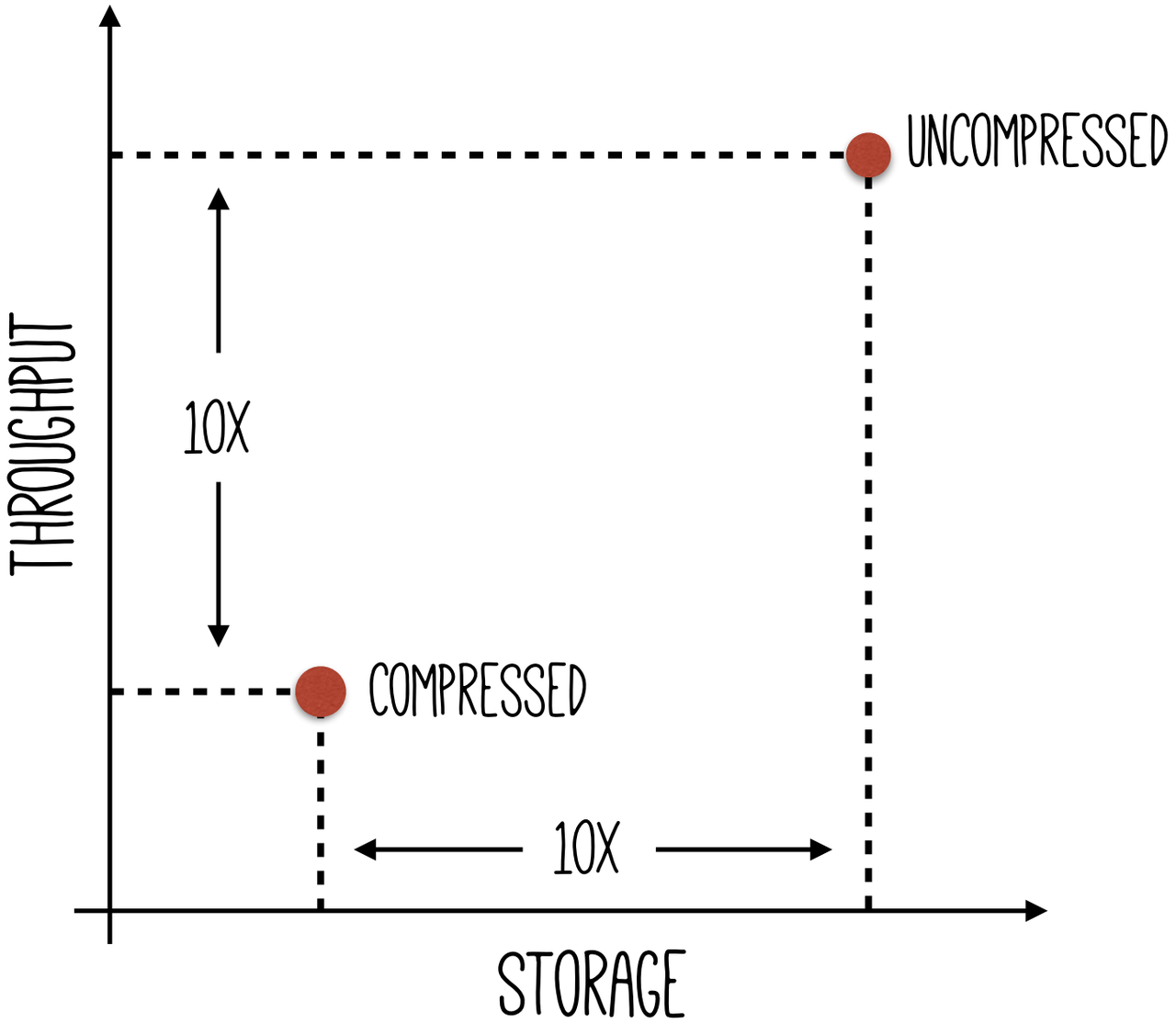

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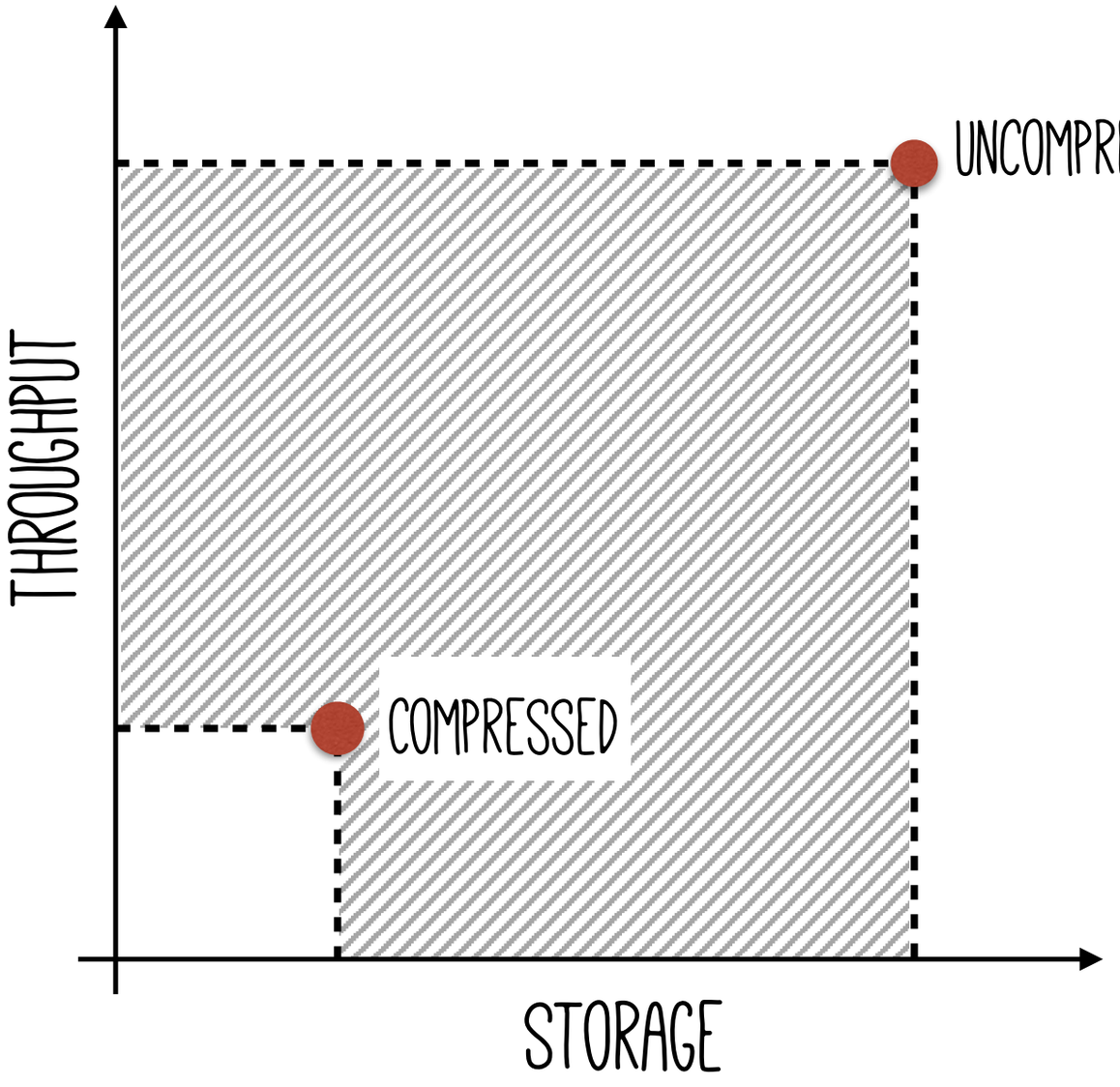
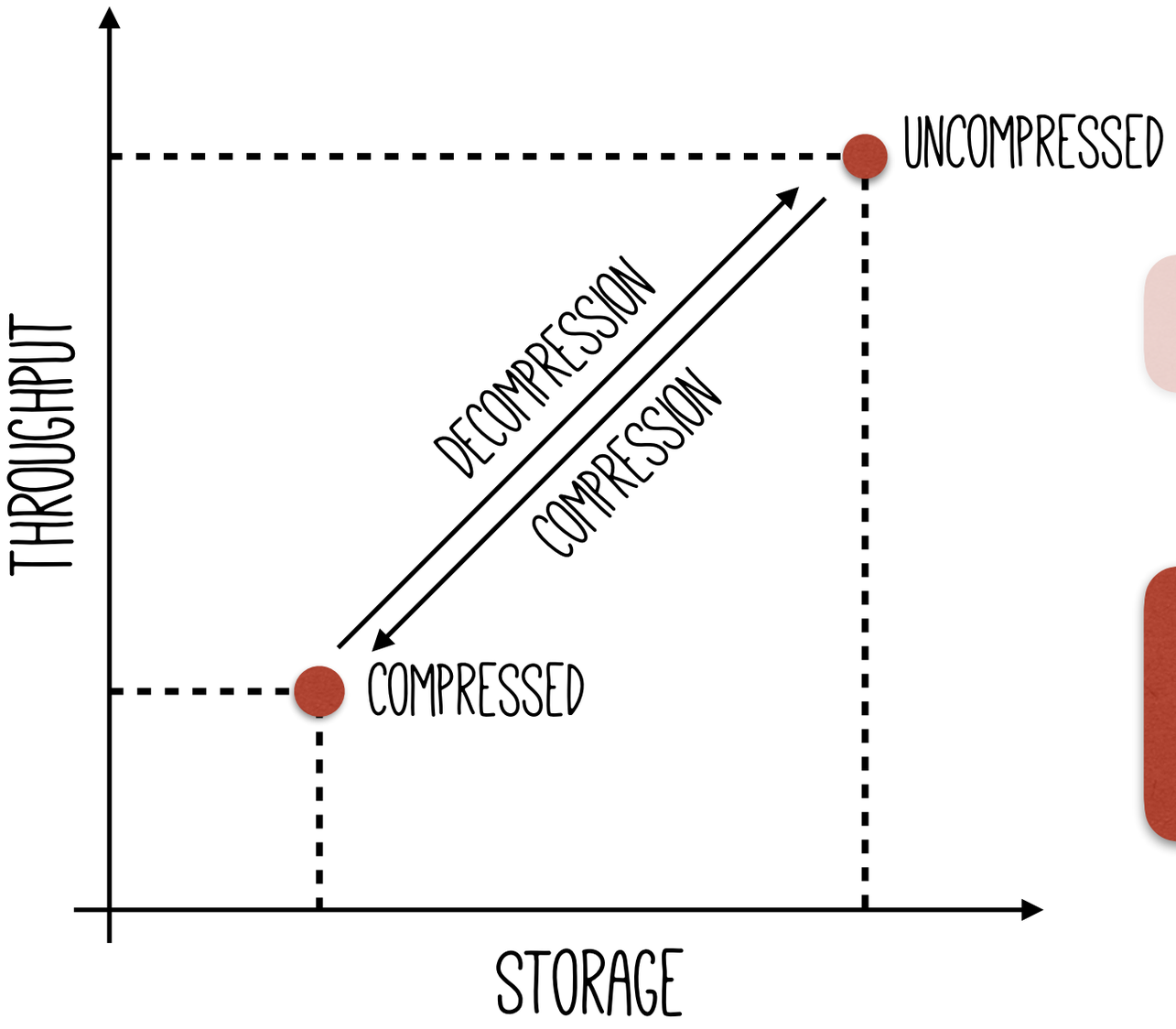


Unachievable points

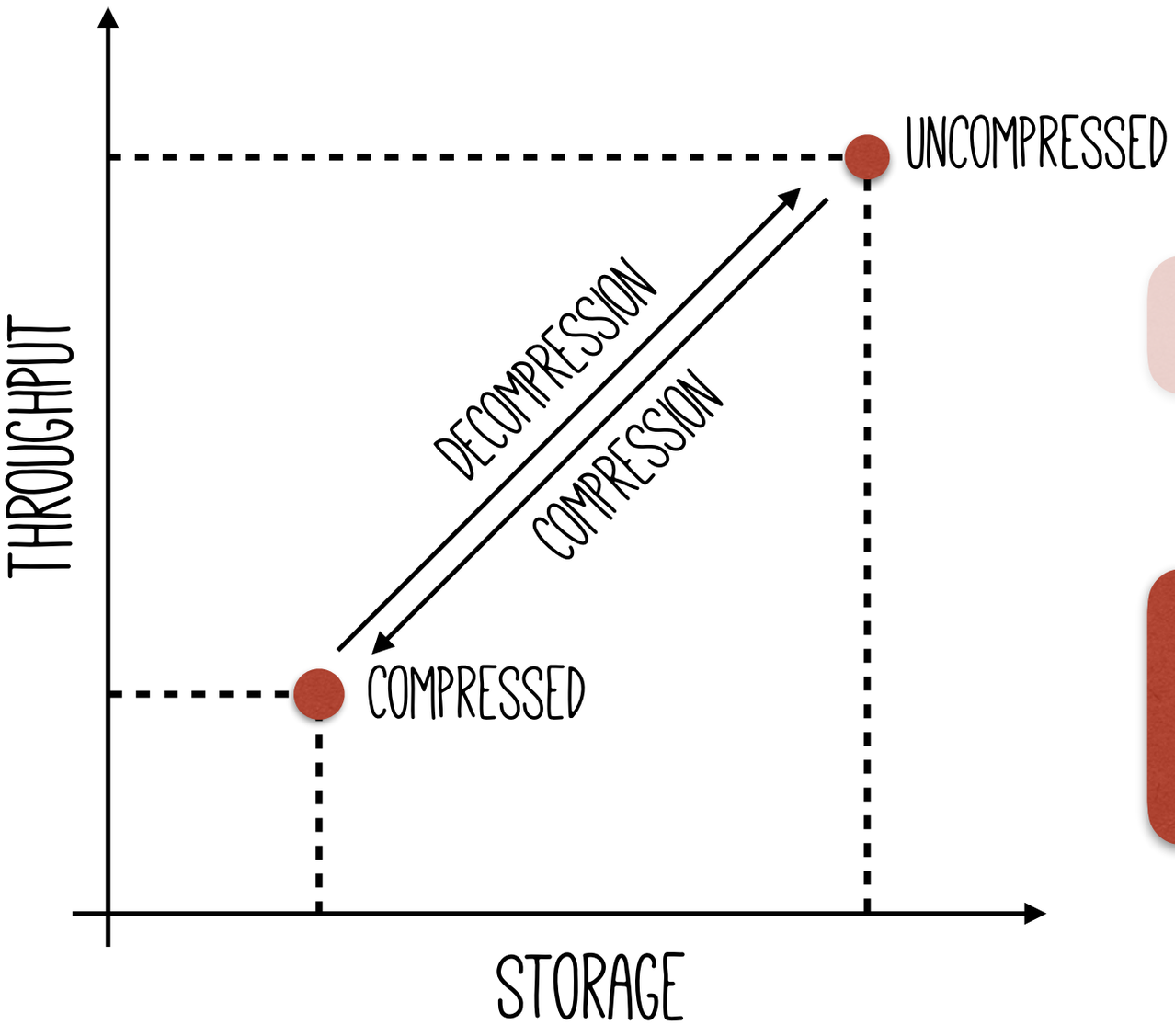
Existing Data Stores



Unachievable points

Switching between the two
incurs high latency & CPU

Existing Data Stores



Unachievable points

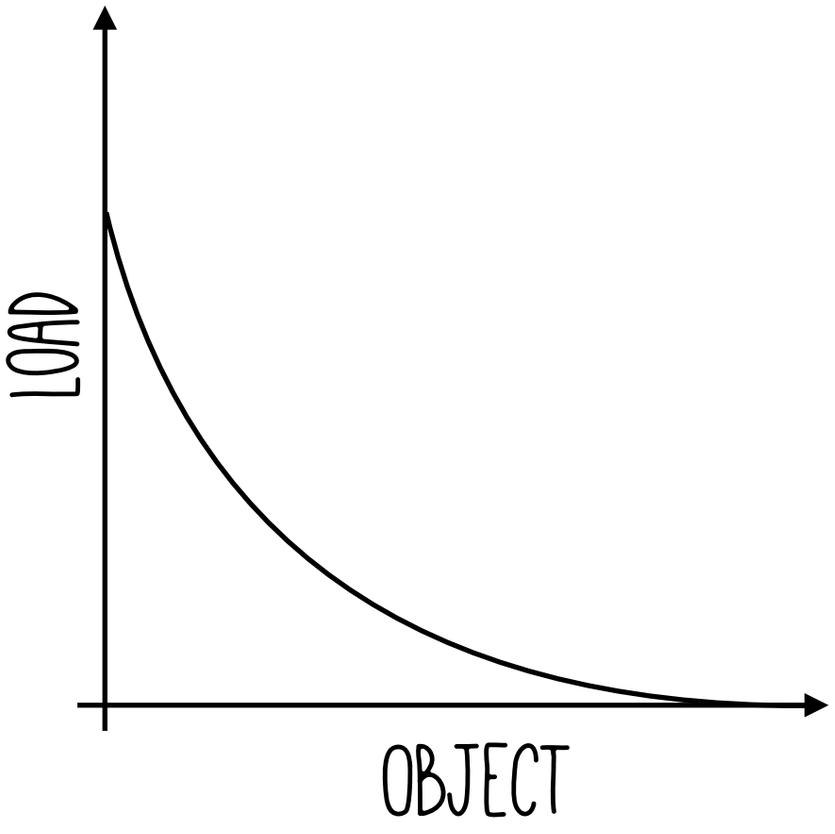
Switching between the two incurs high latency & CPU

Leads to degraded performance when underlying workload or infrastructure changes

A Motivating Example

A Motivating Example

Load across items heavily skewed



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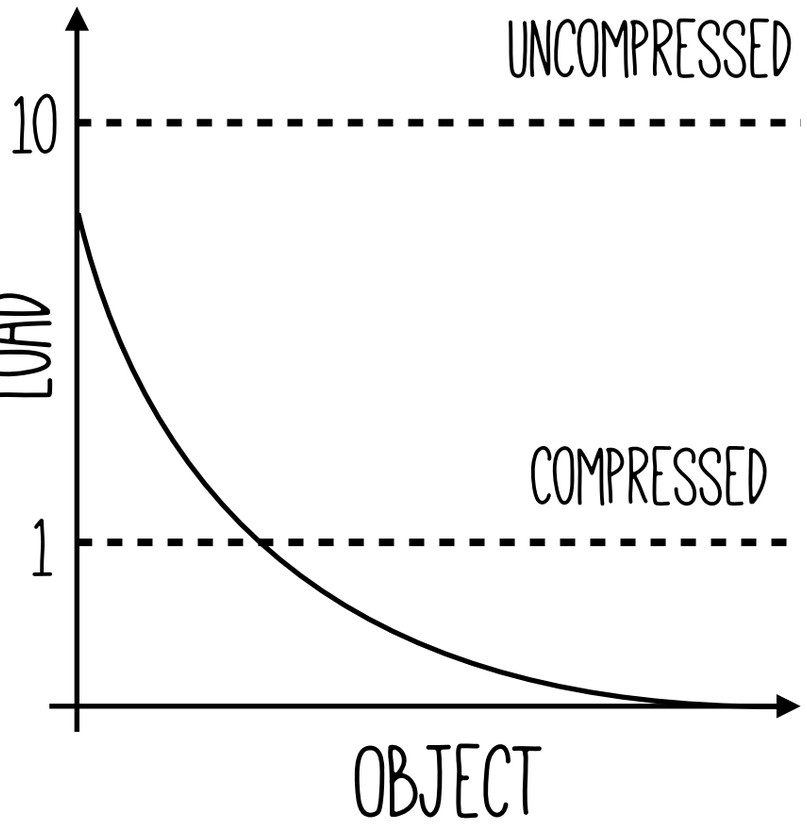

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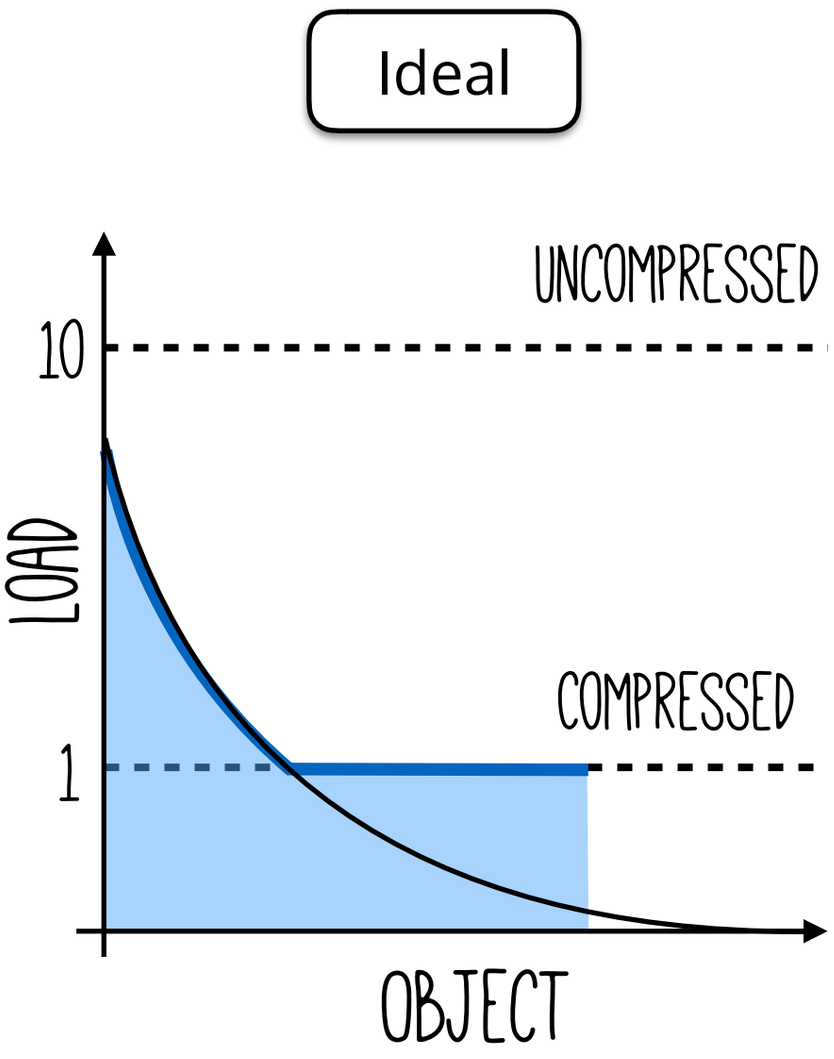

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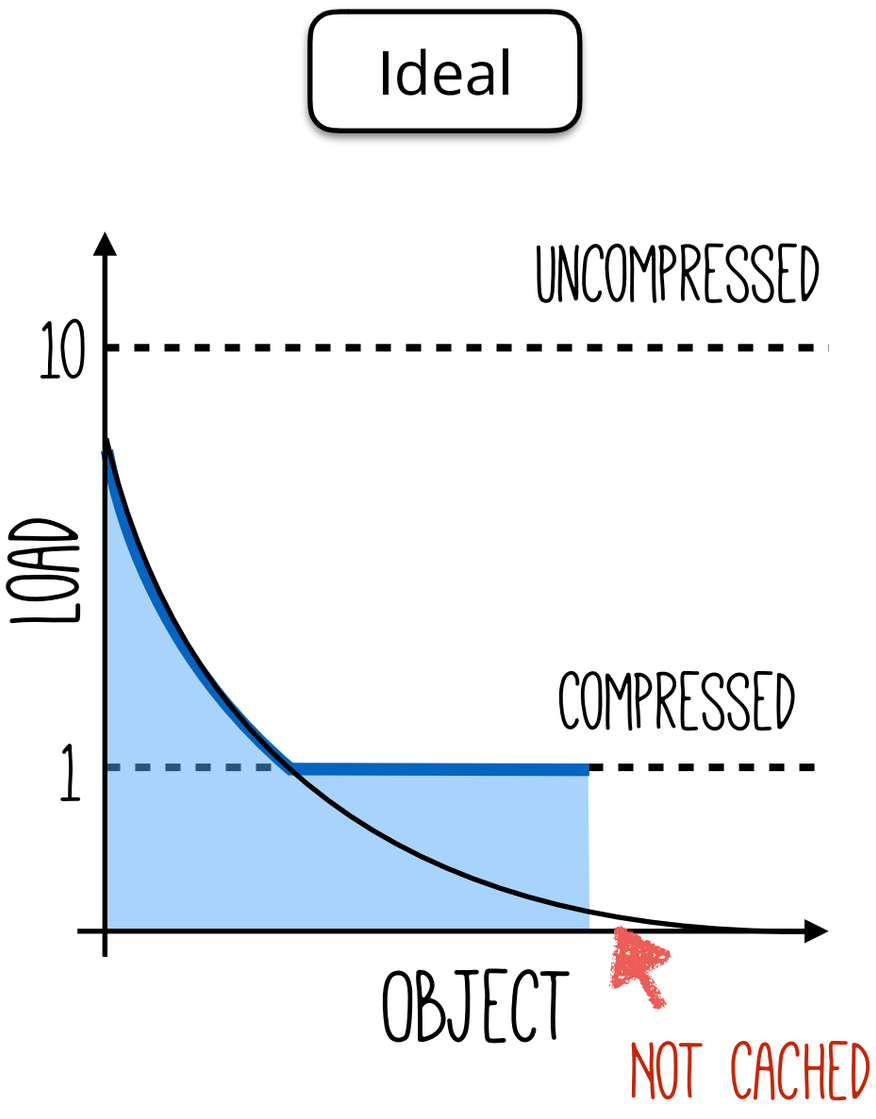
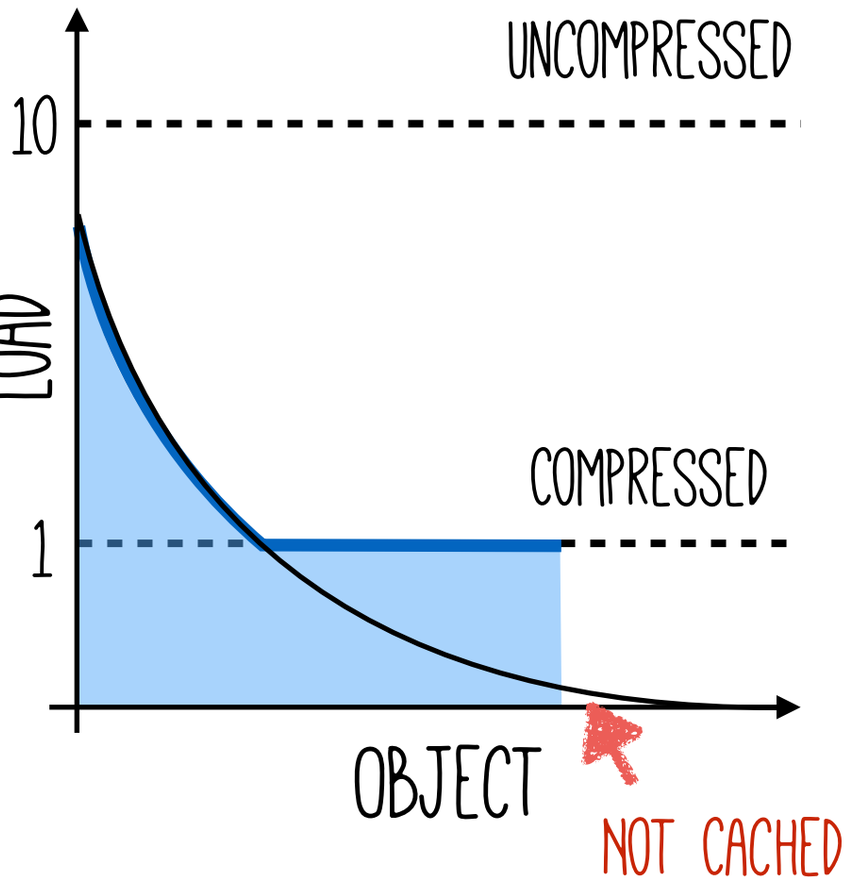


A Motivating Example

Load across items heavily skewed

Ideal

Compressed + Uncompressed



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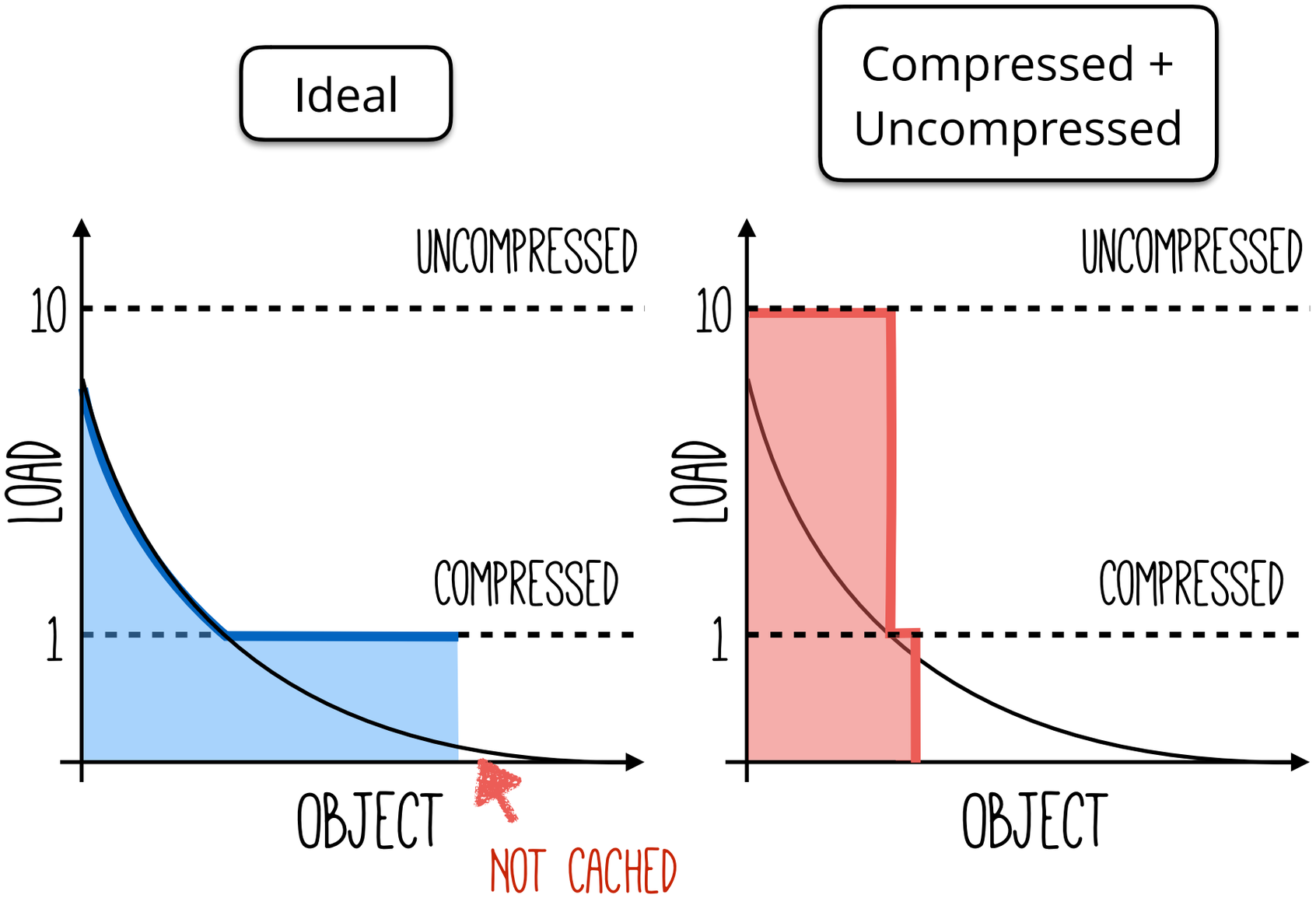

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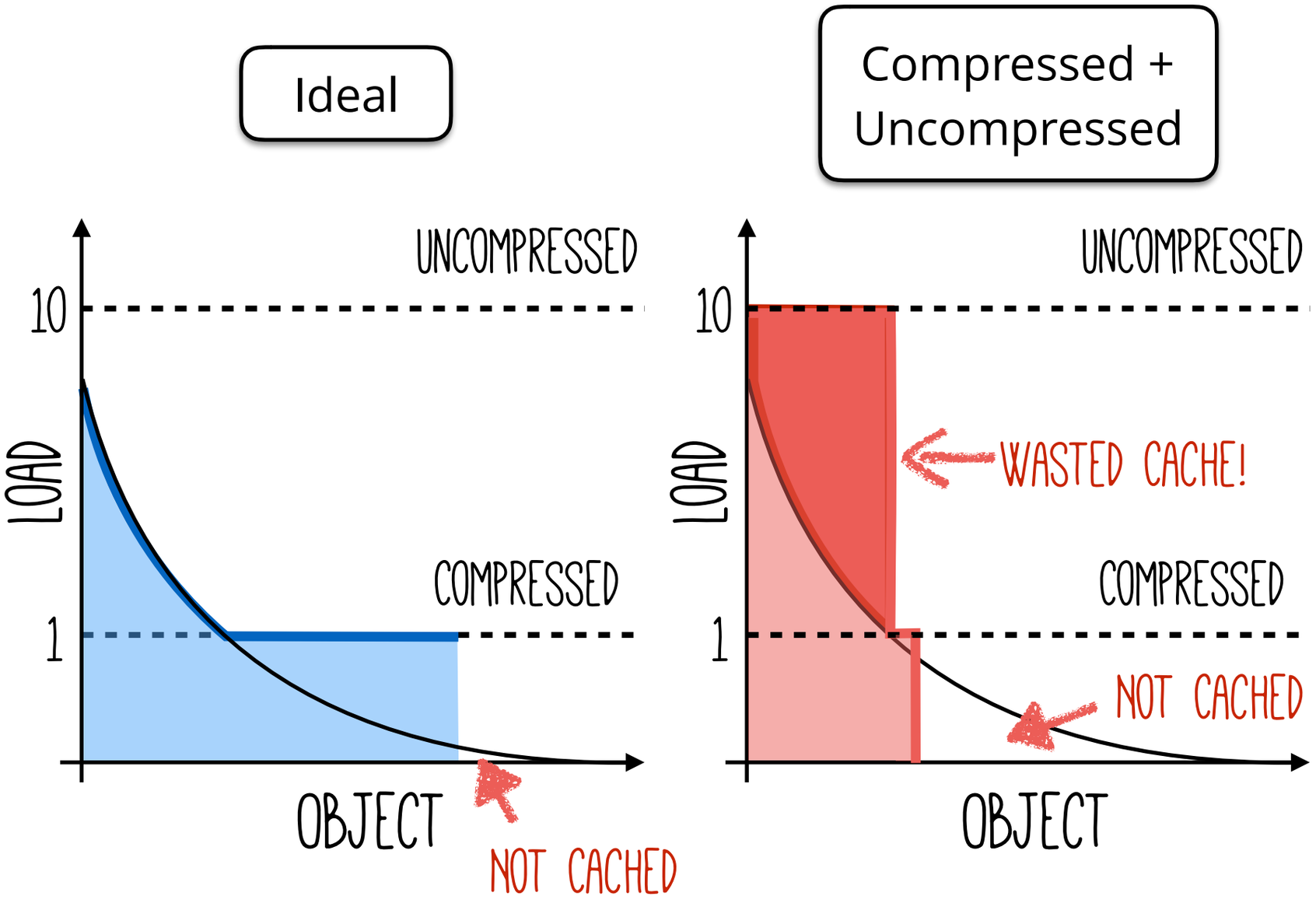

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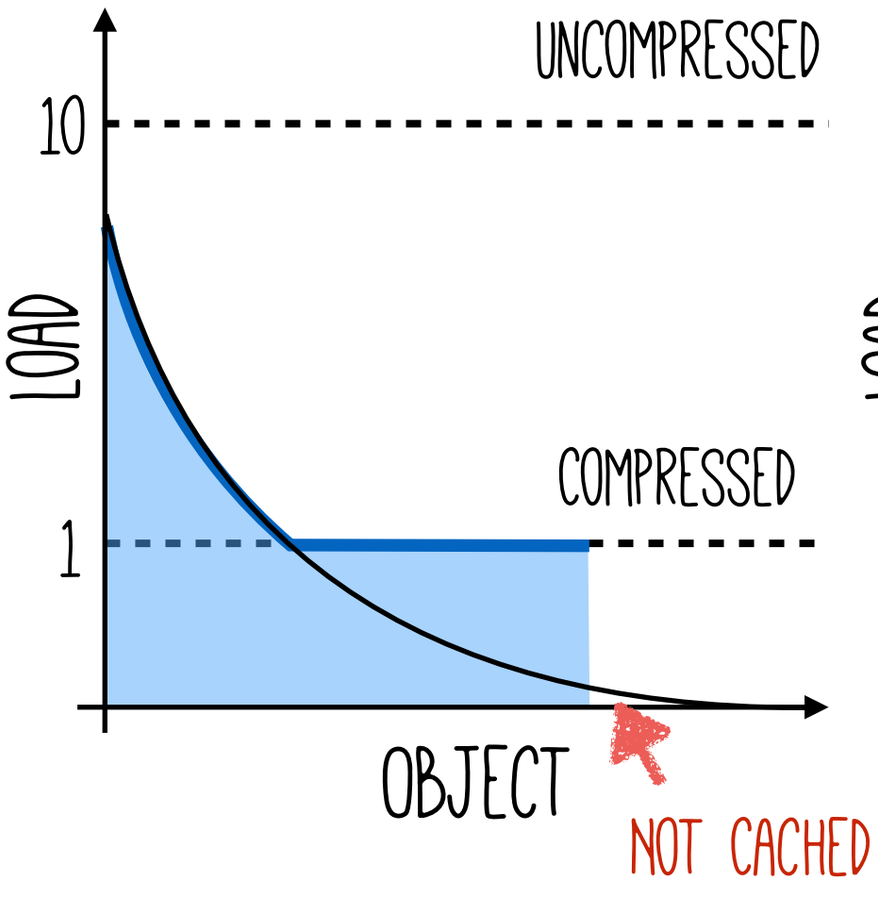

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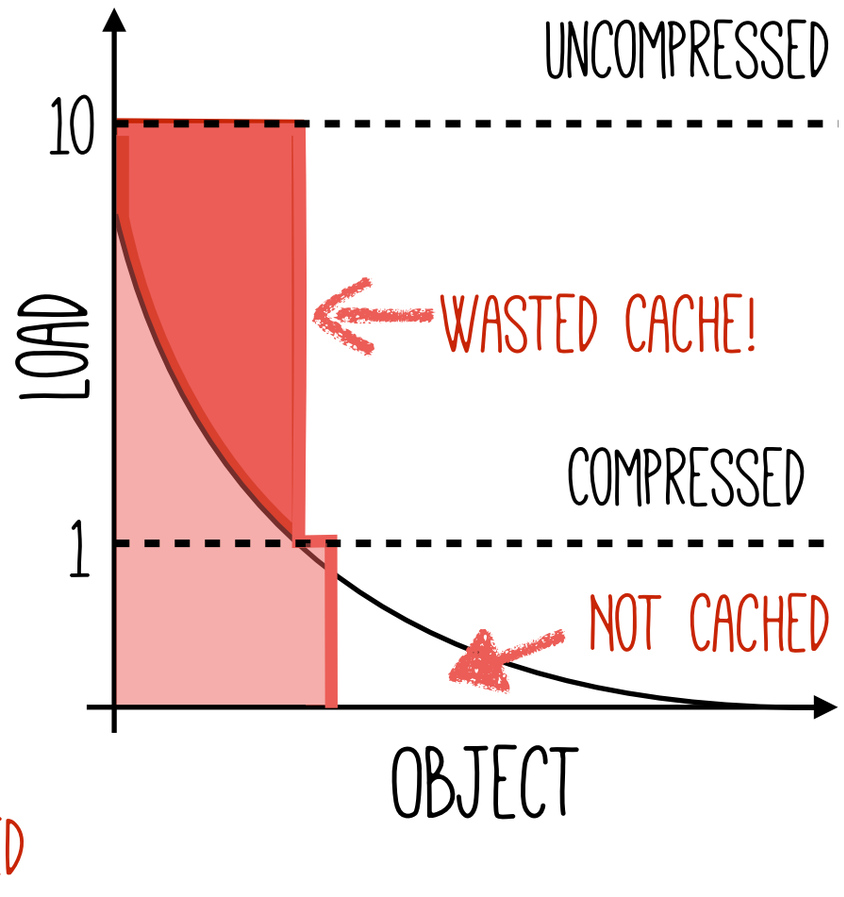

Selective Replication: #Replicas α Load

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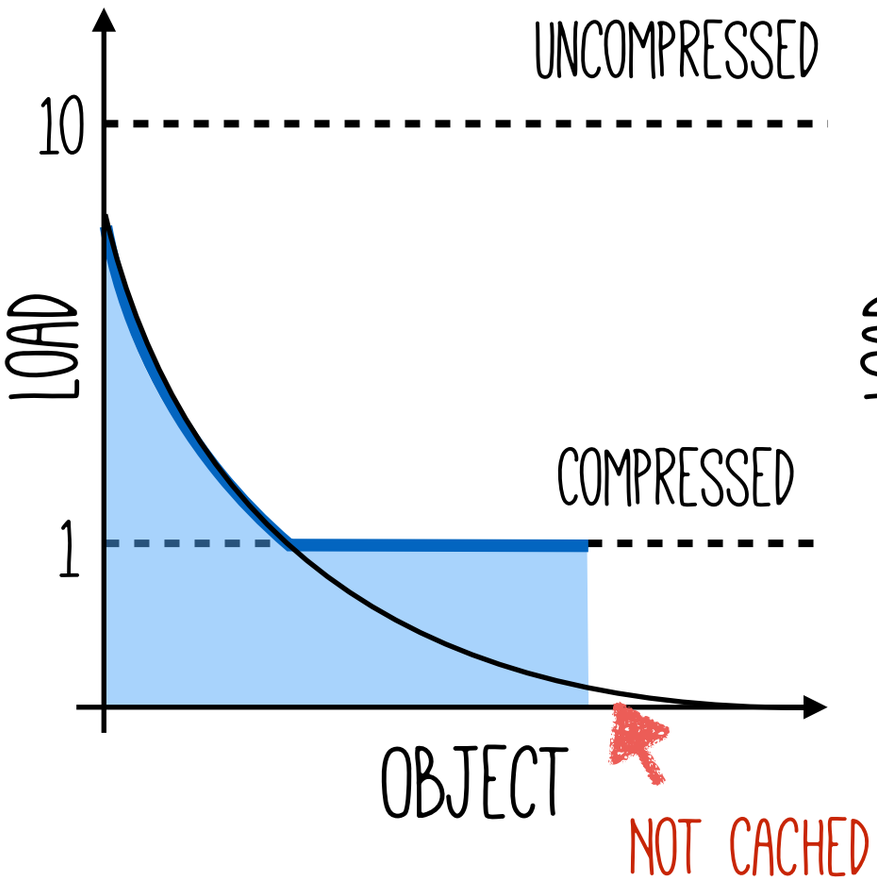

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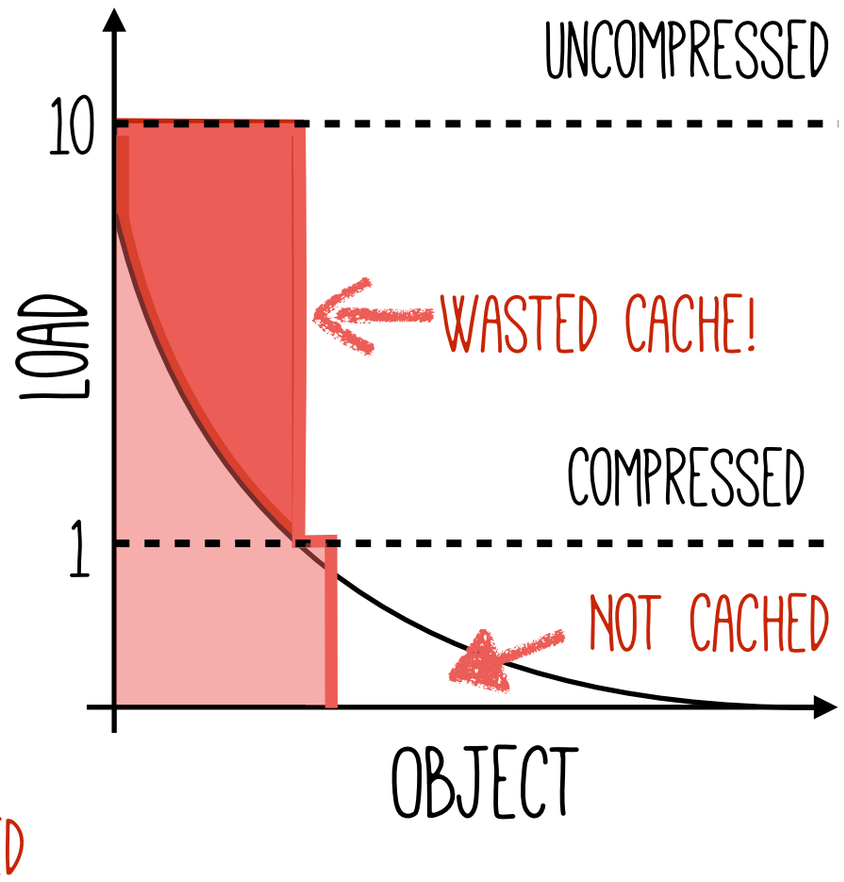

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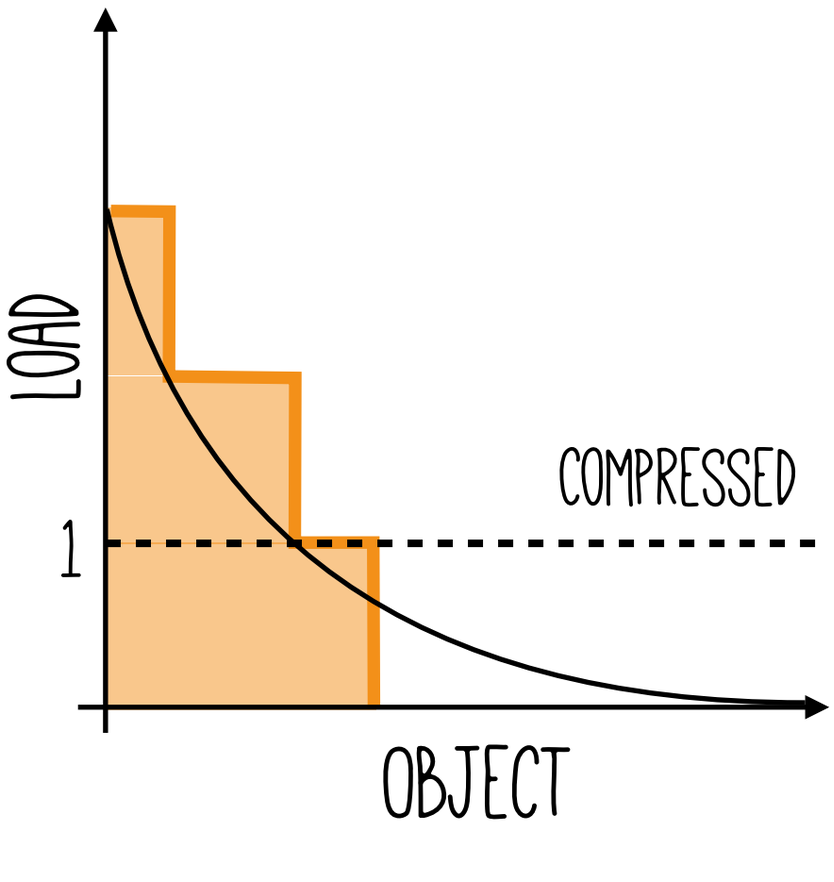

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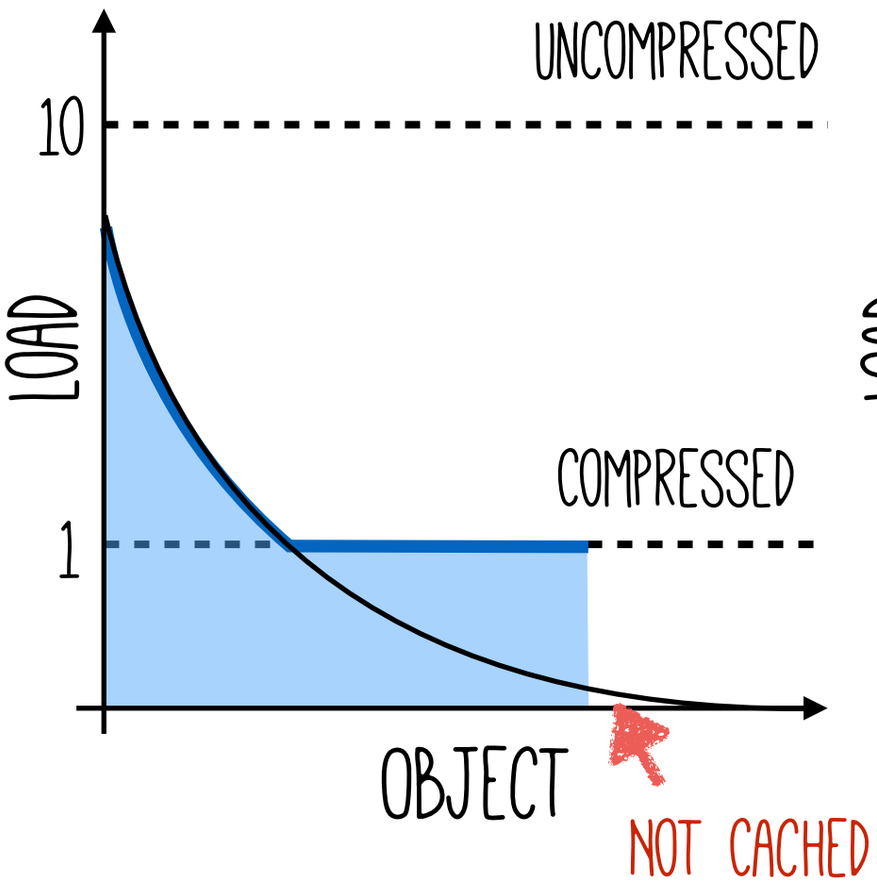

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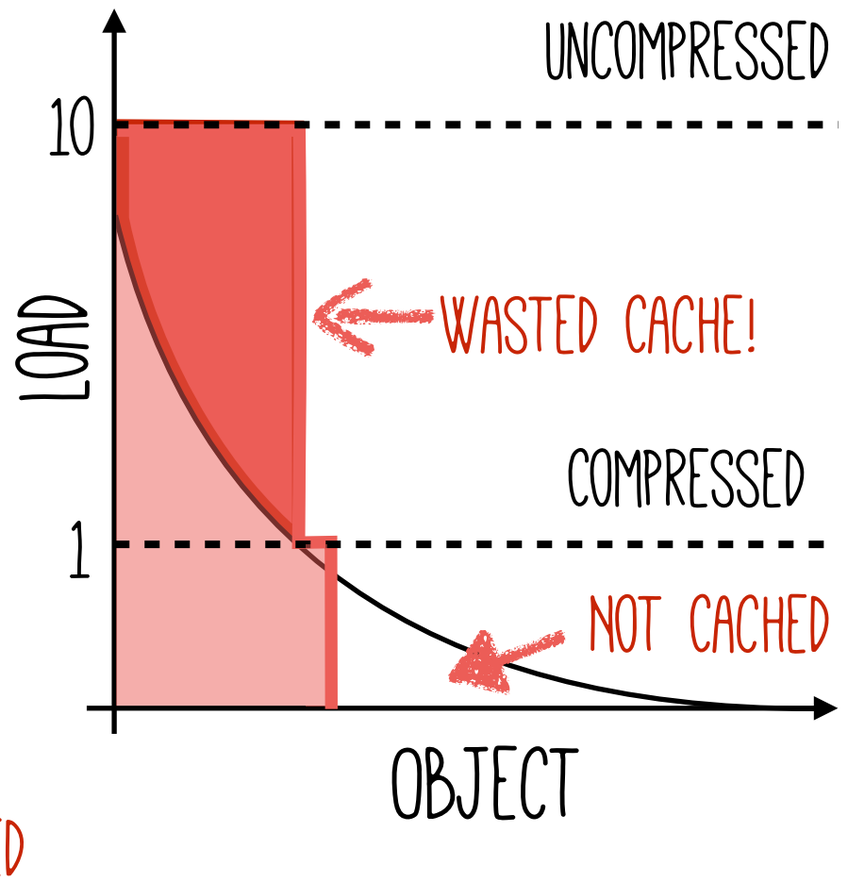

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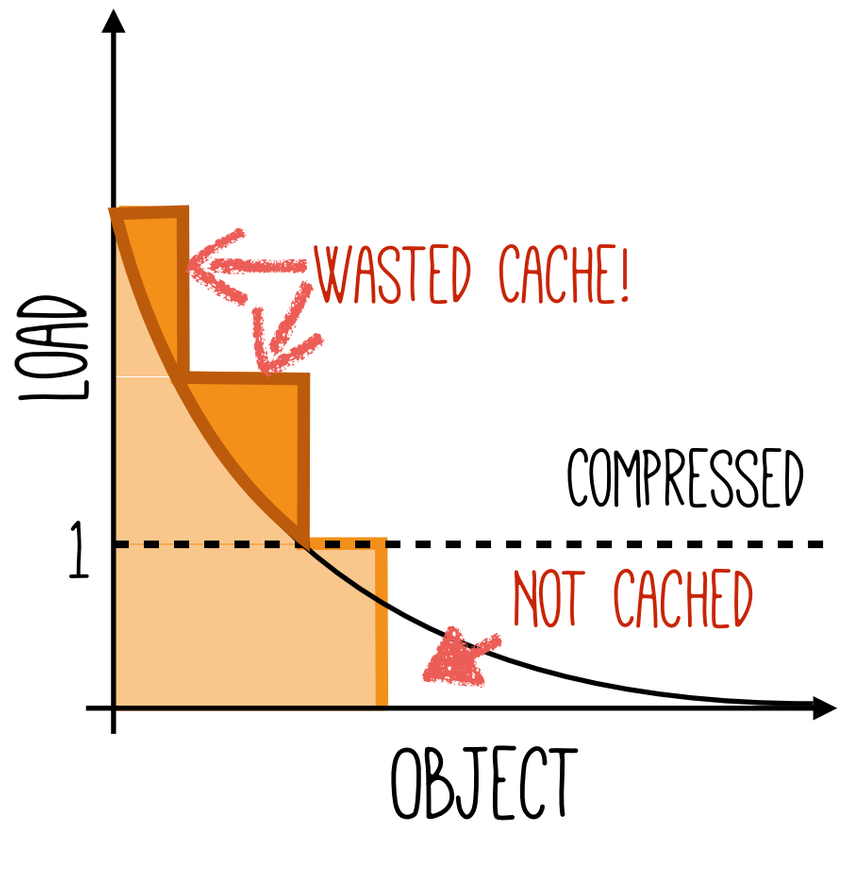

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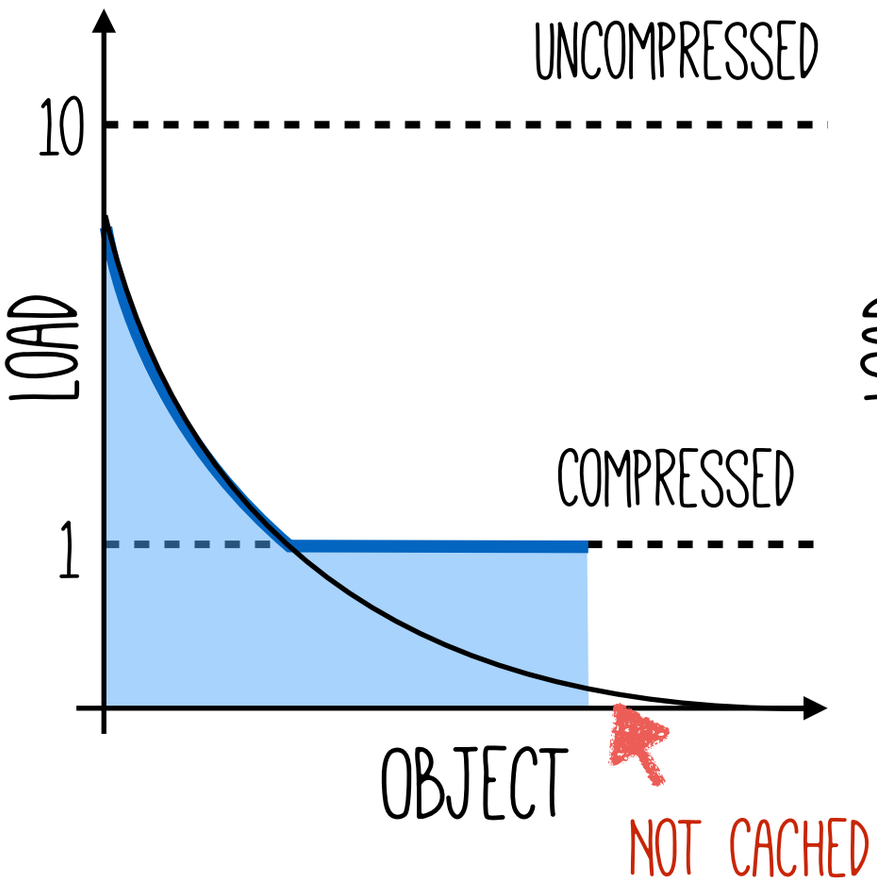

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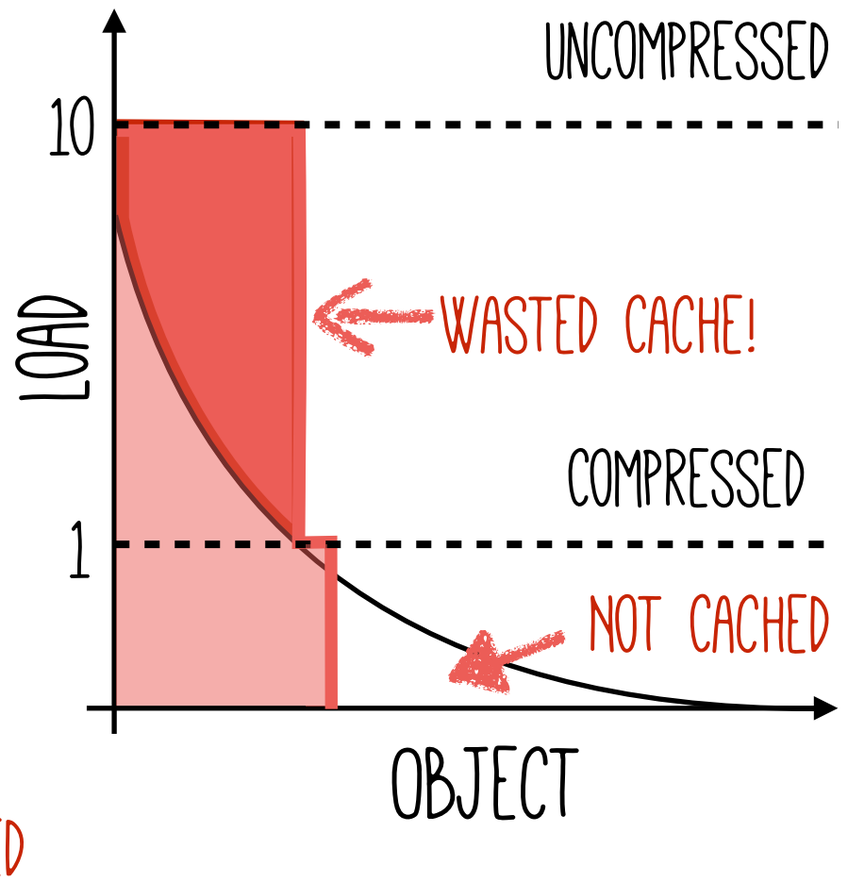

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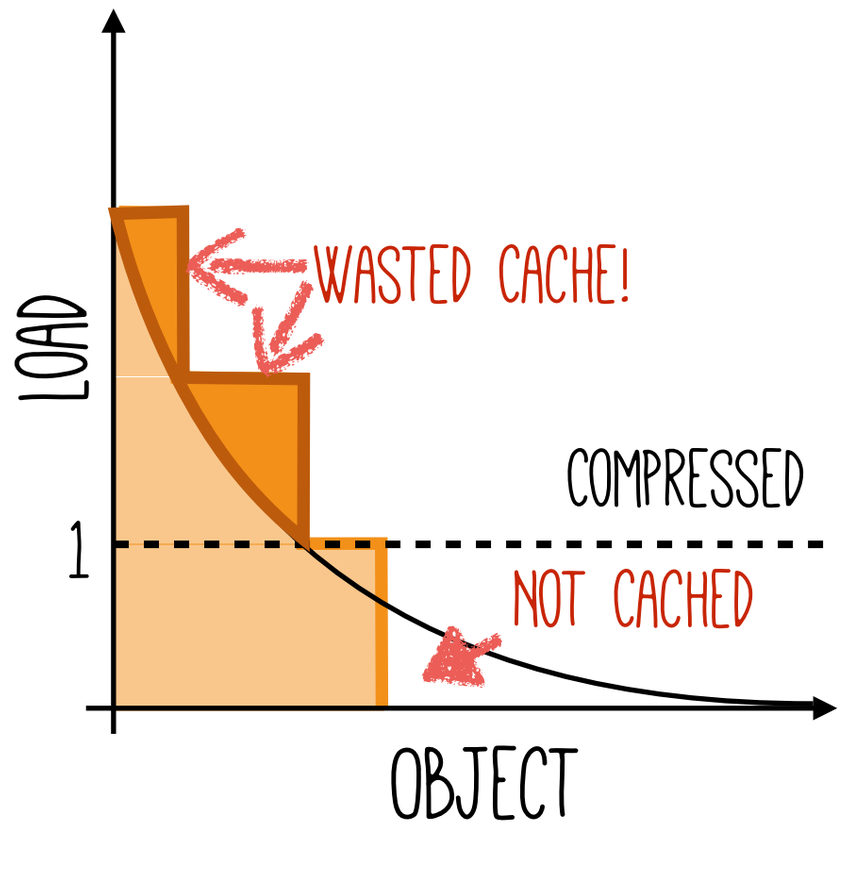

Load changes over time

A Motivating Example

Load across items heavily skewed

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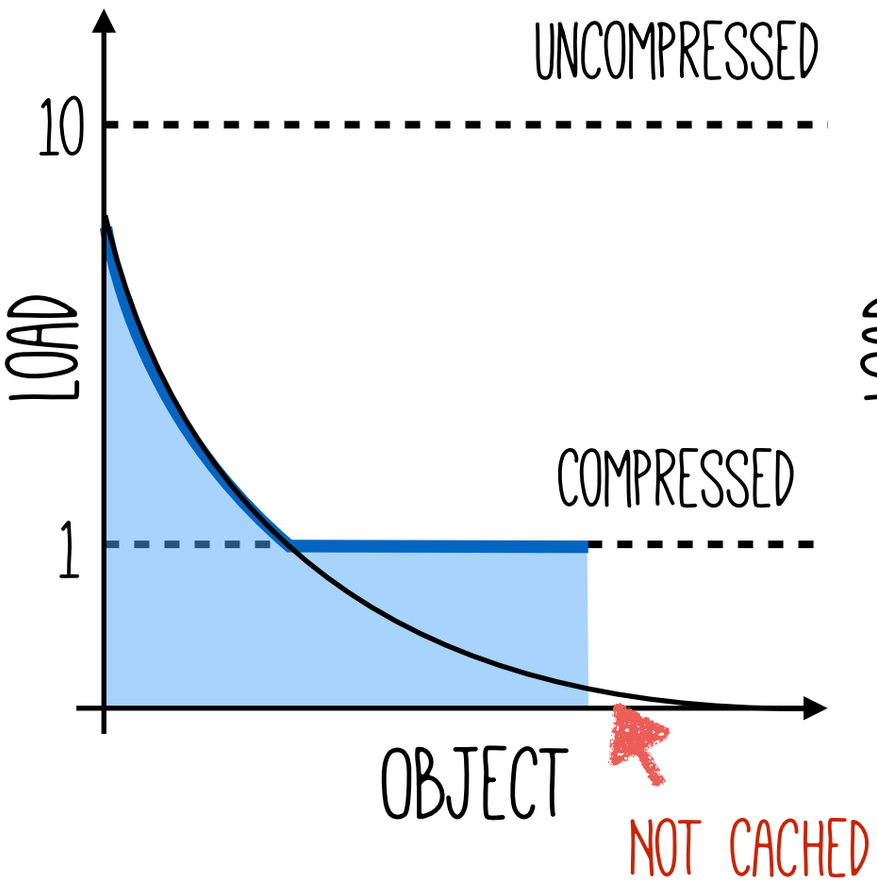

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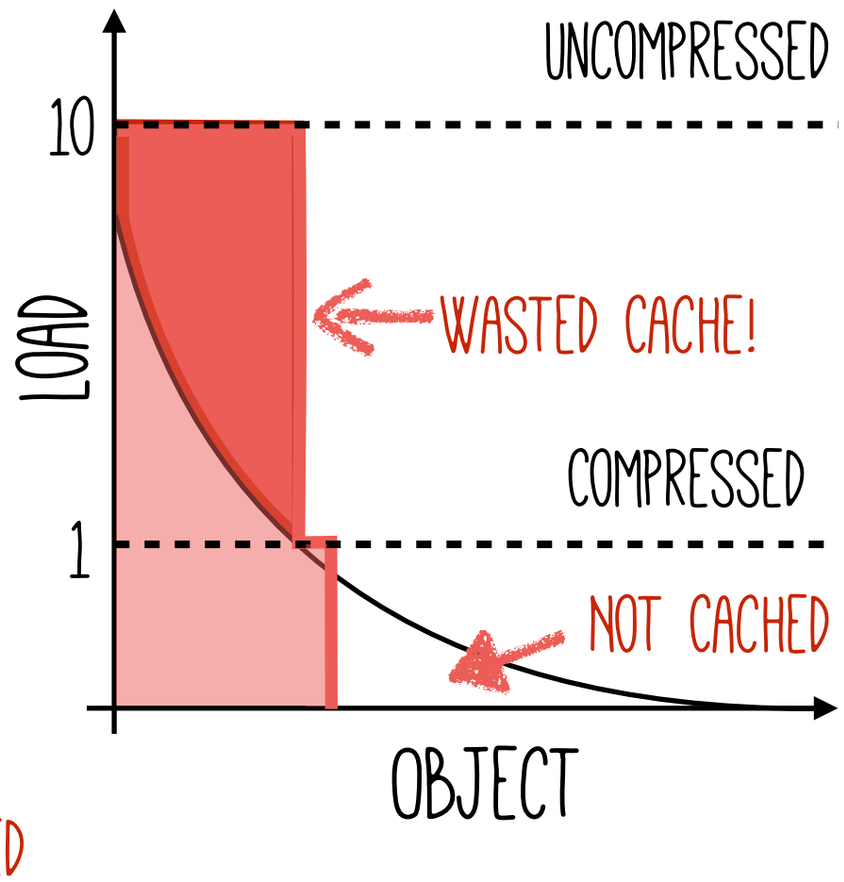

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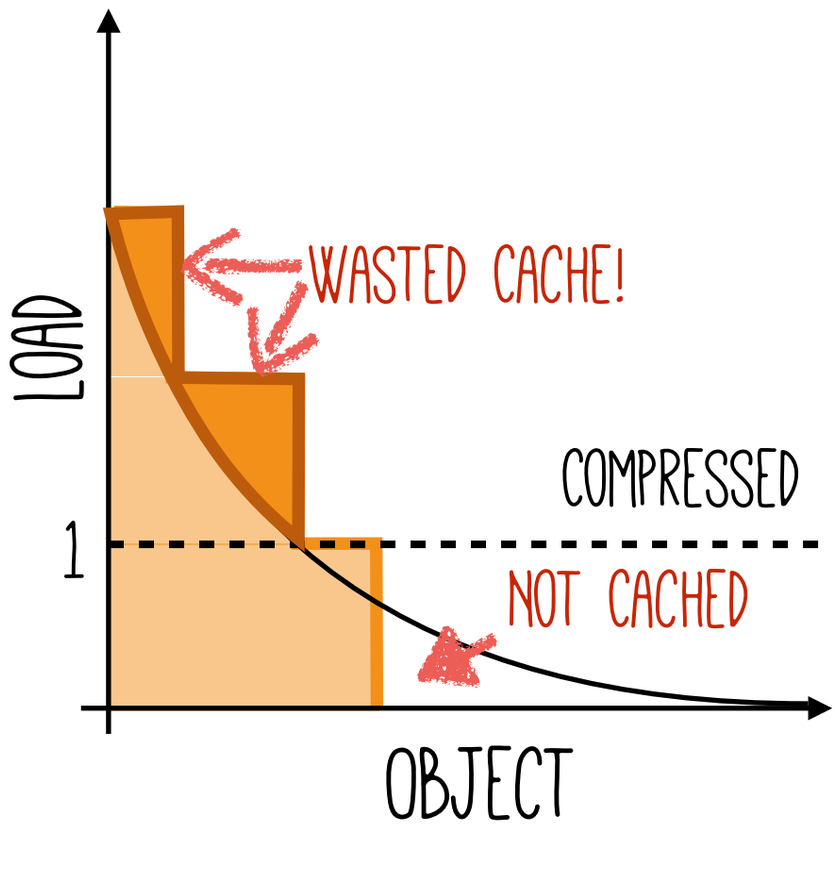
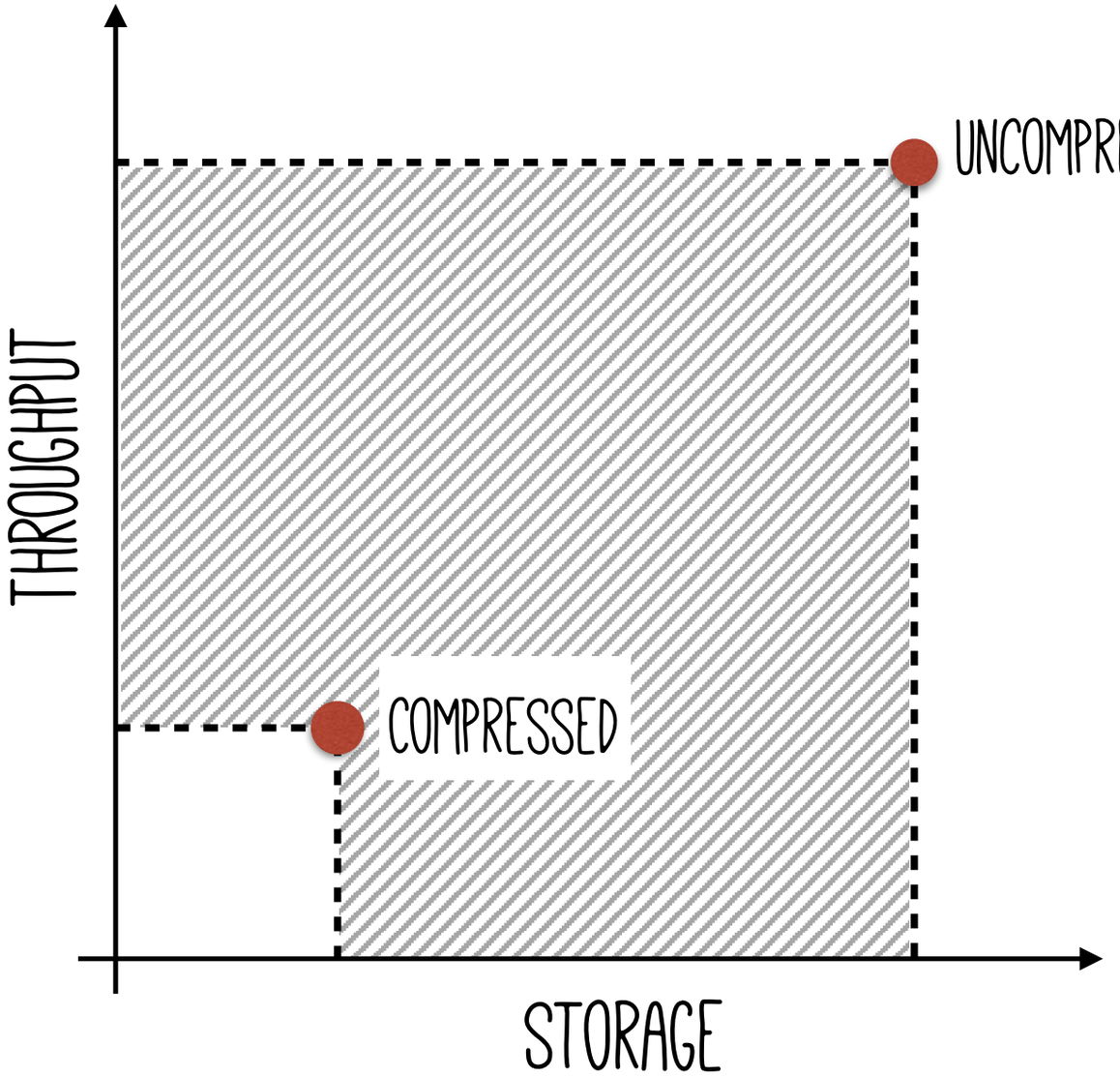


Load changes over time → Degraded performance

BlowFish



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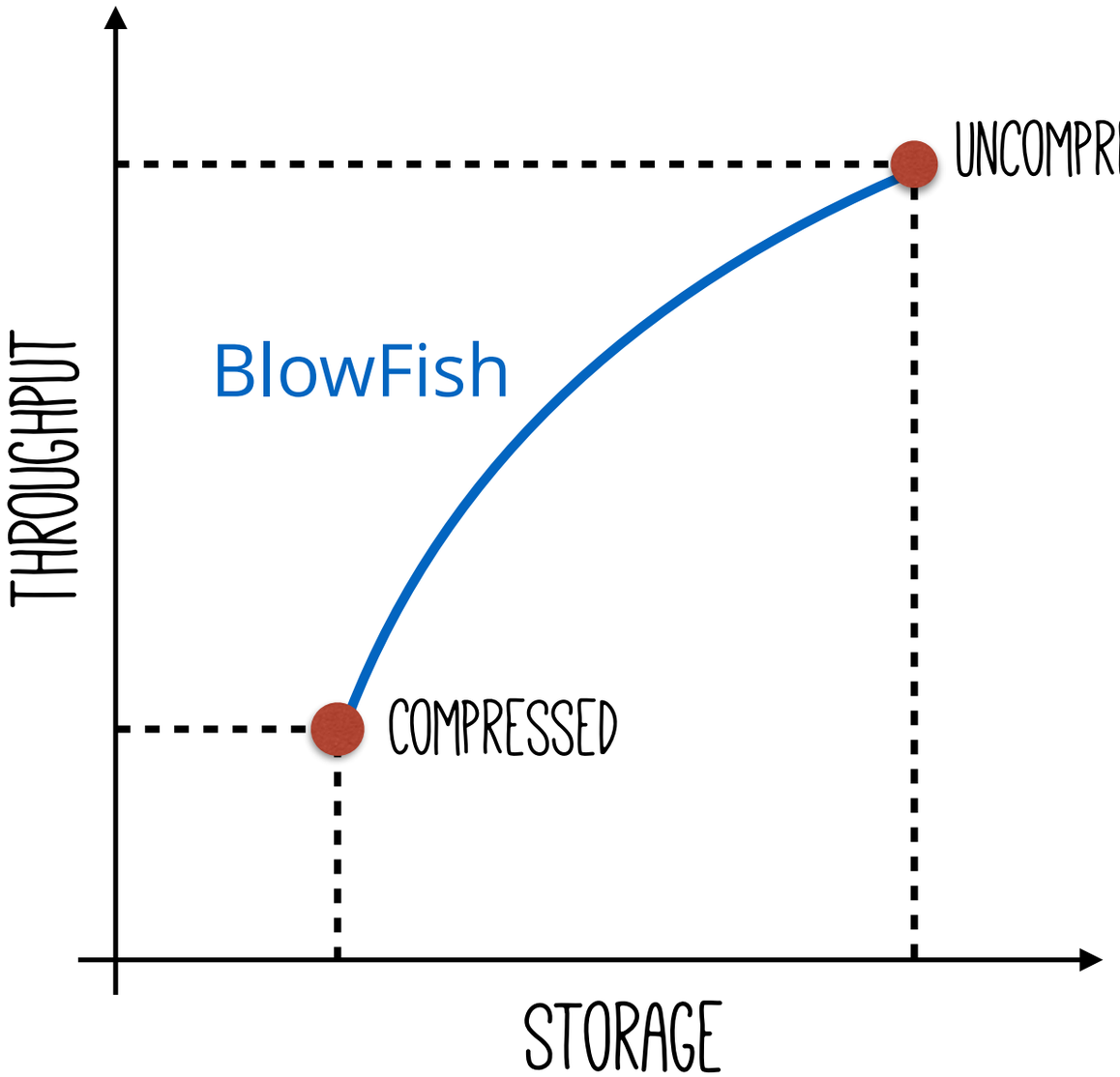
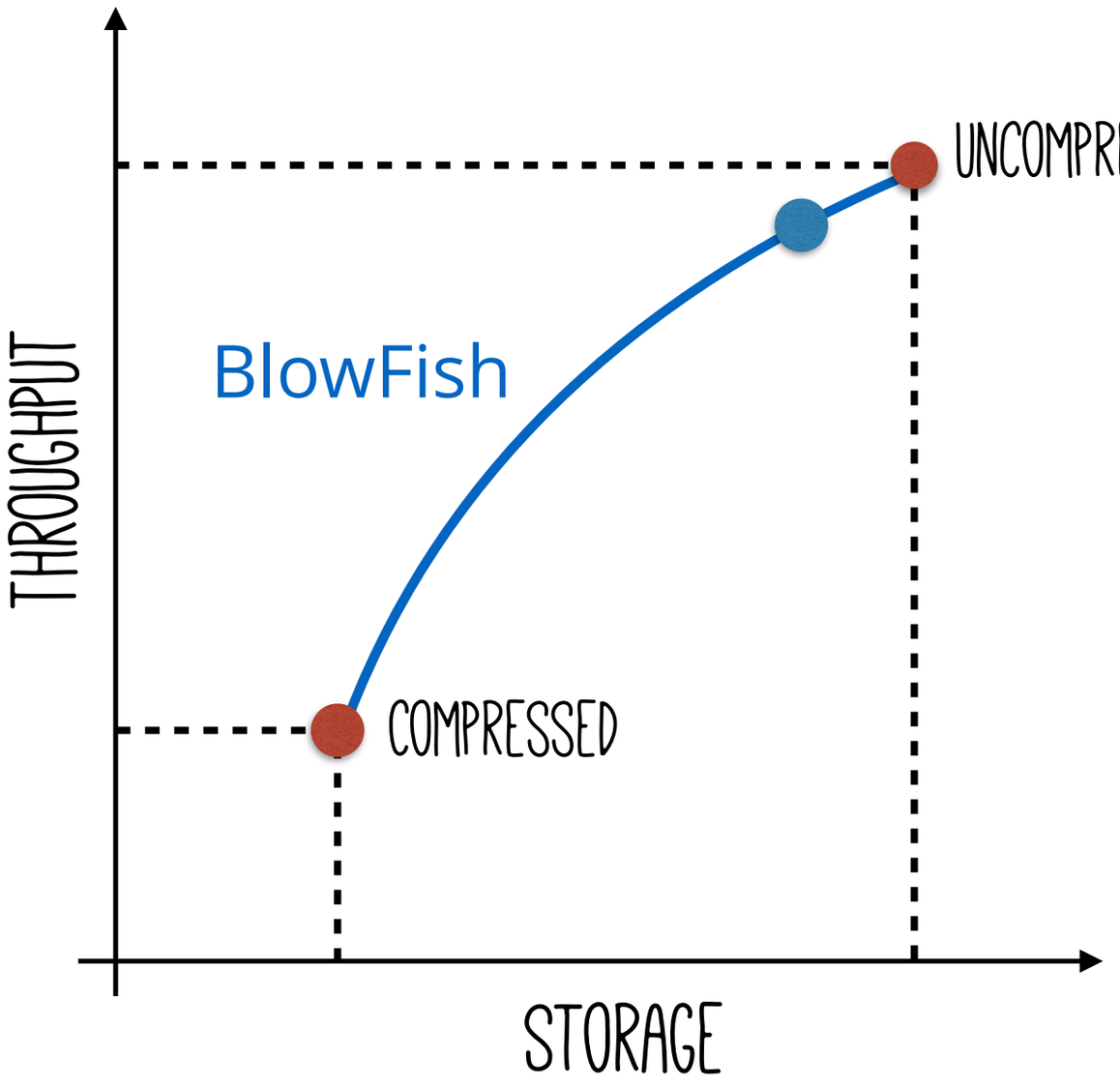


Smooth Tradeoff Curve

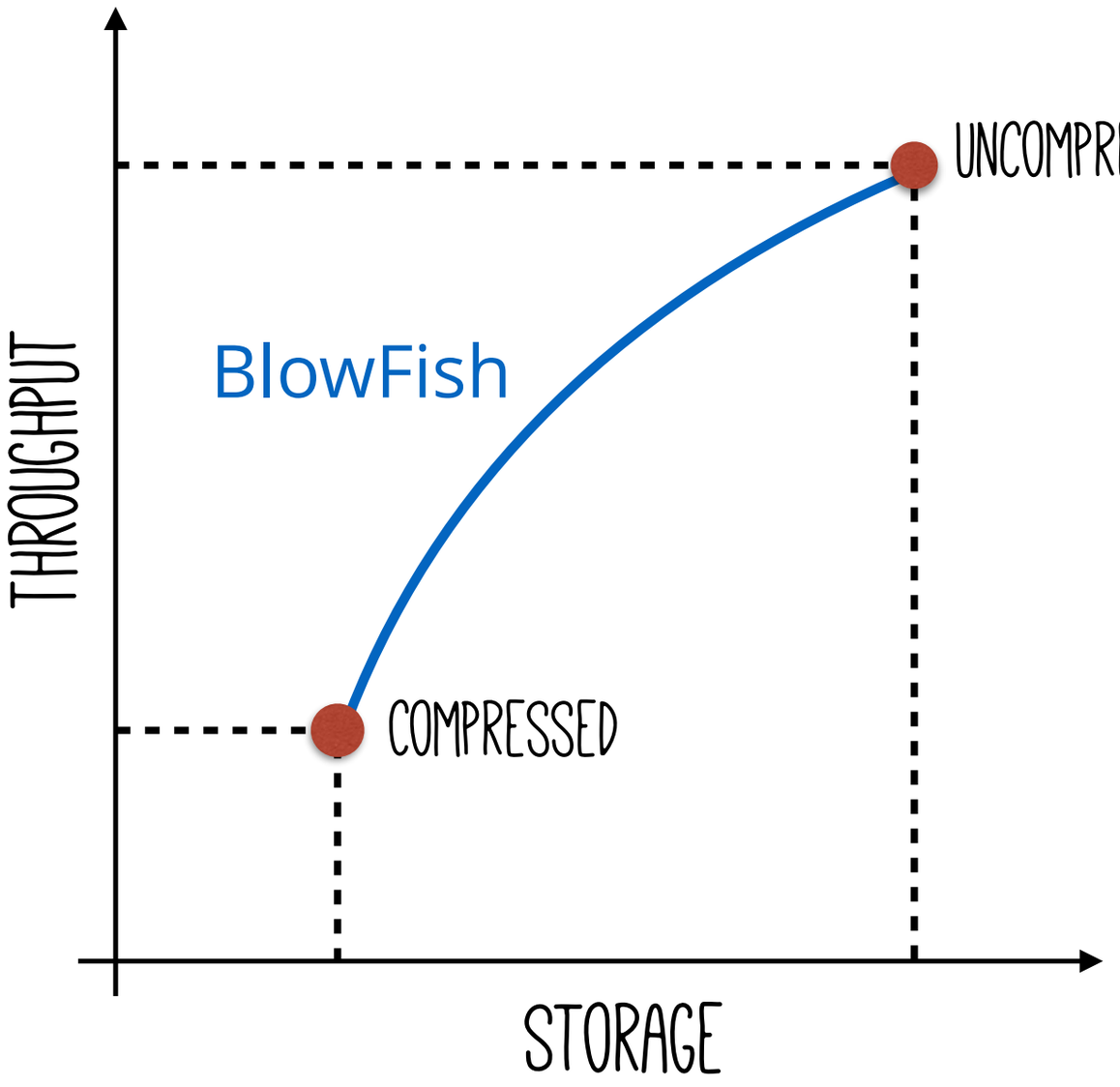
BlowFish



Smooth Tradeoff Curve

Dynamic Navigation

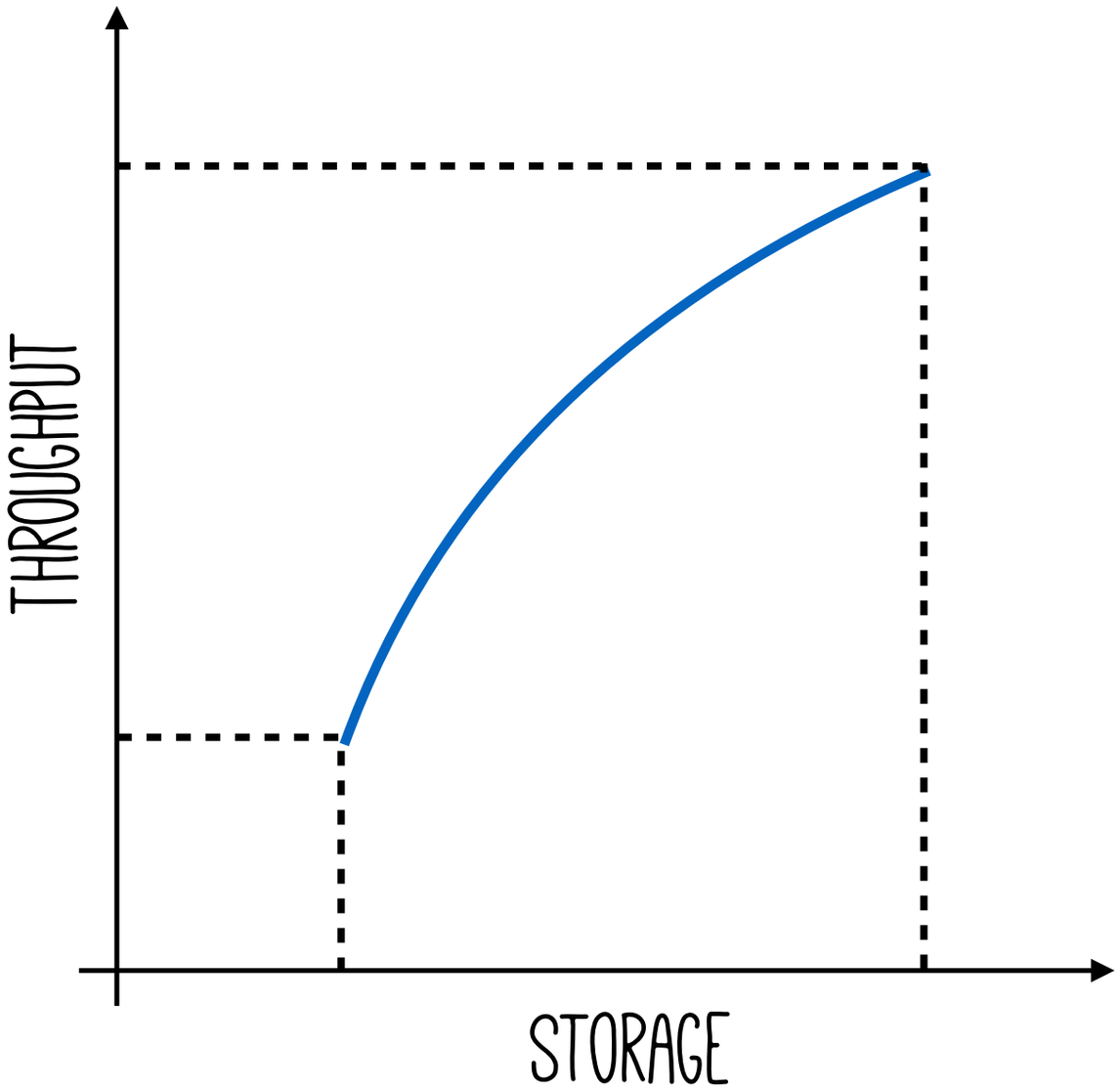
BlowFish

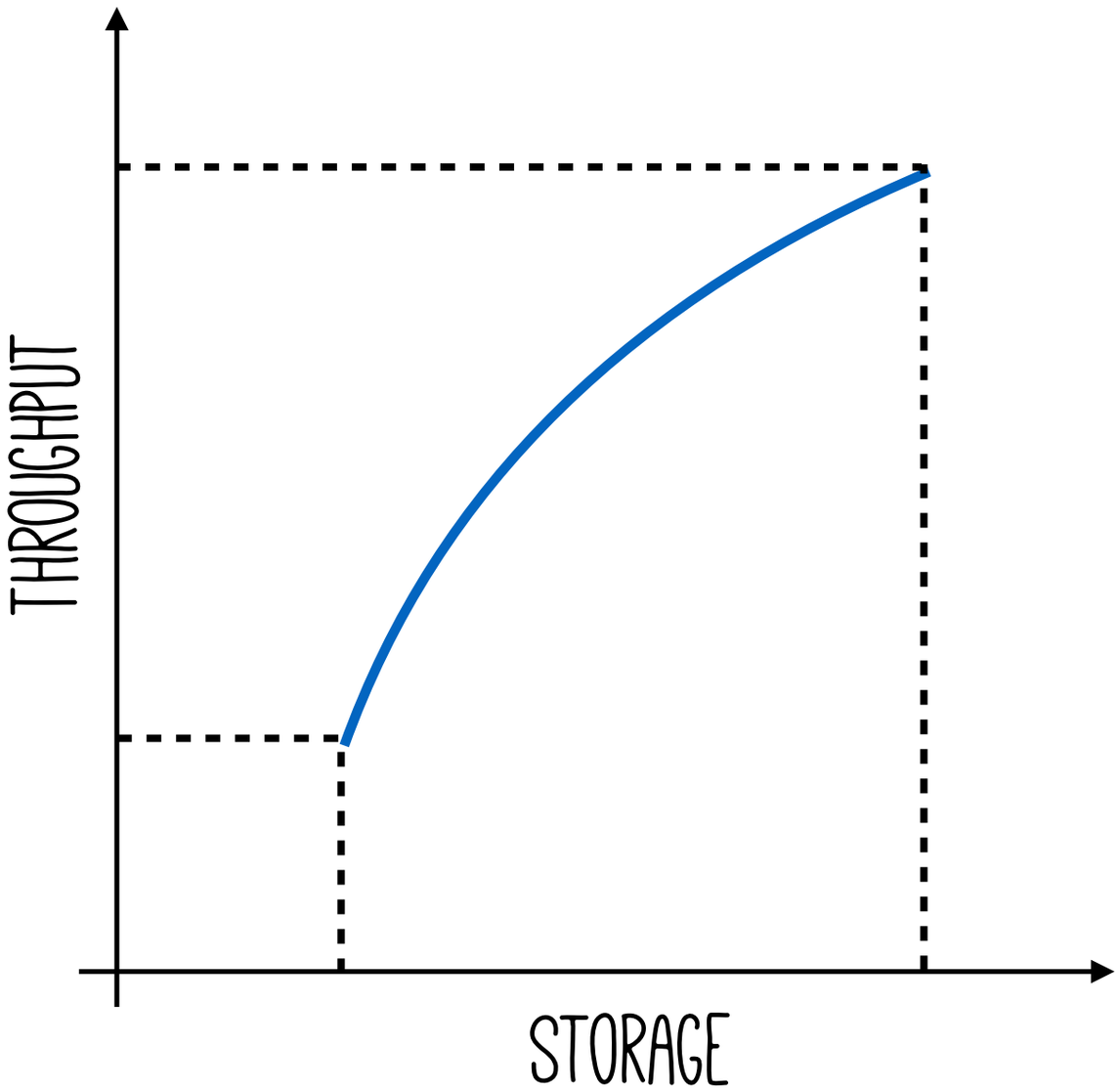


Smooth Tradeoff Curve

Dynamic Navigation

Applications in Several Classical Systems Problems


THROUGHPUT
STORAGE



Storage-Performance Tradeoff

Background

Background

Builds on Succinct [NSDI'15]

Background

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Succinct stores:

Background

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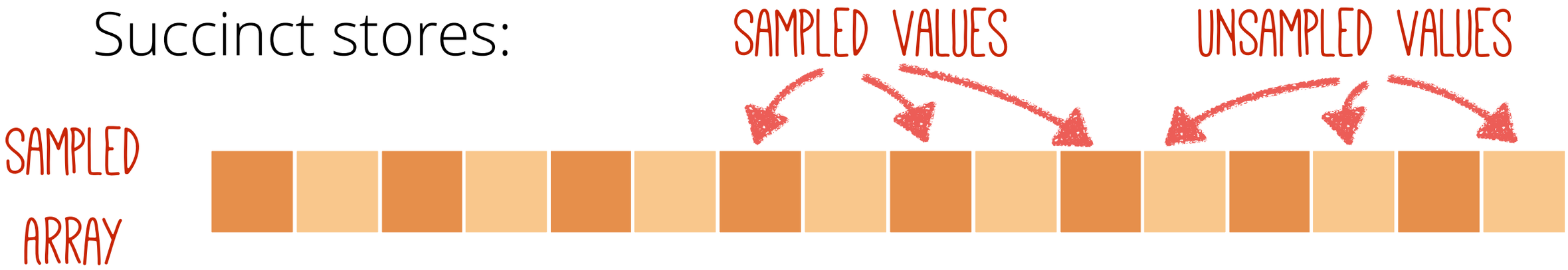
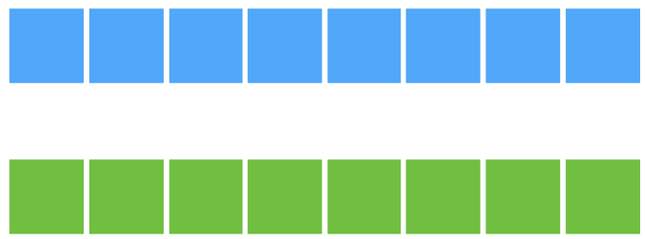


Background

Builds on Succinct [NSDI'15]

Succinct stores:

SAMPLED ARRAY



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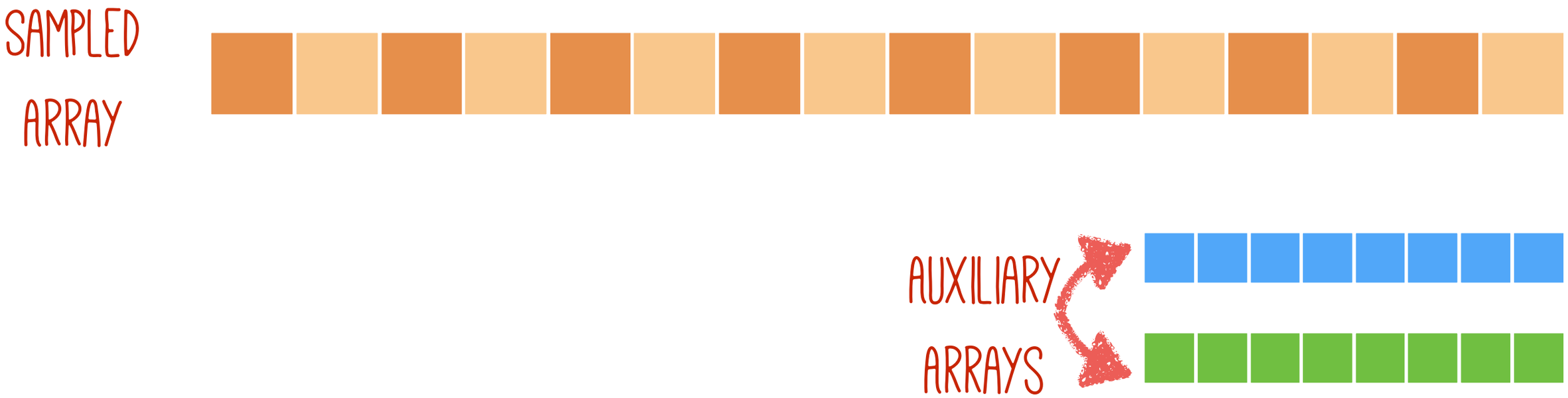

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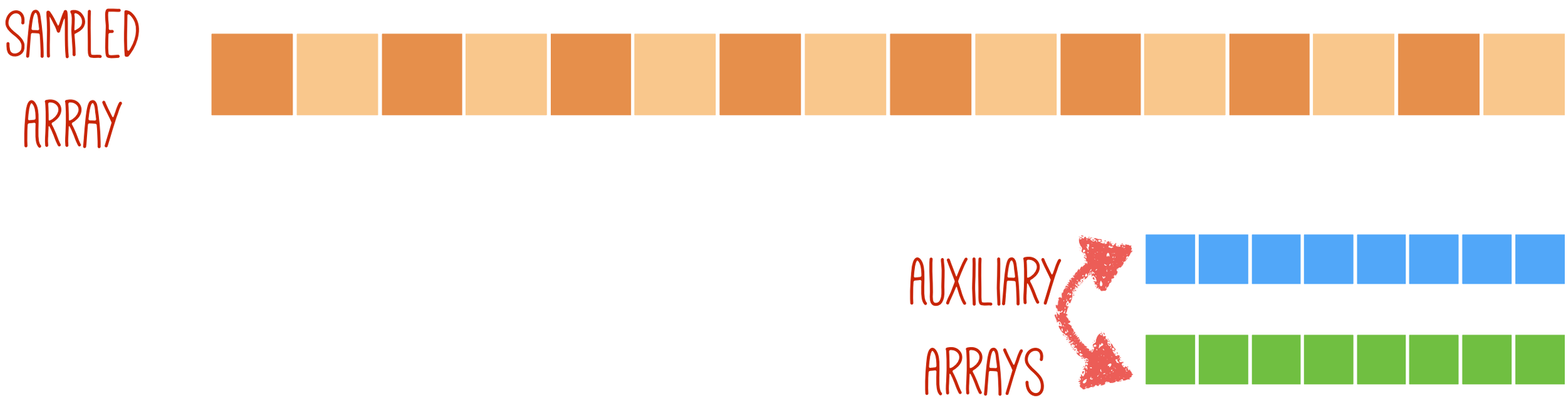

- Small

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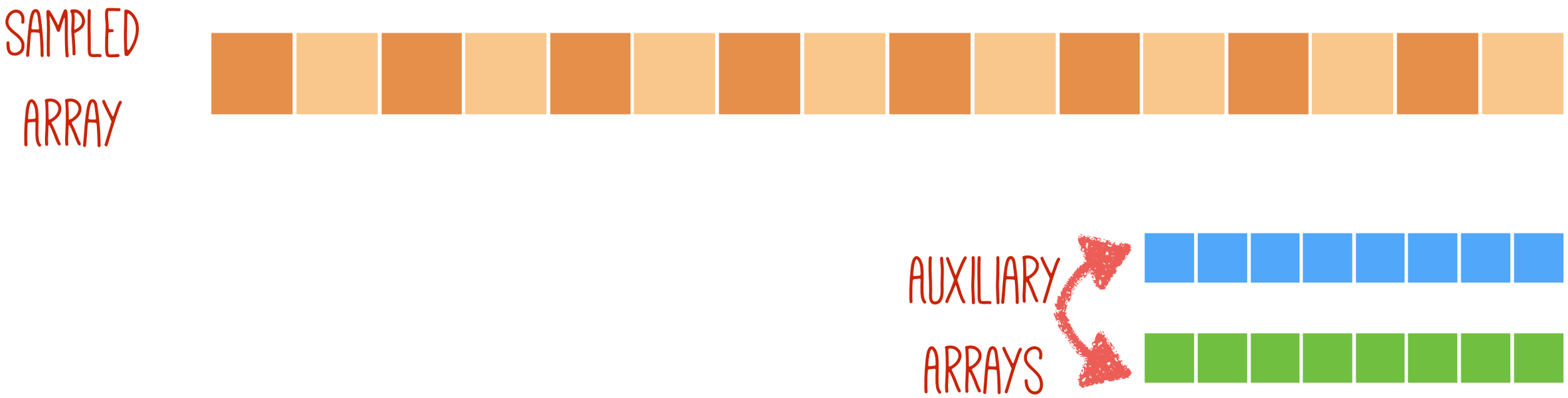

- Small
- Compute unsampled values on the fly

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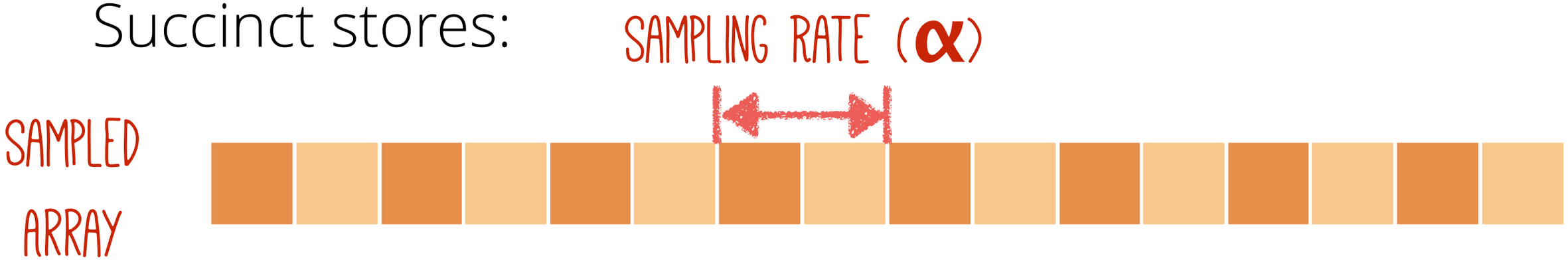
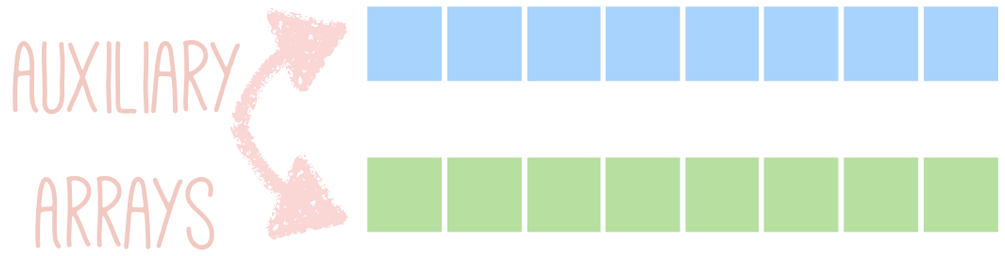


Sampling Rate proxy for
Storage & Performance



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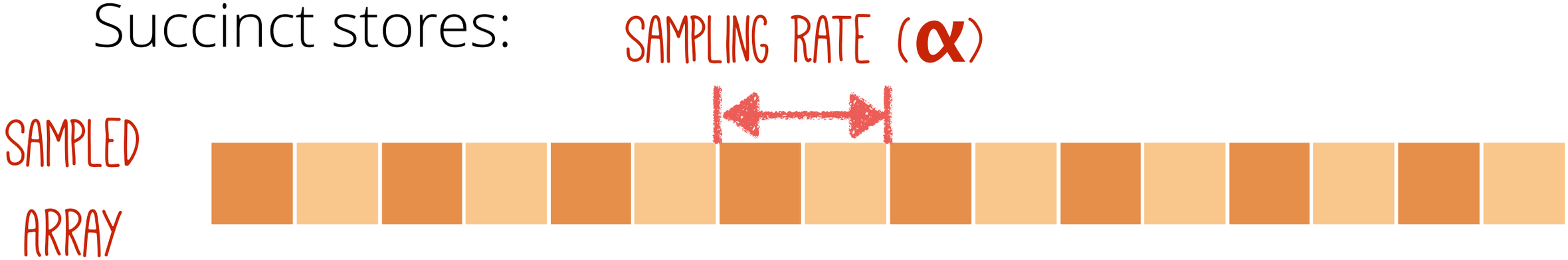
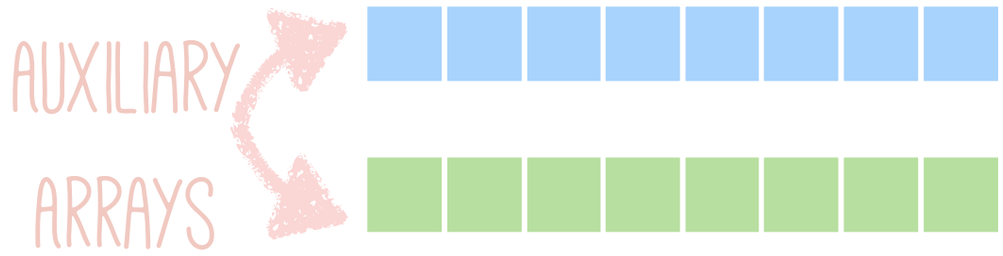


Sampling Rate proxy for
Storage & Performance

Storage ≈ OriginalSize/α

Latency ≈ α



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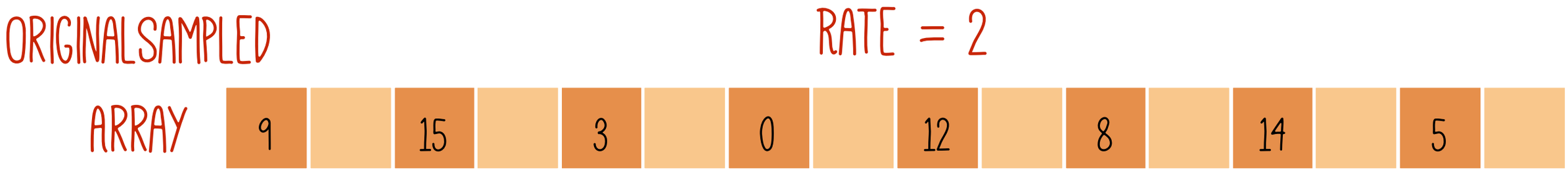
Layered Sampled Array

Inspired by multi-layered video encoding techniques



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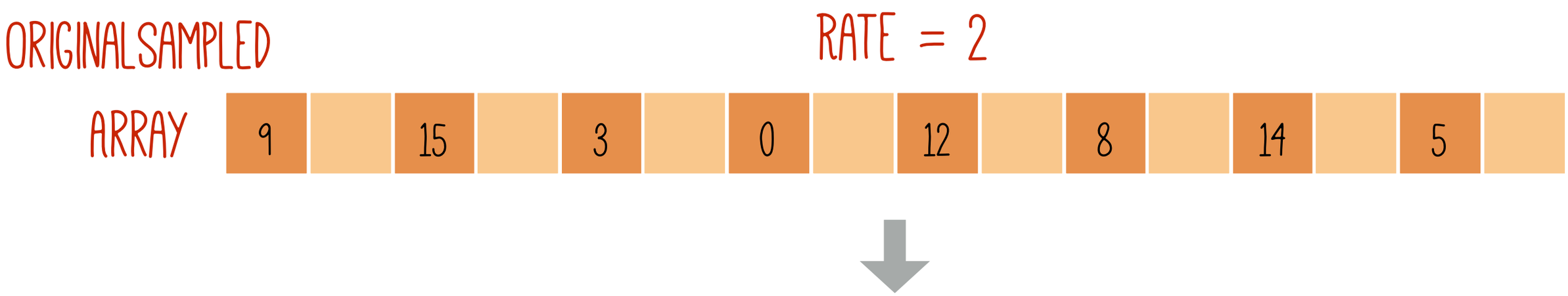

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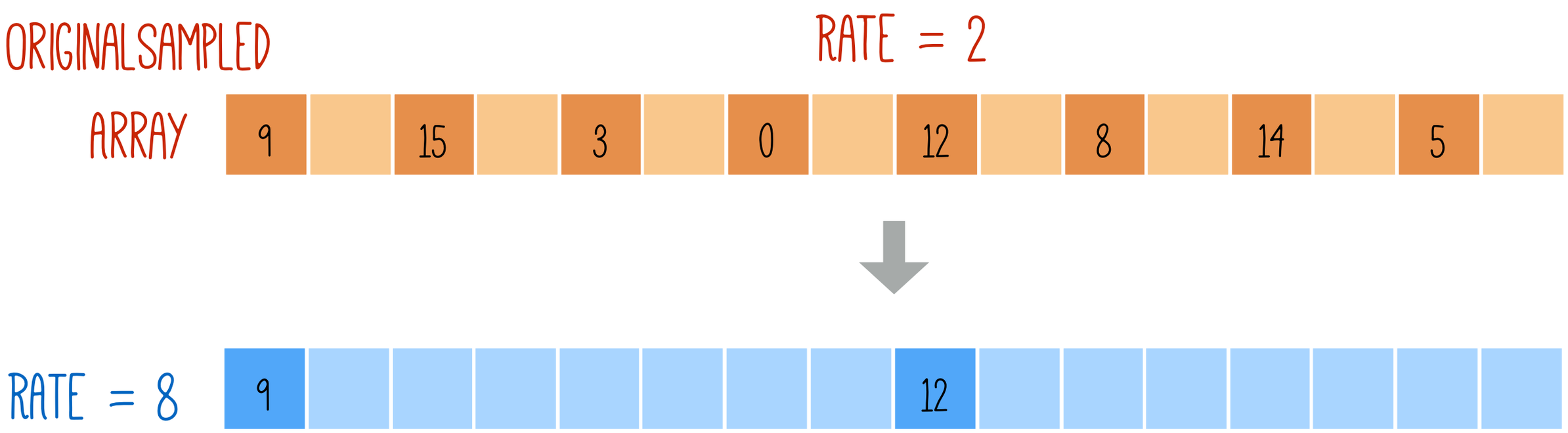

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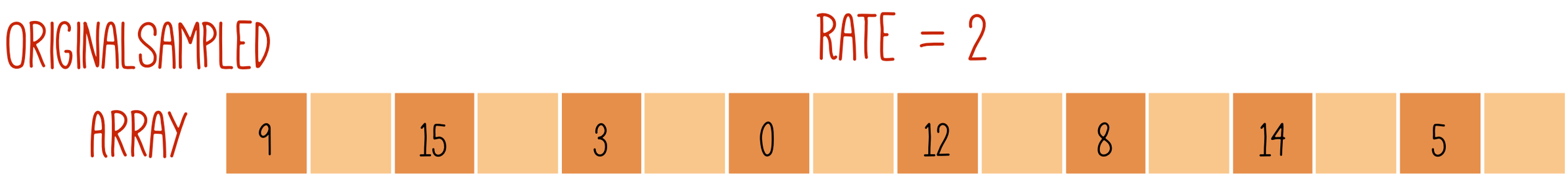

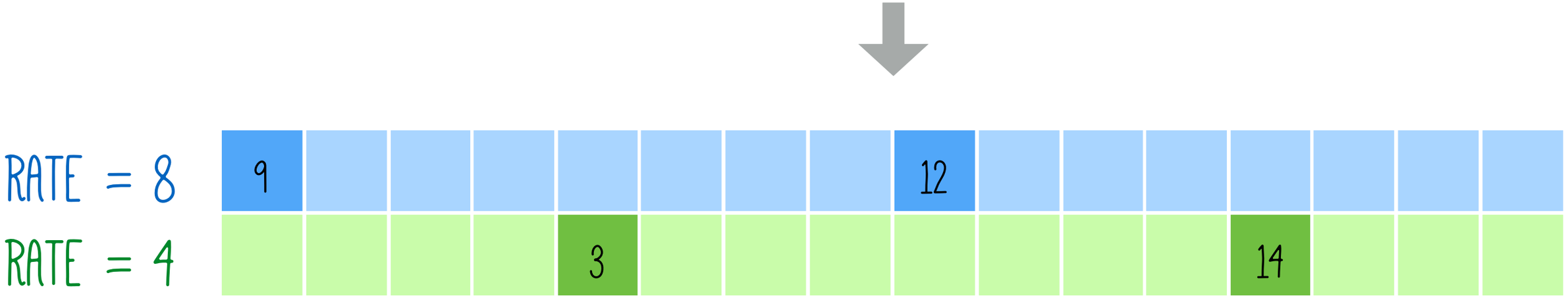

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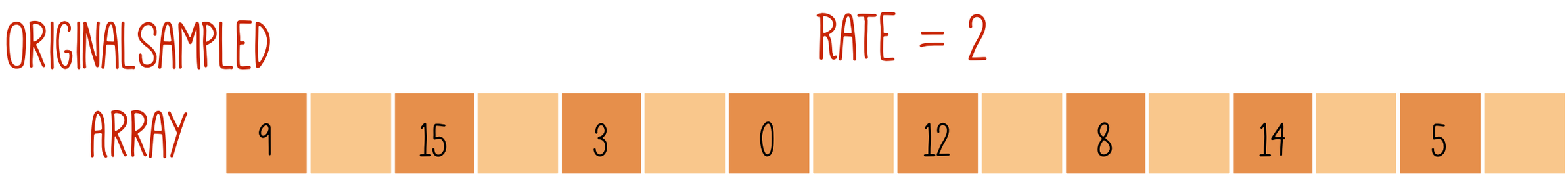

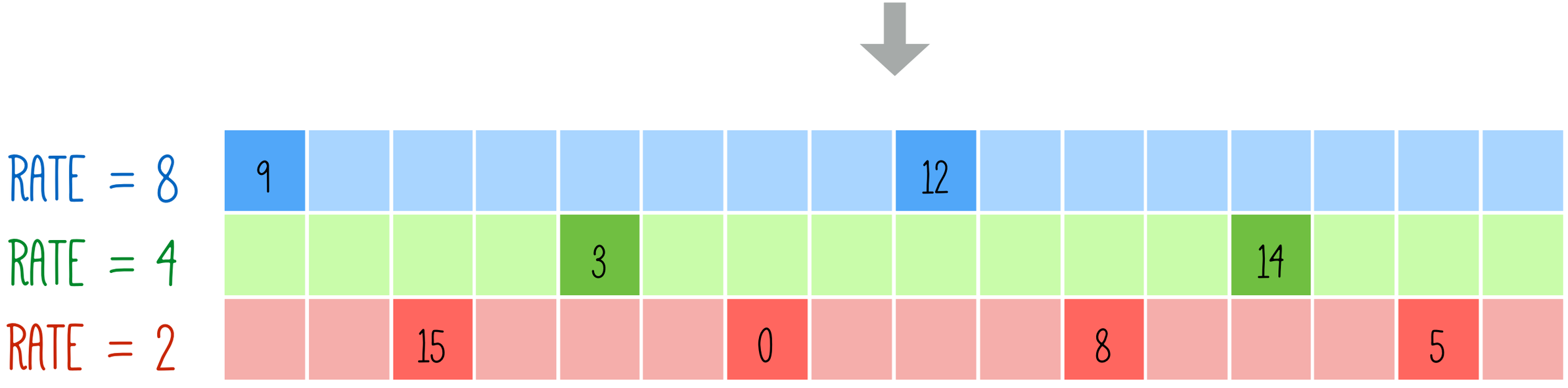

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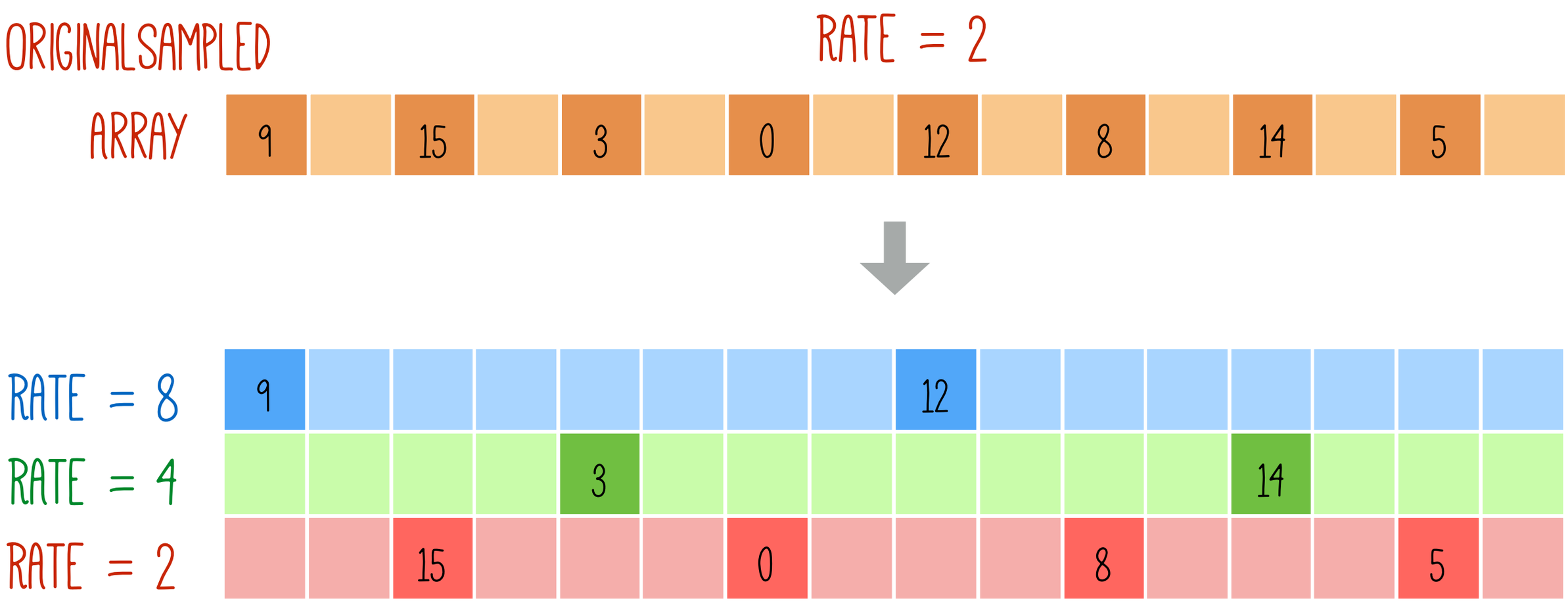

Different combination of layers

Layered Sampled Array

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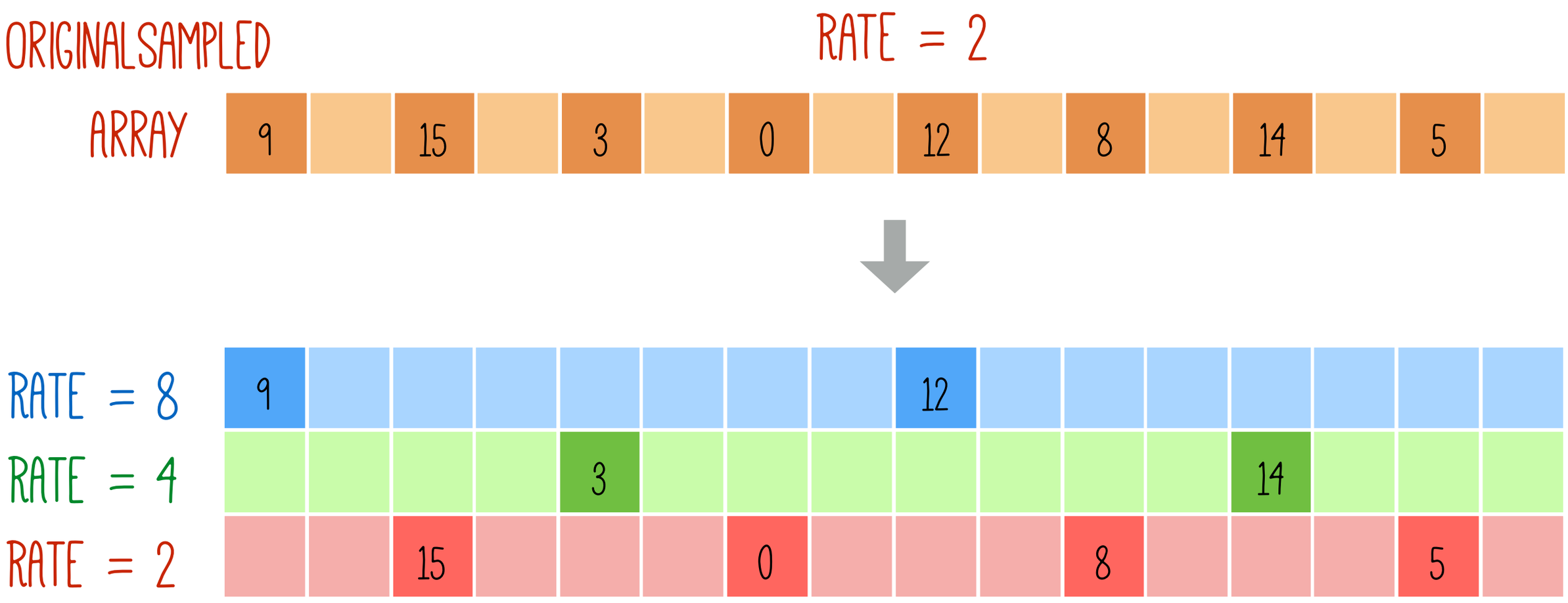

Different combination of layers → **Different points** on tradeoff curve

Technical **Details**

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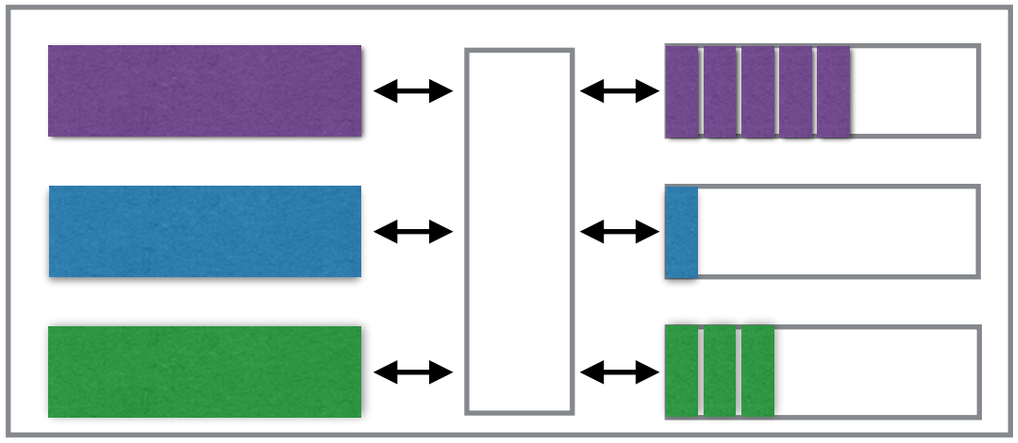

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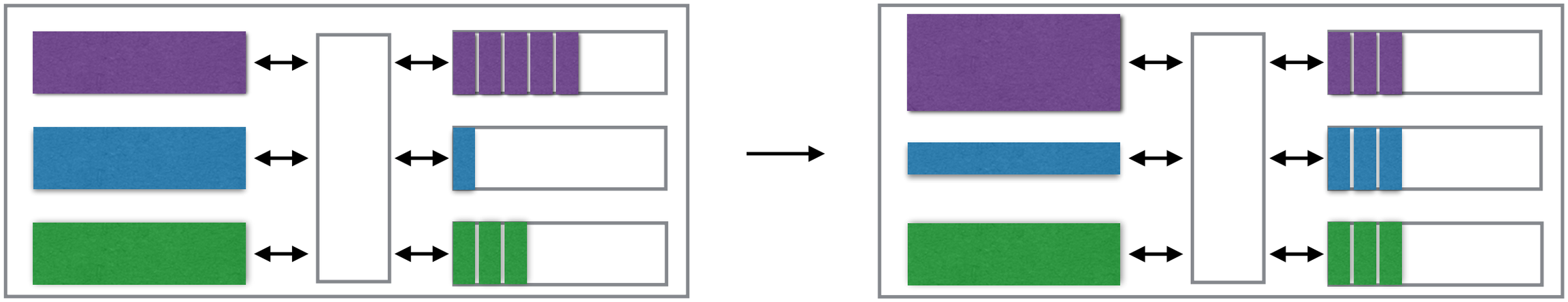

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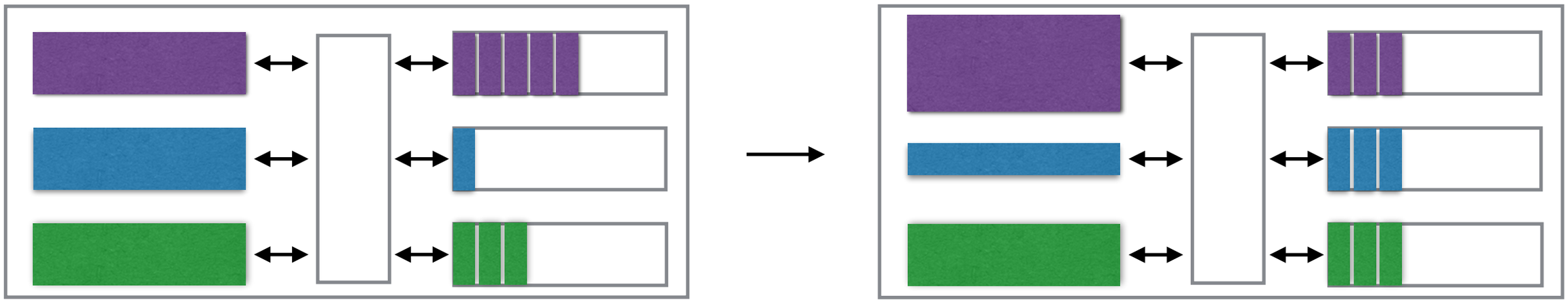

- How should partitions share cache on a server?

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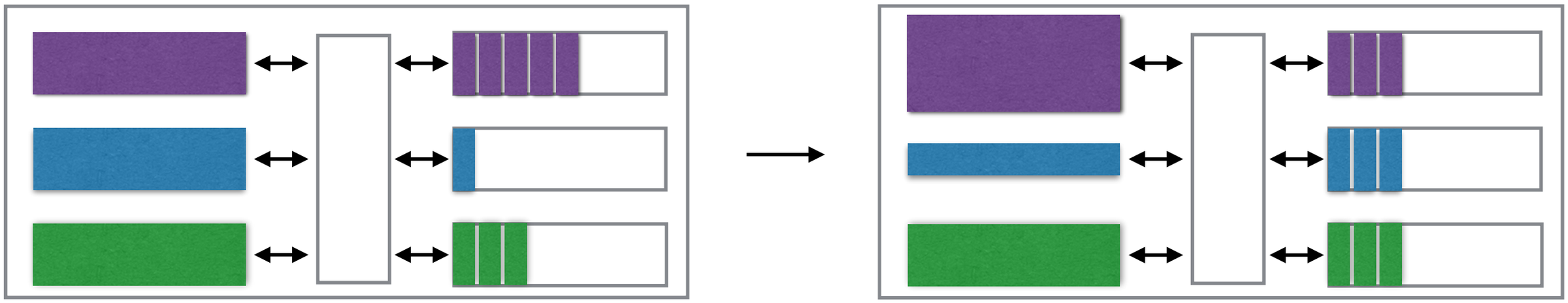

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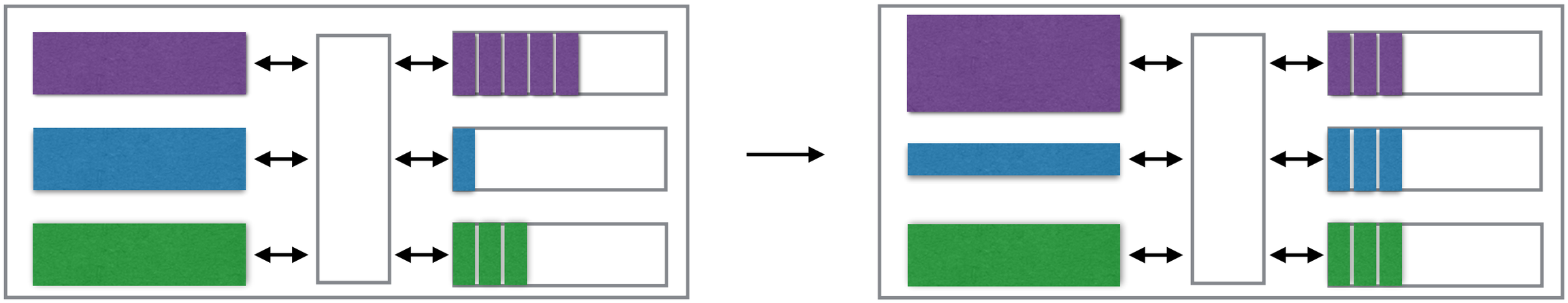
Technical **Details**



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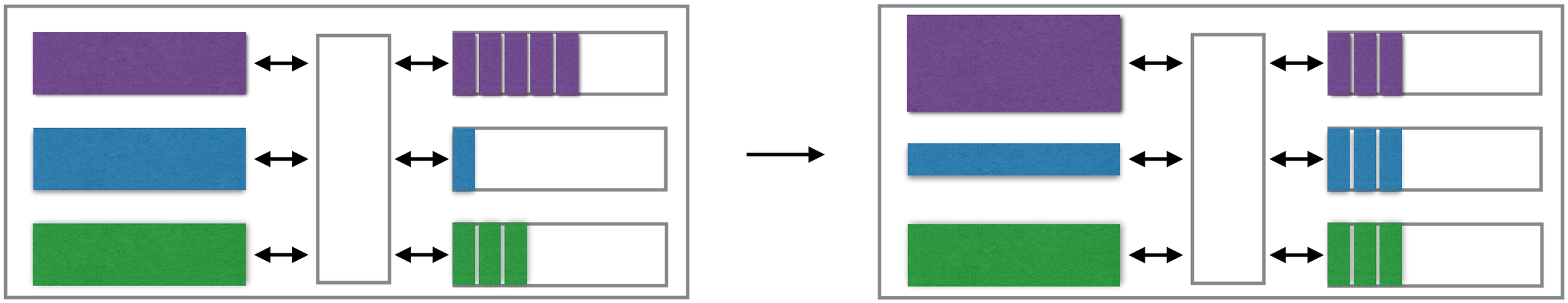

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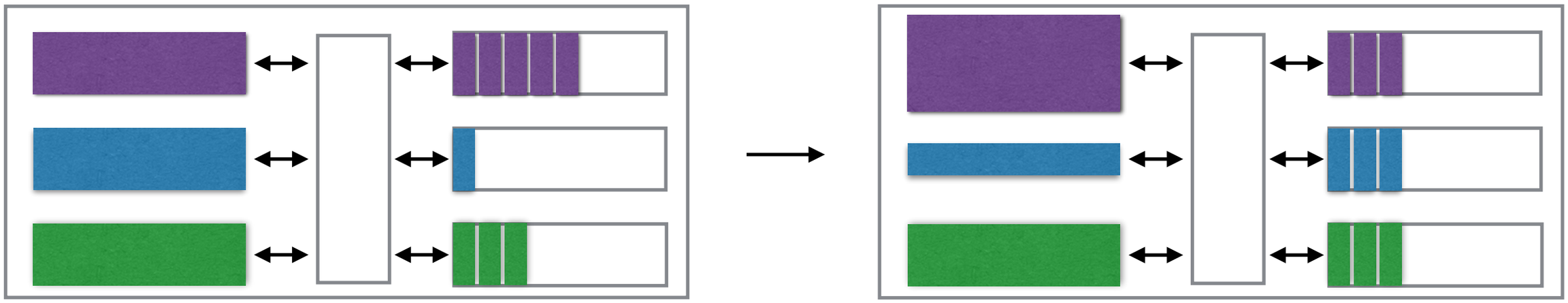

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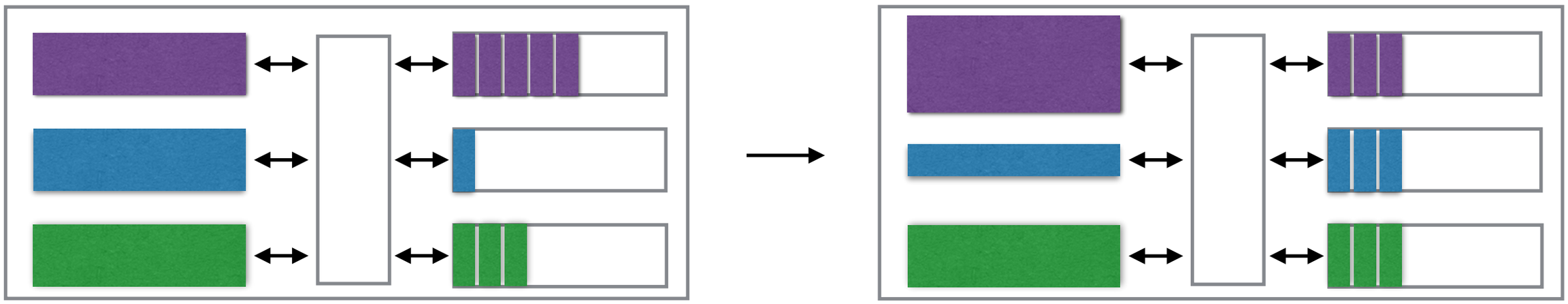

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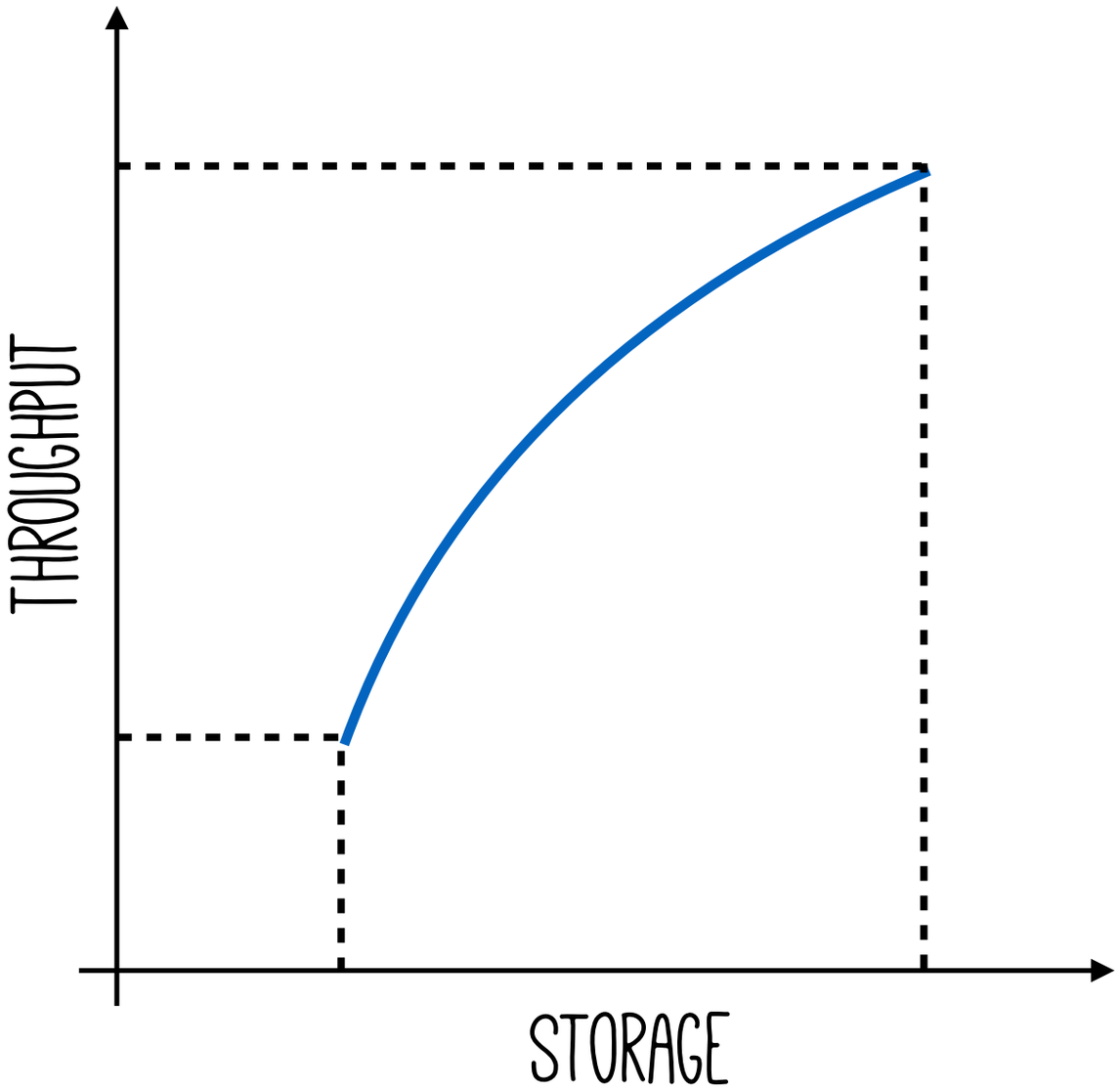
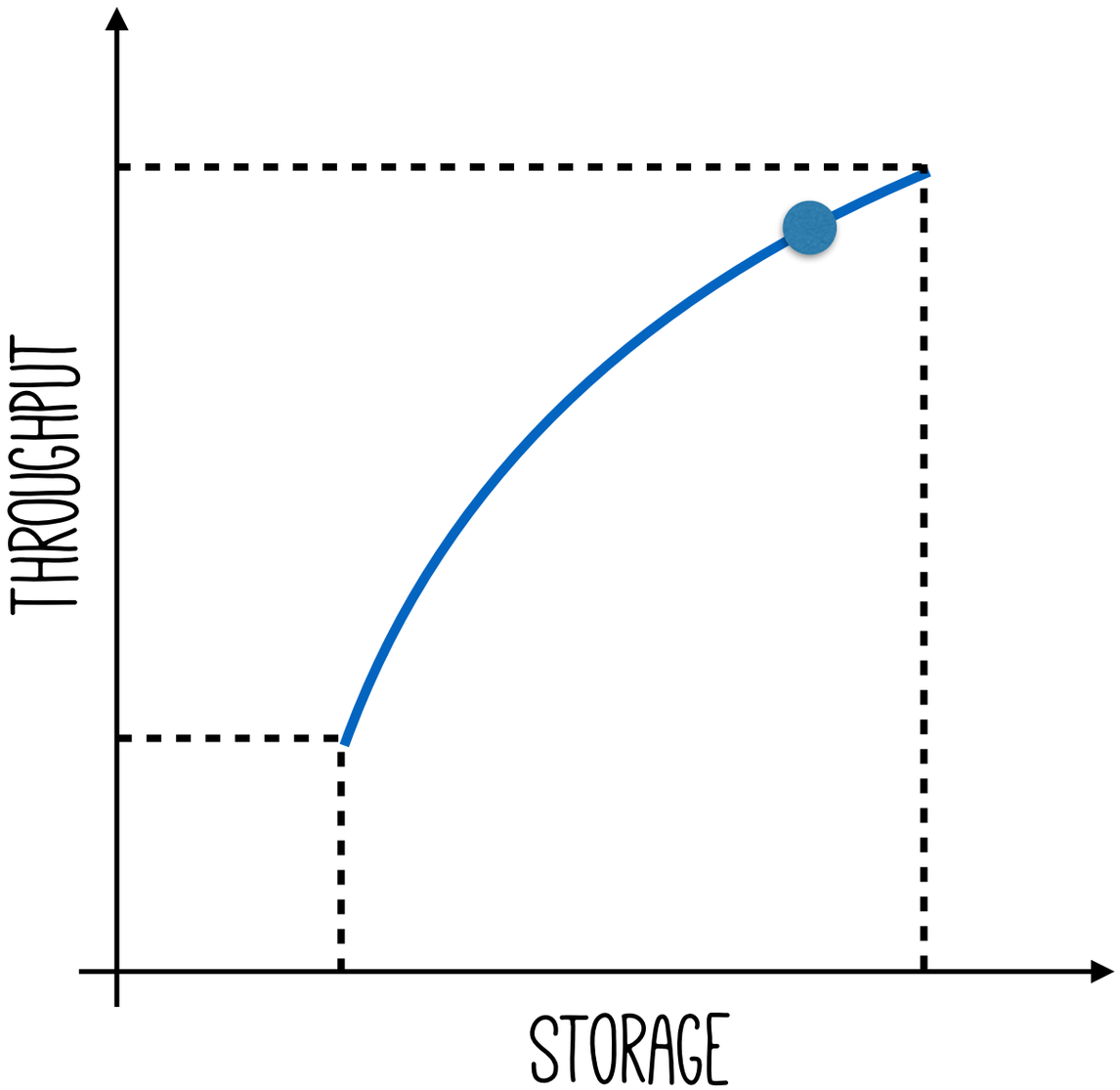
Unified Solution: Back-pressure style scheduling

Cache proportional to load, without explicit coordination


THROUGHPUT
STORAGE



Dynamic Navigation

of tradeoff curve

Layer Additions & Deletions

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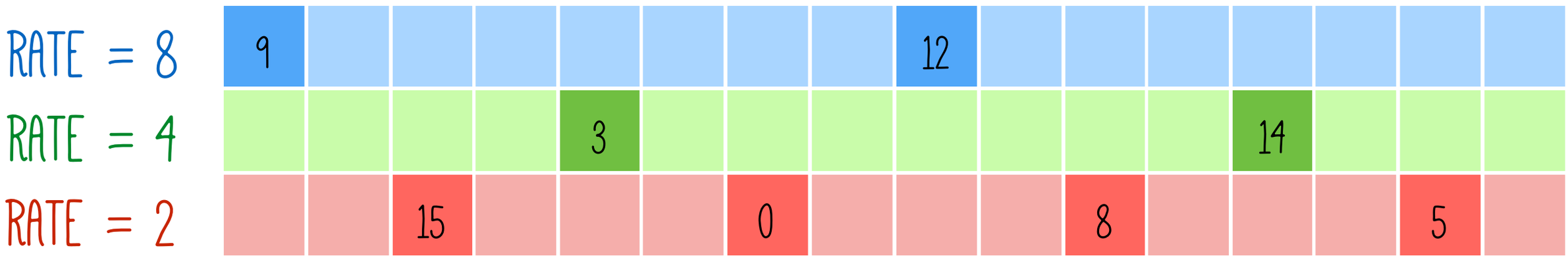

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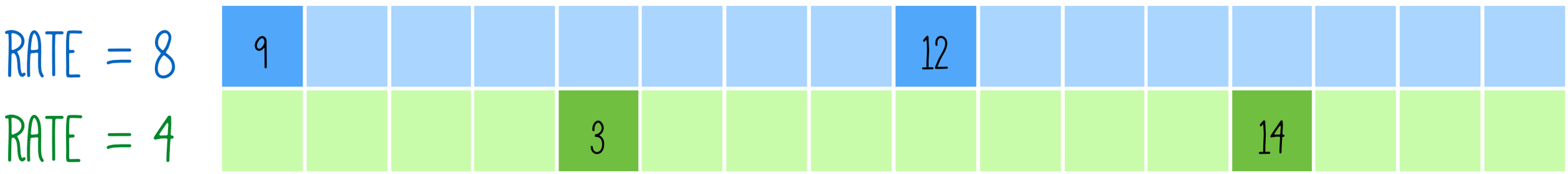

Layer Deletions: simple

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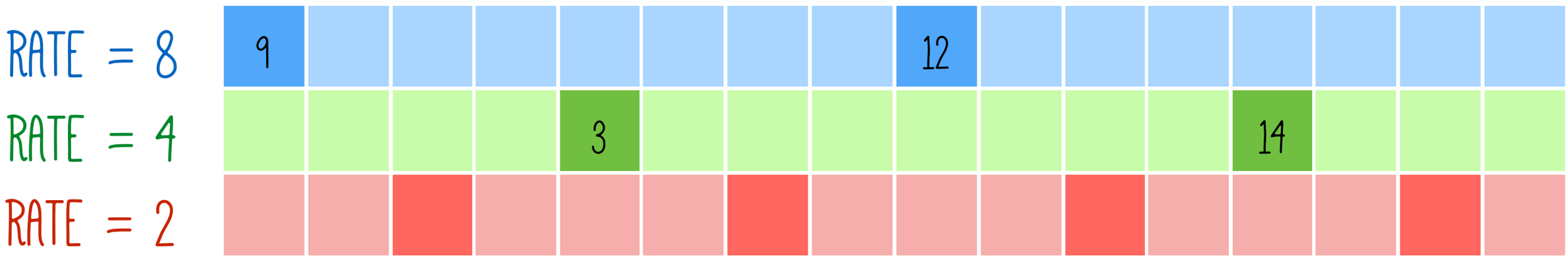

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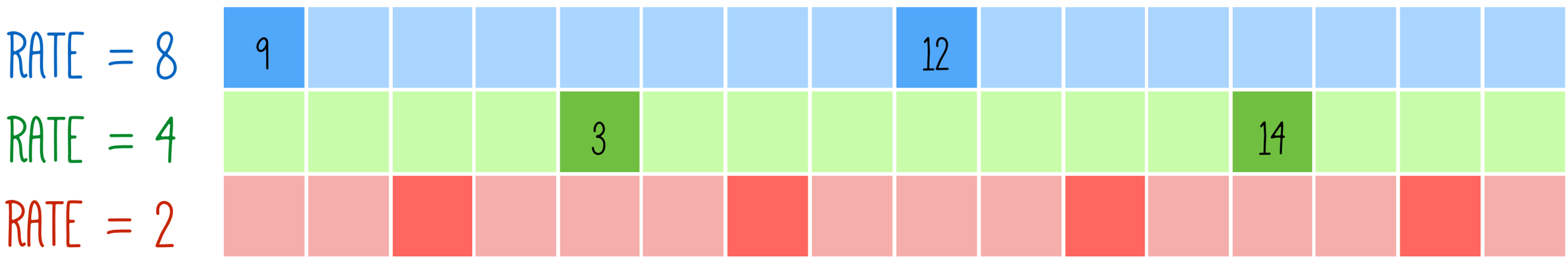

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Unsampled values already computed during query execution

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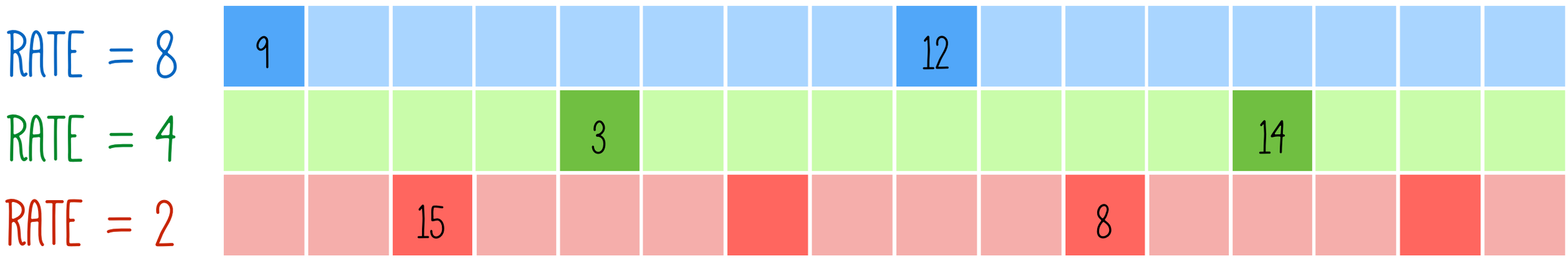

Layer Addition:

Unsampled values already computed during query execution

Layers in LSA populated *opportunistically*!!

Assumptions & Limitations

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- System is not network-bottlenecked

  [MICA, NSDI'14] → True for most data stores today

Applications

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Look at classical systems problems through a new “lens”

Spatial Skew

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Load distribution across partitions is heavily skewed

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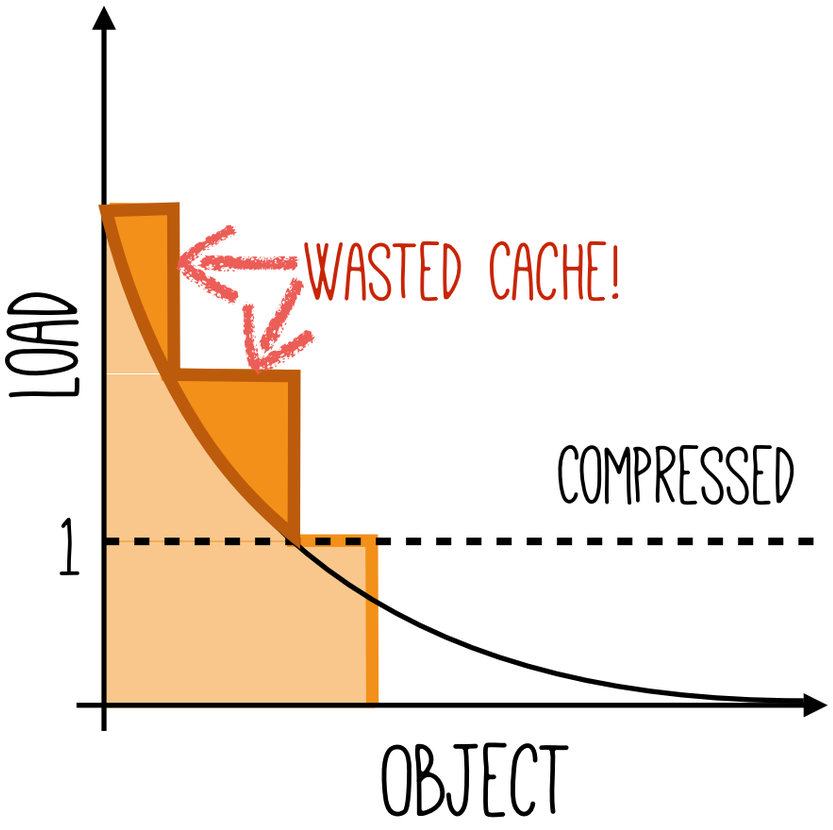

Selective Replication

#Replicas **α** Load

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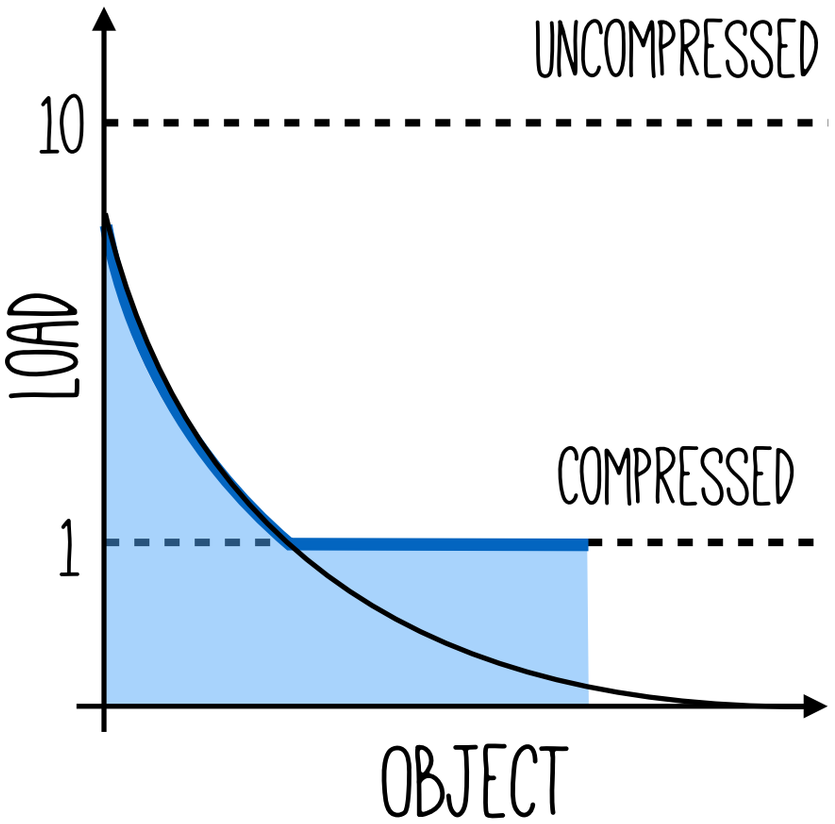

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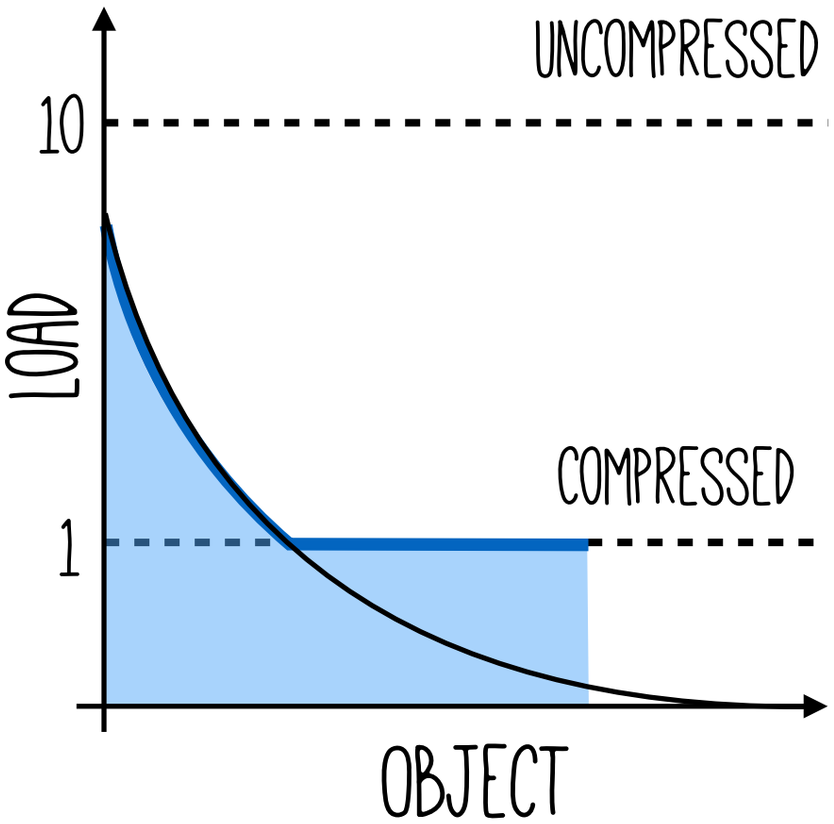

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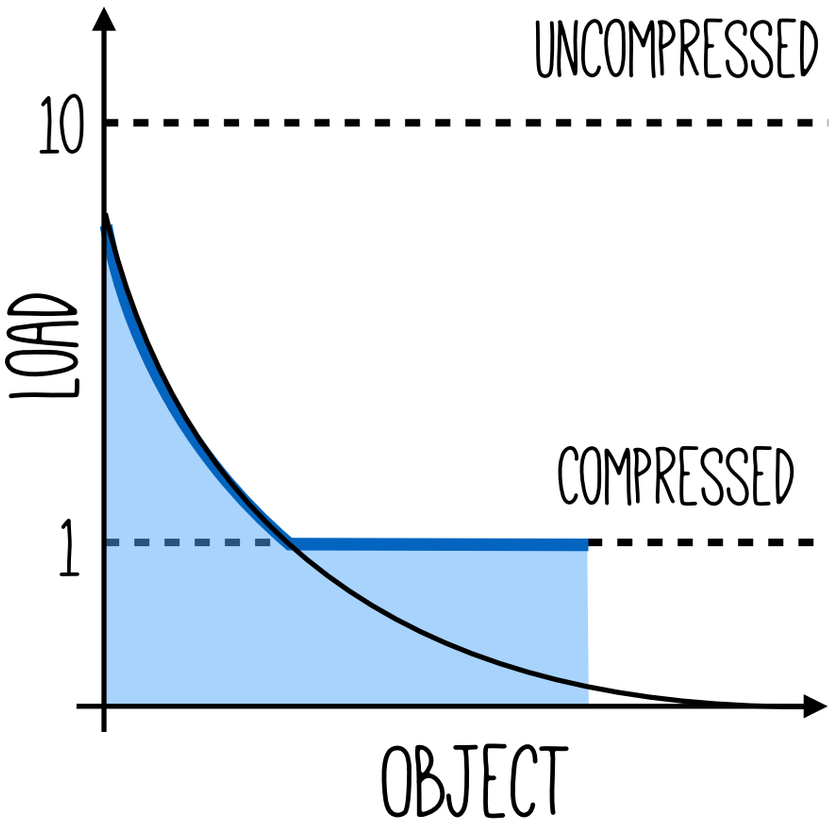

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within 10% of optimal

Changes in Spatial Skew

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Study on Facebook Warehouse Cluster [HotStorage'13]

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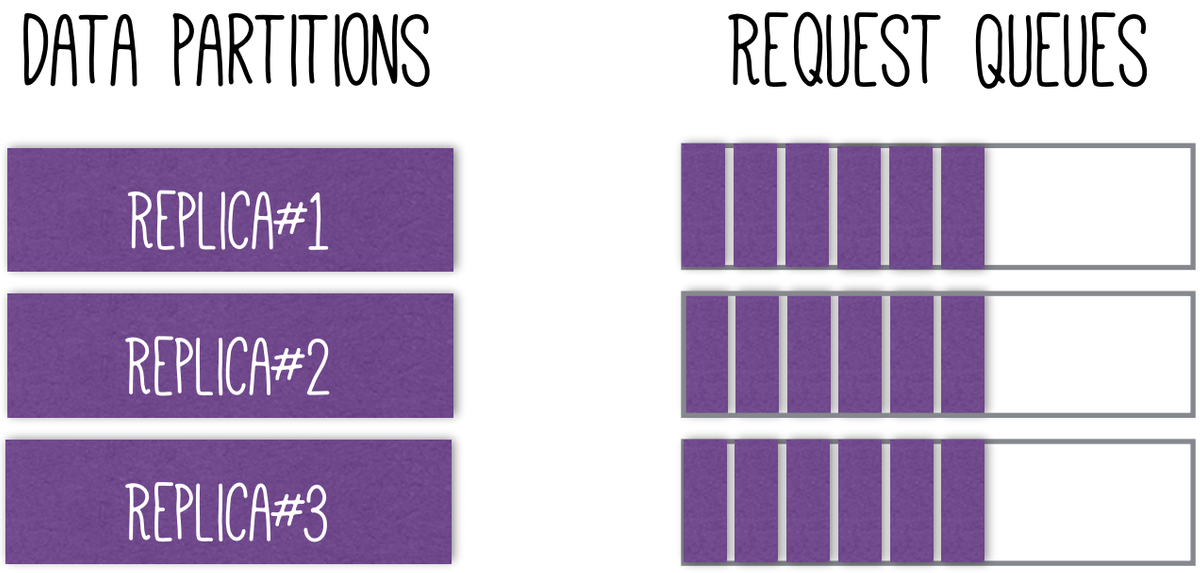

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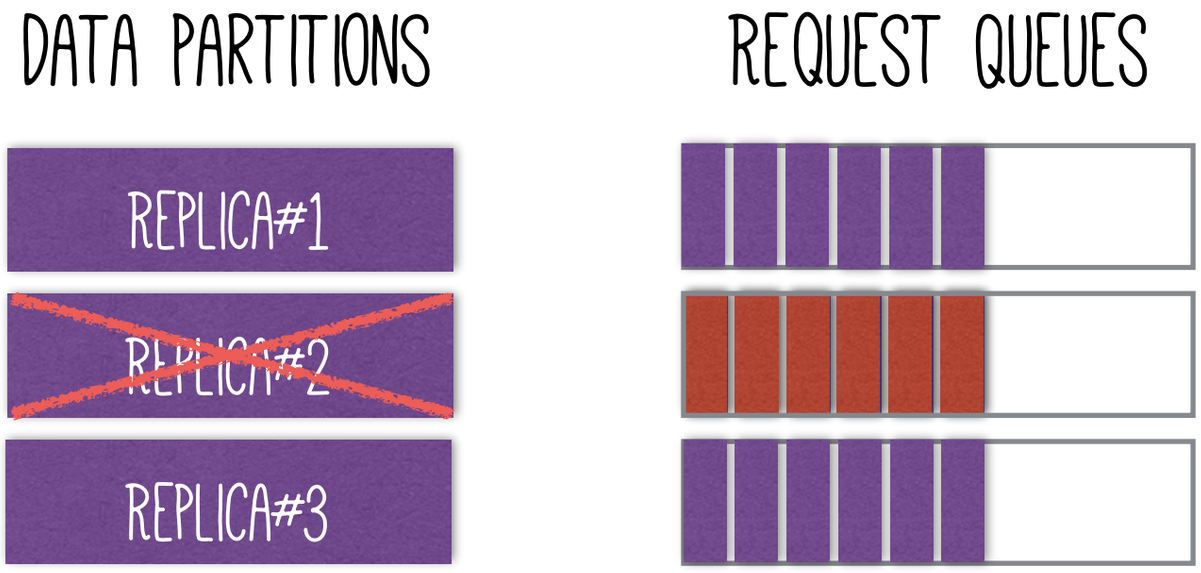

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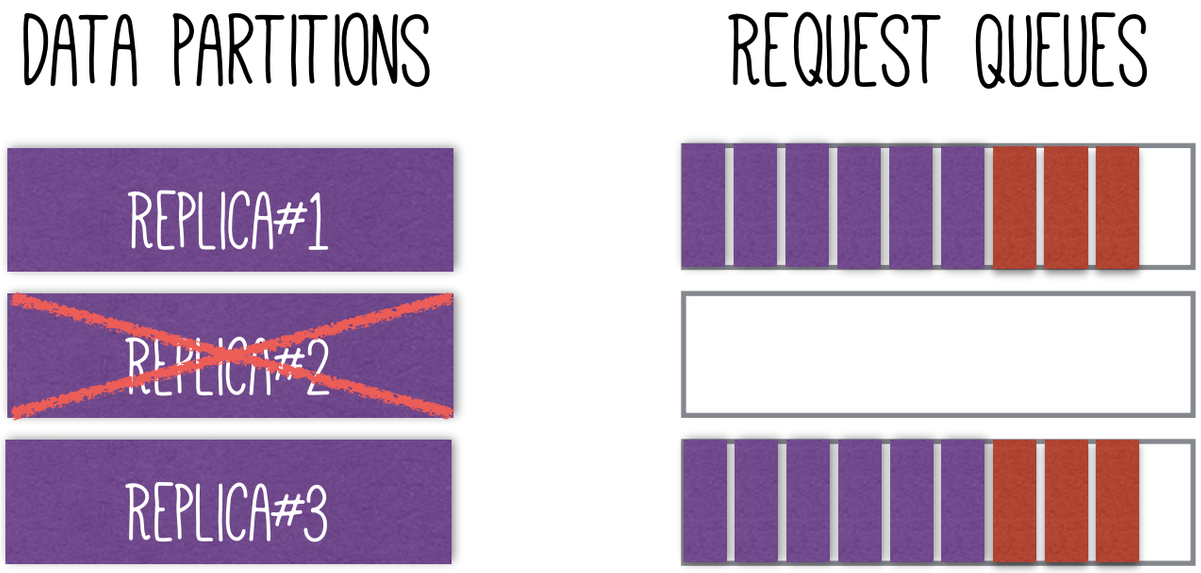

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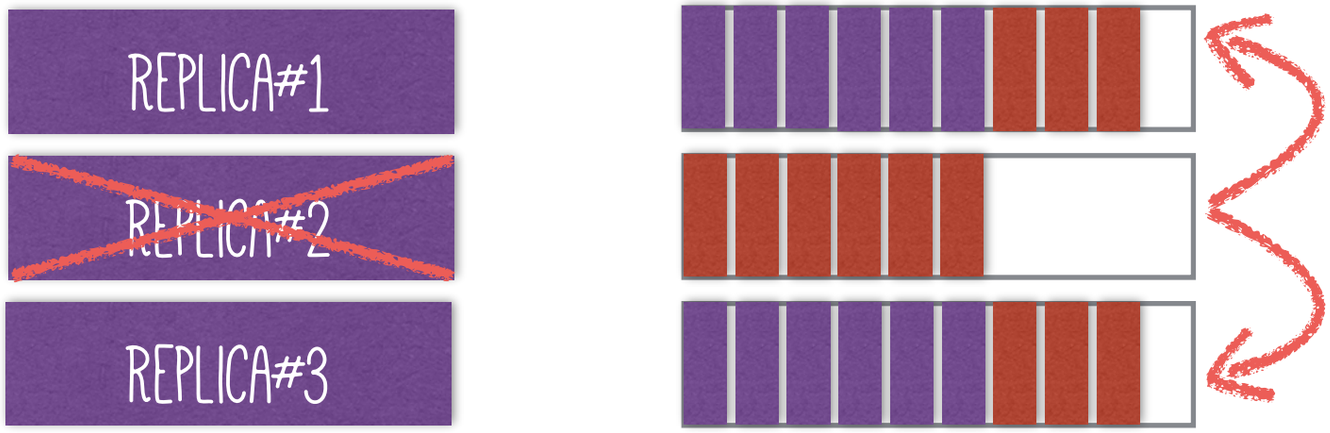

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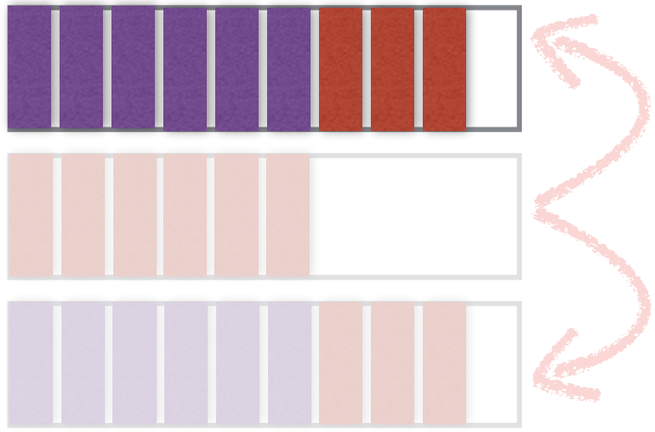

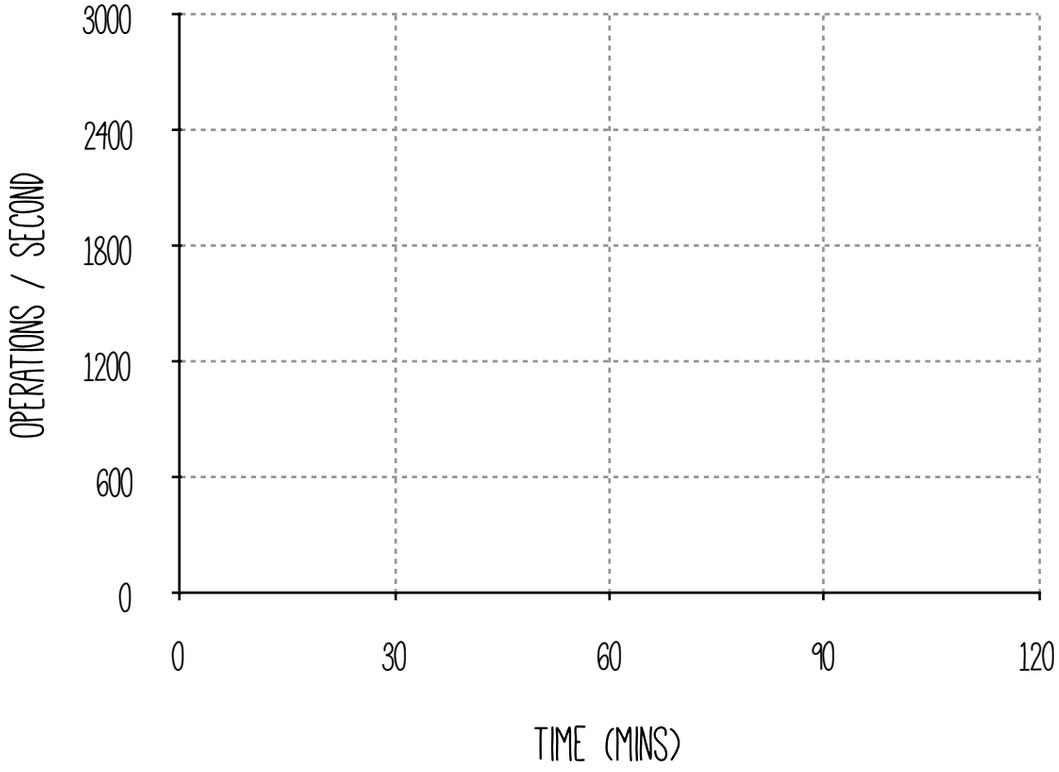

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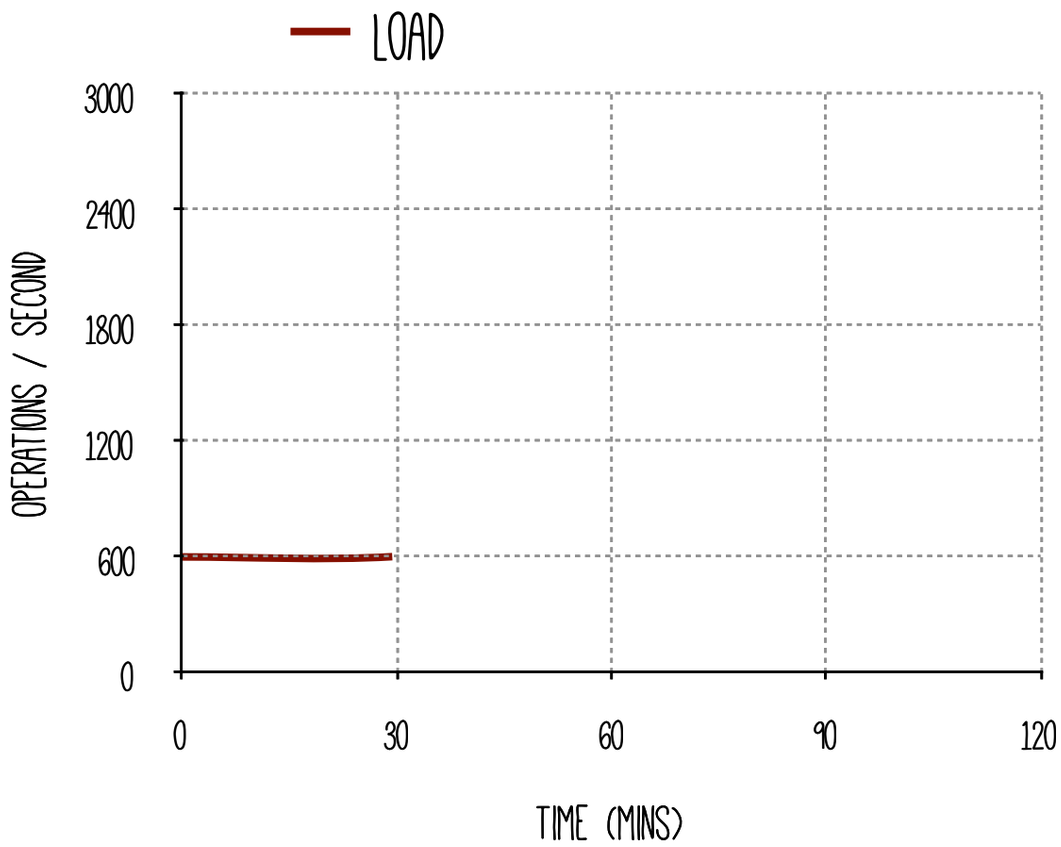

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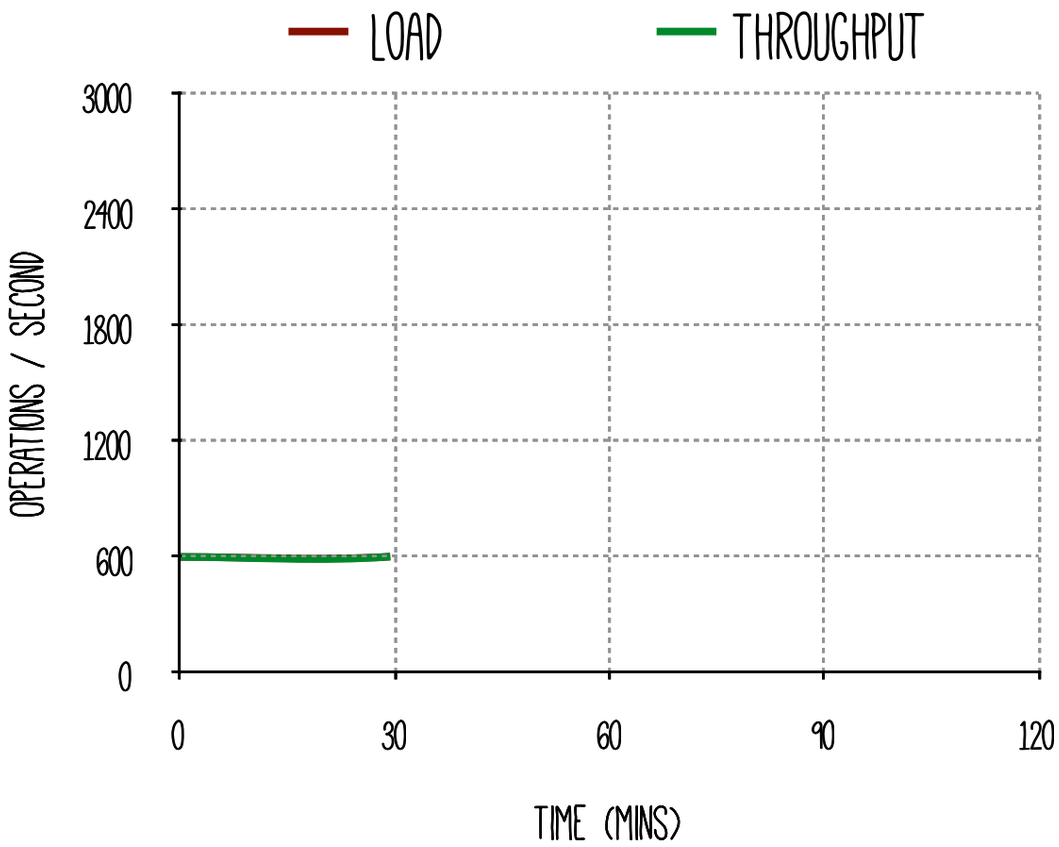

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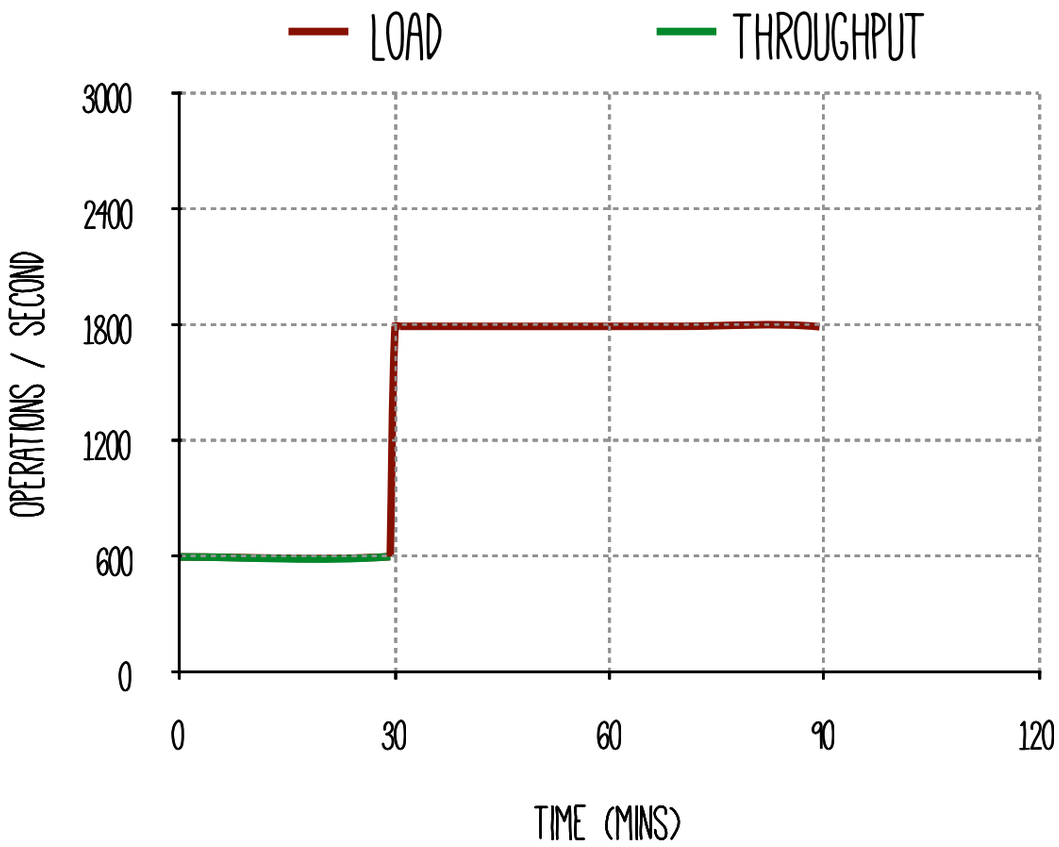

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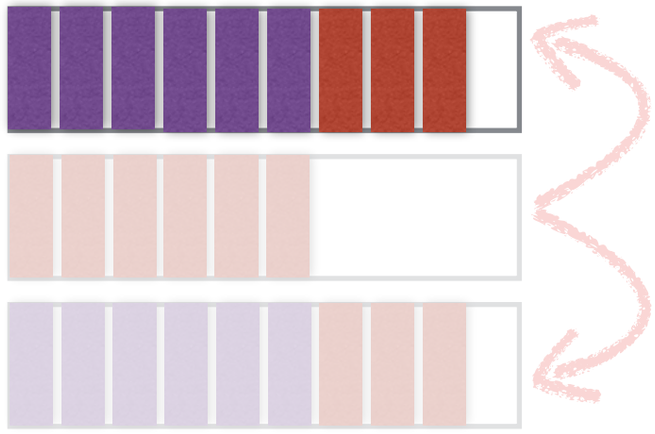

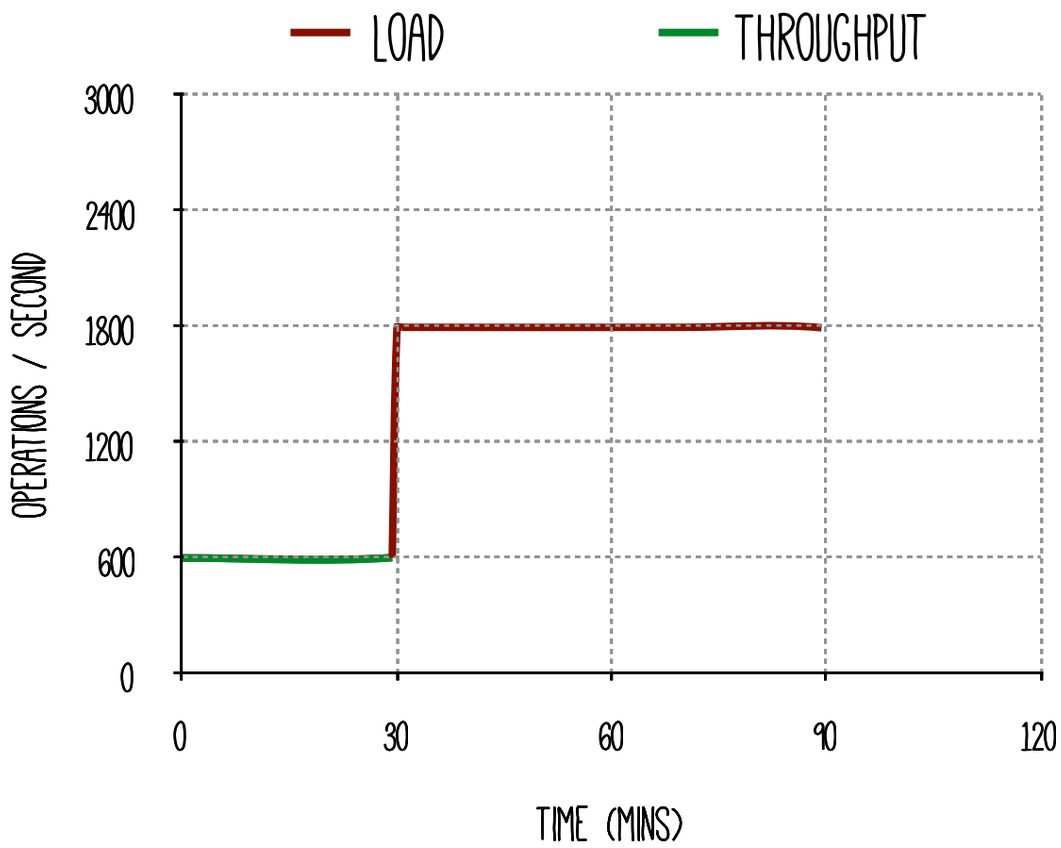

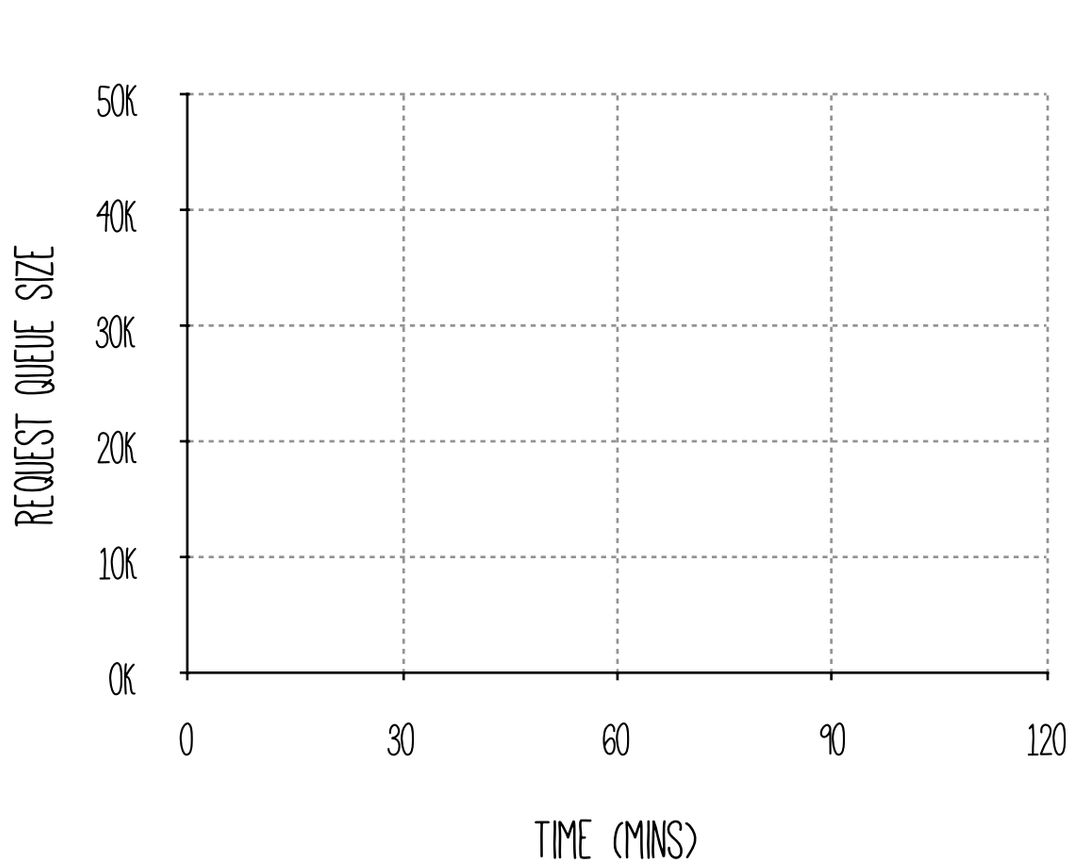

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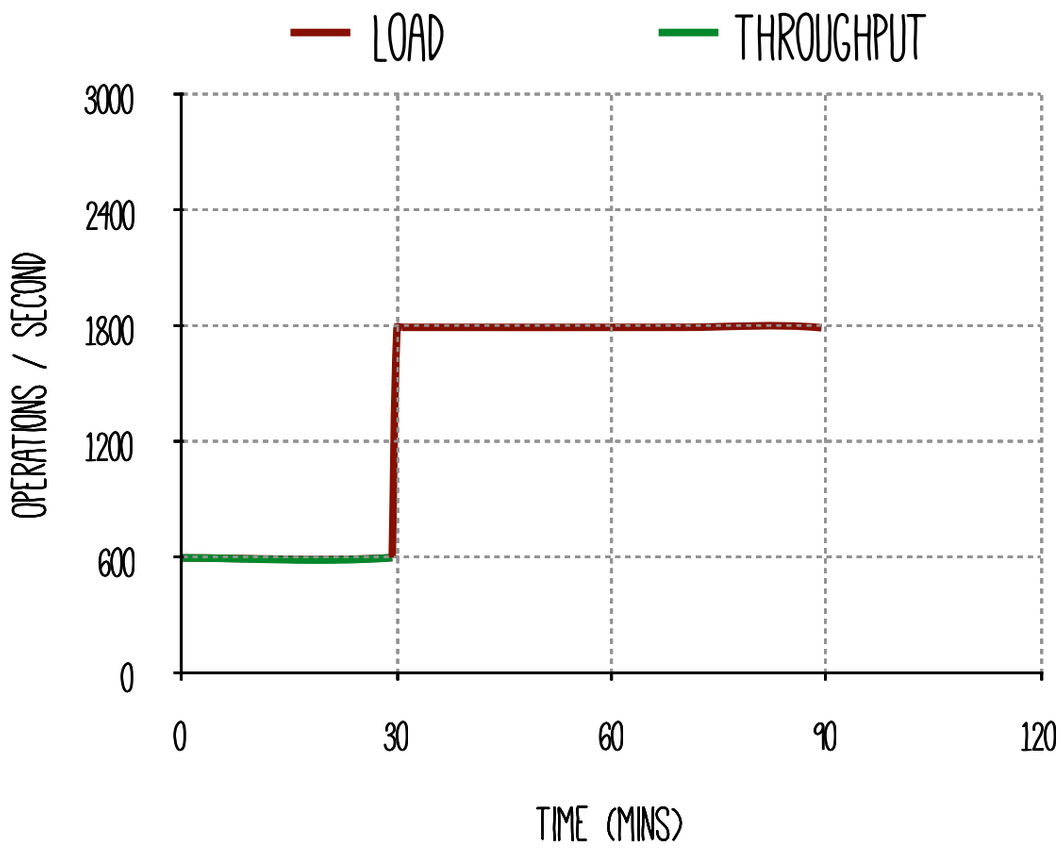

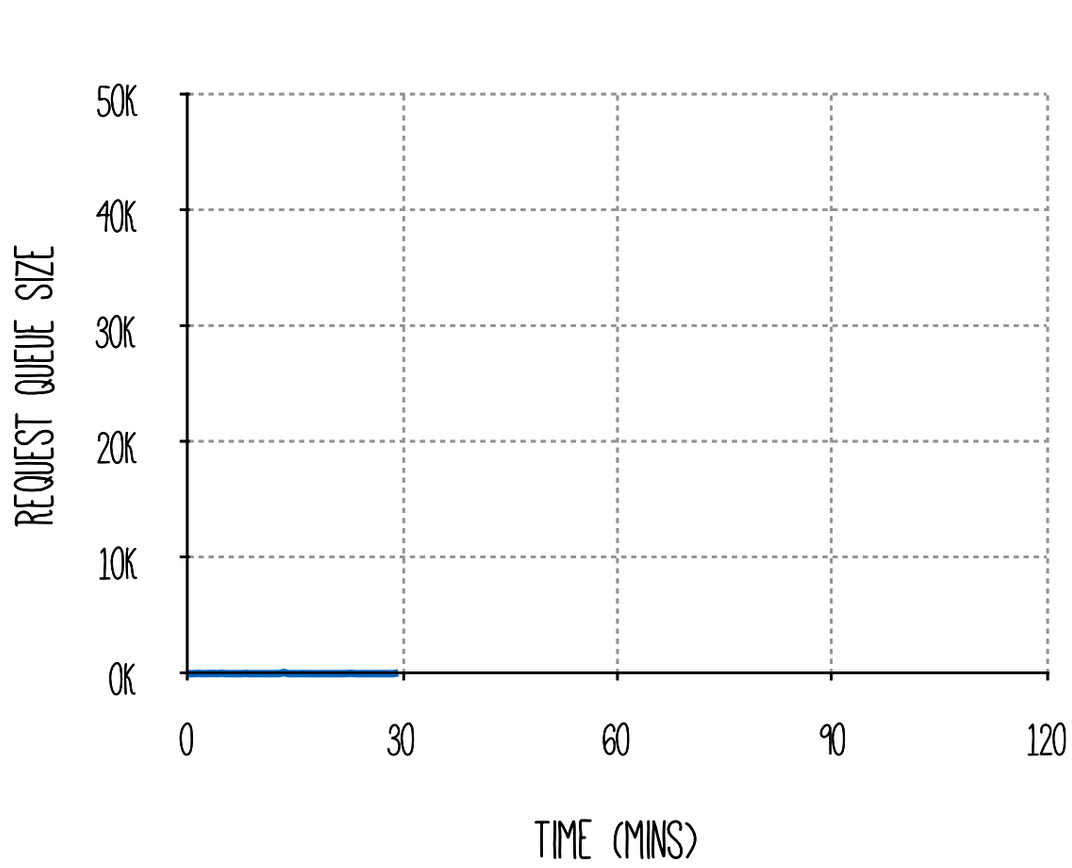

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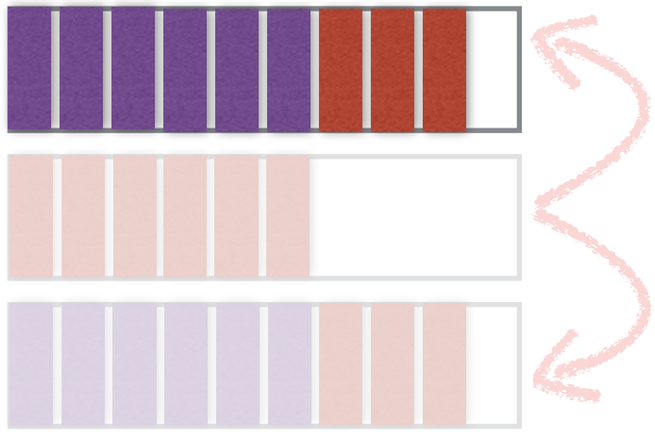

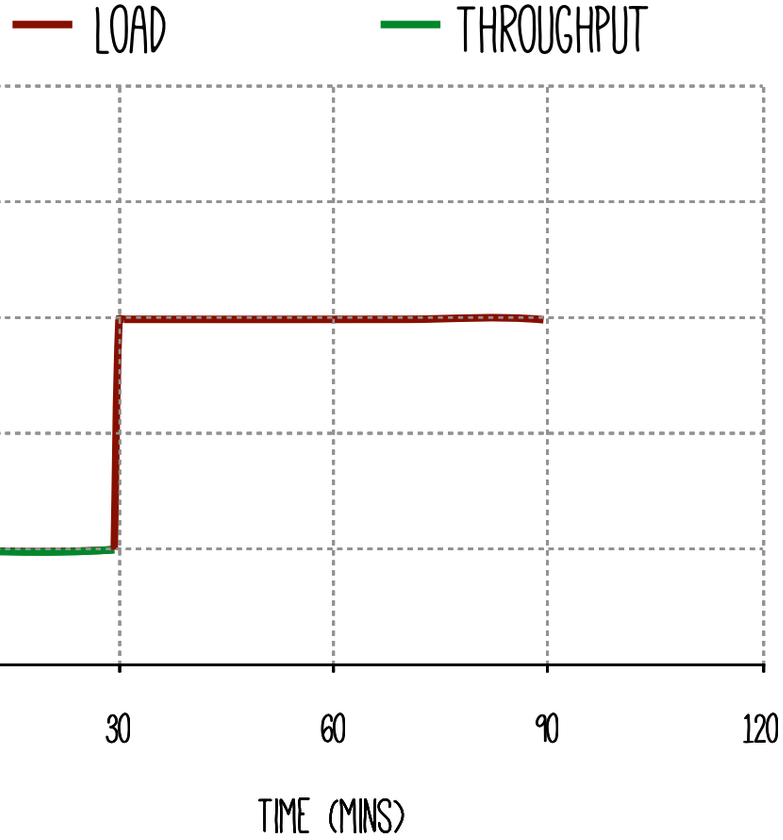

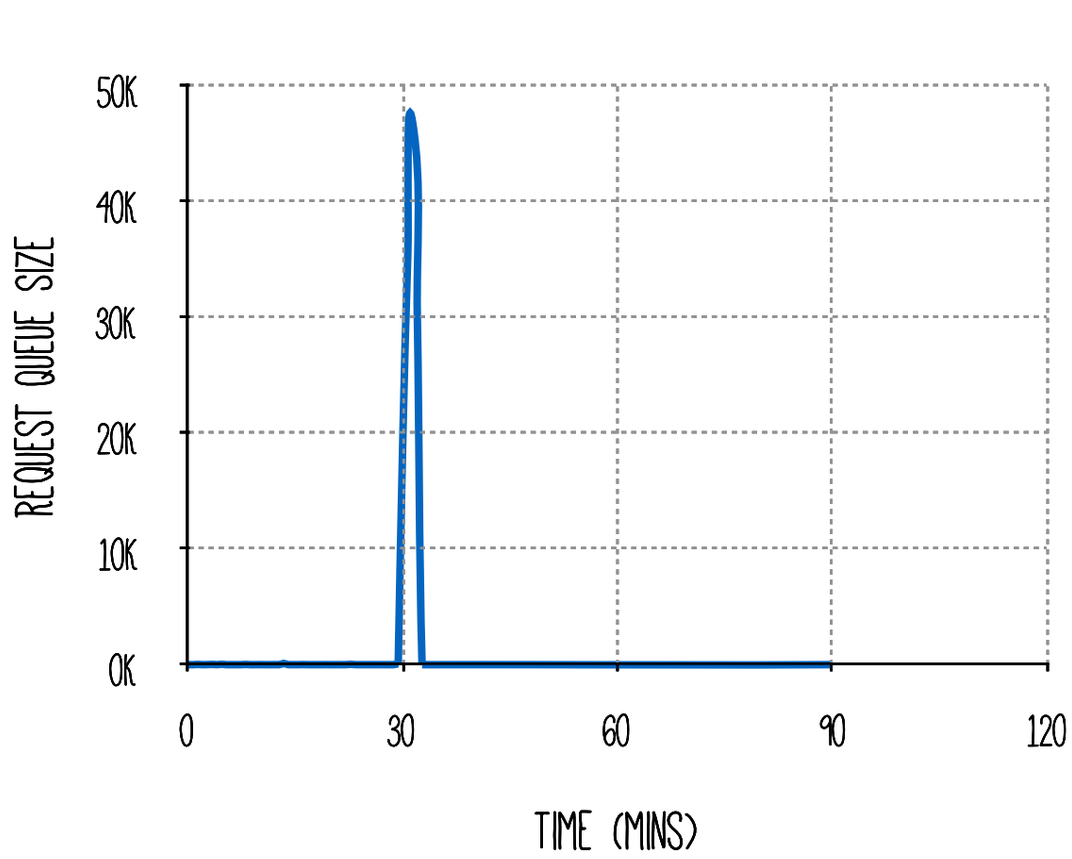

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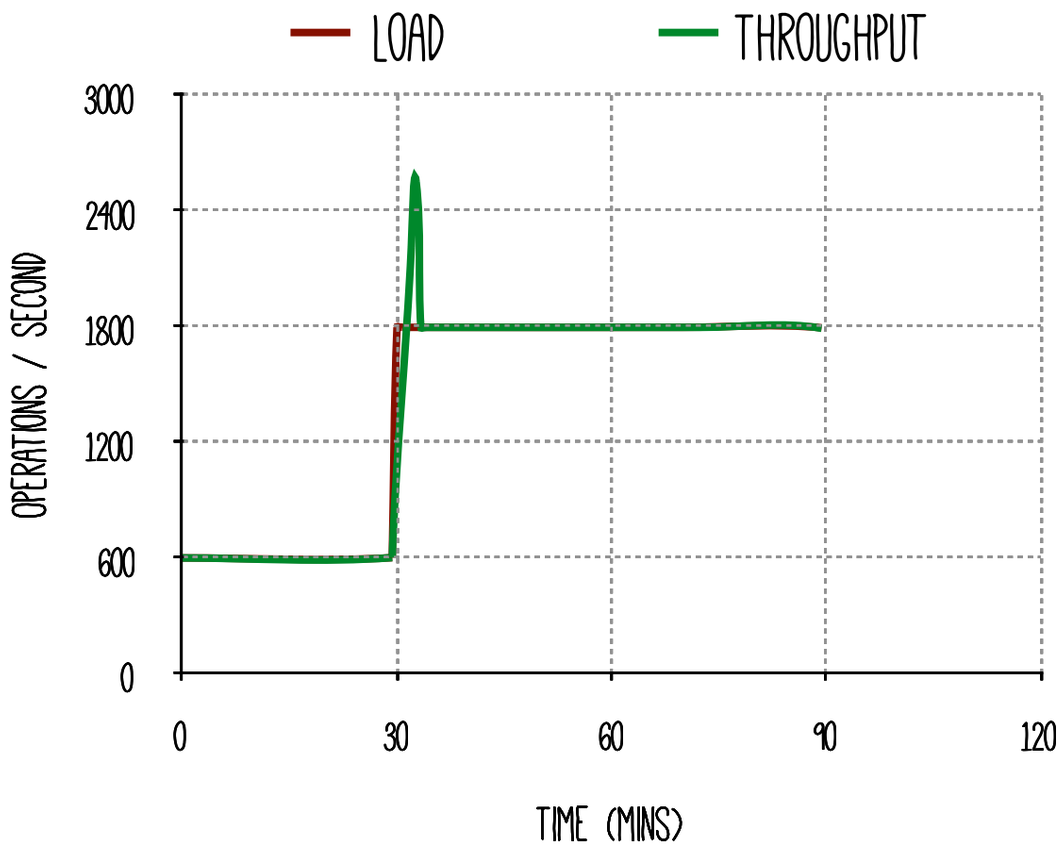

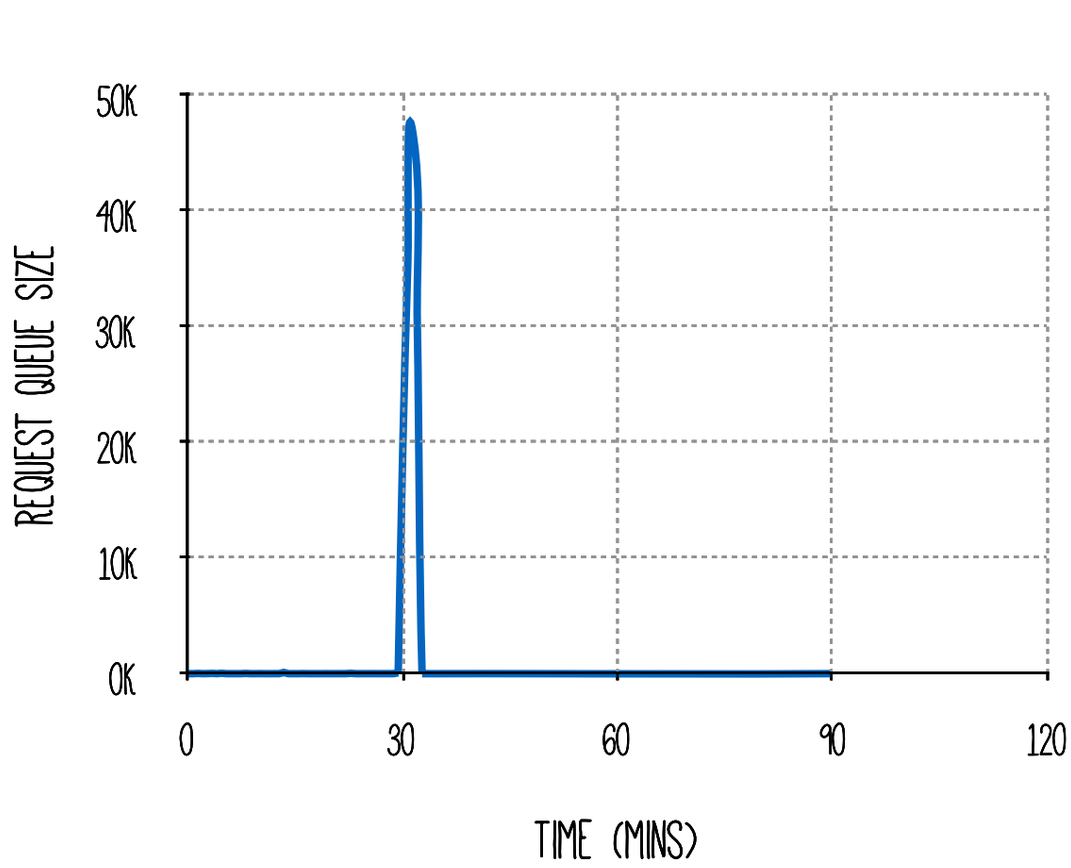

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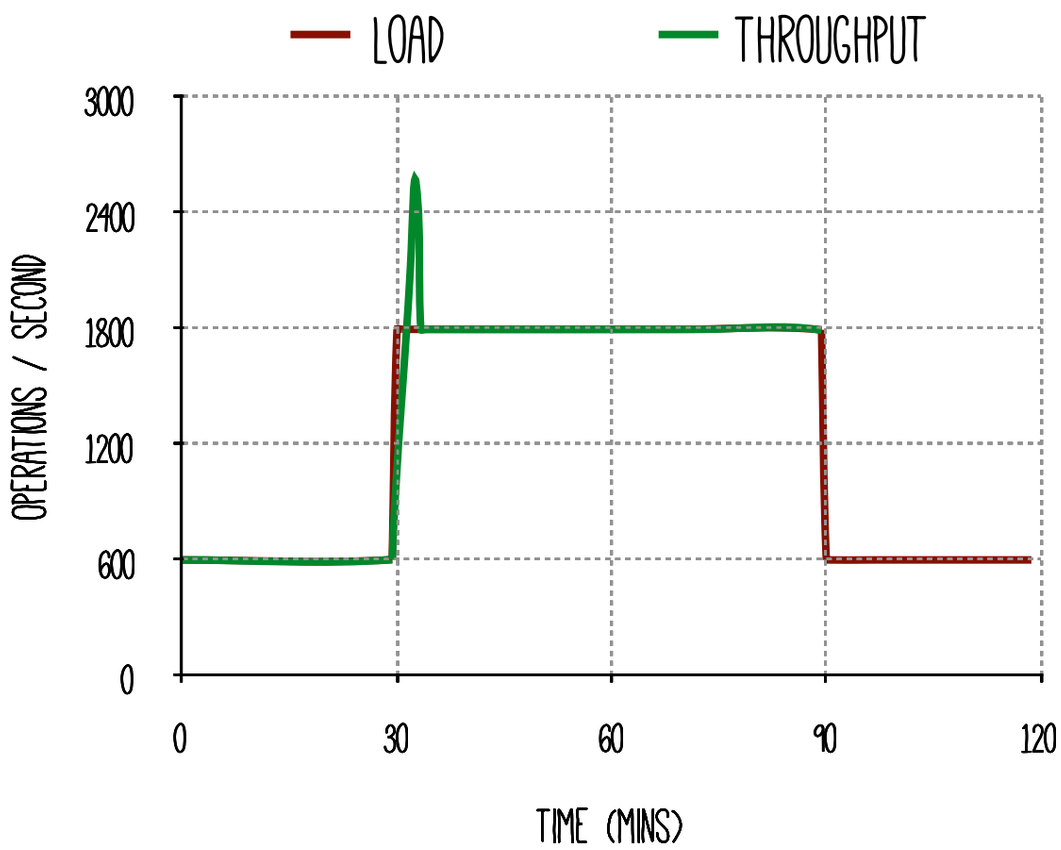

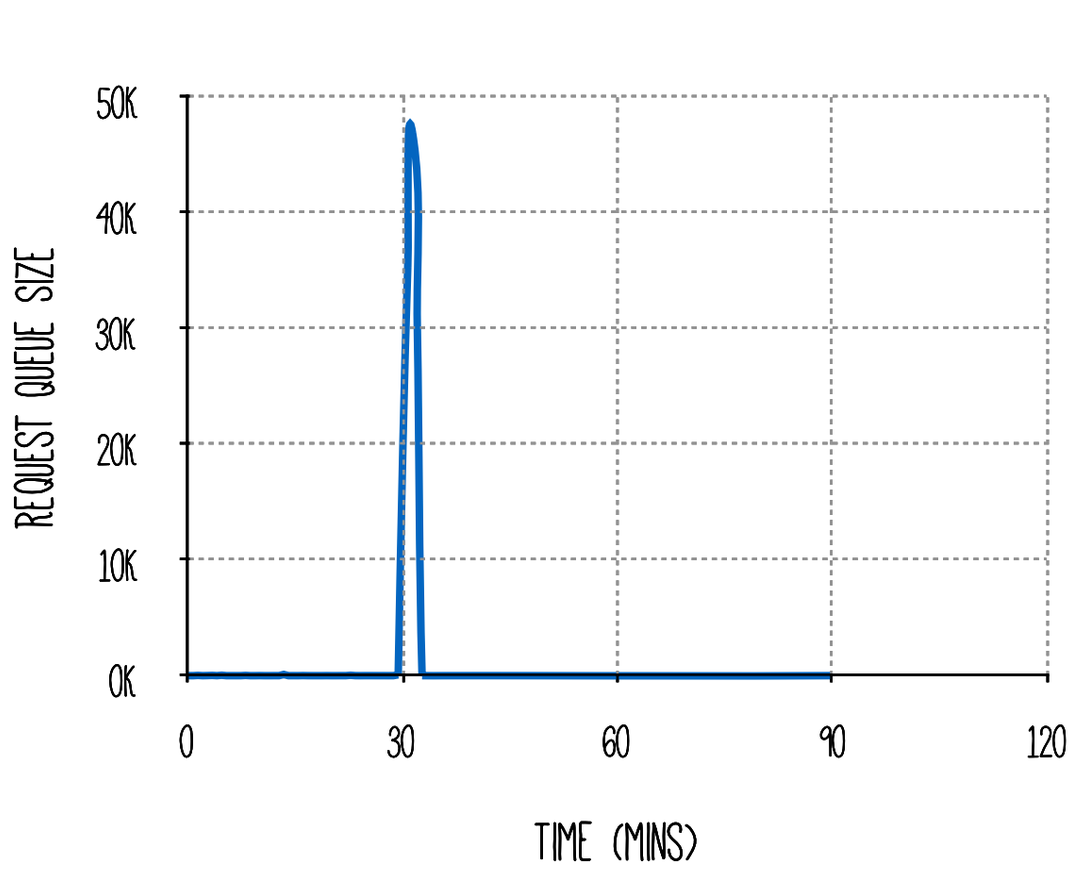

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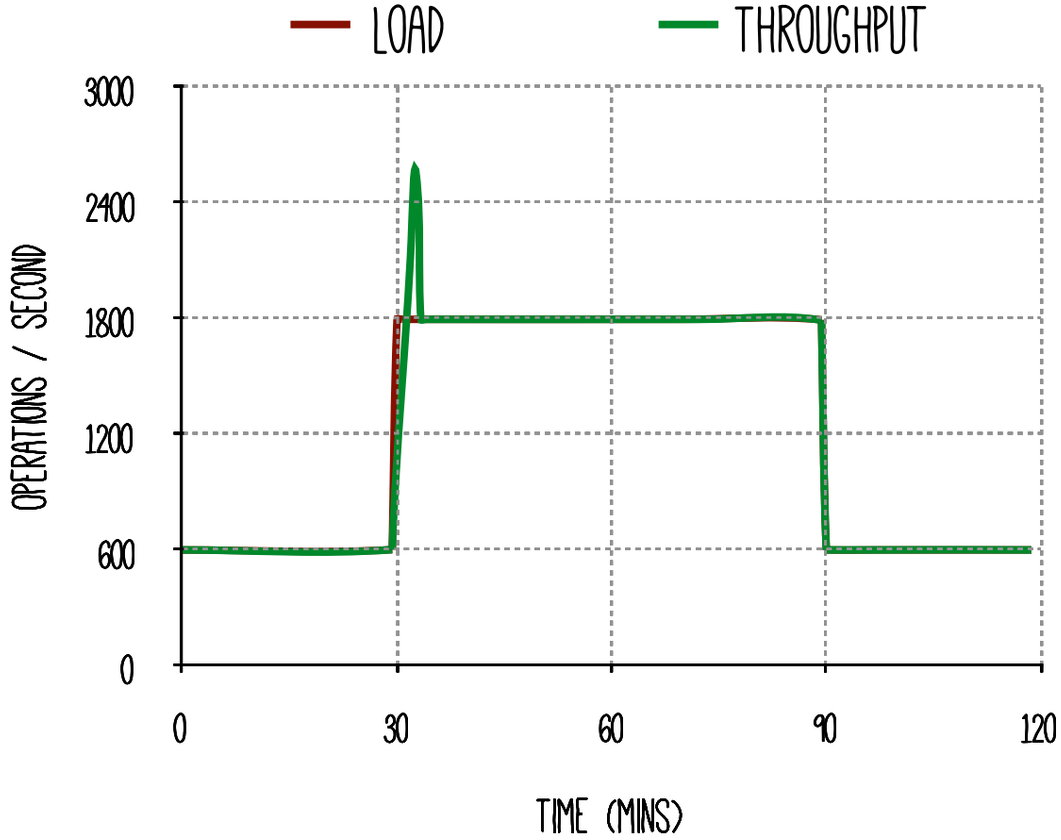

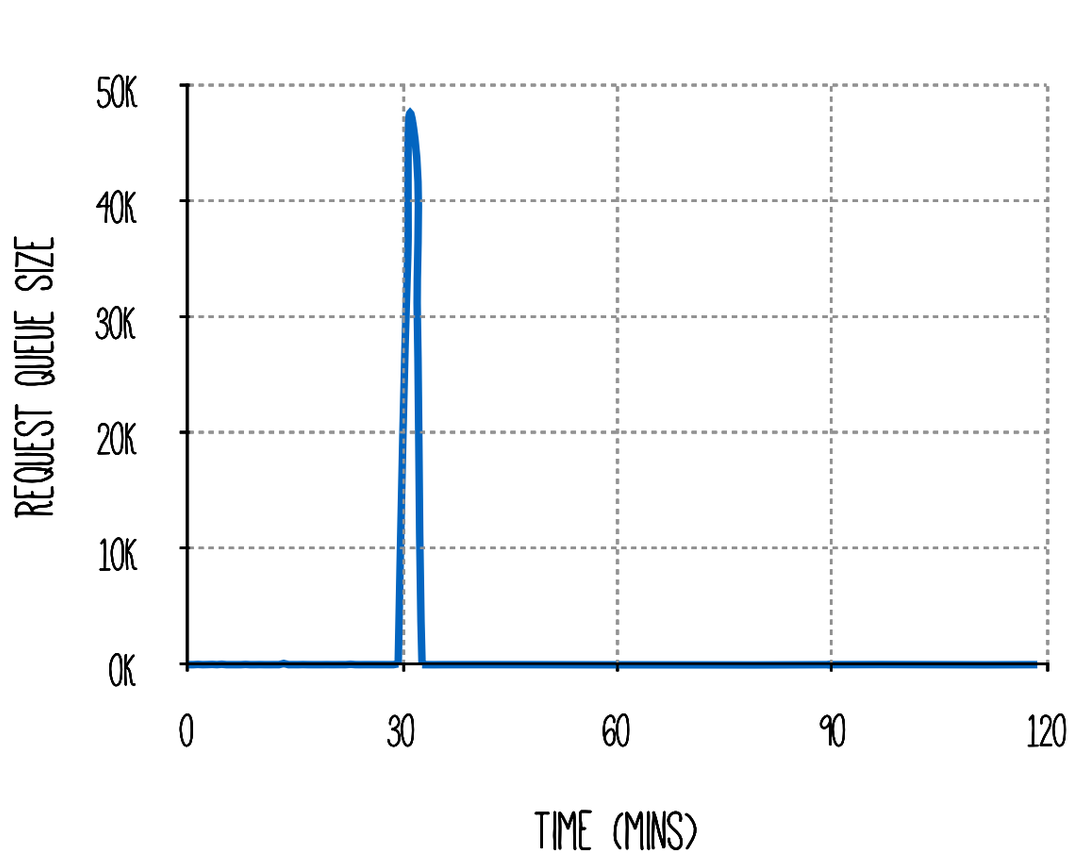

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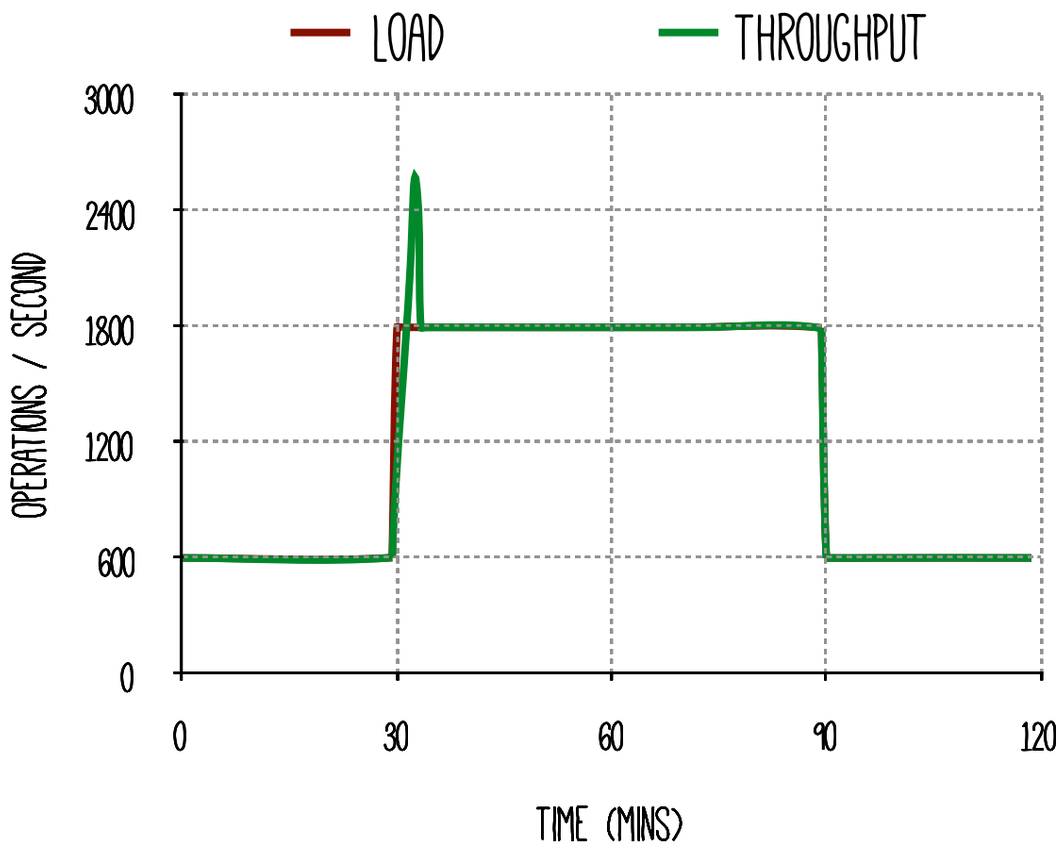
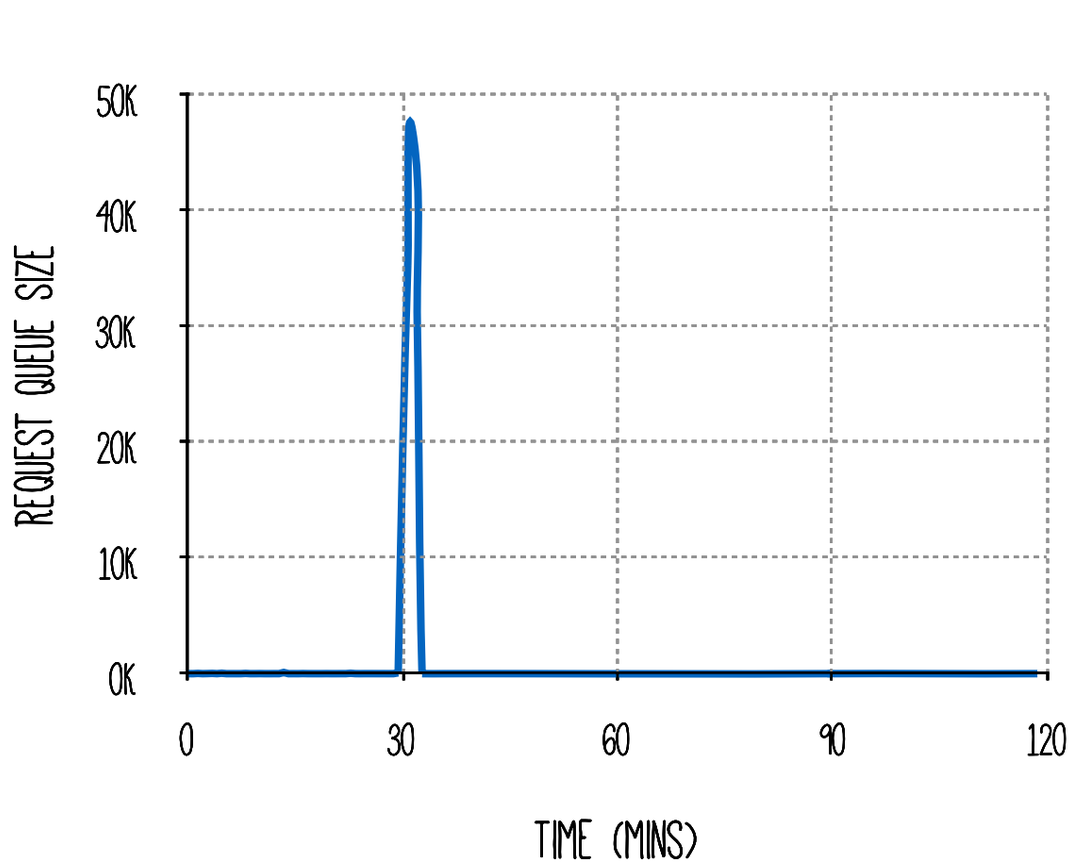
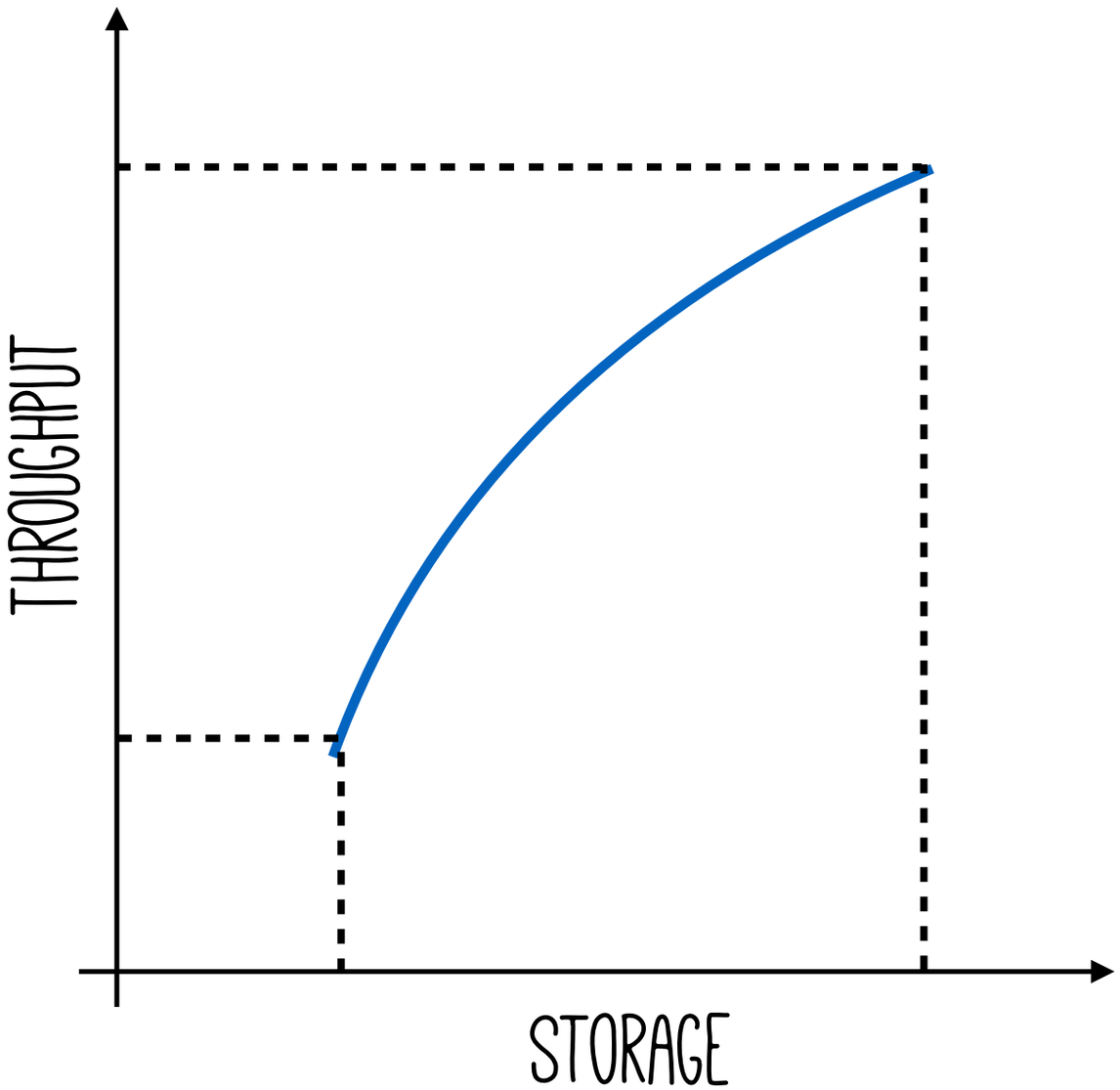




Adapts to 3x higher load in < 5 mins

Summary



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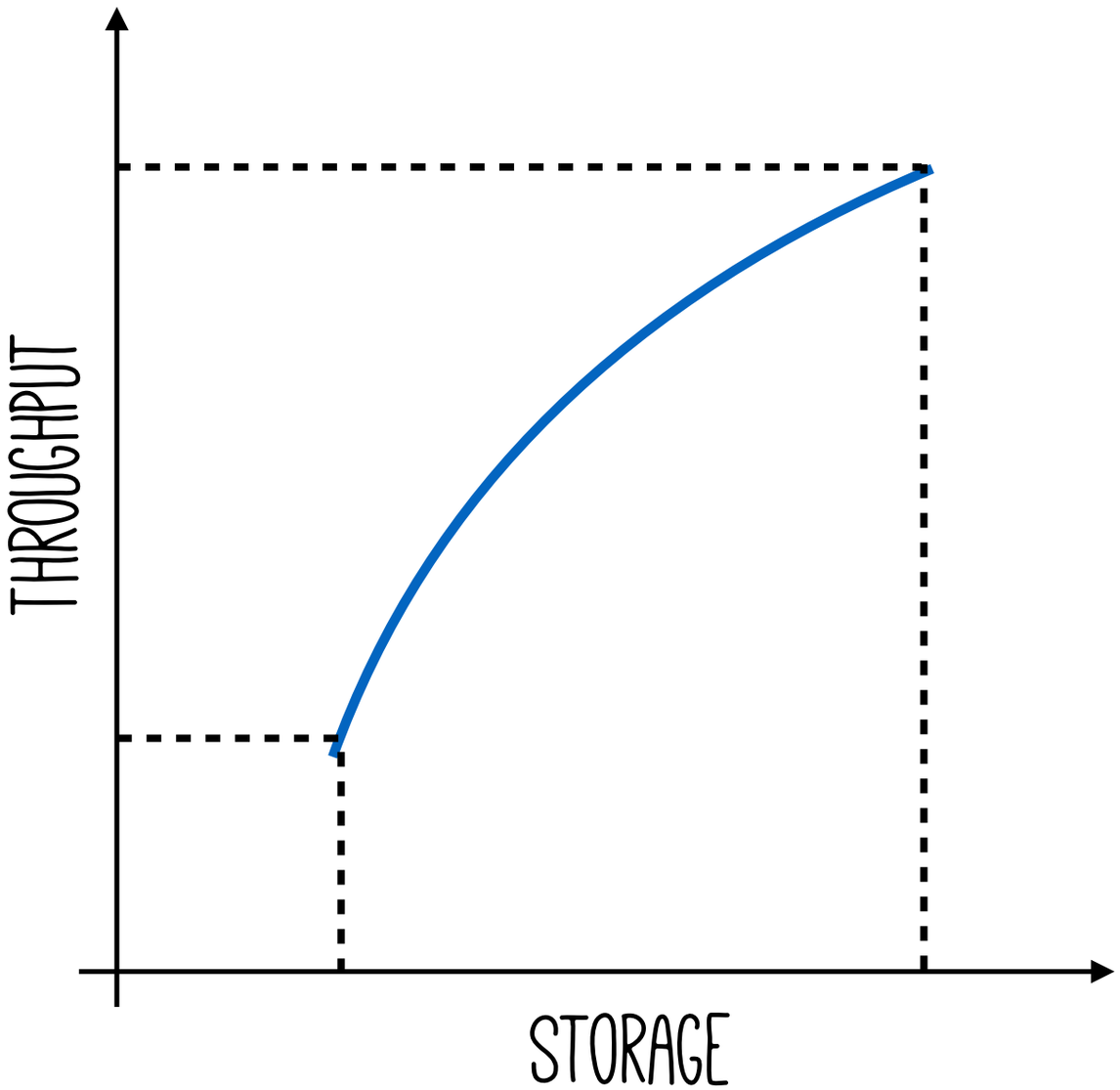

Smooth Tradeoff Curve

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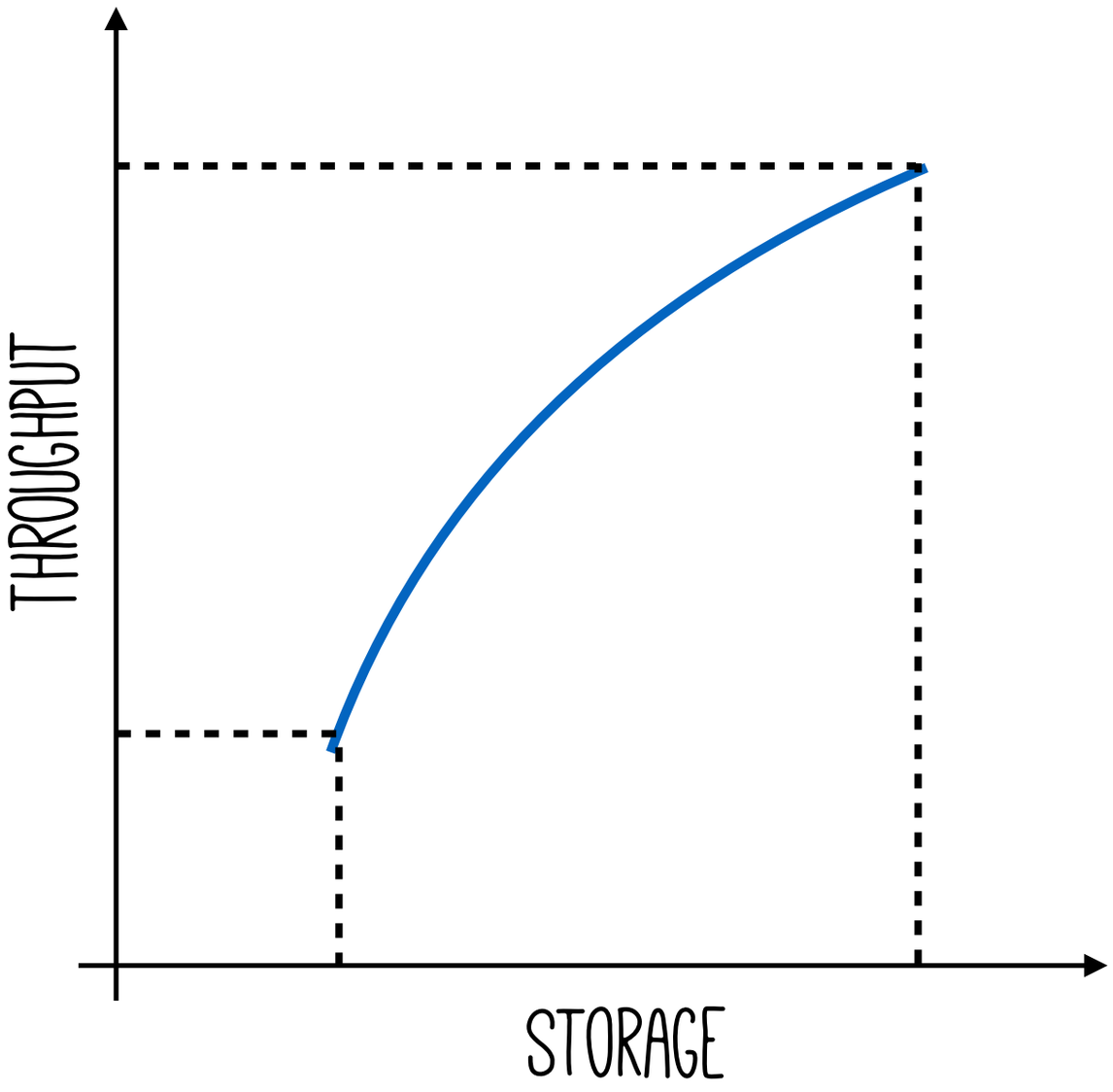
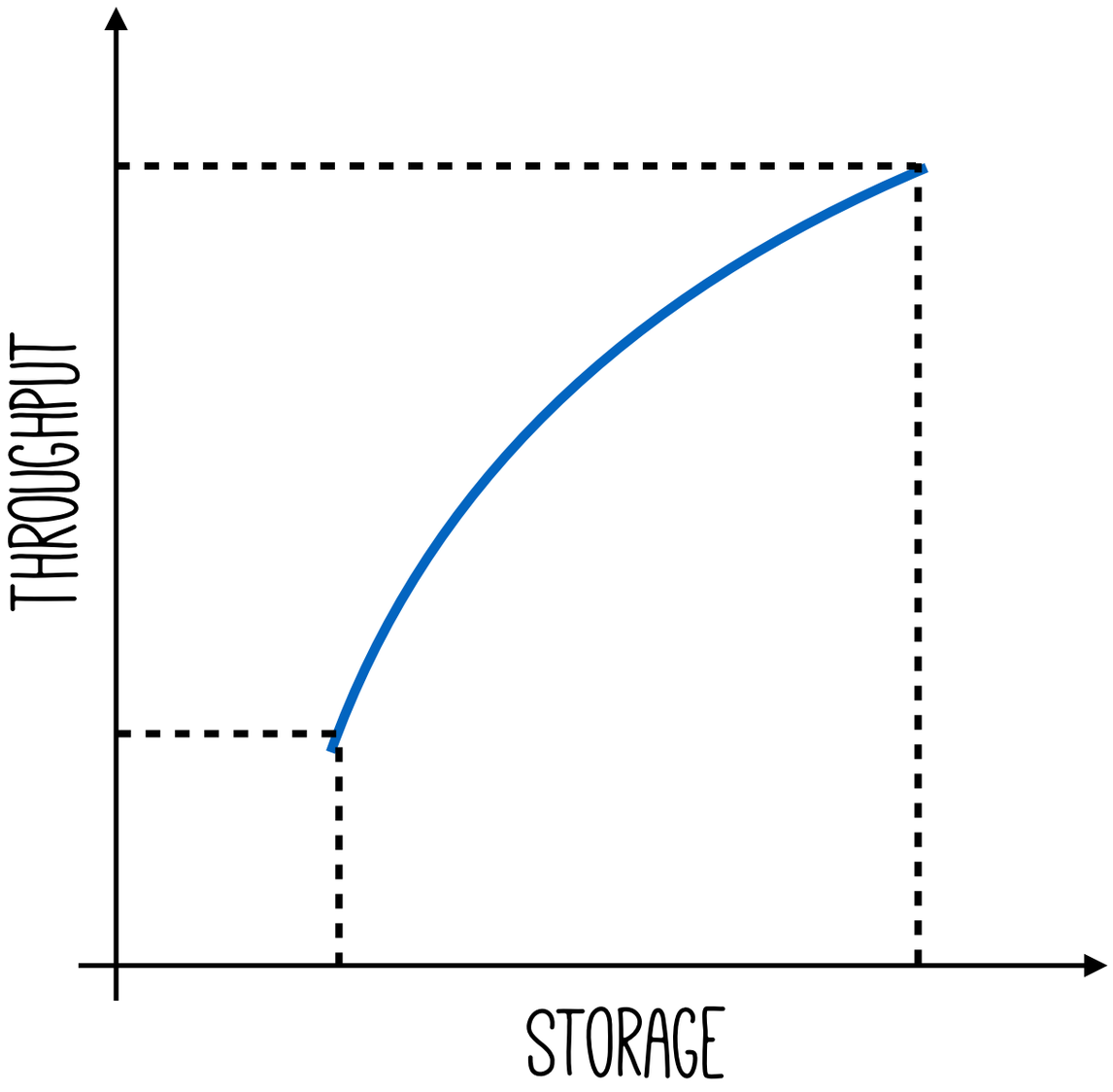


Smooth Tradeoff Curve

Dynamic Navigation

Summary



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Dynamic Navigation

Applications in Several Classical Systems Problems

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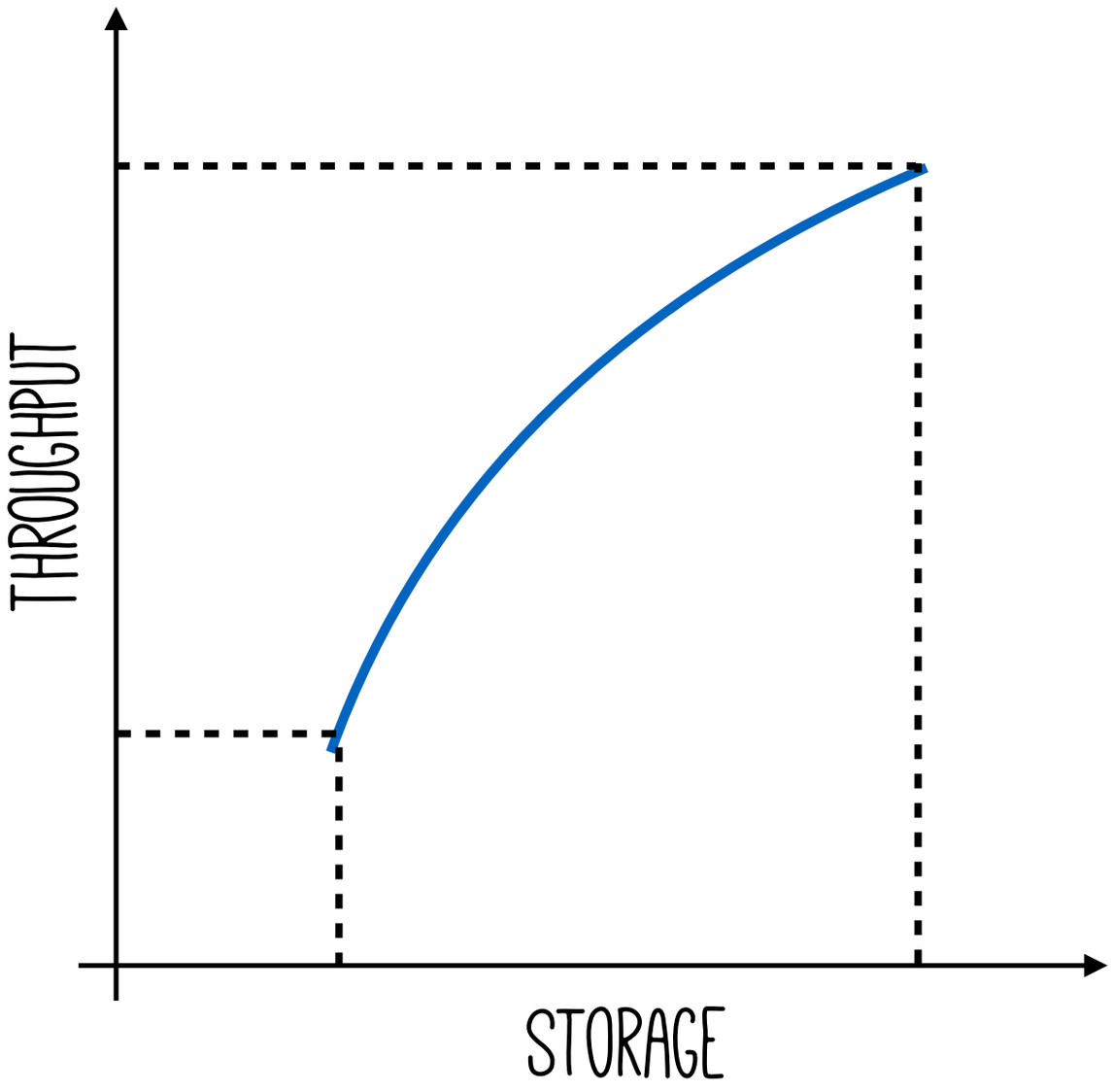

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Thank You! Questions?

Backup Slides