Taming Tail Latency in Key-Value Stores: a Scheduling Perspective

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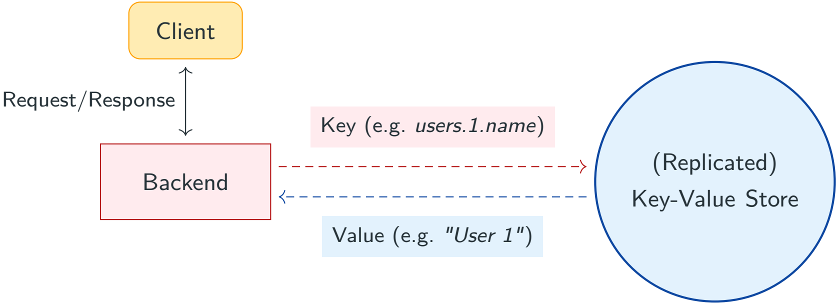
Table of Contents

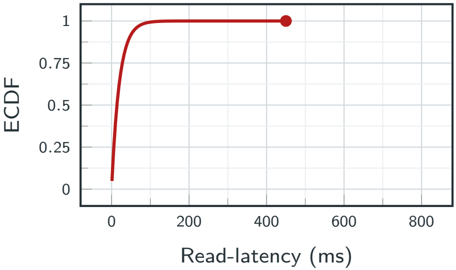
Introduction



- Strongly fault-tolerant
- Highly scalable
- Highly available
- Examples: Dynamo, Cassandra, Redis

Introduction

- One user request requires multiple data items.
- Overall latency is that of the slowest request.
- A small fraction of request may result in overall degradation.



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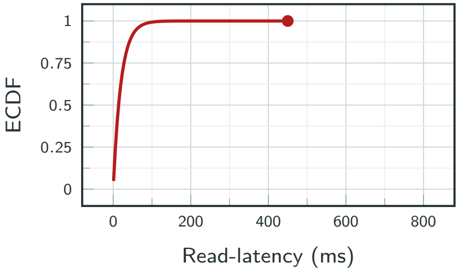

Tail Latency

Slowing a small fraction of requests (< 5 %) may degrade the QoS for most users.

Introduction

How to mitigate tail latency

Common approach: avoid that a request be sent to a busy server when a more available one would have answered faster $\rightarrow$ **this is scheduling!**

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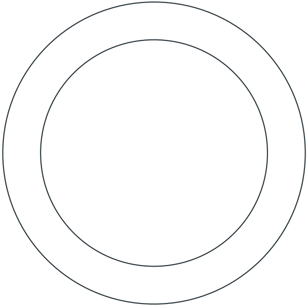
- Can we bound the performance of an offline strategy?
- Which information do we need to build an *efficient* strategy?

Table of Contents

Model

What happens in a KVS



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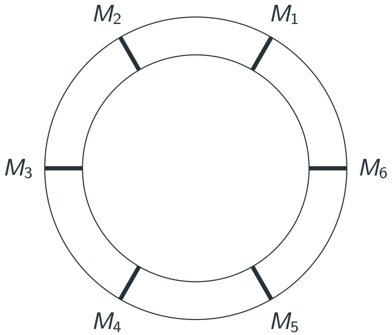
Servers are named $M_1, M_2, \ldots$



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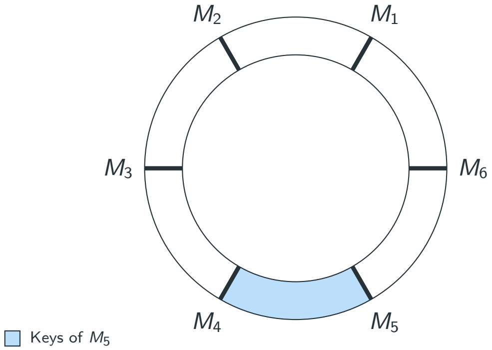

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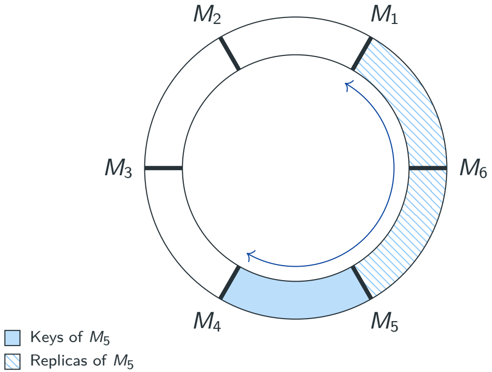

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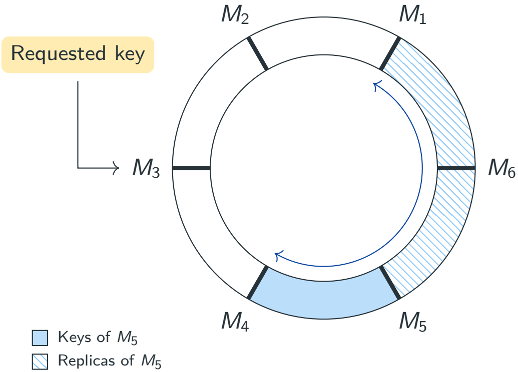

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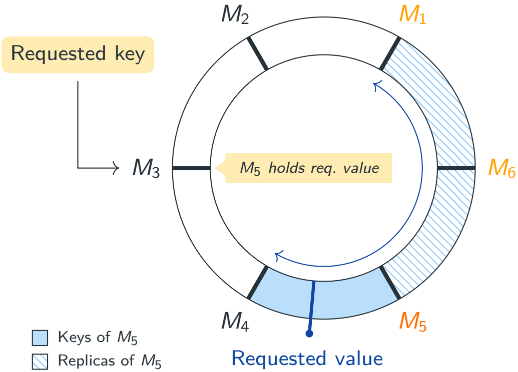

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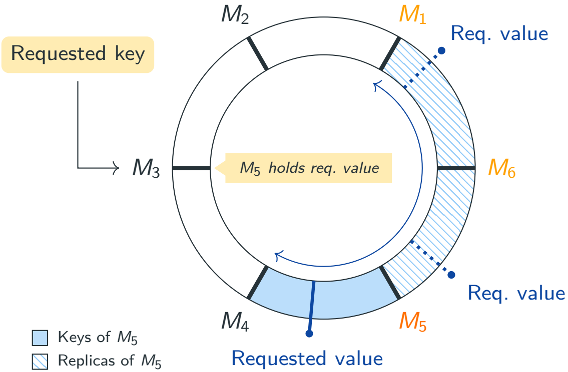

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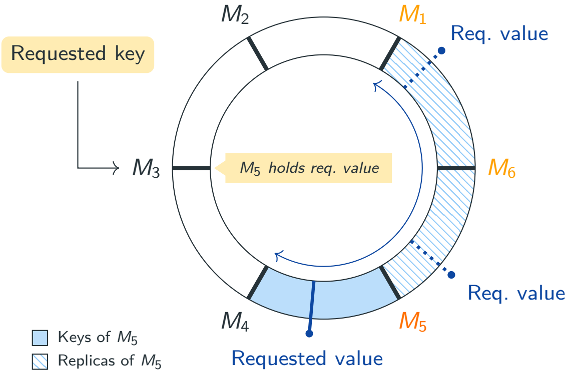

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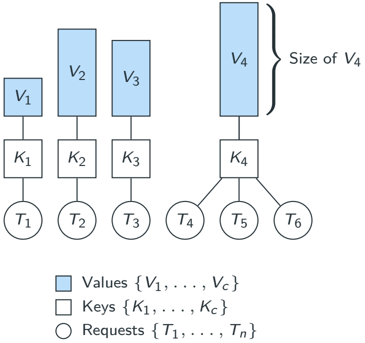
2. ...locate the key
3. ...choose to which server direct the request.
4. The chosen server processes the request.

Model

Application and platform



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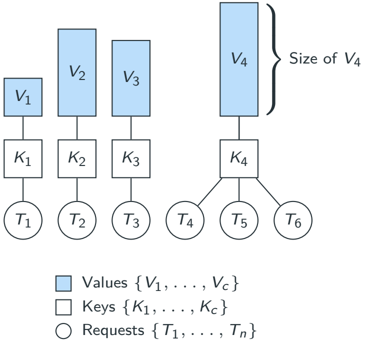

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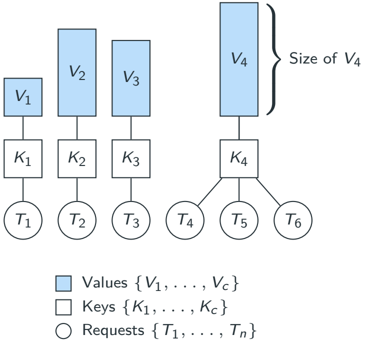

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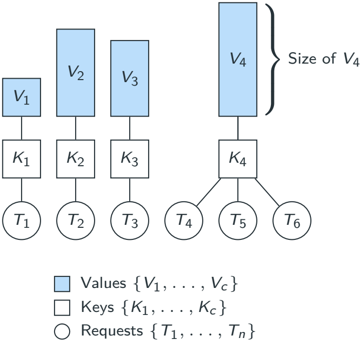

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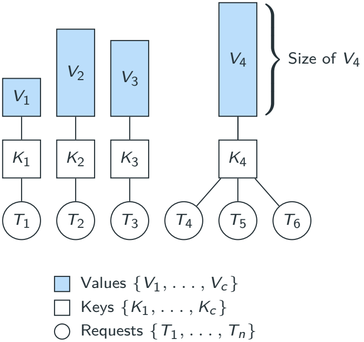

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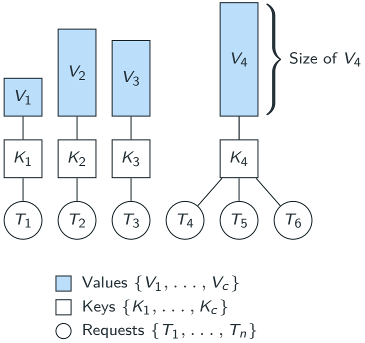

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- Processing time of a request is linear in requested value size.
- A request is released at time r_i.
- Preemption is not allowed.

Read-latency $\longrightarrow$ Flow time $F_i = C_i - r_i$ of each request (where C_i is the completion time)

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Scheduling Problem

Considering our constraints and objective, we are interested in the scheduling problem $P|\mathcal{M}_i, \text{online-}r_i| \max w_i F_i$ (Graham's notation).

Table of Contents

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- Start with the single-server problem; we give an optimal algorithm.

Algorithm 2 Single-Simple

Require: w_i

1: schedule requests by non-increasing order of w_i

Theorem

Single-Simple solves $1||\max w_i C_i$ in polynomial-time.

- By a simple exchange argument, SINGLE-SIMPLE is optimal on parallel platforms (with full replication) when costs are homogeneous.

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Scheduling

Without release times ($F_i = C_i$)

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Theorem

SINGLE-SIMPLE solves $P|p_i = p|\max w_i C_i$ in polynomial-time.

- For heterogeneous costs, we find that it approximates the problem by a factor $2 - 1/m$, with m the number of machines.

Theorem

SINGLE-SIMPLE is a tight $(2 - 1/m)$-approximation for $P||\max w_i C_i$.

- The preemptive version of our problem is solved by Legrand et al.[1]

Theorem

$R|r_i, pmtn|\max w_i F_i$ can be solved in polynomial-time.

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Model restricted replication in unrelated setting

If a request i cannot be executed by a server j, set the corresponding processing time $p_{ij} = \infty$. As a consequence, solving $R|r_i, pmtn|\max w_i F_i$ also solves $P|\mathcal{M}_i, r_i, pmtn|\max w_i F_i$.

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Scheduling
Offline problem

- Recall we do not allow preemption in our model, mainly because of the overhead of migration. By a reduction to the parallel makespan problem, we show that the problem becomes NP-complete when migration is not allowed...

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Theorem

The non-migratory version of $R|r_i, pmtn|\max w_i F_i$ is NP-complete.

- ...but the preemptive version still provides a **lower bound** for our problem!

Table of Contents

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[2] Jaiman, V., Ben Mokhtar, S., Quéma, V., Chen, L. Y., Rivière, E.: Héron: Taming tail latencies in key-value stores under heterogeneous workloads. 37th Symposium on Reliable Distributed Systems (2018).

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Note on EFT

EFT is very difficult to achieve in a real system. One would consider a degraded version in practice; our goal here is to evaluate the best possible situation.

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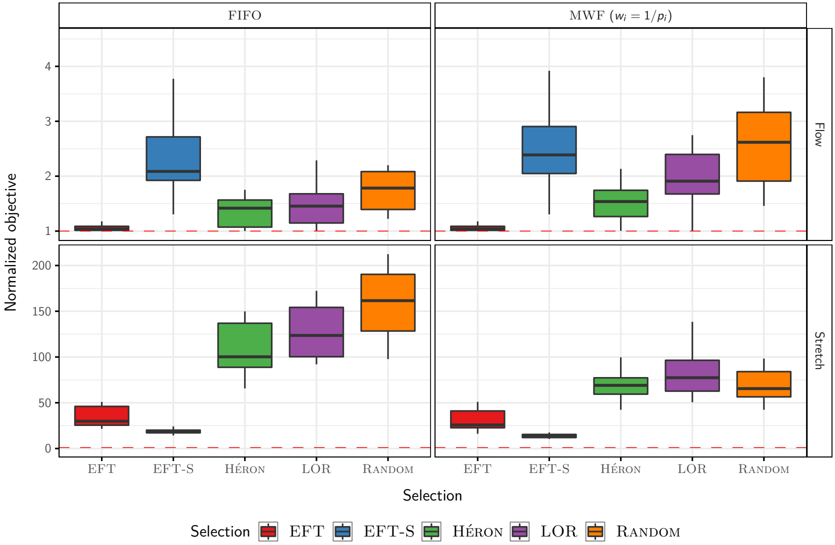
Simulations

Distribution of normalized read-latency and stretch maximums (1000 requests)



Takeaways

- EFT allows to get very close to the lower bound for read-latency.
- EFT is the most stable heuristic for read-latency between scenarios.
- $\mathrm{EFT\text{-}S}$ is not good for read-latency, but it is the best for the stretch.
- MWF improves the stretch objective of all selection heuristics without worsening read-latency too much.

Table of Contents

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- Can we bound the performance of an offline strategy?
  $\rightarrow$ **Yes! The preemptive version provides a lower bound.**
- What information do we need to build an *efficient* strategy?
  $\rightarrow$ **Simulations show that a good knowledge of current load is critical.**