EC-Cache: Load-balanced, Low-latency Cluster Caching with Online Erasure Coding

Rashmi Vinayak
UC Berkeley

Joint work with

Mosharaf Chowdhury, Jack Kosaian (U Michigan)
Ion Stoica, Kannan Ramchandran (UC Berkeley)

Caching for data-intensive clusters

- Data-intensive clusters rely on **distributed, in-memory caching** for high performance
  - Reading from memory orders of magnitude faster than from disk/ssd
  - Example: Alluxio (formerly Tachyon[†])

[†]Li et al. SOCC 2014

Imbalances prevalent in clusters

Sources of imbalance:

- Skew in object popularity
- Background network imbalance
- Failures/unavailabilities

Imbalances prevalent in clusters

Sources of imbalance:

- Skew in object popularity
- Background network imbalance
- Failures/unavailabilites

Small fraction of objects highly popular

- Zipf-like distribution
- Top 5% of objects 7x more popular than bottom 75%[†] (Facebook and Microsoft production cluster traces)

[†]Ananthanarayanan et al. NSDI 2012

Imbalances prevalent in clusters

Sources of imbalance:

- Skew in object popularity
- Background network imbalance
- Failures/unavailabilites

Some parts of the network more congested than others

- Ratio of maximum to average utilization more than 4.5x with > 50% utilization

  (Facebook data-analytics cluster)

Imbalances prevalent in clusters

Sources of imbalance:

- Skew in object popularity
- Background network imbalance
- Failures/unavailabilites

Some parts of the network more congested than others

- Ratio of maximum to average utilization more than 4.5x with > 50% utilization

  (Facebook data-analytics cluster)

- Similar observations from other production clusters[†]

[†] Chowdhury et al. SIGCOMM 2013

Imbalances prevalent in clusters

Sources of imbalance:

- Skew in object popularity
- Background load imbalance
- Failures/unavailabilites

Norm rather than the exception

- median > 50 machine unavailability events every day in a cluster of several thousand servers[†]

  (Facebook data analytics cluster)

[†]Rashmi et al. HotStorage 2013

Imbalances prevalent in cluster

Sources of imbalance:

- Skew in object popularity
- Background network imbalance
- Failures/unavailabilities

➡ Adverse effects:

- load imbalance
- high read latency

Imbalances prevalent in cluster

Sources of imbalance:

- Skew in object popularity
- Background network imbalance
- Failures/unavailabilities

➡ Adverse effects:

- load imbalance
- high read latency

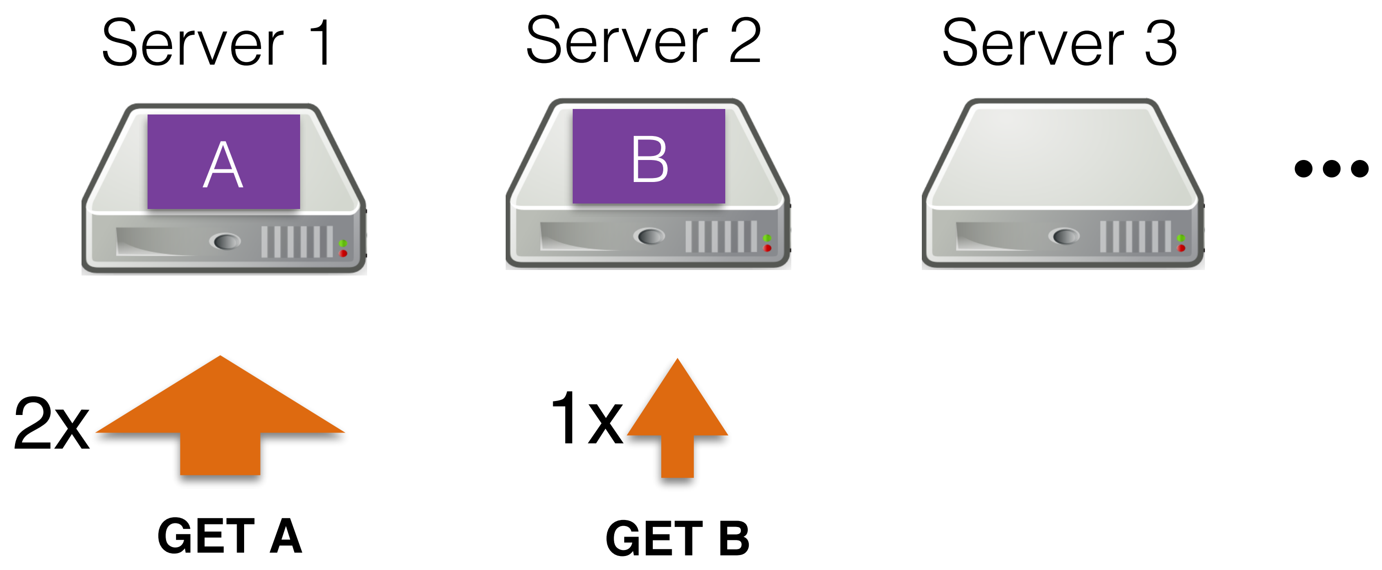
Single copy in memory often not sufficient to get good performance

Popular approach: Selective Replication

- Uses some memory overhead to cache replicas of objects based on their popularity
  - more replicas for more popular objects

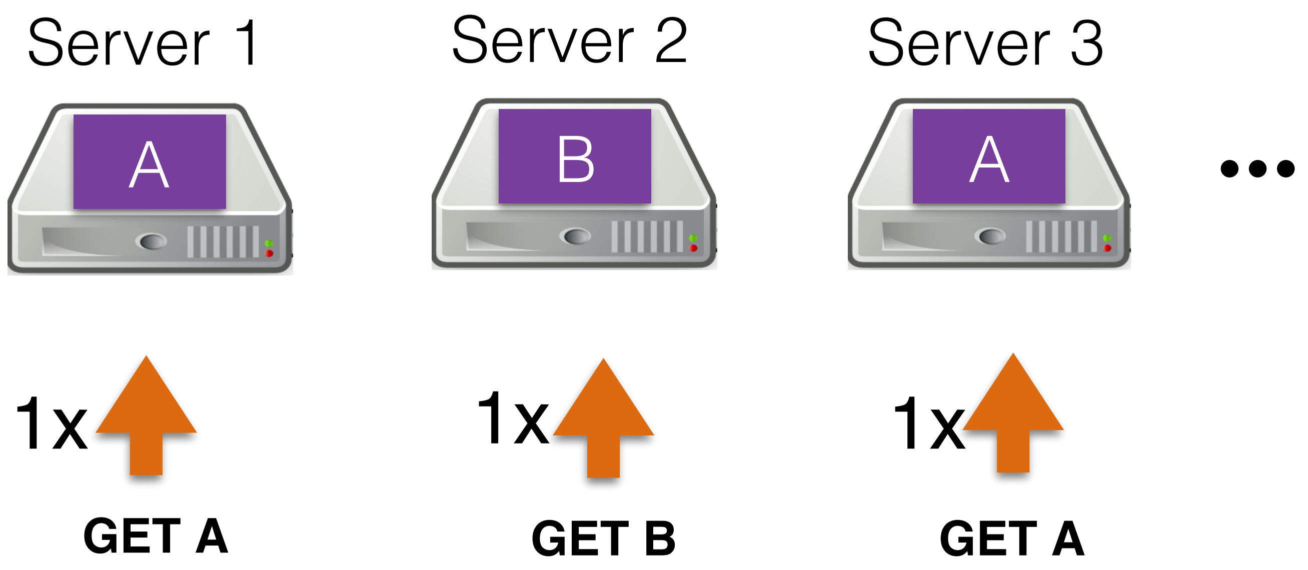
Popular approach: Selective Replication

- Uses some memory overhead to cache replicas of objects based on their popularity
  - more replicas for more popular objects



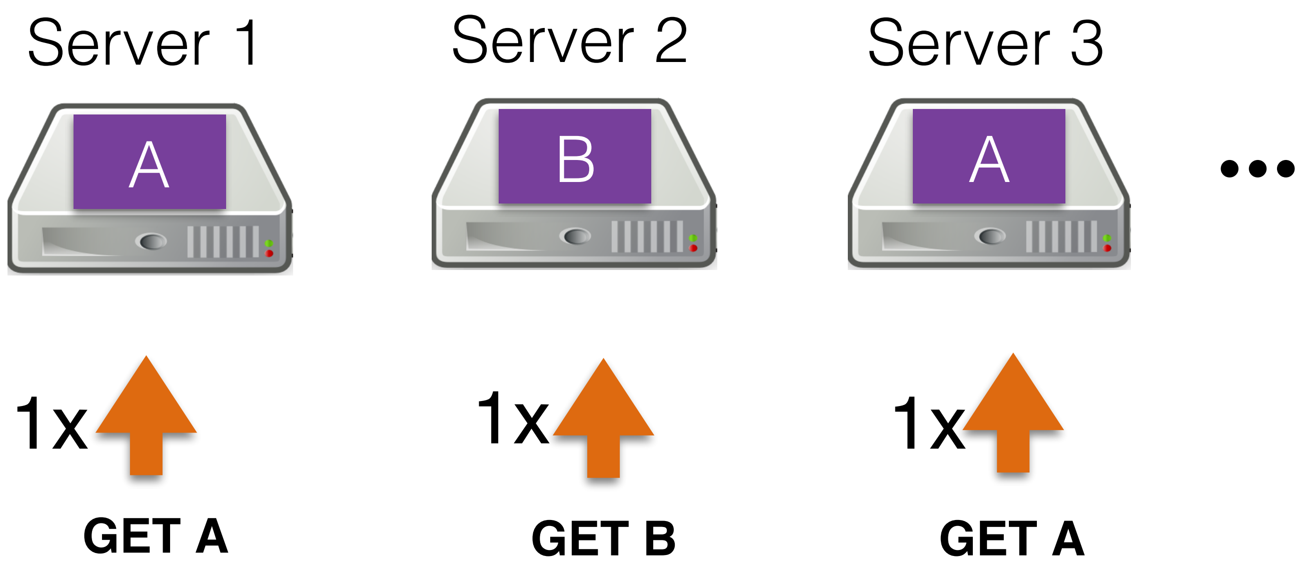
Popular approach: Selective Replication

- Uses some memory overhead to cache replicas of objects based on their popularity
  - more replicas for more popular objects



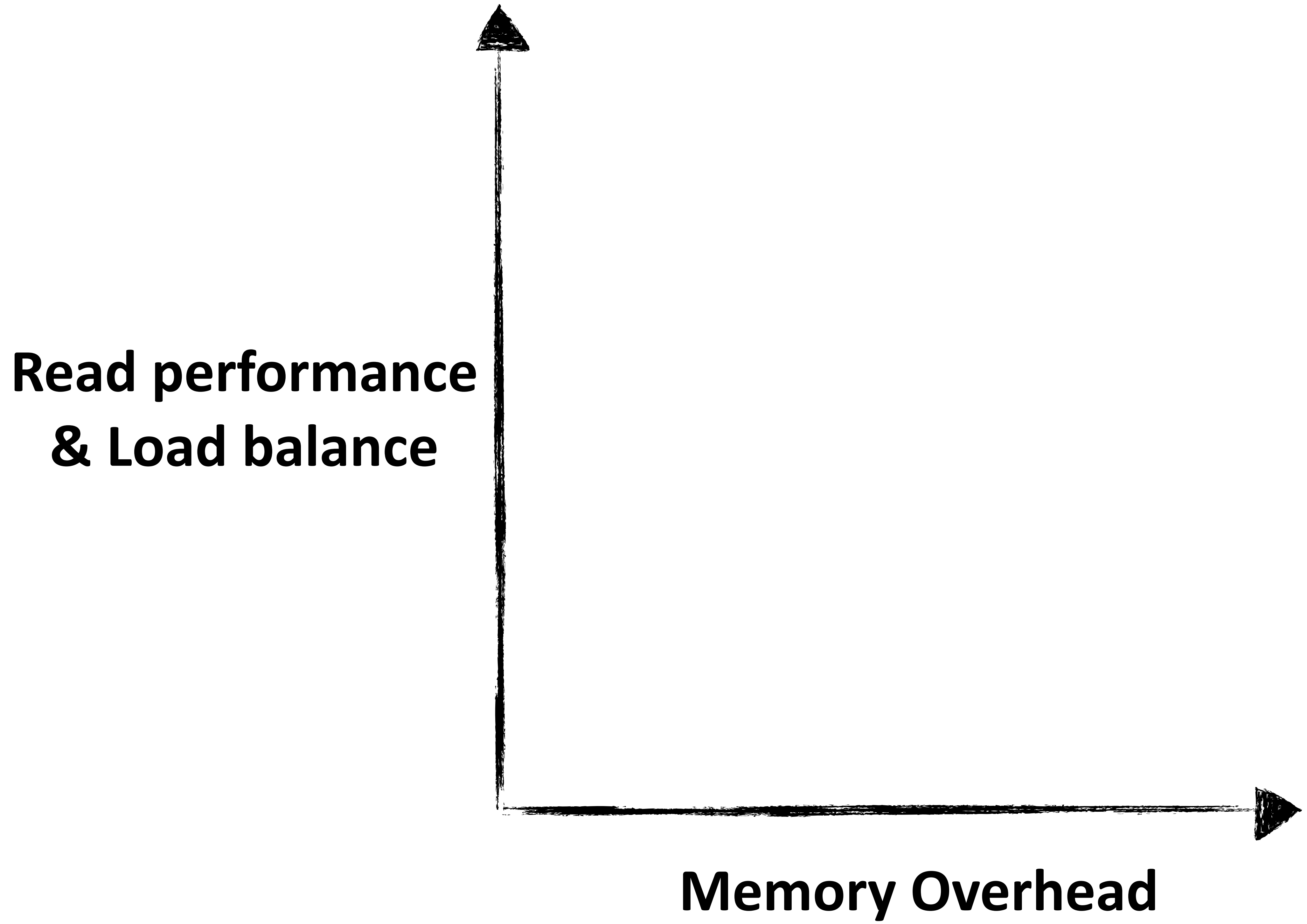
Popular approach: Selective Replication

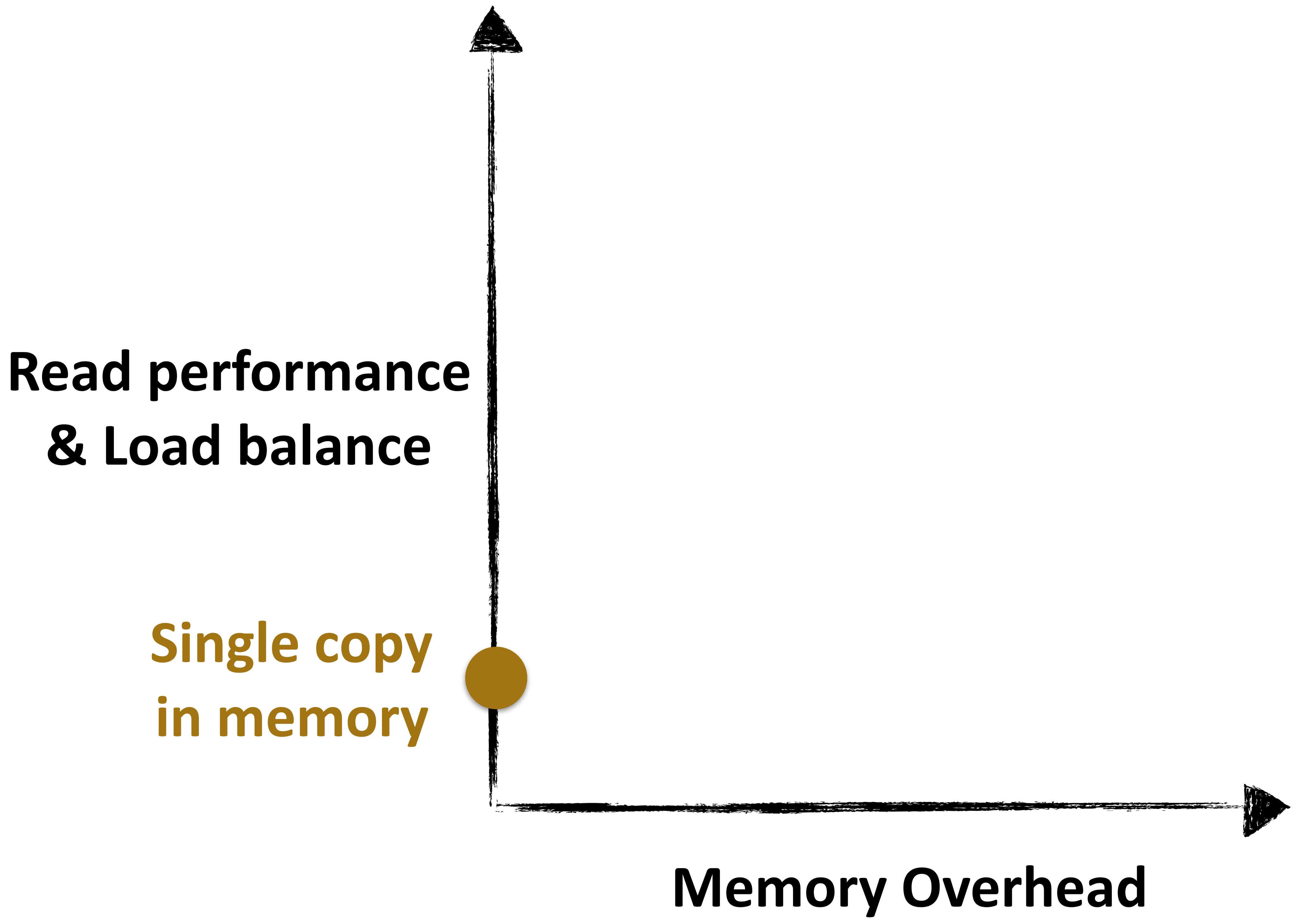
- Uses some memory overhead to cache replicas of objects based on their popularity
  - more replicas for more popular objects

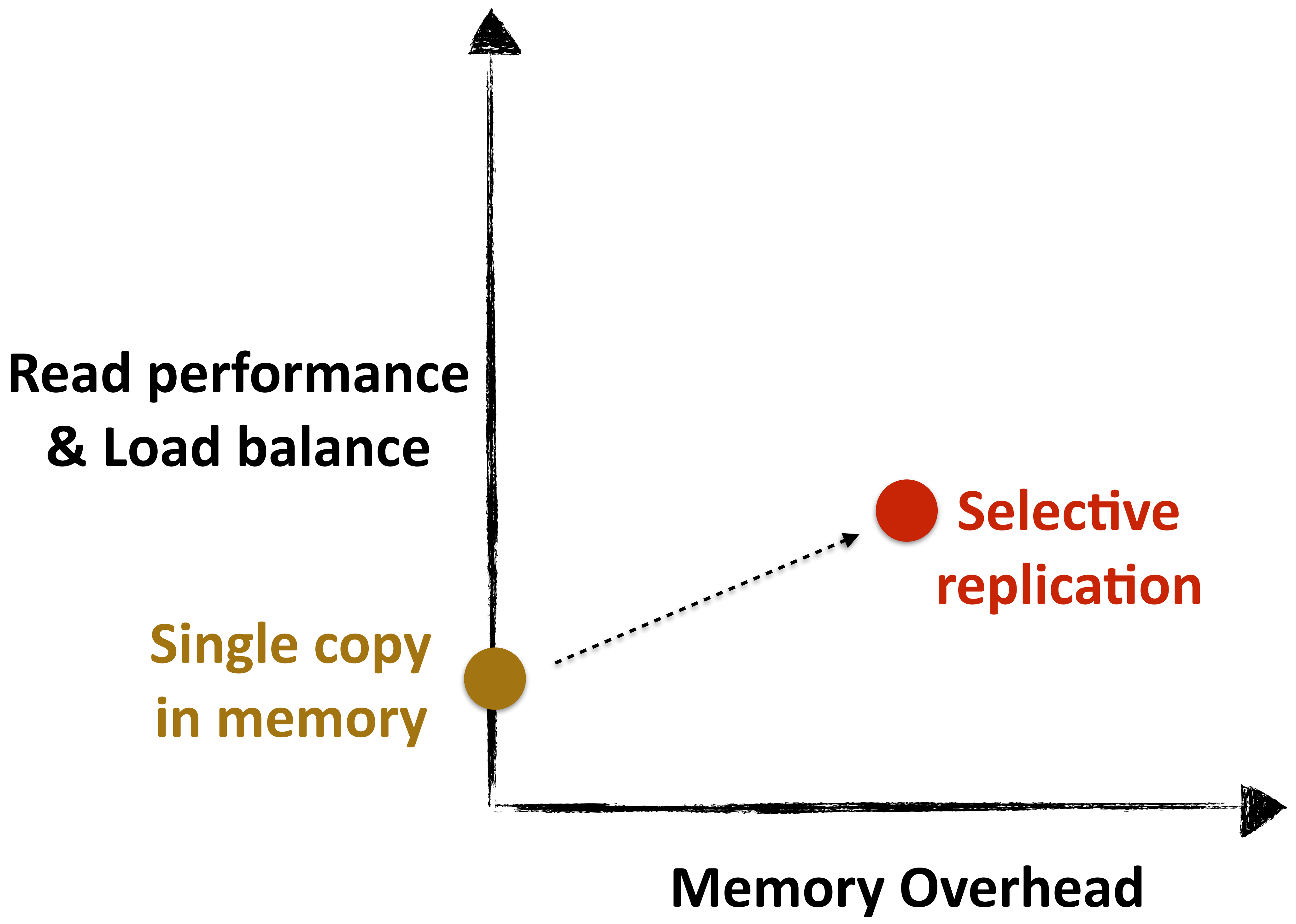


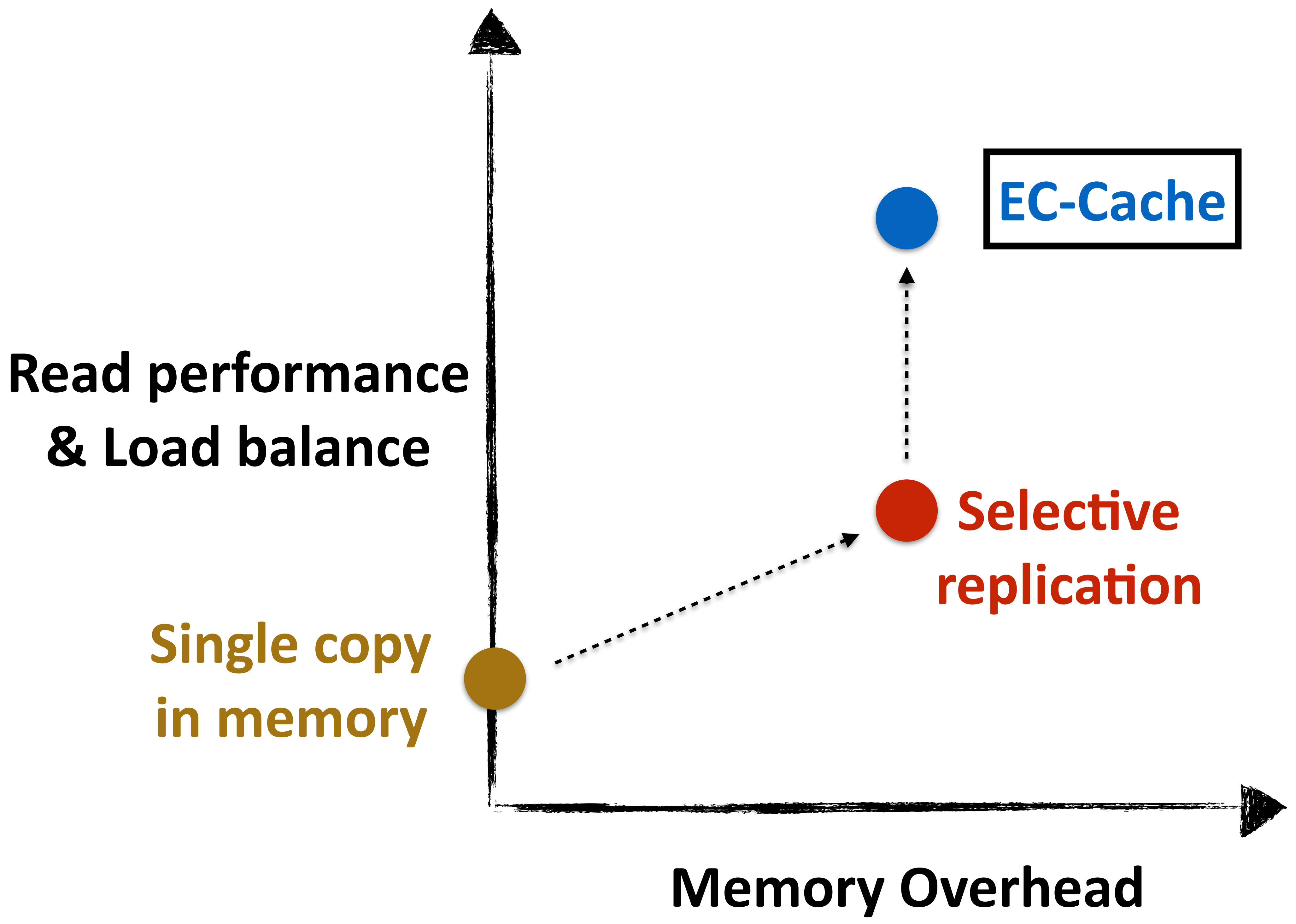
- Used in data-intensive clusters[†] as well as widely used in key-value stores for many web-services such as Facebook Tao[‡]

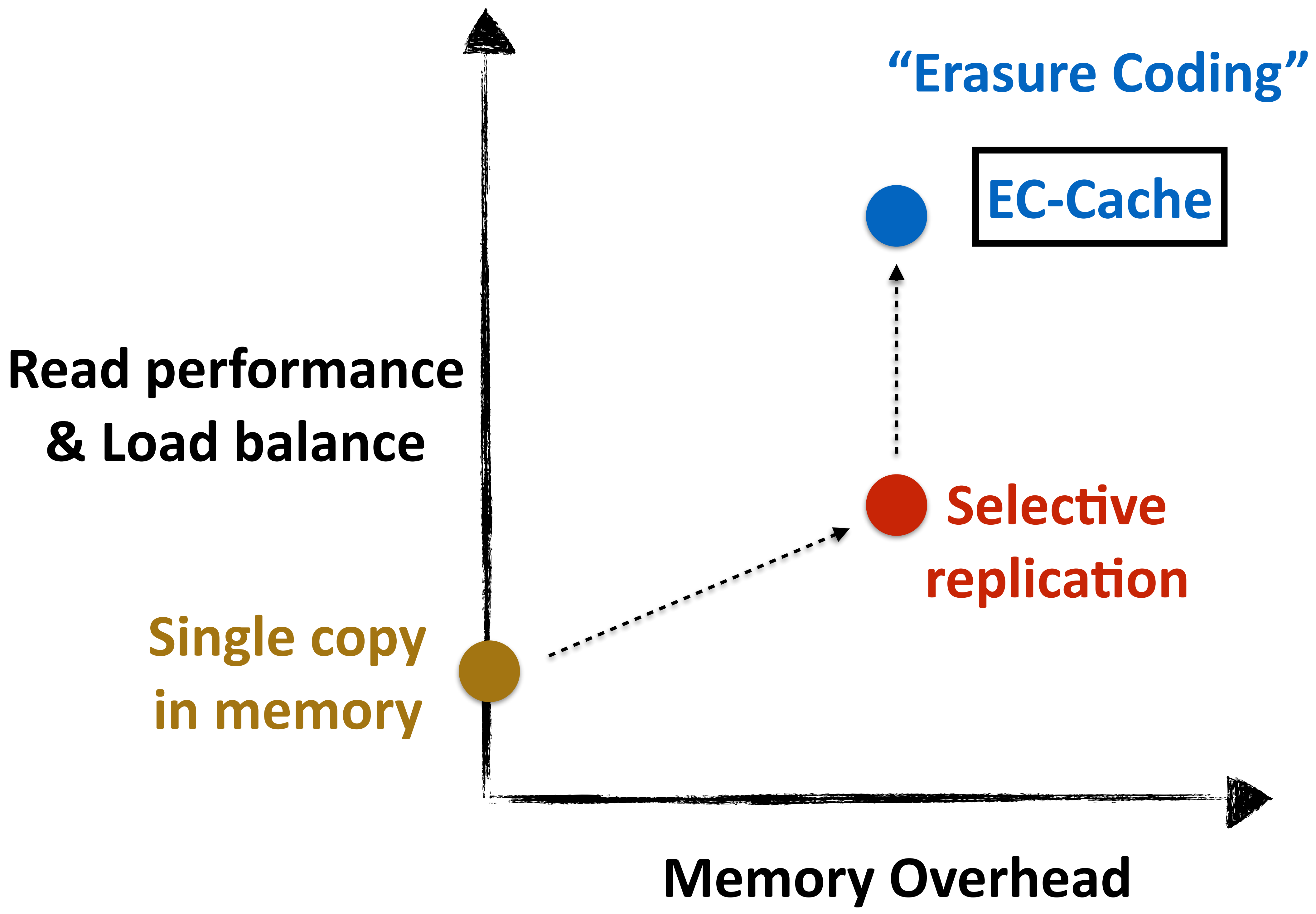
[†]Ananthanarayanan et al. NSDI 2011, [‡]Bronson et al. ATC 2013


Read performance
& Load balance
Memory Overhead


Read performance & Load balance
Single copy in memory
Memory Overhead


Read performance
& Load balance
Single copy
in memory
Selective
replication
Memory Overhead


EC-Cache
Read performance & Load balance
Selective replication
Single copy in memory
Memory Overhead


"Erasure Coding"
EC-Cache
Read performance & Load balance
Selective replication
Single copy in memory
Memory Overhead

Quick primer on erasure coding

Quick primer on erasure coding

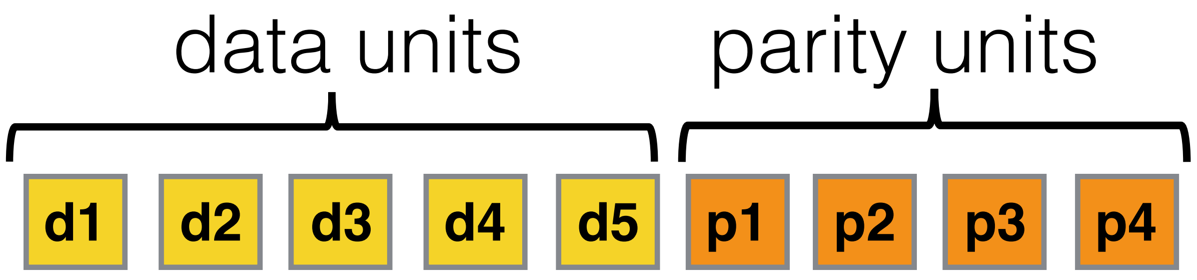
- Takes in ***k*** data units and creates ***r*** “parity” units

Quick primer on erasure coding

- Takes in ***k*** data units and creates ***r*** "parity" units
- ***Any k*** of the (k+r) units are sufficient to decode the original k data units

Quick primer on erasure coding

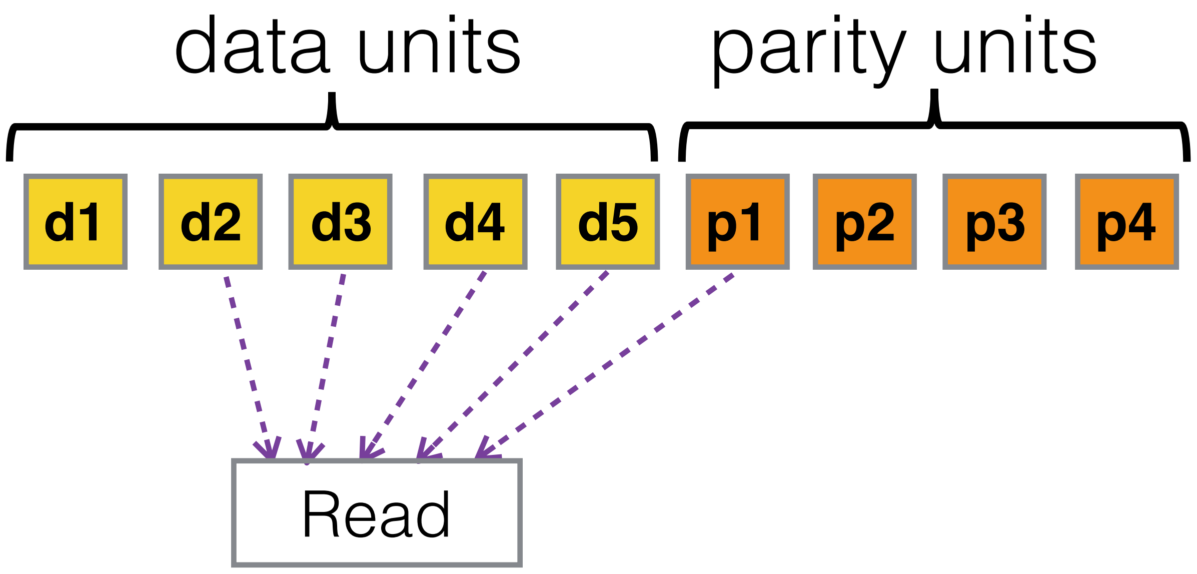
- Takes in ***k*** data units and creates ***r*** "parity" units
- ***Any k*** of the (k+r) units are sufficient to decode the original k data units



- k = 5
- r = 4

Quick primer on erasure coding

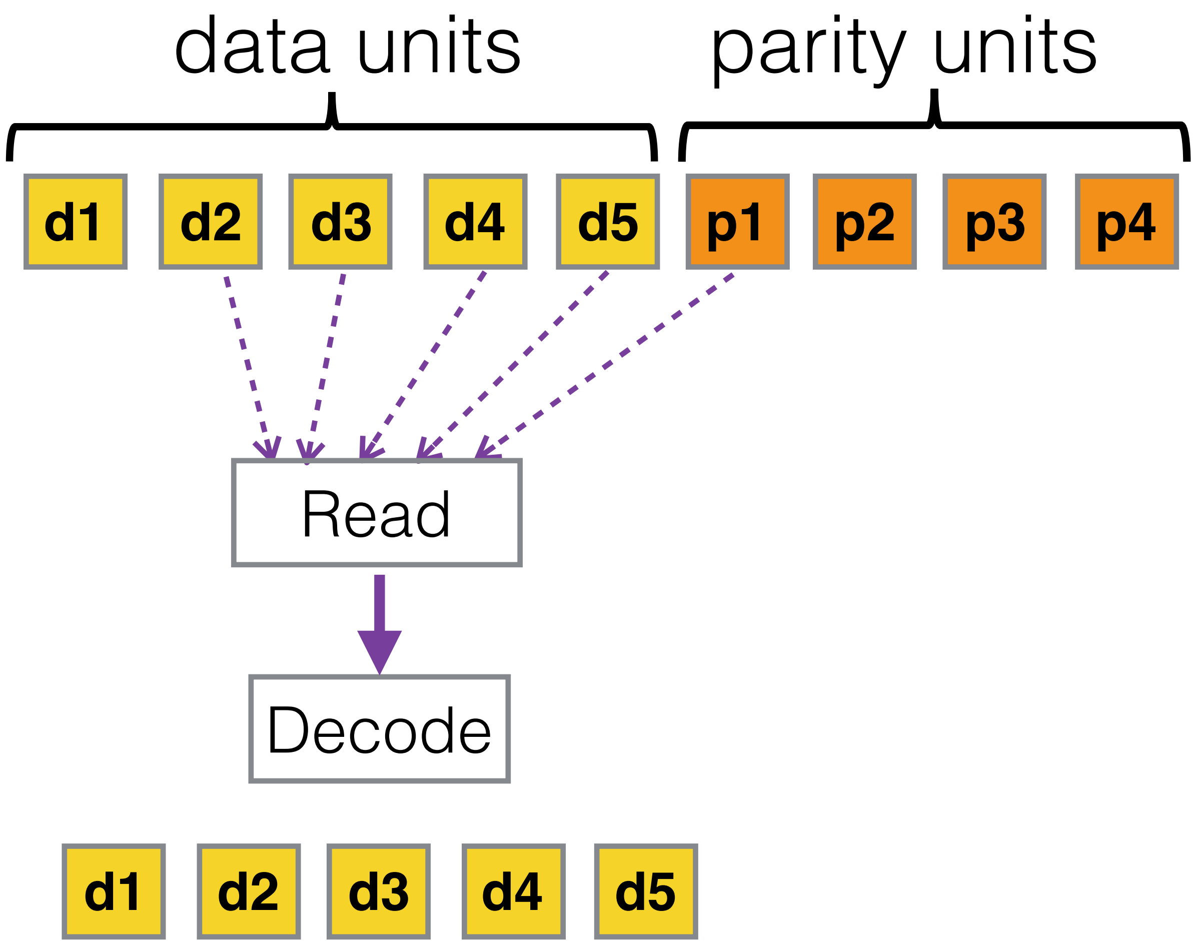
- Takes in ***k*** data units and creates ***r*** "parity" units
- ***Any k*** of the (k+r) units are sufficient to decode the original k data units



- k = 5
- r = 4

Quick primer on erasure coding

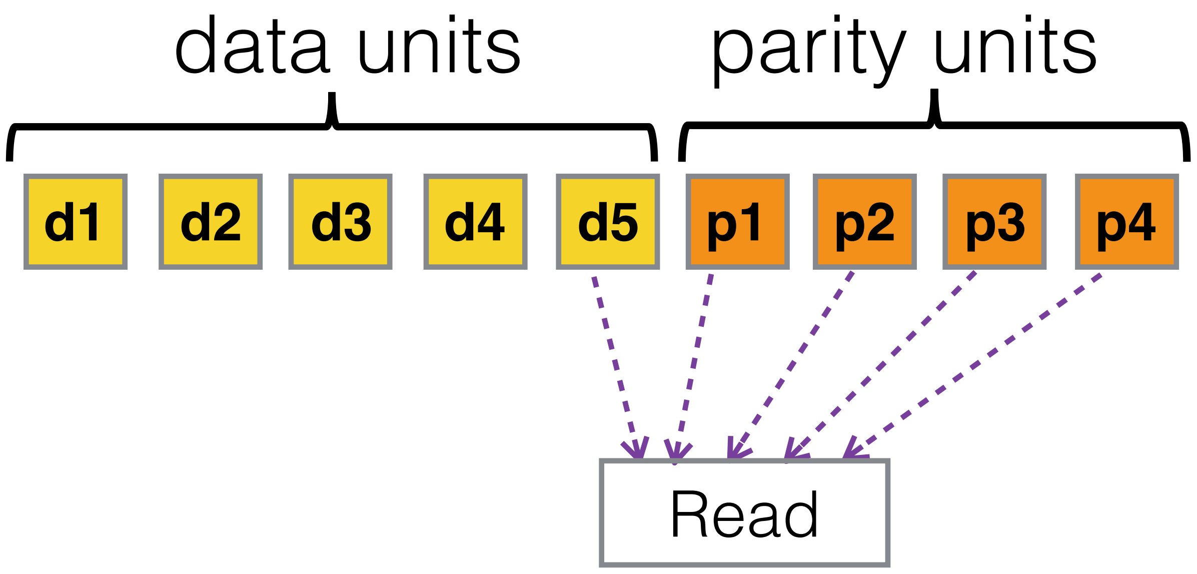
- Takes in ***k*** data units and creates ***r*** "parity" units
- ***Any k*** of the (k+r) units are sufficient to decode the original k data units



- k = 5
- r = 4

Quick primer on erasure coding

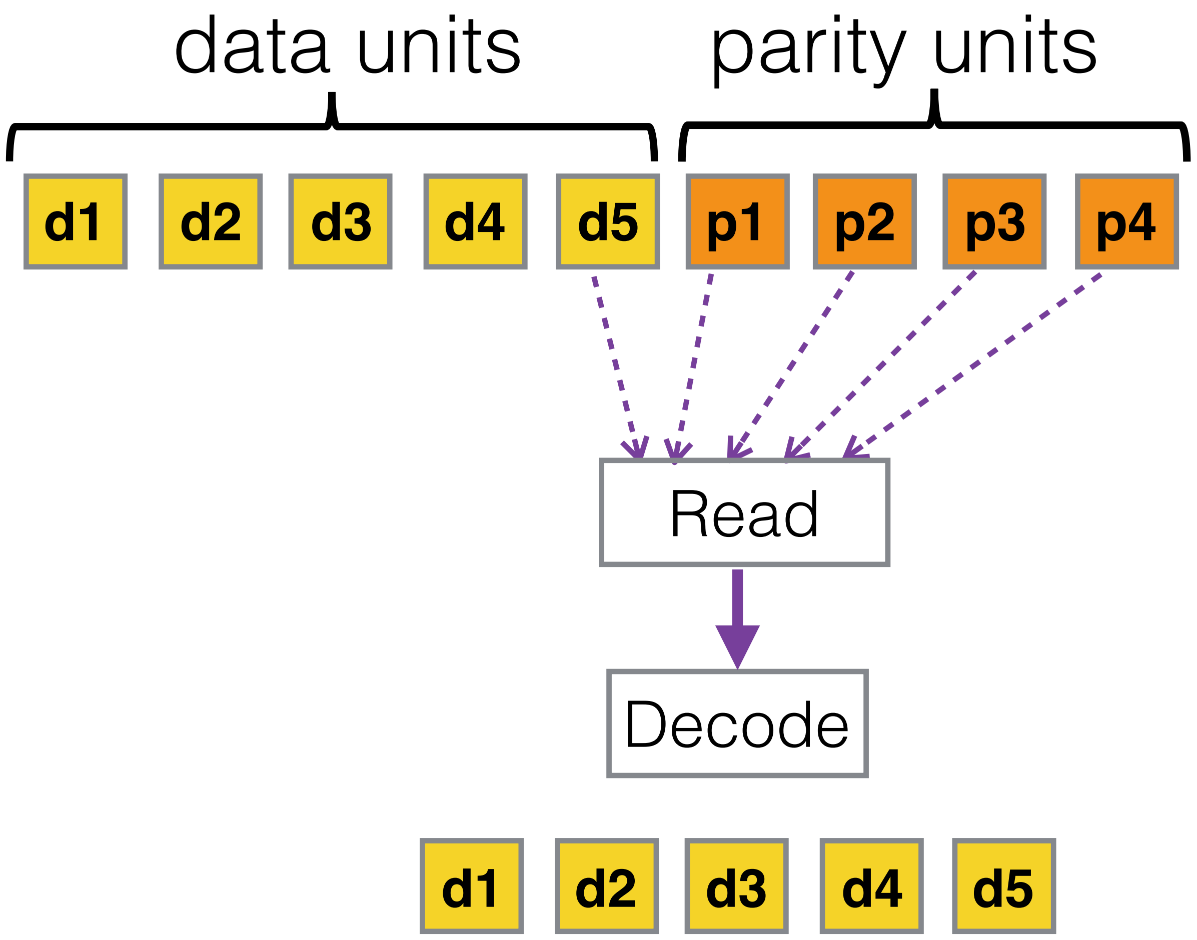
- Takes in ***k*** data units and creates ***r*** "parity" units
- ***Any k*** of the (k+r) units are sufficient to decode the original k data units



- k = 5
- r = 4

Quick primer on erasure coding

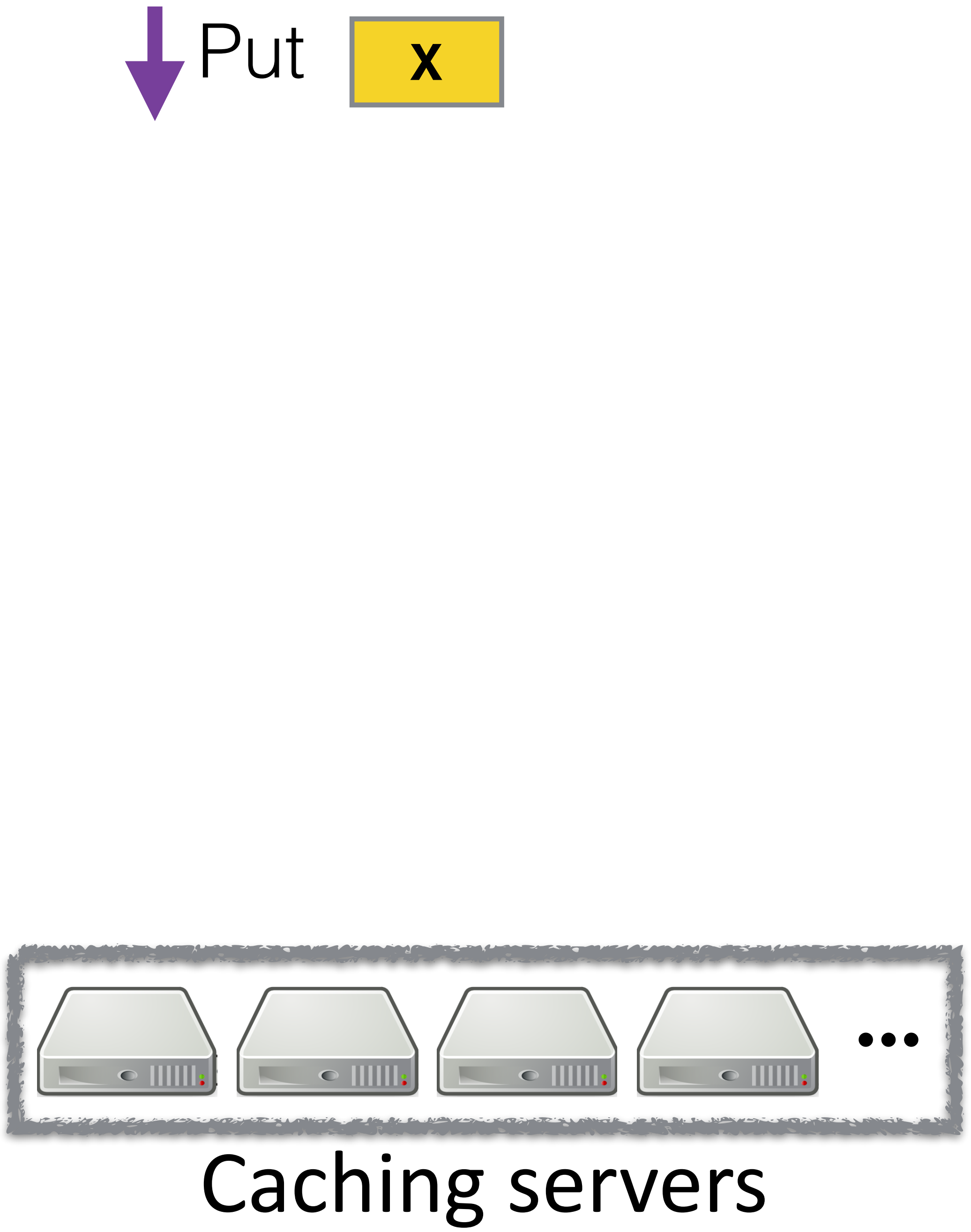
- Takes in ***k*** data units and creates ***r*** "parity" units
- ***Any k*** of the (k+r) units are sufficient to decode the original k data units



- k = 5
- r = 4

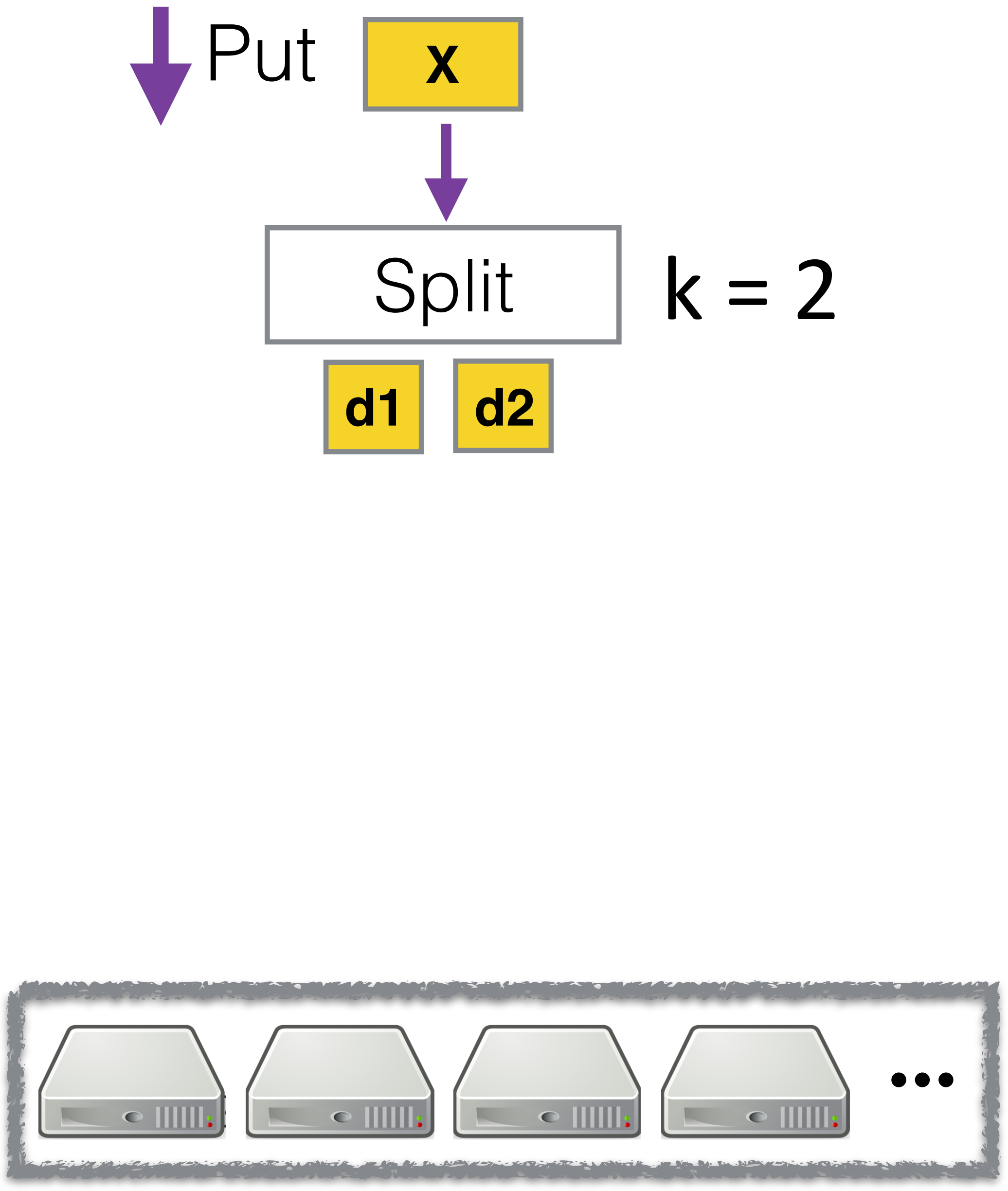
EC-Cache bird’s eye view: Writes

EC-Cache bird's eye view: Writes



EC-Cache bird's eye view: Writes

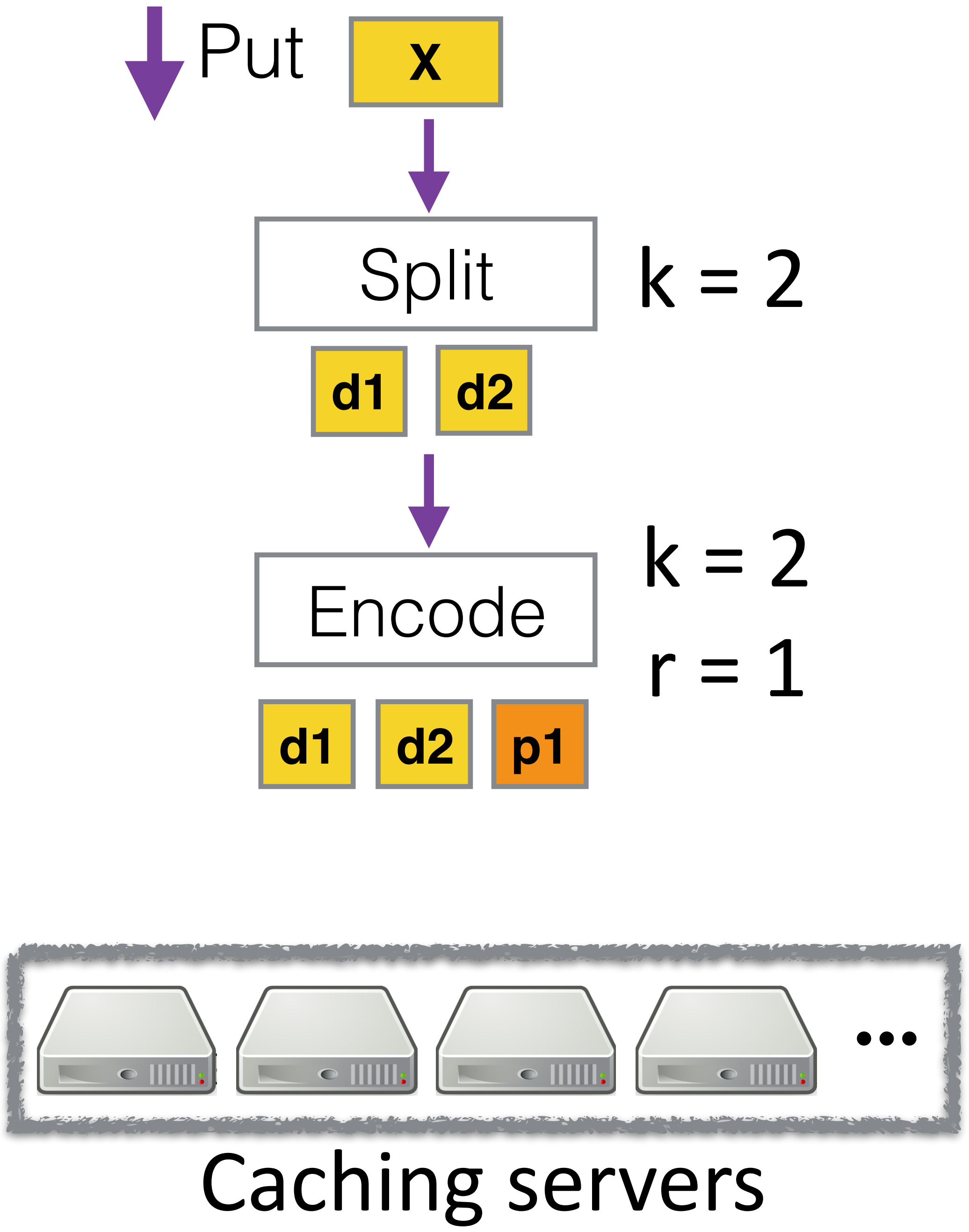
- Object split into k data units



Caching servers

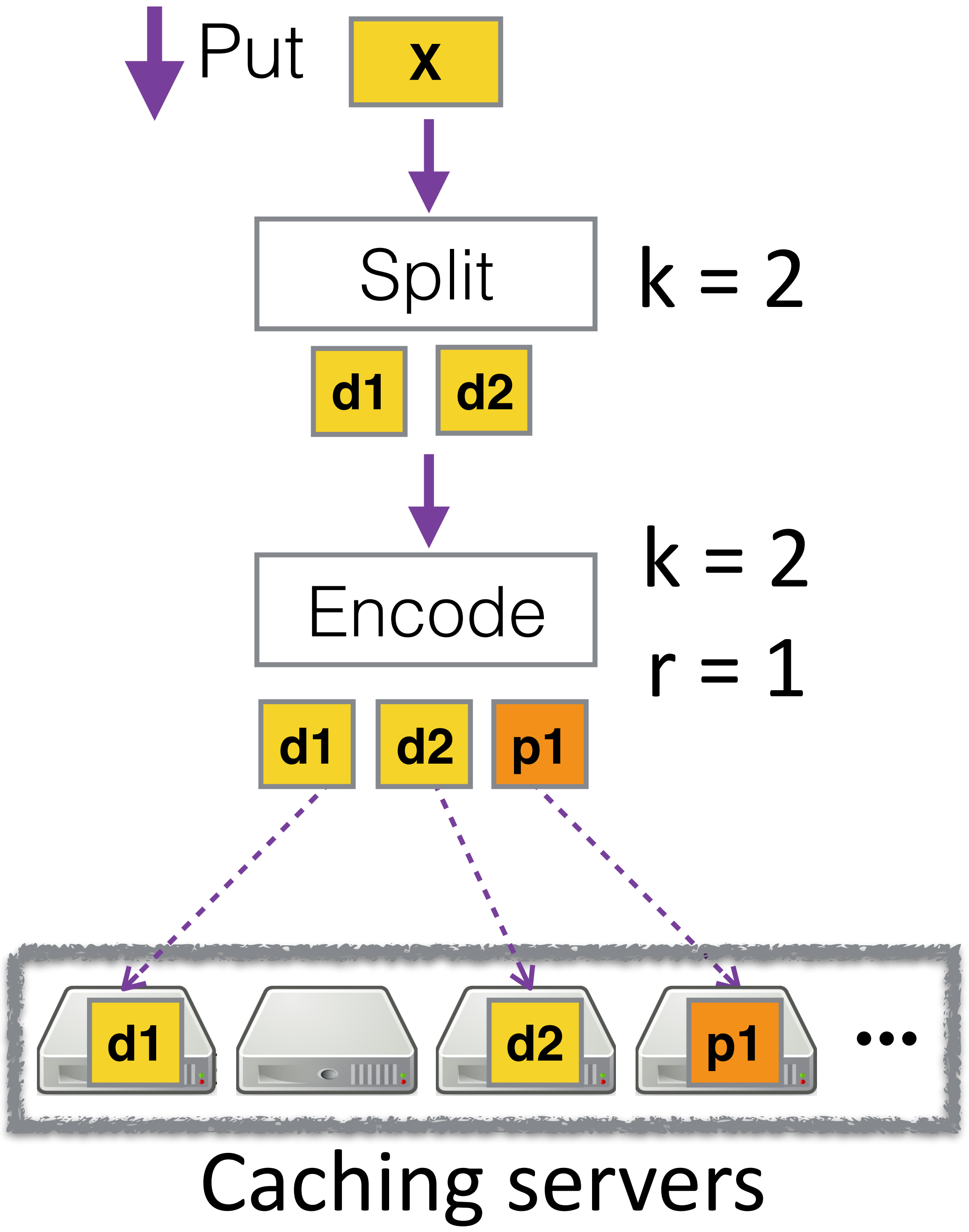
EC-Cache bird's eye view: Writes

- Object split into k data units
- Encoded to generate r parity units



EC-Cache bird's eye view: Writes

- Object split into k data units
- Encoded to generate r parity units
- (k+r) units cached on distinct servers chosen uniformly at random



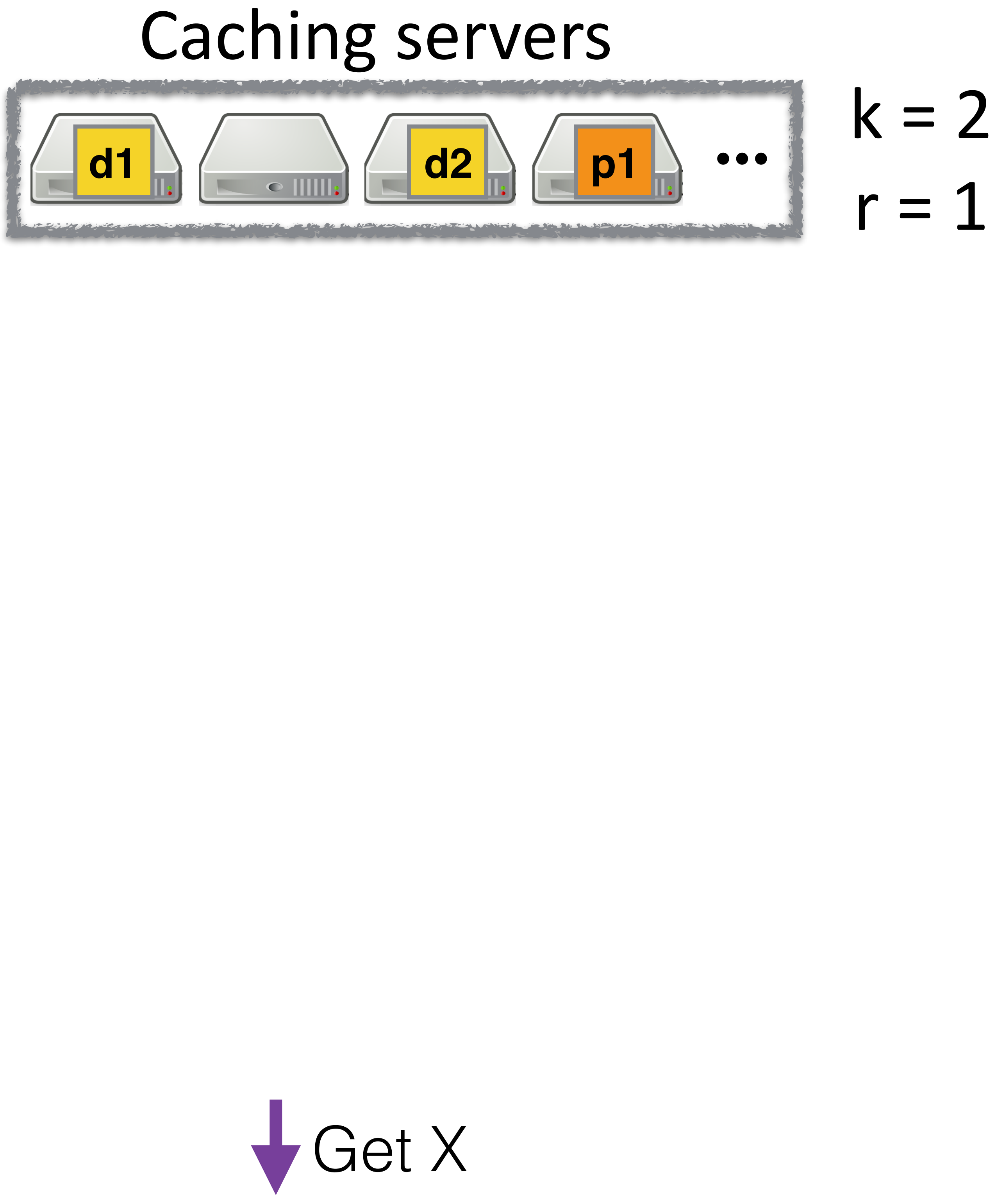
EC-Cache bird's eye view: Reads

EC-Cache bird’s eye view: Reads

- Read from $(k + \Delta)$ units of the object chosen uniformly at random
  - “Additional reads”
- Use the first k units that arrive

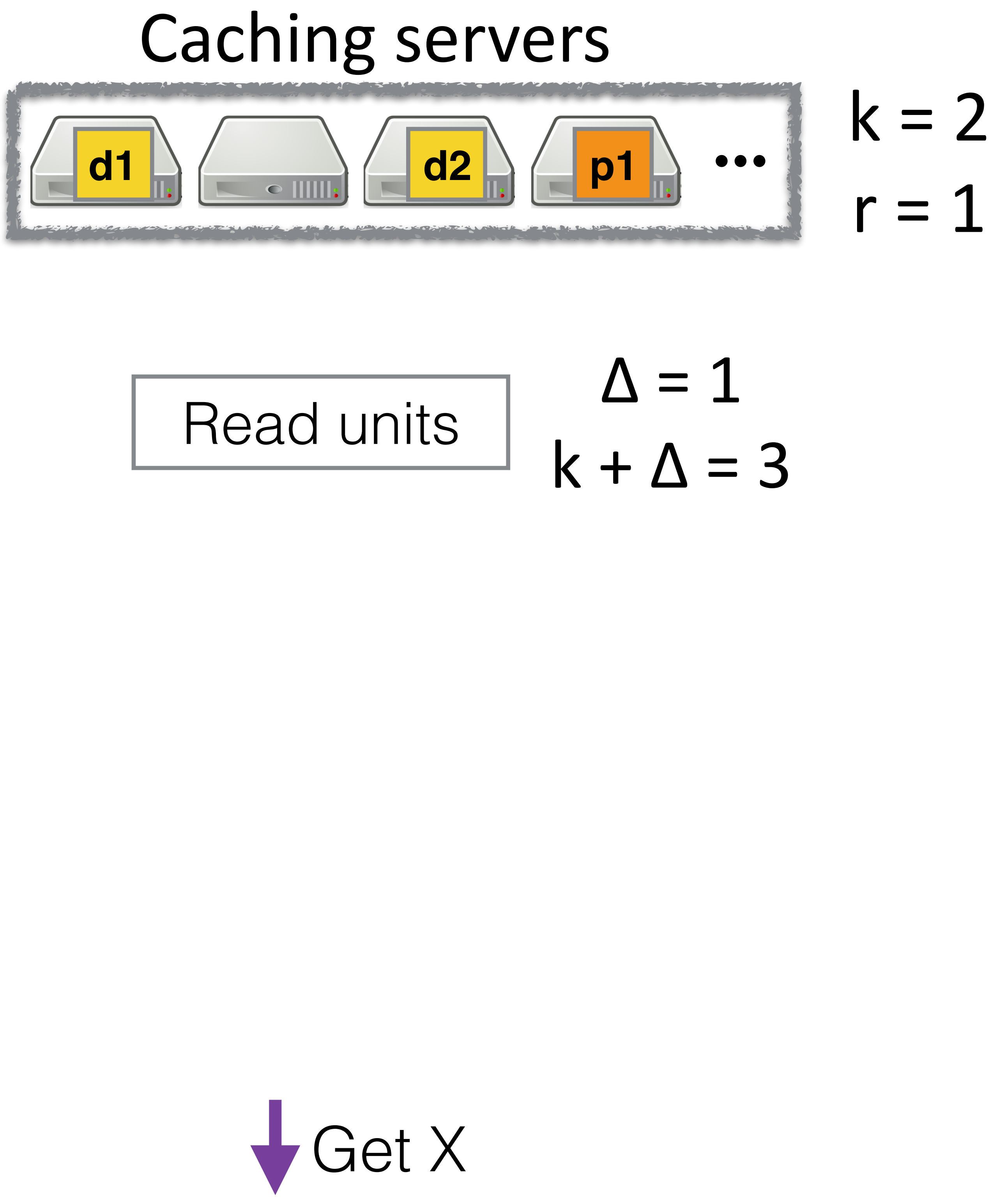
EC-Cache bird's eye view: Reads

- Read from (k + Δ) units of the object chosen uniformly at random
  - "Additional reads"
- Use the first k units that arrive



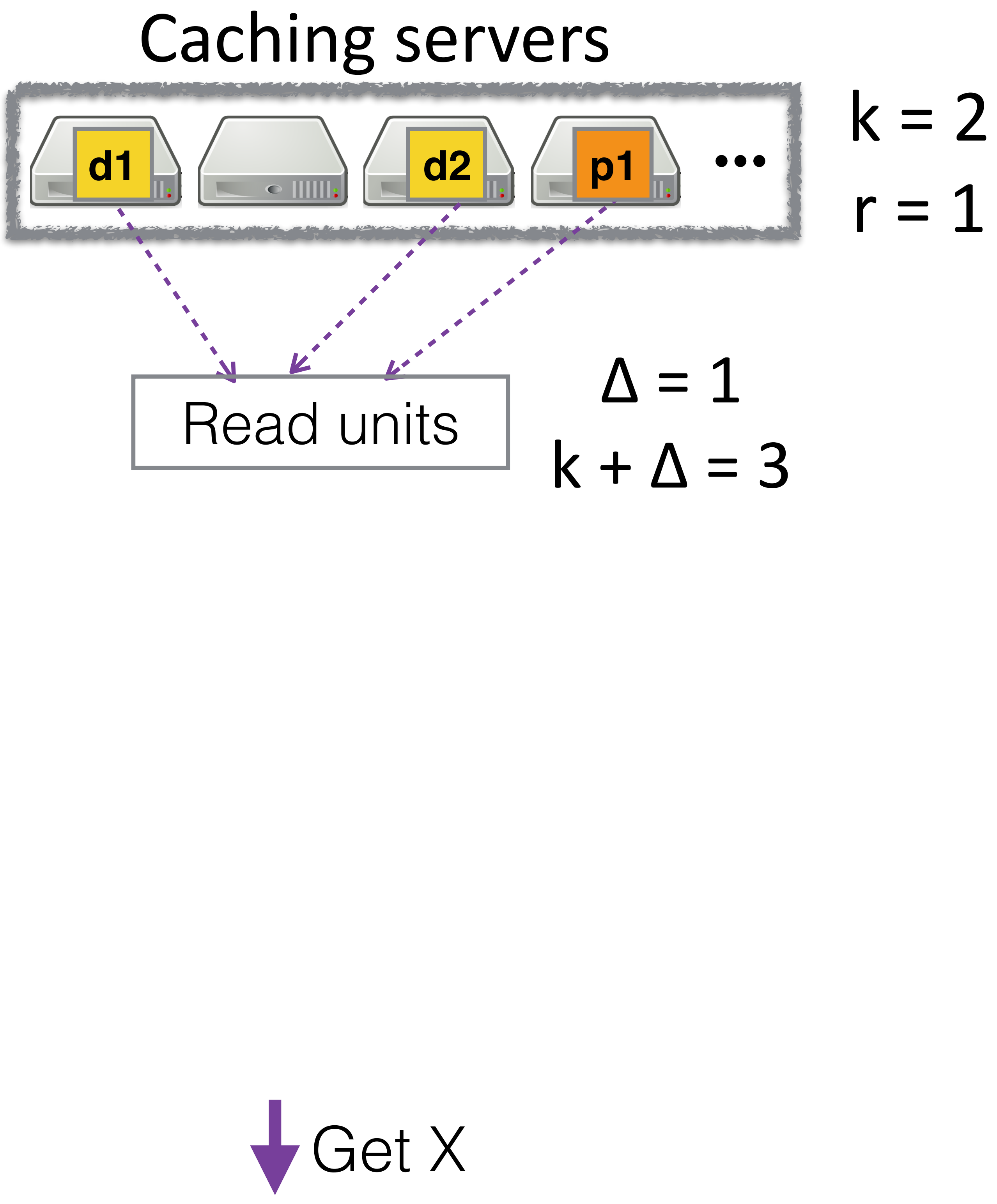
EC-Cache bird's eye view: Reads

- Read from (k + Δ) units of the object chosen uniformly at random
  - "Additional reads"
- Use the first k units that arrive



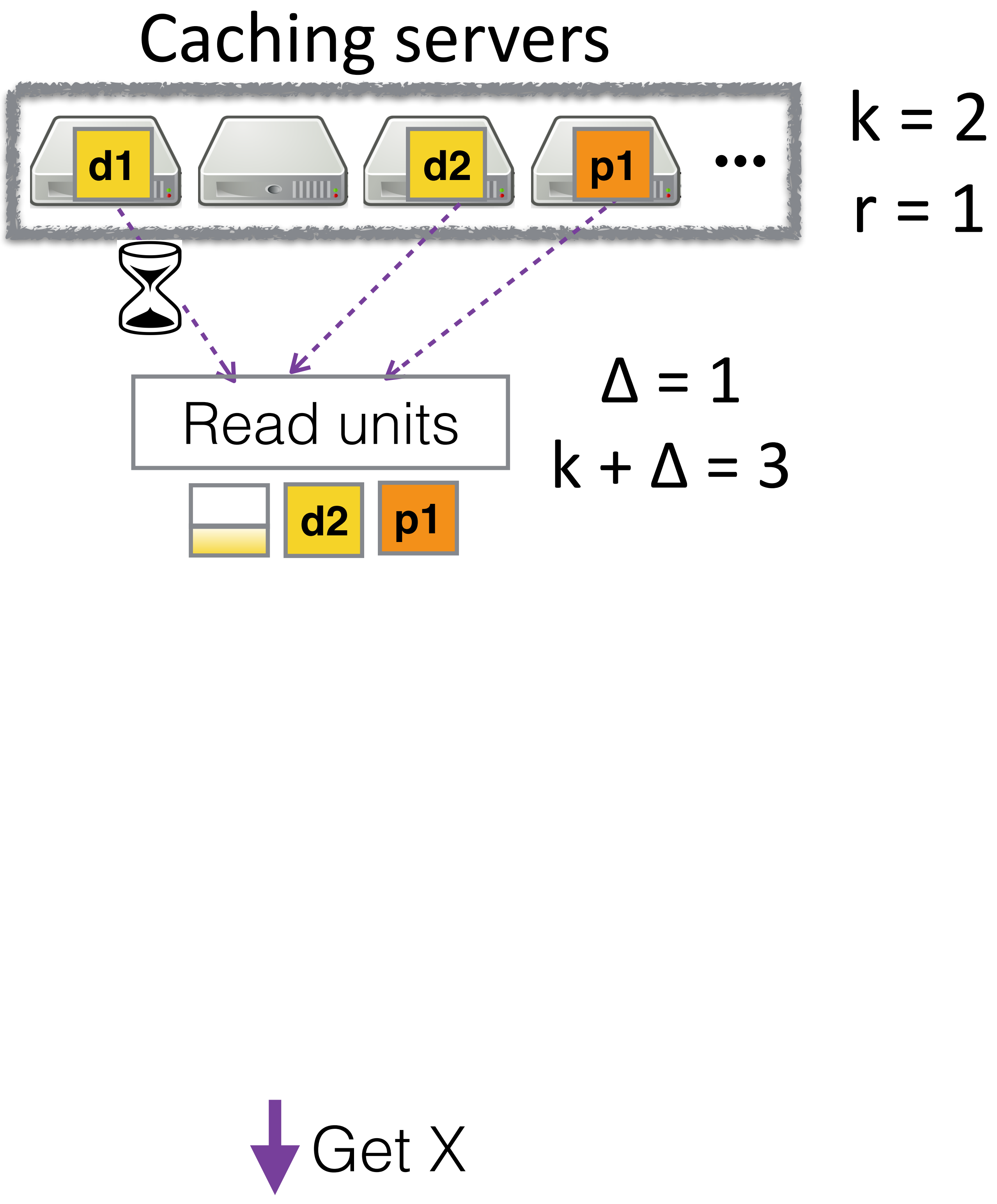
EC-Cache bird's eye view: Reads

- Read from (k + Δ) units of the object chosen uniformly at random
    - "Additional reads"
- Use the first k units that arrive



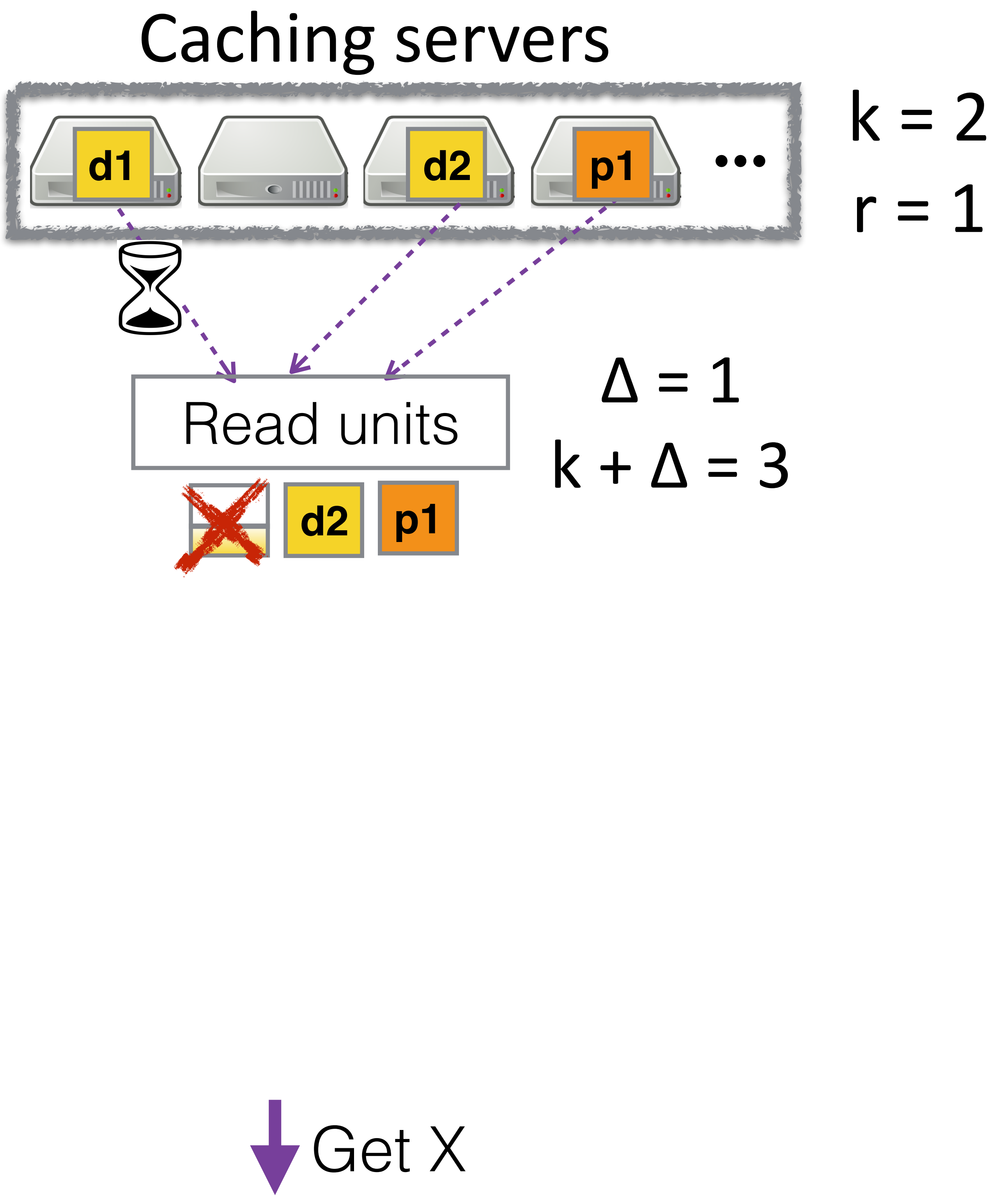
EC-Cache bird's eye view: Reads

- Read from (k + Δ) units of the object chosen uniformly at random
  - "Additional reads"
- Use the first k units that arrive



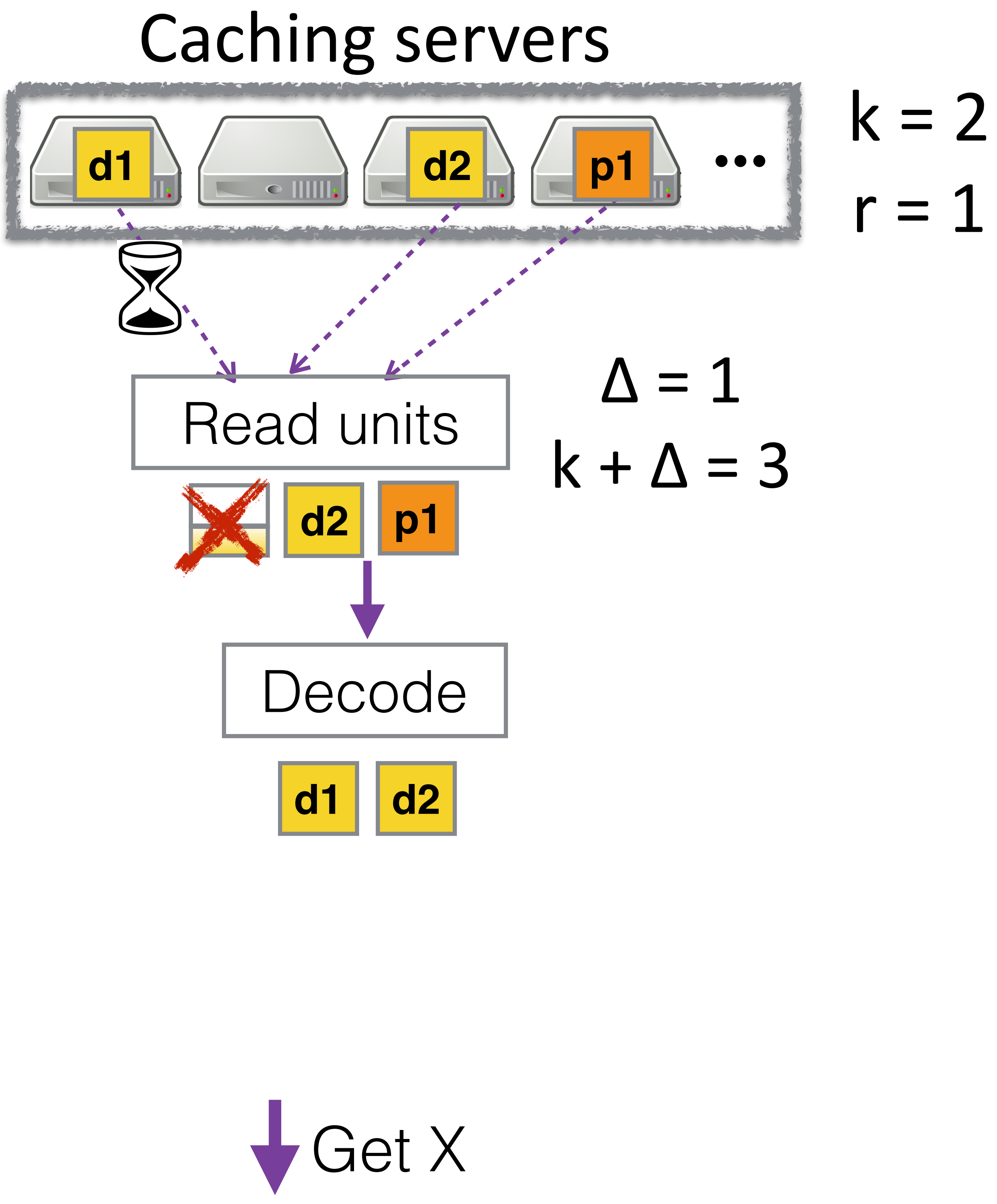
EC-Cache bird's eye view: Reads

- Read from (k + Δ) units of the object chosen uniformly at random
  - "Additional reads"
- Use the first k units that arrive



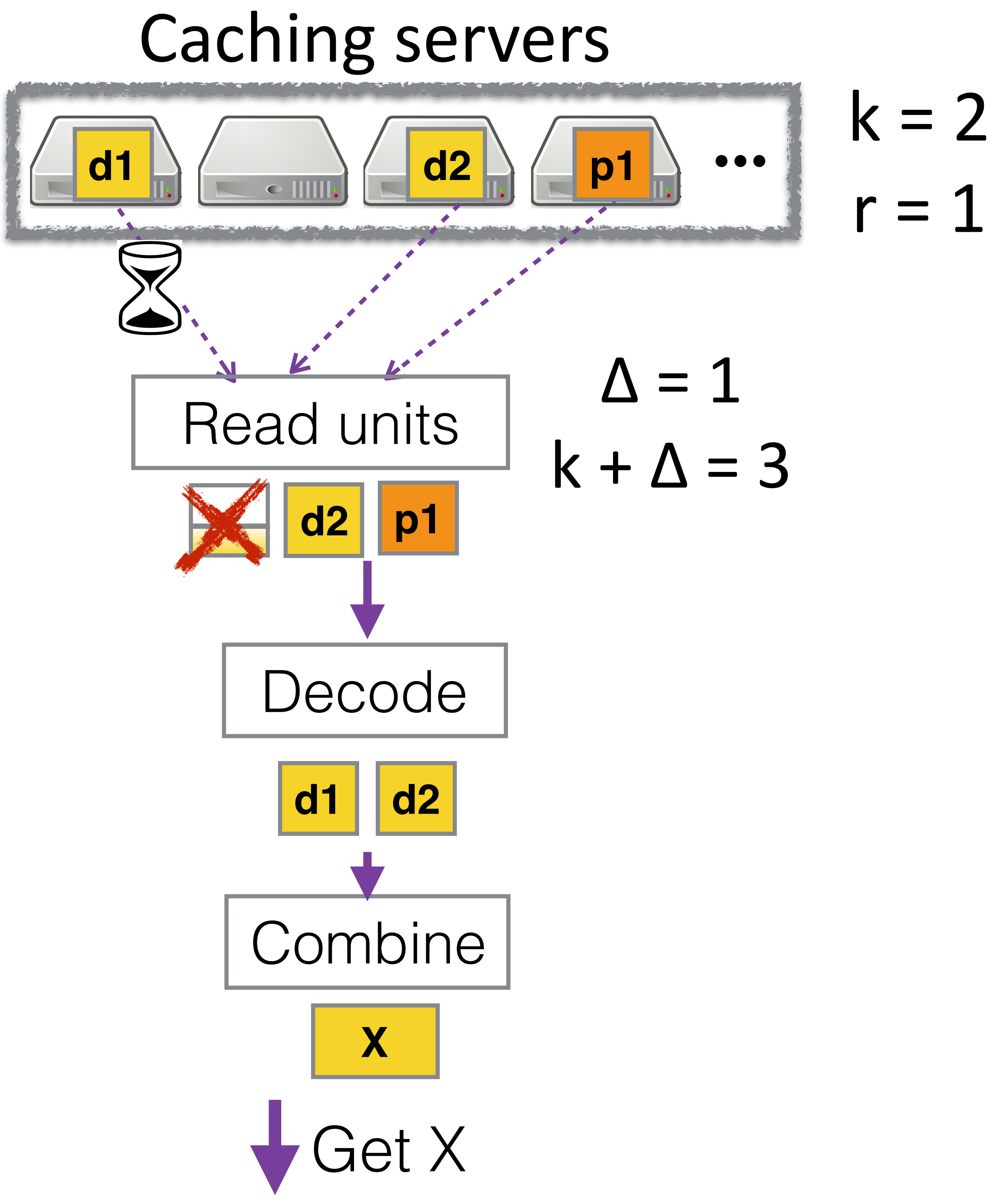
EC-Cache bird's eye view: Reads

- Read from (k + Δ) units of the object chosen uniformly at random
  - "Additional reads"
- Use the first k units that arrive
- Decode the data units



EC-Cache bird's eye view: Reads

- Read from (k + Δ) units of the object chosen uniformly at random
  - "Additional reads"
- Use the first k units that arrive
- Decode the data units
- Combine the decoded units



Erasure coding: How does it help?

Erasure coding: How does it help?

1. **Finer control over memory overhead**
   - Selective replication allows only integer control
   - Erasure coding allows fractional control
   - E.g., k = 10 allows control in of multiples of 0.1

Erasure coding: How does it help?

1. **Finer control over memory overhead**
   - Selective replication allows only integer control
   - Erasure coding allows fractional control
   - E.g., k = 10 allows control in of multiples of 0.1

2. **Object splitting helps in load balancing**
   - Smaller granularity reads help to smoothly spread load
   - Analysis on a certain simplified model:

$$\frac{\mathrm{Var}(L_{\text{EC-Cache}})}{\mathrm{Var}(L_{\text{Selective Replication}})} = \frac{1}{k}$$

Erasure coding: How does it help?

3. **Object splitting reduces median latency but hurts tail latency**

   - Read parallelism helps reduce median latency
   - Straggler effect hurts tail latency (if no additional reads)

Erasure coding: How does it help?

3. **Object splitting reduces median latency but hurts tail latency**
   - Read parallelism helps reduce median latency
   - Straggler effect hurts tail latency (if no additional reads)

4. **"Any k out of (k+r)" property helps to reduce tail latency**
   - Read from (k + Δ) and use the first k that arrive
   - Δ = 1 often sufficient to reign in tail latency

Design considerations

Design considerations

1. Purpose of erasure codes

Storage systems	EC-Cache
• Space-efficient fault tolerance	• Reduce read latency • Load balance

Design considerations

2. Choice of erasure code

Storage systems	EC-Cache

Design considerations

2. Choice of erasure code

Storage systems	EC-Cache
• Optimize resource usage during reconstruction operations† • Some codes do not have "any k out of (k+r)" property	

†Rashmi et al. SIGCOMM 2014, Sathiamoorthy et al. VLDB 2013, Huang et al. ATC 2012

Design considerations

2. Choice of erasure code

Storage systems	EC-Cache
• Optimize resource usage during reconstruction operations[†] • Some codes do not have “any k out of (k+r)” property	• No reconstruction operations in caching layer; data persisted in underlying storage • “Any k out of (k+r)” property helps in load balancing and reducing latency when reading objects

[†]Rashmi et al. SIGCOMM 2014, Sathiamoorthy et al. VLDB 2013, Huang et al. ATC 2012

Design considerations

3. **How do we use erasure coding: across vs. within objects**

Storage systems	EC-Cache

Design considerations

3. How do we use erasure coding: across vs. within objects

Storage systems	EC-Cache
• Some systems encode across objects (e.g., HDFS-RAID); some within (e.g., Ceph) • Does not affect fault tolerance	

Design considerations

3. How do we use erasure coding: across vs. within objects

Storage systems	EC-Cache
• Some systems encode across objects (e.g., HDFS-RAID); some within (e.g., Ceph) • Does not affect fault tolerance	• Need to encode within objects - To spread load across both data & parity • Encoding across: Very high BW overhead for reading object using parities[†]

[†]Rashmi et al. SIGCOMM 2014, HotStorage 2013

Implementation

- EC-Cache on top of Alluxio (formerly Tachyon)
  - Backend caching servers: cache data — unaware of erasure coding
  - EC-Cache client library: all read/write logic handled

Implementation

- EC-Cache on top of Alluxio (formerly Tachyon)
  - Backend caching servers: cache data — unaware of erasure coding
  - EC-Cache client library: all read/write logic handled
- Reed-Solomon code
  - Any k out of (k+r) property

Implementation

- EC-Cache on top of Alluxio (formerly Tachyon)
  - Backend caching servers: cache data — unaware of erasure coding
  - EC-Cache client library: all read/write logic handled
- Reed-Solomon code
  - Any k out of (k+r) property
- Intel ISA-L hardware acceleration library
  - Fast encoding and decoding

Evaluation set-up

Evaluation set-up

- Amazon EC2
- 25 backend caching servers and 30 client servers

Evaluation set-up

- Amazon EC2
- 25 backend caching servers and 30 client servers
- Object popularity: Zipf distribution with high skew

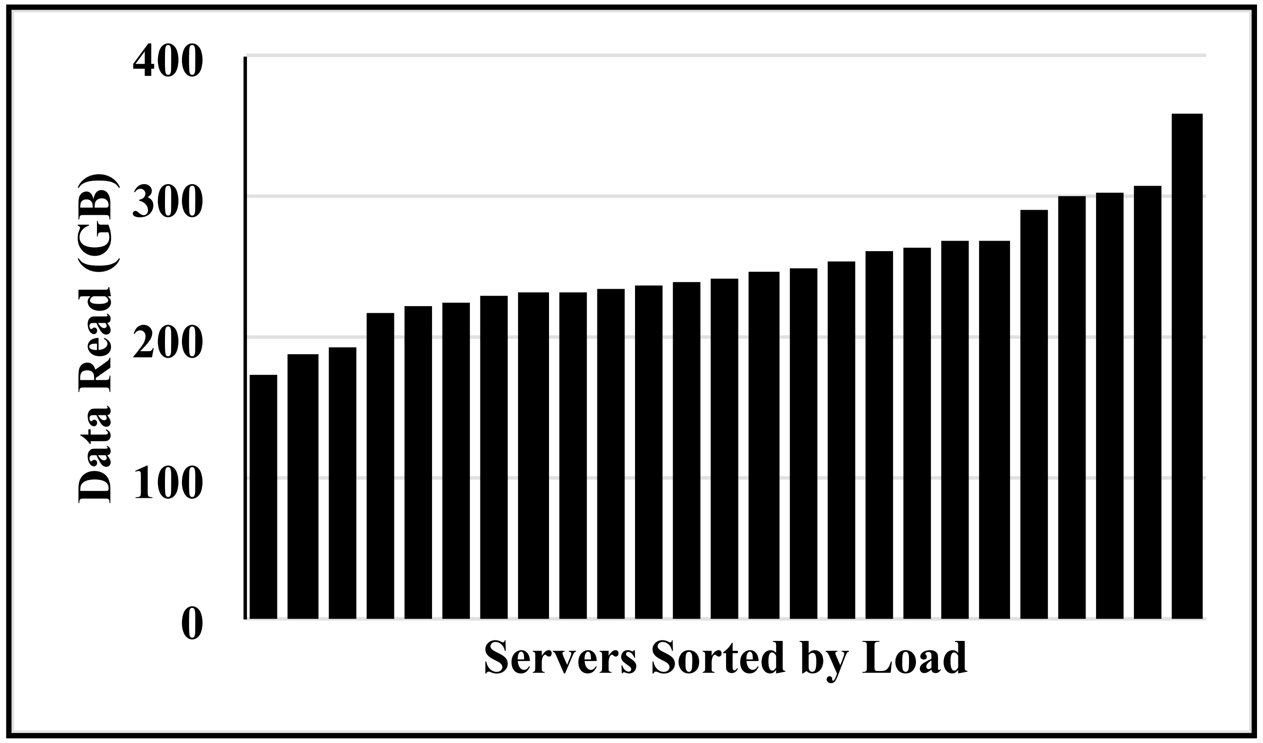
Evaluation set-up

- Amazon EC2
- 25 backend caching servers and 30 client servers
- Object popularity: Zipf distribution with high skew
- EC-Cache uses $k = 10$, $\Delta = 1$
  - BW overhead = 10%

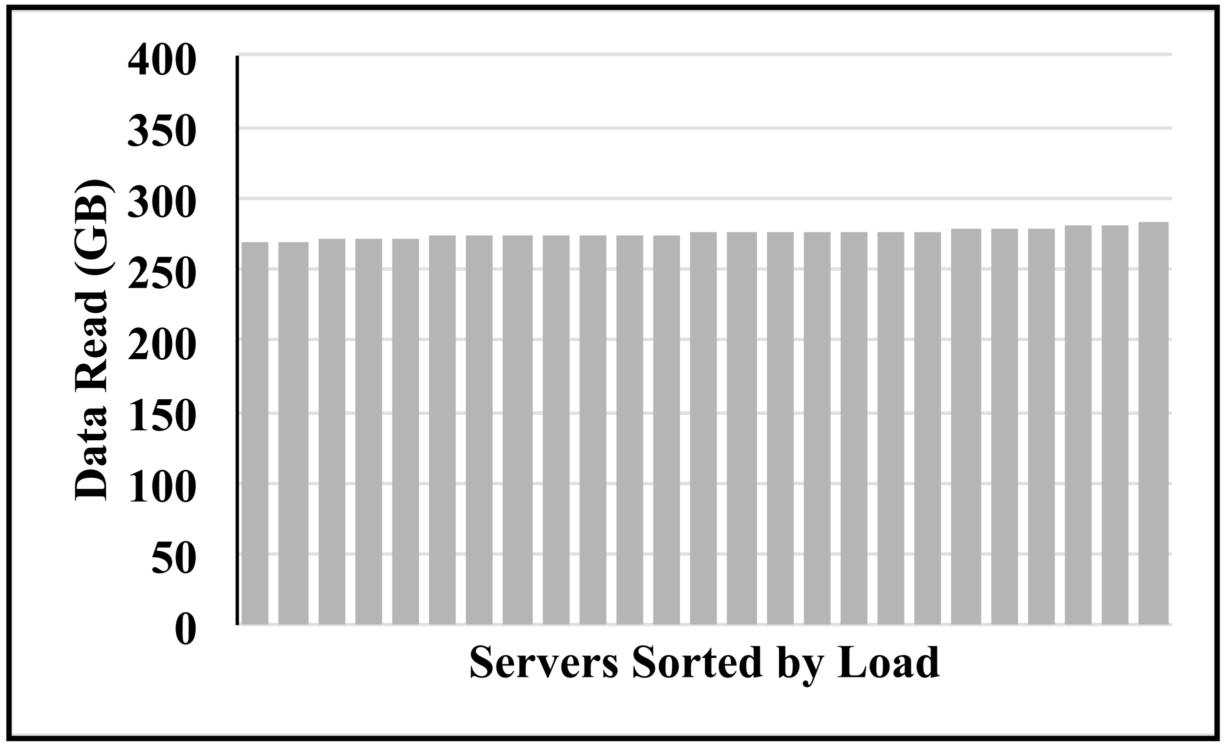
Evaluation set-up

- Amazon EC2
- 25 backend caching servers and 30 client servers
- Object popularity: Zipf distribution with high skew
- EC-Cache uses $k = 10$, $\Delta = 1$
  - BW overhead = 10%
- Varying object sizes

Load balancing

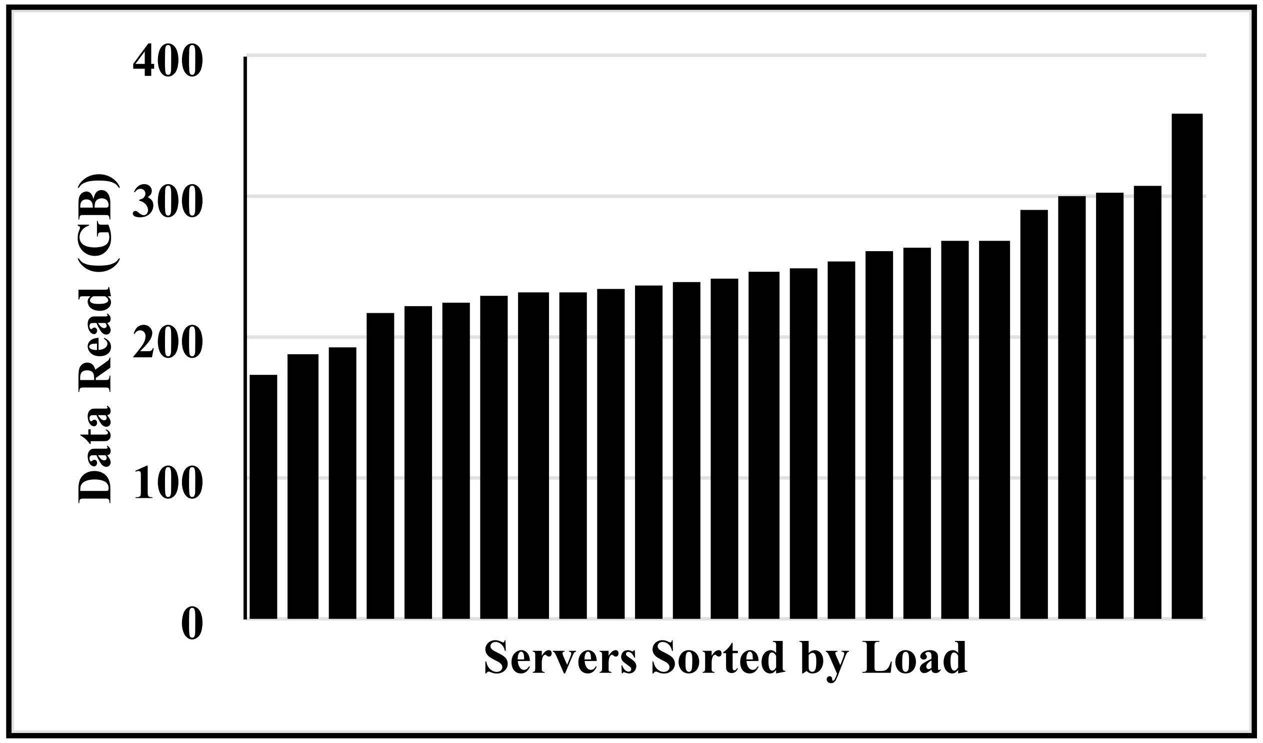


Selective Replication

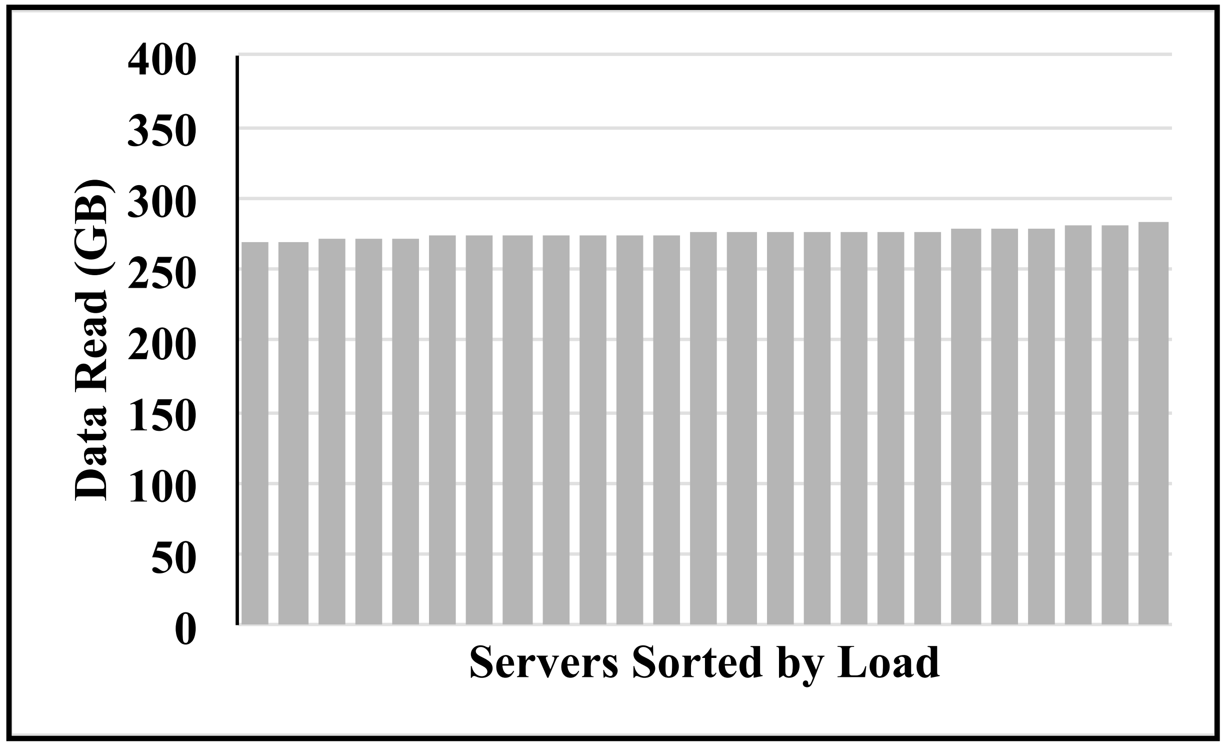


EC-Cache

Load balancing



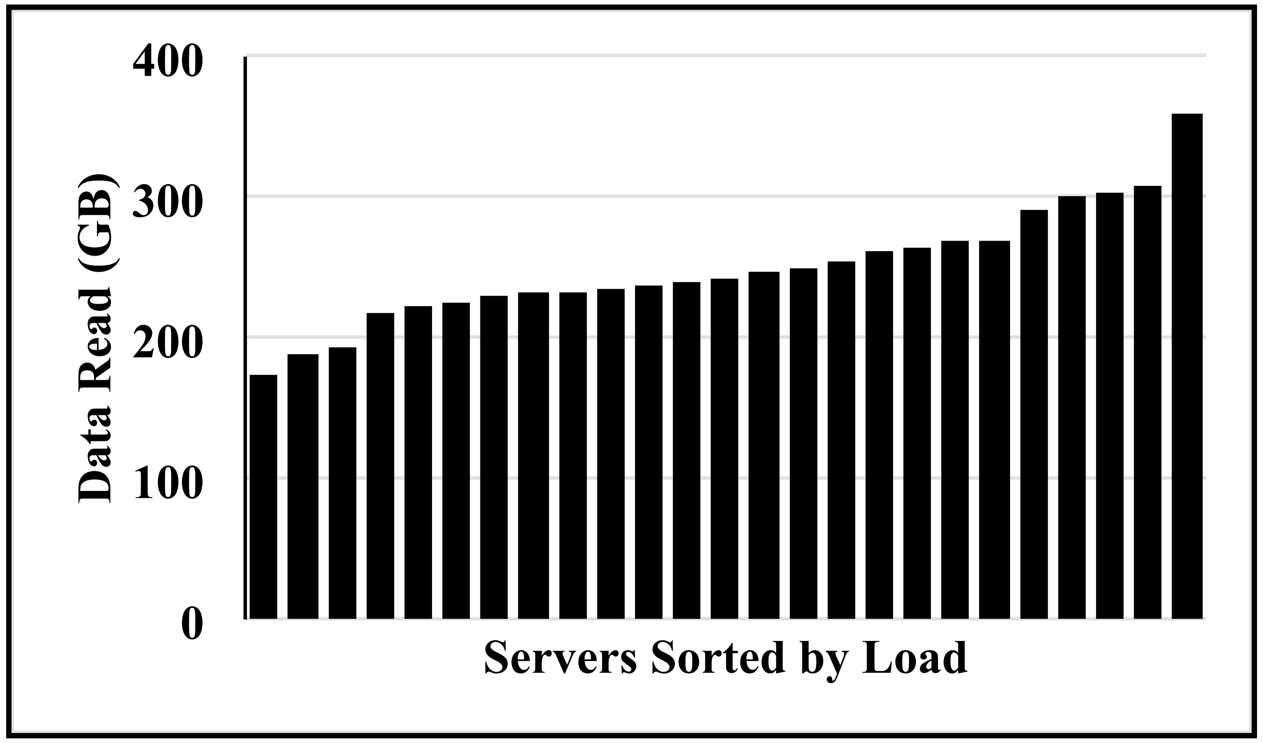
Selective Replication



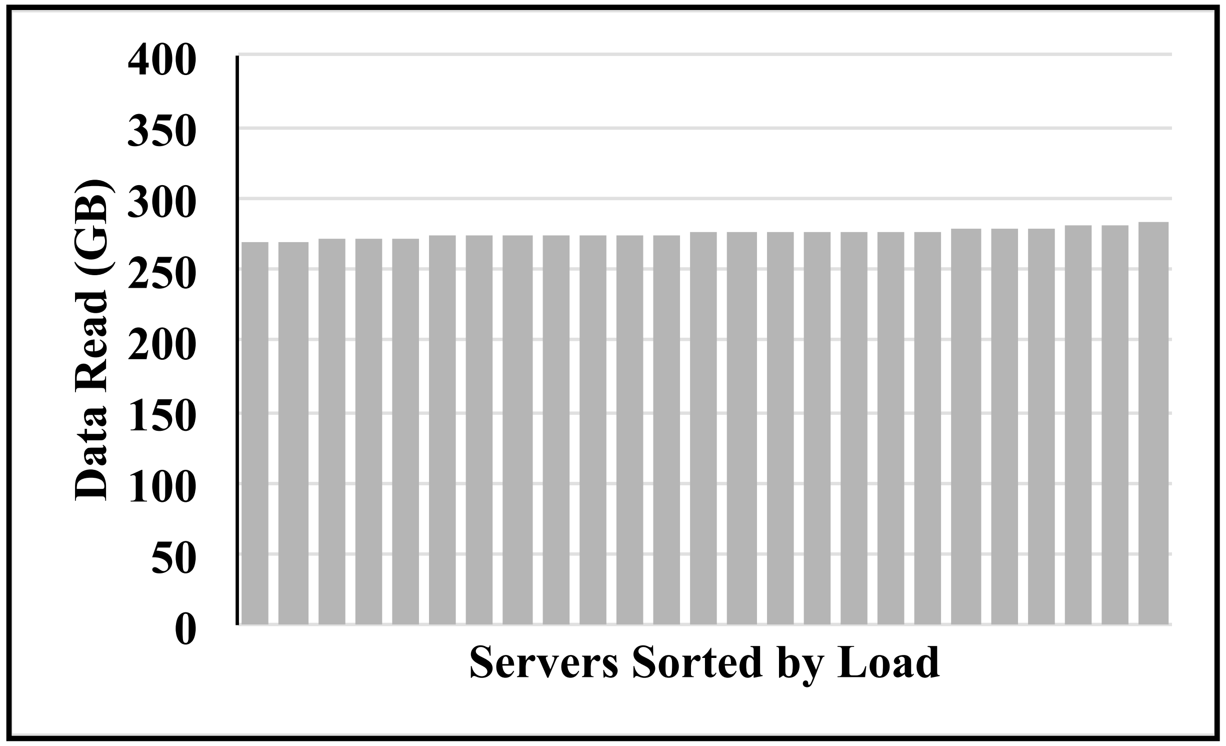
EC-Cache

- Percent imbalance metric: $\lambda = \left(\frac{L_{\max} - L_{\text{avg}^\star}}{L_{\text{avg}^\star}}\right) * 100$

Load balancing



Selective Replication



EC-Cache

- Percent imbalance metric:

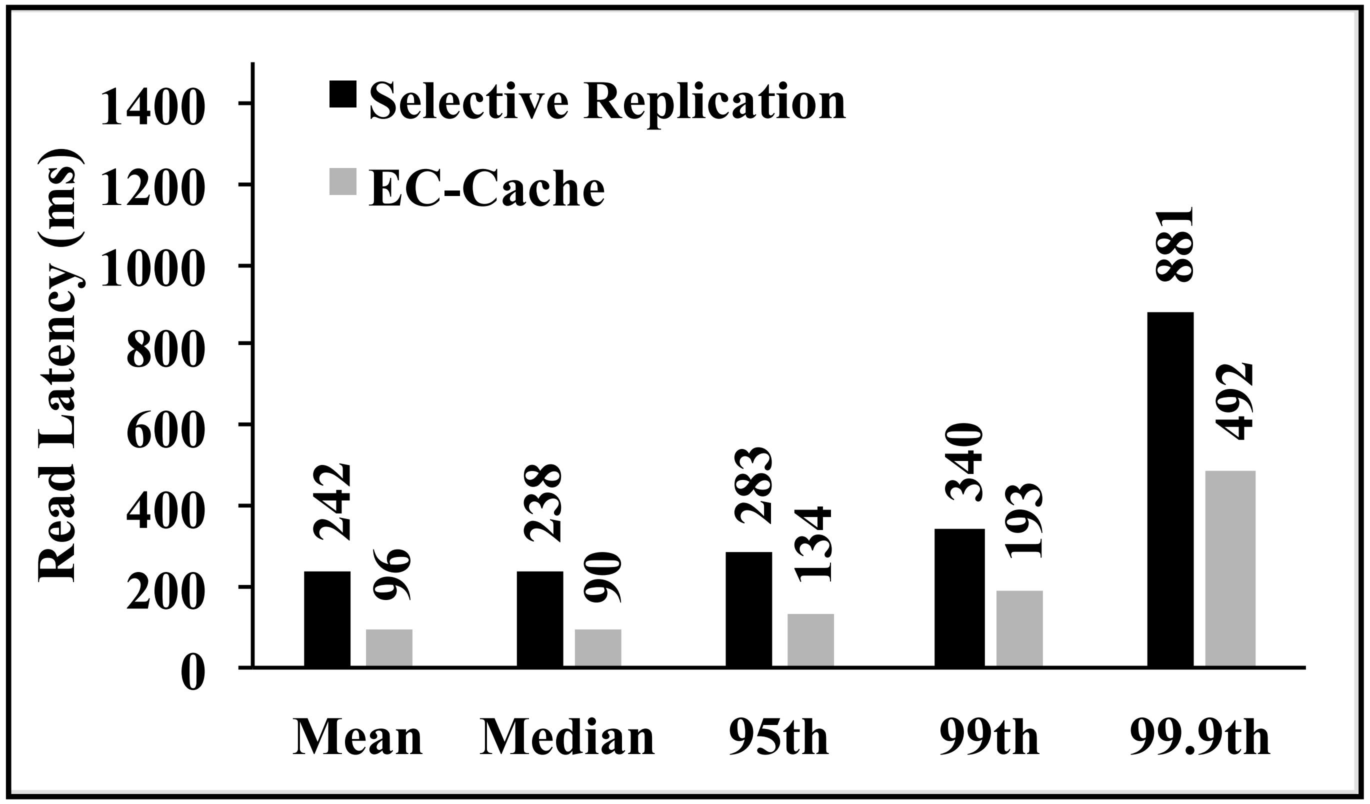
$$\lambda = \left(\frac{L_{\max} - L_{\text{avg}^\star}}{L_{\text{avg}^\star}} \right) * 100$$

$\lambda_{SR} = 43.45\%$

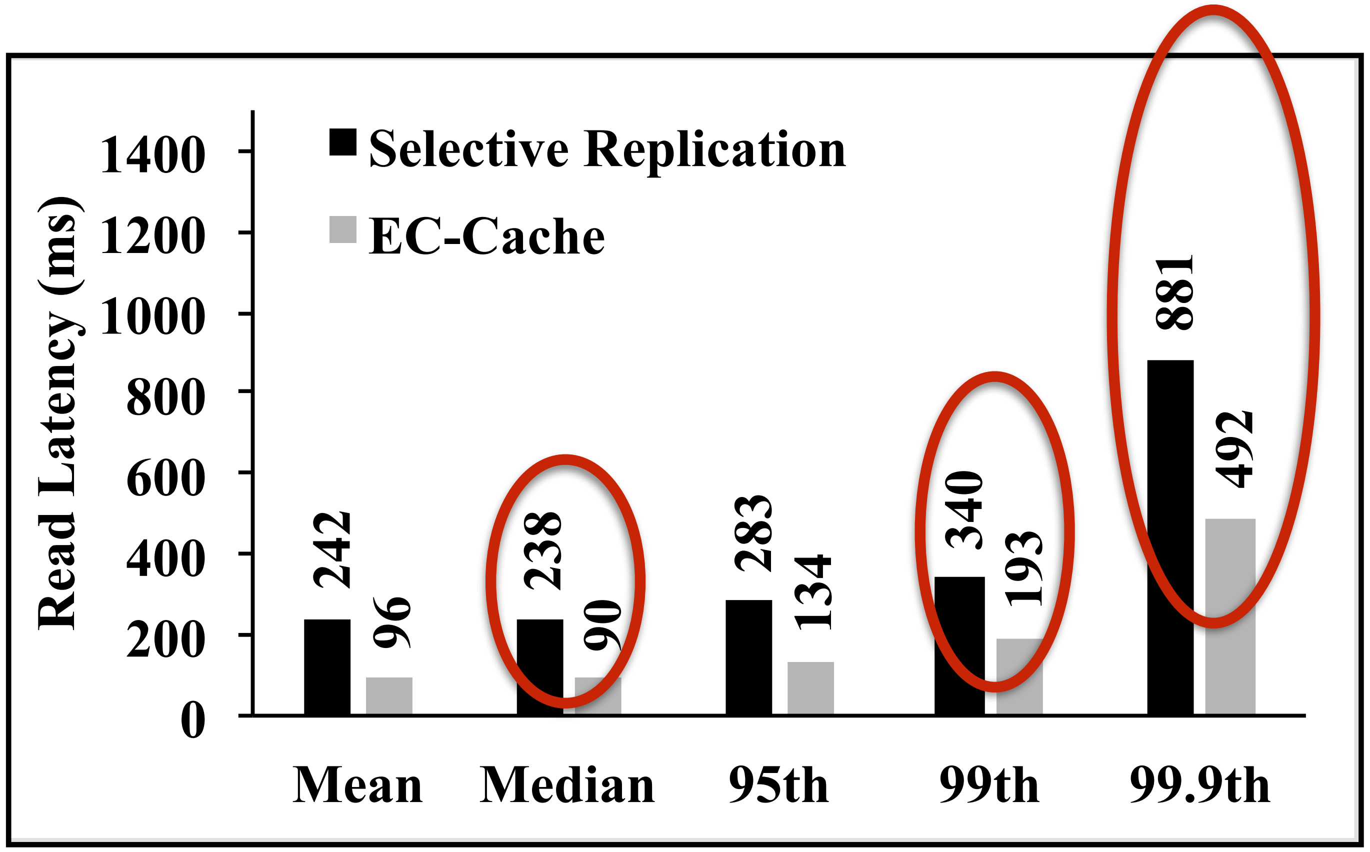
$\lambda_{EC} = 13.14\%$

> 3x reduction in load imbalance metric

Read latency



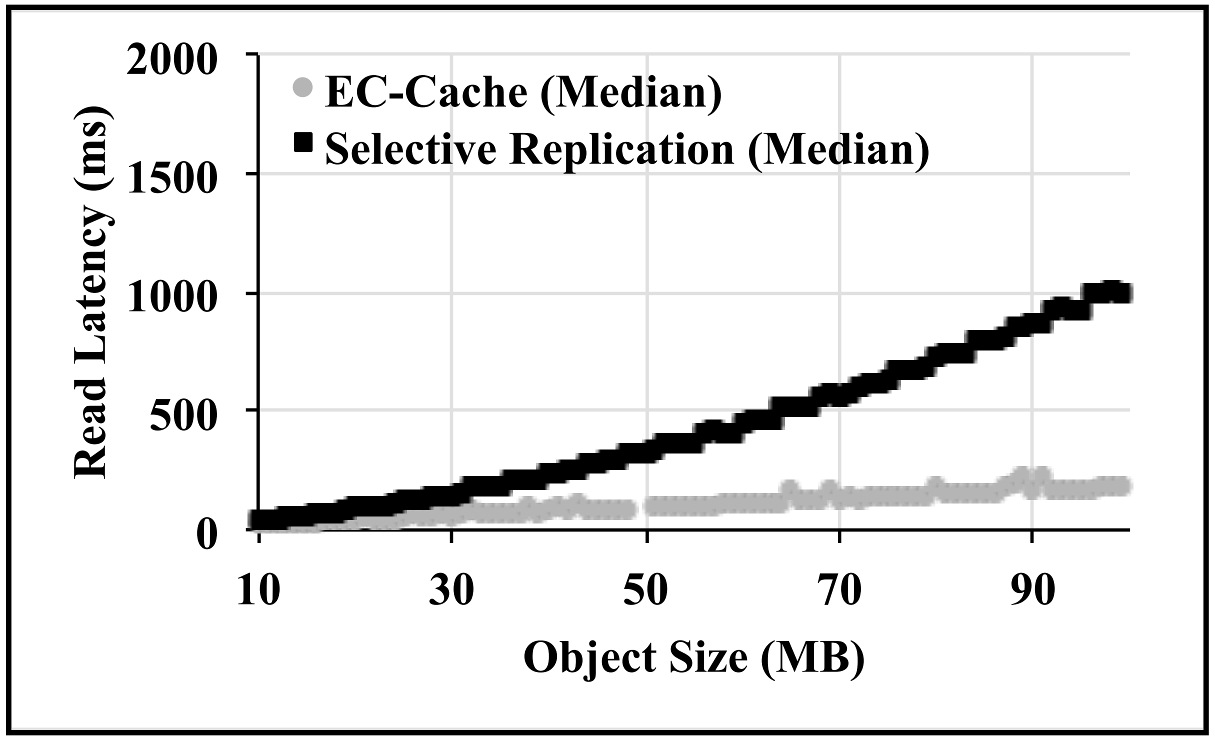
Read latency



- Median: **2.64x** improvement
- 99th and 99.9th: **~1.75x** improvement

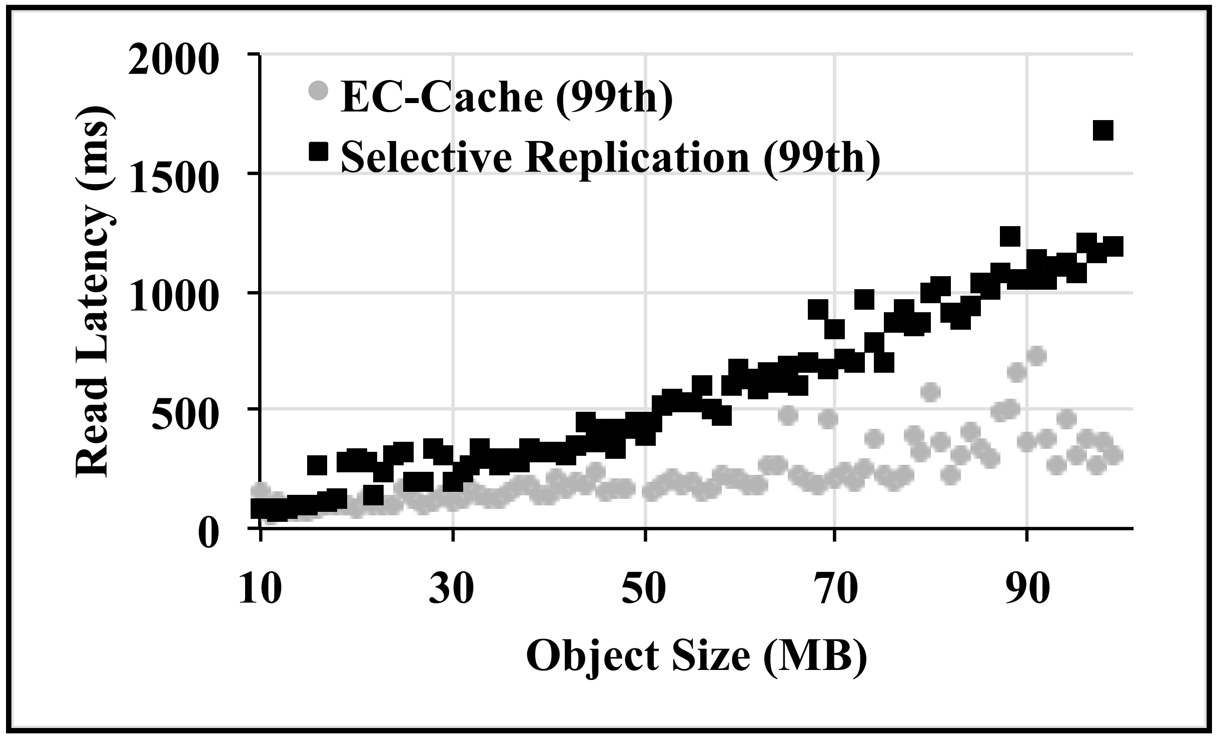
Varying object sizes

Median latency



5.5x improvement for 100MB

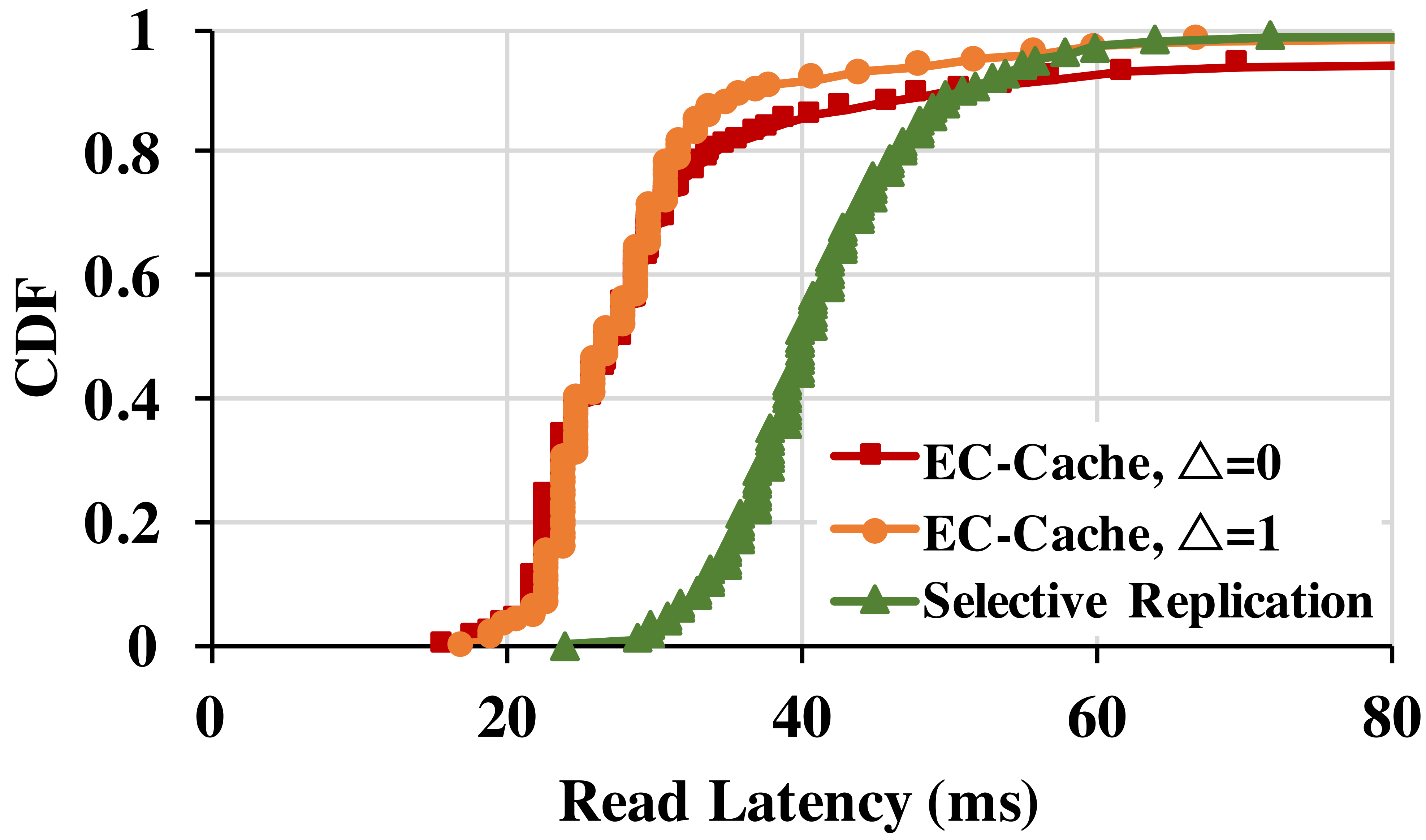
Tail latency



3.85x improvement for 100 MB

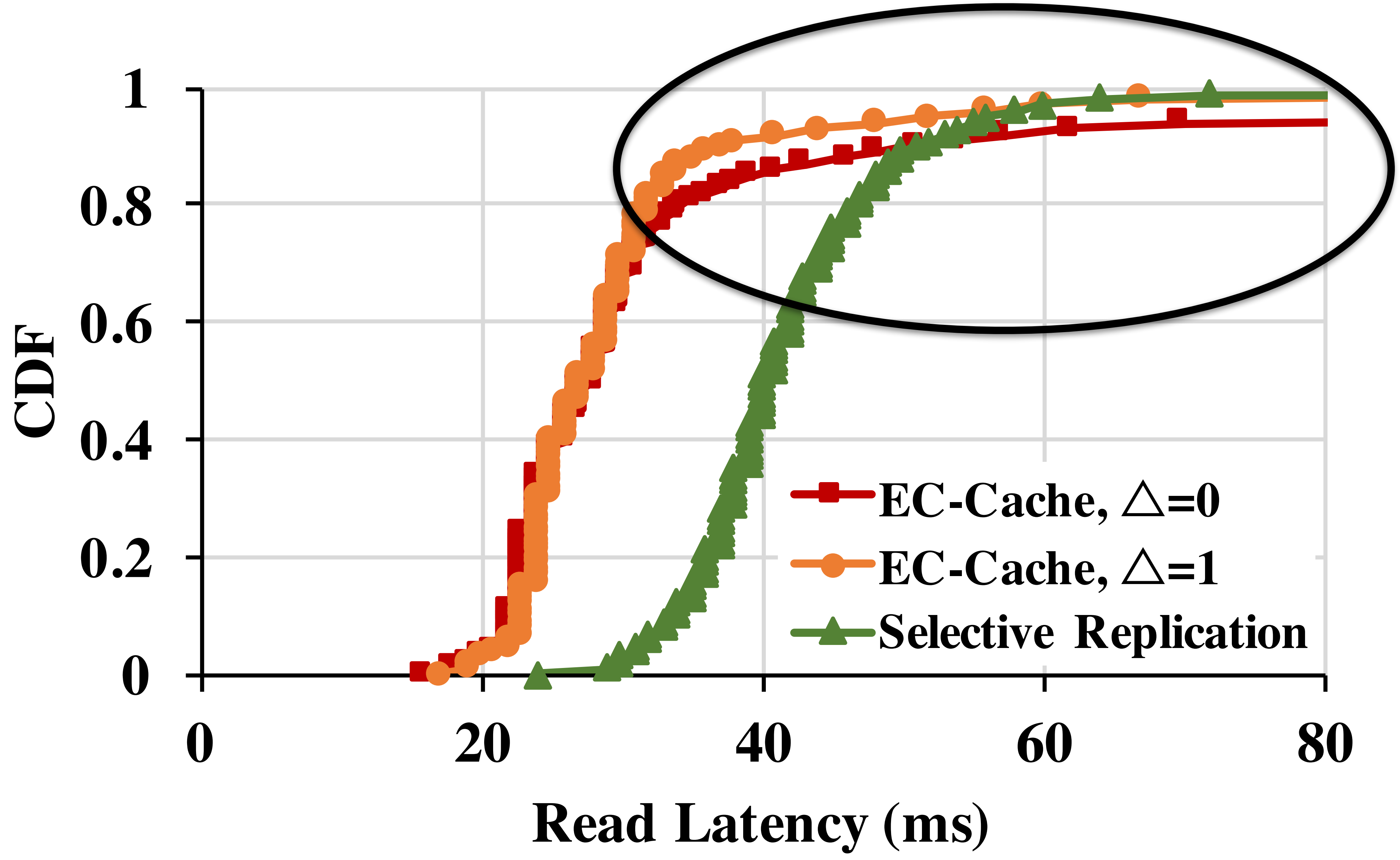
More improvement for larger object sizes

Role of additional reads (Δ)



Role of additional reads (Δ)

Significant degradation in tail latency without additional reads (i.e., Δ = 0)



Additional evaluations in the paper

- With background network imbalance
- With server failures
- Write performance
- Sensitivity analysis for all parameters

Summary

- EC-Cache
  - Cluster cache employing erasure coding for load balancing and reducing read latencies
  - Demonstrates new application and new goals for which erasure coding is highly effective

Summary

- EC-Cache
  - Cluster cache employing erasure coding for load balancing and reducing read latencies
  - Demonstrates new application and new goals for which erasure coding is highly effective
- Implementation on Alluxio
- Evaluation
  - Load balancing: > 3x improvement
  - Median latency: > 5x improvement
  - Tail latency: > 3x improvement

Summary

- EC-Cache
  - Cluster cache employing erasure coding for load balancing and reducing read latencies
  - Demonstrates new application and new goals for which erasure coding is highly effective
- Implementation on Alluxio
- Evaluation
  - Load balancing: > 3x improvement
  - Median latency: > 5x improvement
  - Tail latency: > 3x improvement

Thanks!