SJTU SAIL (Software Architecture and Infrastructure Lab)

SHANGHAI JIAO TONG UNIVERSITY

Serverless Ephemeral Storage

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SAIL

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Understanding Ephemeral Storage for Serverless Analytics

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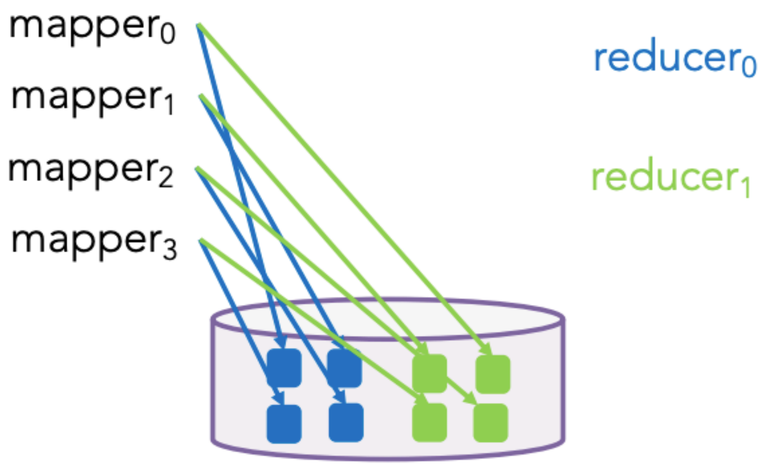
https://www.usenix.org/conference/atc18/presentation/klimovic-serverless

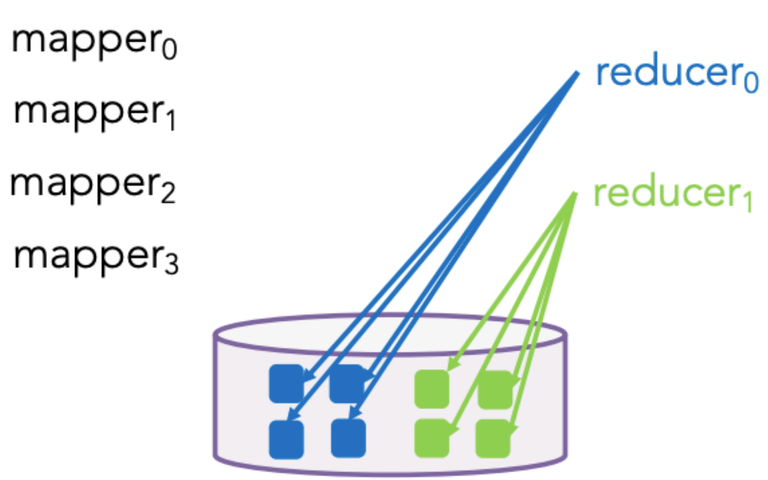
Why Need Ephemeral Storage

- Real applications(Analytics jobs) involve multiple stages of execution

- Serverless tasks need an efficient way to communicate **intermediate data** between different stages of execution

ephemeral data





Questions

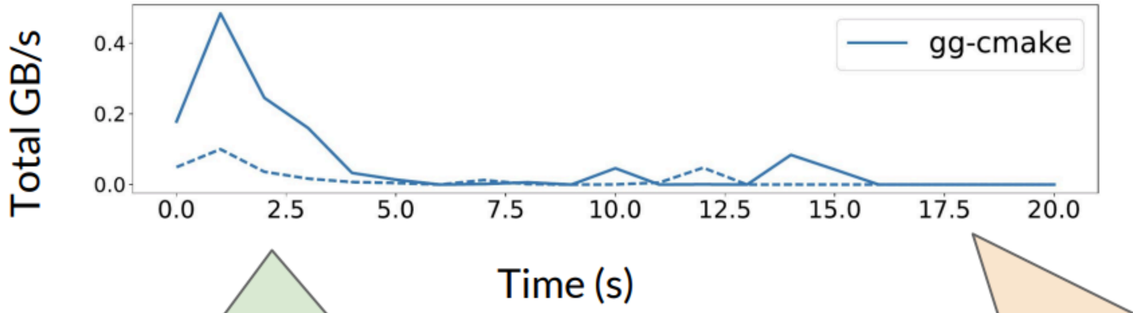
1. What are the ephemeral I/O characteristics of serverless analytics applications?
2. How do applications perform using existing systems (e.g., S3, Redis) for ephemeral I/O?
3. What storage media (DRAM, Flash, HDD) satisfies I/O requirements at the lowest cost?

1. Application Ephemeral I/O Patterns

Application Type

Distributed Compilation

Ephemeral I/O Throughput: Write (dotted), Read (solid)



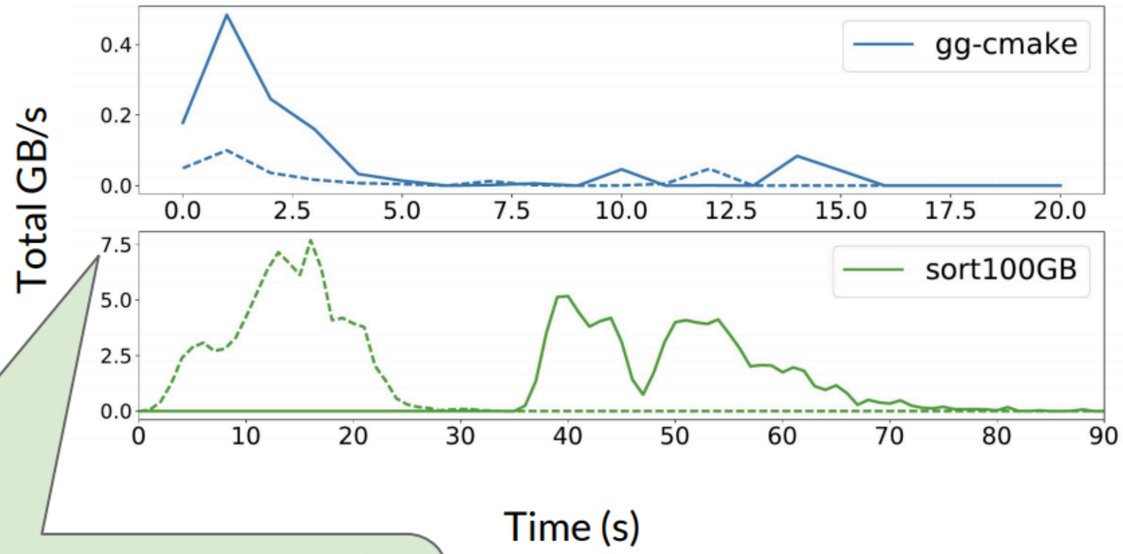
Ephemeral Data Capacity

0.85 GB

High throughput and IOPS due to high parallelism: lambdas each compile independent files

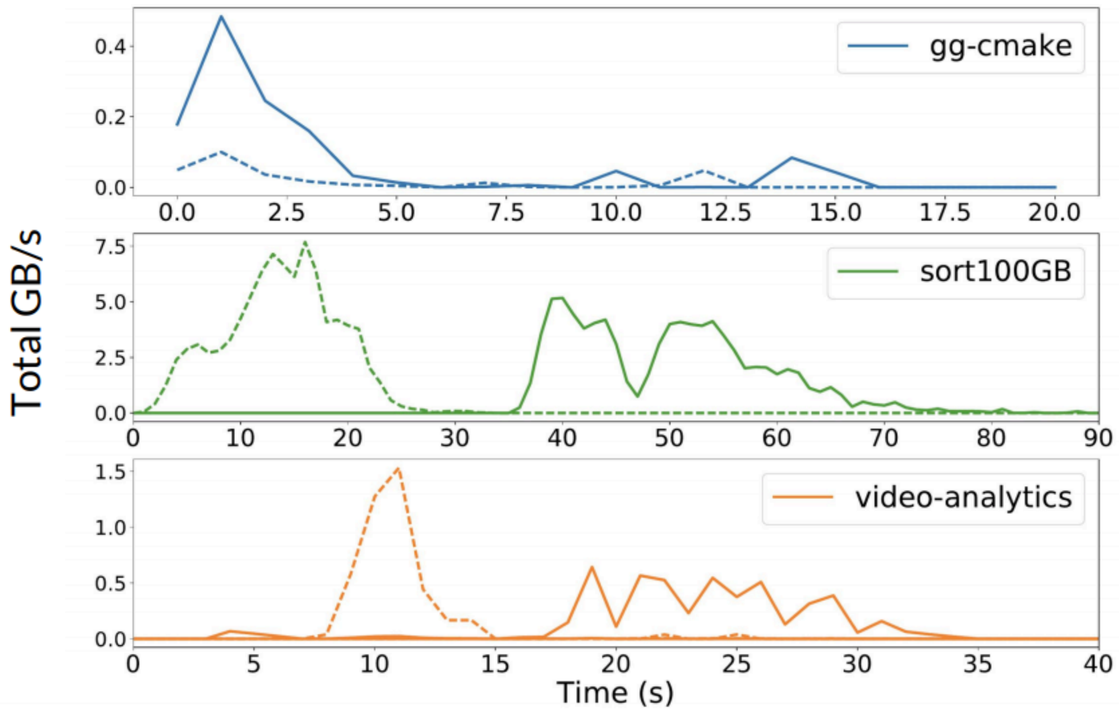
Archiving and linking lambdas are serialized as they depend on previous lambdas → low parallelism, low I/O rate

1. Application Ephemeral I/O Patterns

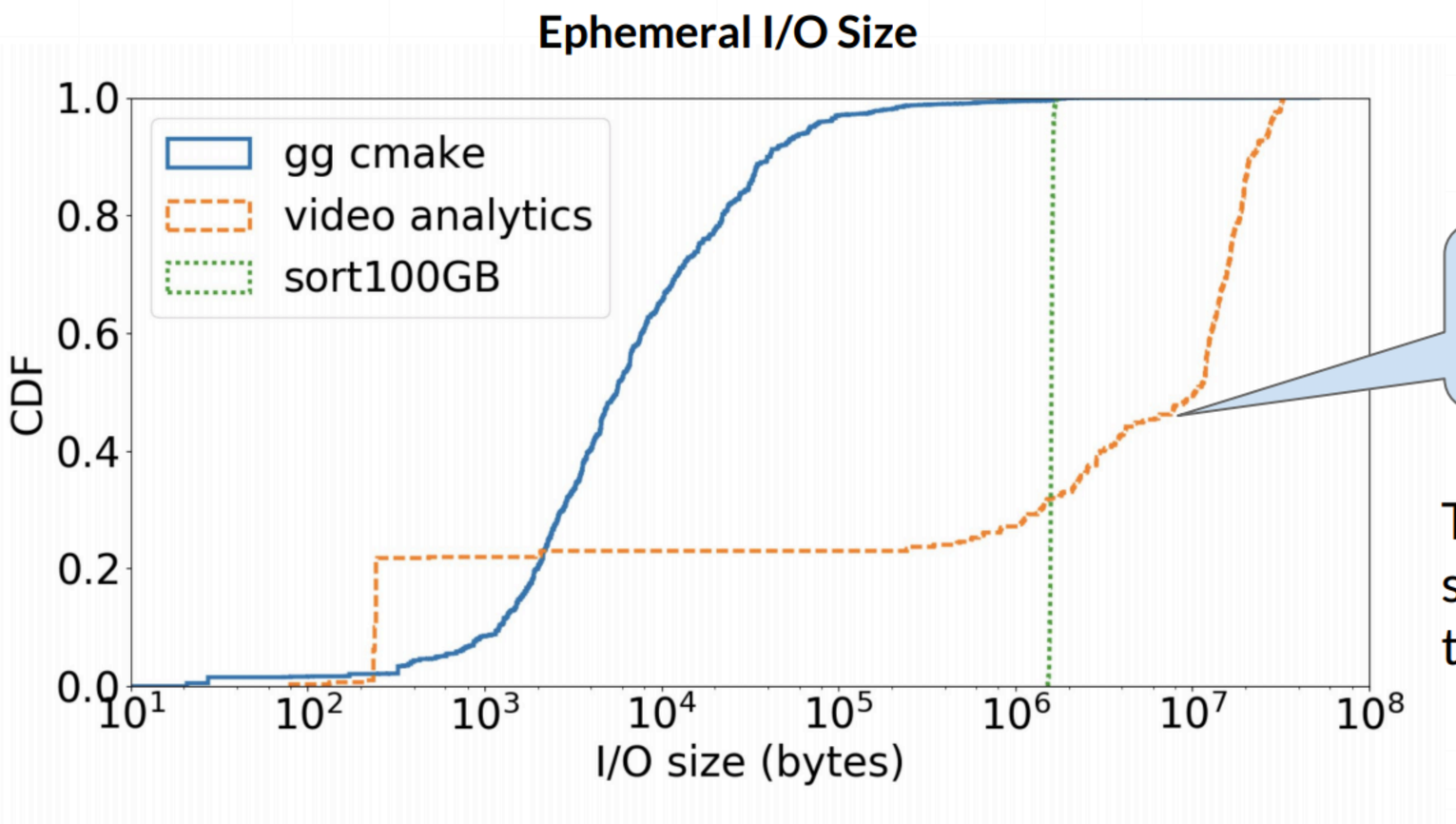
Application Type	Ephemeral I/O Throughput: Write (dotted), Read (solid)	Ephemeral Data Capacity
Distributed Compilation		0.85 GB
MapReduce		100 GB

High throughput due to high I/O intensity and parallelism (up to 7.5 GB/s with 500 concurrent lambdas)

1. Application Ephemeral I/O Patterns

Application Type	Ephemeral I/O Throughput: Write (dotted), Read (solid)	Ephemeral Data Capacity
Distributed Compilation		0.85 GB
MapReduce		100 GB
Video Analytics		6 GB

1. Application Ephemeral I/O Patterns



Wide range of I/O sizes (bytes to 100s of MBs)

Thus, an ephemeral storage system should support high throughput ***and*** low latency.

2. Existing Storage Systems

Cloud object storage system (e.g. Amazon S3)

- Pay only for the capacity and throughput you use
- Resources managed by cloud provider

In-memory key-value store (e.g. Redis)

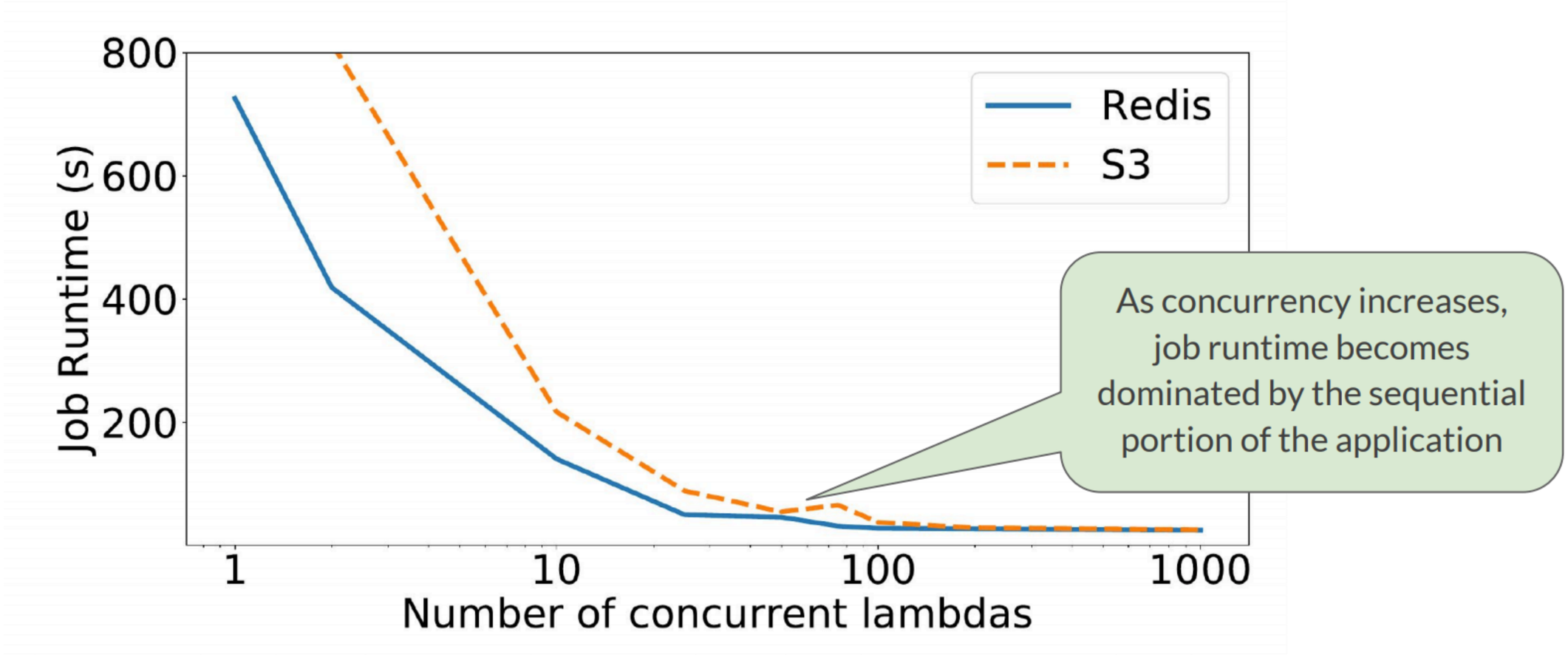
- High performance at the higher cost of DRAM
- Manually select and scale storage instance

Distributed Flash-based data store (e.g. Crail-ReFlex)

- Use Flash for high bandwidth at lower cost
- Manually select and scale storage instances

Latency sensitivity

Distributed compilation job shows some sensitivity to latency due to small I/Os



The impact of application parallelism

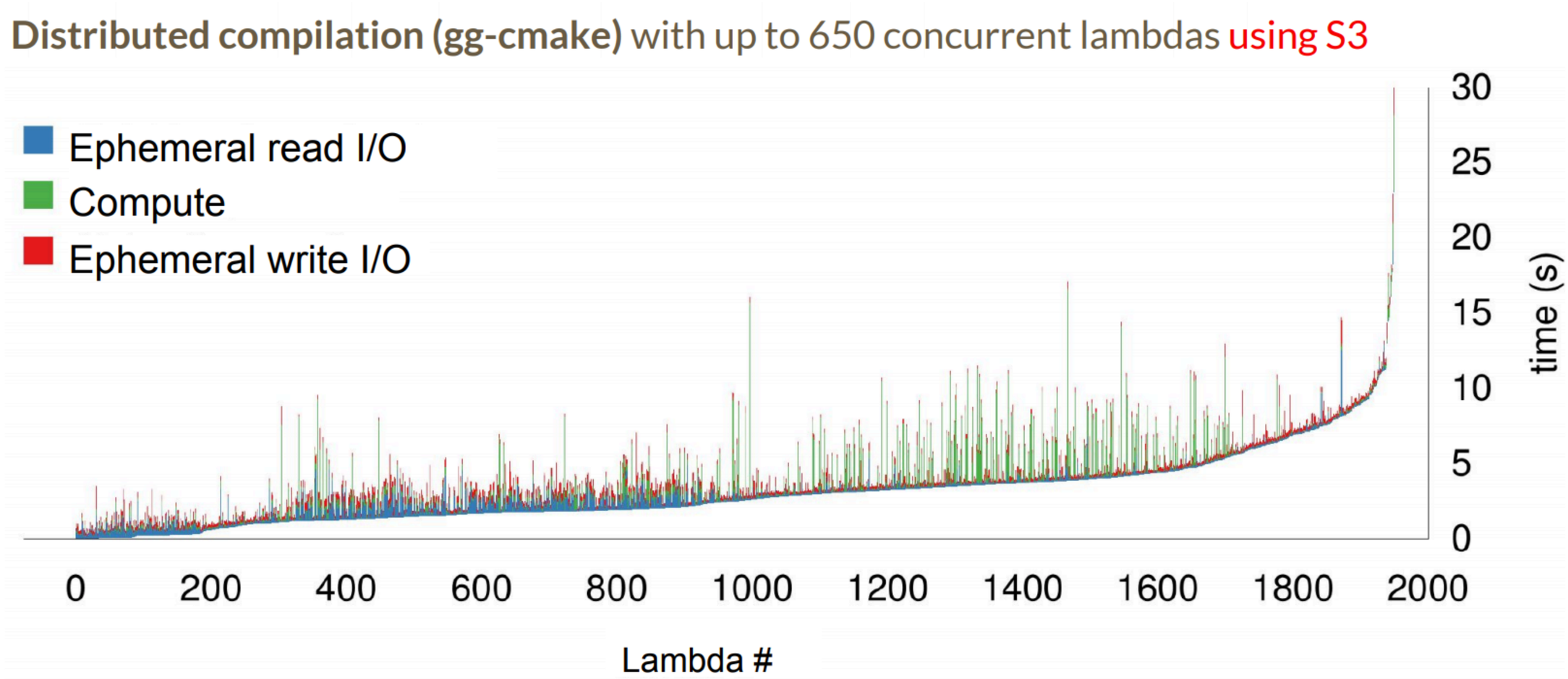


Figure based on Fig. 6 in "A thunk to remember: make -j1000 (and other jobs) on functions-as-a-service infrastructure (preprint)." Fouladi, S., et al.

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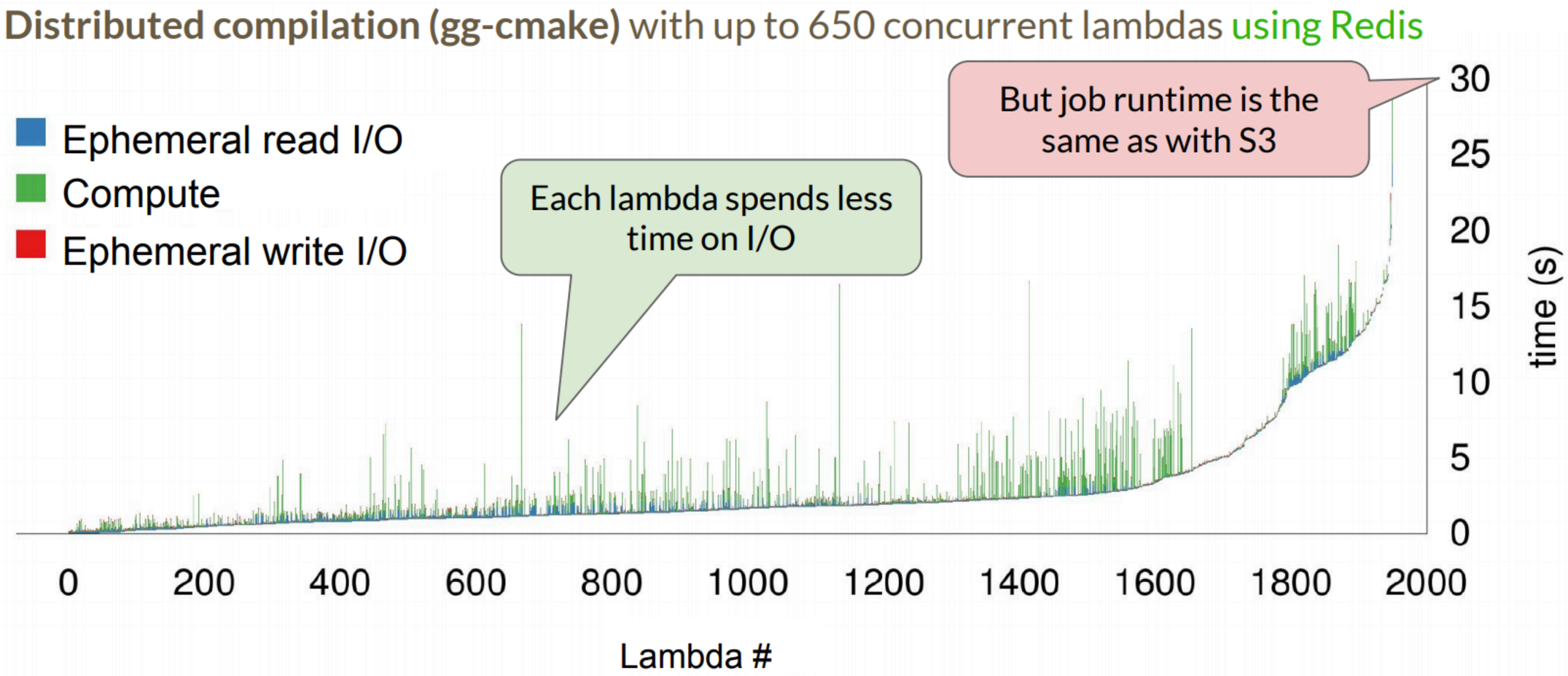

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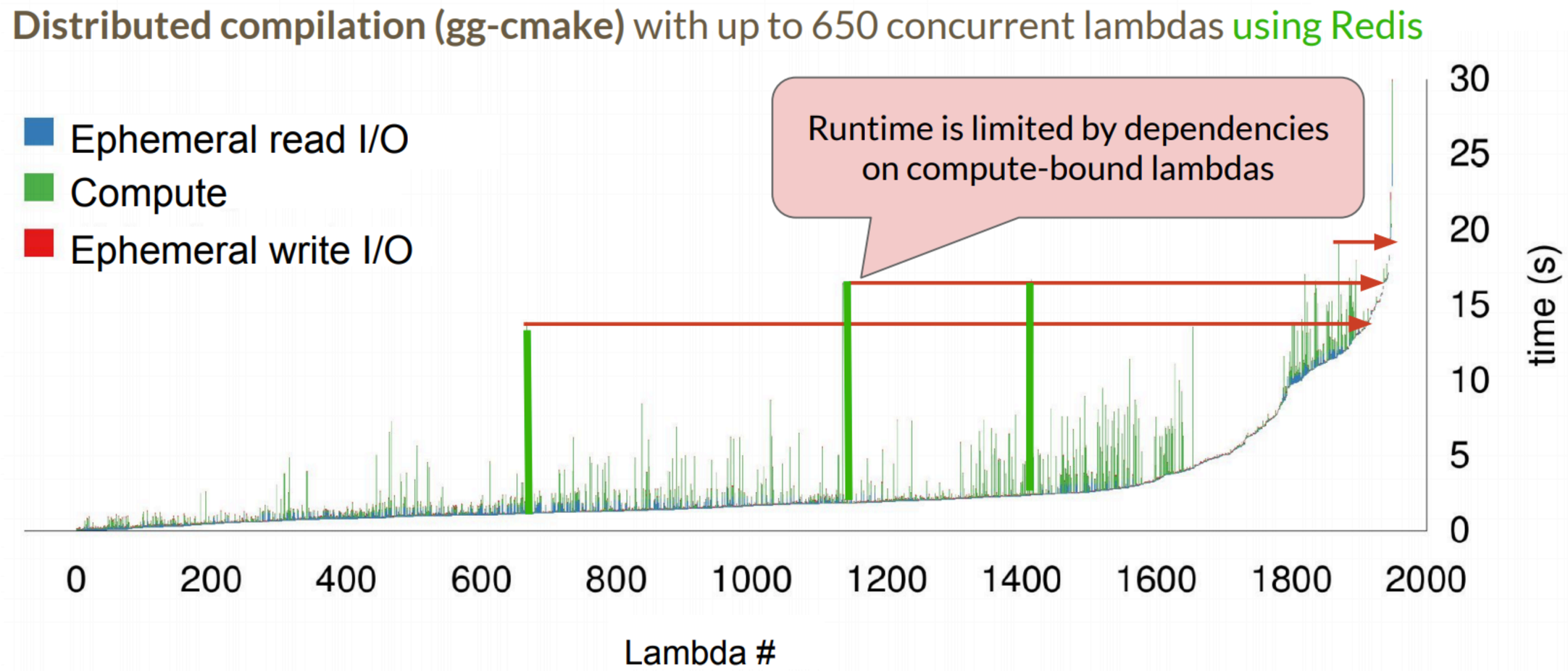

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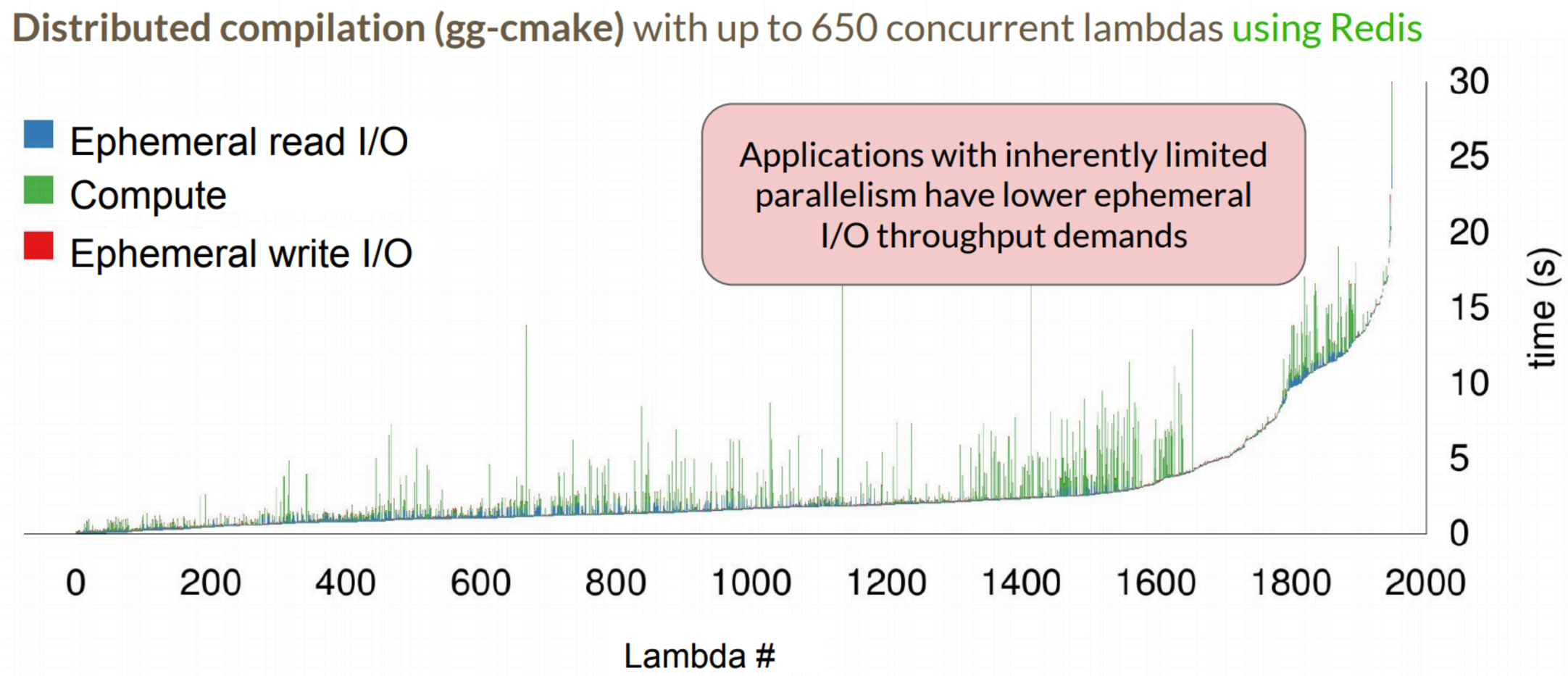

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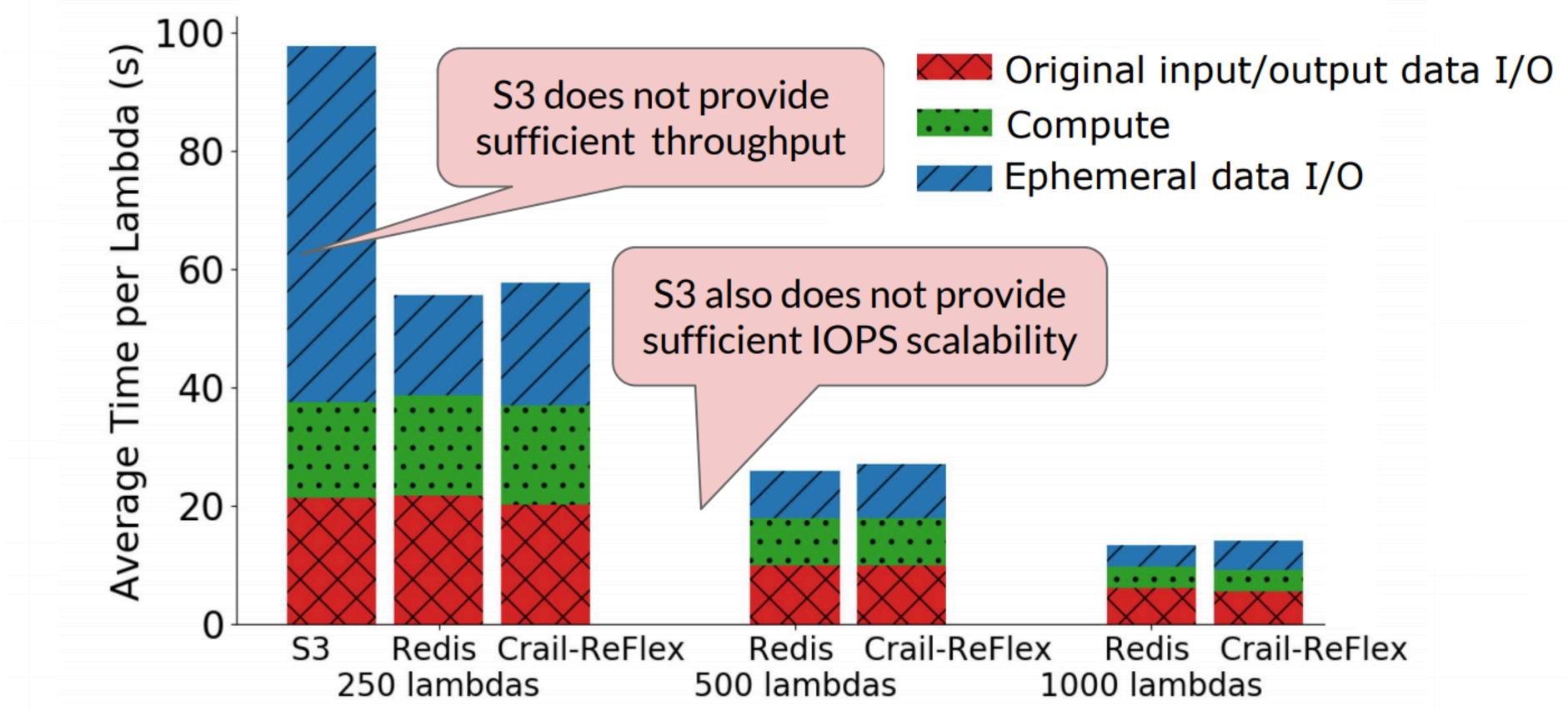
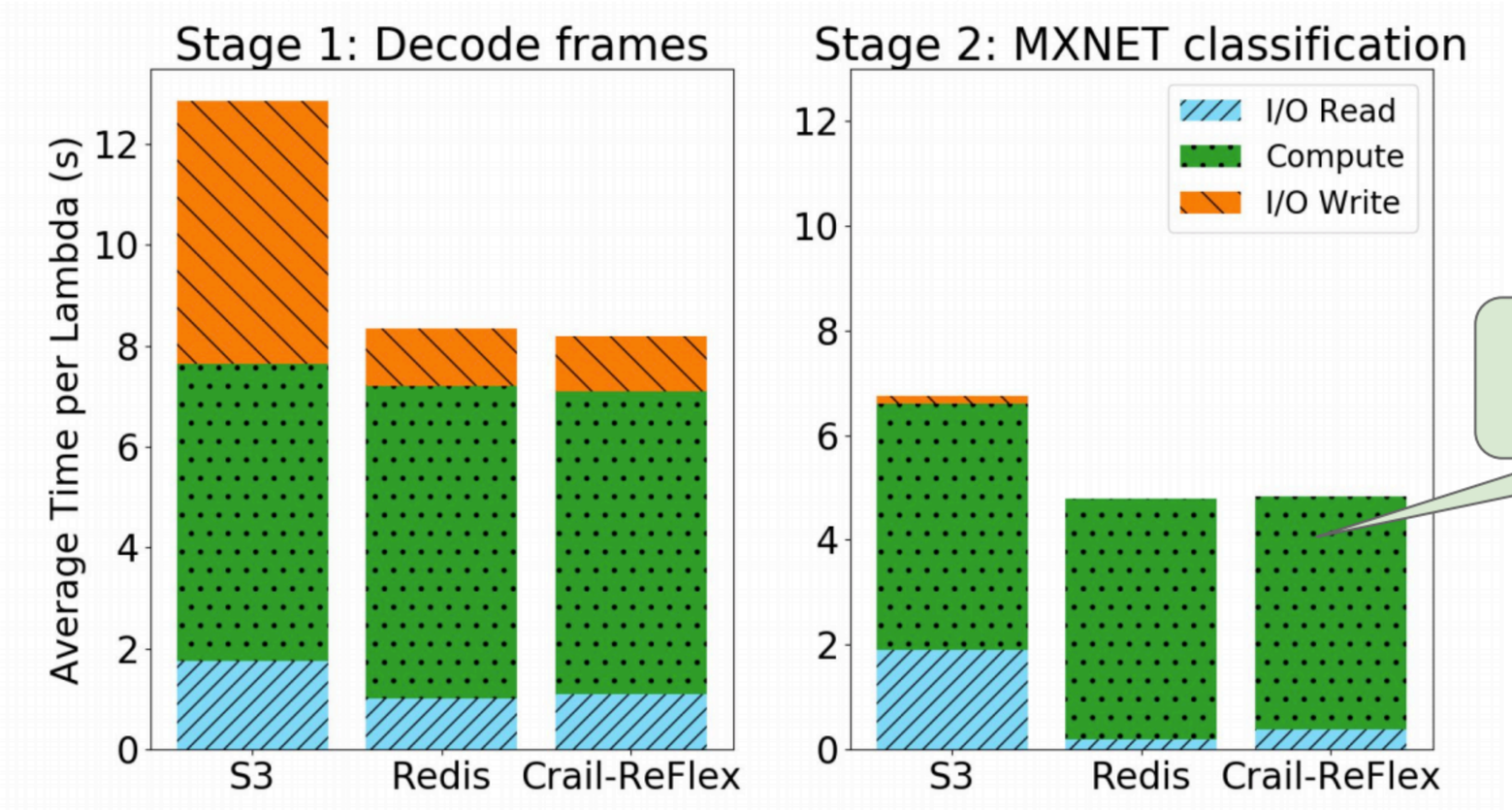
High I/O Intensity

MapReduce sort (100 GB) demands high throughput



High I/O Intensity

Video analytics has both high I/O and compute intensity



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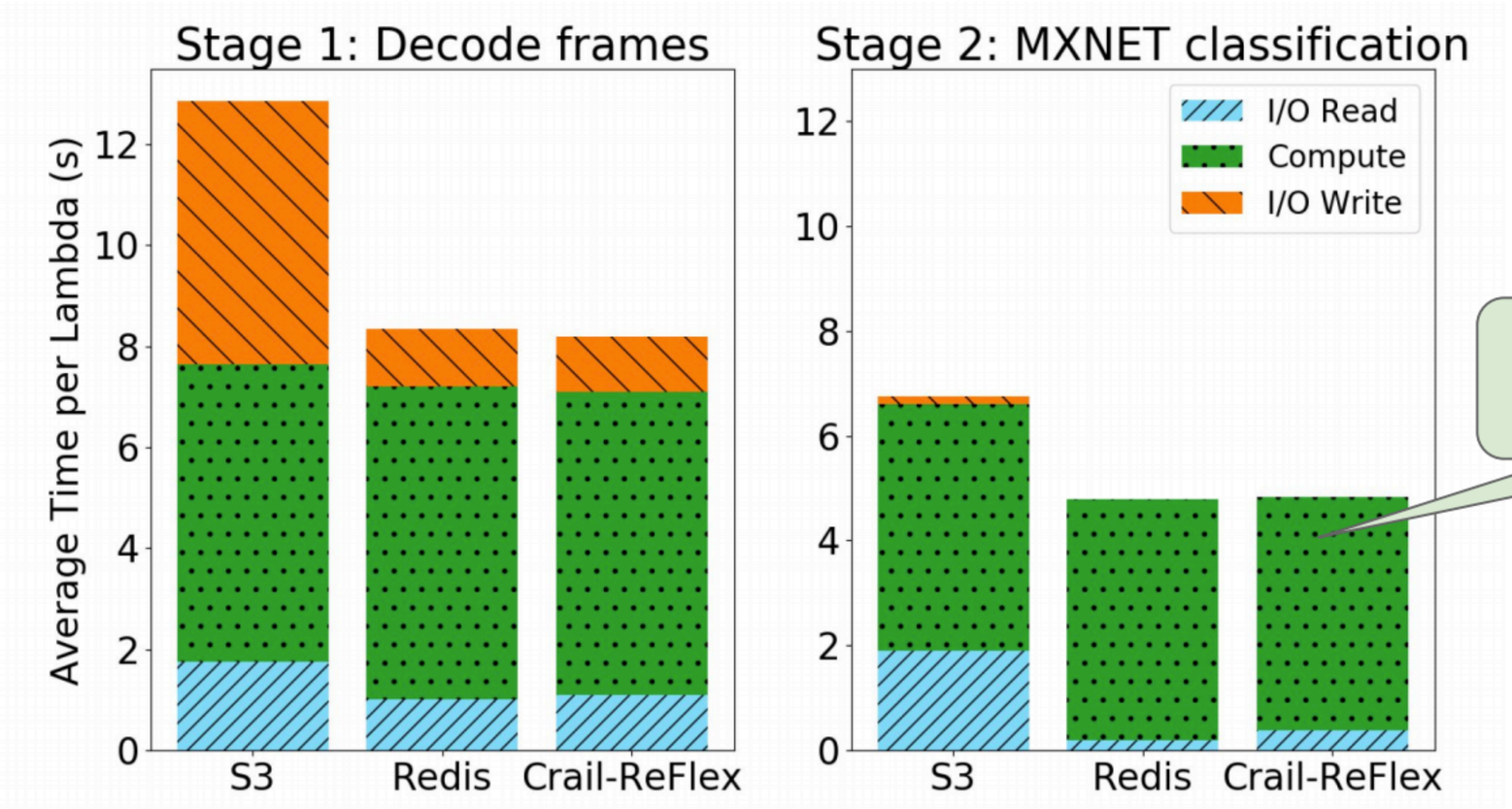
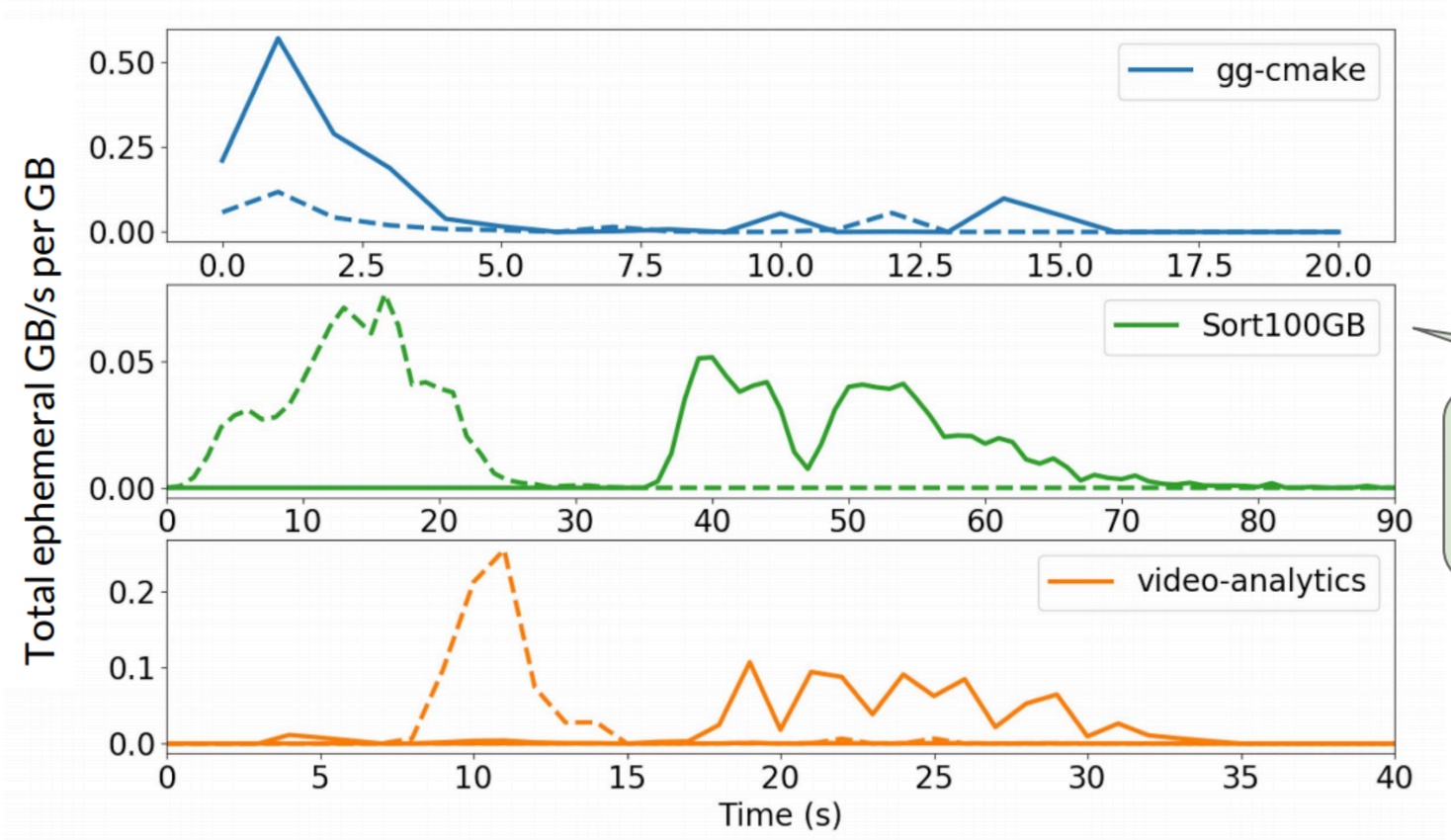


3. Choice of Storage Media

- Compare throughput:capacity ratios of DRAM, Flash, HDD



DRAM: 20 GB/s / 64 GB = 0.3

Flash: 3.2 GB/s / 500 GB = 0.006

Disk: 0.7 GB/s / 6000 GB = 0.0001

Application throughput:capacity ratios are in DRAM - Flash regimes

Using Flash vs. DRAM, jobs achieve similar performance at lower cost per bit

Putting it all together…

- Ephemeral storage wishlist for serverless analytics:
  - ★ **High throughput and IOPS**
  - ★ **Low latency,** particularly important for small requests
  - ★ **Fine-grain, elastic scaling** to adapt to elastic application load
  - ★ **Automatic rightsizing** of resource allocations
  - ★ **Low cost**, pay-what-you-use

- Existing systems provide some but not all of these properties

OSDI 2018

Pocket: Elastic Ephemeral Storage for Serverless Analytics

Ana Klimovic*, Yawen Wang*, Patrick Stuedi+ , Animesh Trivedi+,
Jonas Pfefferle+, Christos Kozyrakis*

https://www.usenix.org/conference/osdi18/presentation/klimovic

Requirements of Ephemeral Storage

- High performance for a wide range of object sizes
- Cost efficiency, i.e., fine-grain, pay-what-you-use resource billing
- ~~Fault-tolerance~~

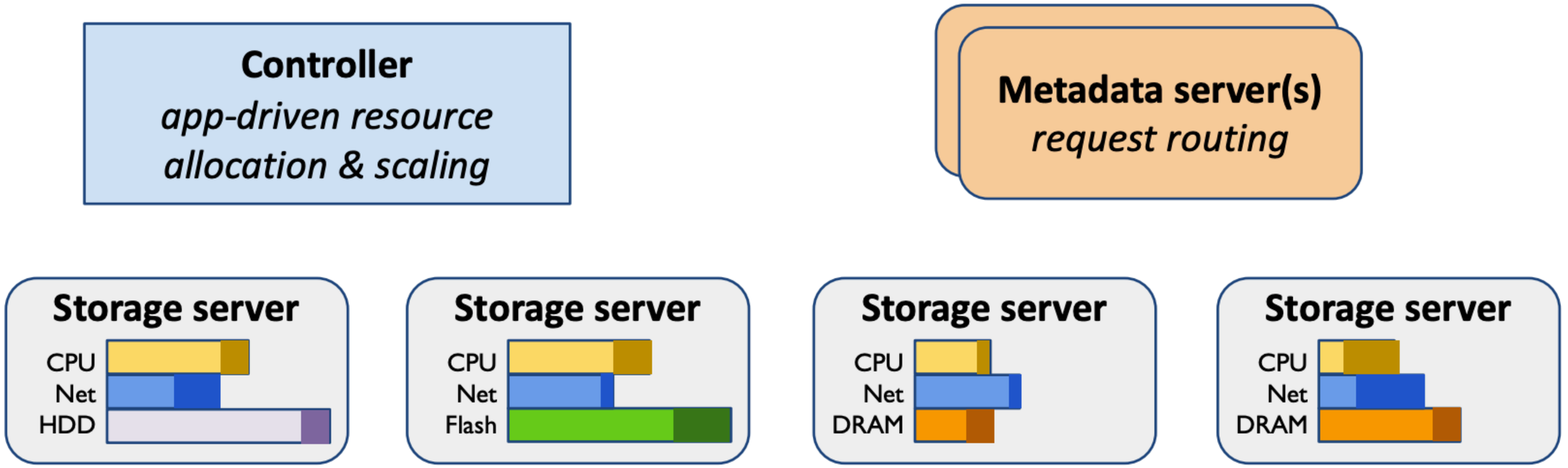
Pocket

- An elastic, distributed data store for ephemeral data sharing in serverless analytics

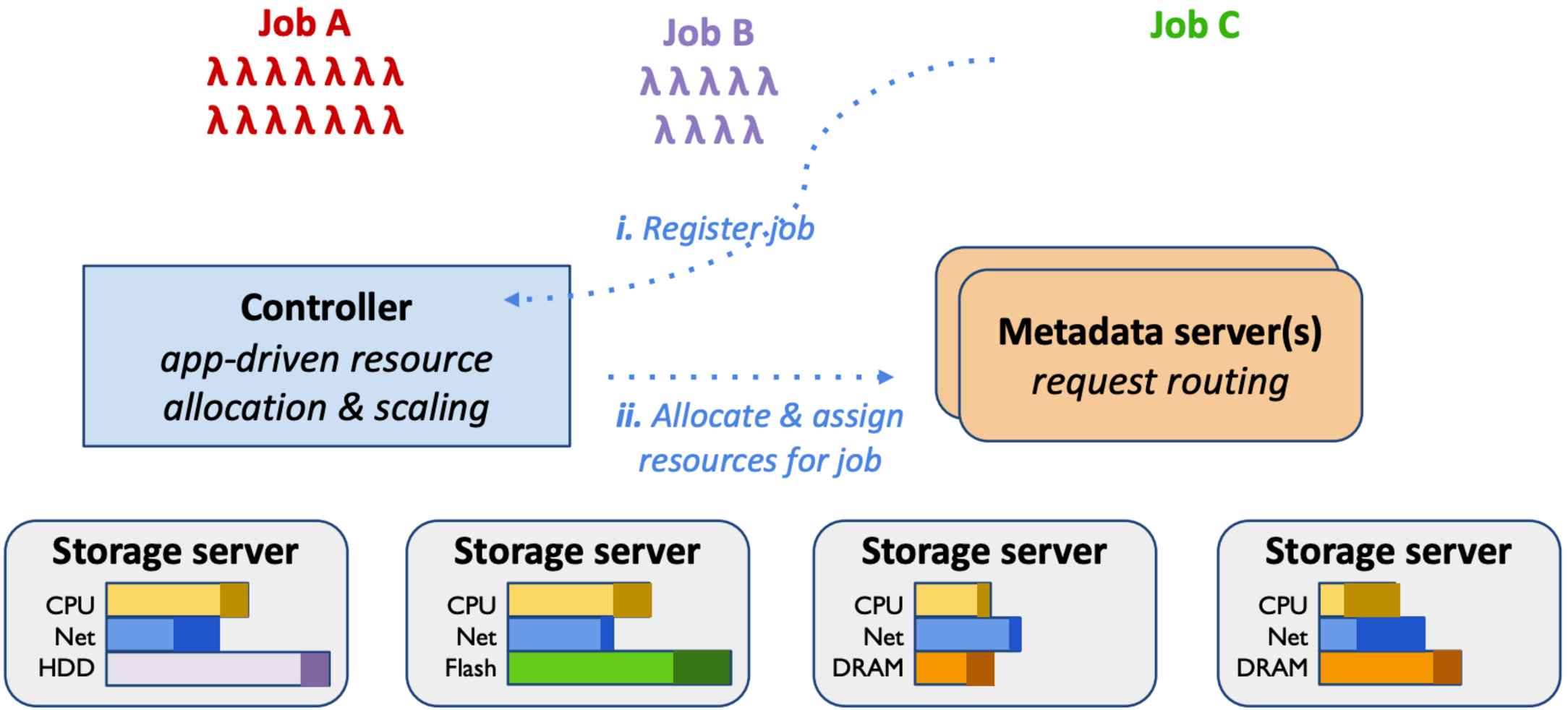
- Pocket achieves high performance and cost efficiency by:
  - Leveraging multiple storage technologies
  - Rightsizing resource allocations for applications
  - Autoscaling storage resources in the cluster based on usage

- Pocket achieves similar performance to Redis, an in-memory key value store, while saving ~60% in cost for various serverless analytics jobs

Pocket Design



Using Pocket



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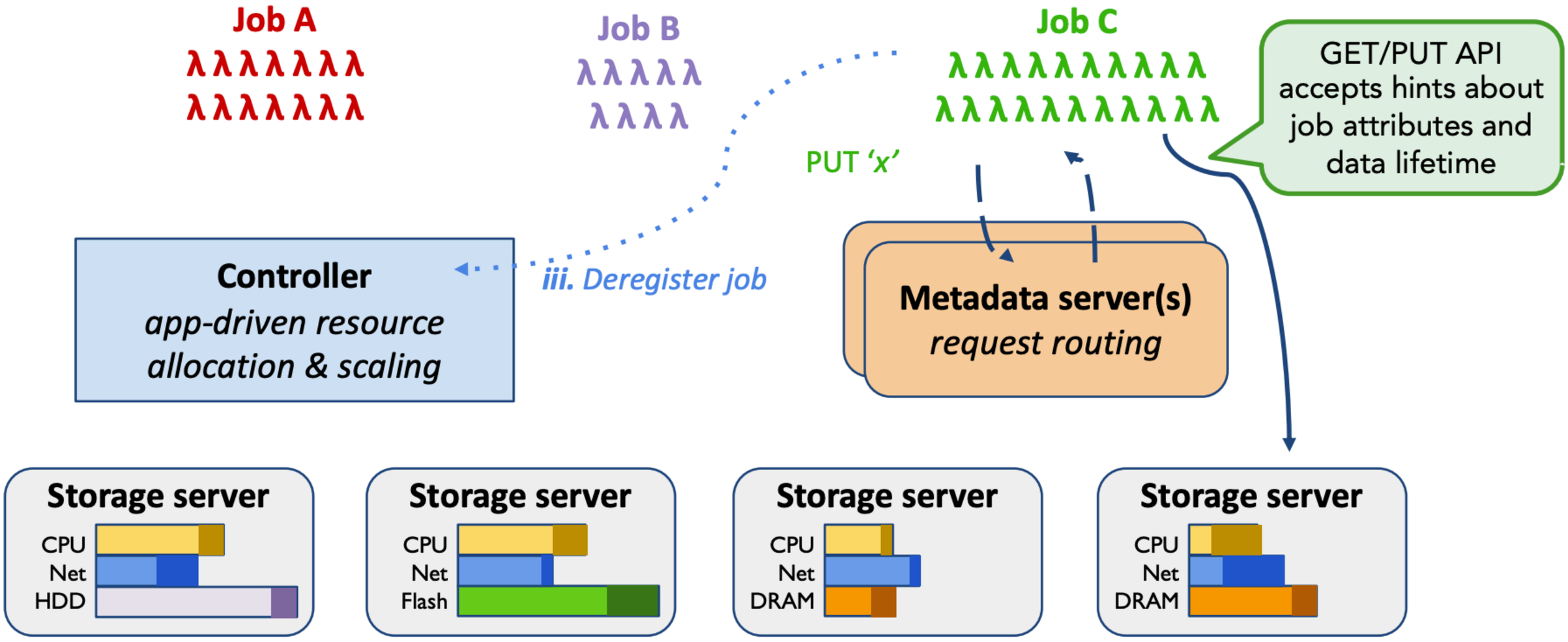
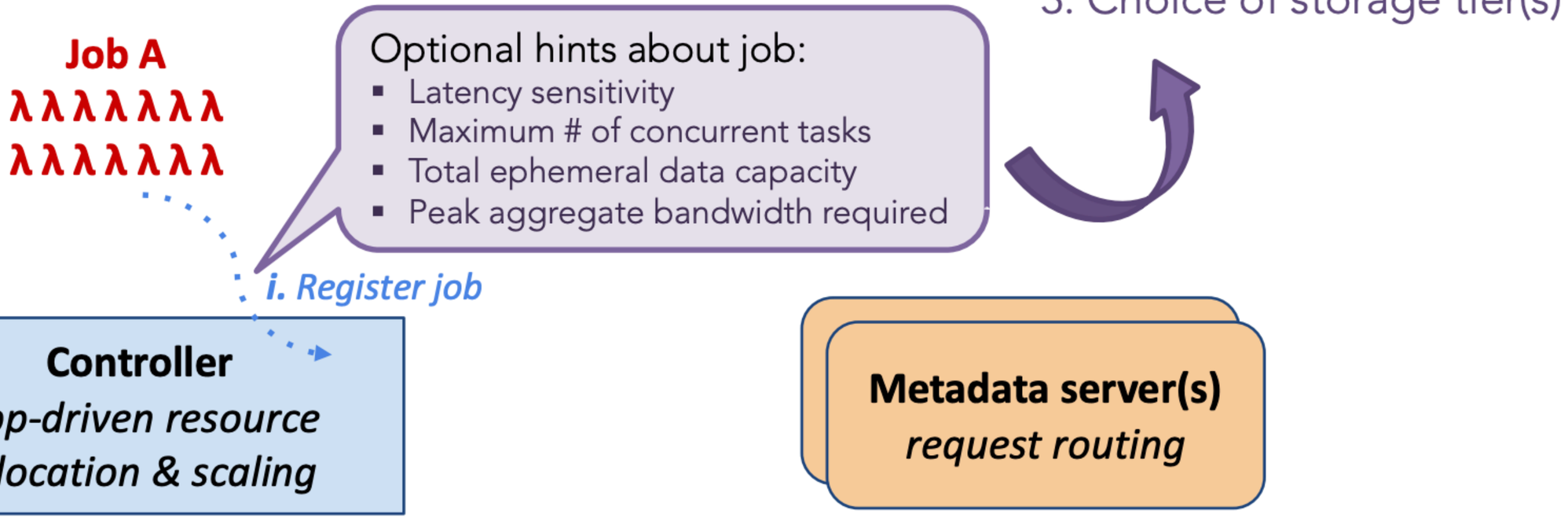


Assigning Resources to Jobs

1. Throughput allocation
2. Capacity allocation
3. Choice of storage tier(s)



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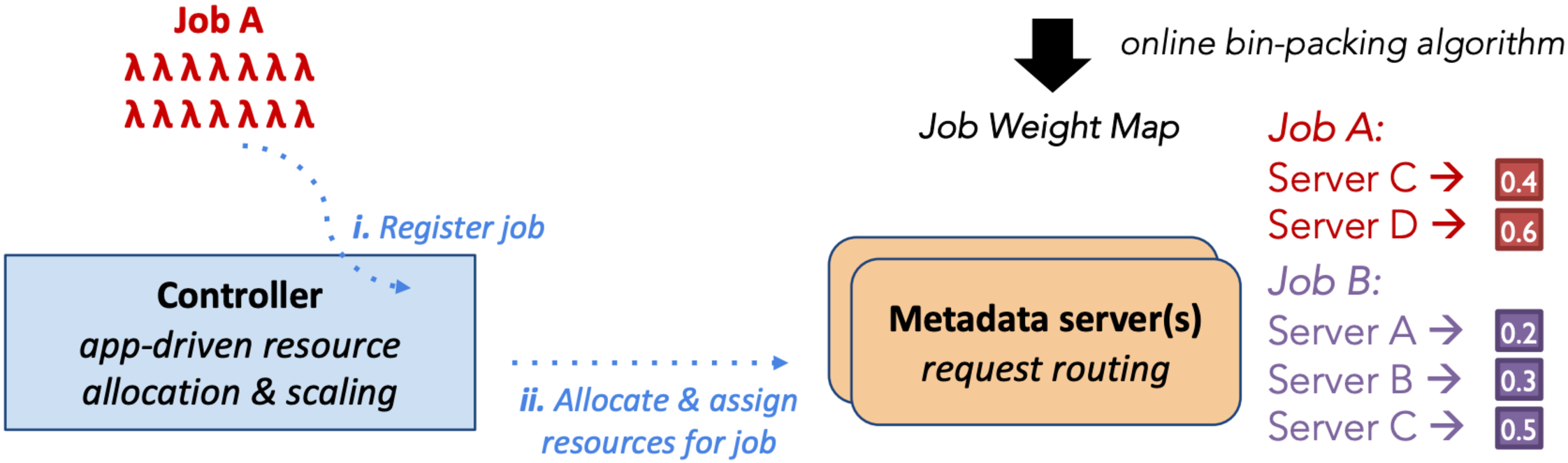


Autoscaling the Pocket Cluster

- **Goal**: scale cluster resources dynamically based on resource usage

- **Mechanisms**:
  - Monitor CPU, network bandwidth, and storage capacity utilization
  - Add/remove storage & metadata nodes to keep utilization within range
  - Steer data for incoming jobs to active nodes
  - Drain inactive nodes as jobs terminate

- **Avoid migrating data**

Implementation

- Pocket's metadata and storage server implementation is based on the ***Apache Crail*** distributed storage system

- Use ***ReFlex*** for the Flash storage tier

- Pocket runs the storage and metadata servers in containers, orchestrated using ***Kubernetes***

Pocket Evaluation

- We deploy Pocket on Amazon EC2

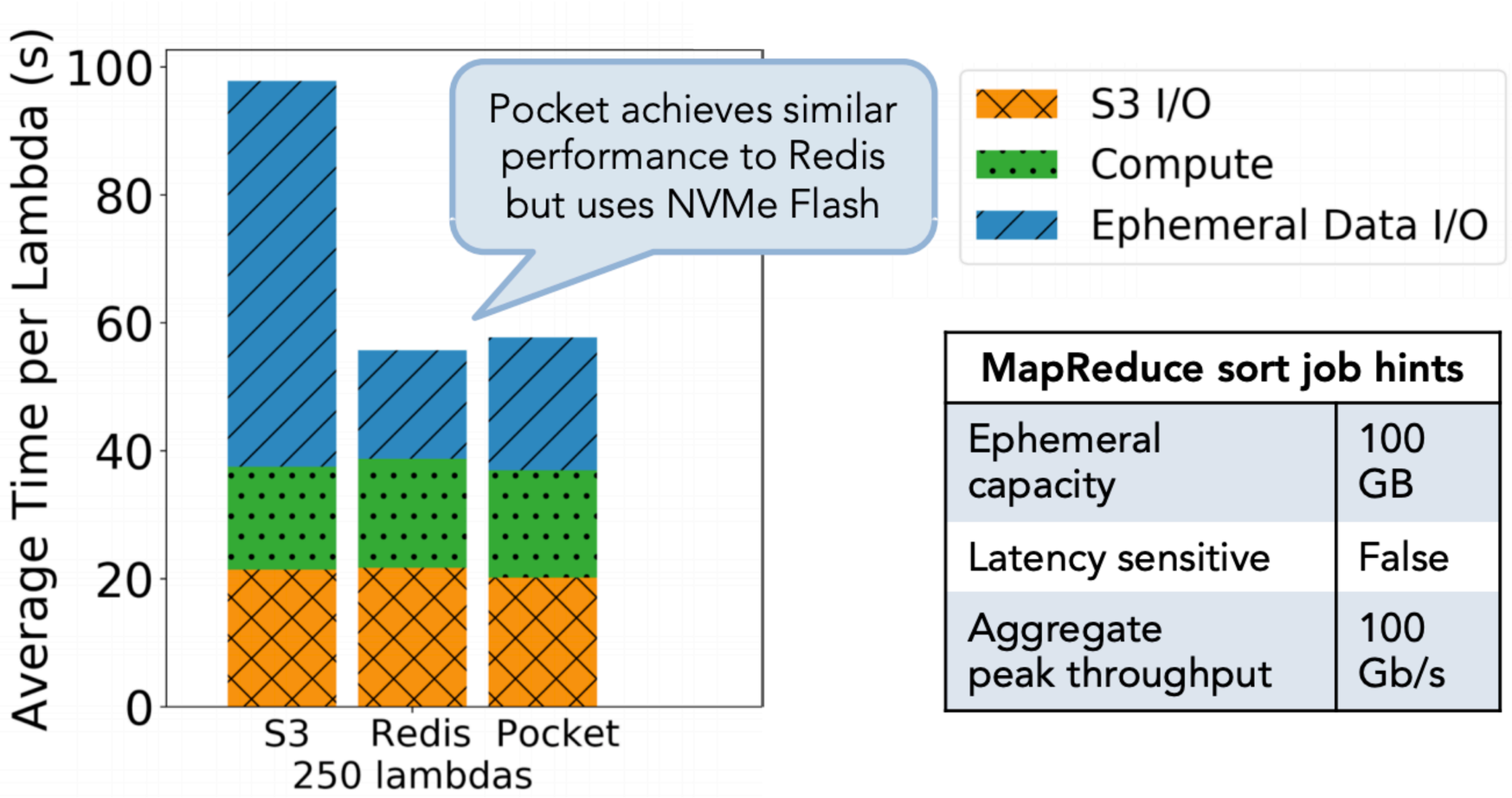
Controller	m5.xlarge
Metadata server	m5.xlarge
DRAM server	r4.2xlarge
NVMe Flash server	i3.2xlarge
SATA/SAS SSD server	i2.2xlarge
HDD server	h1.2xlarge

- We use AWS Lambda as our serverless platform

- Applications: MapReduce sort, video analytics, distributed compilation

Application Performance with Pocket

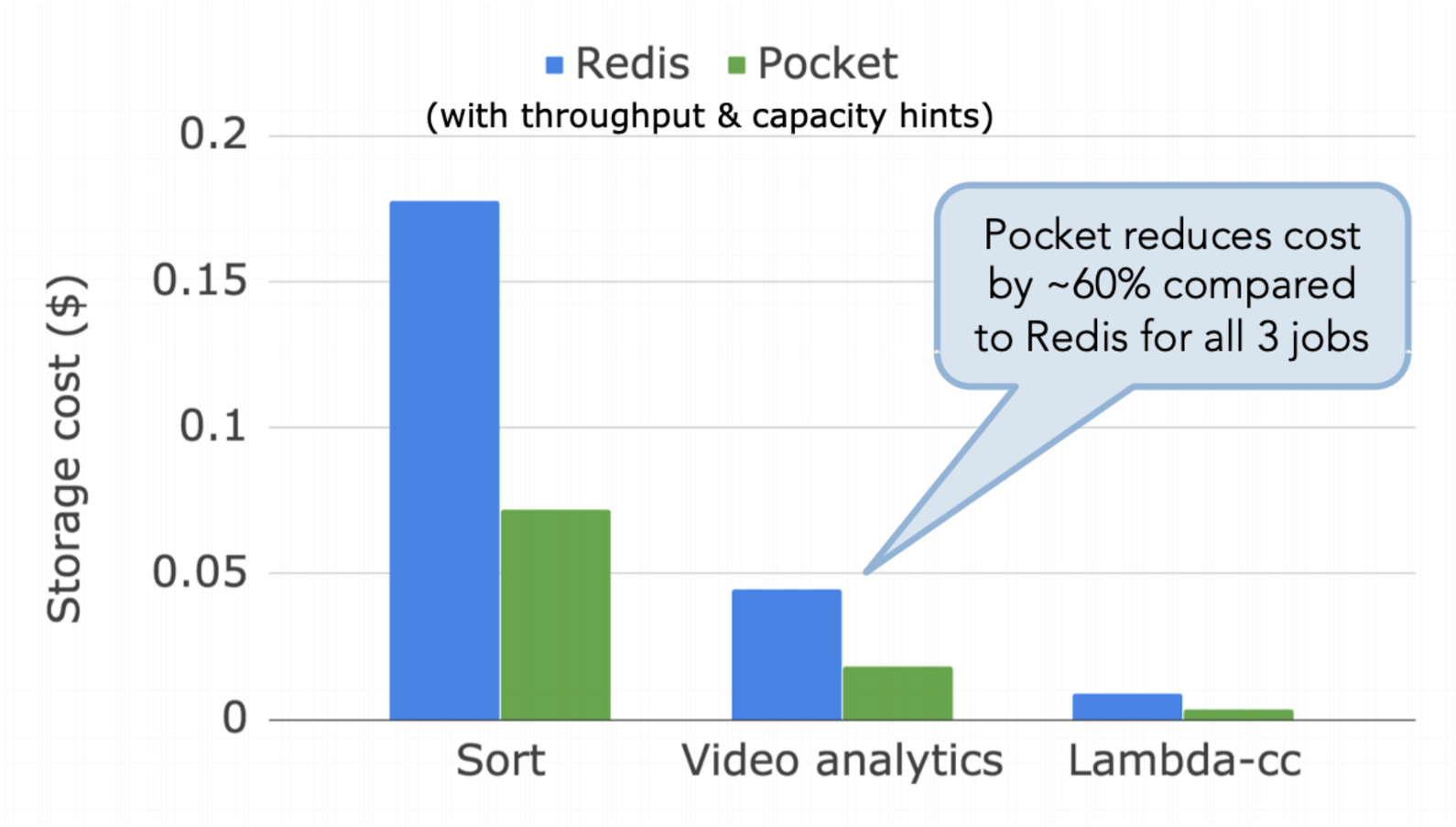
- Compare Pocket to S3 and Redis, which are commonly used today



MapReduce sort job hints	
Ephemeral capacity	100 GB
Latency sensitive	False
Aggregate peak throughput	100 Gb/s

Application Performance with Pocket

- Pocket leverages job attribute hints for cost-effective resource allocation and amortizes VM costs across multiple jobs, offering a pay-what-you-use model



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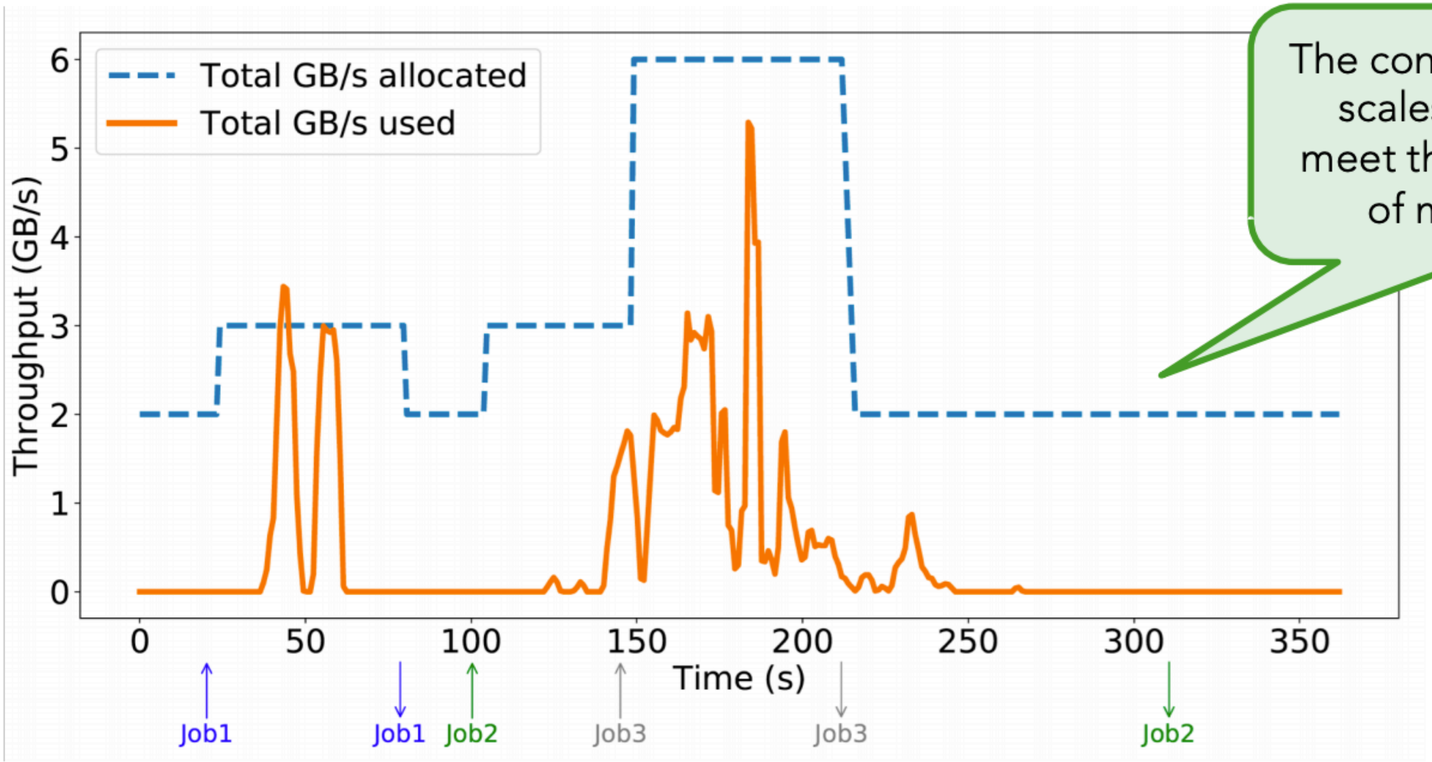

Job hints	Job1: Sort	Job2: Video analytics	Job3: Sort
Latency sensitive	False	False	False
Ephemeral data capacity	10 GB	6 GB	10 GB
Aggregate throughput	3 GB/s	2.5 GB/s	3 GB/s

Conclusion

- Pocket is a distributed ephemeral storage system that:
  - Leverages multiple storage technologies
  - Rightsizes resource allocations for applications
  - Autoscales storage cluster resources based on usage