Efficient Management of Ephemeral Data in Serverless Computing

Patrick Stuedi
IBM Research

Serverless Analytics

- Serverless frameworks are increasingly being used for **interactive analytics**

PyWren
(SoCC'17)

ExCamera
(NSDI'17)

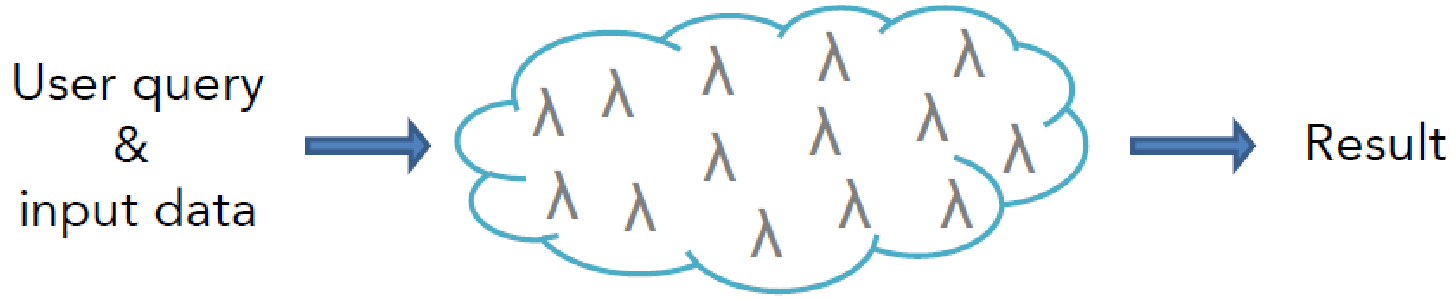
databricks
serverless

gg: The Stanford Builder

Amazon Aurora
Serverless

Serverless Analytics

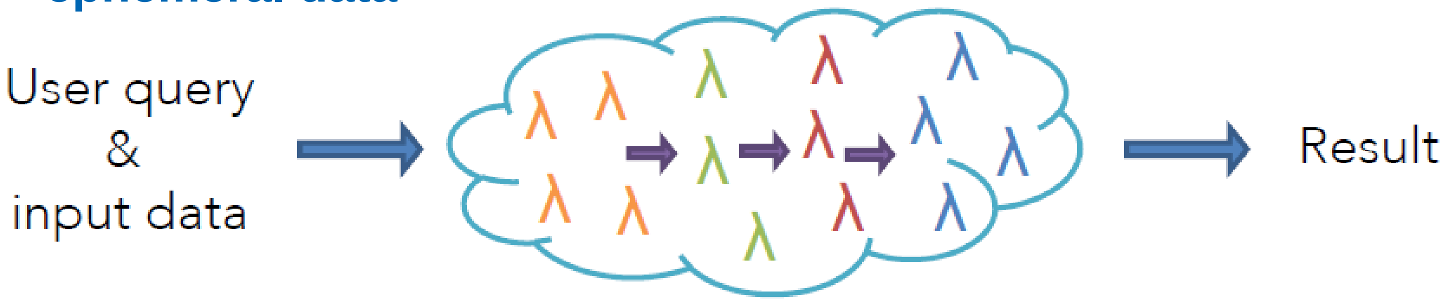
- Serverless frameworks are increasingly being used for **interactive analytics**
  - Exploit massive parallelism with large number of serverless tasks



Challenge: Data Sharing

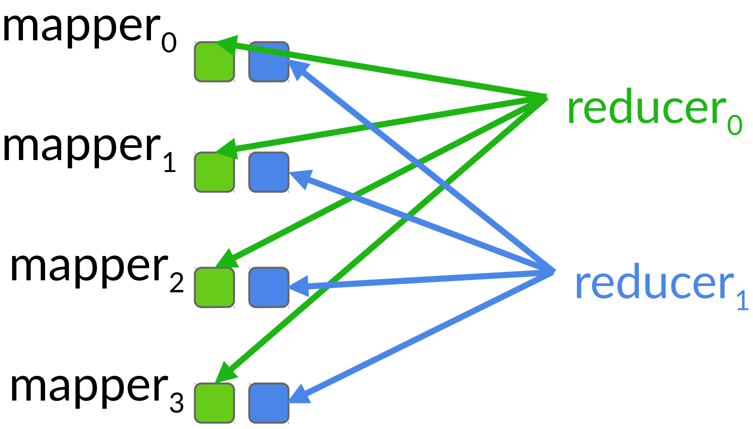
- Serverless analytics involve multiple stages of execution
- Serverless tasks need an efficient way to communicated **intermediate data** between different stages

ephemeral data



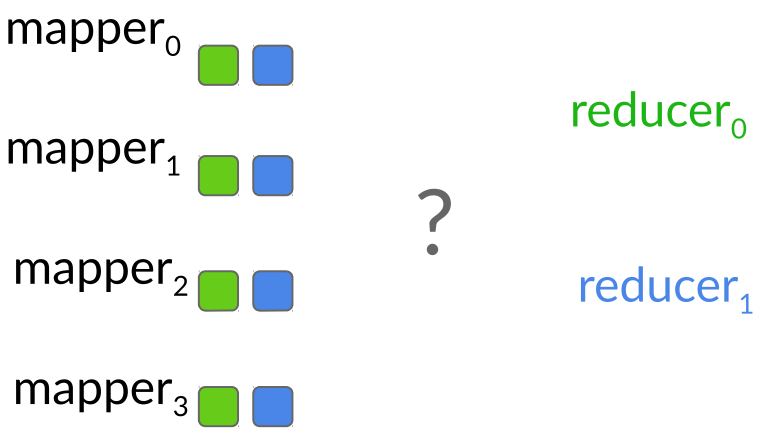
In traditional analytics..

- Ephemeral data is exchanged directly between the tasks



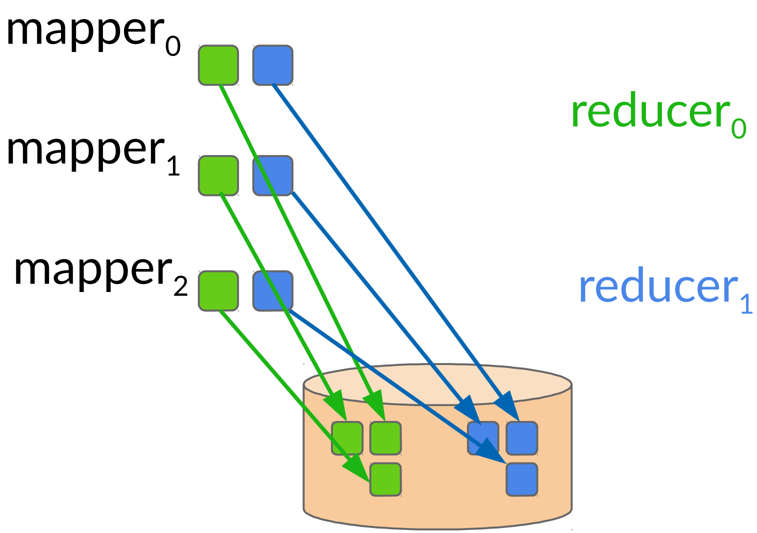
In serverless analytics..

- Direct communication between serverless tasks is difficult
  - Tasks are short lived and stateless



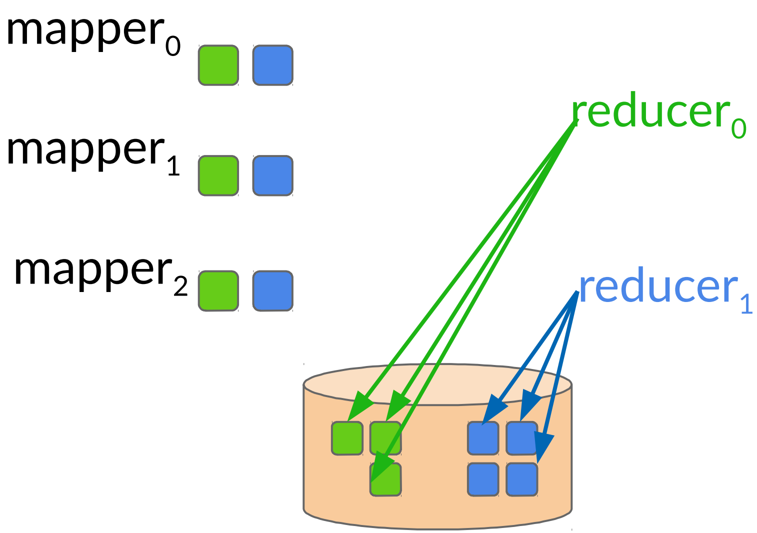
In serverless analytics..

- Direct communication between serverless tasks is difficult
  - Tasks are short lived and stateless



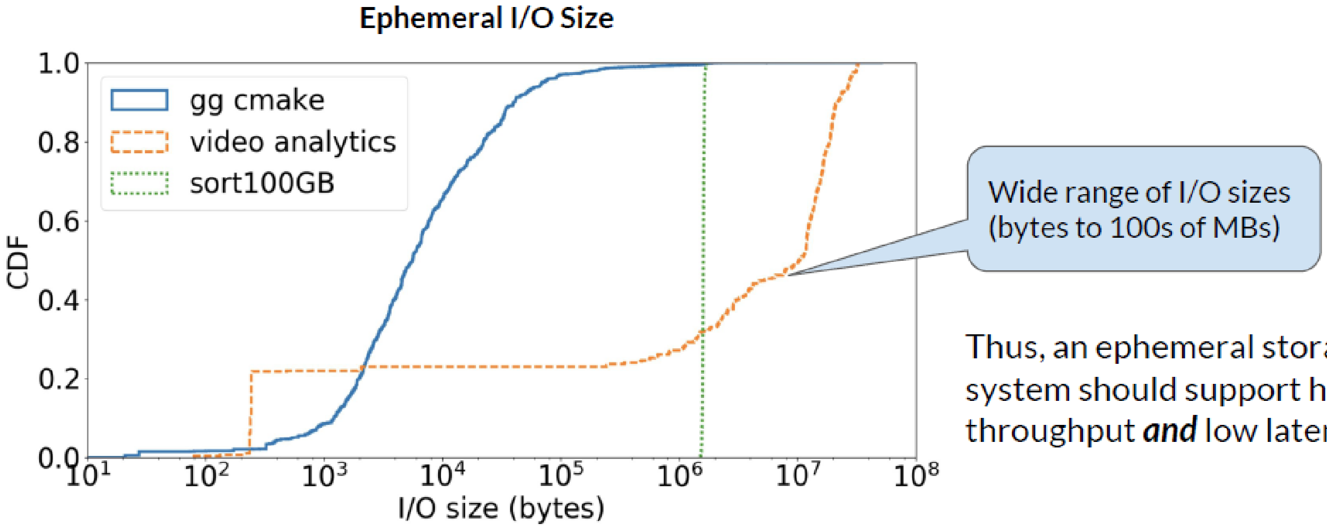
In serverless analytics..

- Direct communication between serverless tasks is difficult
  - Tasks are short lived and stateless



Requirements for Ephemeral Storage

1 High performance for a wide range of object sizes

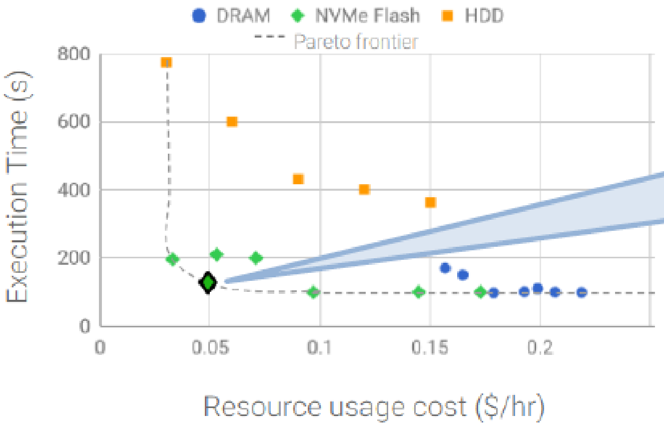


Thus, an ephemeral storage system should support high throughput *and* low latency.

Requirements for Ephemeral Storage

1. High performance for a wide range of object sizes
2. Fine grain, pay what you use resource billing

Example of performance-cost tradeoff for a serverless video analytics application



Finding the Pareto optimal resource allocation is non-trivial…and gets harder with multiple jobs.

Requirements for Ephemeral Storage

1. High performance for a wide range of object sizes
2. Fine grain, pay what you use resource billing
3. ~~Fault-tolerance~~

Requirements for Ephemeral Storage

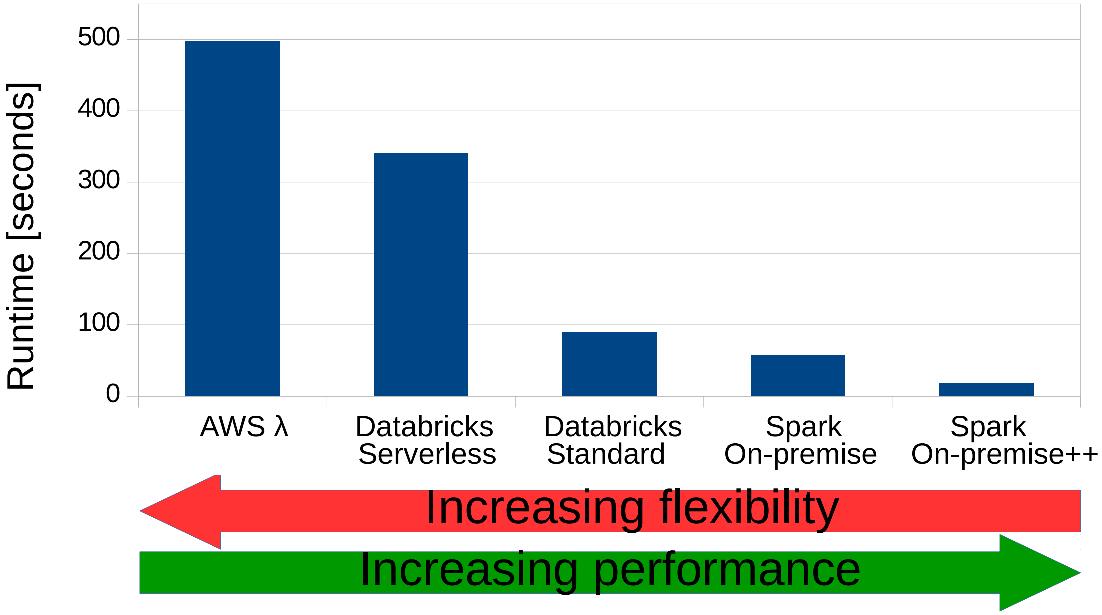
1. High performance for a wide range of object sizes
2. Fine grain, pay what you use resource billing
3. ~~Fault-tolerance~~

Existing cloud storage systems do not meet the elasticity, performance and cost demands of serverless analytics jobs

Serverless Analytics: 2 Projects

1. Serverless Spark
   - Add serverless properties to Spark (elasticity, on-demand scaling, etc)
2. Pocket: elastic ephemeral storage for the cloud
   - Improve applications running on serverless frameworks in the cloud (AWS λ, IBM Cloud Functions, etc)

Project 1:
Spark Serverless Motivation



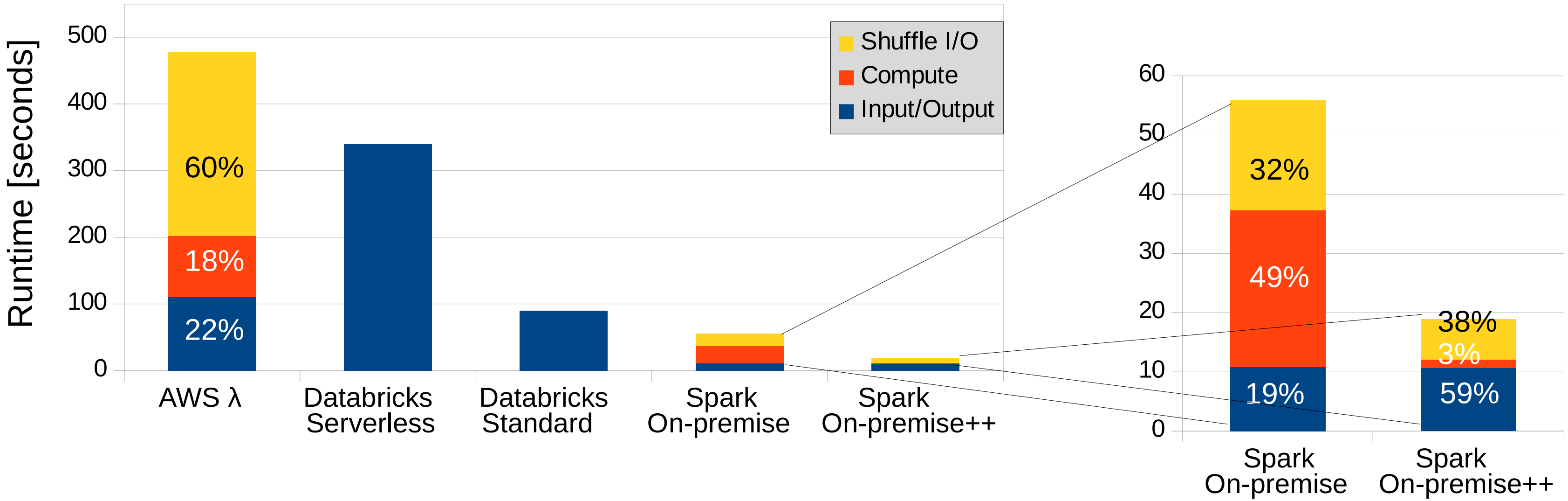
Example:
Sorting 100GB

Spark/On-Premise++: Running Apache Spark on a High-Performance Cluster using RDMA and NVMe Flash, Spark Summit’17

Why is it so hard?

- **Scheduler:** when to best add/remove resources?
- **Container startup:** may have to dynamically spin up containers
- **Storage overheads:**
  - Input data needs to be fetched from remote storage (e.g., S3)
  - Intermediate needs to be temporarily stored on remote storage (S3, Redis)

I/O Overhead: Sorting 100GB



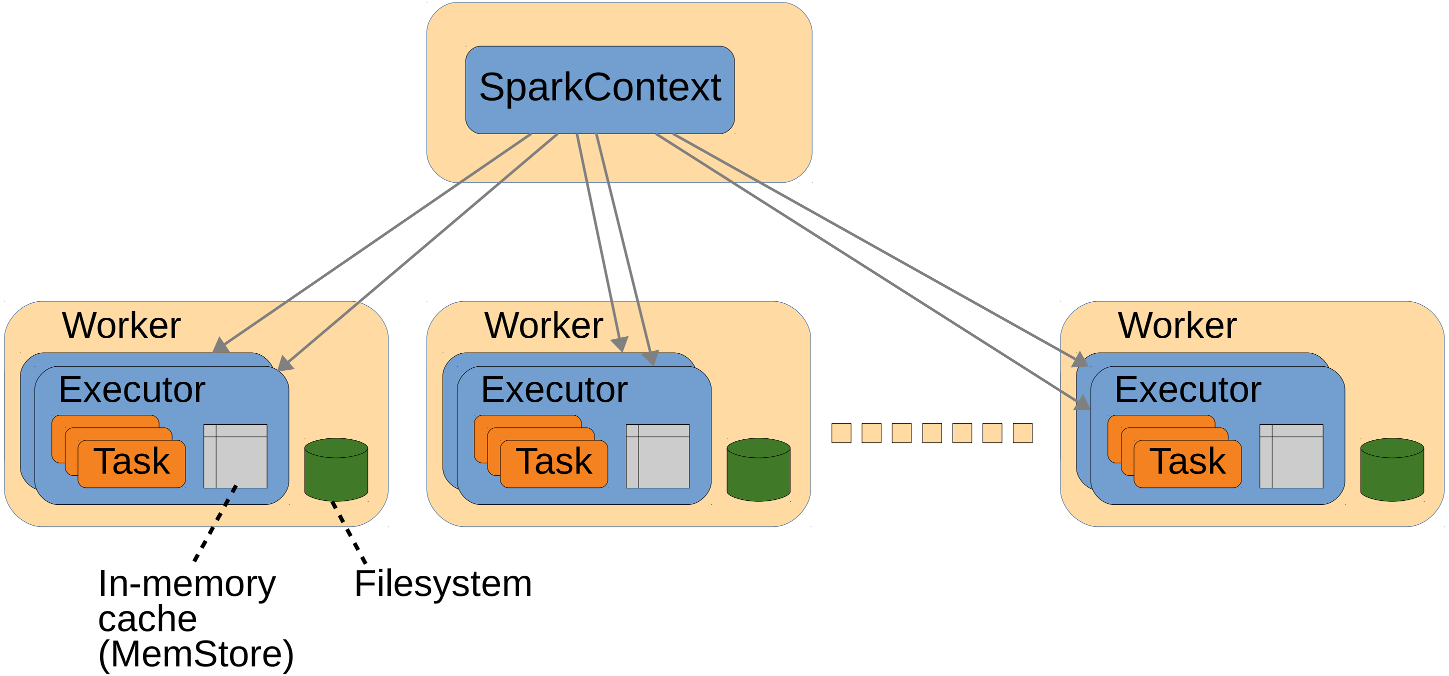
Shuffle overheads are significantly higher when intermediate data is stored remotely

Spark Serverless: Idea

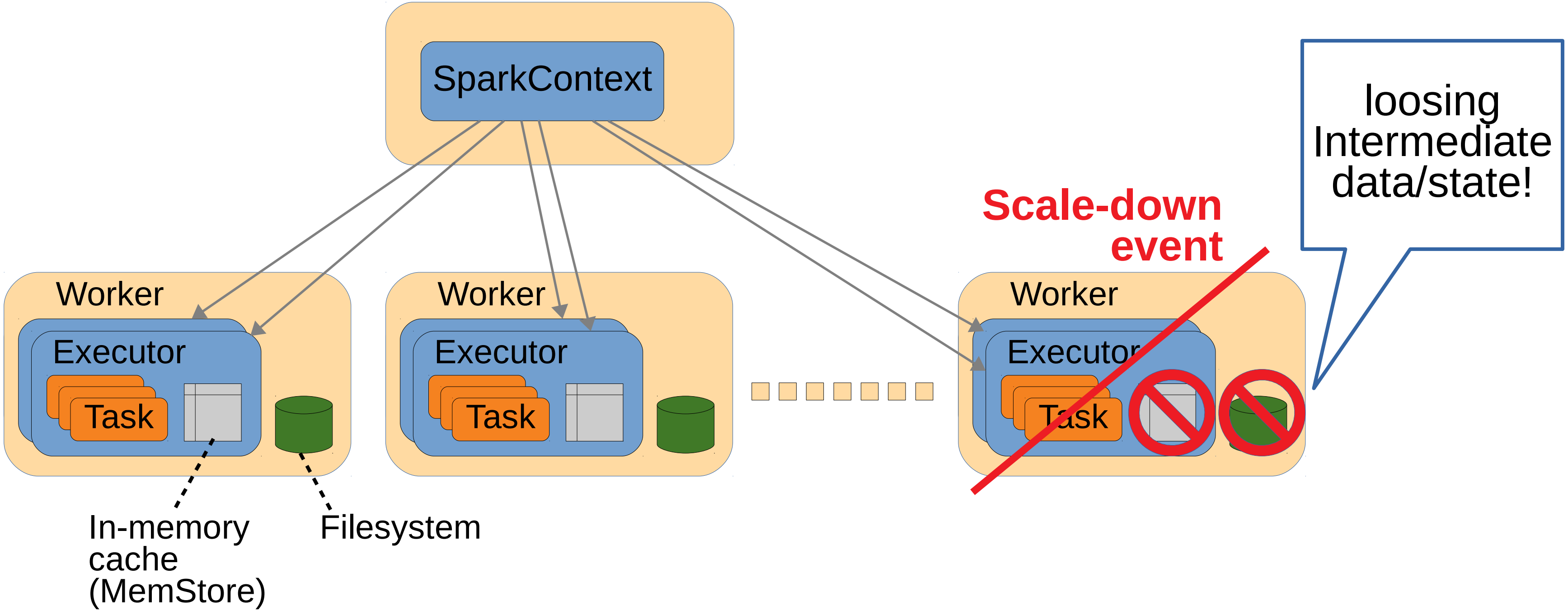
Instead of improving performance of serverless frameworks, can we…

- ...add serverless properties to Spark?
  - Elasticity, on-demand scaling
  - Sharing of a Spark resources (compute, memory) among users
- Use Case:
  - Enable sharing of Spark deployment among many users in a company, research lab, etc.
- Challenge:
  - Maintain original Spark performance

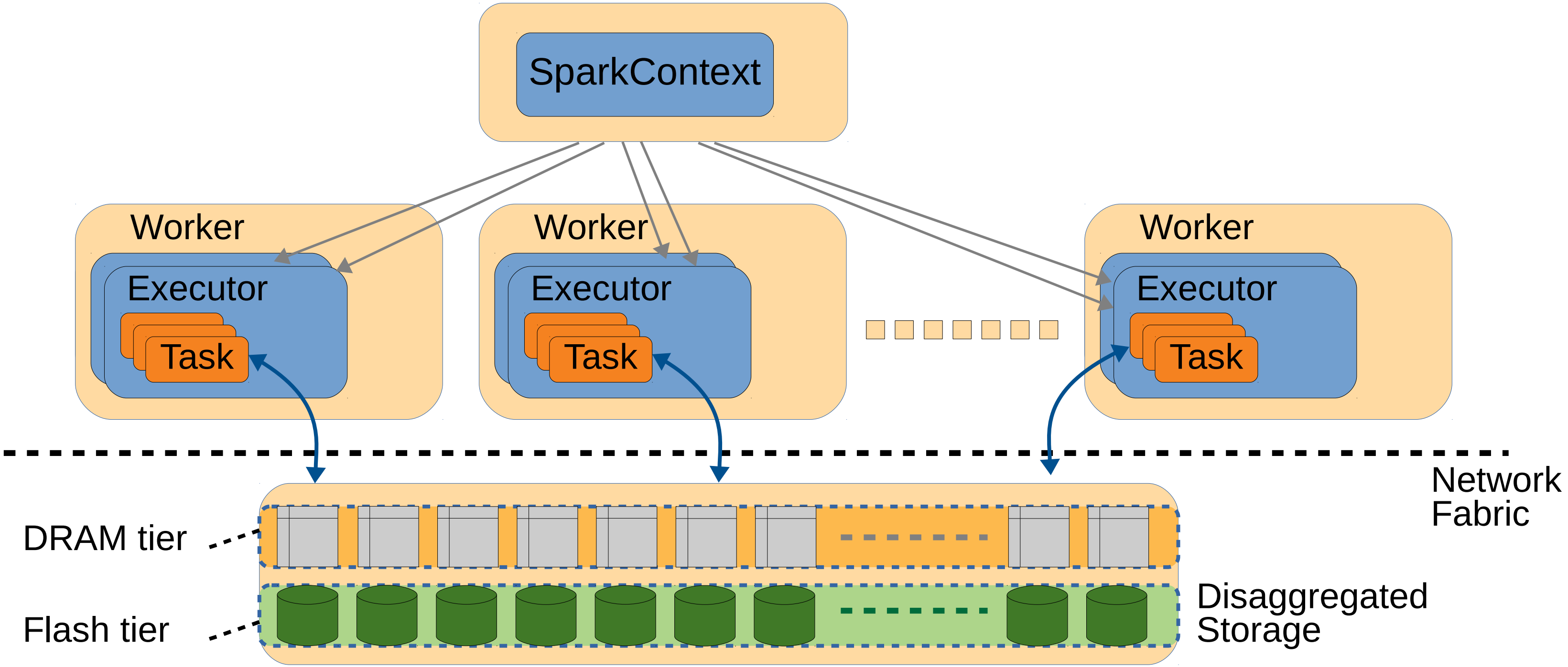
Spark Serverless: What’s missing?



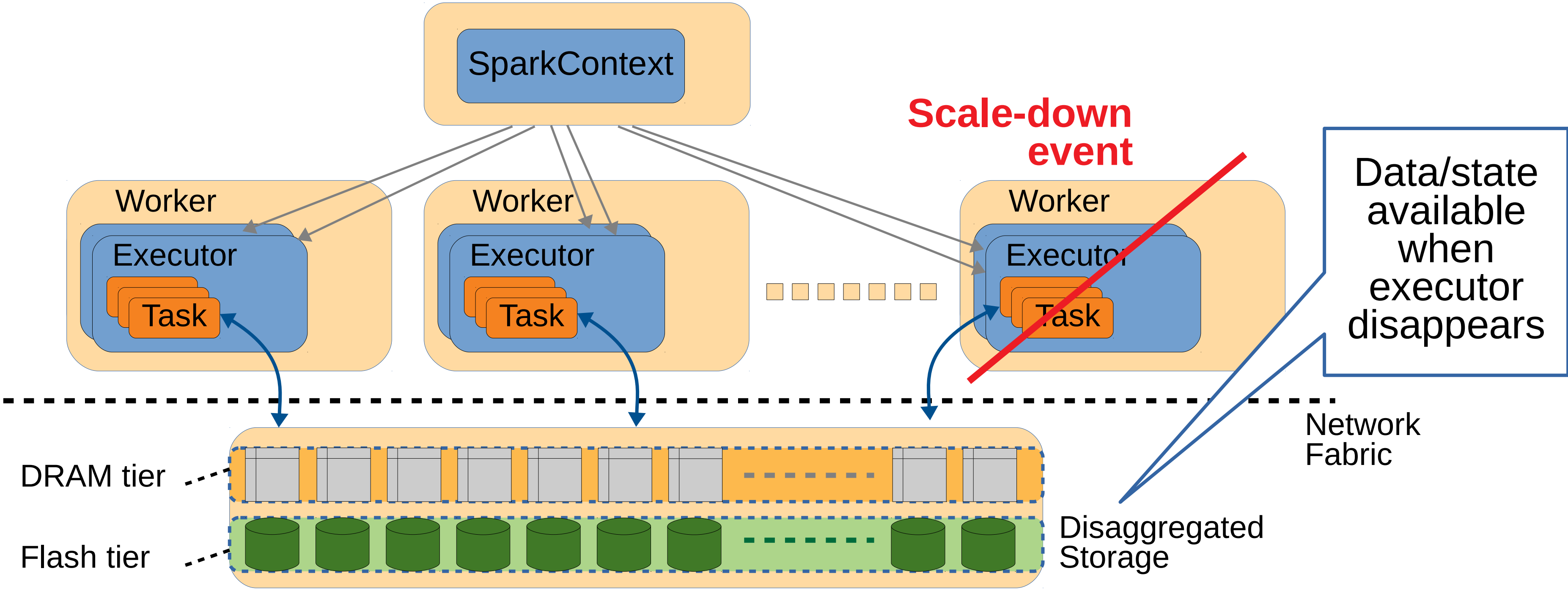
Spark Serverless: What’s missing?



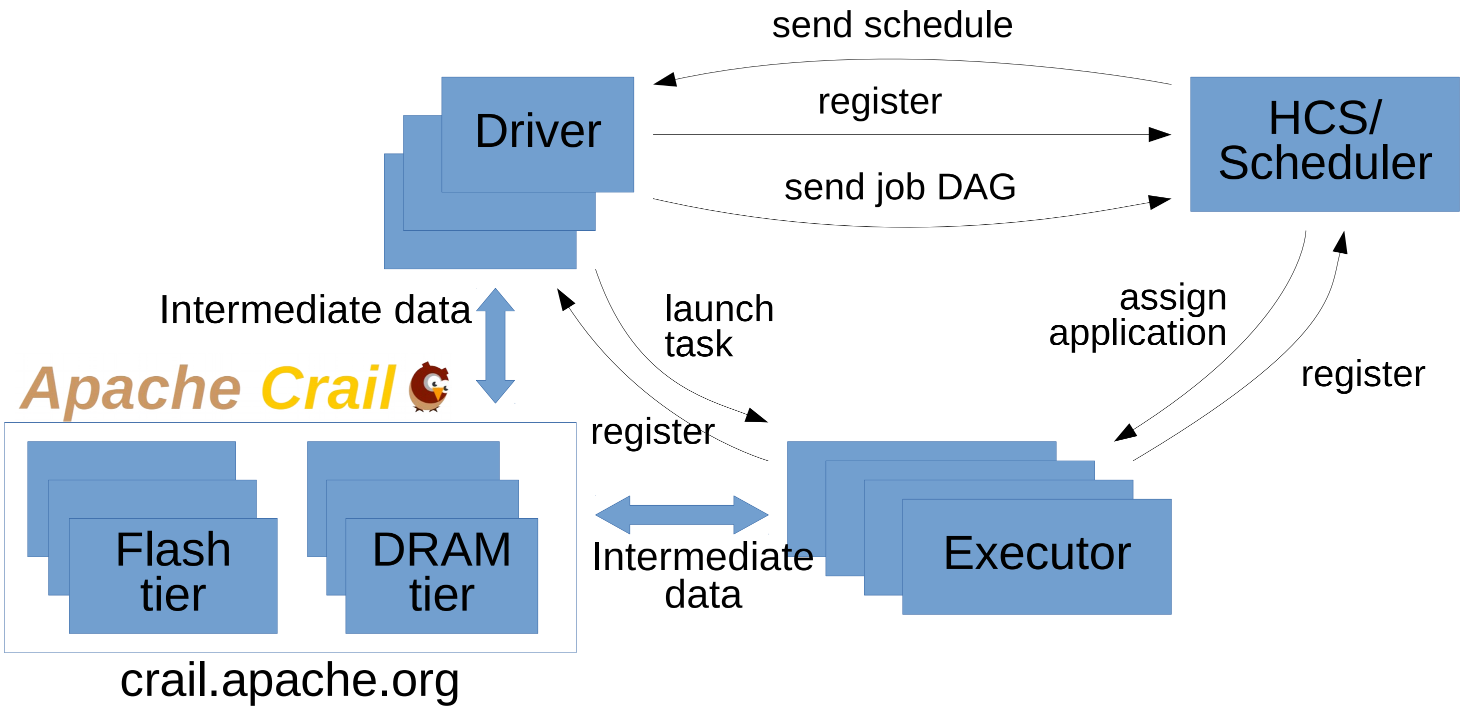
Disaggregation of Ephemeral Data



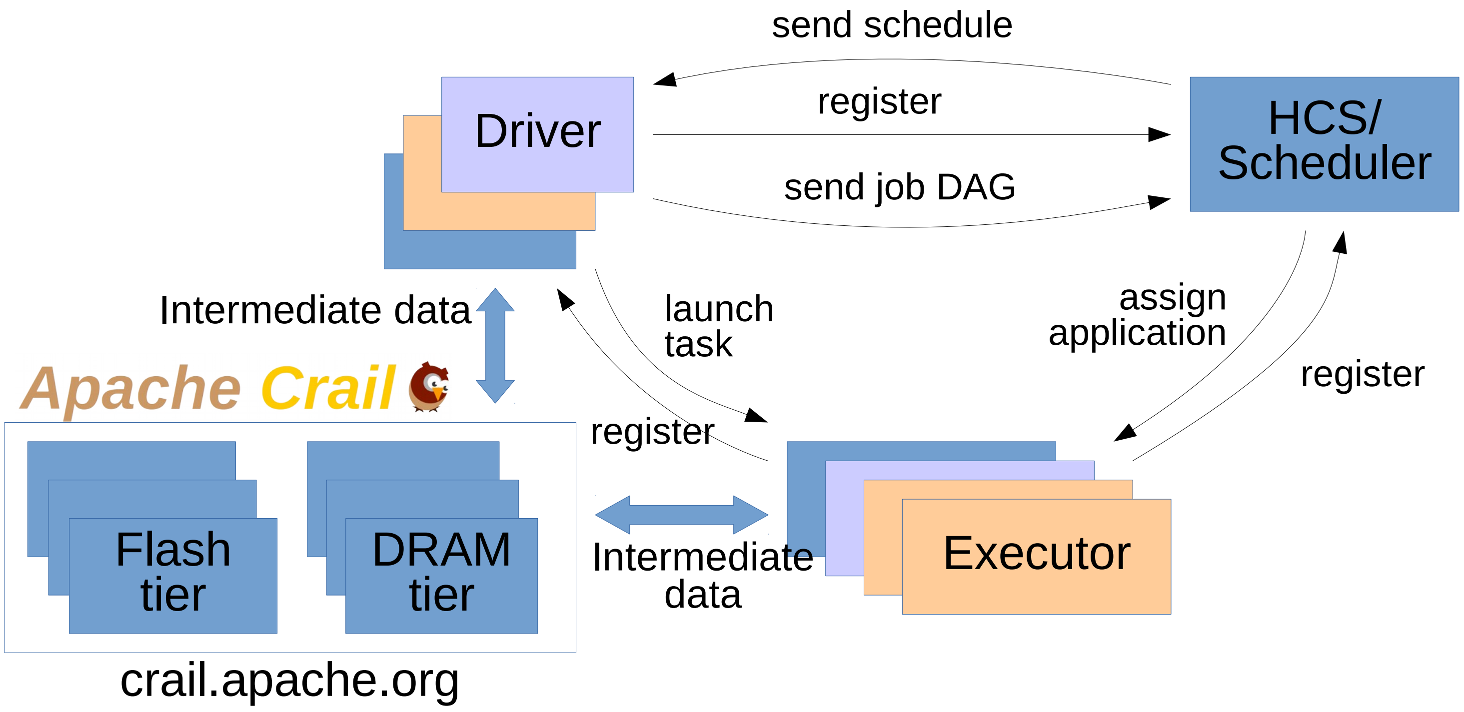
Disaggregation of Ephemeral Data



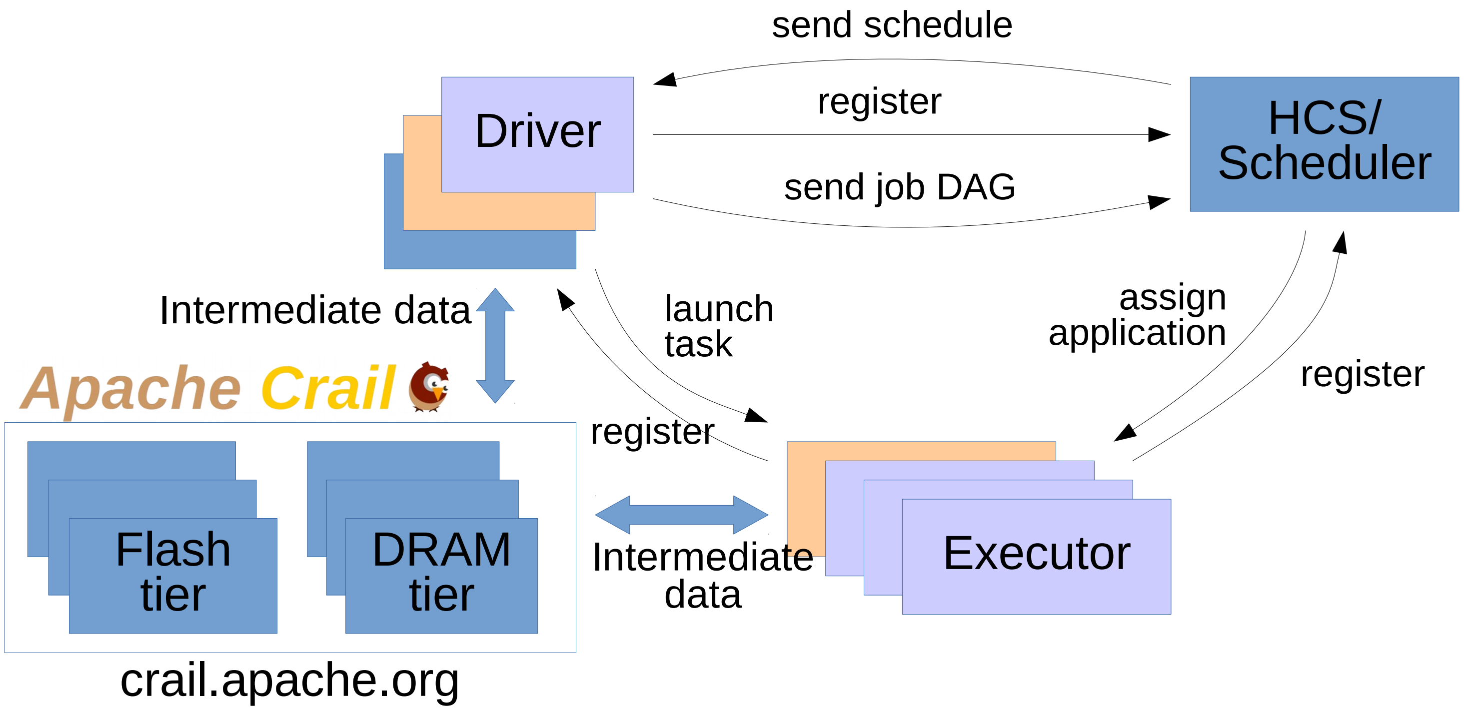
Spark-Serverless Architecture



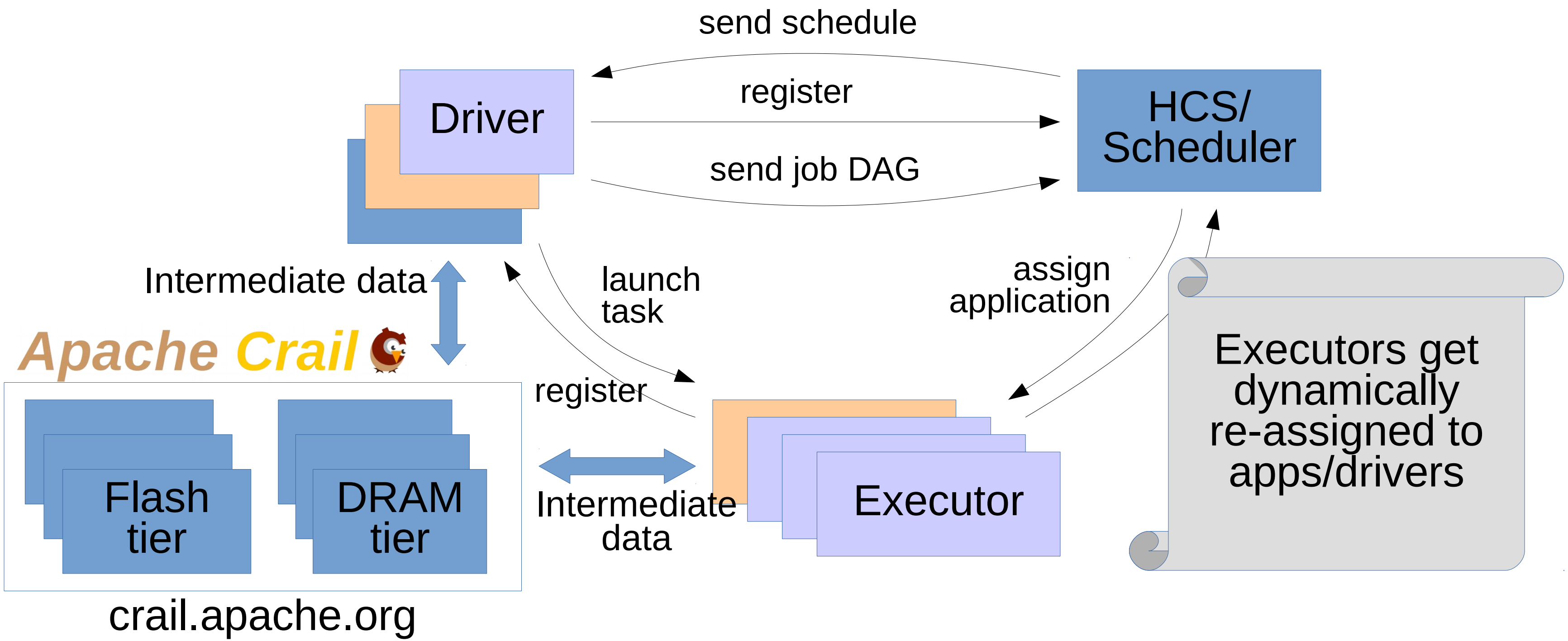
Architecture Overview



Architecture Overview



Architecture Overview



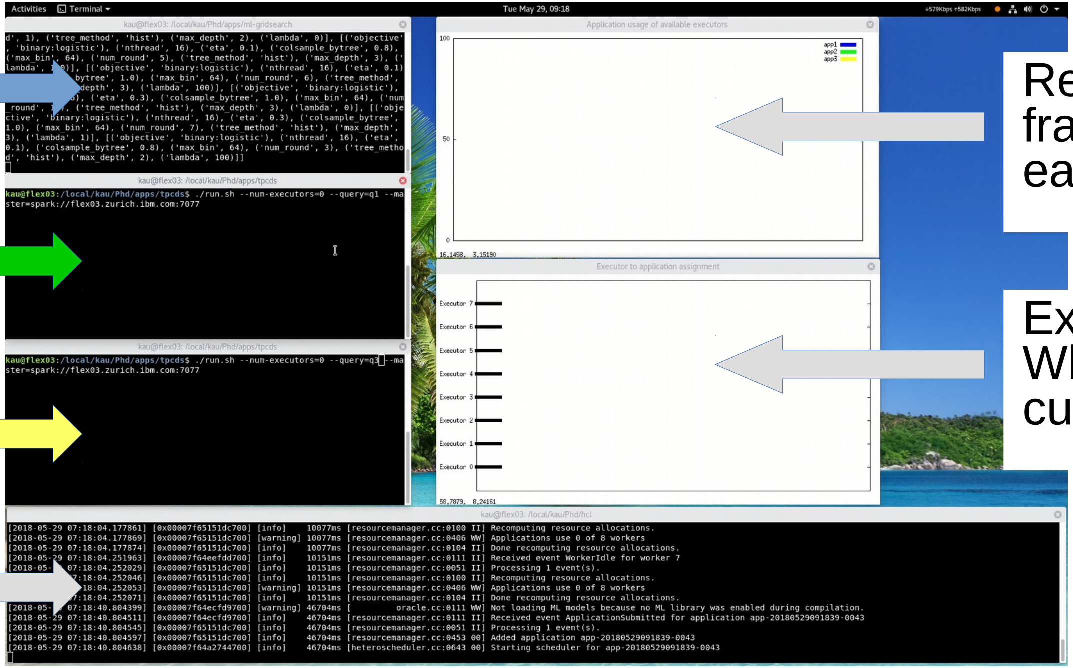
Video: Putting things together

Application 1:
GridSearch

Application 2:
SQL TPC-DS

Application 3:
SQL TPC-DS

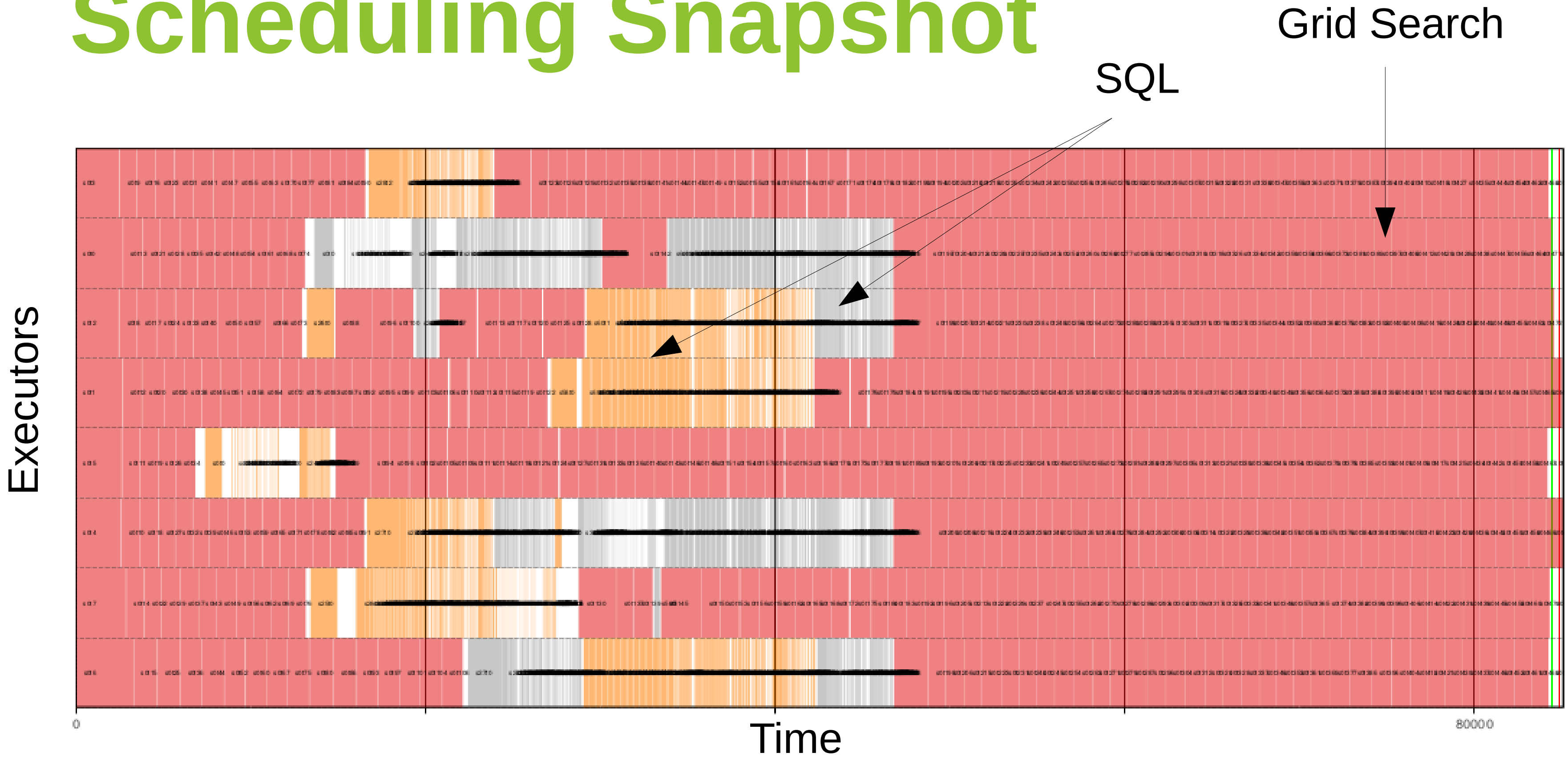
HCL
Scheduler



Resource view:
fraction of resources
each app consumes

Executor view:
Which app an executor
currently runs

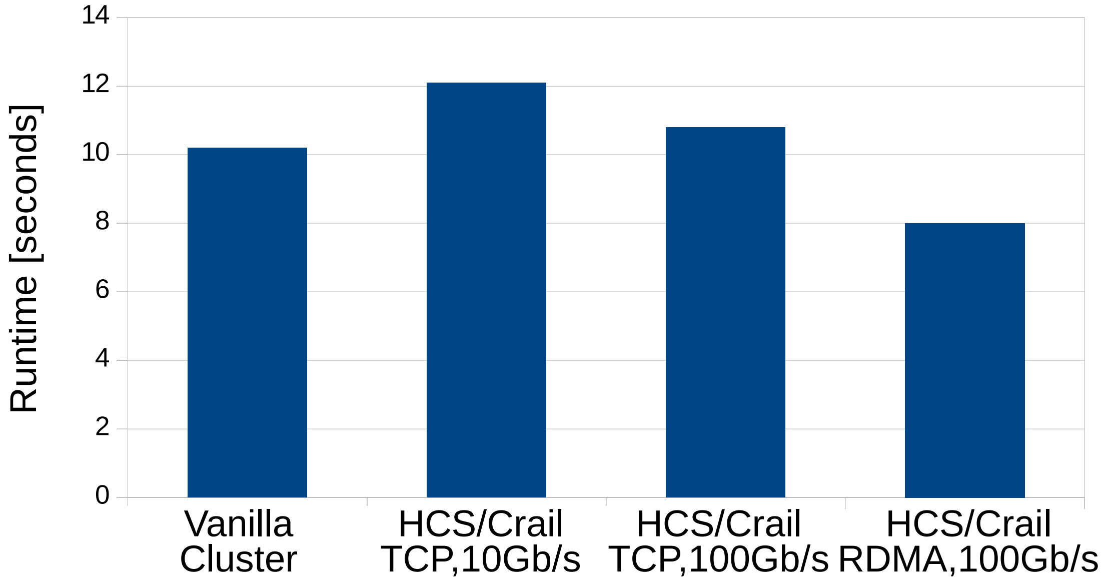
Scheduling Snapshot



Let’s look at performance...

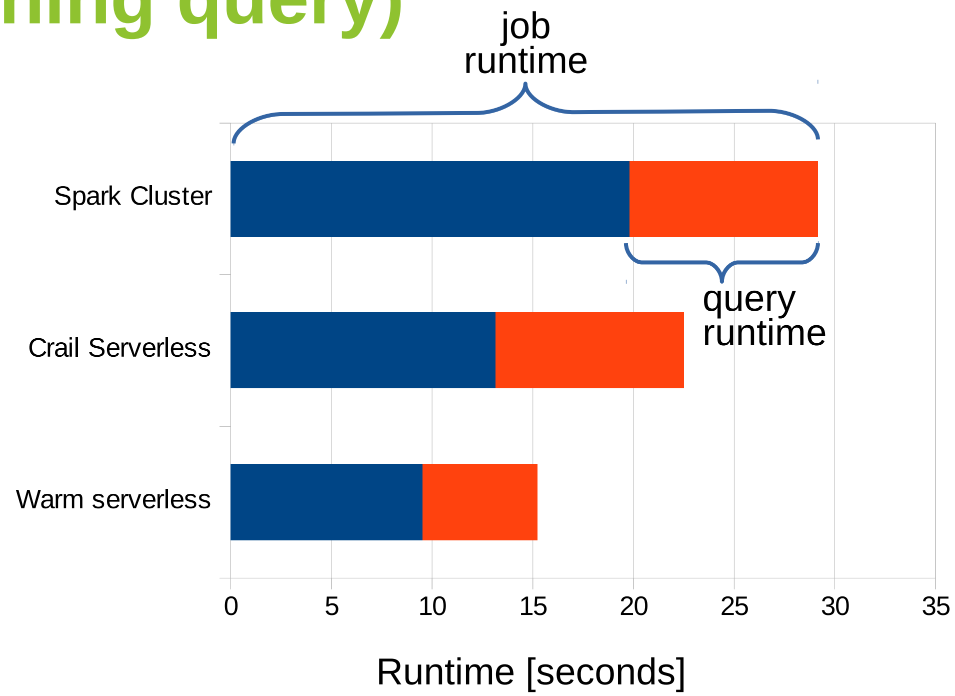
- Compute cluster size: 8 nodes: IBM Power8 Minsky
- Storage cluster size: 8 nodes, IBM Power8 Minsky
- Cluster hardware:
  - DRAM: 512 GB
  - Storage: 4x 1.2 TB NVMe SSD
  - Network: 10Gb/s Ethernert, 100Gb/s RoCE
  - GPU: NVIDIA P100, NVLink
- Workload
  - SQL: TCP-DS

Spark-SQL: TPC-DS (Query #87)
(long running query)



Efficiently disaggregating ephemeral data enables Spark cluster to grow and shrink without a performance cost

Spark-SQL: TPC-DS (Query #3)
(short running query)



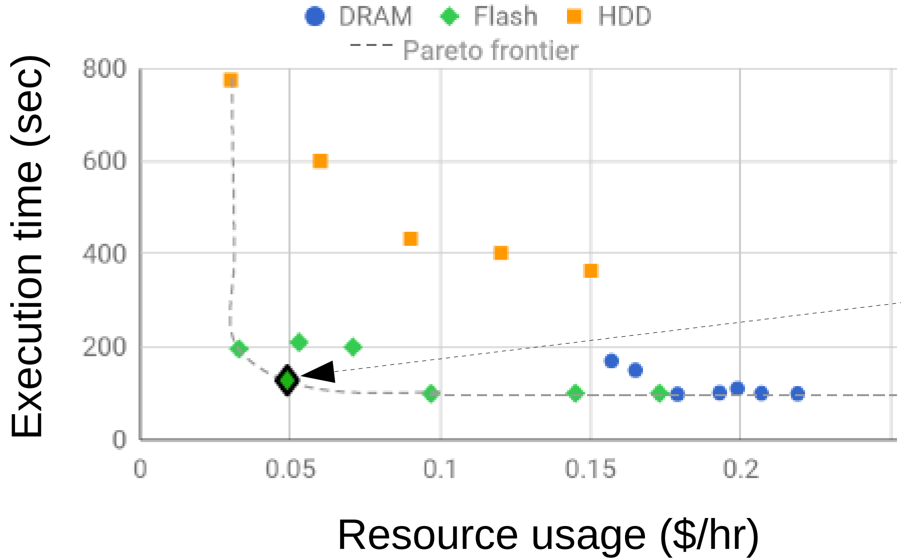
Short-running queries benefit from the shared (already-up) Spark deployment

Project 2:
Serverless Analytics in the Cloud

- Context: Serverless analytics in the cloud
  - AWS λ, IBM Cloud Functions, Azure Functions
- Current practice for storing ephemeral data:
  - S3:
    - High latencies for small data sets
  - Redis, AWS ElasticCache:
    - Inconvenient for storing large objects
    - No dynamic scaling
    - Costly (DRAM)
- Can we use Apache Crail?
  - Not as is, no dynamic scaling

Pocket

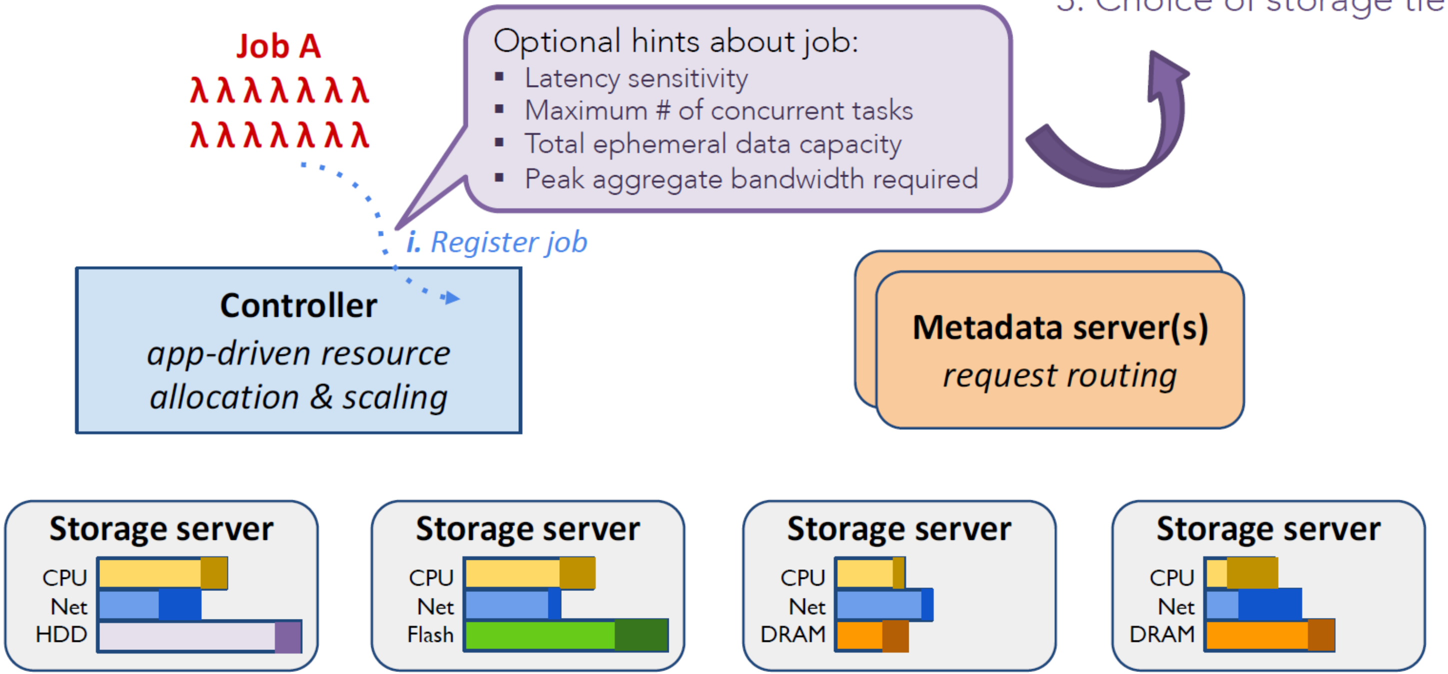
- An elastic distributed data store for ephemeral data sharing in serverless analytics



Pocket dynamically rightsizes storage resources (nodes, media) in an attempt to find a spot with a good performance price ratio

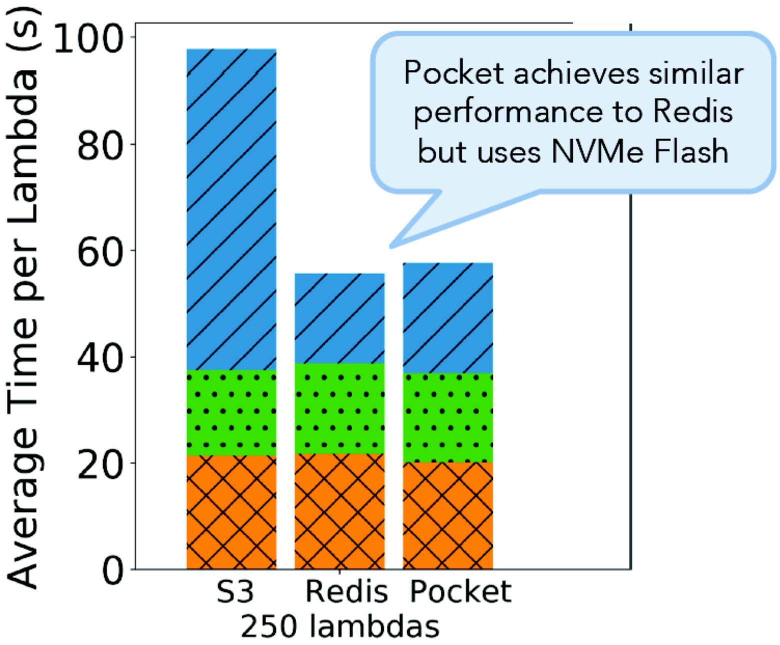
How Pocket works

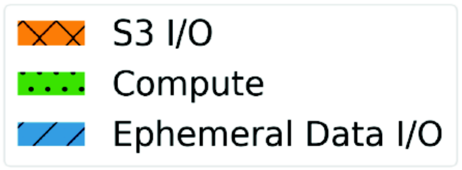
1. Throughput allocation
2. Capacity allocation
3. Choice of storage tier(s)



Pocket: Resource Utilization

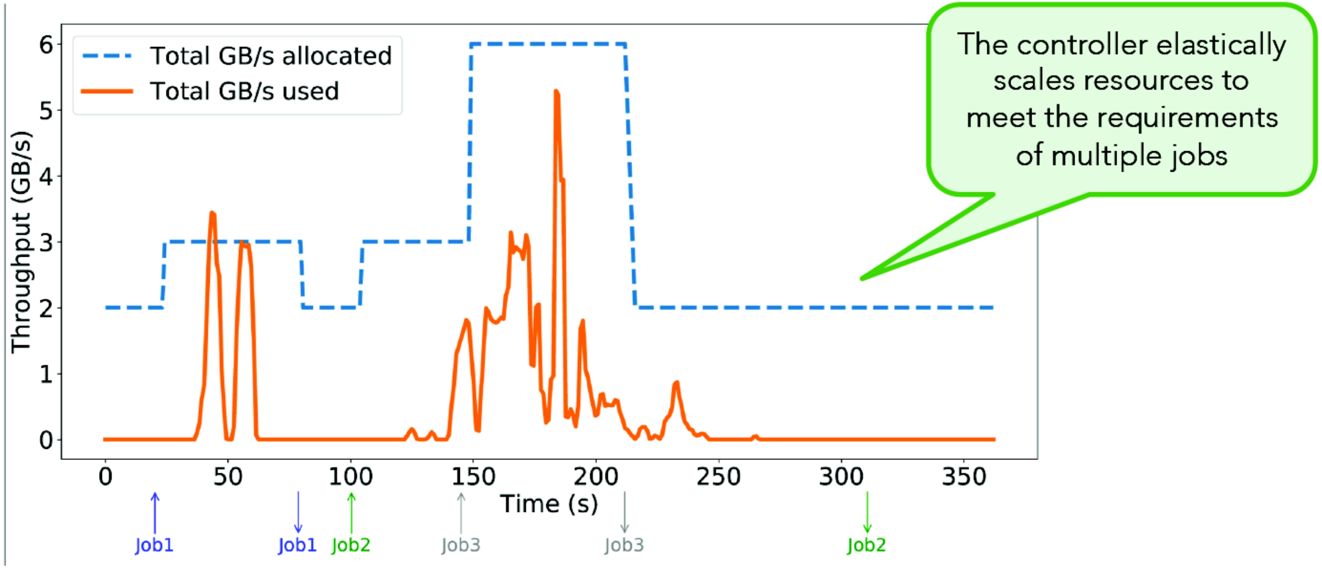
- Comparing Pocket to S3 and Redis





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

Autoscaling a Pocket Cluster



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

- Serverless frameworks are increasingly being used for **interactive analytics**
- Efficiently managing ephemeral data is important for serverless analytics

2 Projects:

- Spark-serverless
  - Add support to Spark for fine-grained on-demand scaling
  - Permit growing/shrinking of Spark executors by disaggregating shuffle data using Apache Crail
- Pocket
  - Elastic distributed data store for ephemeral data sharing in serverless analytics
  - Can be used together with frameworks like AWS λ, IBM Cloud Functions, etc.

References

- Pocket: Ephemeral Storage for Serverless Analytics, **OSDI'18**
- Navigating Storage for Serverless Computing, **Usenix ATC'18**
- Crail: A High-Performance I/O Architecture for Distributed Data Processing, **IEEE Data Bulletin 2017**
- Running Apache Spark on a High-Performance Cluster Using RDMA and NVMe Flash, **Spark Summit'17**
- Serverless Machine Learning using Crail, **Spark Summit'18**
- Apache Crail, http://crail.apache.org

Thanks to

Ana Klimovic, Yawen Wang, Michael Kaufmann, Adrian Schuepbach, Jonas Pfefferle, Animesh Trivedi, Bernard Metzler

Slides (Intro & Pocket) from Pocket presentation (OSDI’18, Ana Klimovic)