SPARK+AI SUMMIT 2018

Serverless Machine Learning on Modern Hardware

Patrick Stuedi
IBM Research

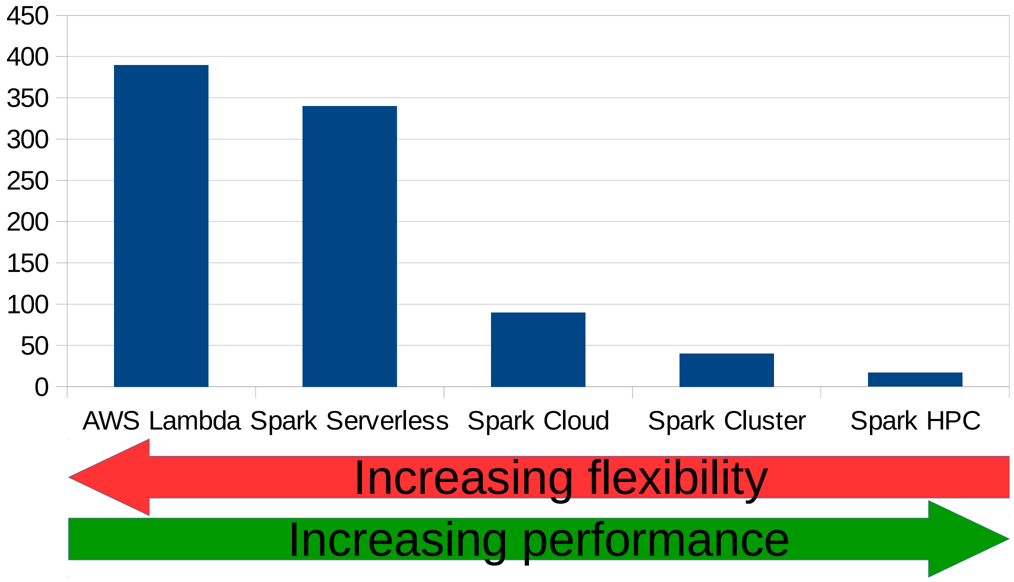
#Res6SAIS

Serverless Computing

- No need to setup/manage a cluster
- Automatic, dynamic and fine-grained scaling
- Sub-second billing
- AWS Lambda, Google Cloud Functions, Azure Functions, Databricks Serverless

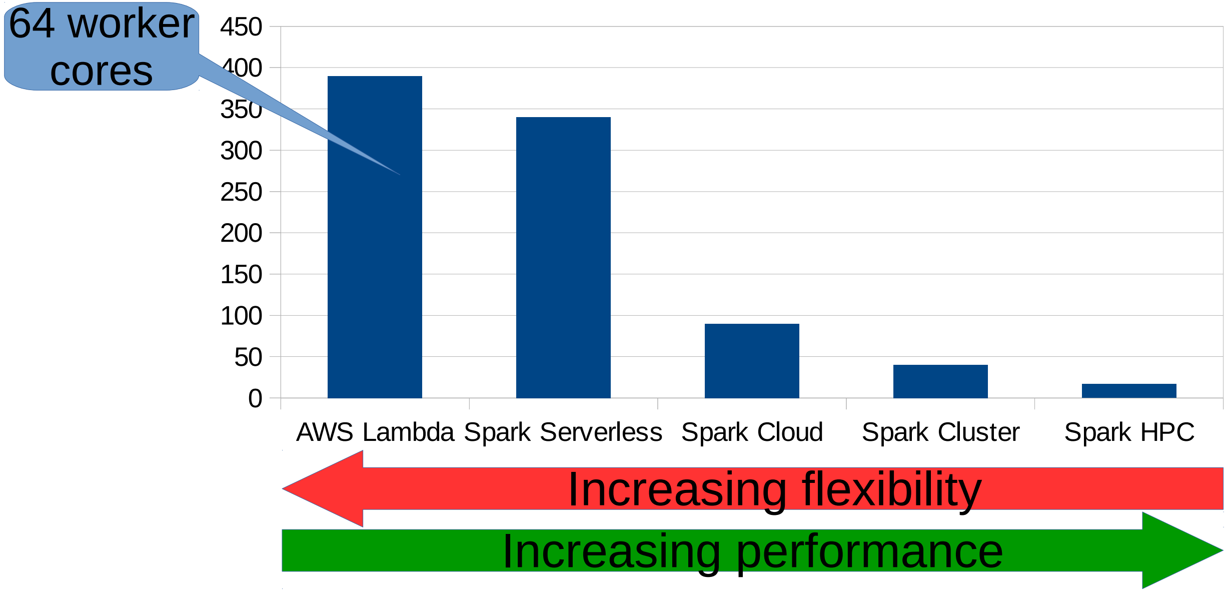
Challenge: Performance

Example:
Sorting 100GB



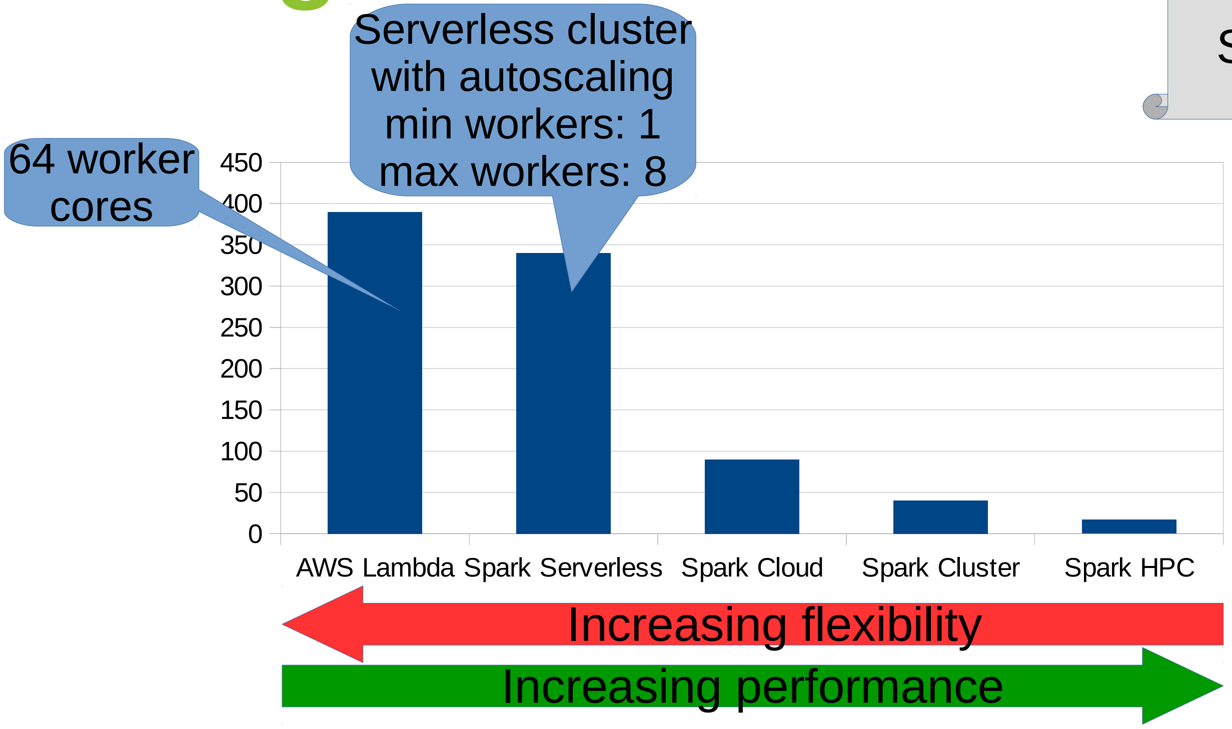
Challenge: Performance

Example:
Sorting 100GB



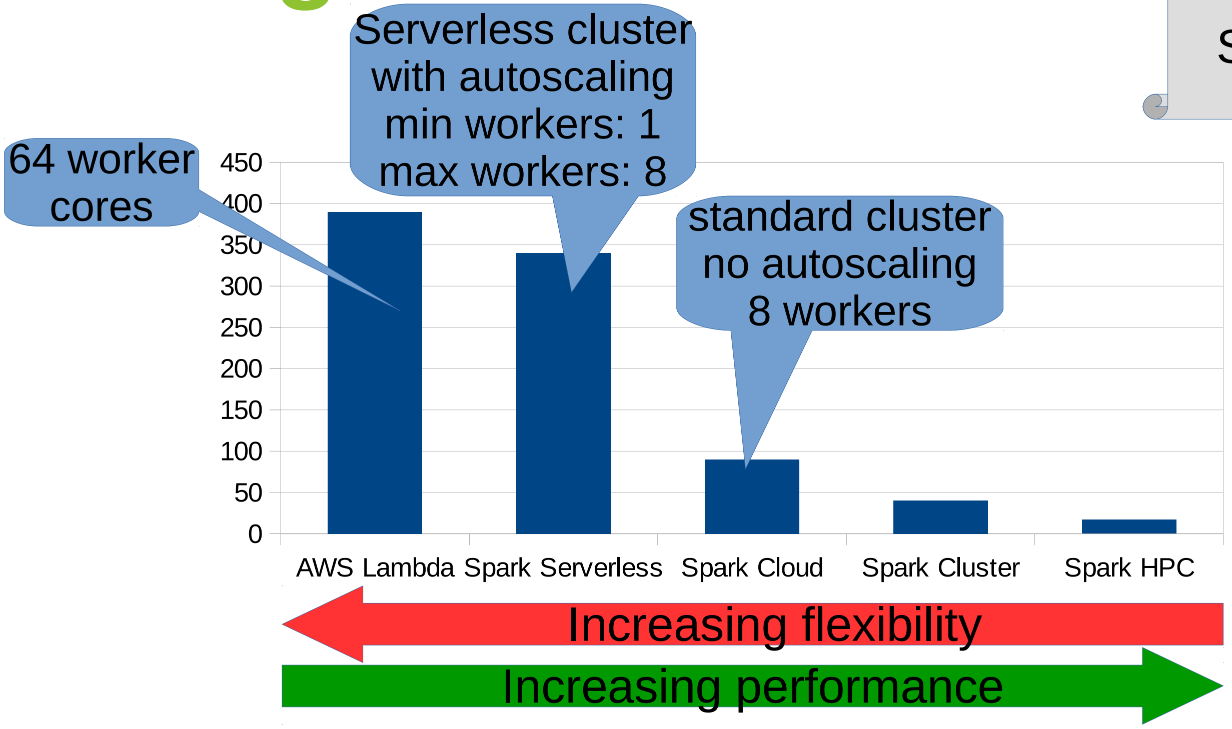
Challenge: Performance

Example:
Sorting 100GB



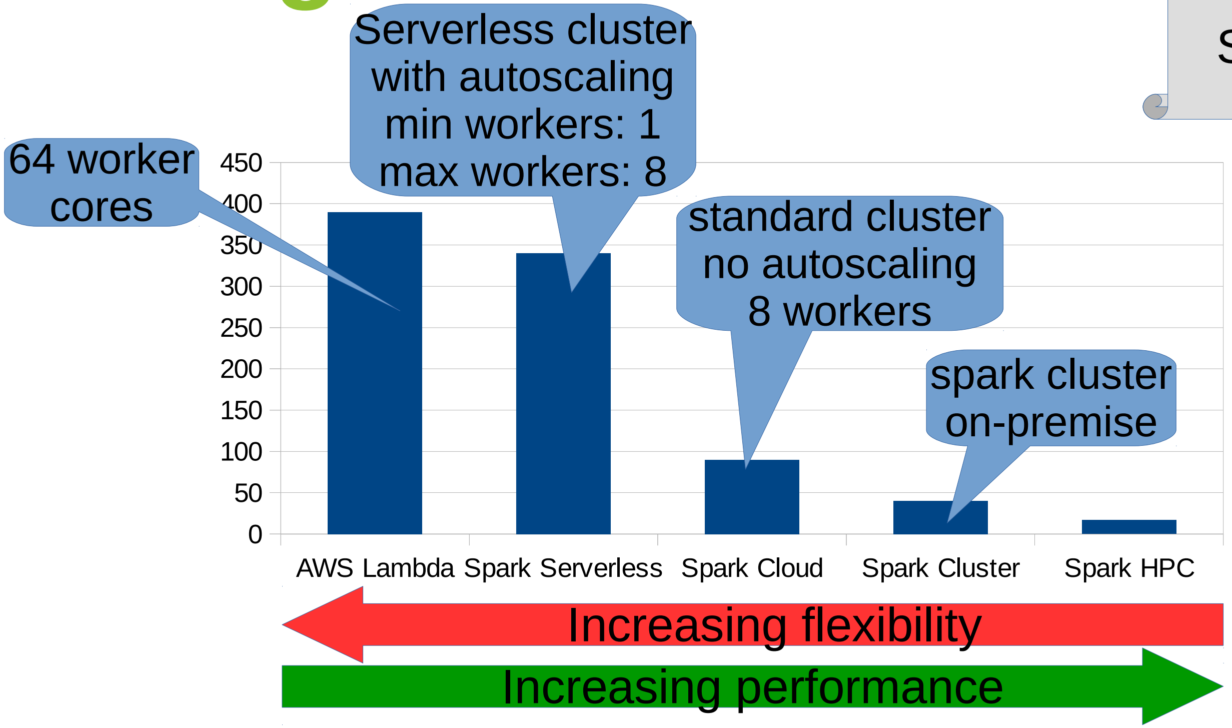
Challenge: Performance

Example:
Sorting 100GB

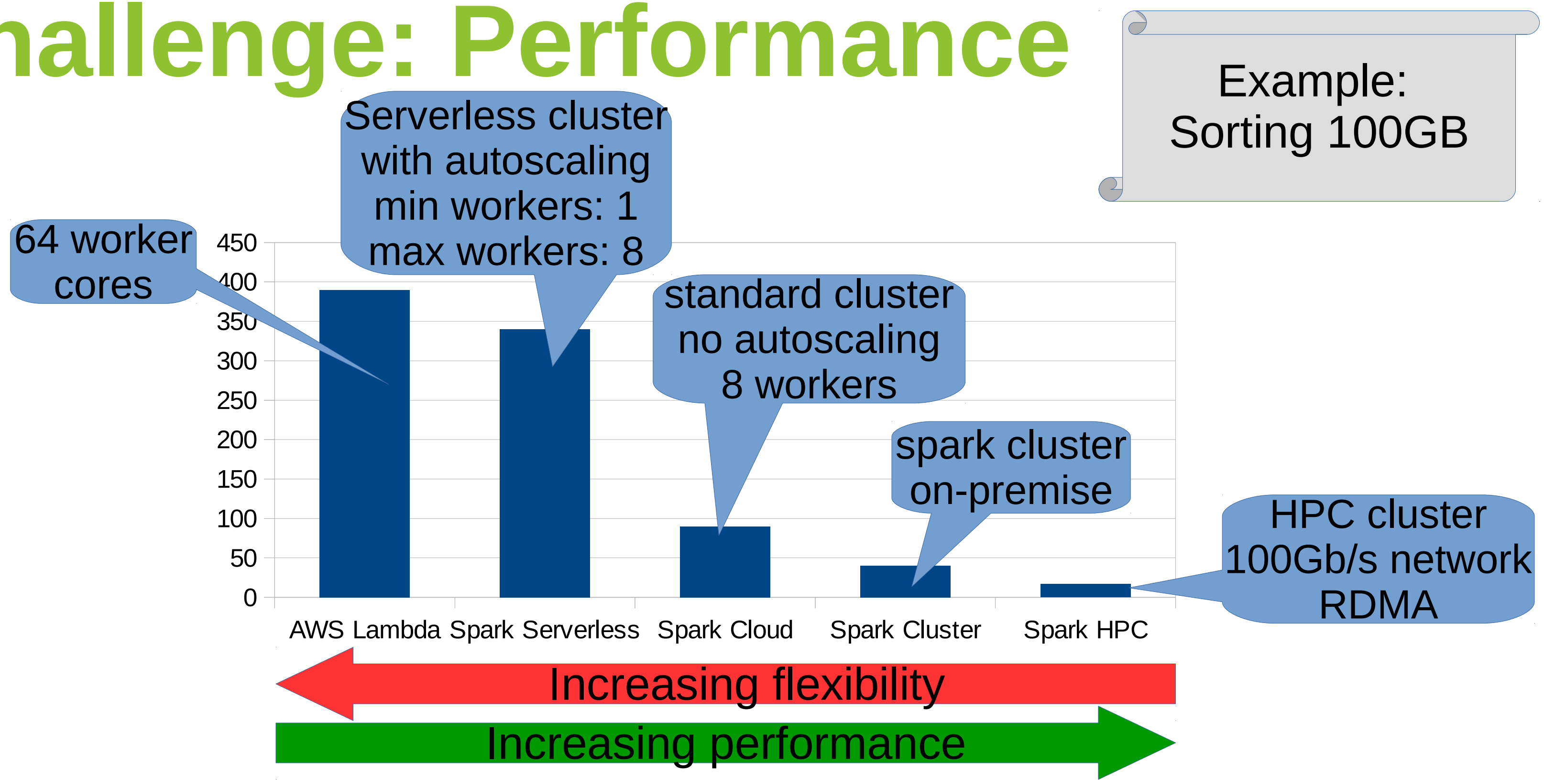


Challenge: Performance

Example:
Sorting 100GB



Challenge: Performance



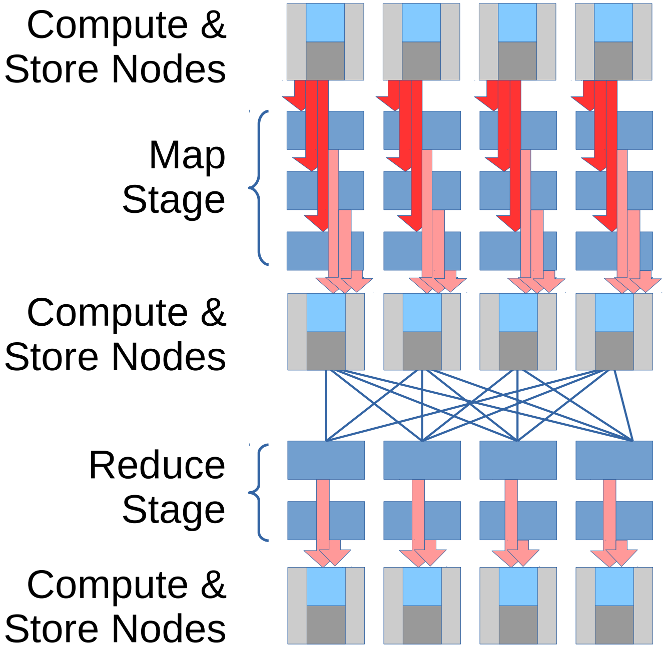
Why is it so hard?

- **Scheduler:** when to best add/remove resources?
- **Container startup:** may have to dynamically spin up containers per function
- **Storage:** input data needs to be fetched from remote storage (e.g., S3)
  - As opposed to compute-local storage, e.g., HDFS
- **Data sharing:** intermediate needs to be temporarily stored on remote storage (S3, Redis)
  - Affects operations like shuffle, broadcast, etc.,

Why is it so hard?

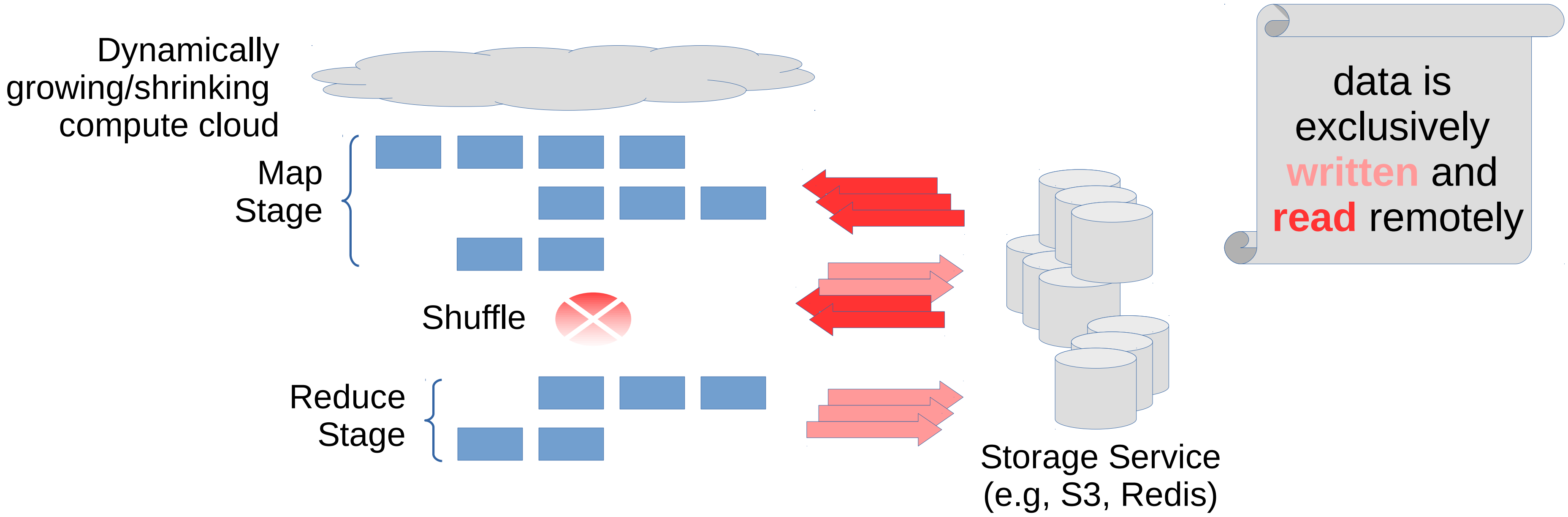
- **Scheduler:** when to best add/remove resources?
- **Container startup:** may have to dynamically spin up containers per function
- **Storage**: input data needs to be fetched from remote storage (e.g., S3)
  - As opposed to compute-local storage, e.g., HDFS
- **Data sharing:** intermediate needs to be temporarily stored on remote storage (S3, Redis)
  - Affects operations like shuffle, broadcast, etc.,

Example: MapReduce (Cluster)

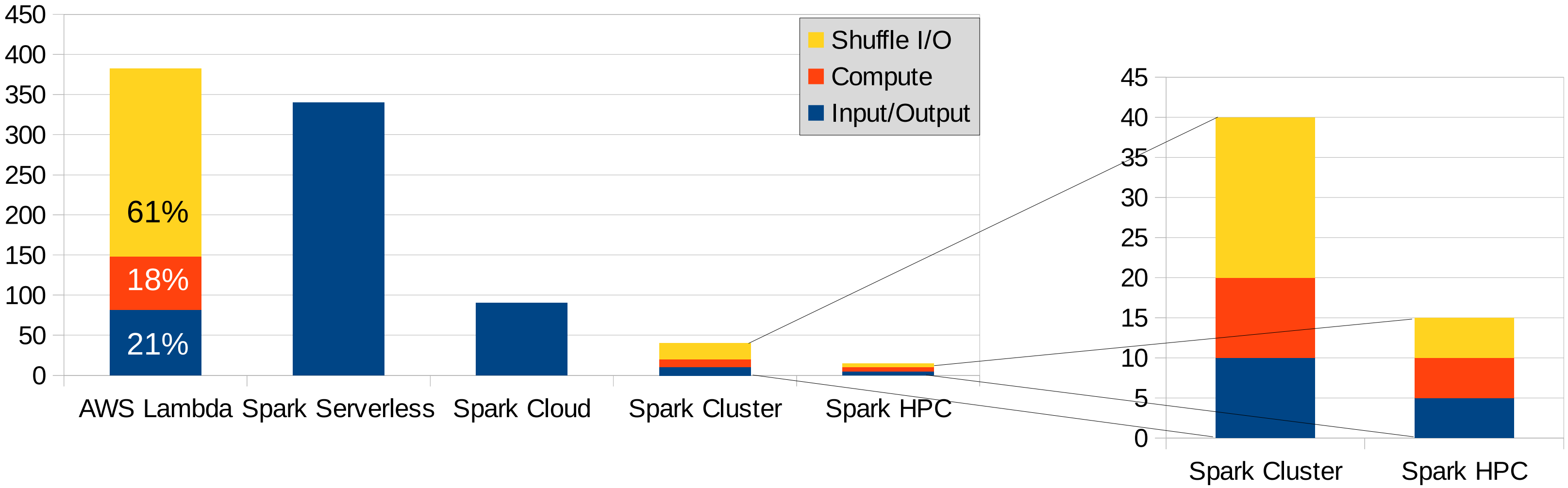


data is mostly **written** and **read** locally

Example: MapReduce (Serverless)



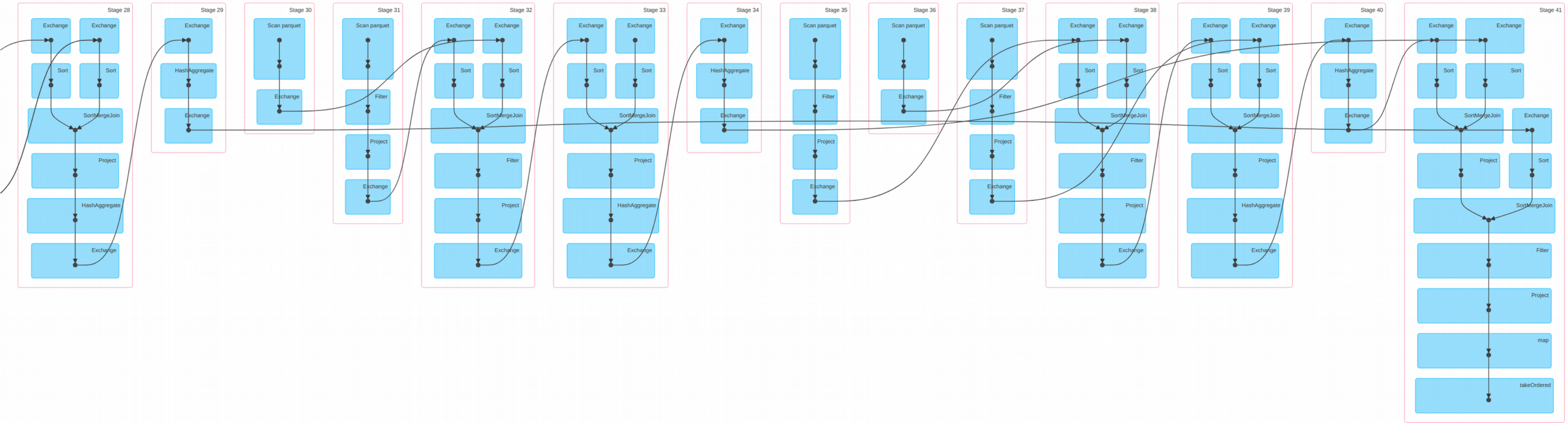
I/O Overhead: Sorting 100GB



Input/output and shuffle overheads are significantly higher when data is stored remotely

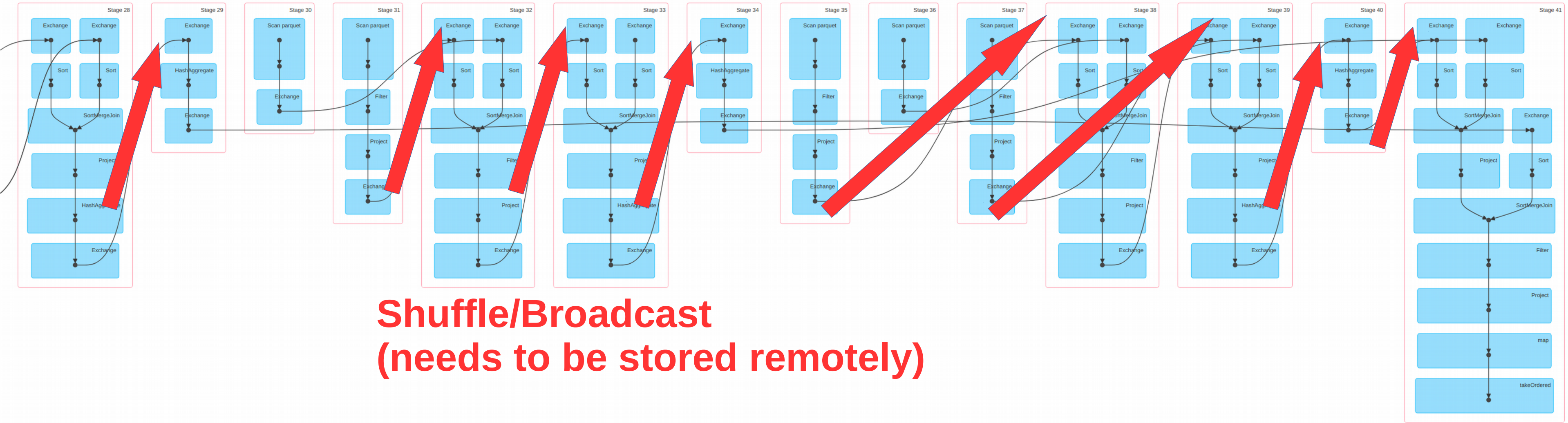
What about other workloads?

Example: SQL, Query 77 / TPC-DS benchmark



What about other workloads?

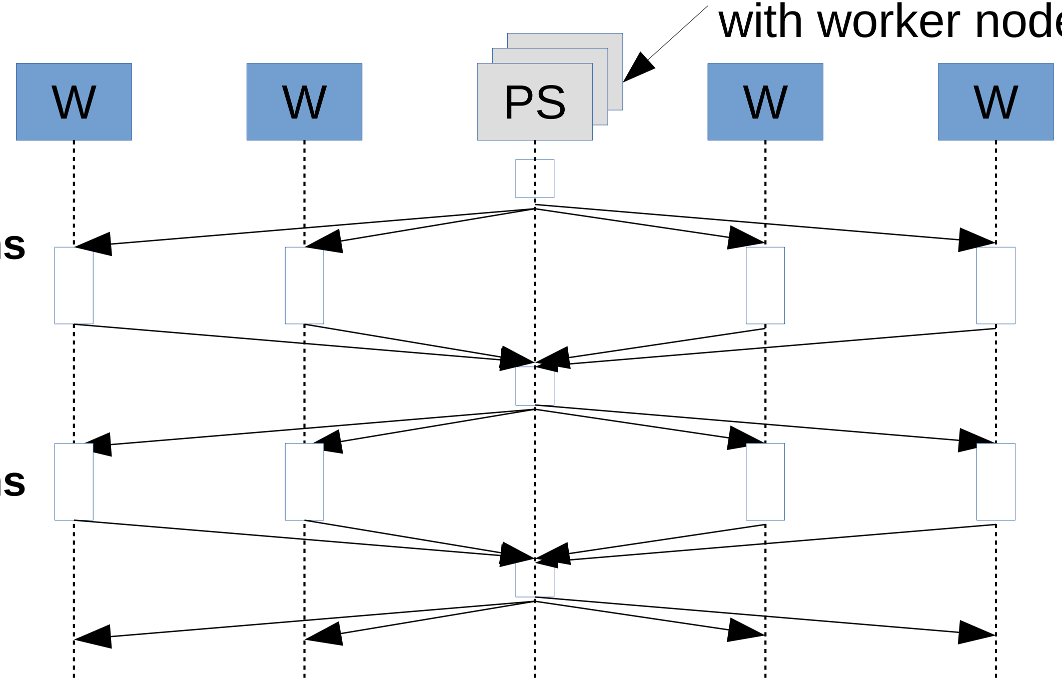
Example: SQL, Query 77 / TPC-DS benchmark



What about other workloads?

Example: Iterative ML (e.g., linear regression)

could be co-located
with worker nodes



***) fetch model params**
***) compute**
***) update model**

⋮

***) fetch model params**
***) compute**
***) update model**

⋮

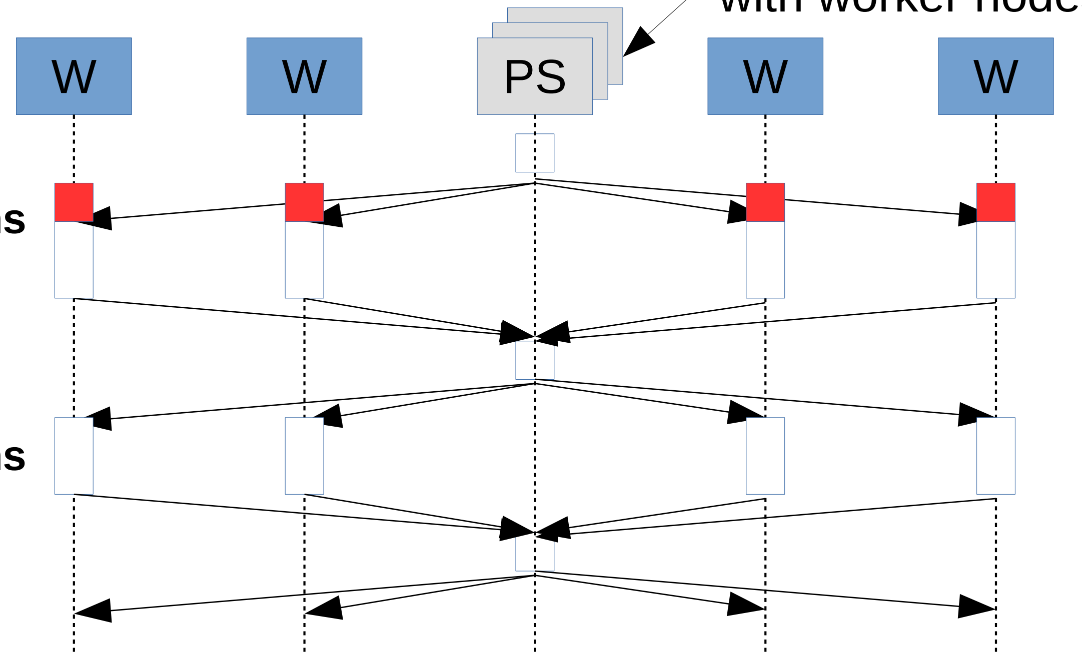
What about other workloads?

Example: Iterative ML (e.g., linear regression)

could be co-located
with worker nodes

*) read training data
*) fetch model params
*) compute
*) update model

*) use cached data
*) fetch model params
*) compute
*) update model



What about other workloads?

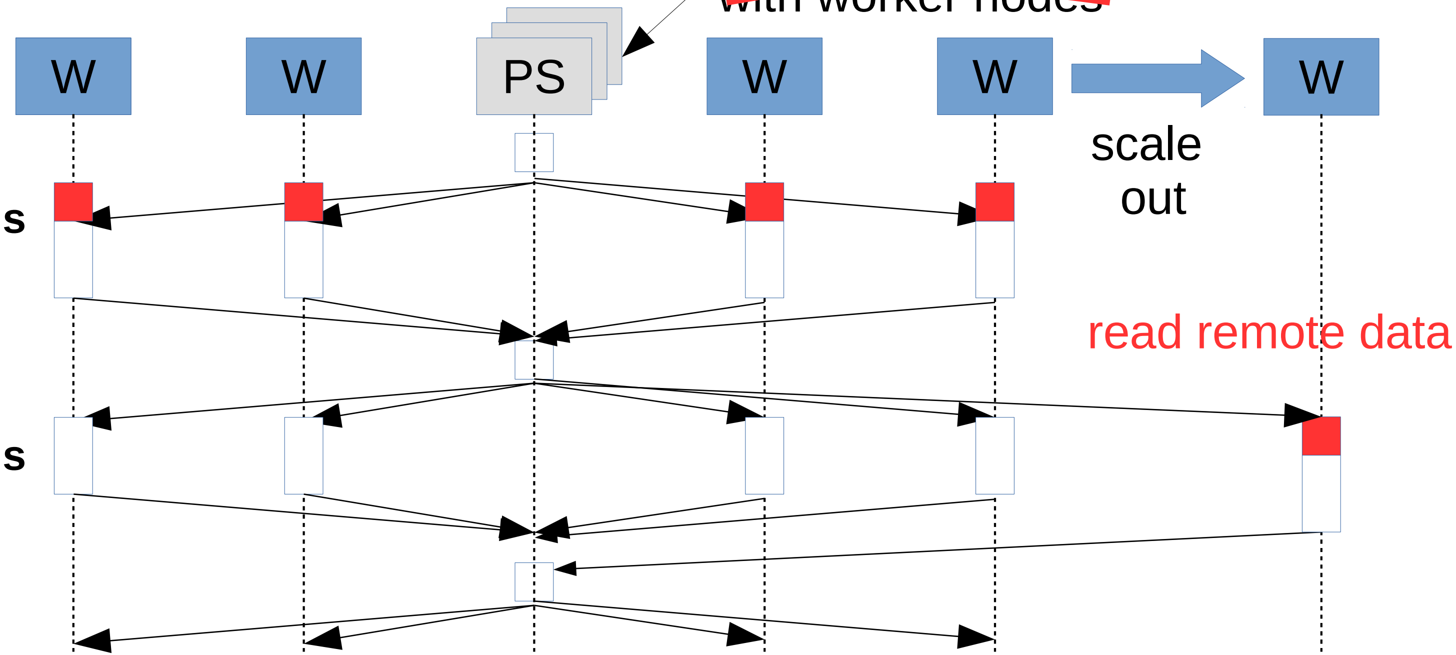
Example: Iterative ML (e.g., linear regression)

~~could be co-located with worker nodes~~

Needs to be remote

*) read training data
*) fetch model params
*) compute
*) update model

*) use cached data
*) fetch model params
*) compute
*) update model

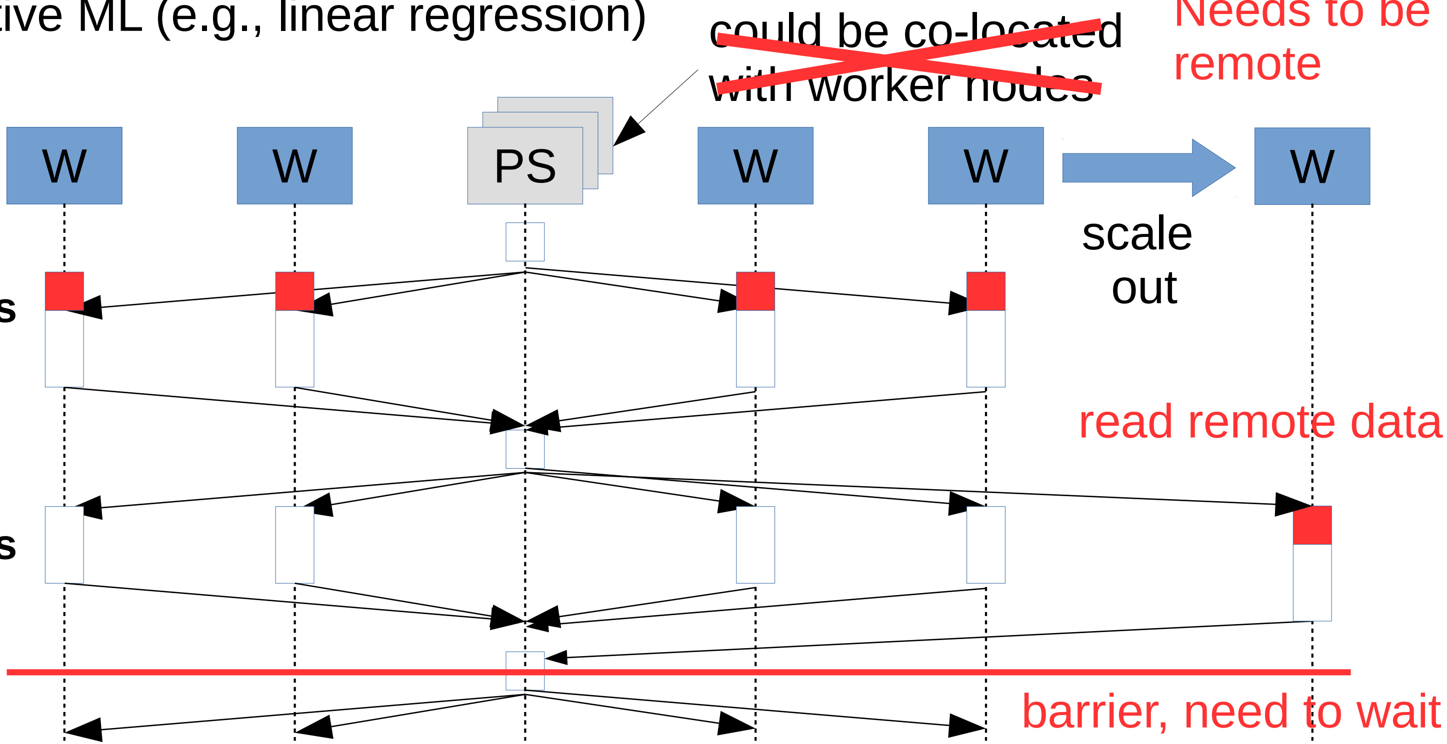


What about other workloads?

Example: Iterative ML (e.g., linear regression)

*) read training data
*) fetch model params
*) compute
*) update model

*) use cached data
*) fetch model params
*) compute
*) update model



Can we..

- Use Spark to run such workloads in a serverless fashion?
  - Dynamic scaling of compute nodes as jobs are running
  - No cluster configuration
  - No startup time
- Reduce the performance overheads to a minimum?

Design Options

- **Scheduling:**
  1. Use serverless framework to schedule executors
  2. Use serverless framework to schedule tasks
  3. Enable Spark to dynamically scale up and down executors
- **Intermediate data:**
  1. Executors cooperate with scheduler to flush data remotely
  2. Consequently store all intermediate state remotely

Design Options

- **Scheduling:**

High startup Latency!

1. Use serverless framework to schedule executors
2. Use serverless framework to schedule tasks
3. Enable Spark to dynamically scale up and down executors

- **Intermediate data:**

1. Executors cooperate with scheduler to flush data remotely
2. Consequently store all intermediate state remotely

Design Options

- **Scheduling:**
  1. Use serverless framework to schedule executors
  2. Use serverless framework to schedule tasks
  3. Enable Spark to dynamically scale up and down executors

High startup Latency!

Slow!

- **Intermediate data:**
  1. Executors cooperate with scheduler to flush data remotely
  2. Consequently store all intermediate state remotely

Design Options

- **Scheduling:**
  1. Use serverless framework to schedule executors
  2. Use serverless framework to schedule tasks
  3. Enable Spark to dynamically scale up and down executors

High startup Latency!

Slow!

- **Intermediate data:**
  1. Executors cooperate with scheduler to flush data remotely
  2. Consequently store all intermediate state remotely

Design Options

- **Scheduling:**
  1. Use serverless framework to schedule executors
  2. Use serverless framework to schedule tasks
  3. Enable Spark to dynamically scale up and down executors
- **Intermediate data:**
  1. Executors cooperate with scheduler to flush data remotely
  2. Consequently store all intermediate state remotely

High startup Latency!

Slow!

Complex!

Design Options

- **Scheduling:**
  1. Use serverless framework to schedule executors
  2. Use serverless framework to schedule tasks
  3. Enable Spark to dynamically scale up and down executors

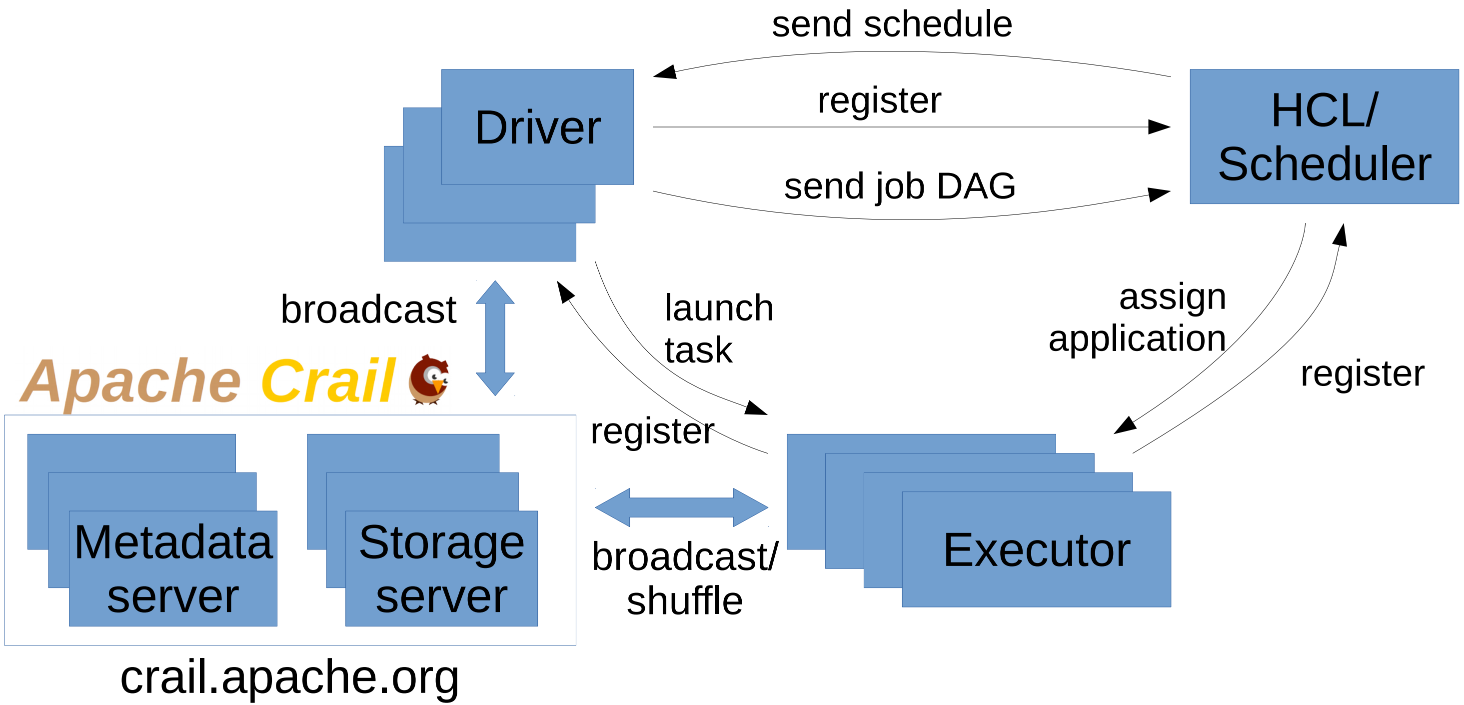
High startup Latency!

Slow!

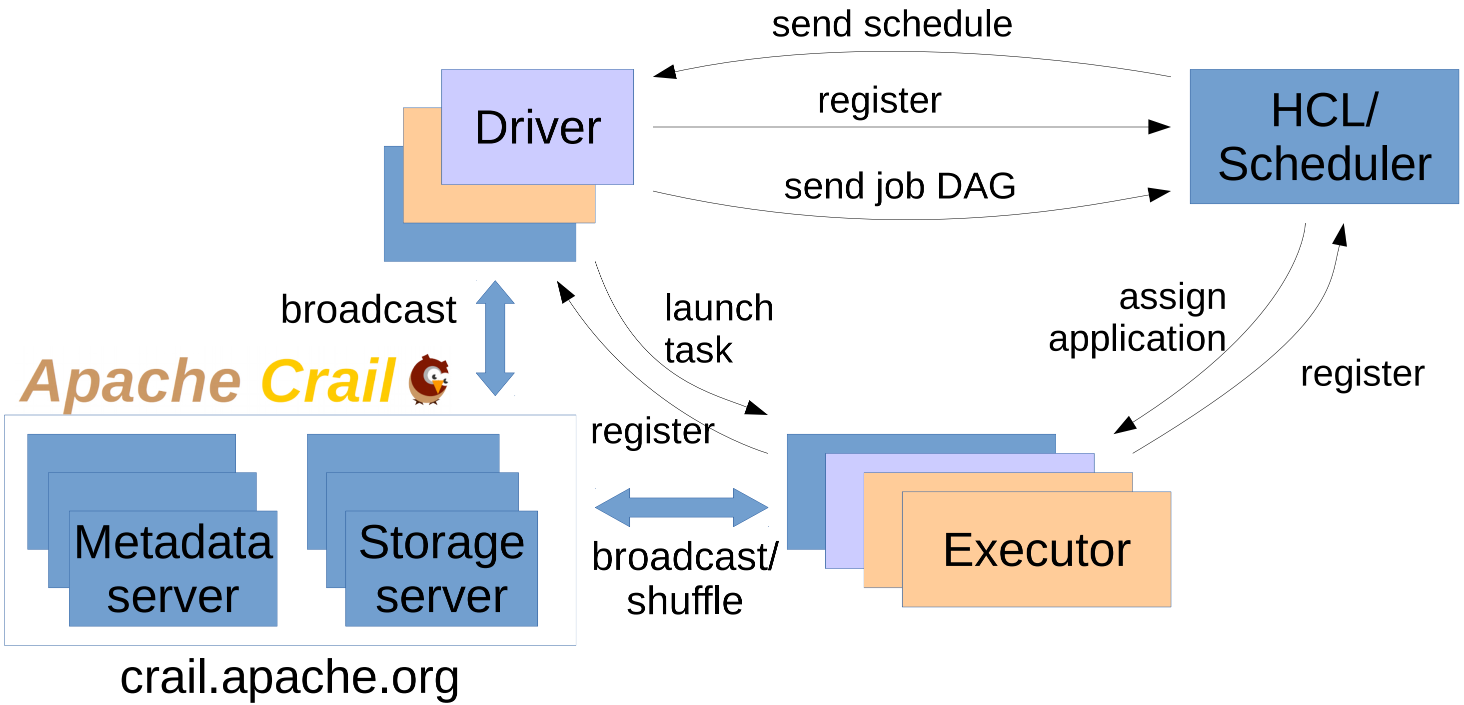
- **Intermediate data:**
  1. Executors cooperate with scheduler to flush data remotely
  2. Consequently store all intermediate state remotely

Complex!

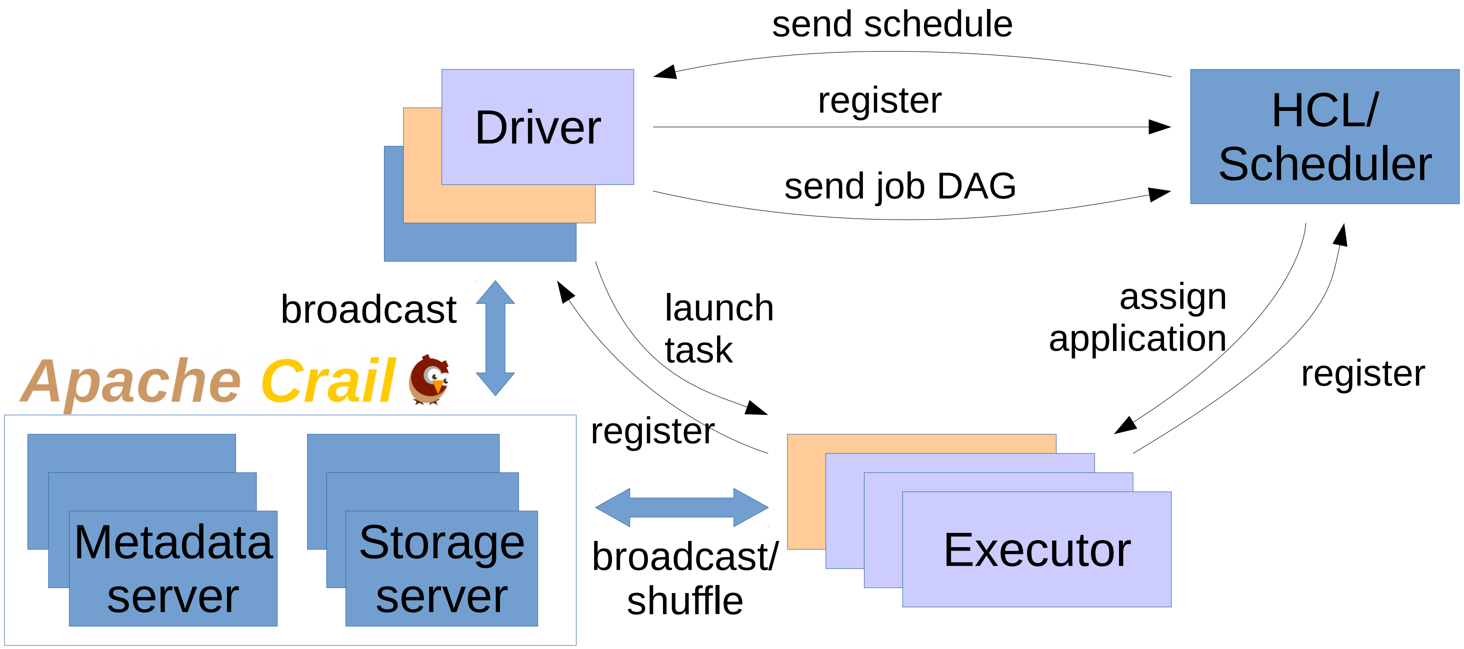
Architecture Overview



Architecture Overview

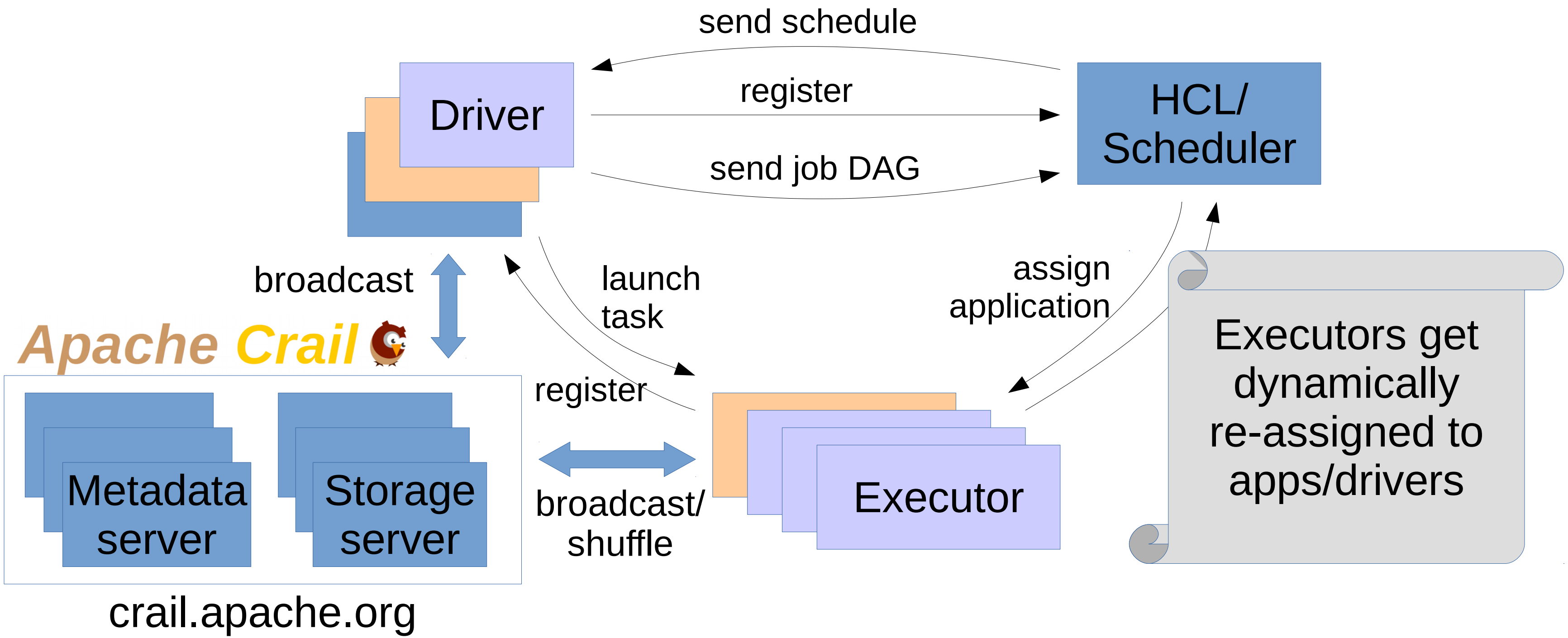


Architecture Overview

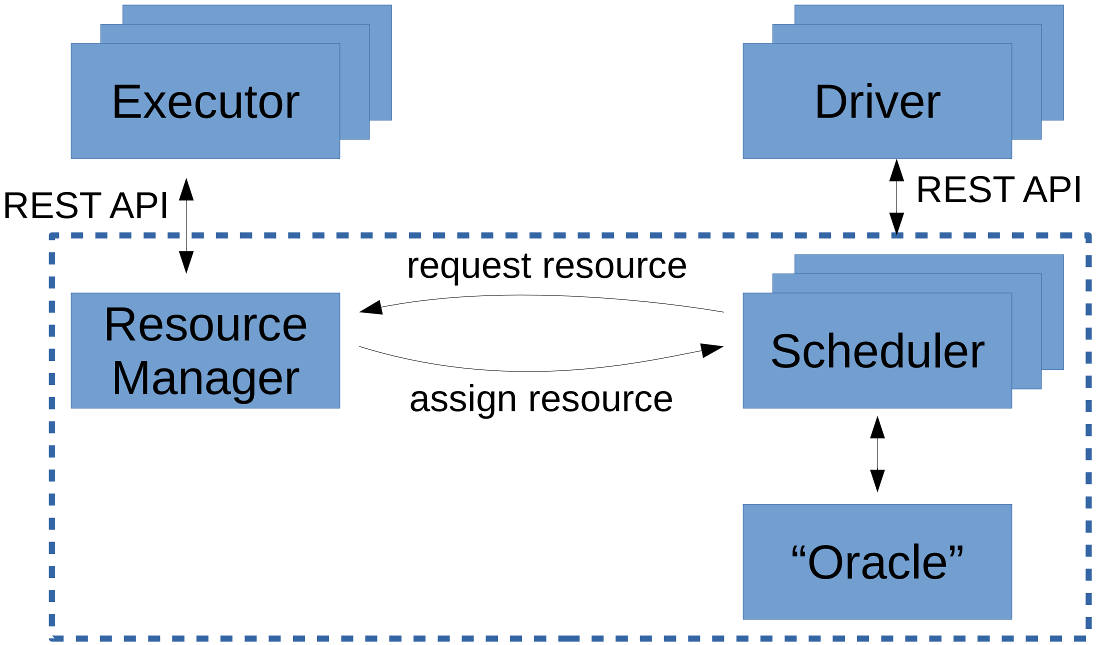


crail.apache.org

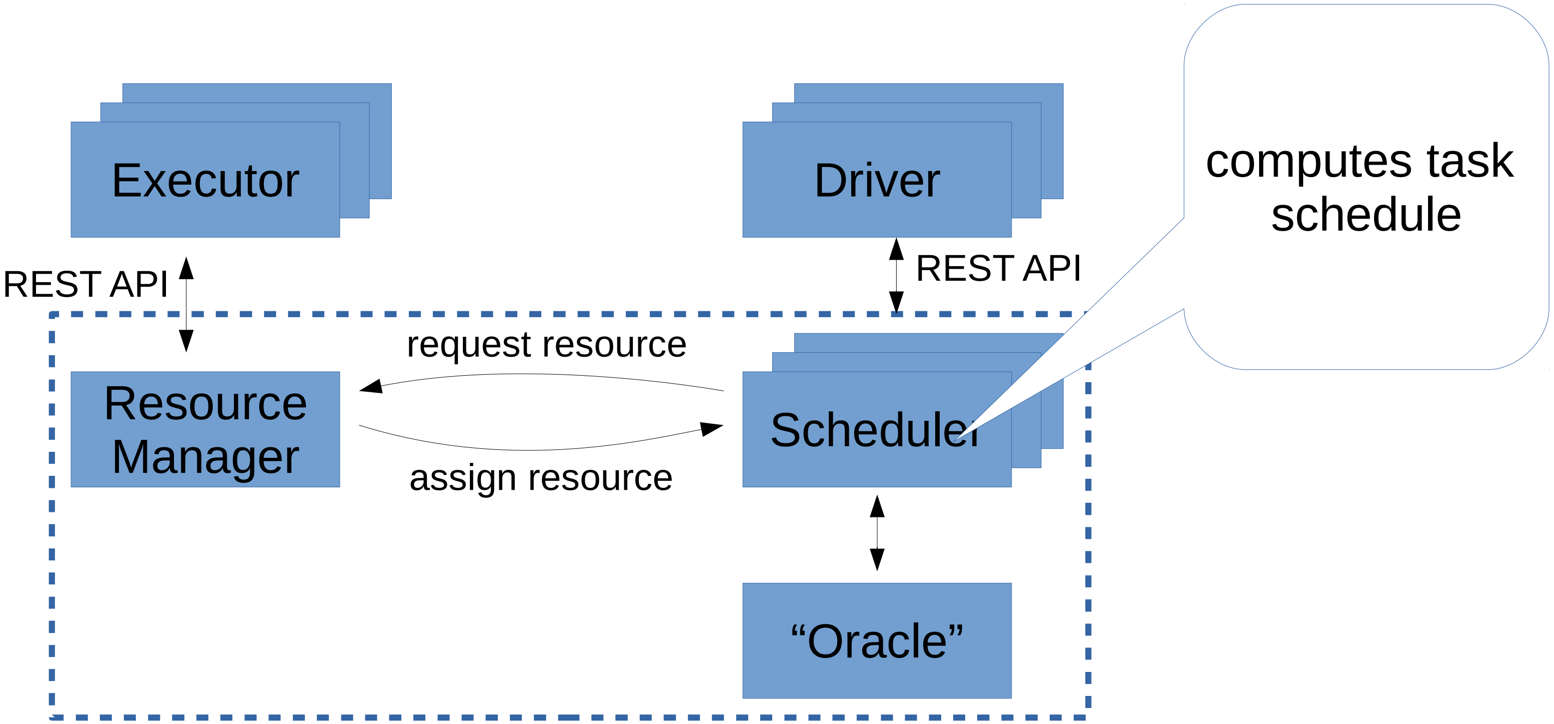
Architecture Overview



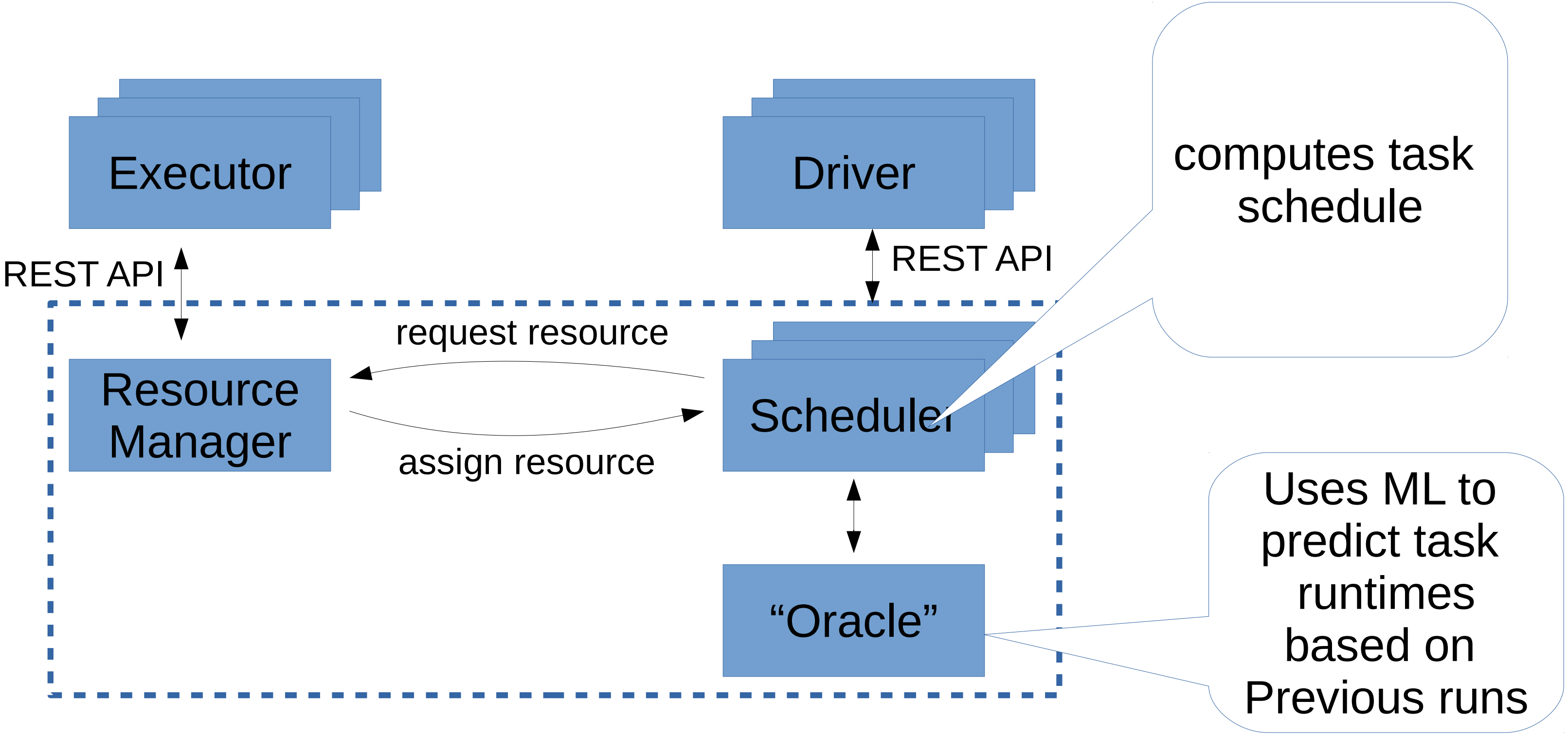
HCL Scheduler



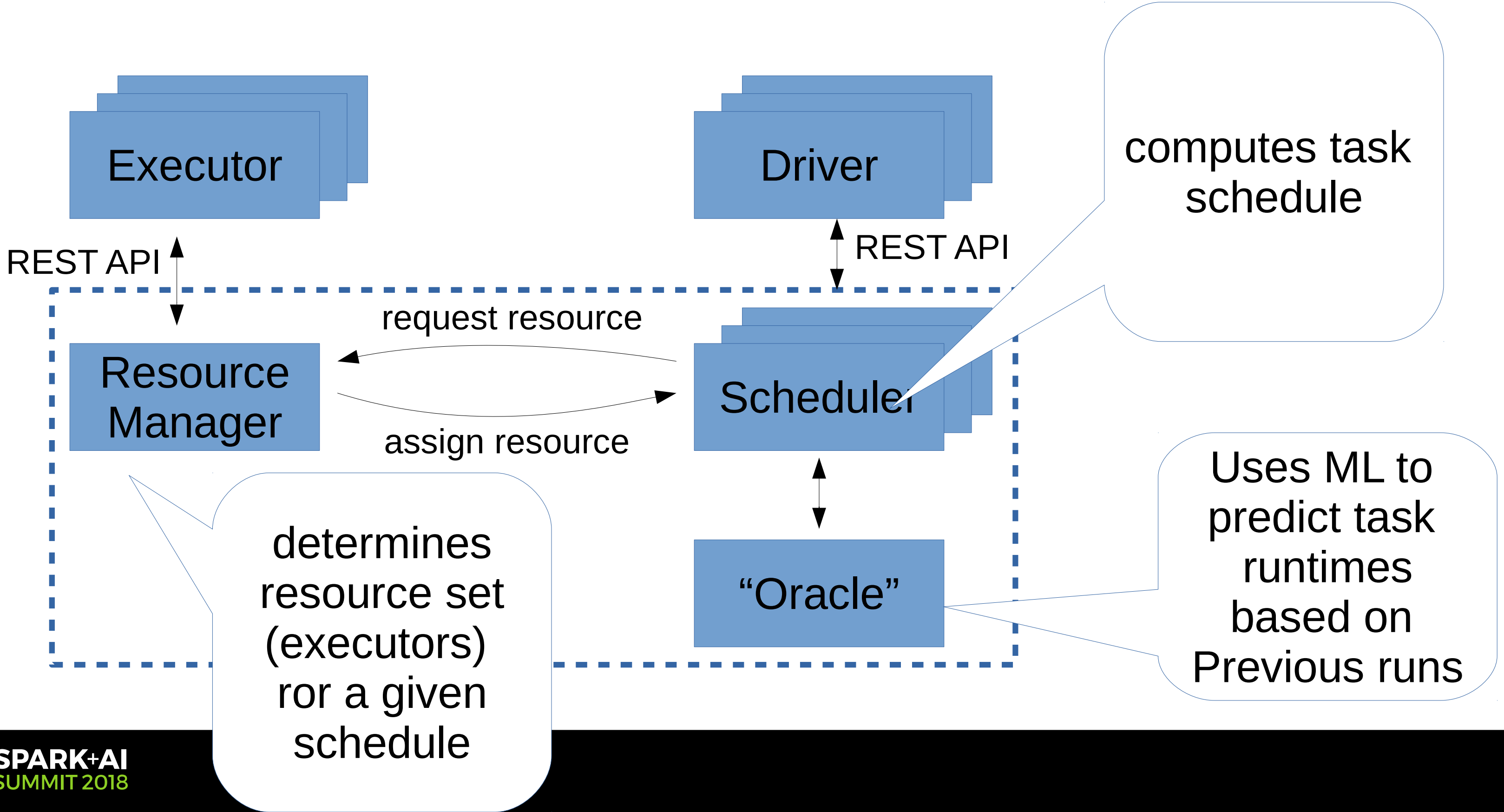
HCL Scheduler



HCL Scheduler

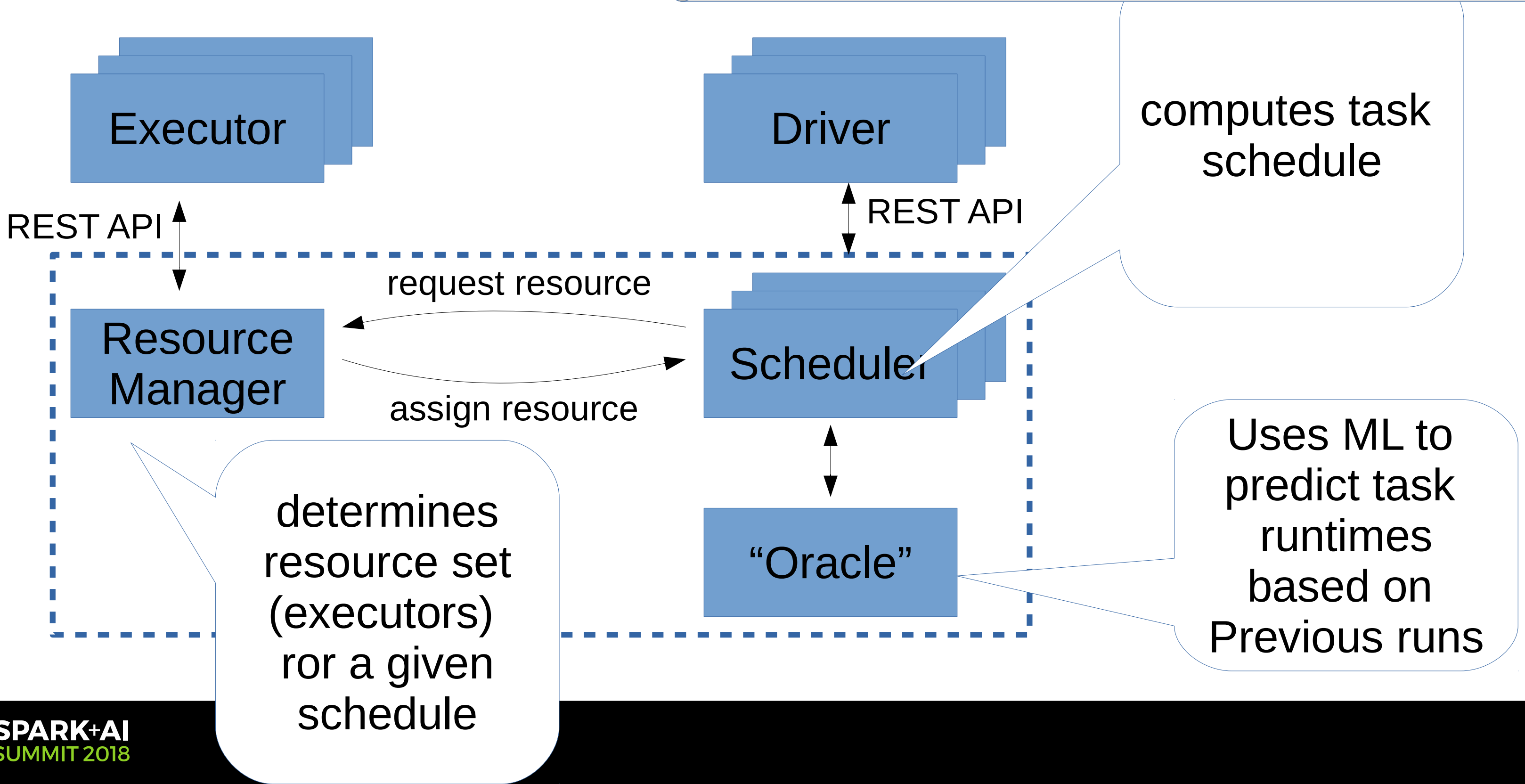


HCL Scheduler



HCL Scheduler

“The HCl Scheduler:
Going all-in on Heterogeneity”,
Michael Kaufmann et al., HotCloud’17



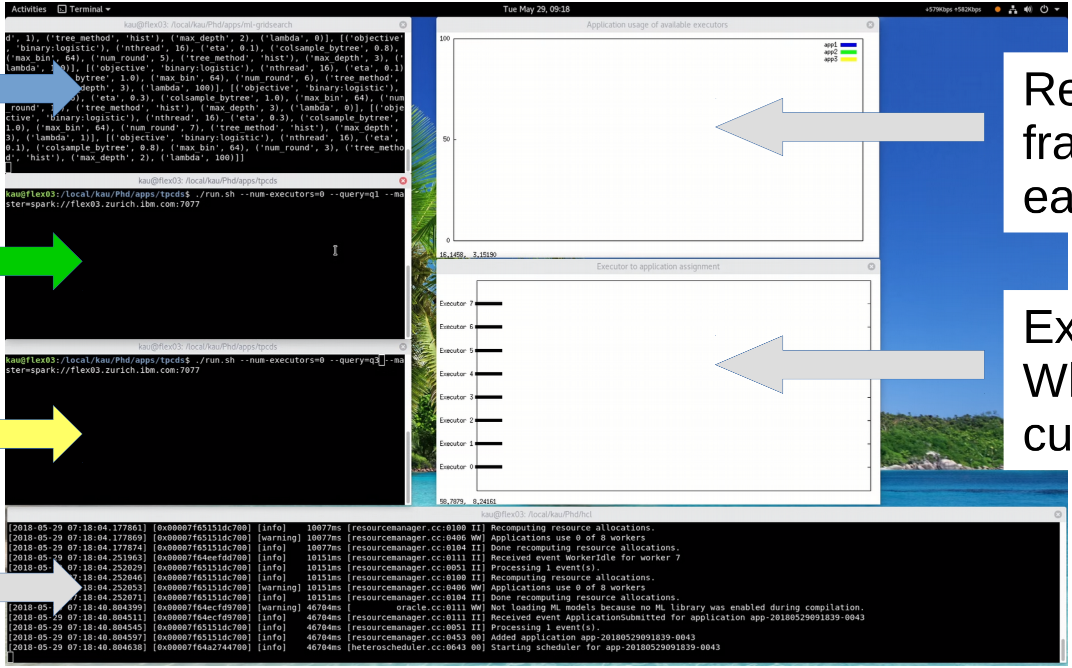
Video: Putting things together

Application 1:
GridSearch

Application 2:
SQL TPC-DS

Application 3:
SQL TPC-DS

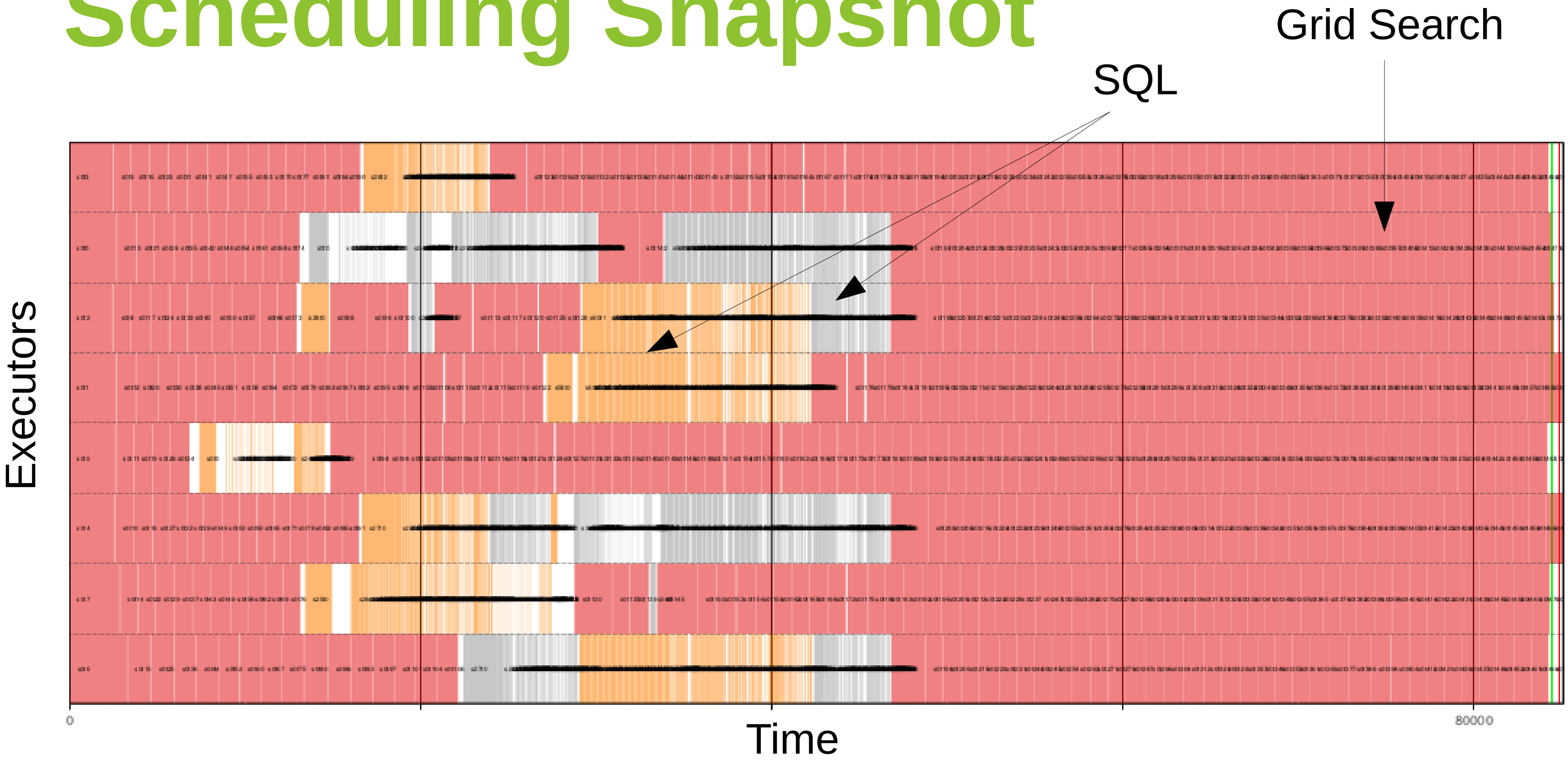
HCL
Scheduler



Resource view:
fraction of resources
each app consumes

Executor view:
Which app an executor
currently runs

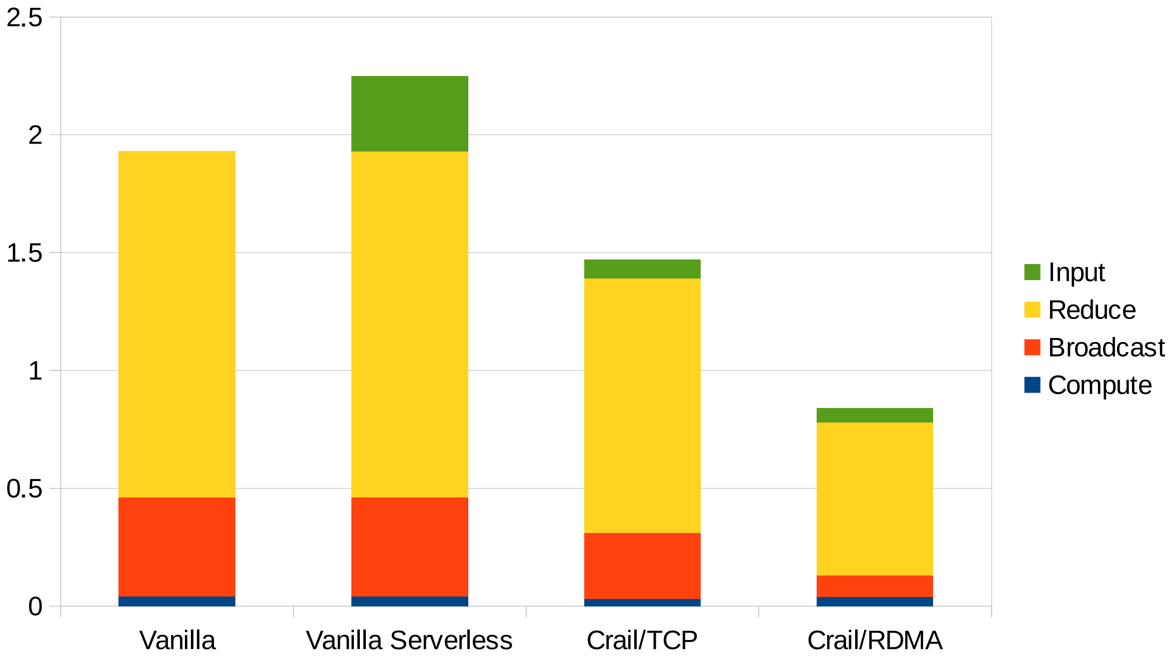
Scheduling Snapshot



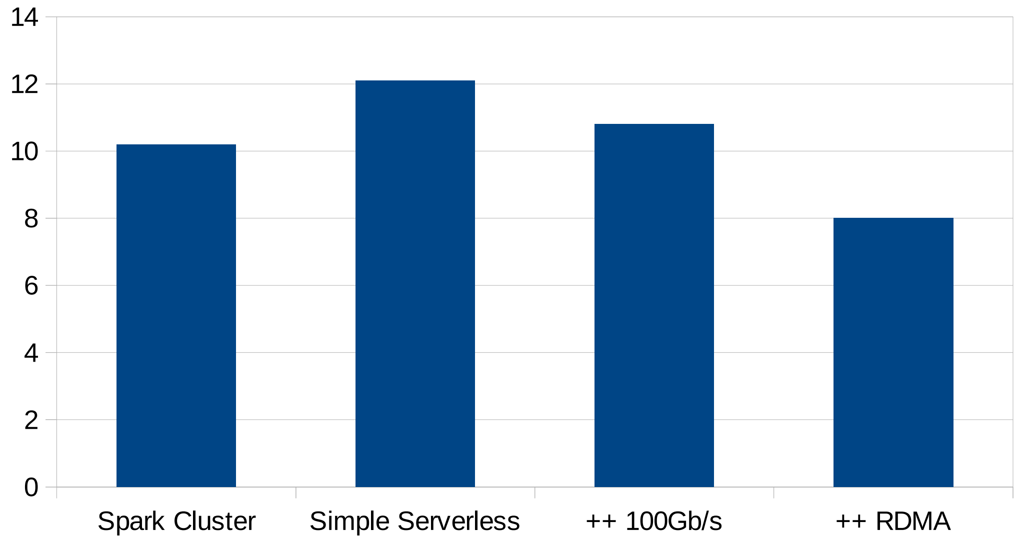
Let’s look at performance...

- Cluster size: 16 nodes
- Cluster hardware:
  - DRAM: 512 GB
  - Storage: 4x 1.2 TB NVMe SSD
  - Network: 10Gb/s Ethernert, 100Gb/s RoCE
- Workloads
  - ML: Linear Regression using the CoCoa framework
  - SQL: TCP-DS

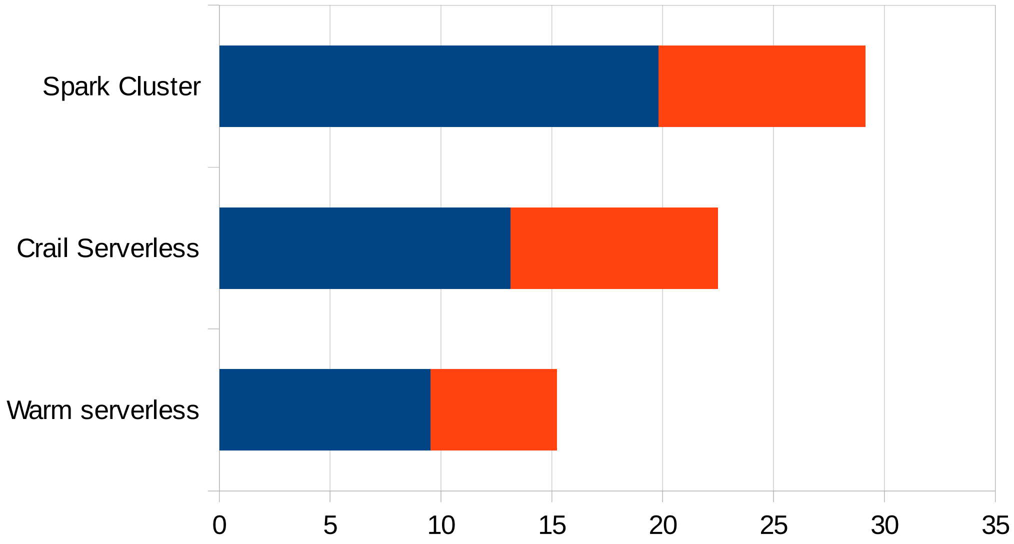
ML: Linear Regression



Long running SQL query



TPC-DS: Query #3



Conclusion

- Efficient serverless computing is challenging
  - Local state (e.g. shuffle, cached input, network state) is lost as compute cloud scales up/down
- This talk: turning Spark into a serverless framework by
  - Implementing a new serverless scheduler
  - Consequently storing compute state remotely using Apache Crail
- Supports arbitrary Spark workloads with almost no performance ovherhad
  - MapReduce, SQL, Iterative Machine Learning
- Implicit support for fast network and storage hardware
  - e.g, RDMA, NVMe

Future Work

- Containerize the platform
- Add support for dynamic re-partitioning on scale events
- Add support for automatic caching
- Add more sophisticated scheduling policies

Links

- Containerize the platform
- Add support for dynamic re-partitioning on scale events
- Add support for automatic caching
- Add more sophisticated scheduling policies

Thanks to

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