

Serverless Machine Learning on Modern Hardware

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IBM Research

#Res6SAIS

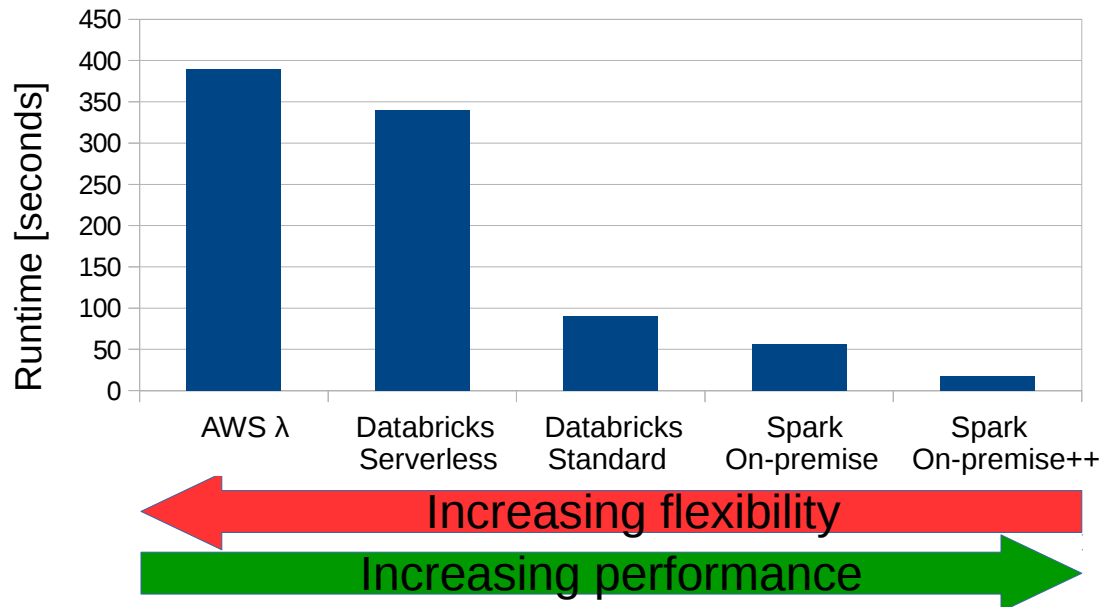
Serverless Computing



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

Challenge: Performance

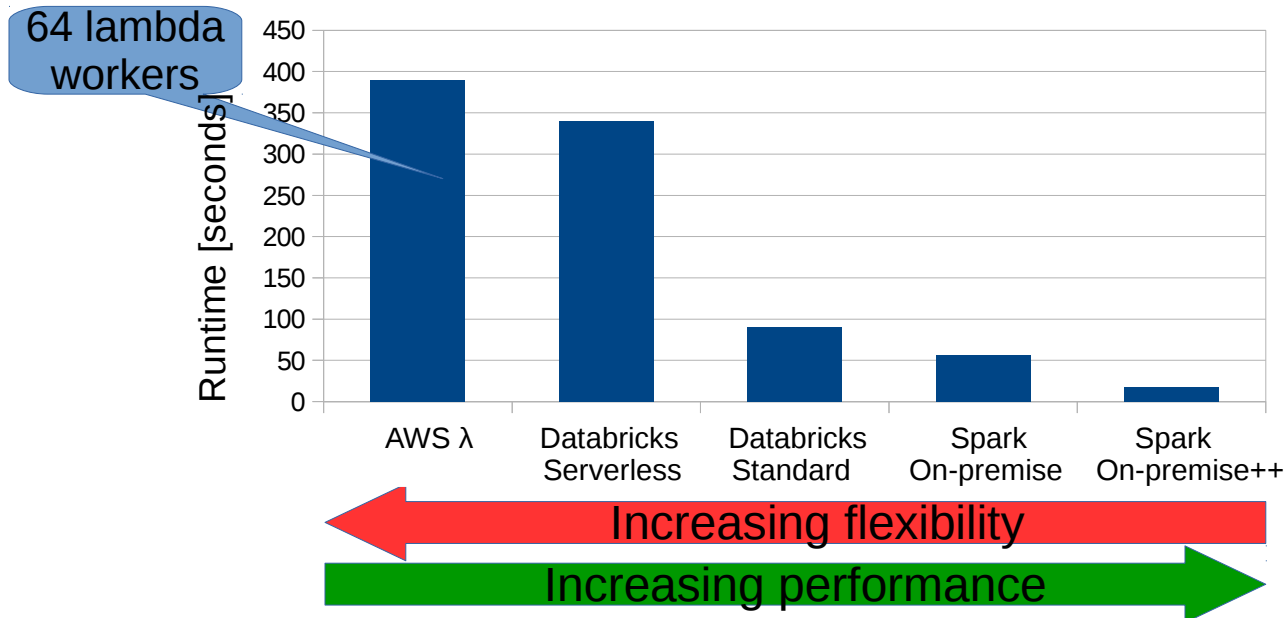
Example:
Sorting 100GB



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

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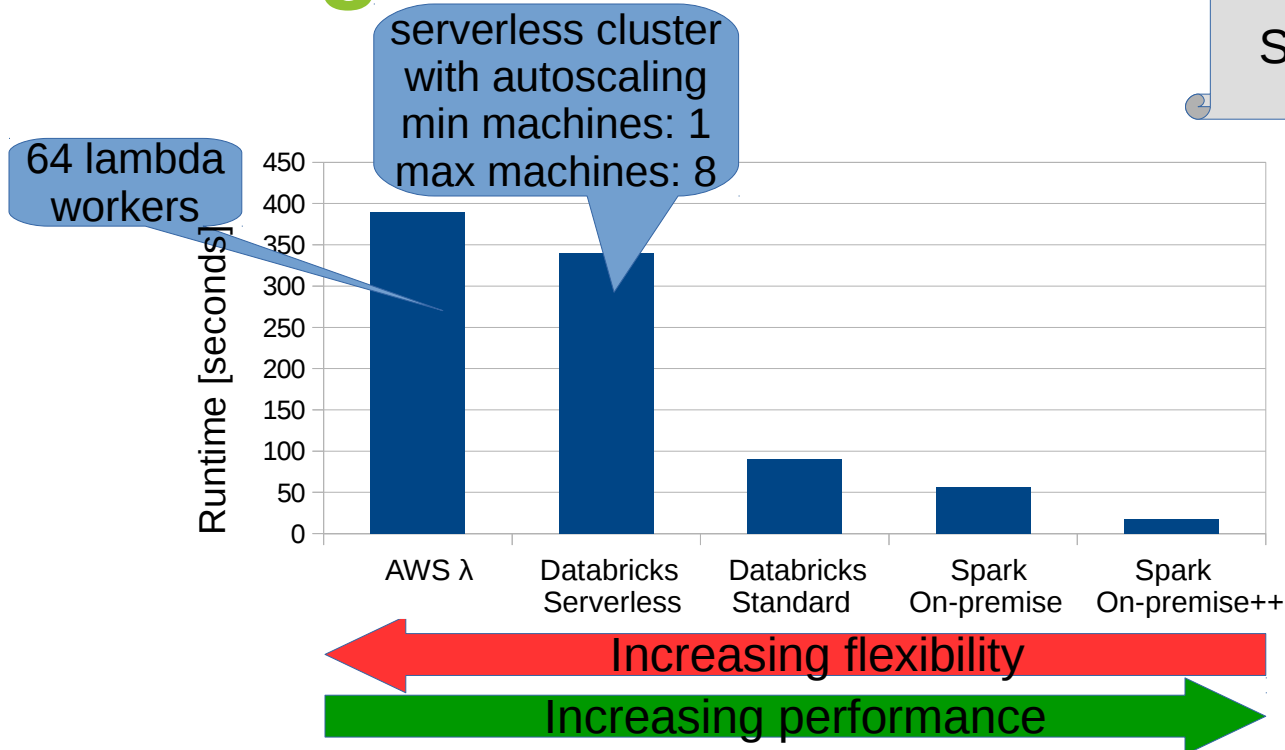
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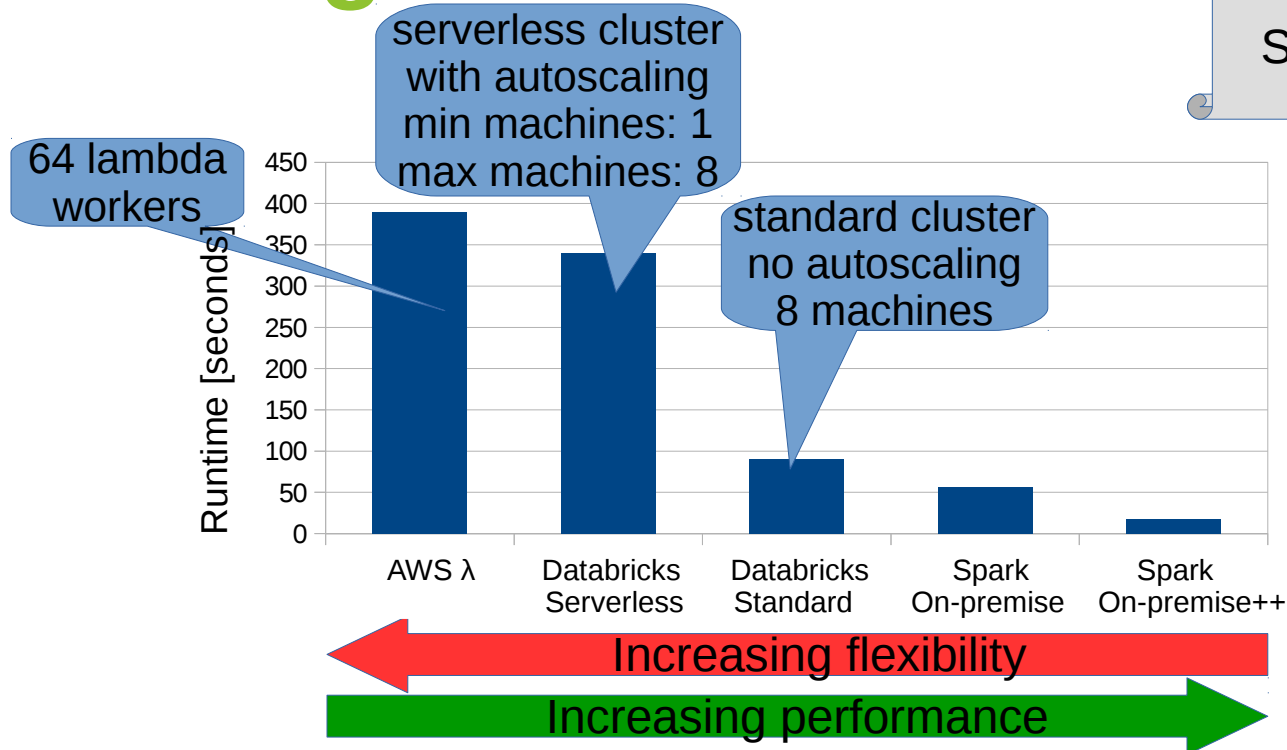
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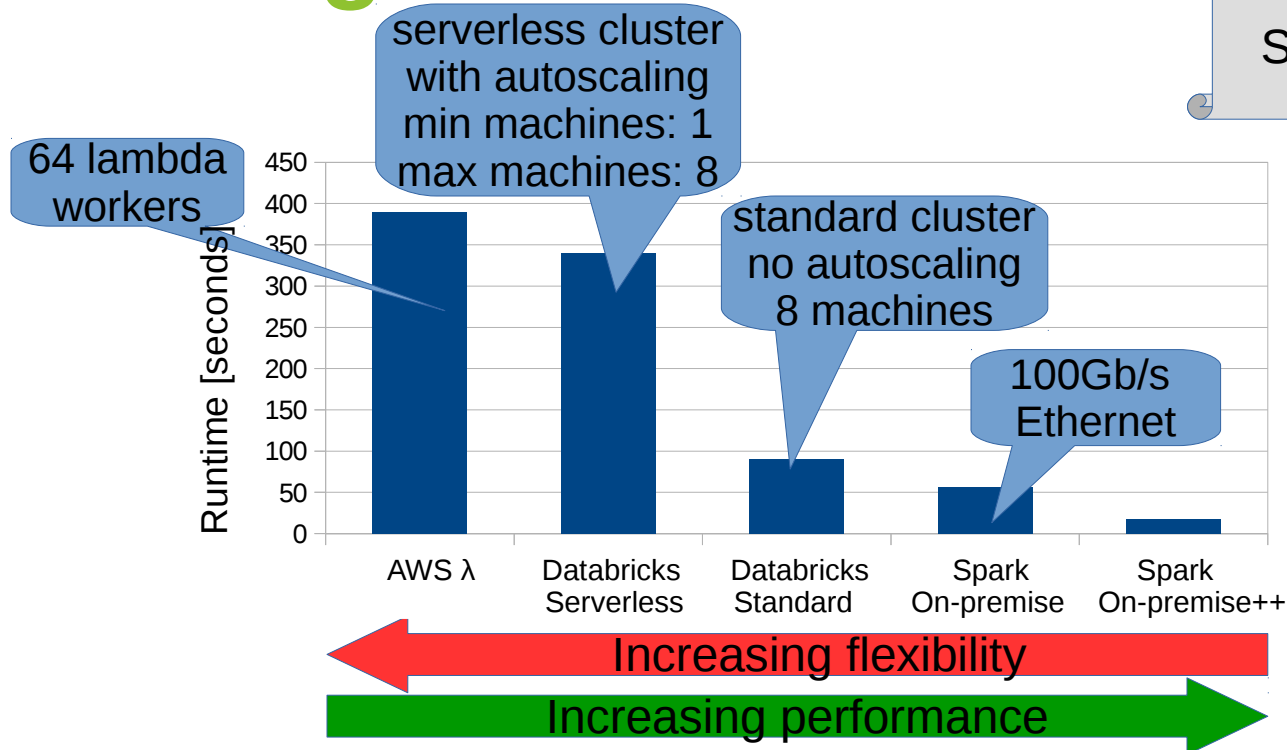
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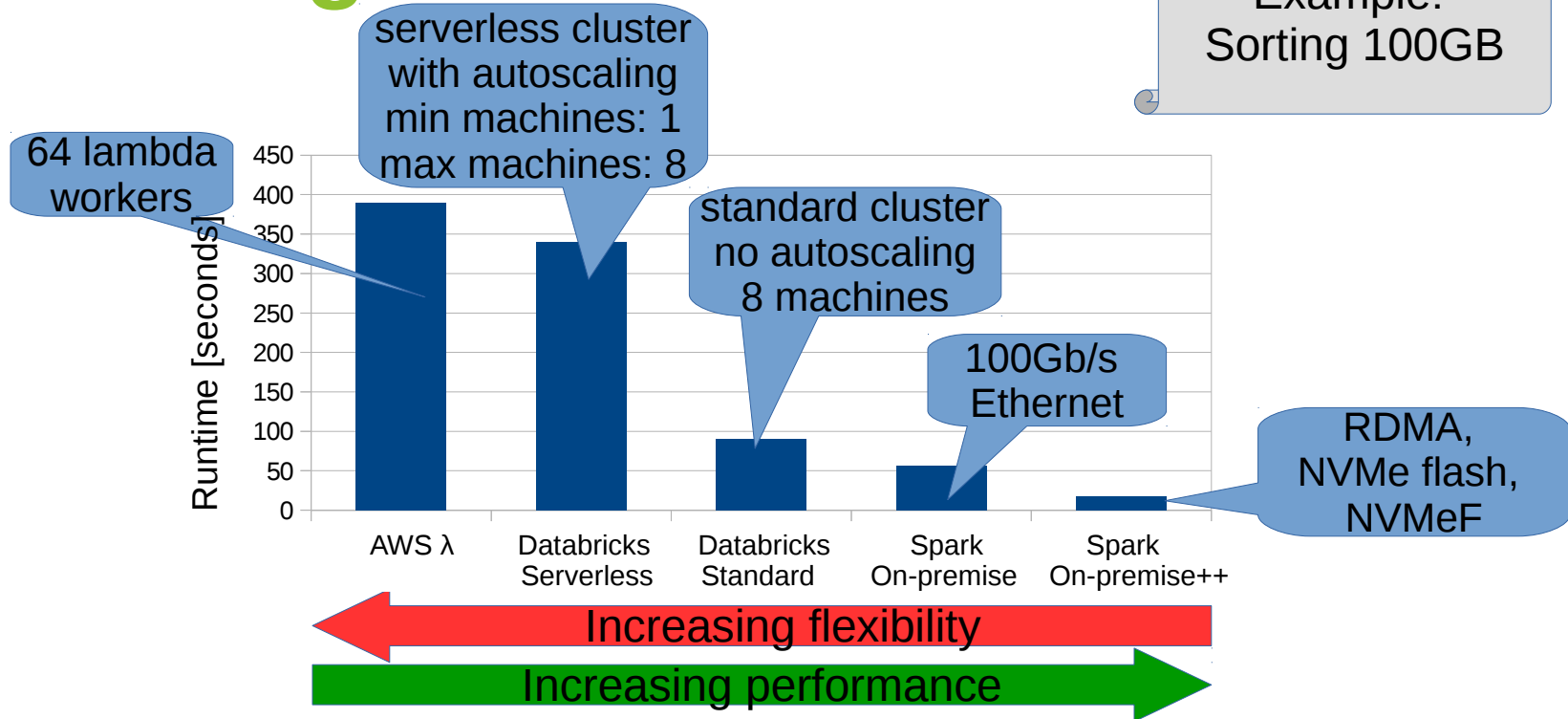
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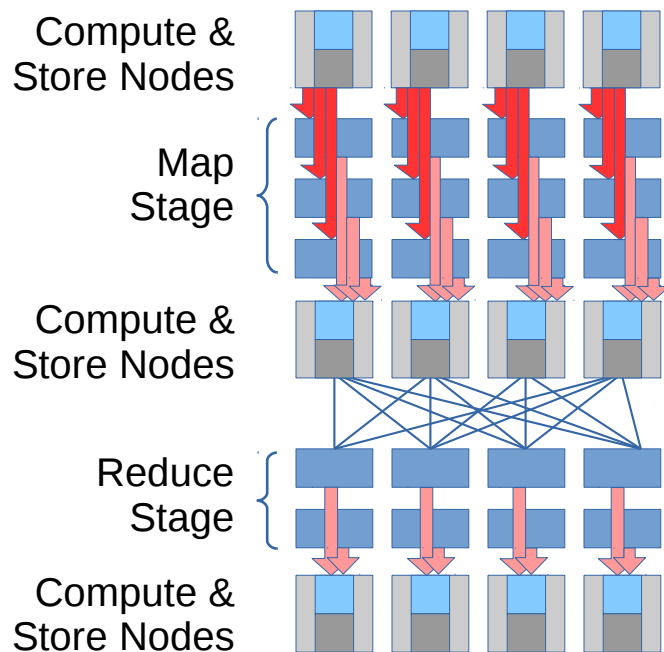
Why is it so hard?

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

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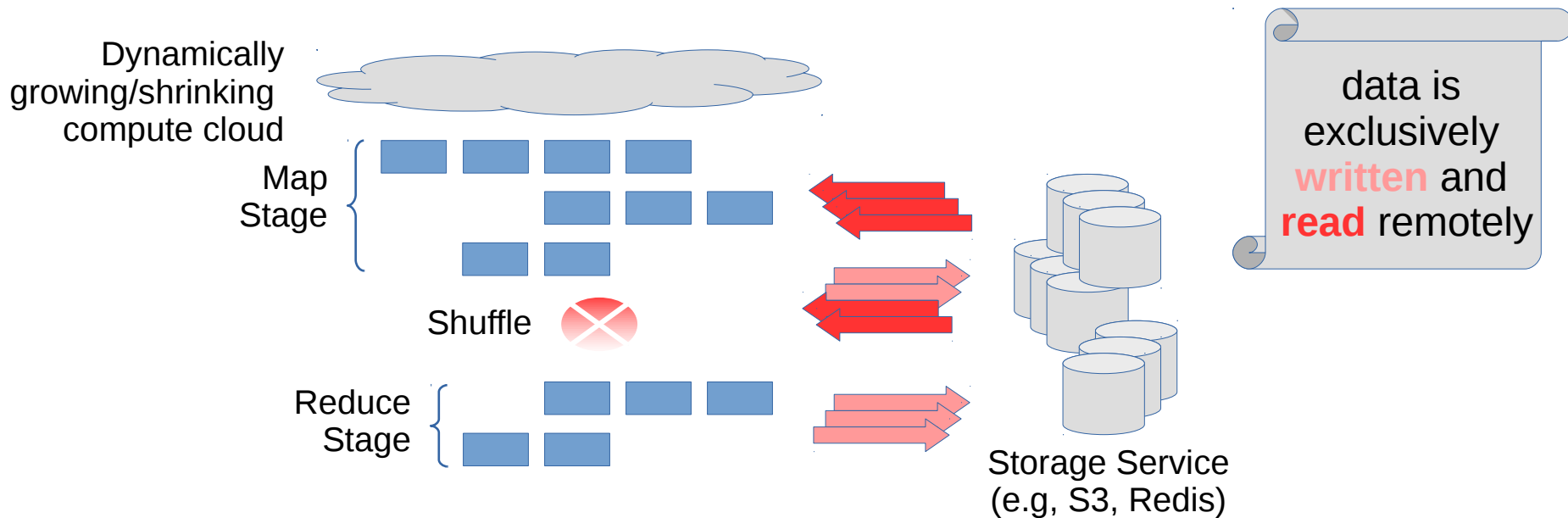
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Example: MapReduce (Cluster)

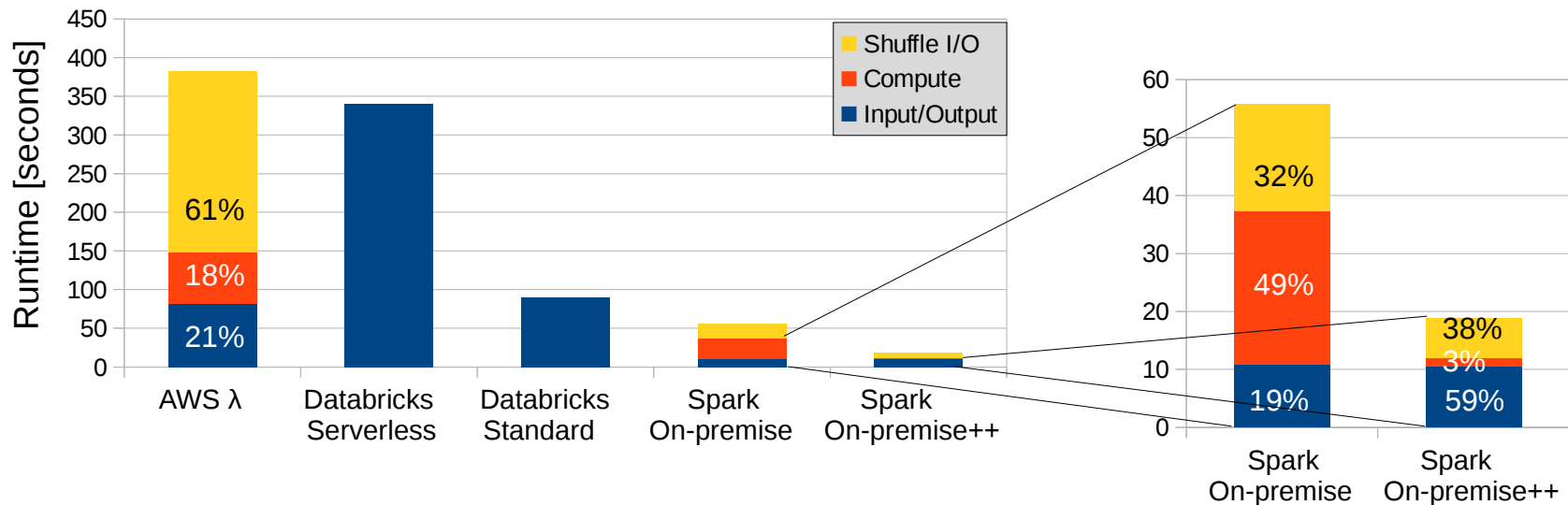


data is mostly
written and
read locally

Example: MapReduce (Serverless)



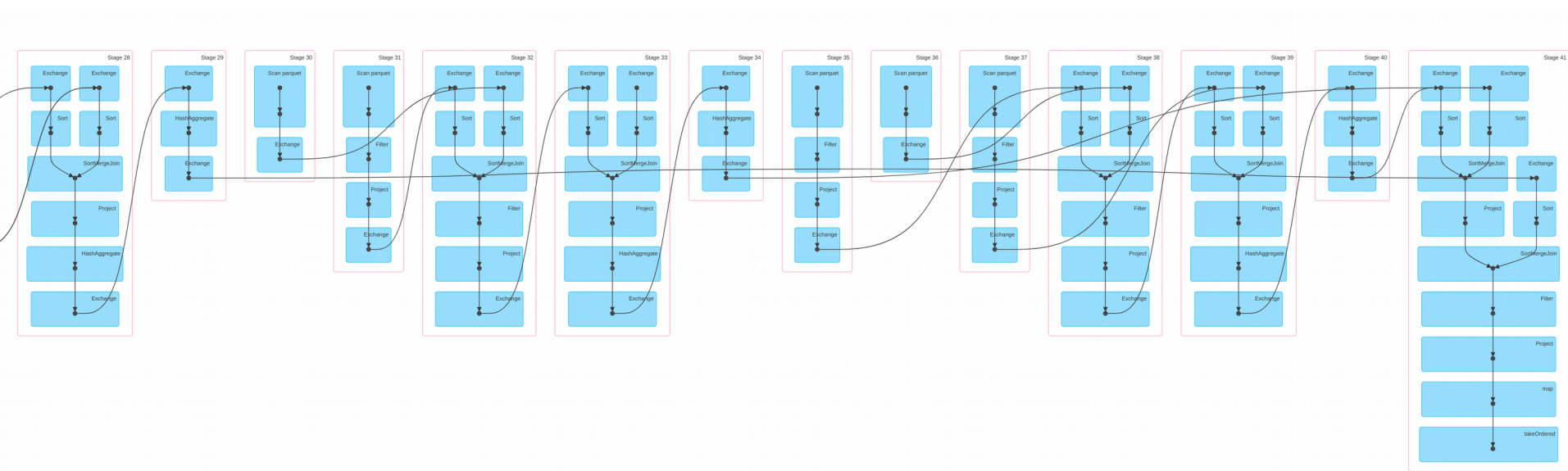
I/O Overhead: Sorting 100GB



Shuffle overheads are significantly higher when intermediate data is stored remotely

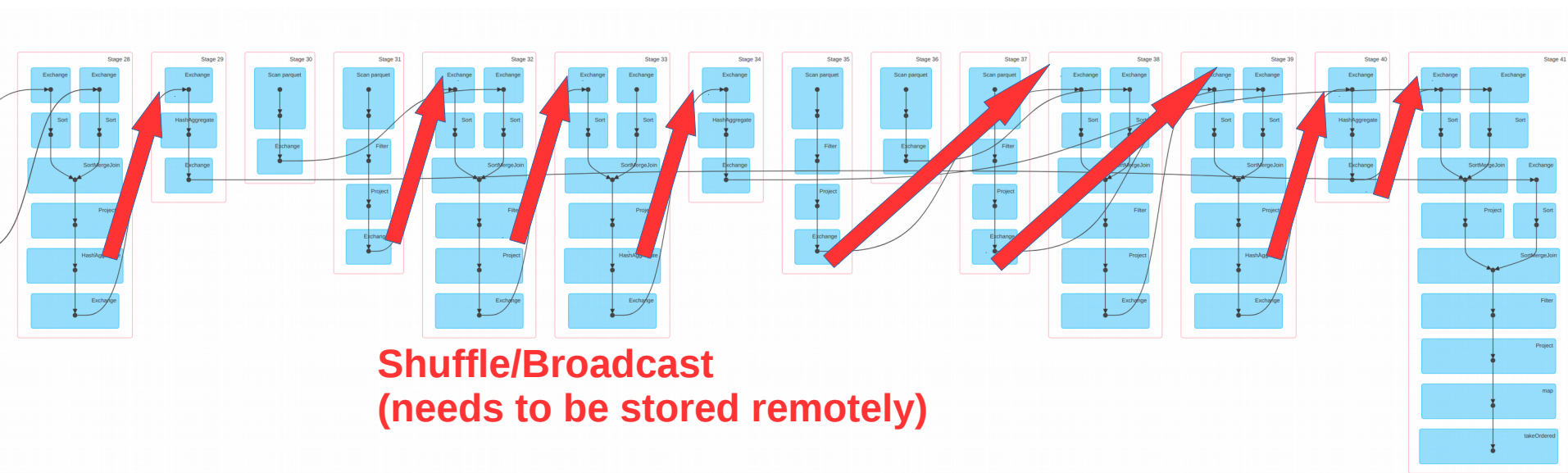
What about other workloads?

Example: SQL, Query 77 / TPC-DS benchmark



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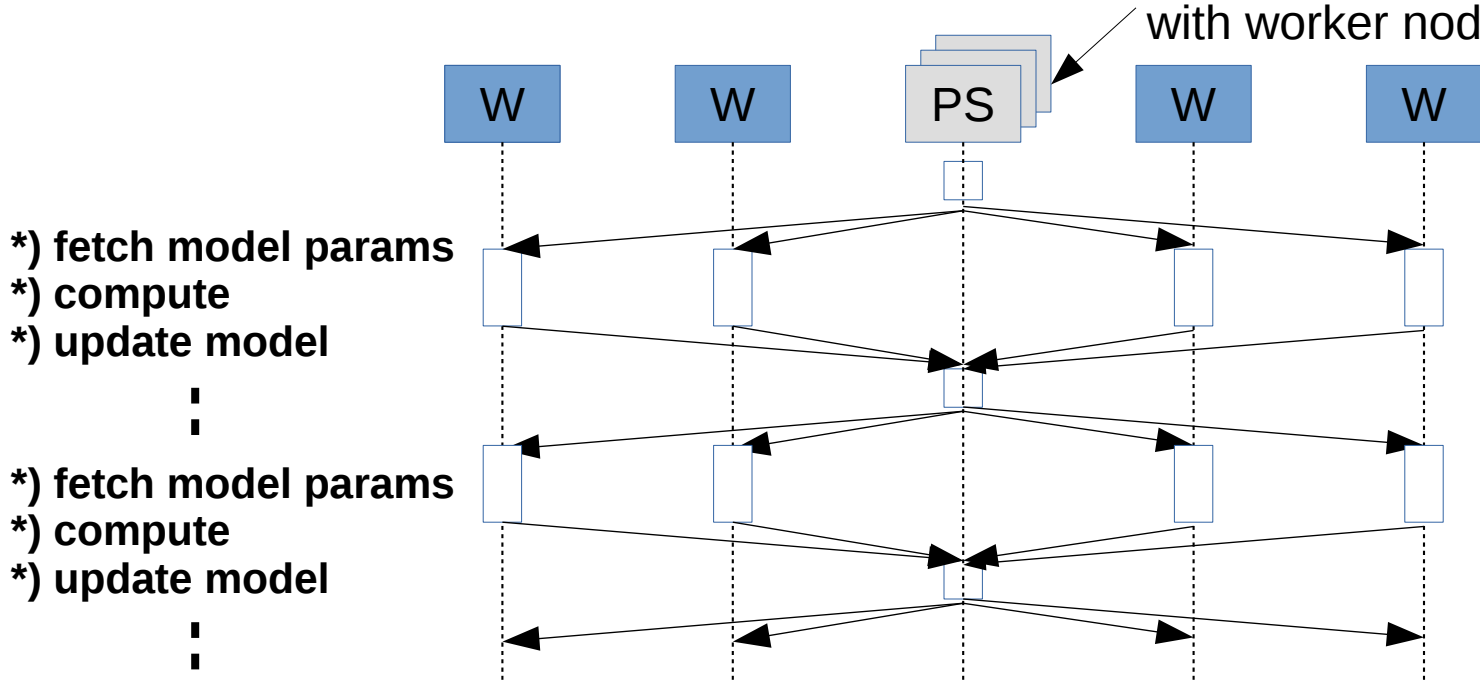
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What about other workloads?

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

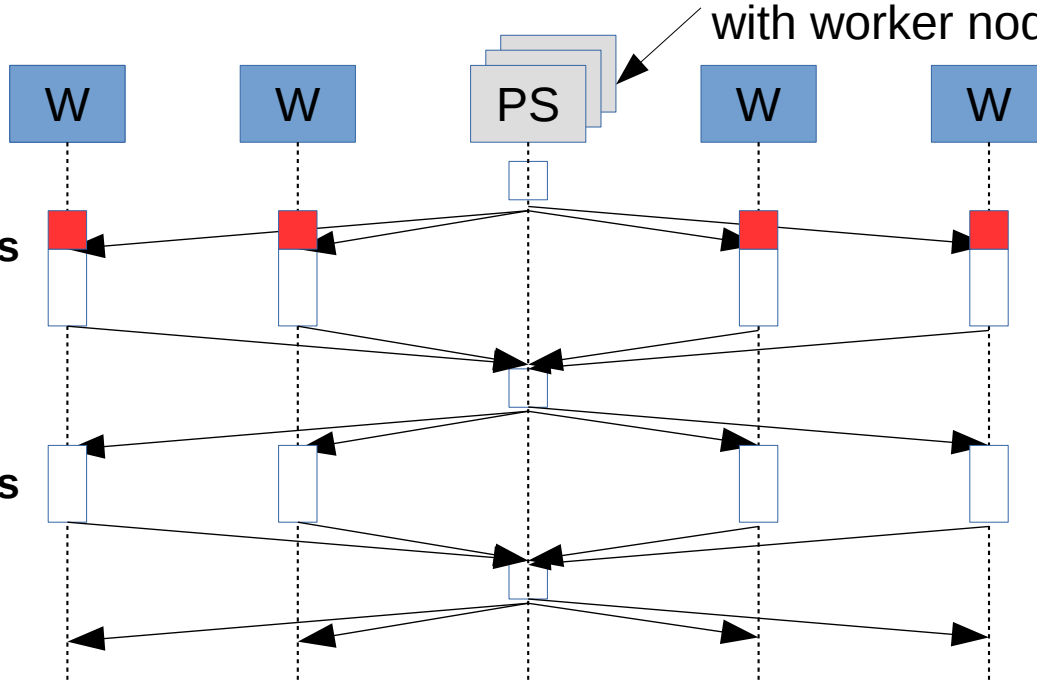
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What about other workloads?

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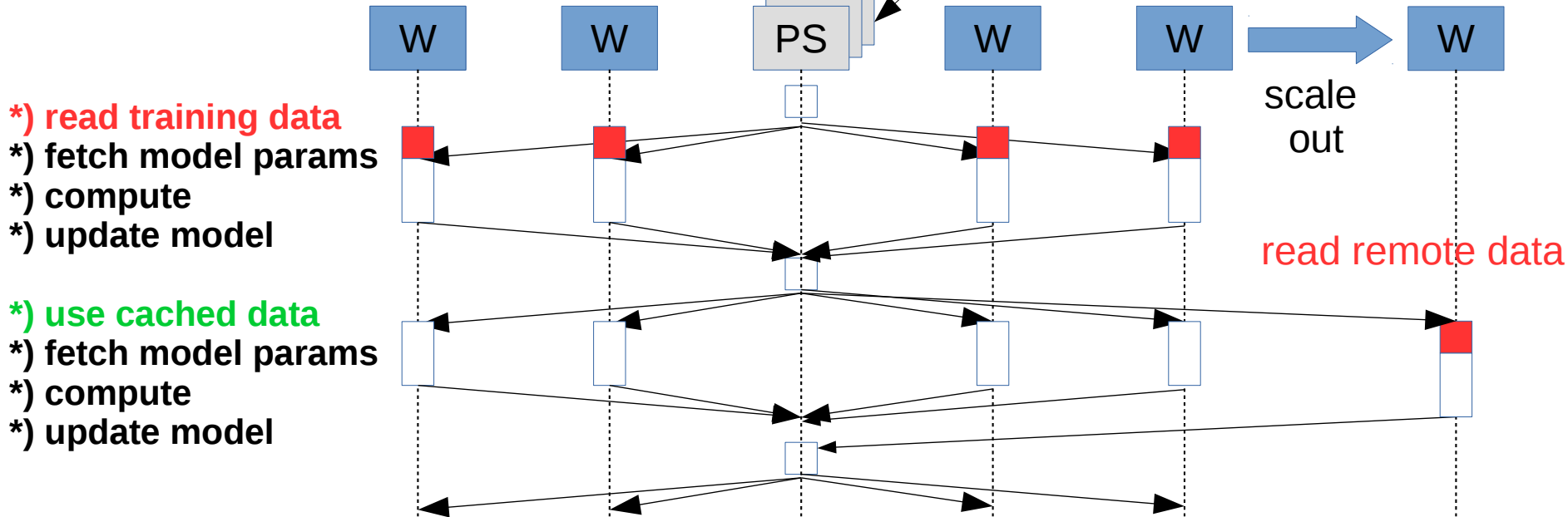
- *) read training data**
- *) fetch model params**
- *) compute**
- *) update model**

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

What about other workloads?

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

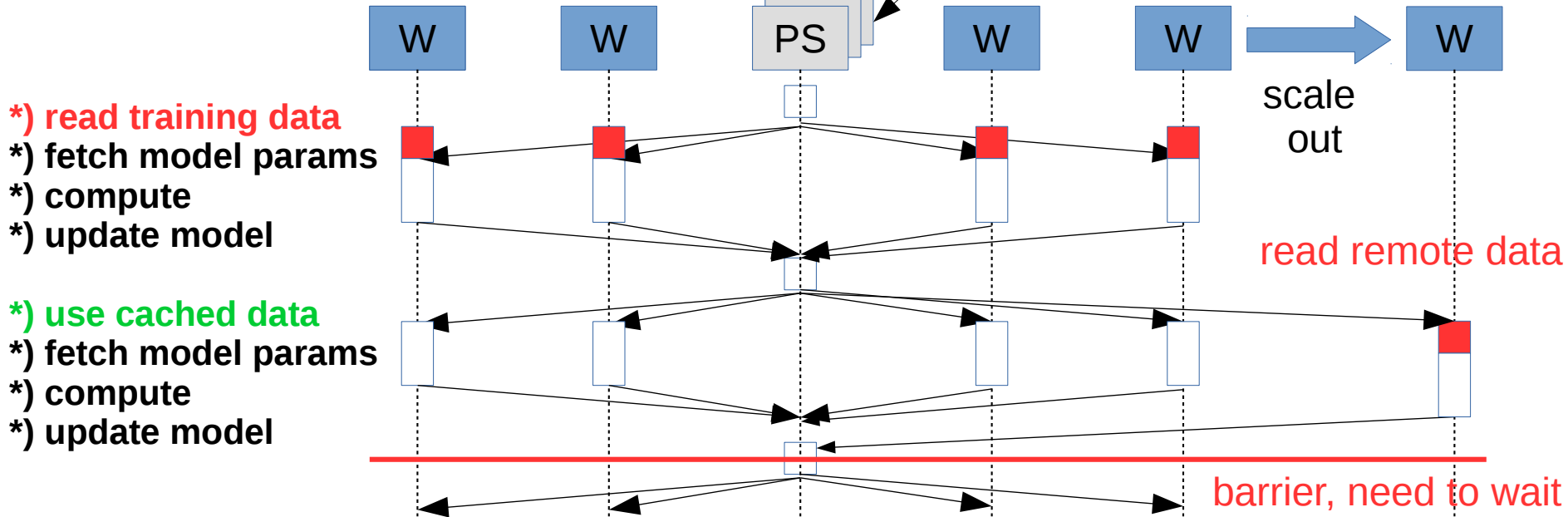
~~could be co-located
with worker nodes~~ Needs to be
remote



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

~~could be co-located with worker nodes~~ Needs to be remote



Can we..

- ..use Spark to run such workloads in a serverless fashion?
 - Dynamic scaling of compute nodes while jobs are running
 - No cluster configuration
 - No startup time overhead
- ..eliminate the performance overheads?
 - Workloads should run as fast as on a dedicated cluster

Design Options

- **Scheduling:**

- 1 Use serverless framework to schedule executors
- 2 Use serverless framework to schedule tasks
- 3 Enable sharing of executors among different applications

- **Intermediate data:**

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

Design Options

- **Scheduling:**

High startup
Latency!

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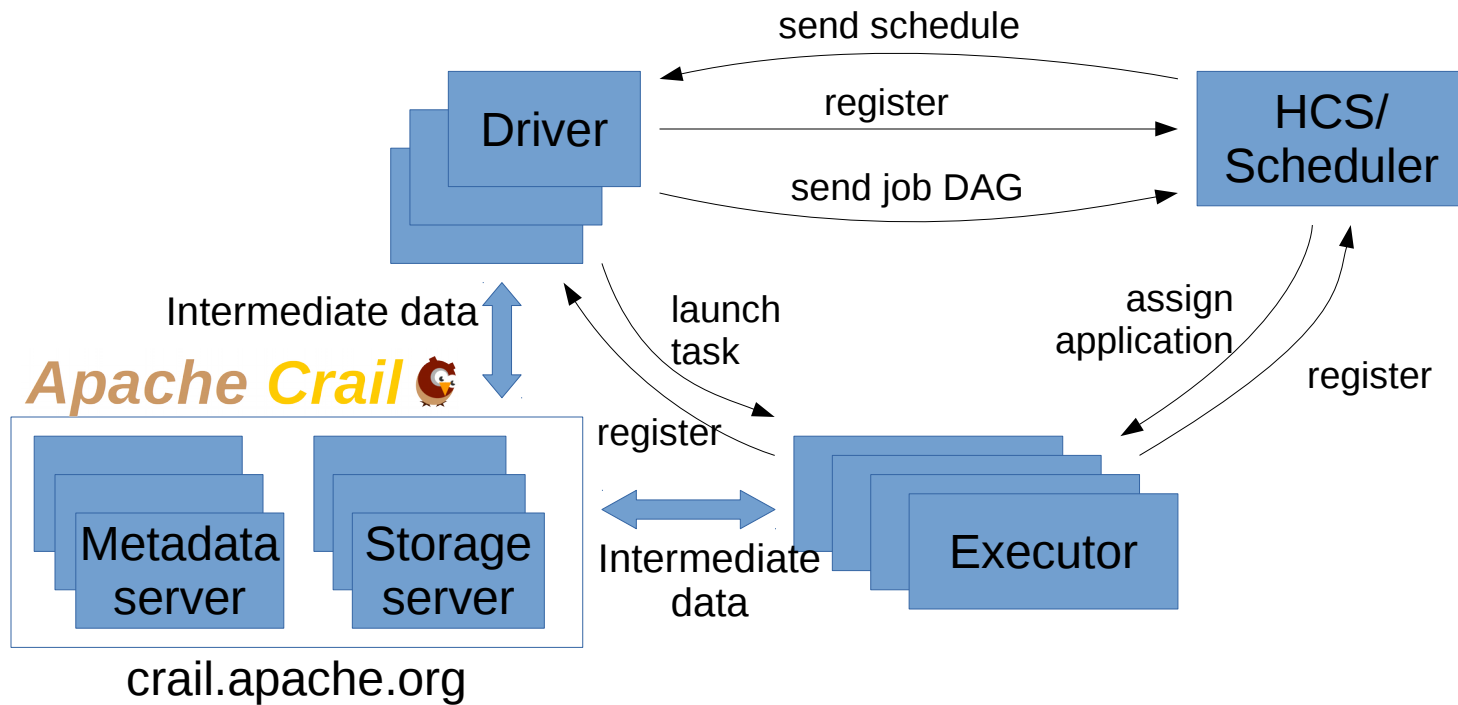
Slow!

- **Intermediate data:**

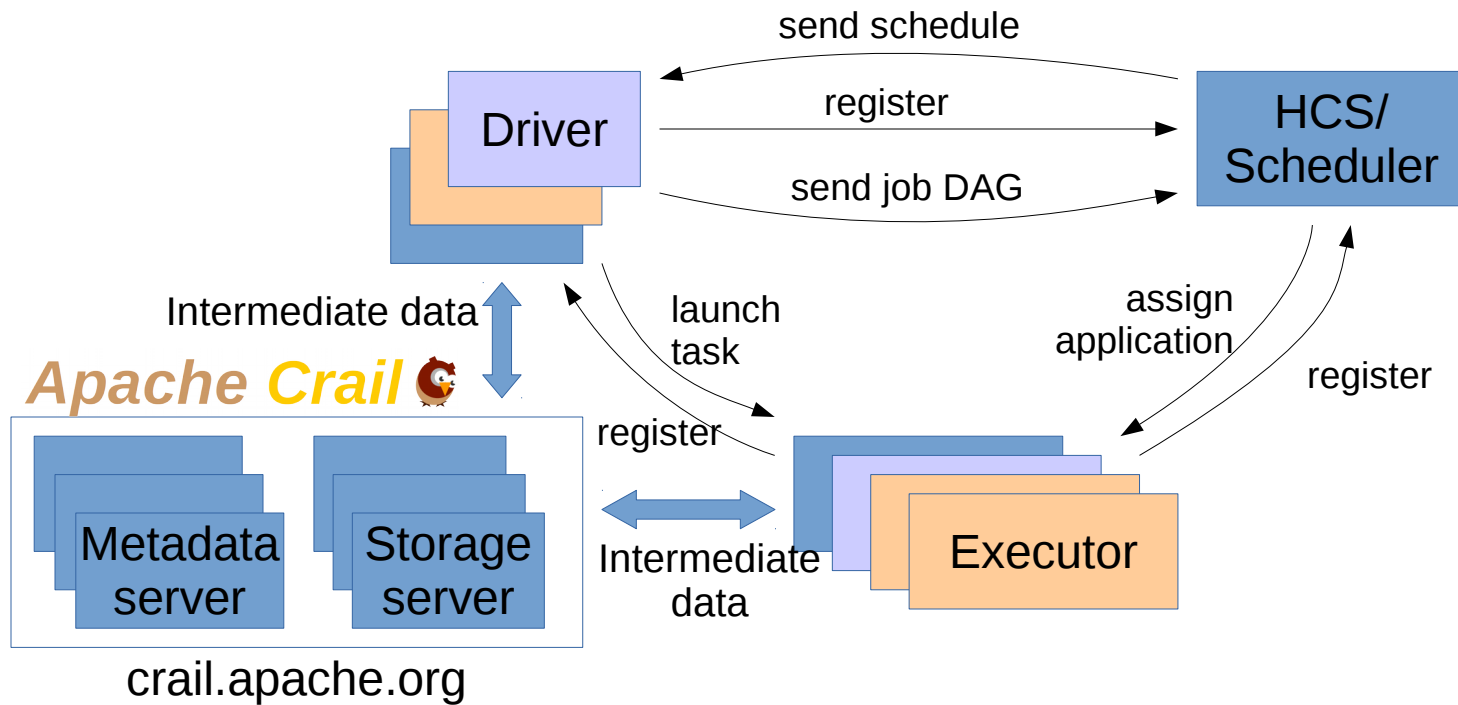
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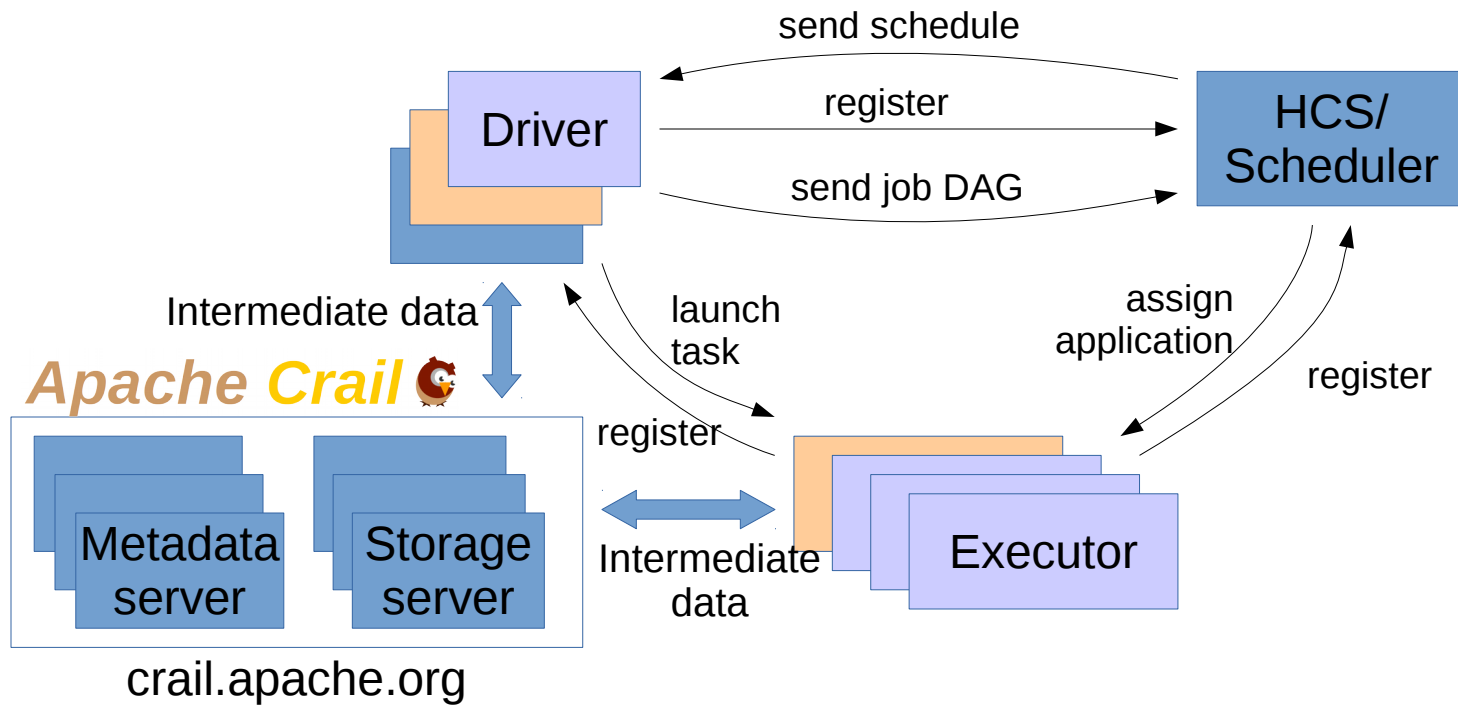
Architecture Overview



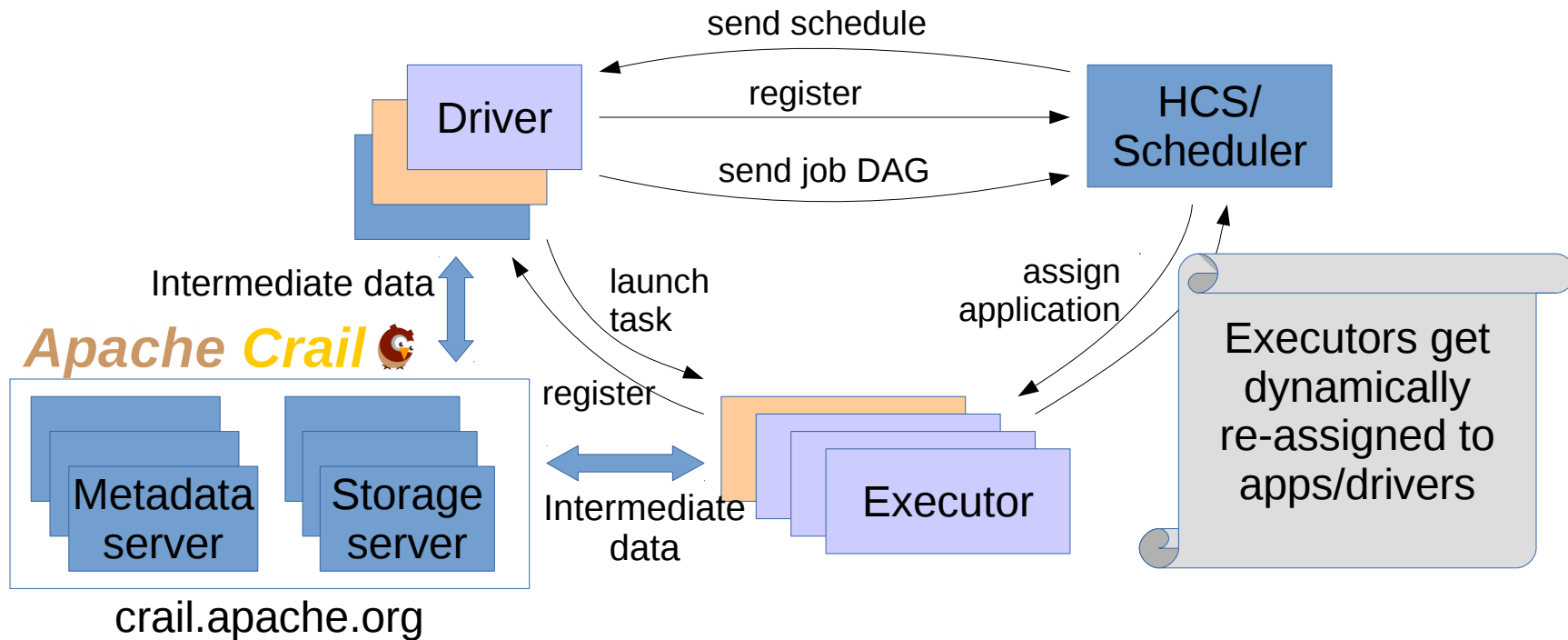
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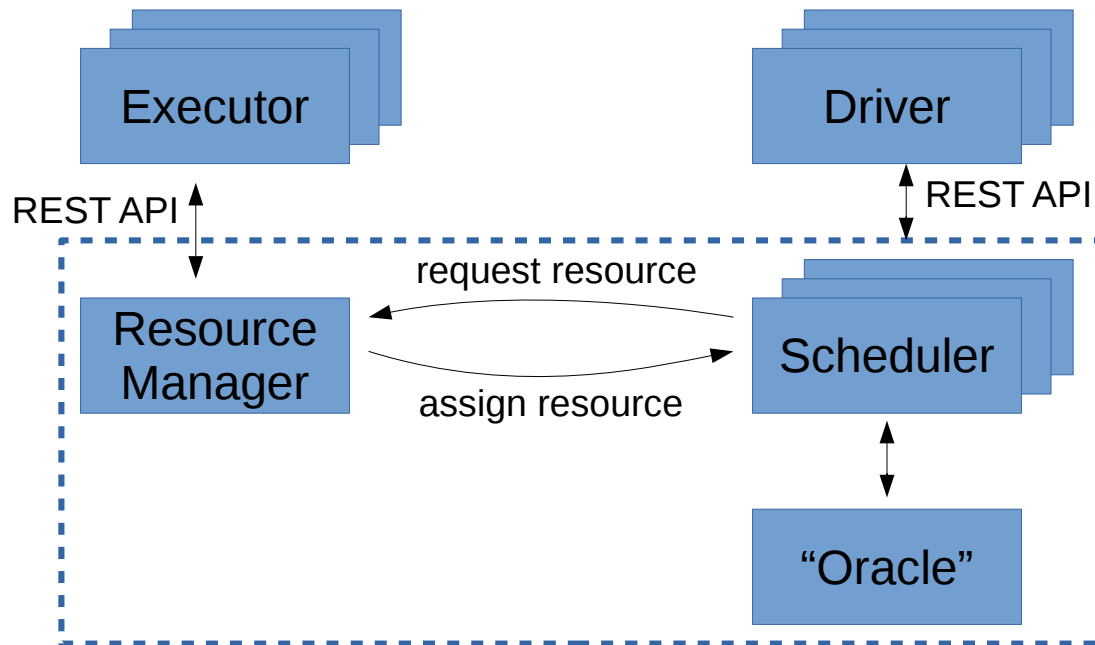
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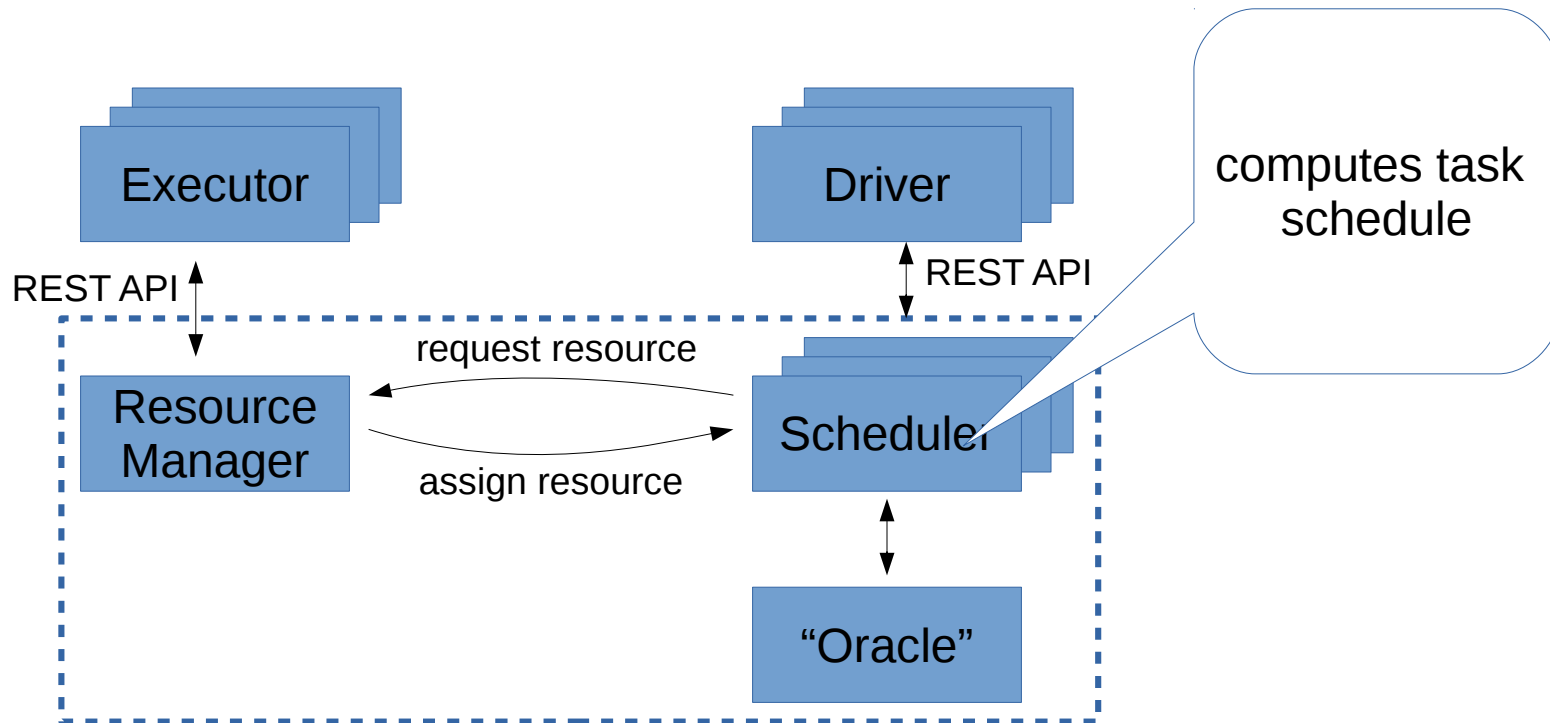
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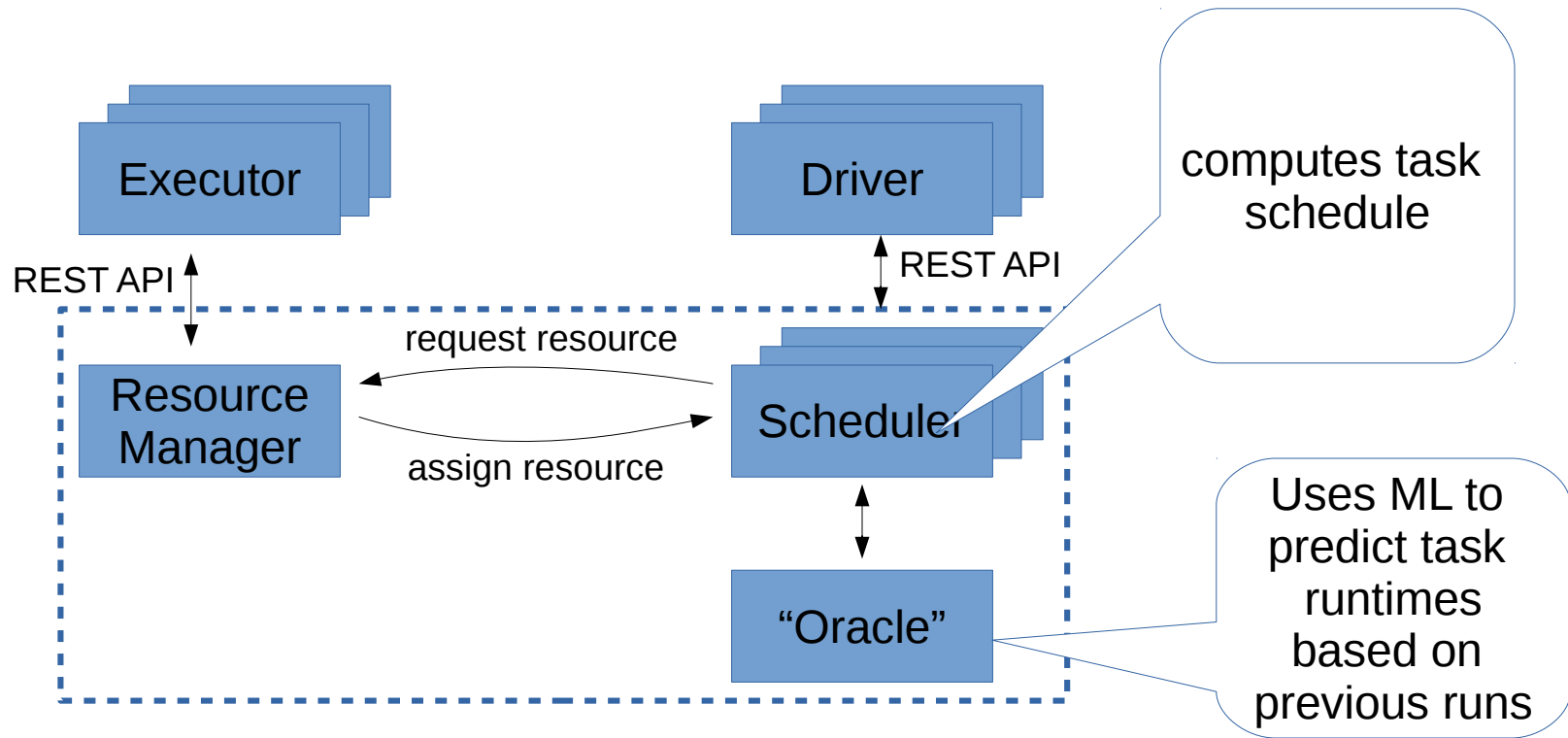
HCS Scheduler



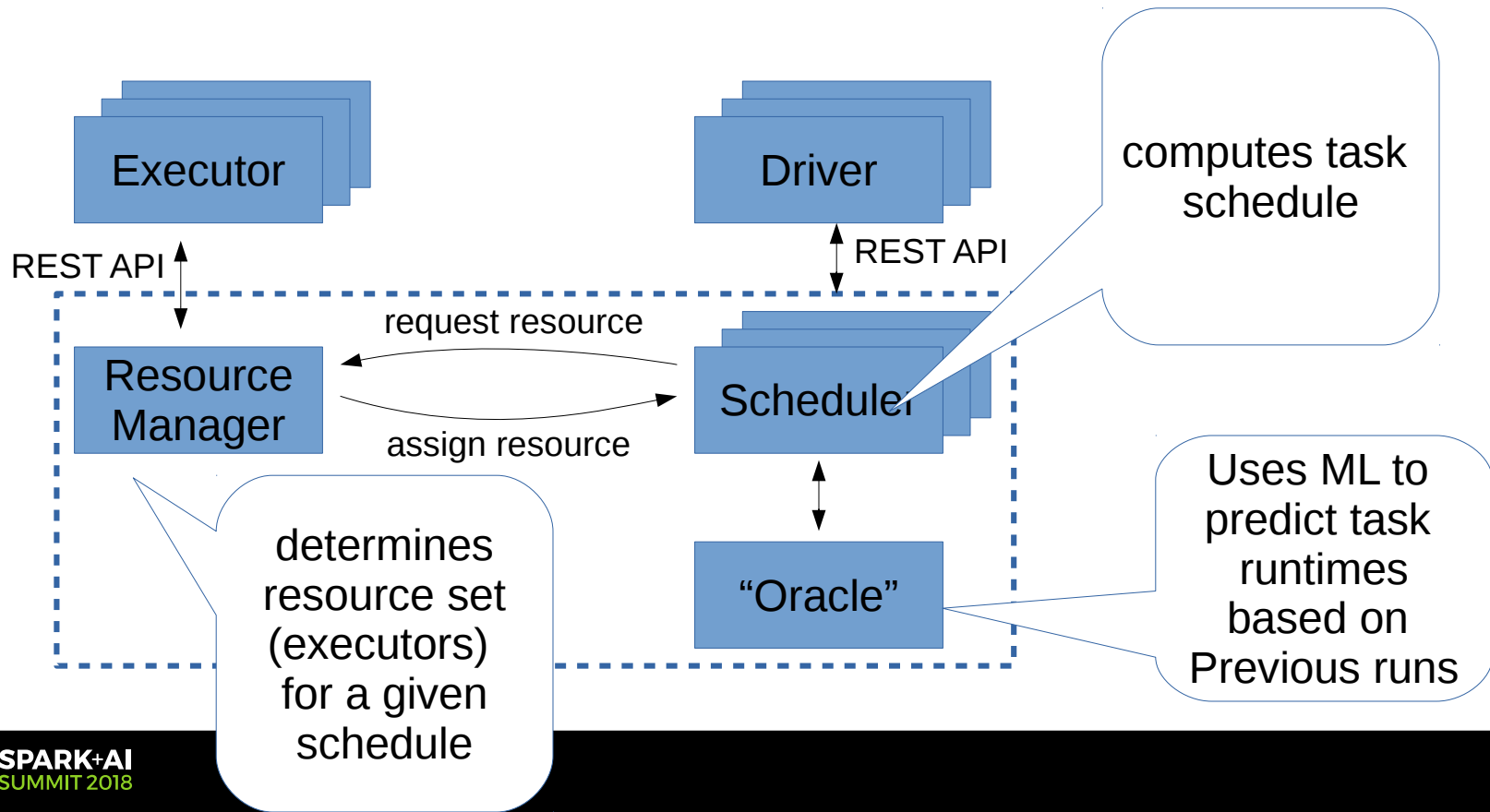
HCS Scheduler



HCS Scheduler

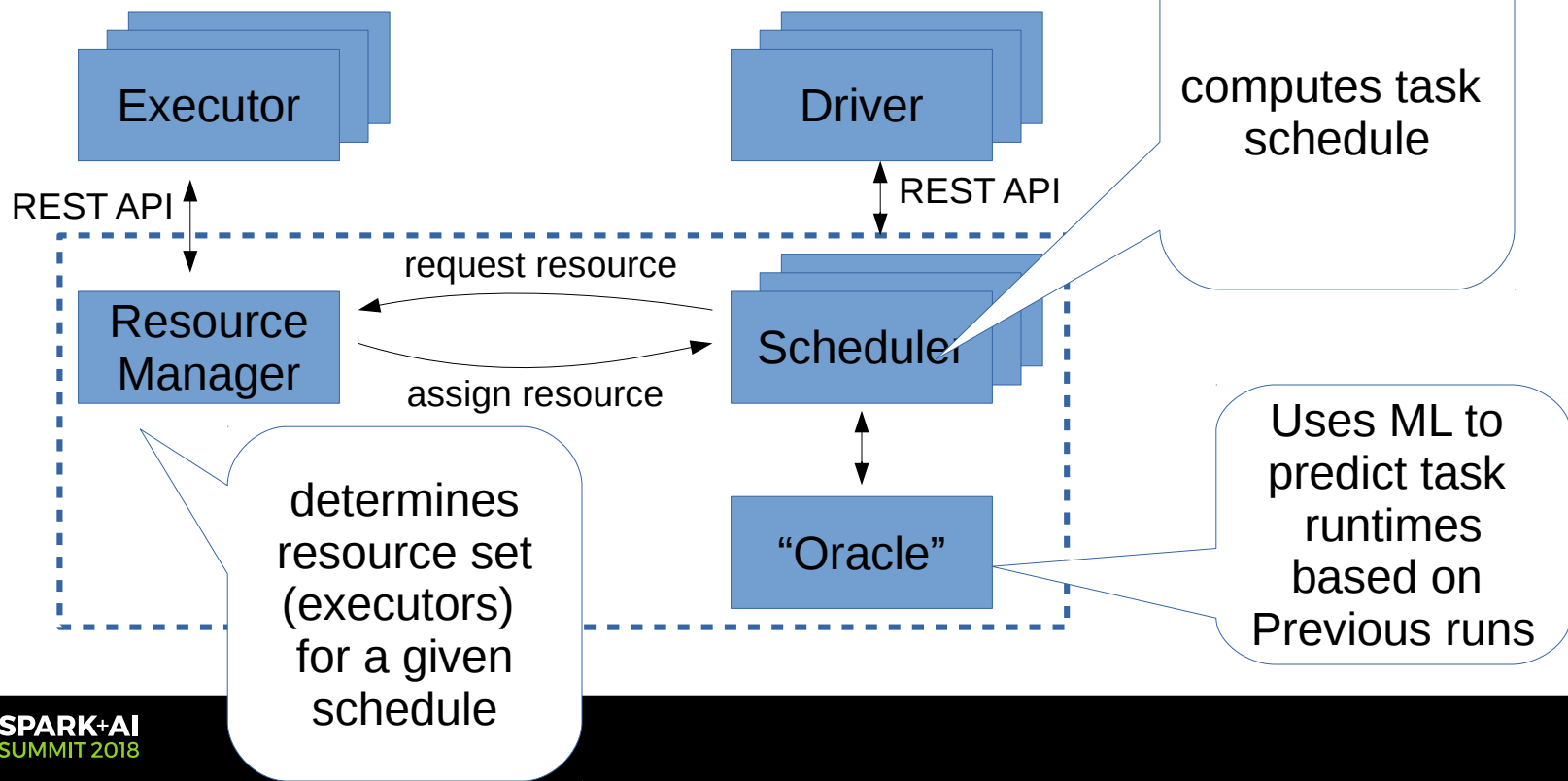


HCS Scheduler



HCS Scheduler

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



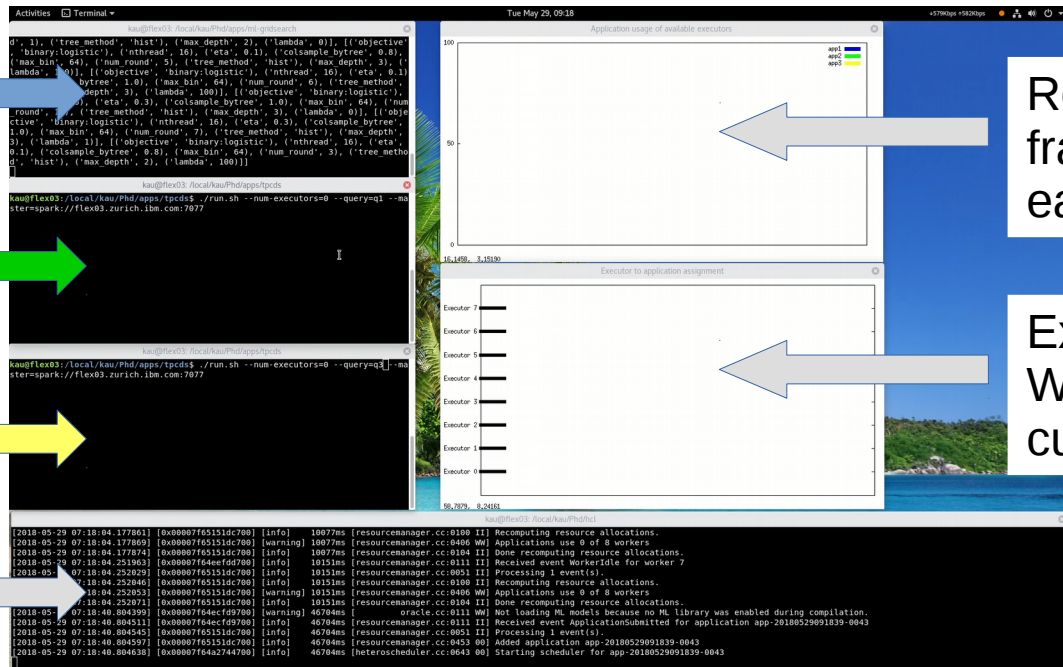
Video: Putting things together

Application 1:
GridSearch

Application 2:
SQL TPC-DS

Application 3:
SQL TPC-DS

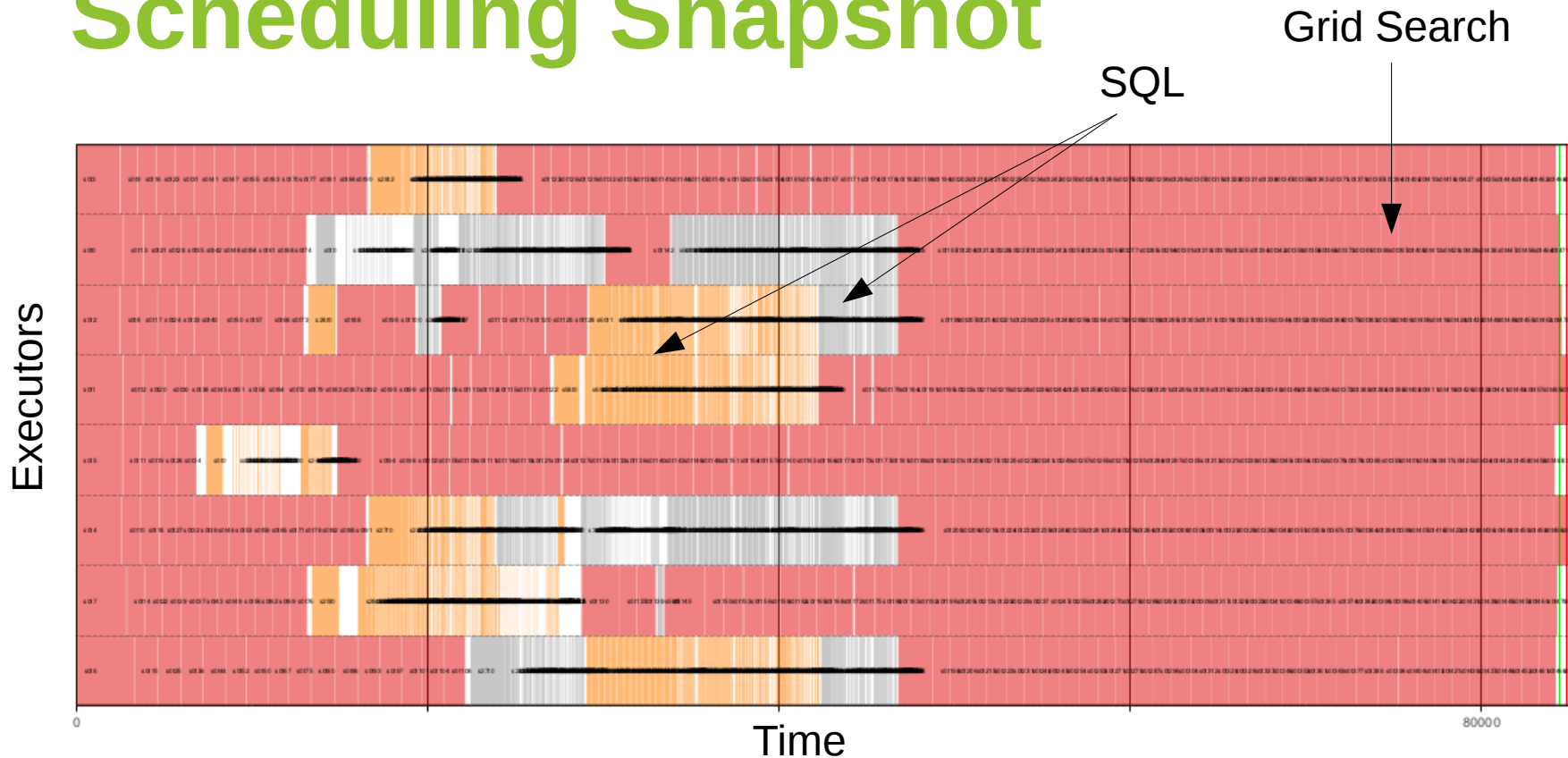
HCL
Scheduler



Resource view:
fraction of resources
each app consumes

Executor view:
Which app an executor
currently runs

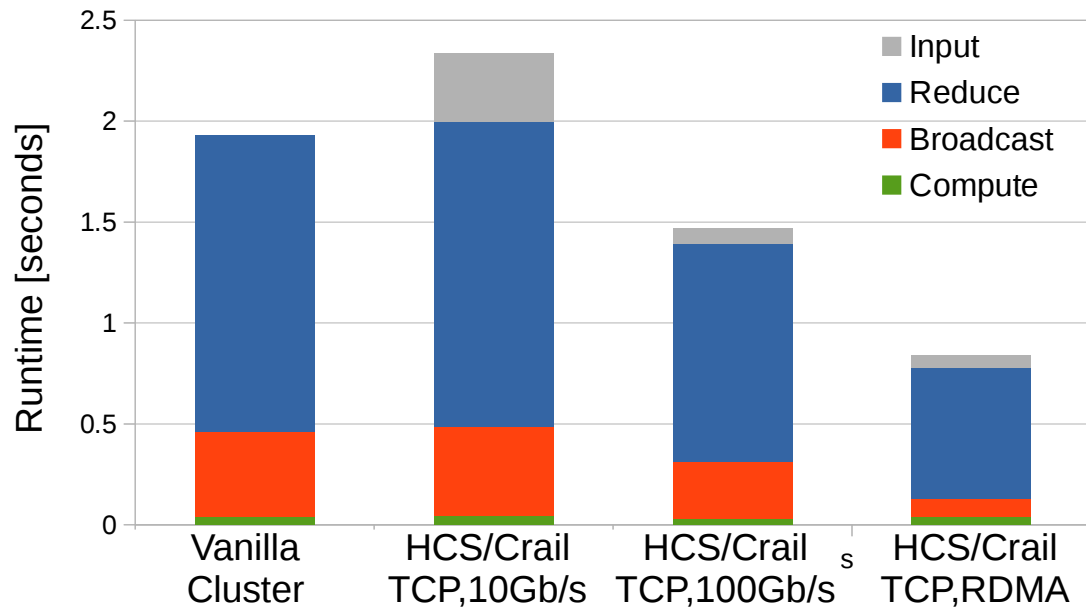
Scheduling Snapshot



Let's look at performance...

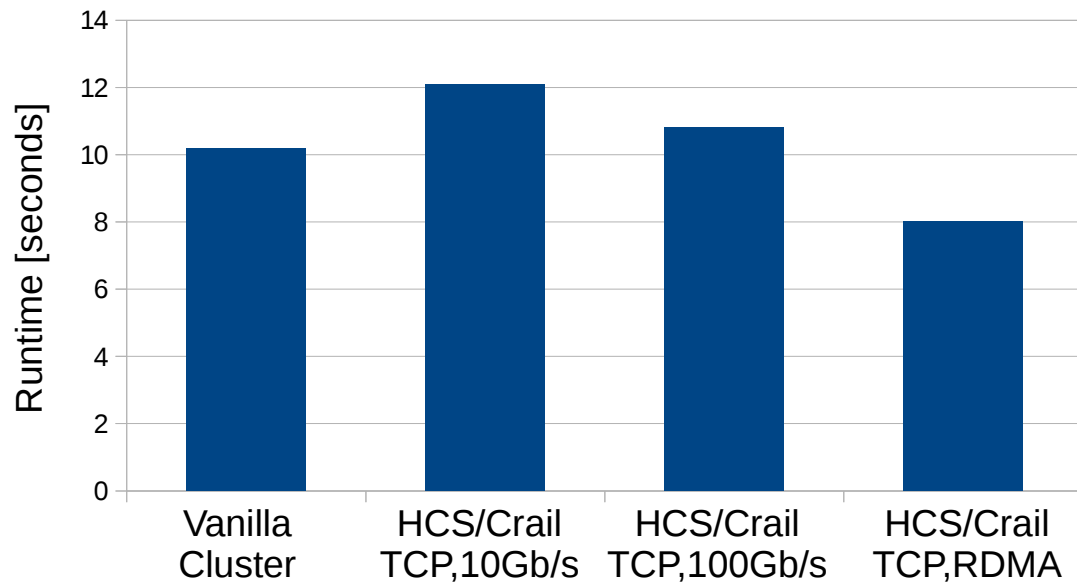
- Compute cluster size: 8 nodes: IBM Power8 Minsky
- Storage cluster size: 8 nodes, IBM Power8 Minsky
- Cluster hardware:
 - DRAM: 512 GB
 - Storage: 4x 1.2 TB NVMe SSD
 - Network: 10Gb/s Ethernet, 100Gb/s RoCE
 - GPU: NVIDIA P100, NVLink
- Workloads
 - ML: Logistic Regression using the CoCo framework
 - SQL: TCP-DS

ML: Logistic Regression

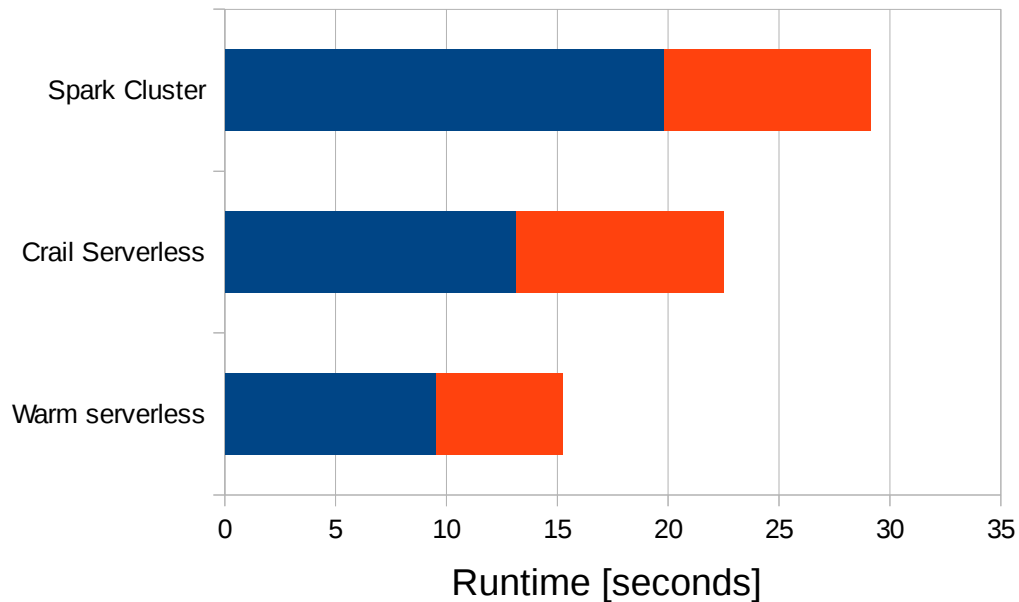


KDDA data set
6.5 GB

TPC-DS: Query #87



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 HCS, a new serverless scheduler
 - Consequently storing compute state remotely using Apache Crail
- Supports arbitrary Spark workloads with almost no performance overhead
 - MapReduce, SQL, Iterative Machine Learning
- Implicit support for fast network and storage hardware
 - e.g, RDMA, NVMe, NVMe-oF

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

 Running Apache Spark on a High-Performance Cluster Using RDMA and NVMe Flash, Spark Summit'17, <https://tinyurl.com/yd453uzq>

 Apache Crail, <http://crail.apache.org>

 HCS Scheduler, github.com/zrlio/hcs

 Spark-HCS, github.com/zrlio/spark-hcs

 Spark-IO, github.com/zrlio/spark-io

Thanks to

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