

Serverless Machine Learning on Modern Hardware

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IBM Research

#Res6SAIS

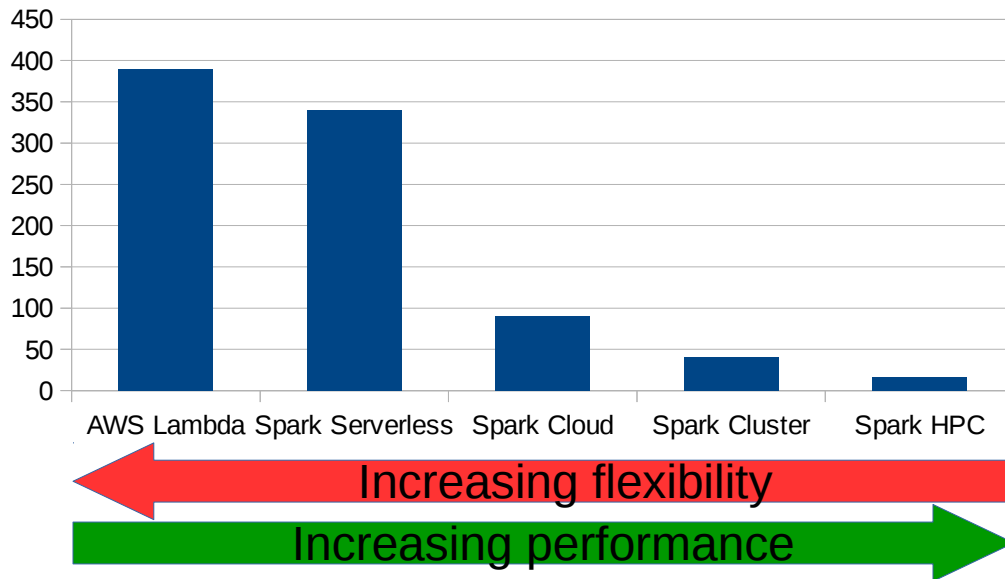
Serverless Computing



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

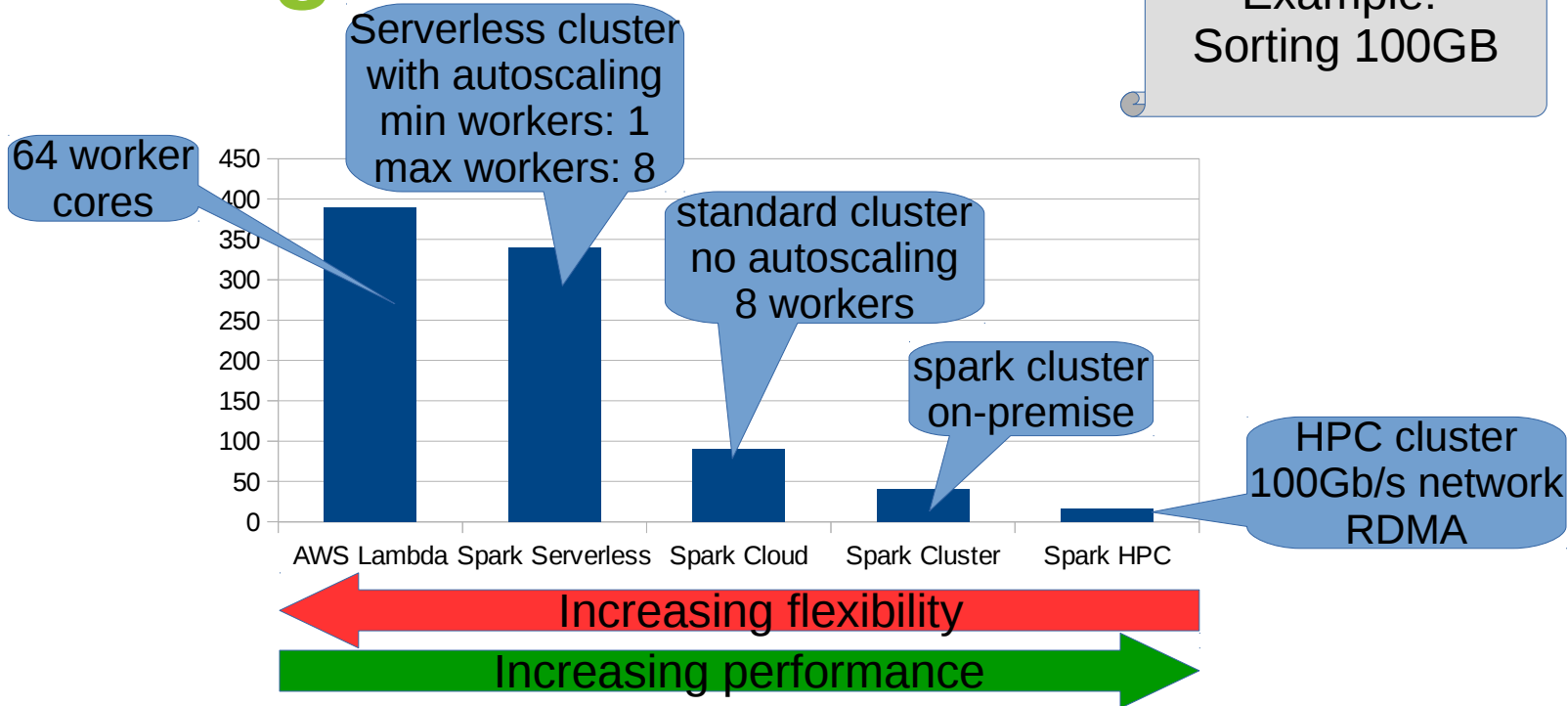
Challenge: Performance

Example:
Sorting 100GB



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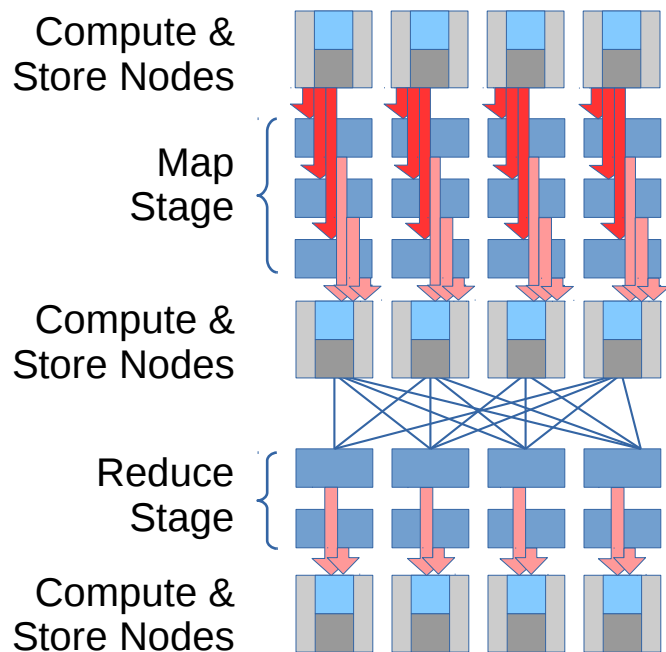
Why is it so hard?

- **Scheduler:** when to best add/remove resources?
- **Container startup:** may have to dynamically spin up containers 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.,

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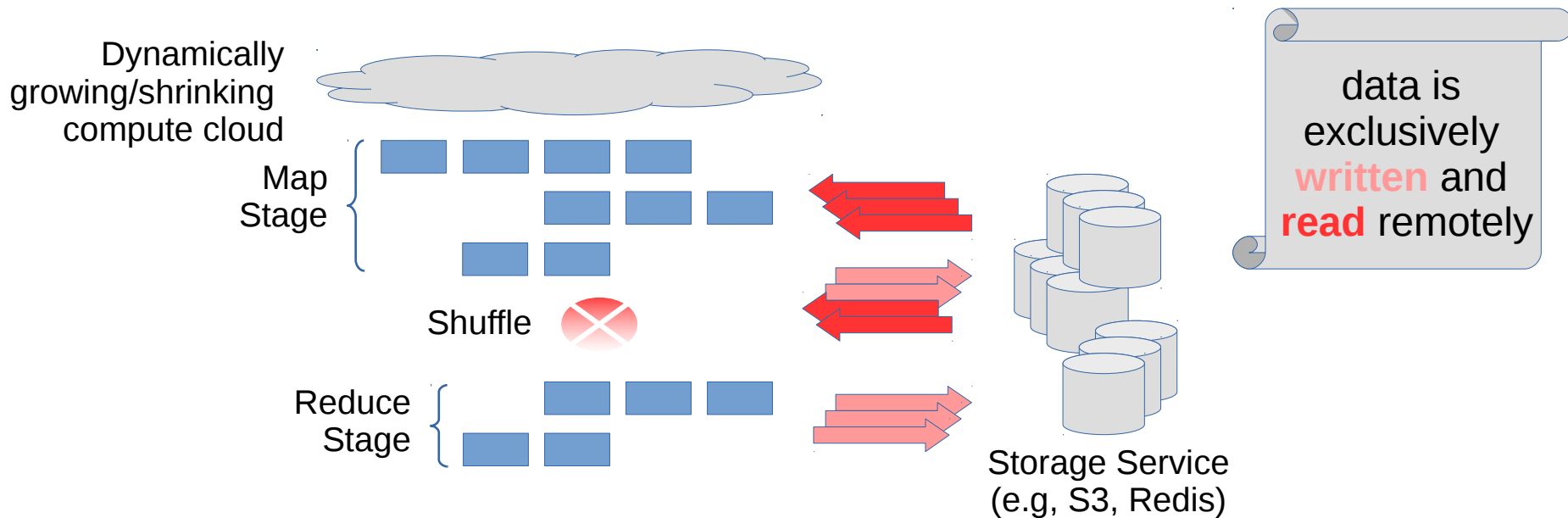
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Example: MapReduce (Cluster)

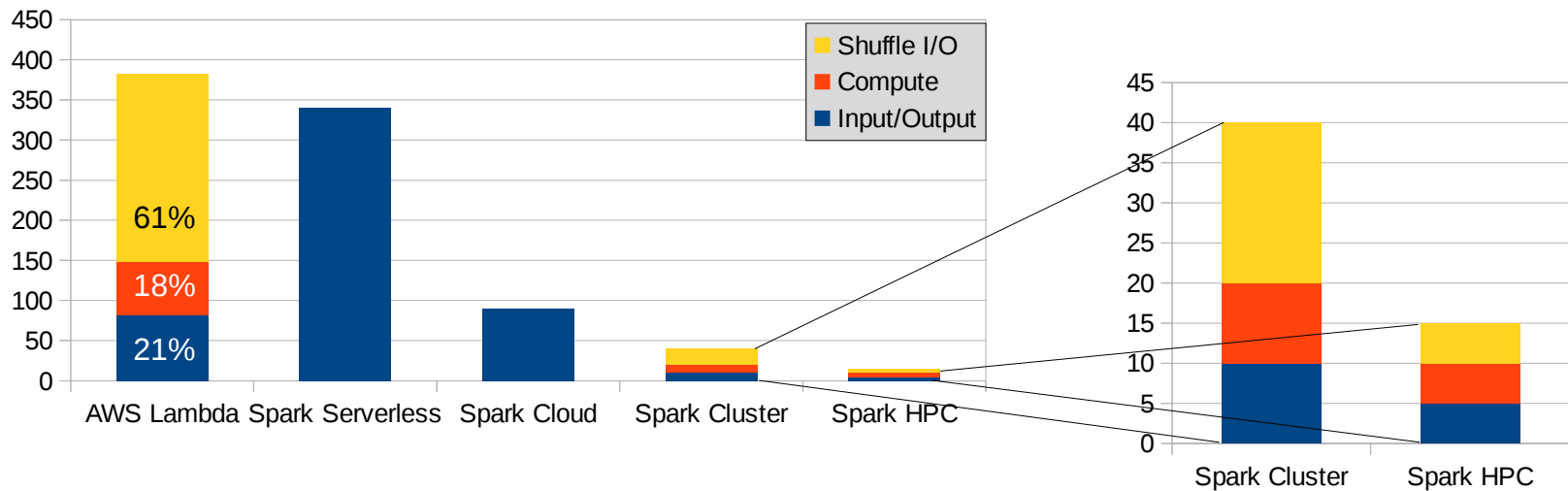


data is mostly
written and
read locally

Example: MapReduce (Serverless)



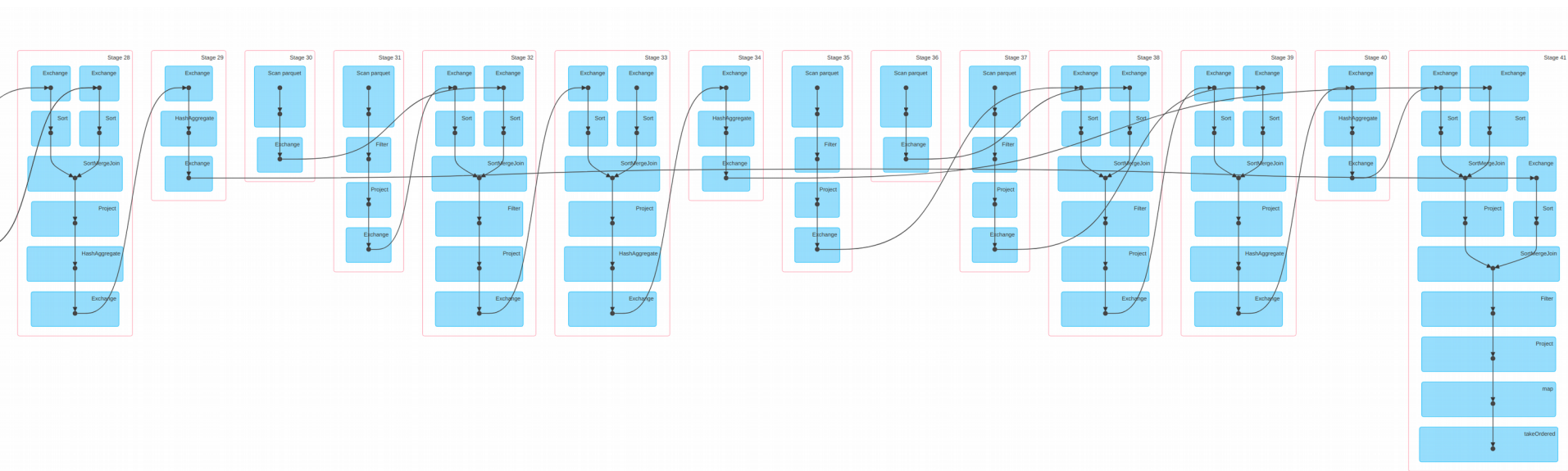
I/O Overhead: Sorting 100GB



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

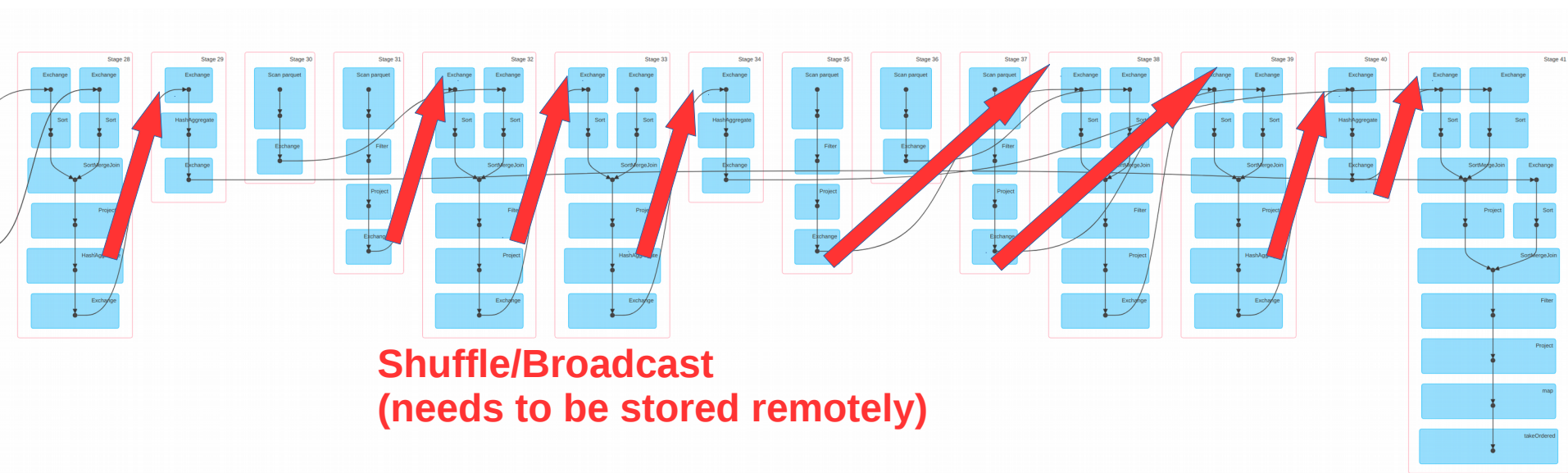
What about other workloads?

Example: SQL, Query 77 / TPC-DS benchmark



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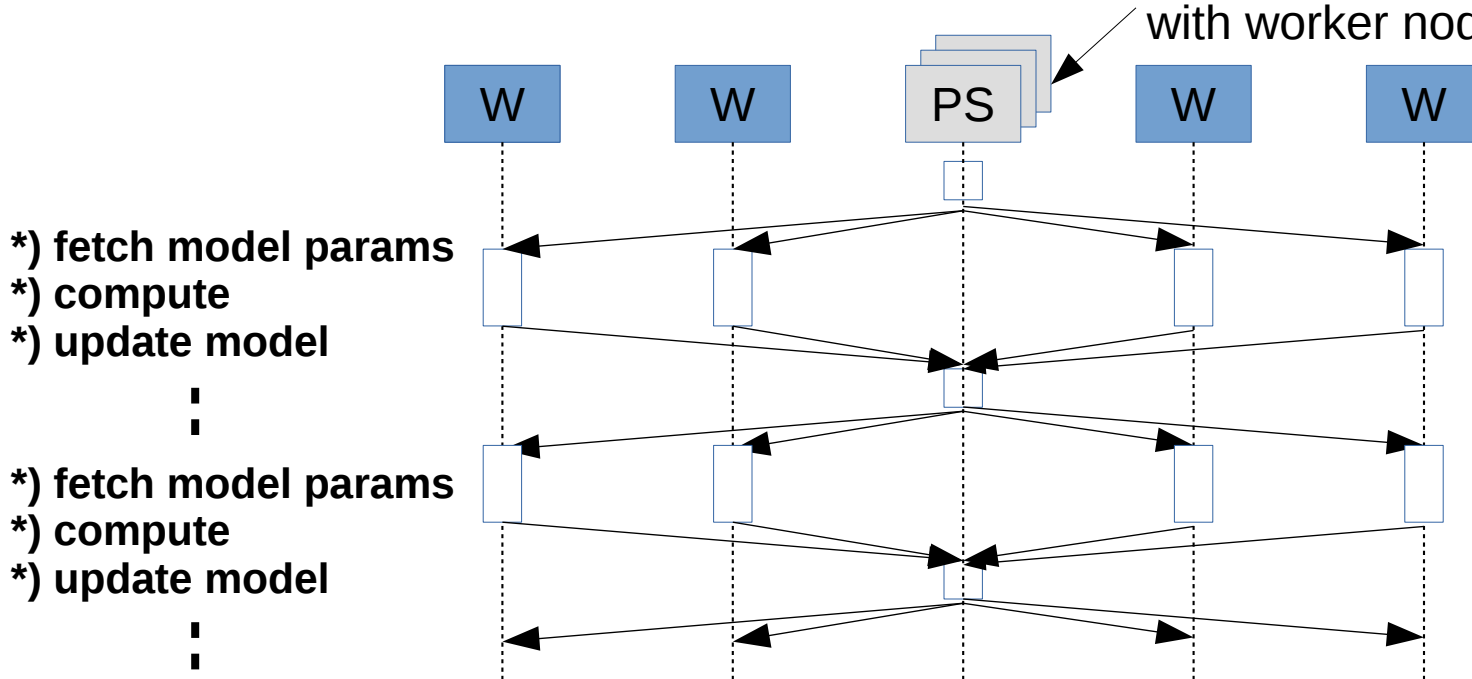
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What about other workloads?

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

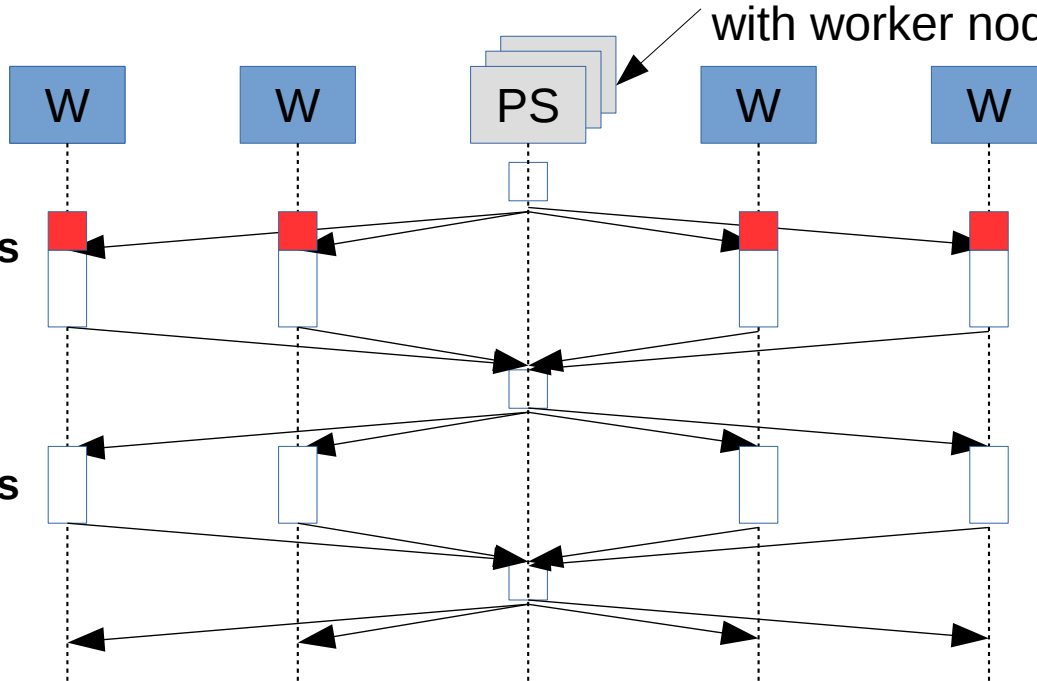
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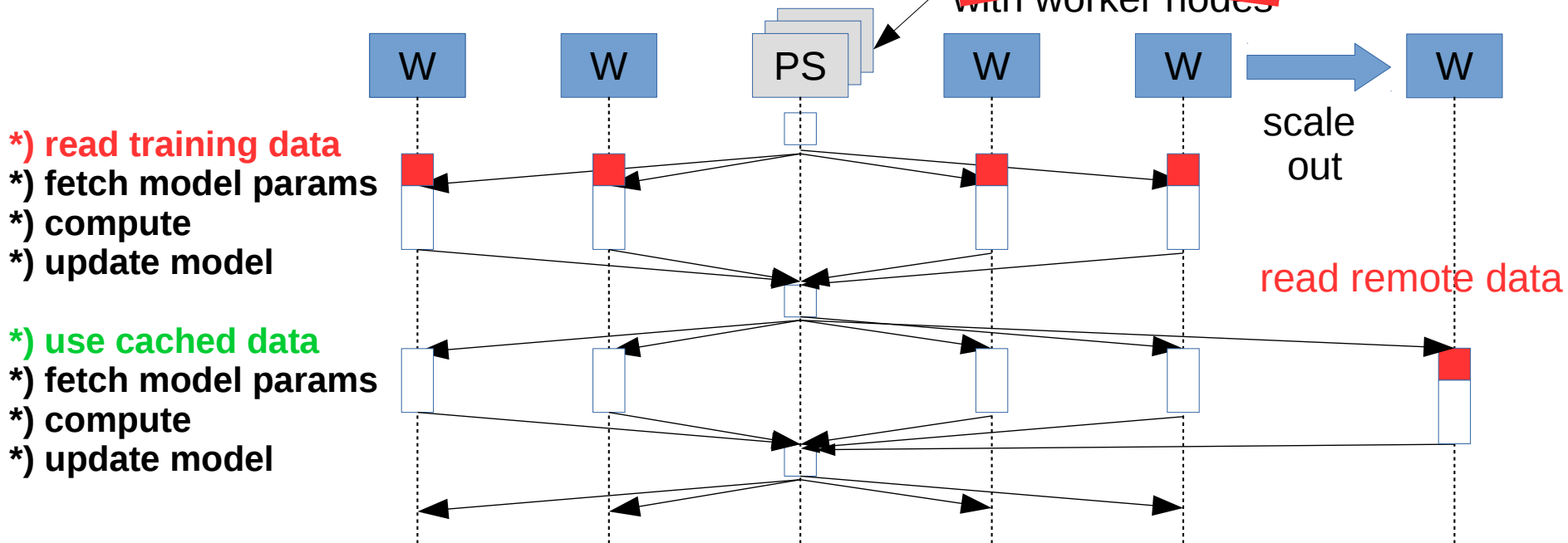
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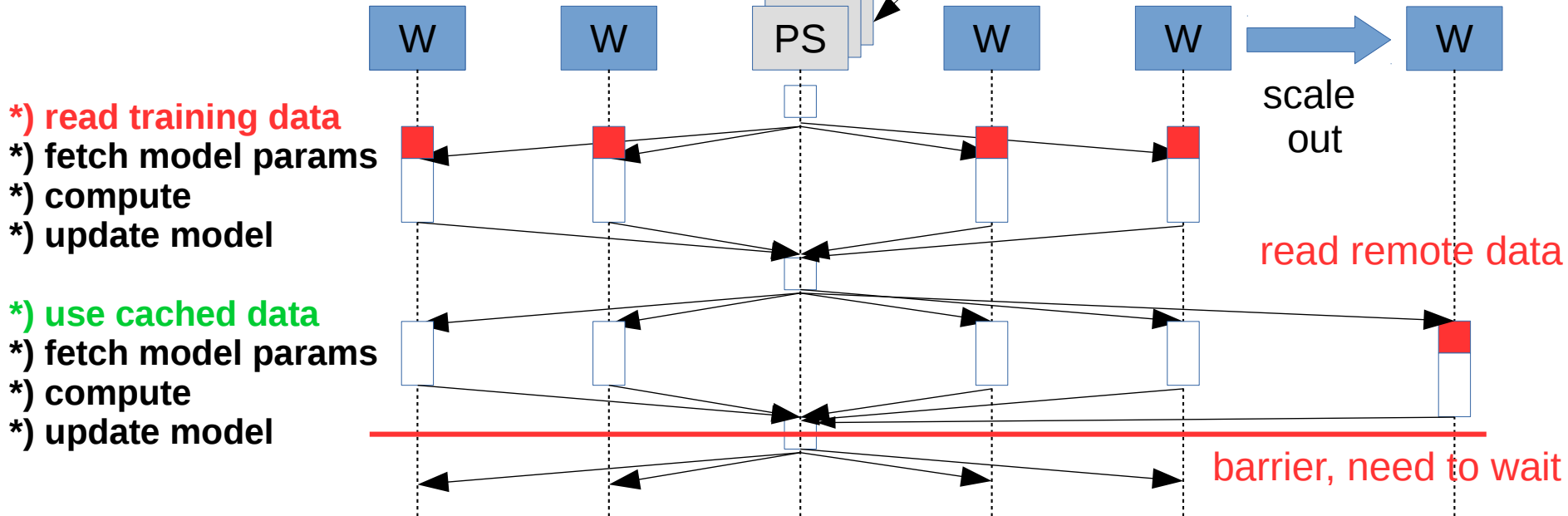
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Can we..

- 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!

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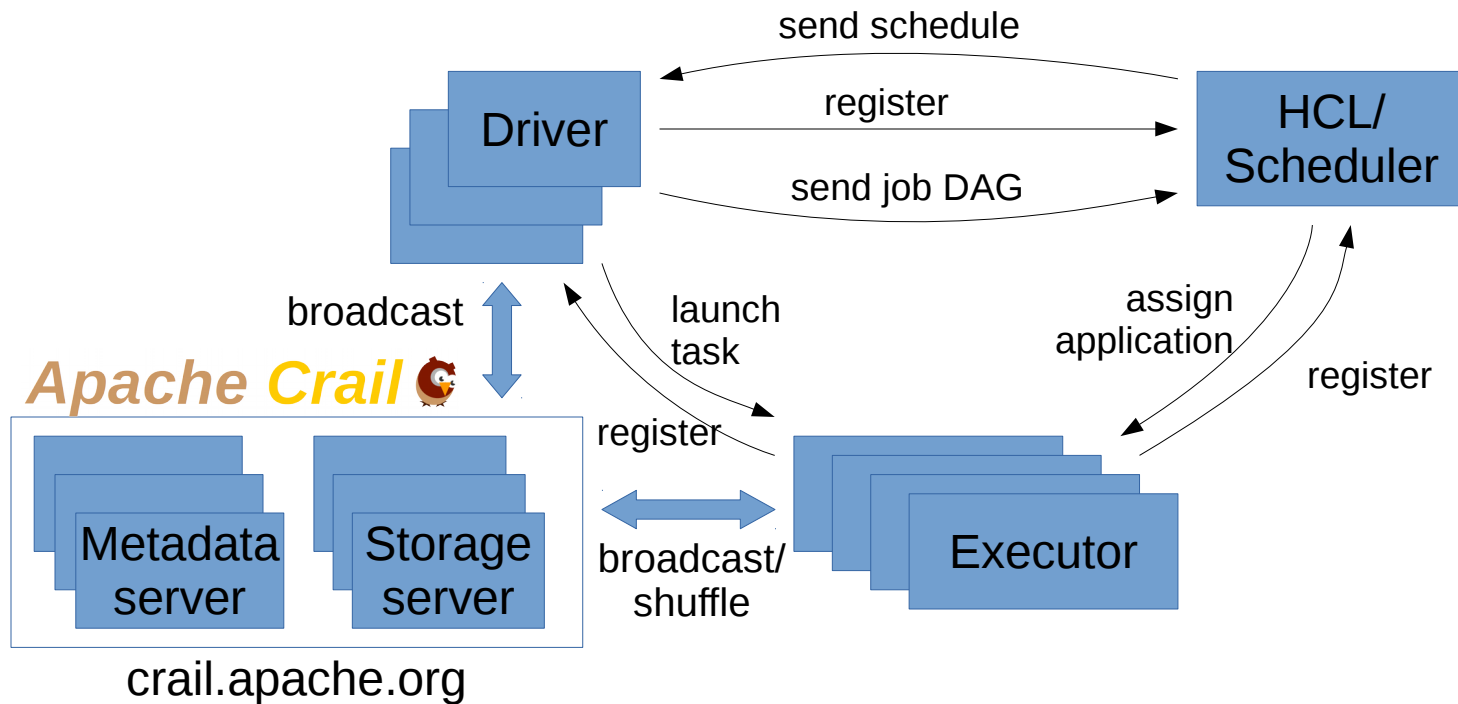
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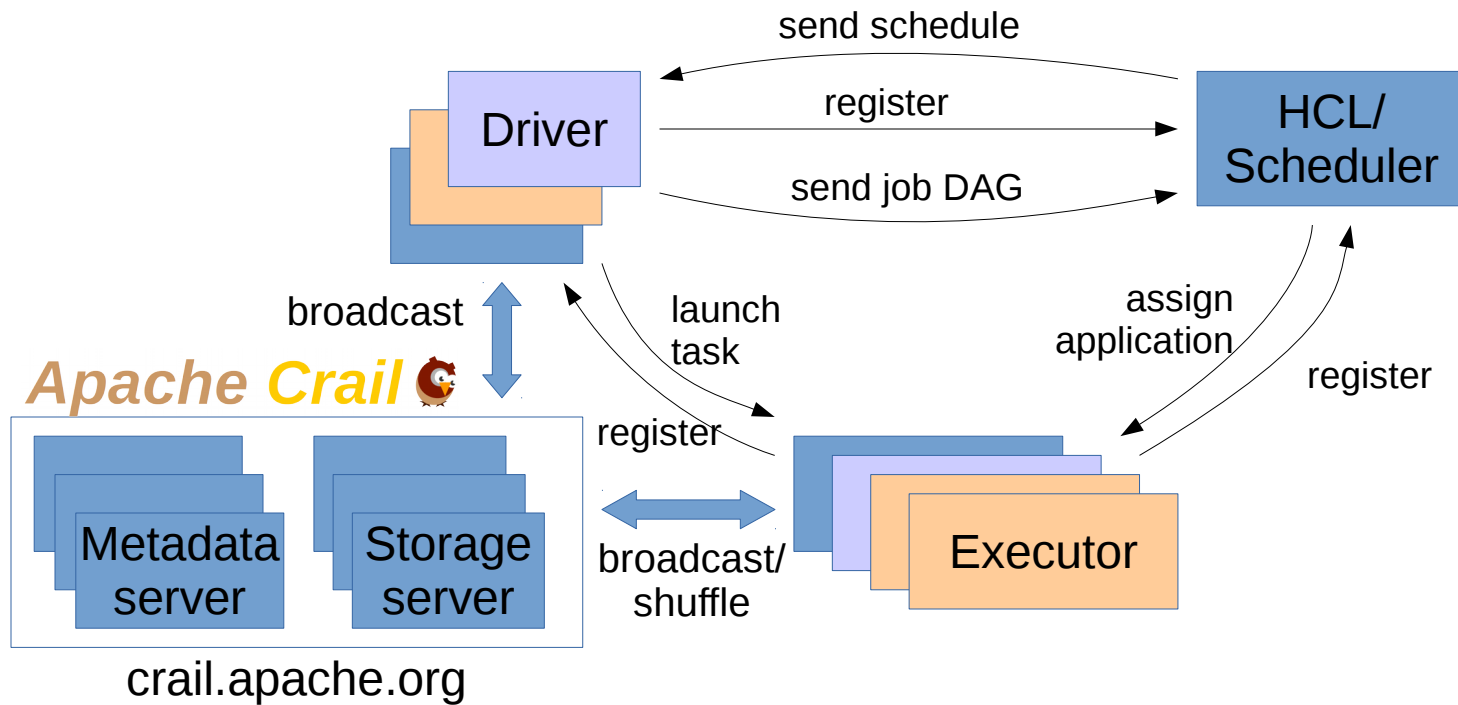
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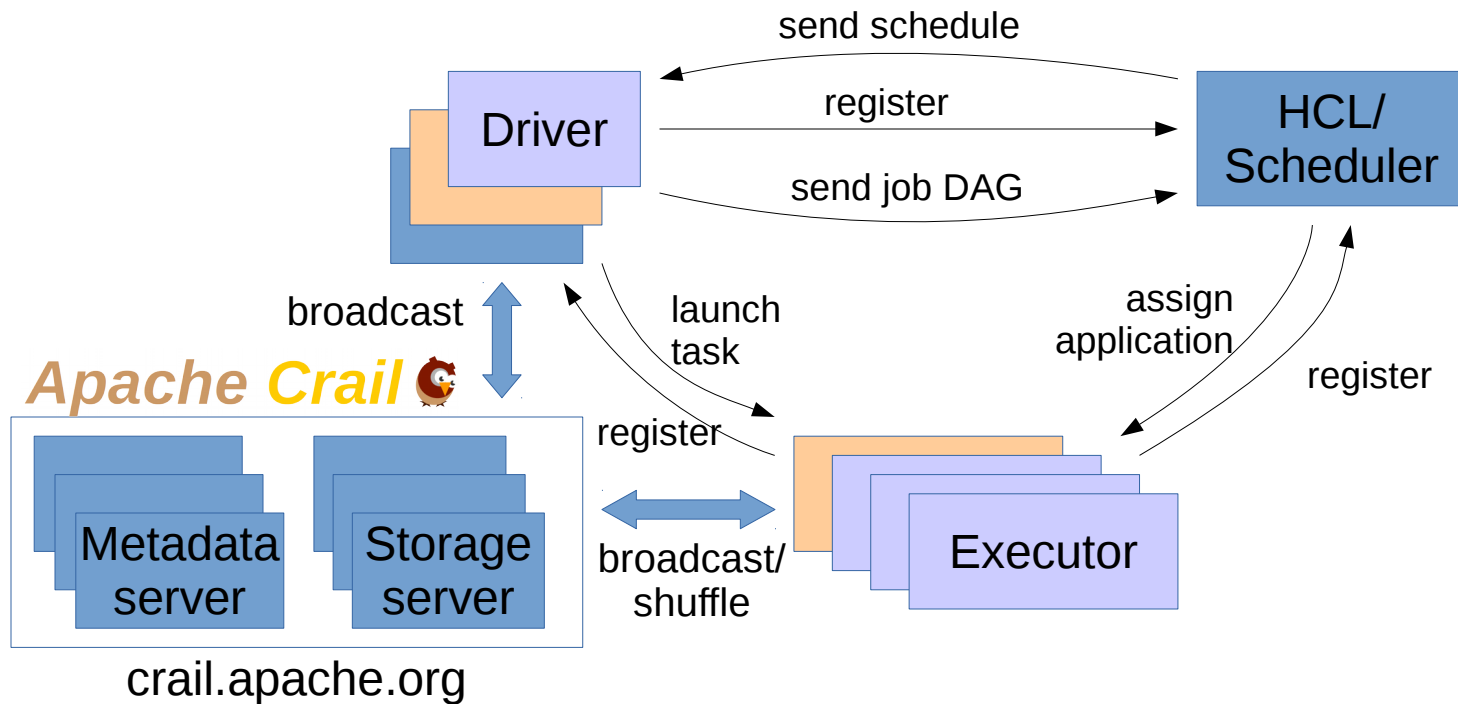
Architecture Overview



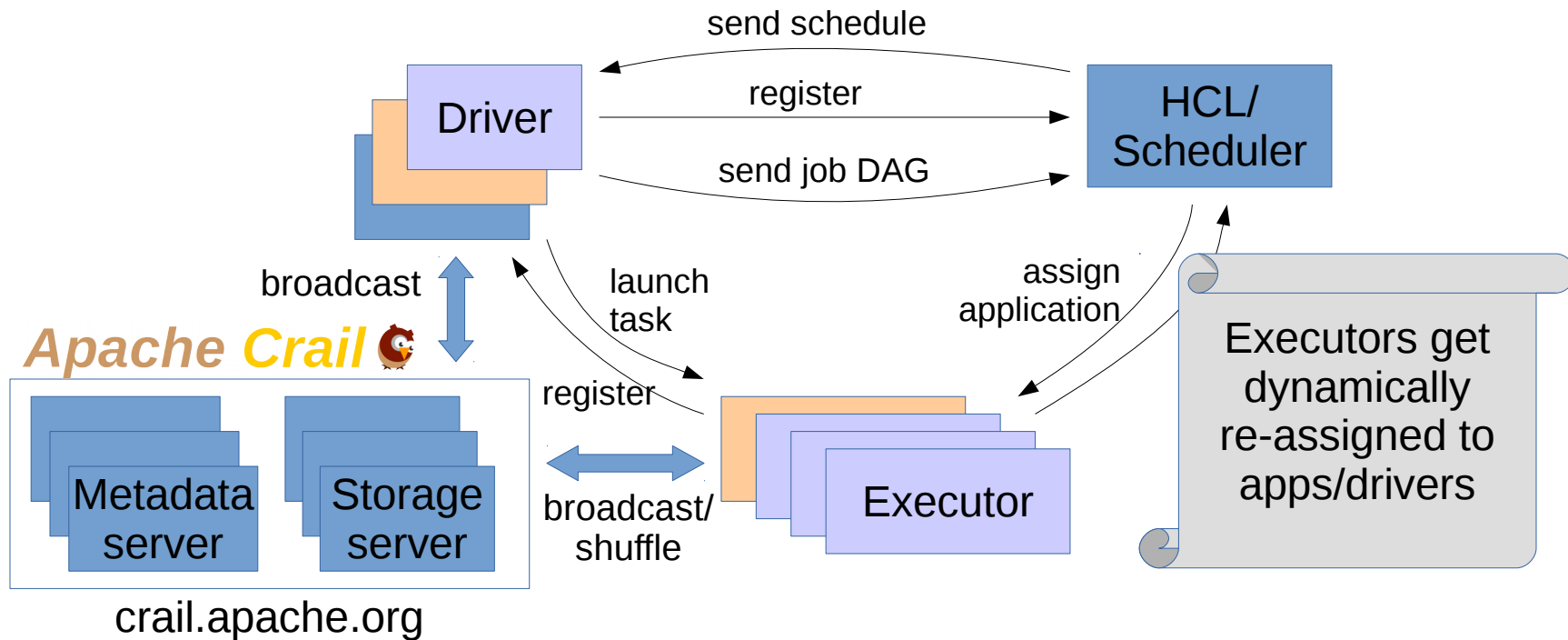
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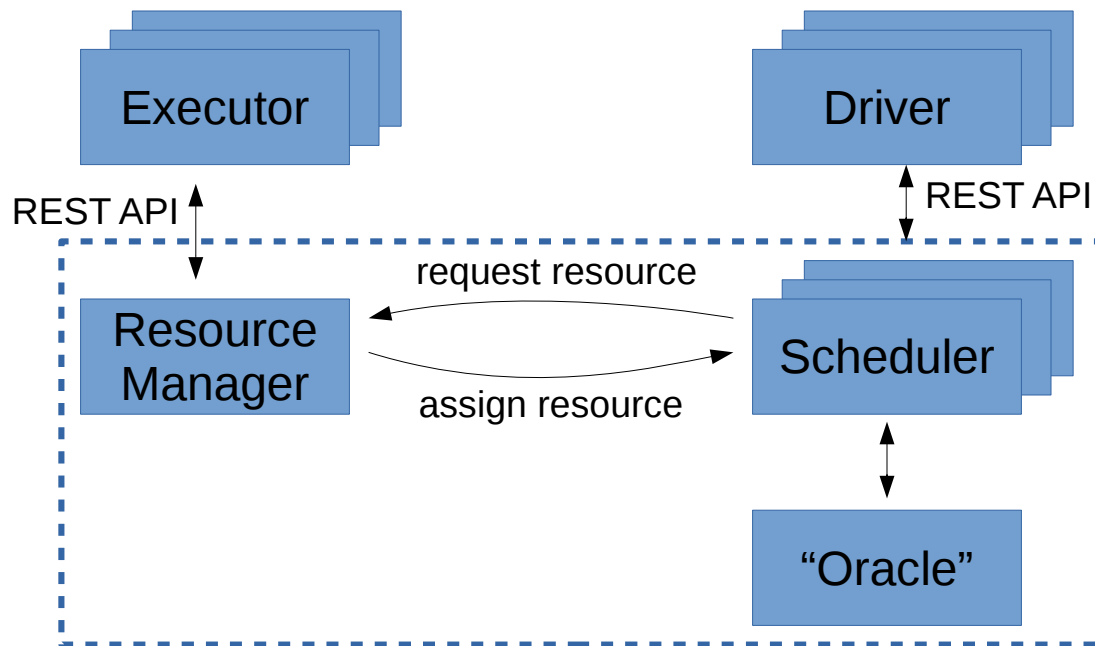
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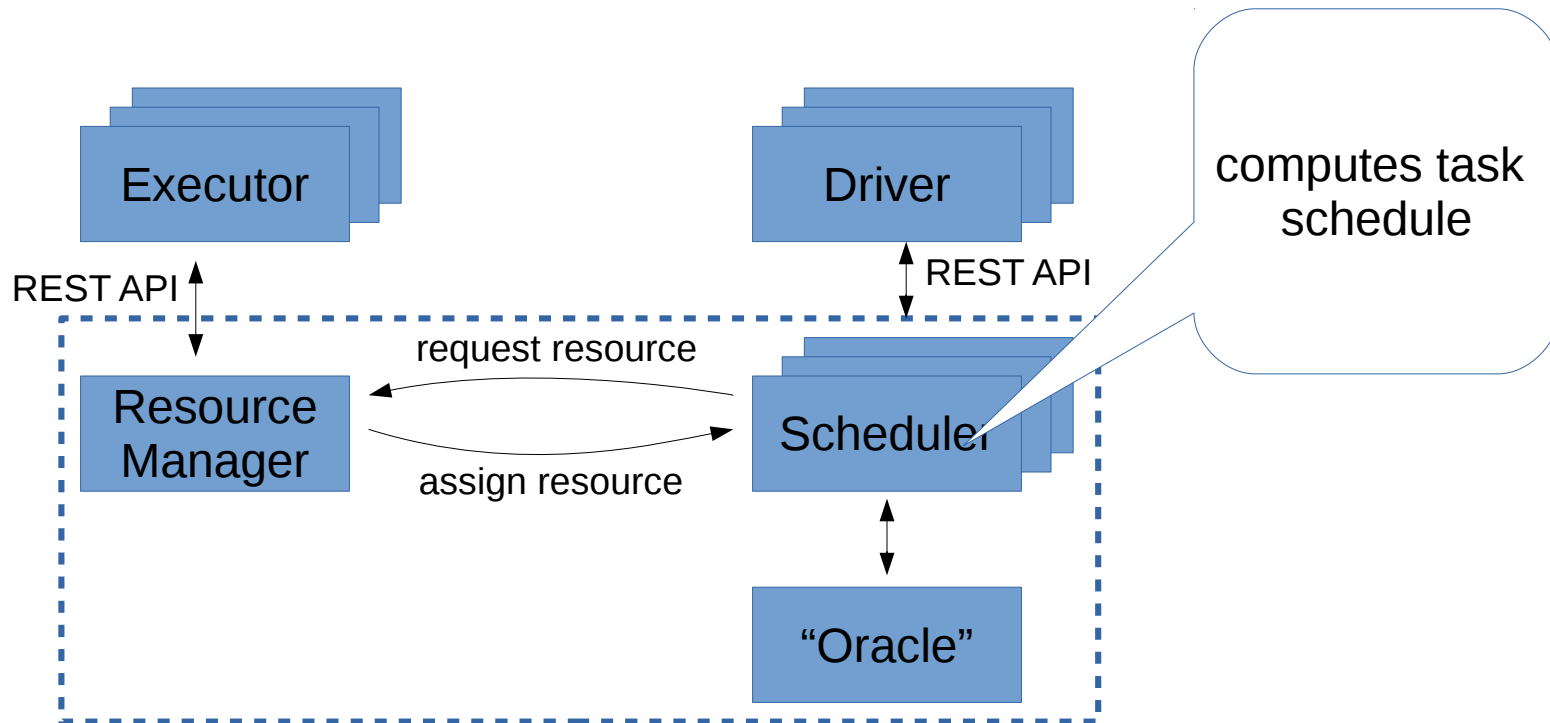
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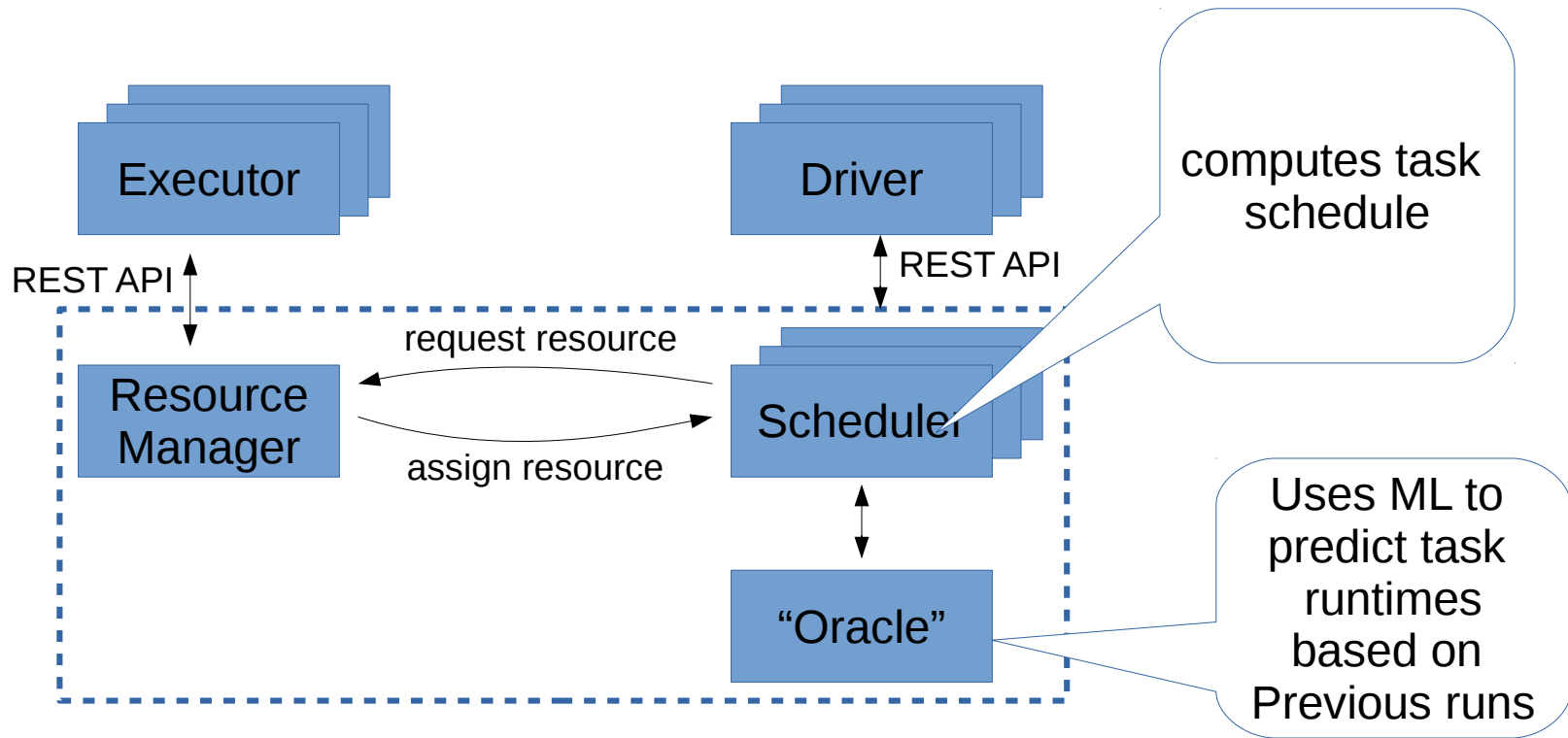
HCL Scheduler



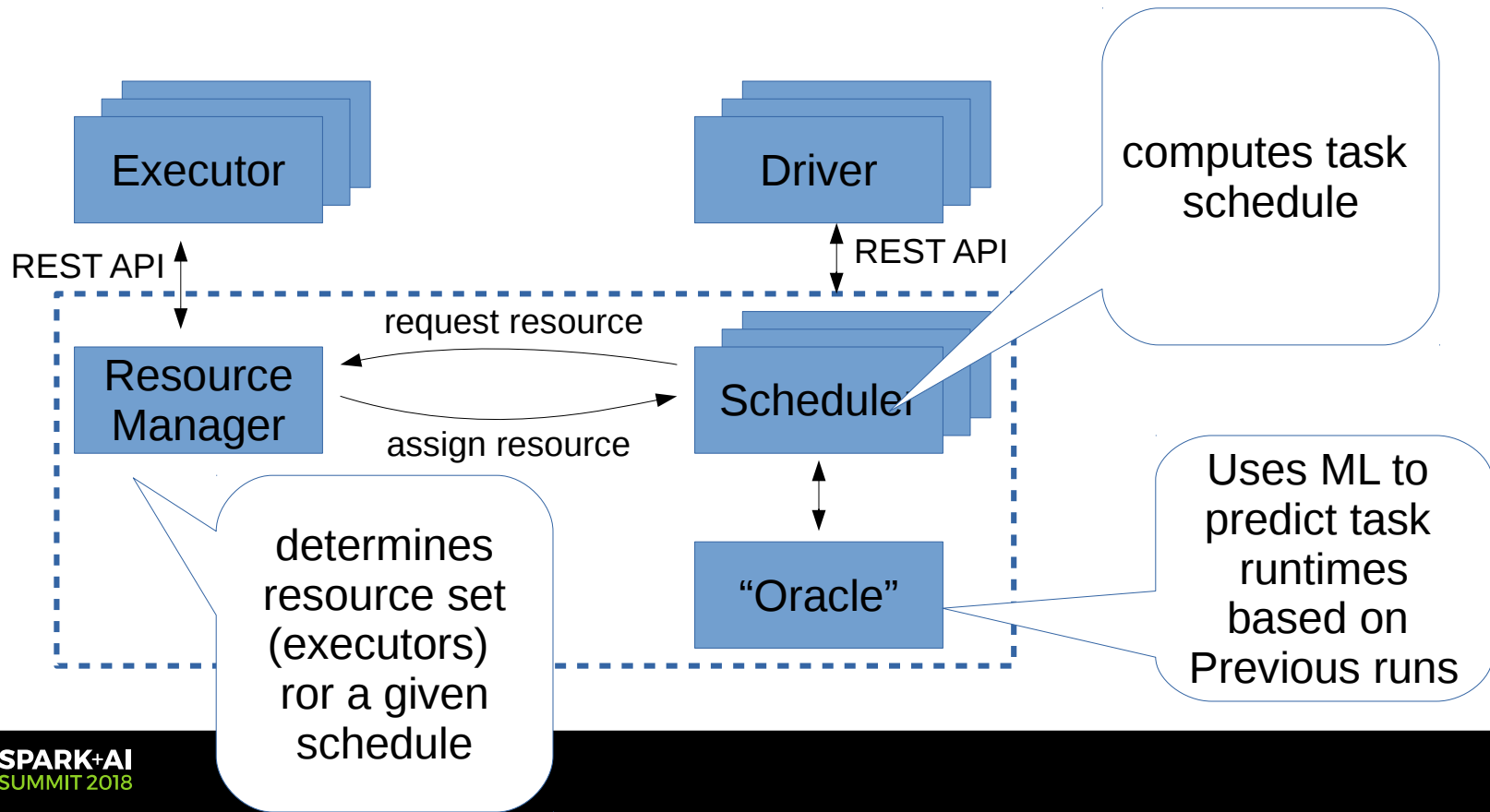
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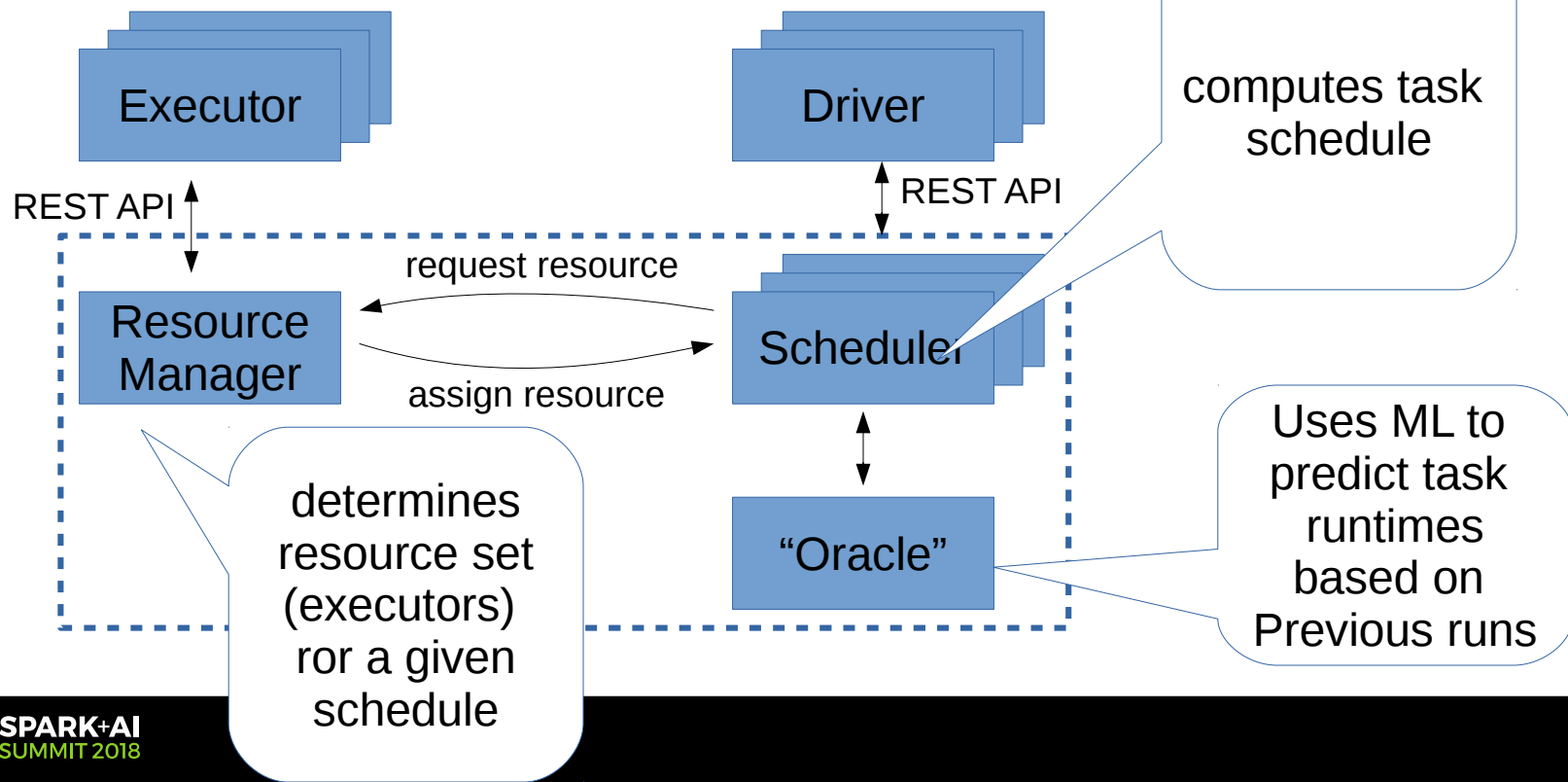


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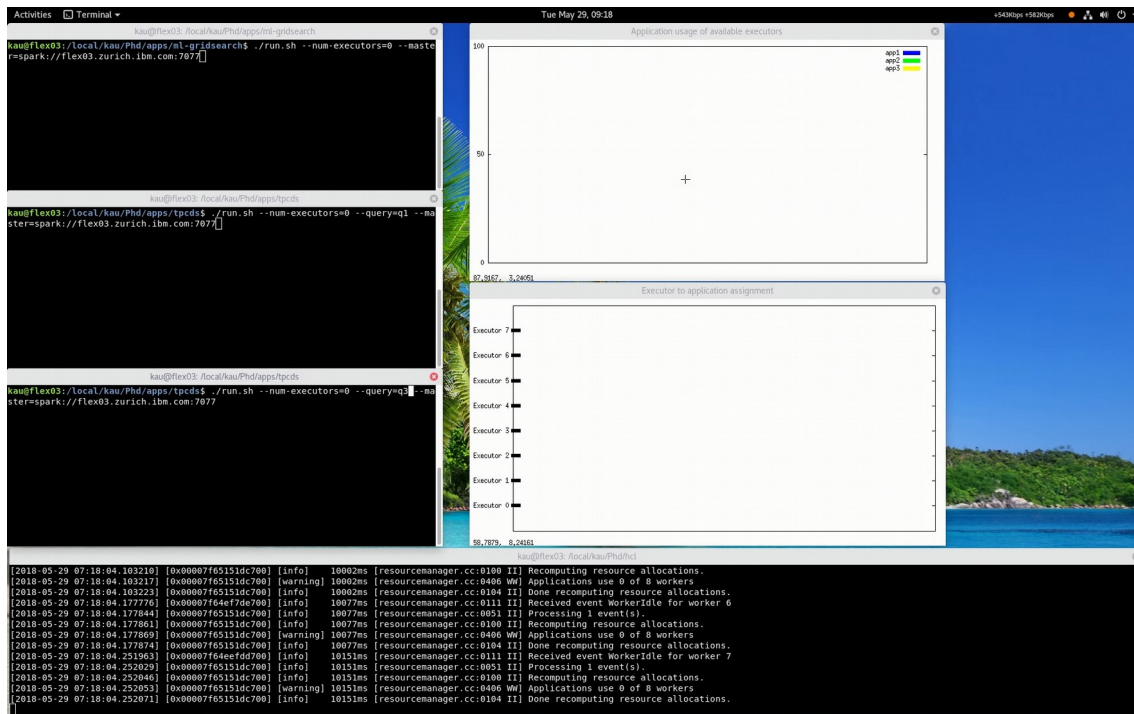


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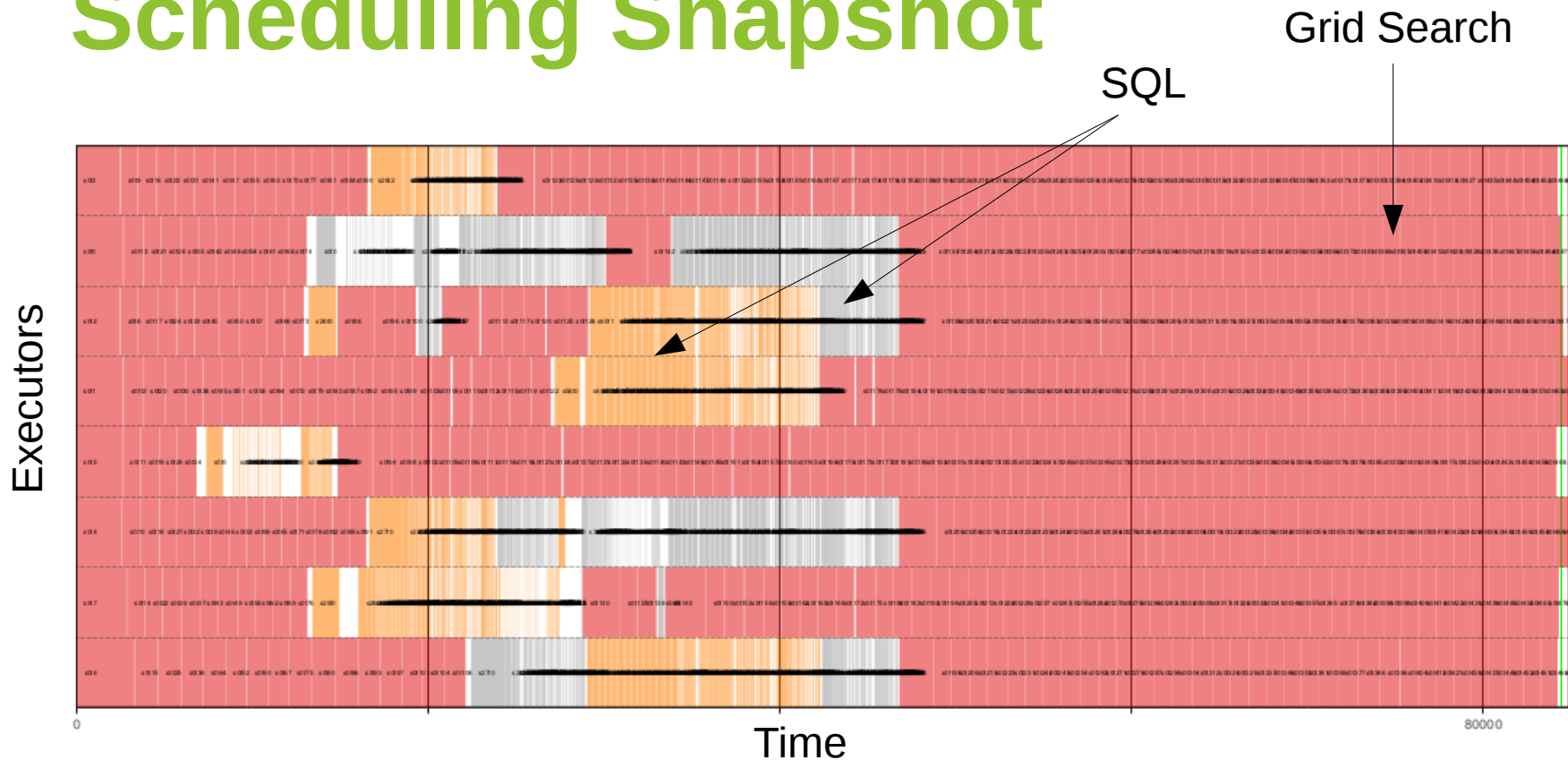
“The HCI Scheduler:
Going all-in on Heterogeneity”,
Michael Kaufmann et al., HotCloud’17



Putting things together



Scheduling Snapshot



What about Performance?

- Workloads:
 - Deep learning (digit recognition) using Spark/Tensorflow, MNIST data set
 - SQL: TPC-DS
- Clusters:
 - 8 node cluster, 10Gb/s Ethernet
 - 8 node cluster, 100Gb/s RoCE
- Software
 - Spark2.3, Tensorflow 1.2

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 overhead
 - MapReduce, SQL, Iterative Machine Learning
- Implicit support for fast network and storage hardware
 - e.g, RDMA, NVMe

Future Work

- 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

Backup

Workloads and Frameworks

	Microservices	Workflows	MapReduce	SQL	ML
AWS λ, Google CF, Azure F					
AWS λ + AWS StepFunction					
PyWren					
Databricks Serverless					

Serverless frameworks not designed to run arbitrary workloads