Serverless Machine Learning on Modern Hardware

IBM Research

#Res6SAIS

Thanks

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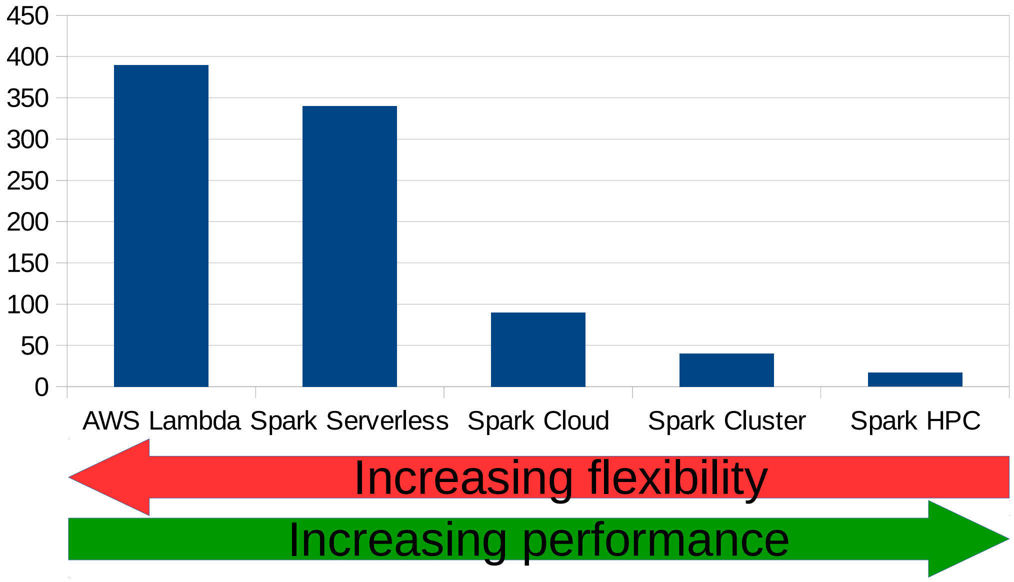
#Res6SAIS

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

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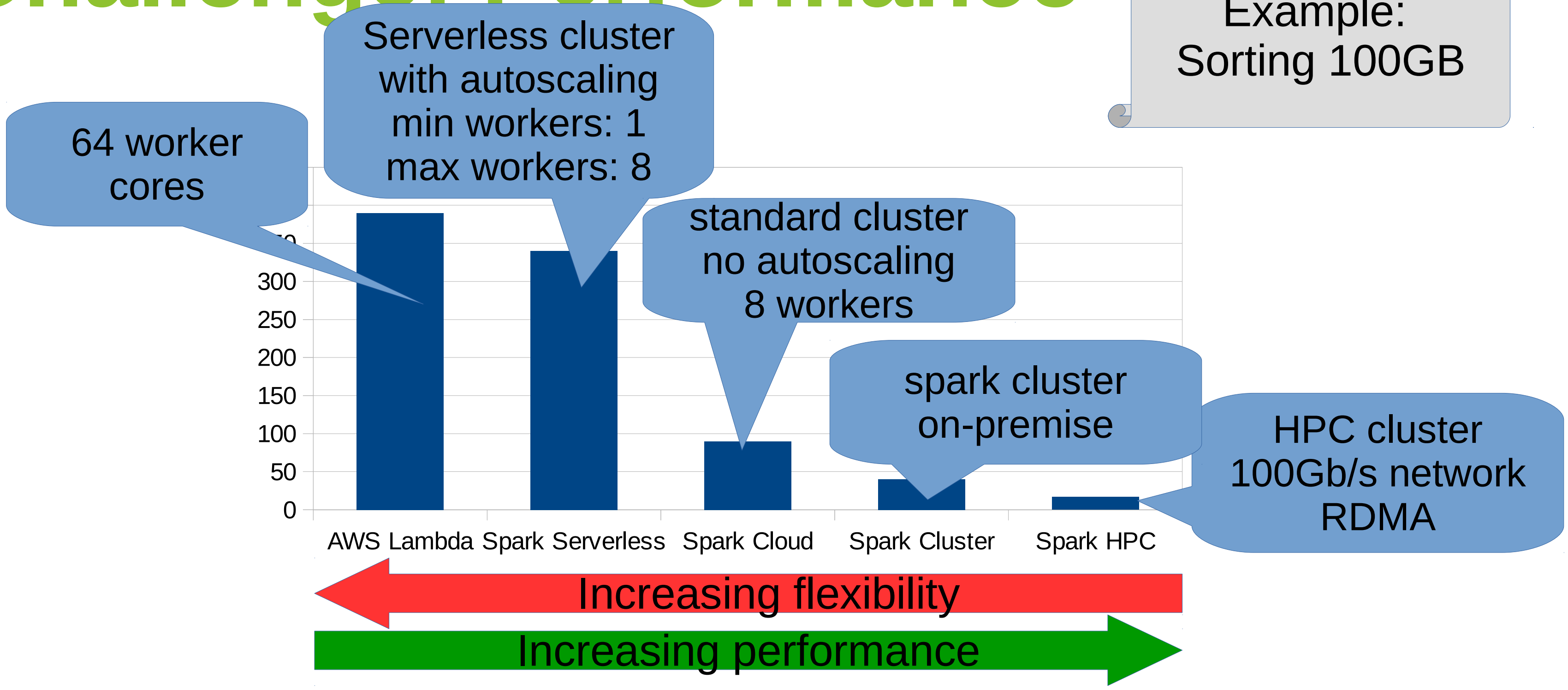

Challenge: Performance (2)

- **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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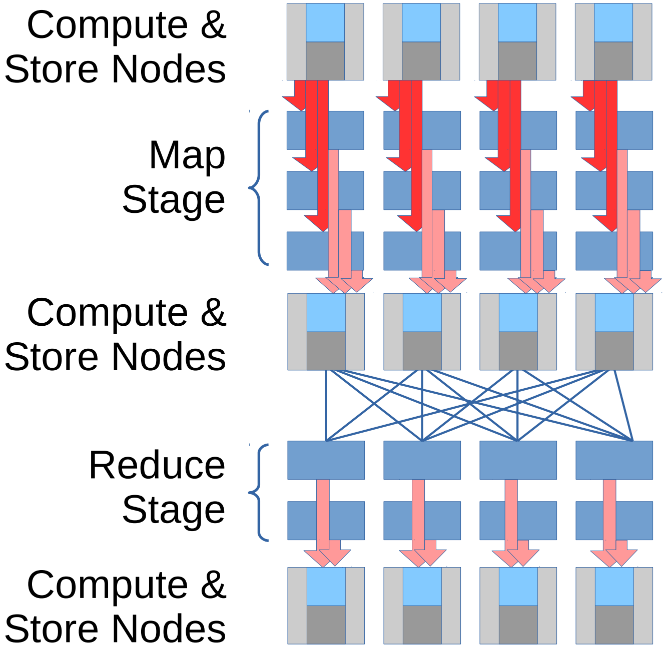
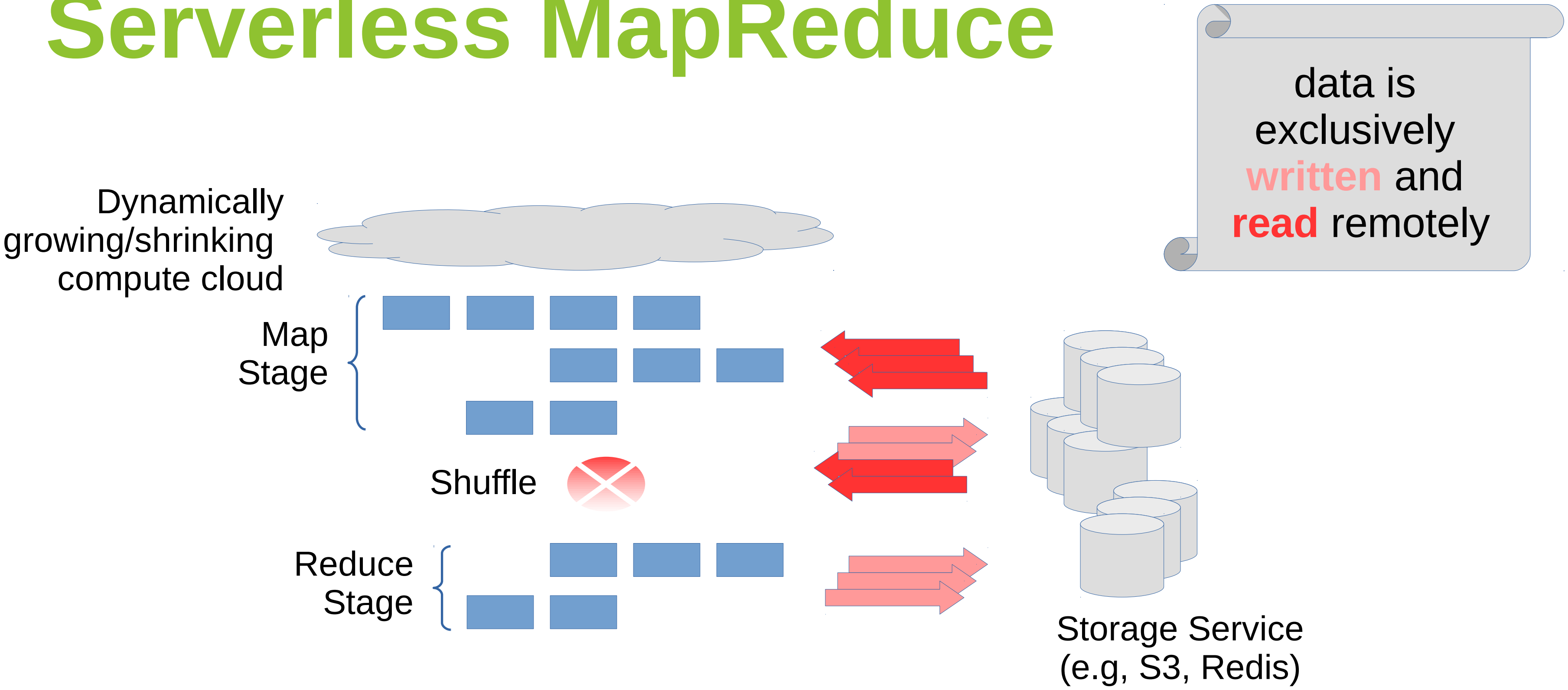
Example: MapReduce (Cluster)



data is mostly written and read locally

Serverless MapReduce



I/O Overhead

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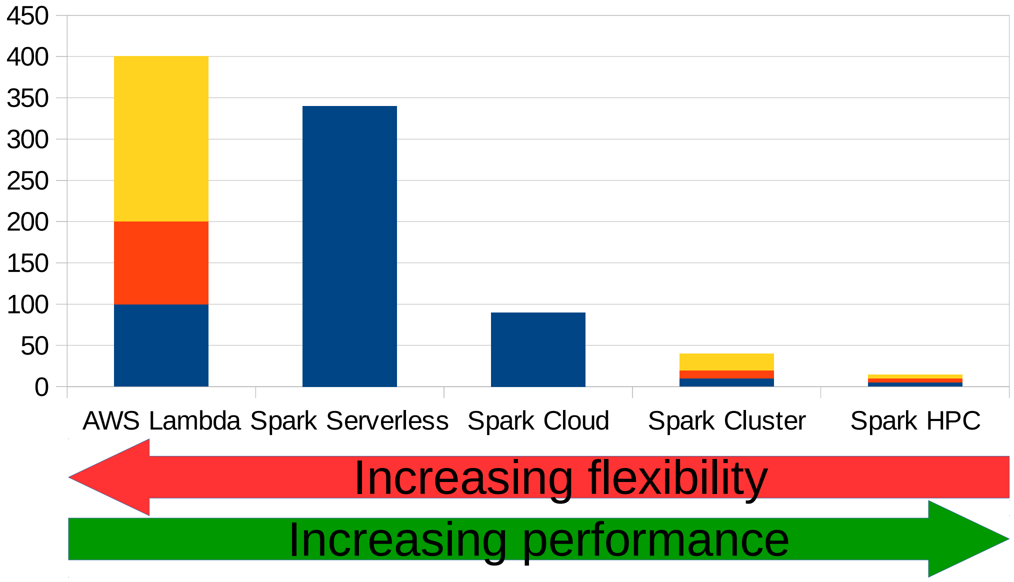
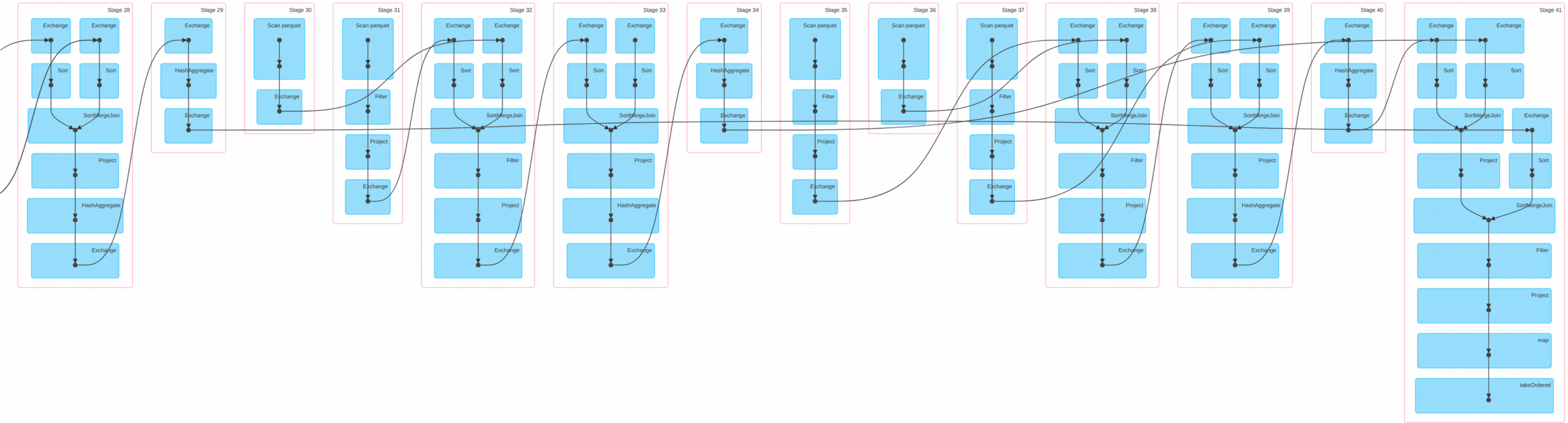


What about other workloads?

Example: SQL, Query 77 / TPC-DS benchmark



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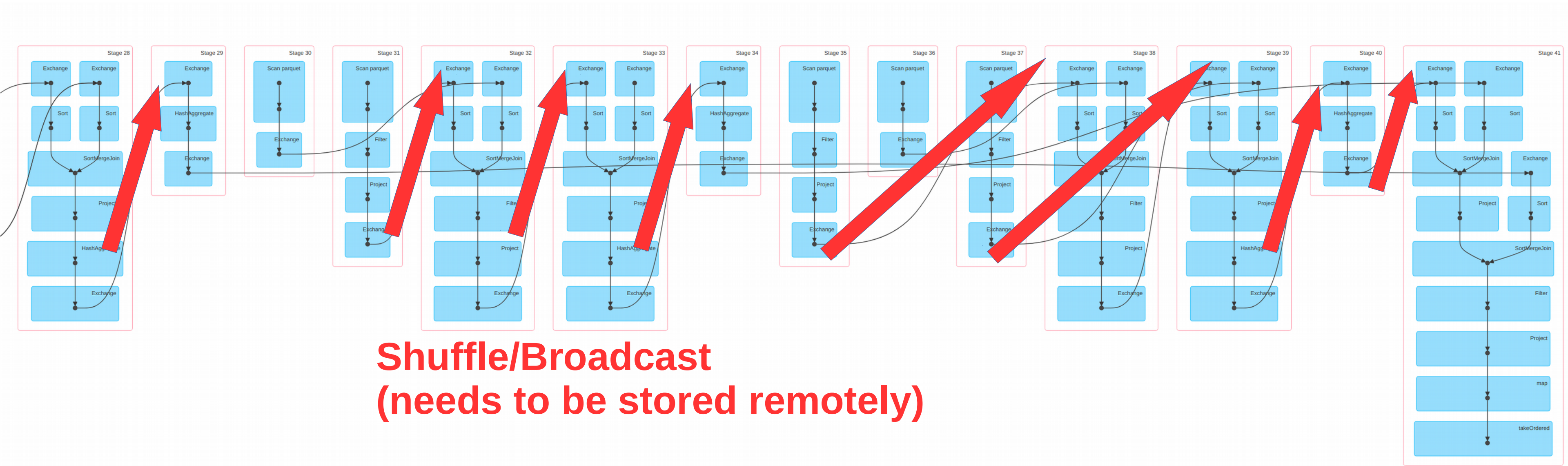

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Example: Iterative ML (e.g., linear regression)

could be co-located
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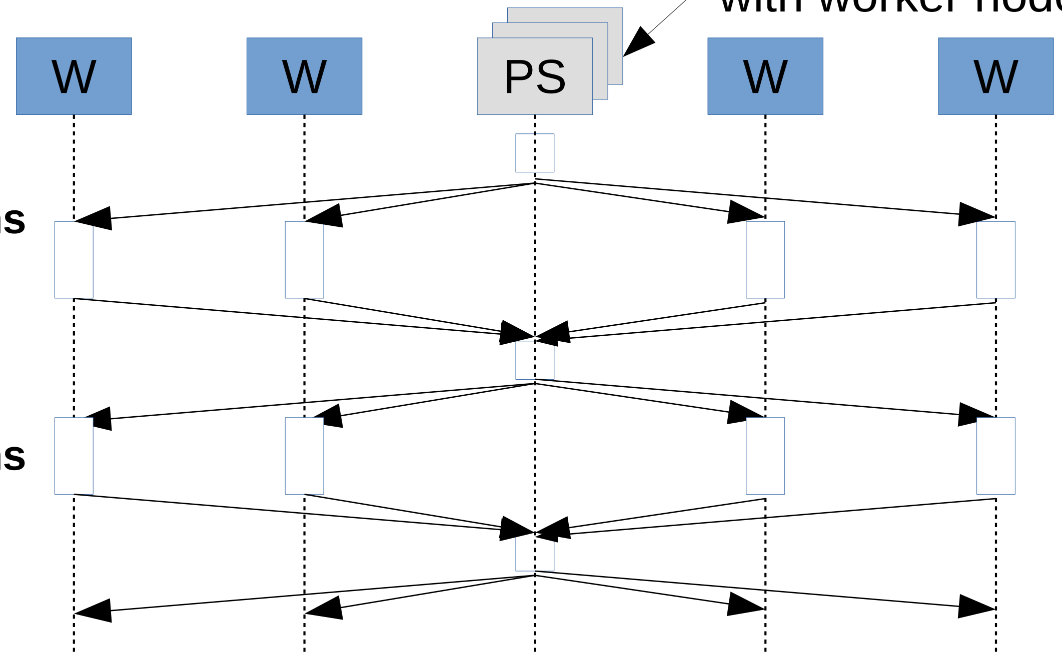

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*) compute
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⋮

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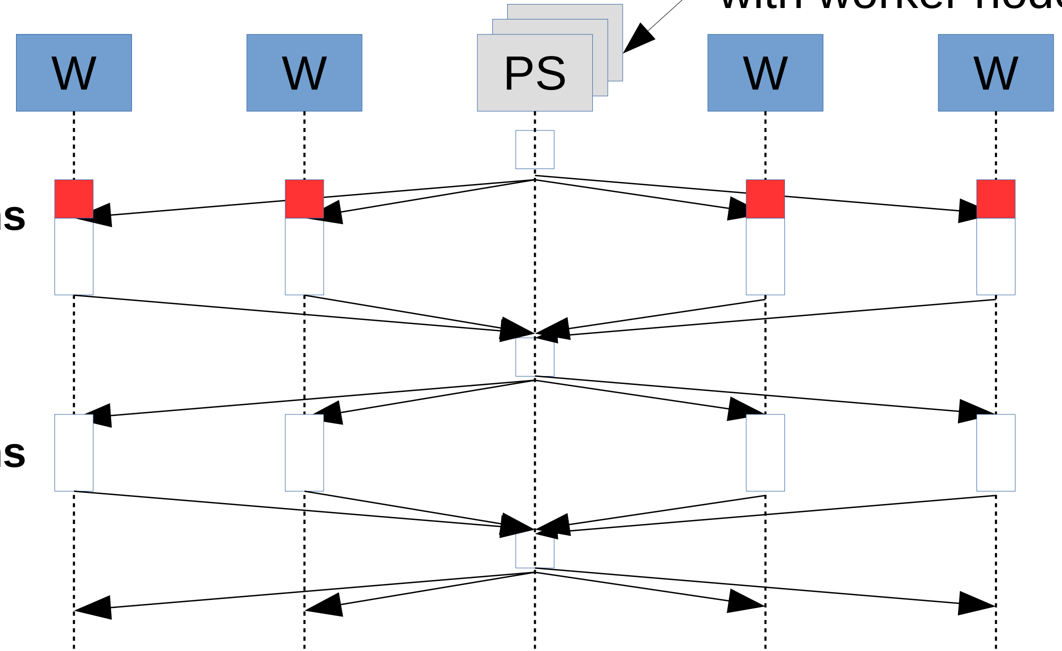

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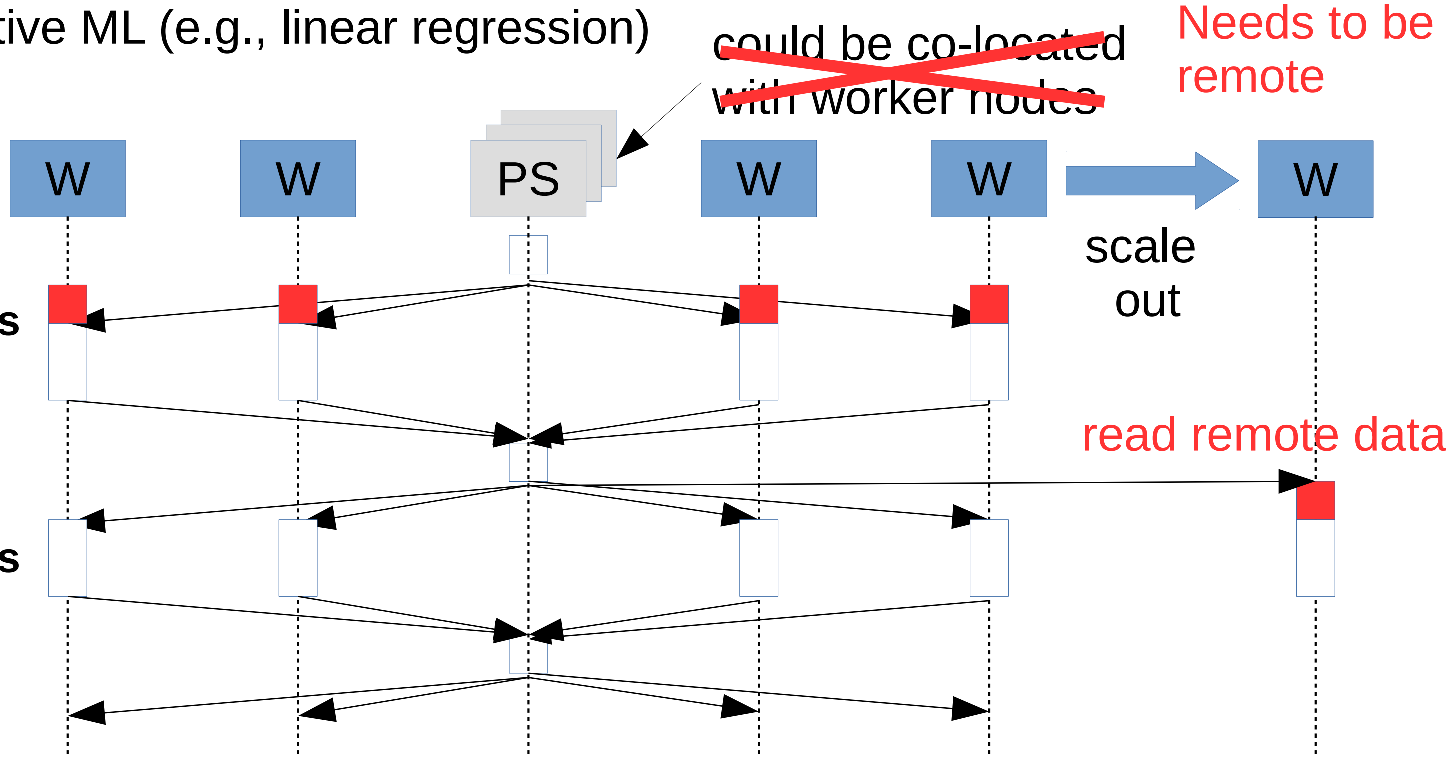

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Can we..

- ..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

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High startup Latency!

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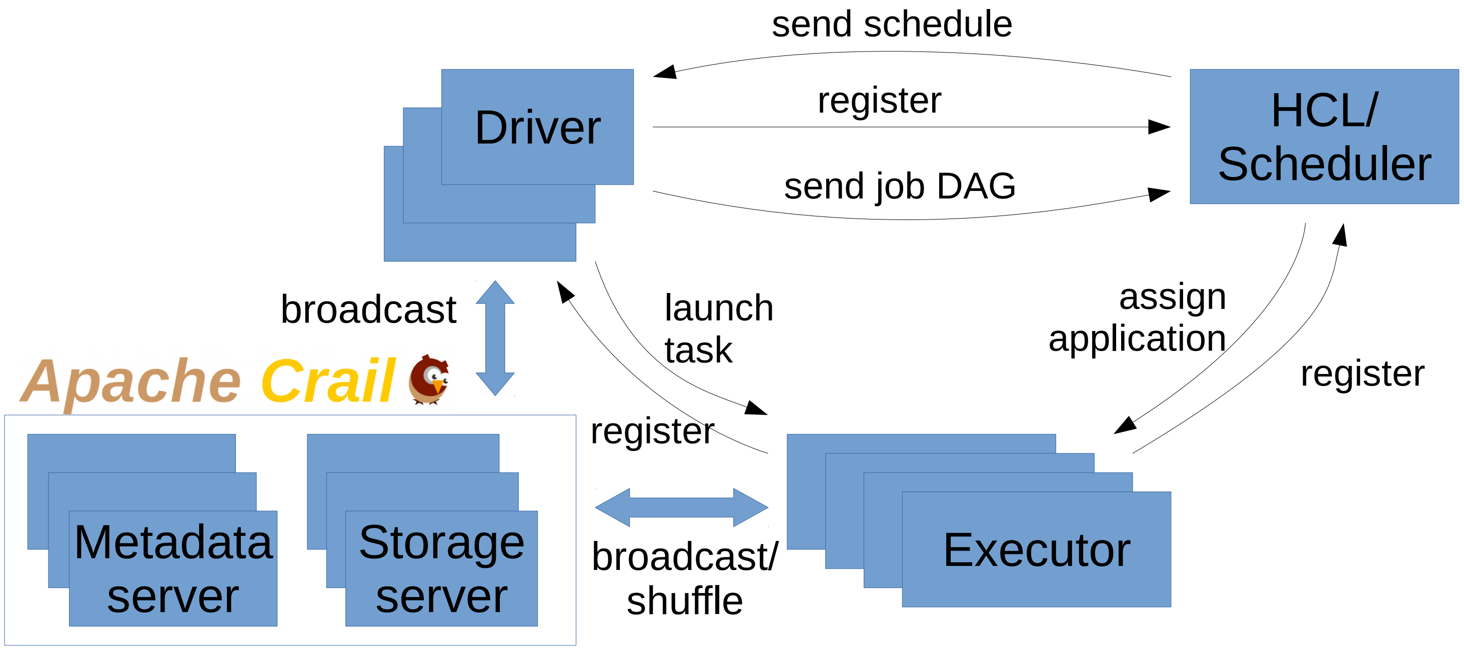
Architecture Overview



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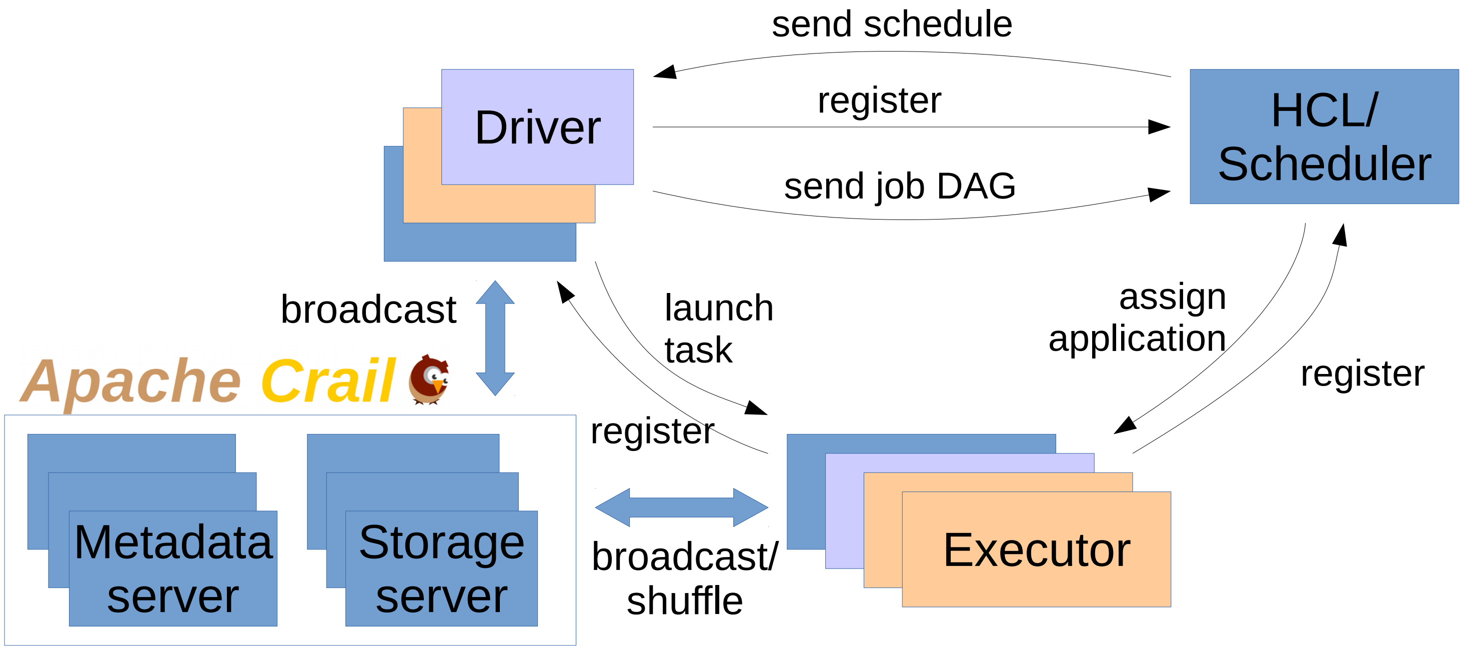

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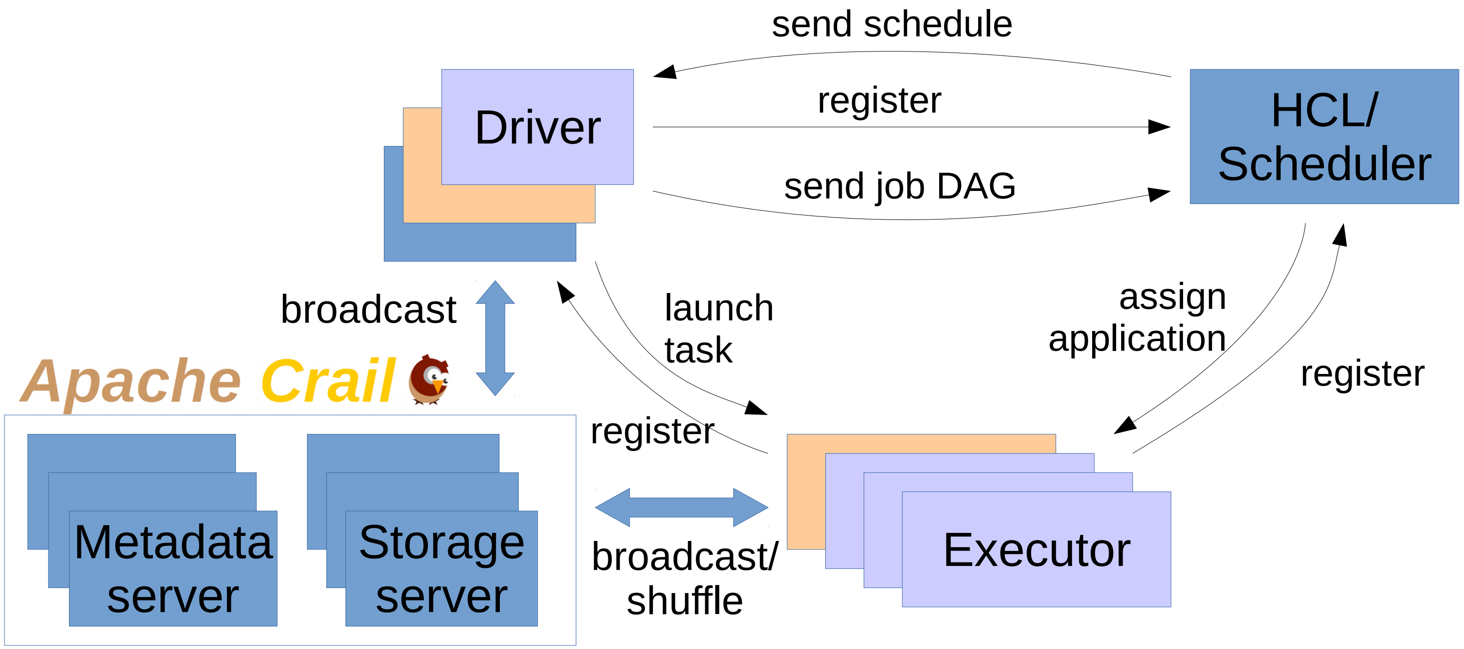

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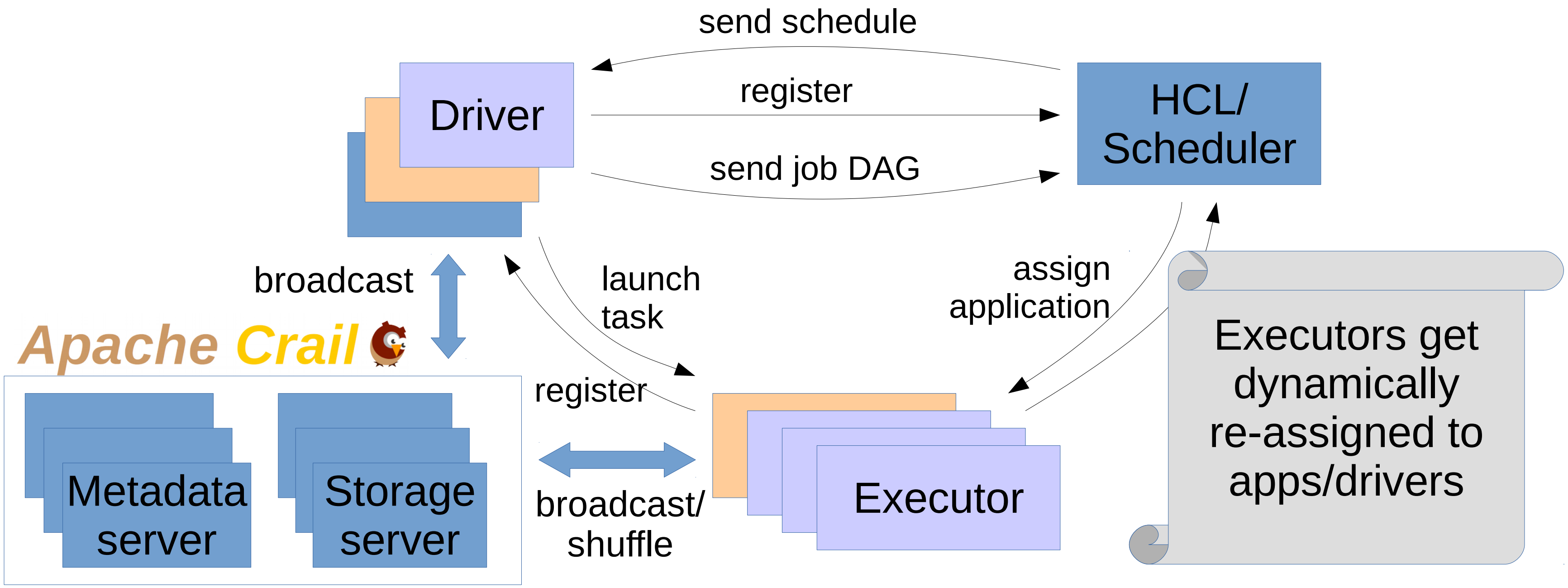
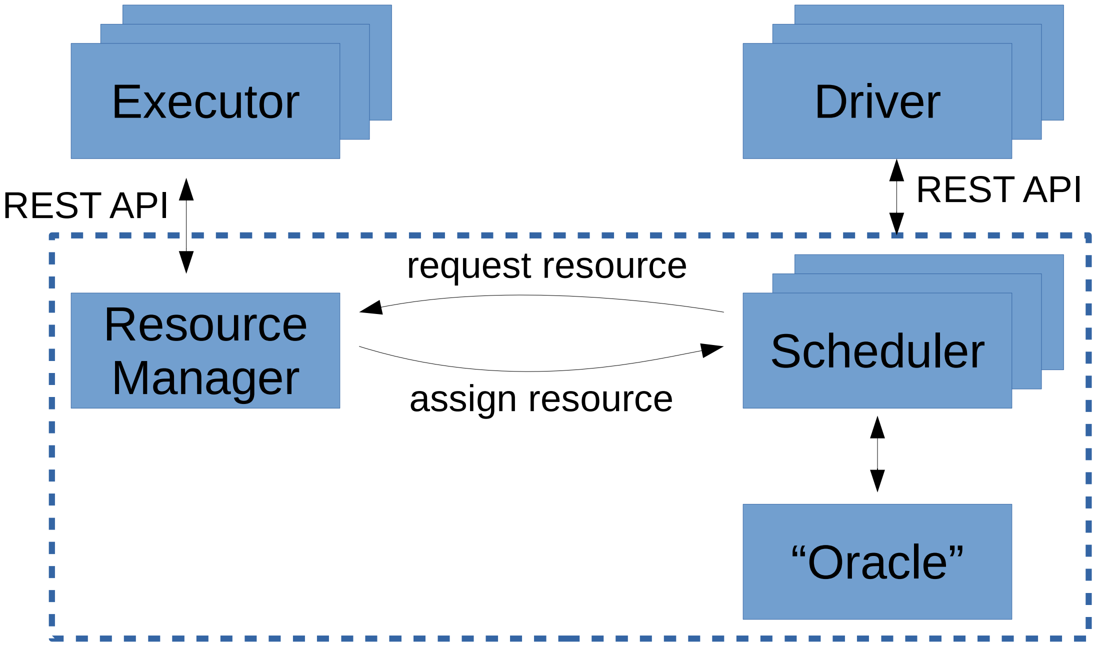


HCL Scheduler



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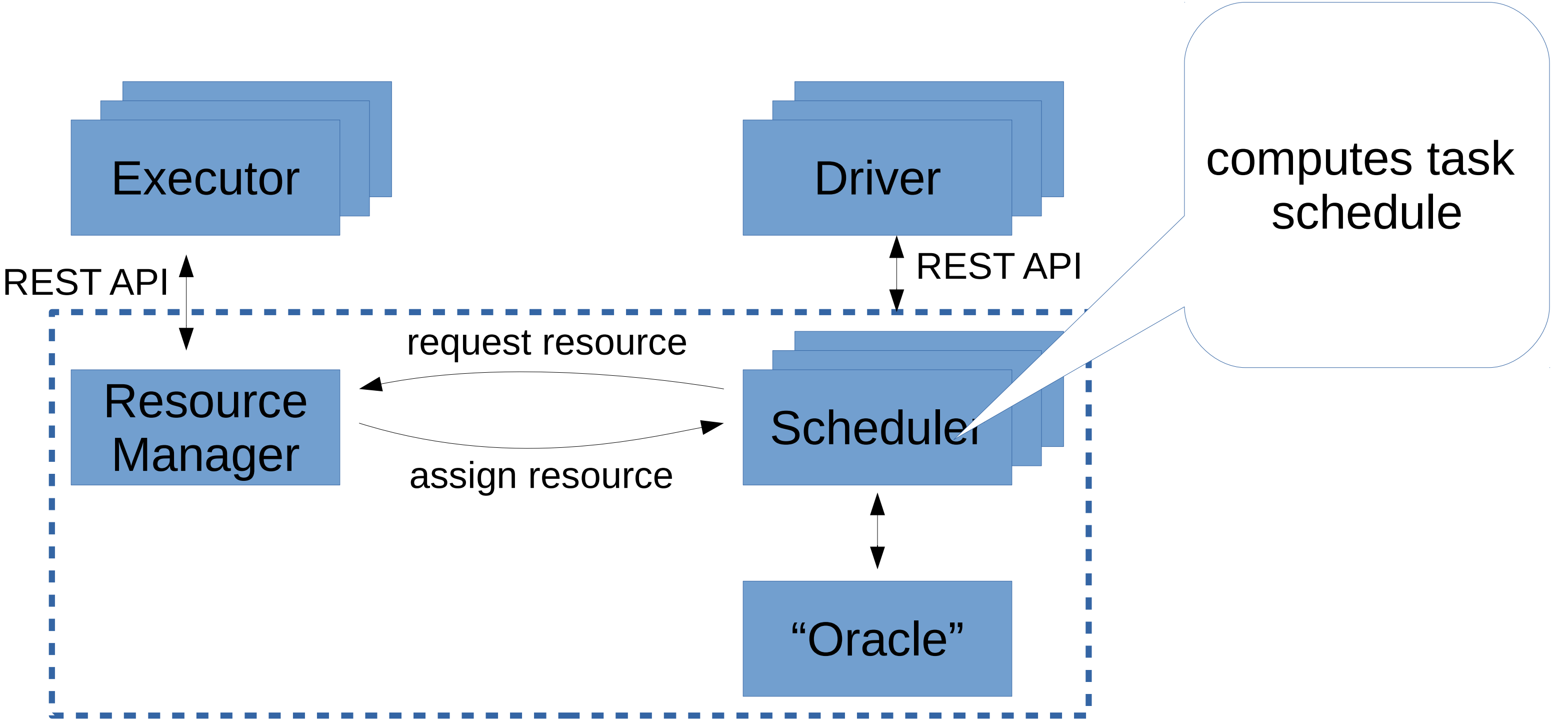

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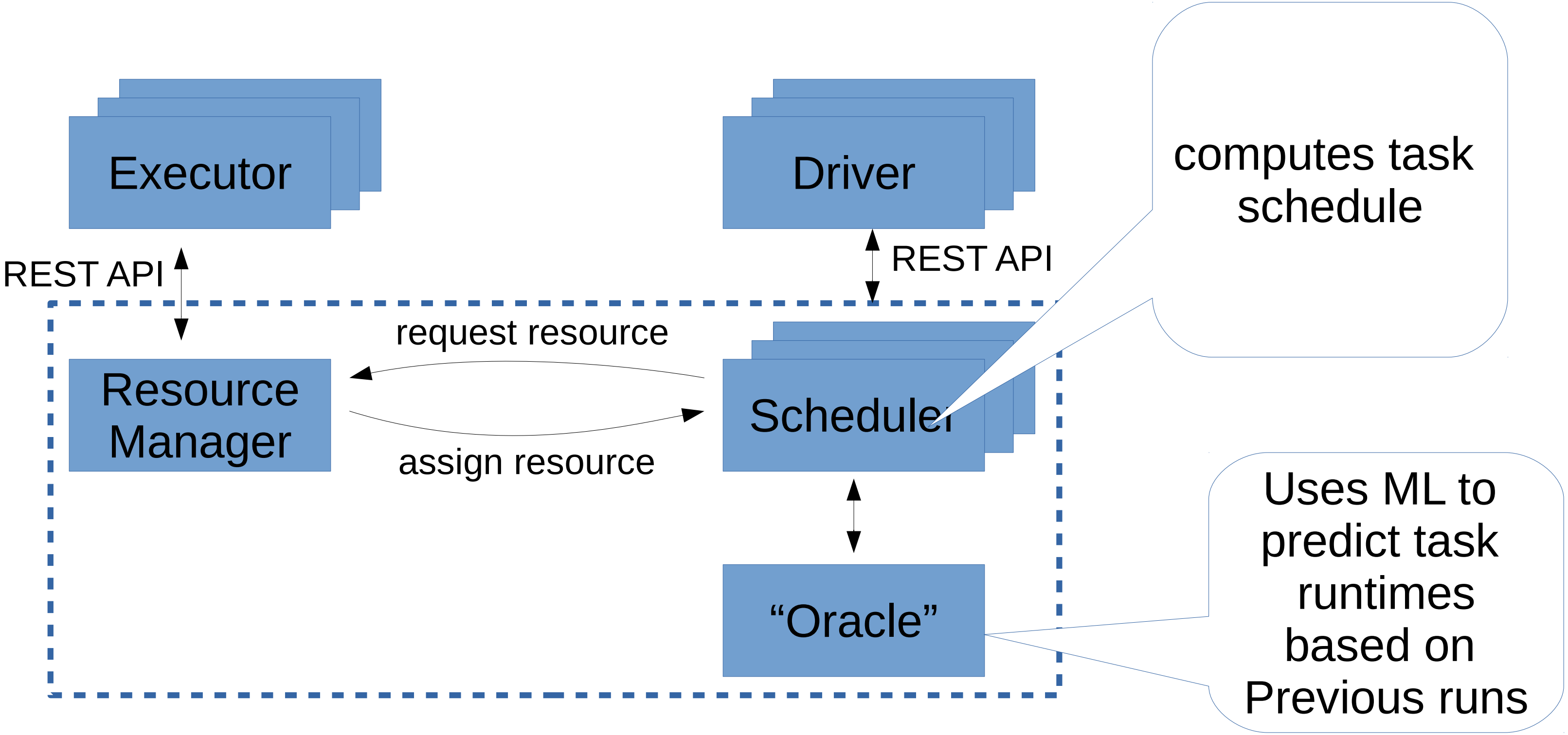

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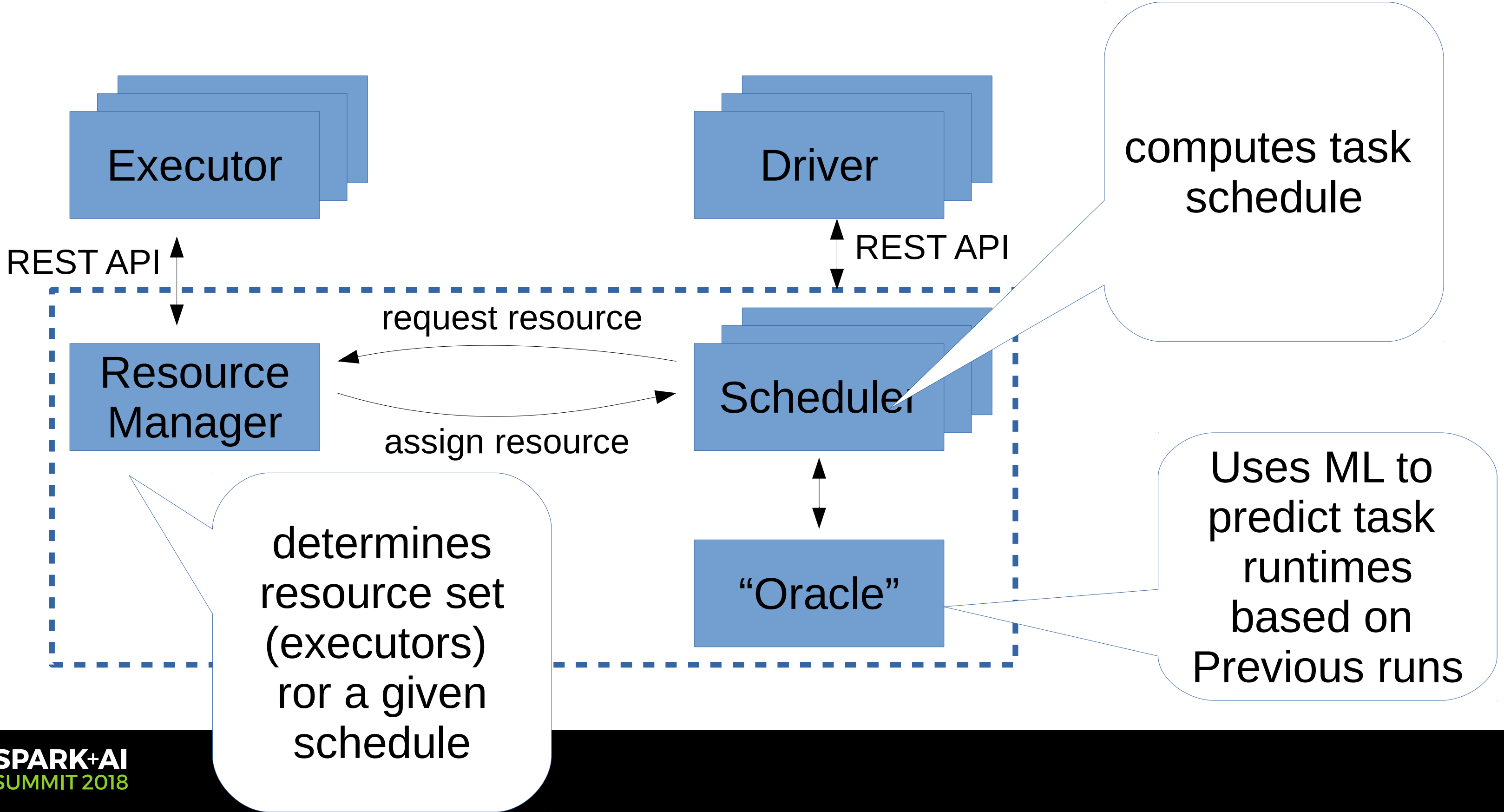
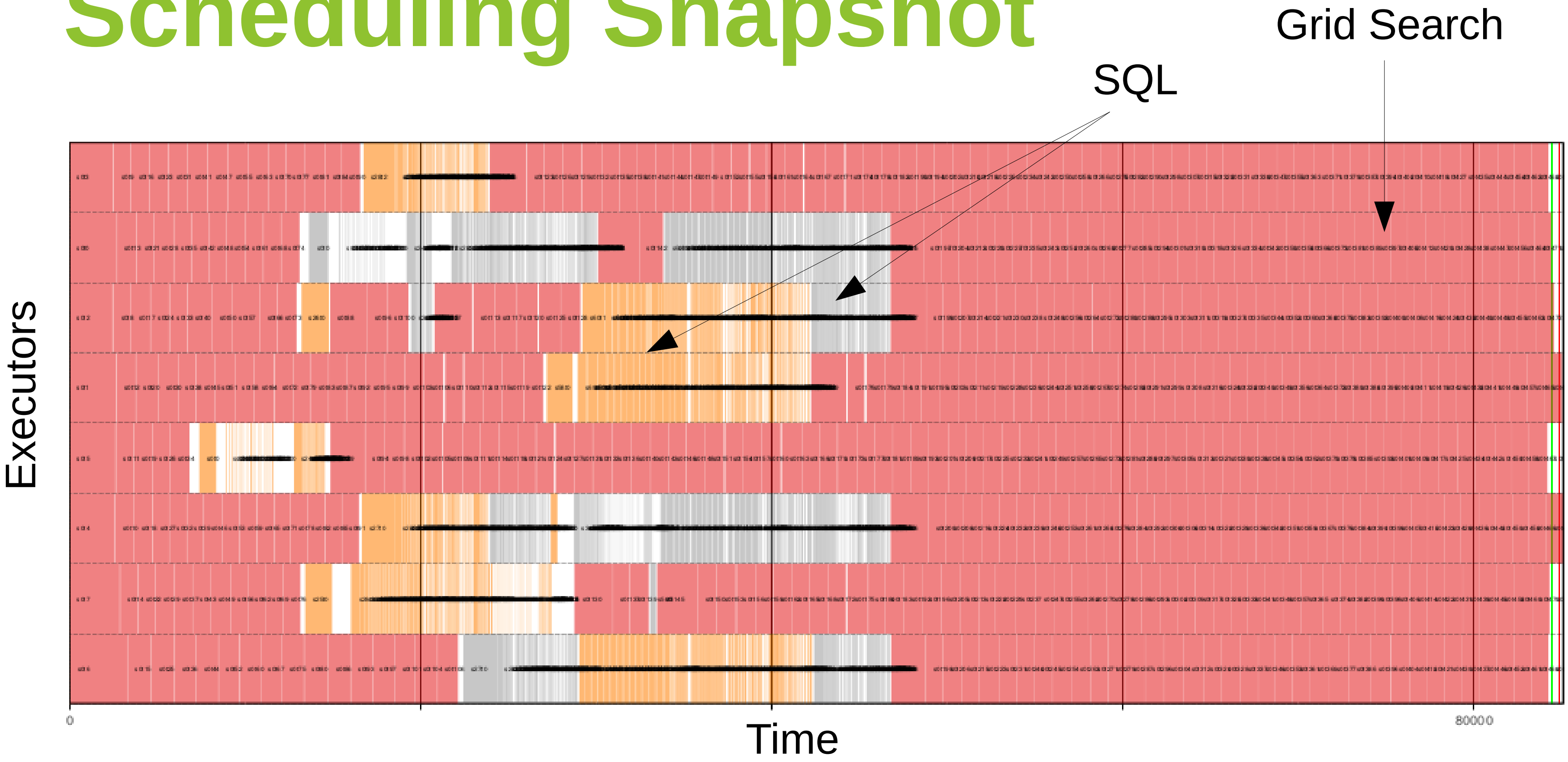


Video: Serverless ML and SQL

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

- Offering serverless to a wide range of workloads is challenging
  - Requires maintenance of state
  - Requires efficient decoupling of storage and compute
- Efficient scheduling and fast remote storage enable Spark to run in a serverless fashion
  -

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