Serverless Machine Learning on Modern Hardware

IBM Research

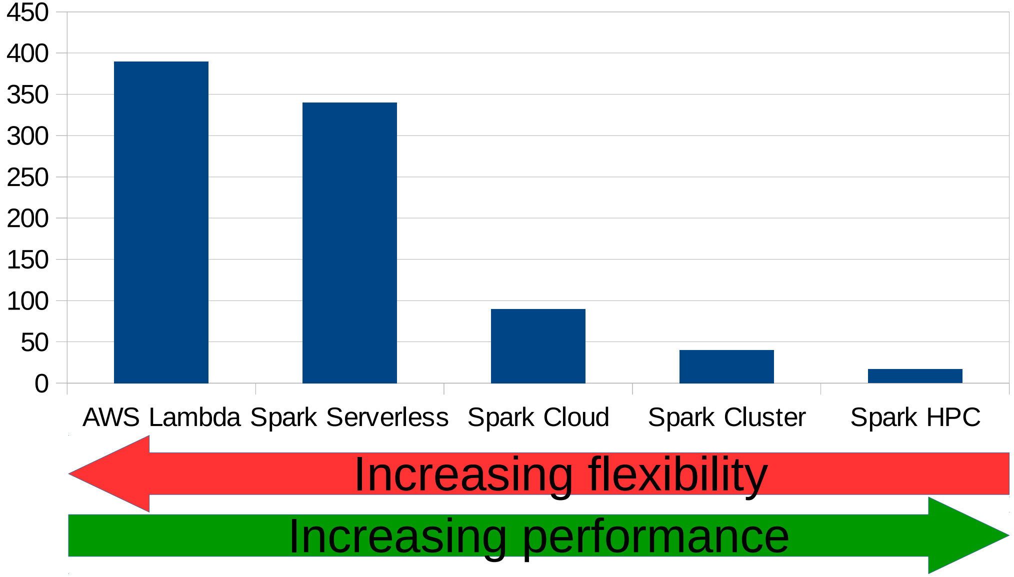
#Res6SAIS

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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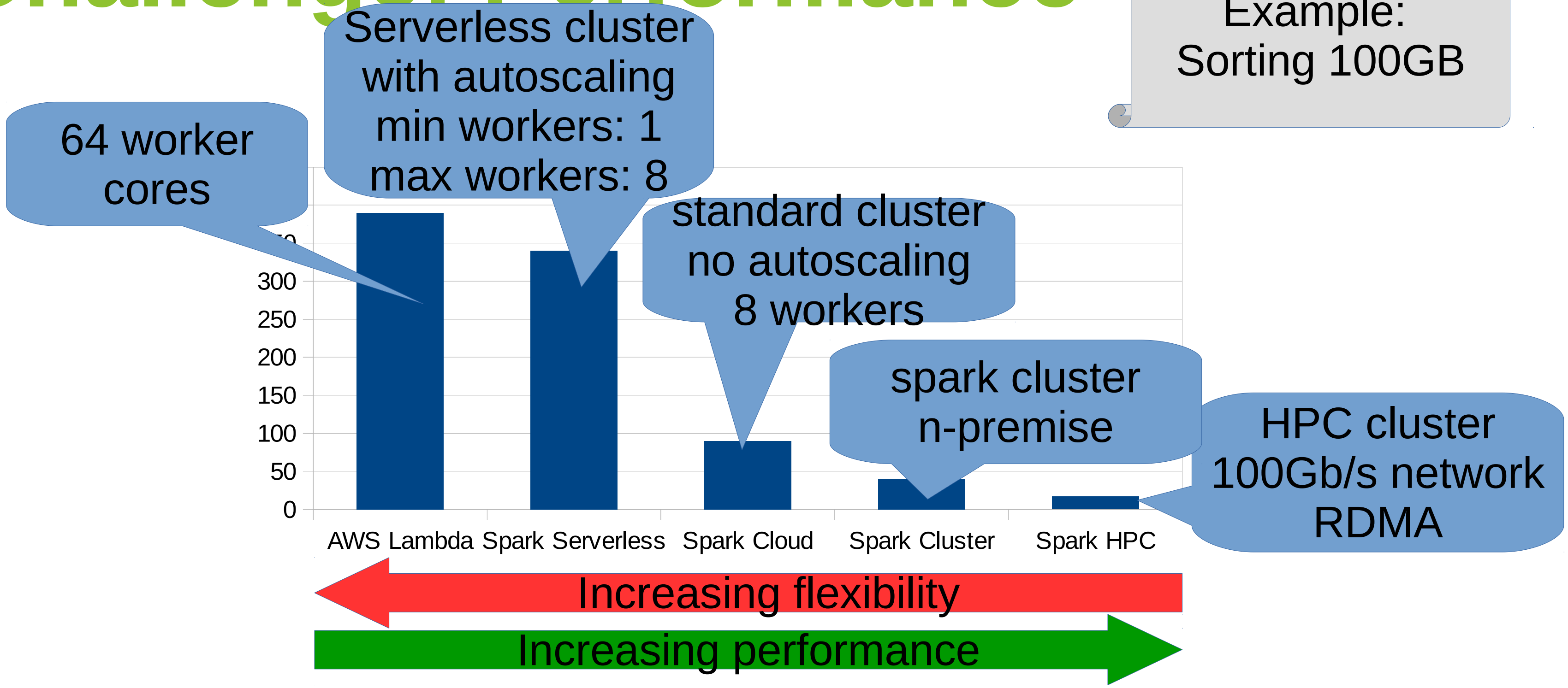

Challenge: Performance (2)

- **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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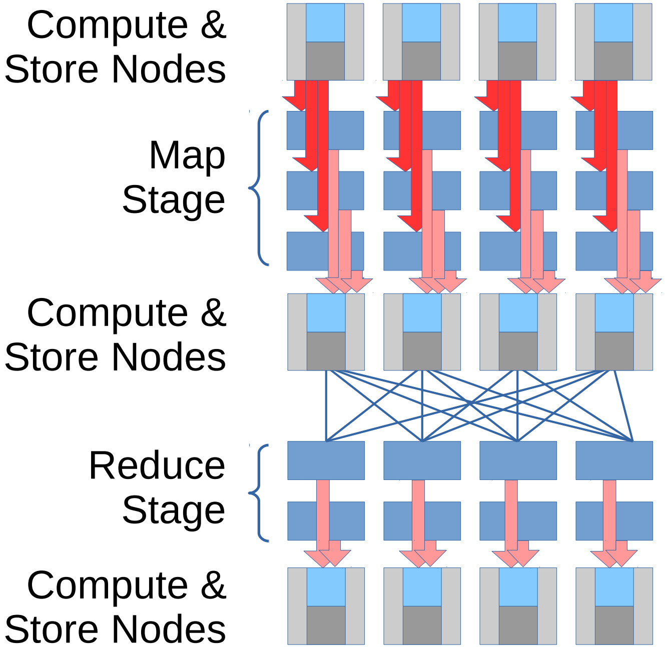
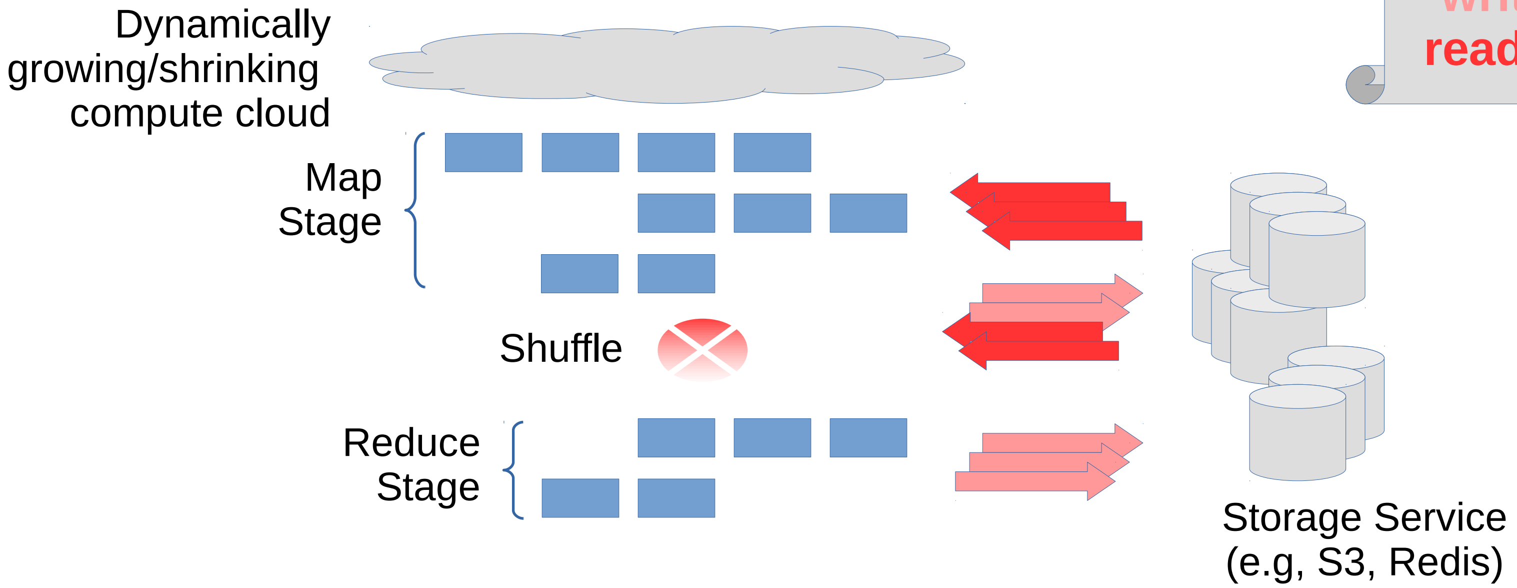
Example: MapReduce (Cluster)



data is mostly
written and
read locally

Serverless MapReduce

data is exclusively written and **read** remotely



I/O Overhead

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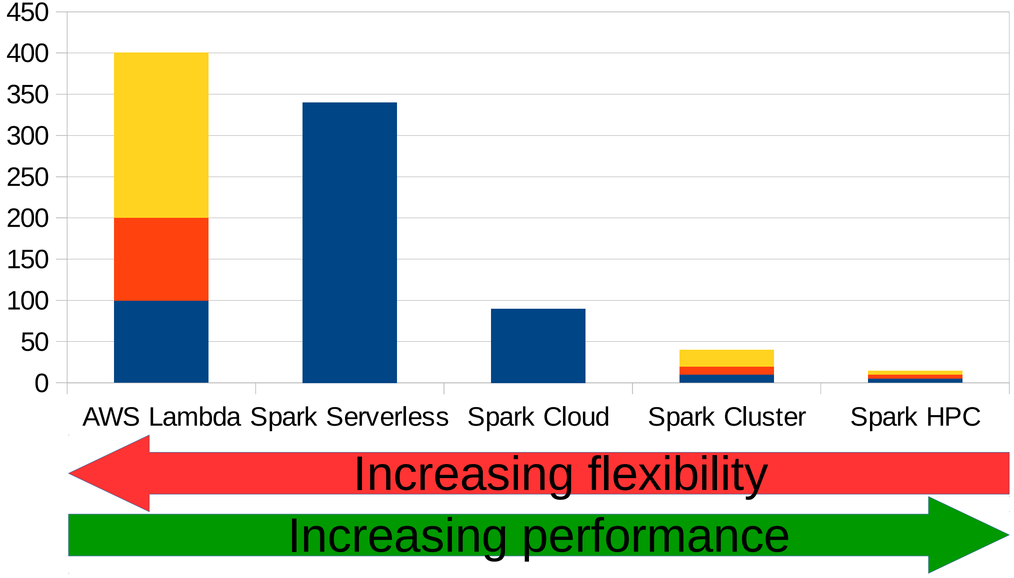
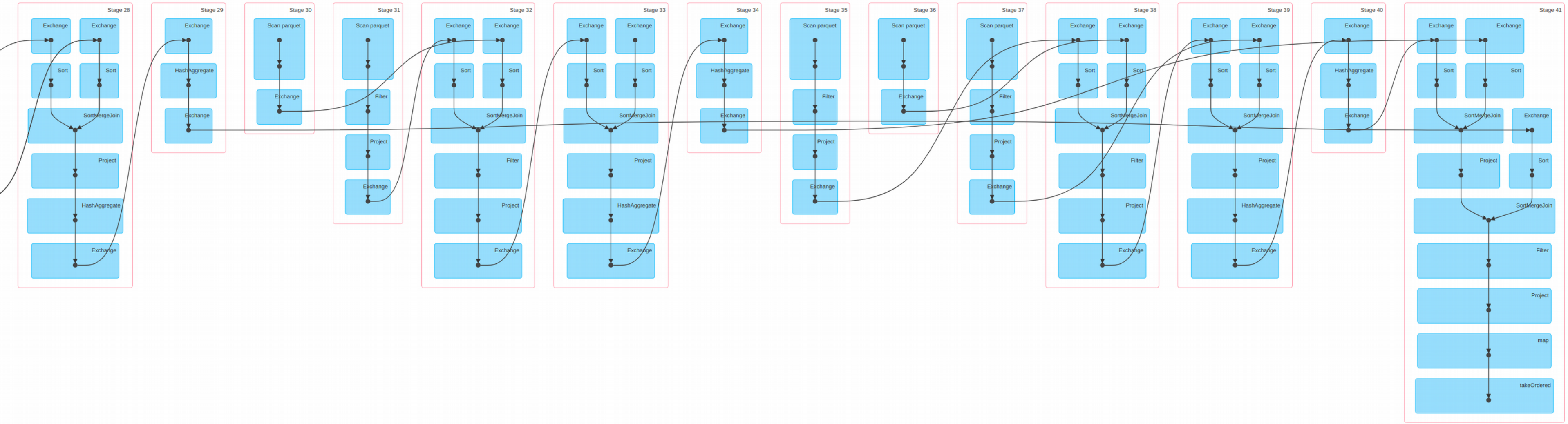


What about other workloads?

Example: SQL, Query 77 / TPC-DS benchmark



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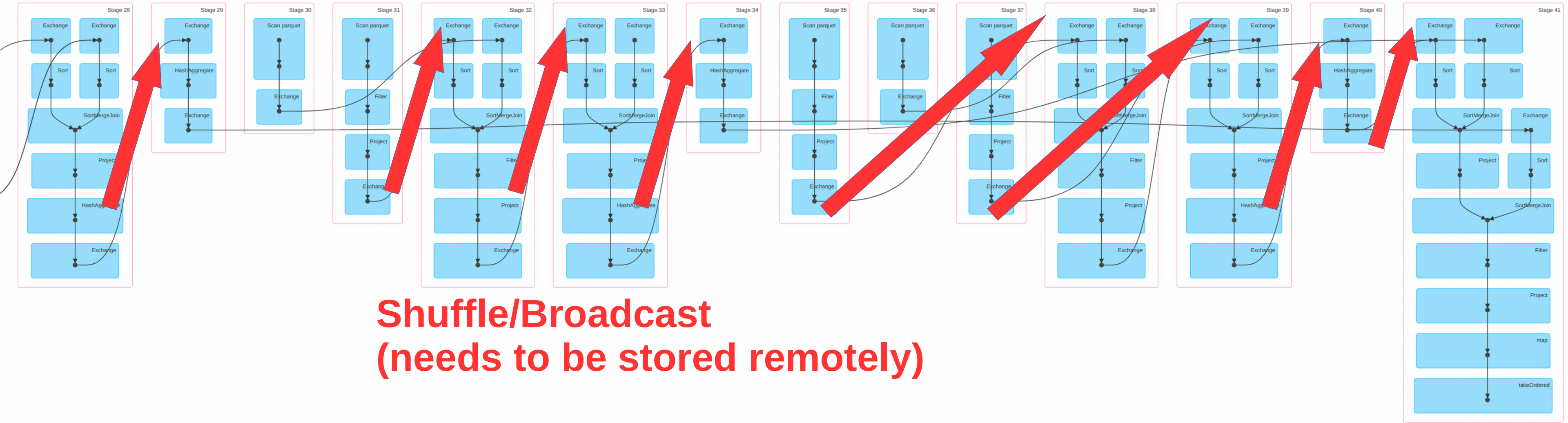

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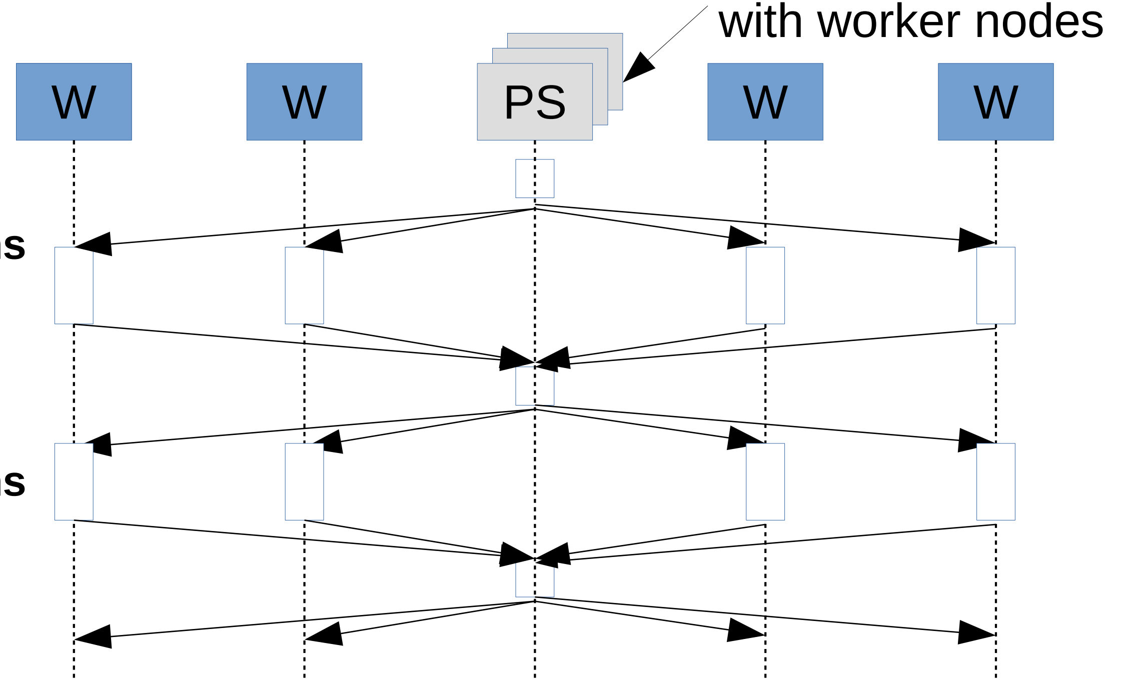
Example: Iterative ML (e.g., linear regression)



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

:

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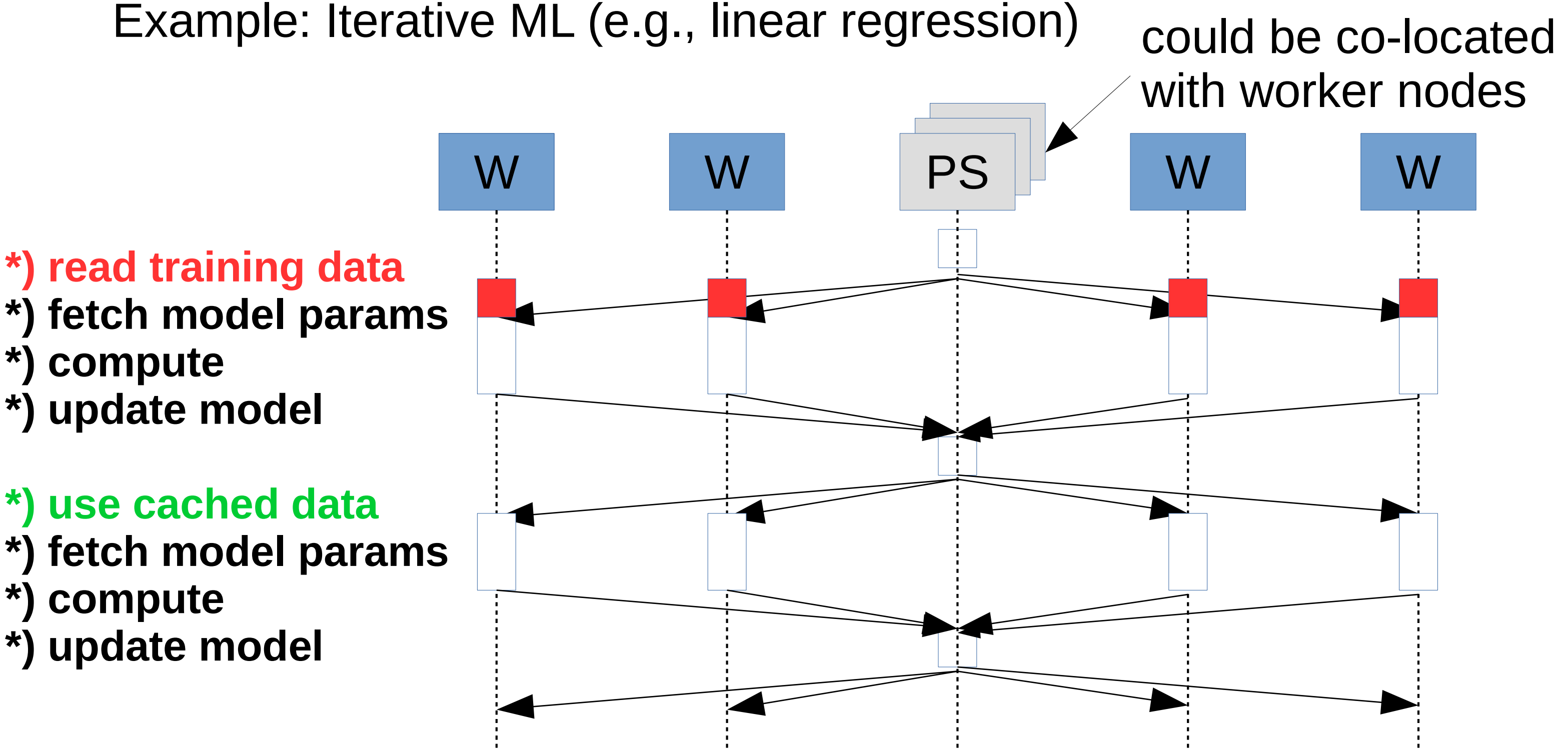

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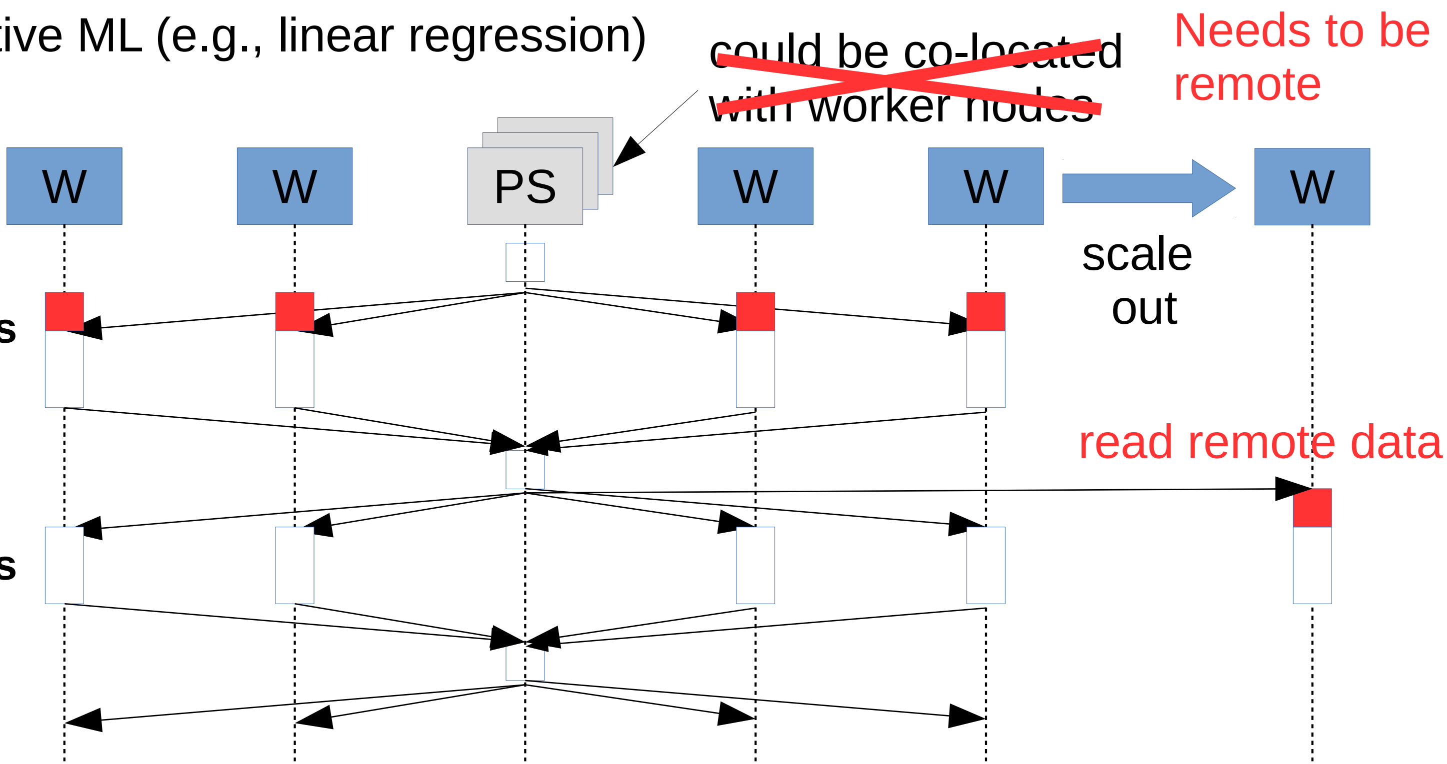

*) read training data
*) fetch model params
*) compute
*) update model

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

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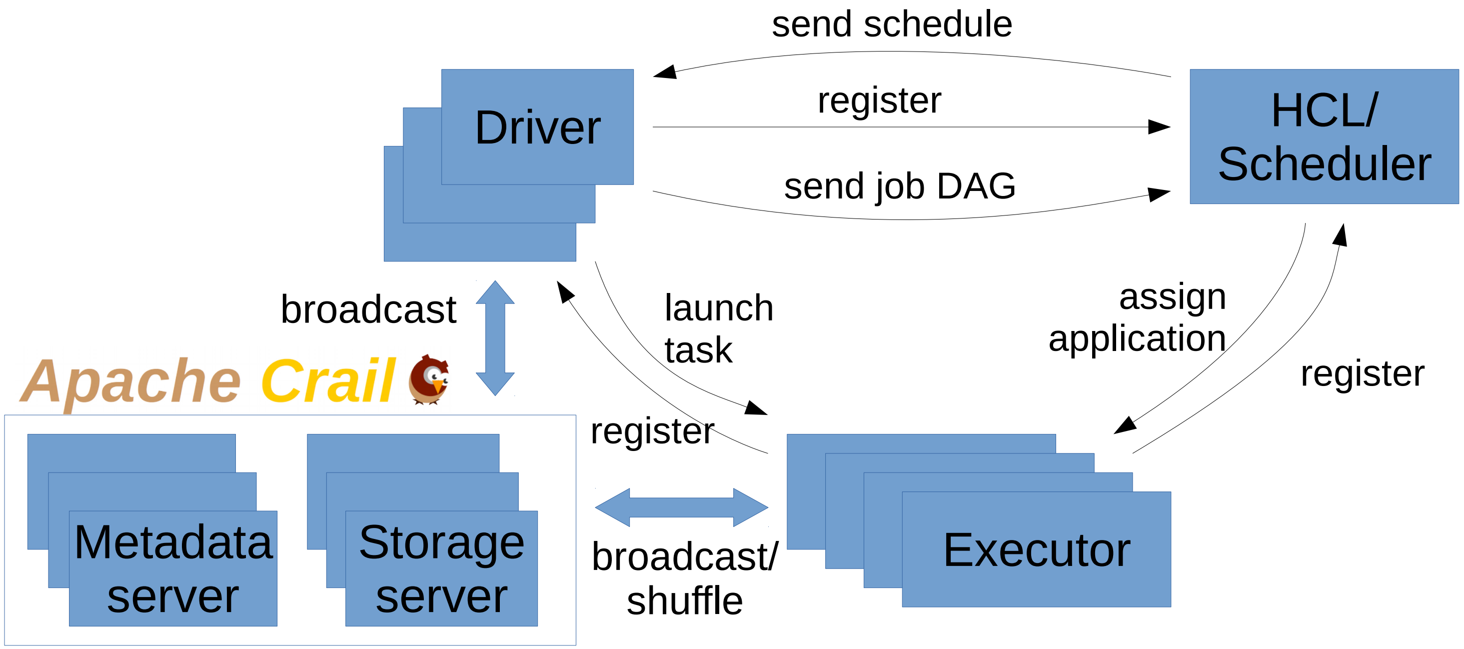

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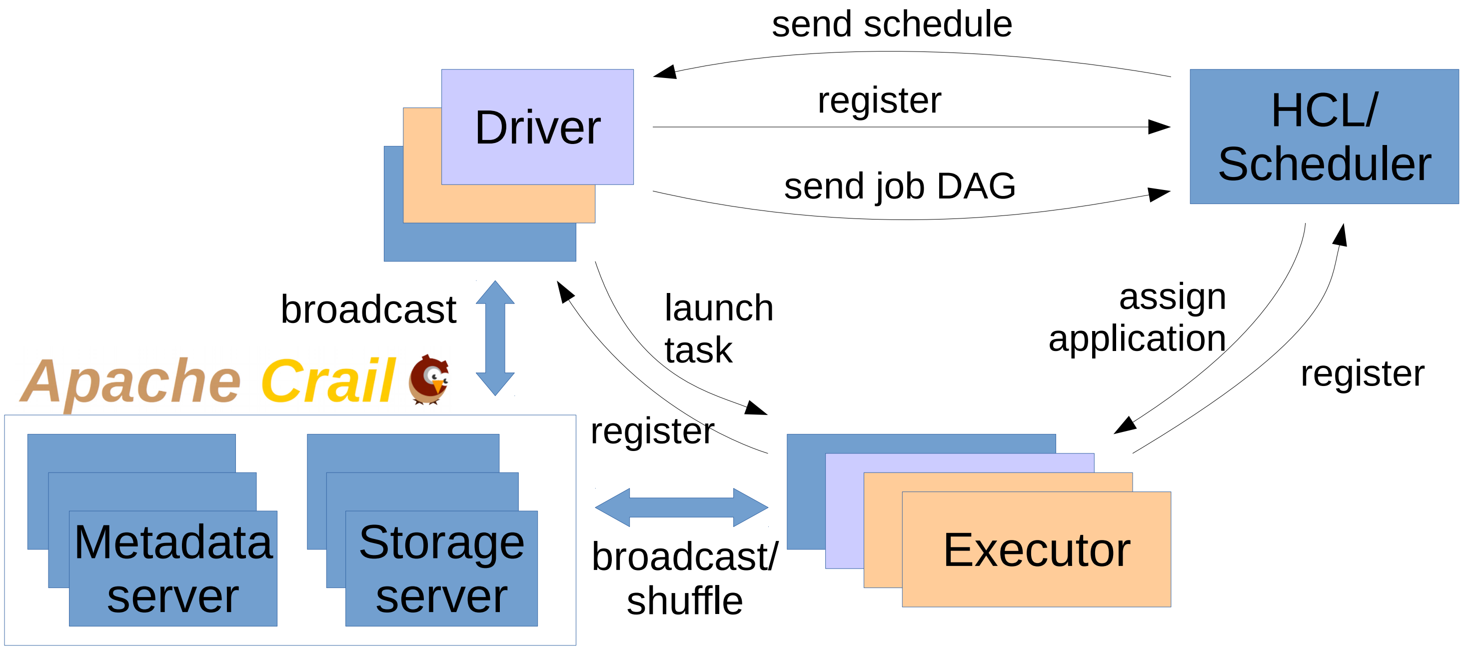

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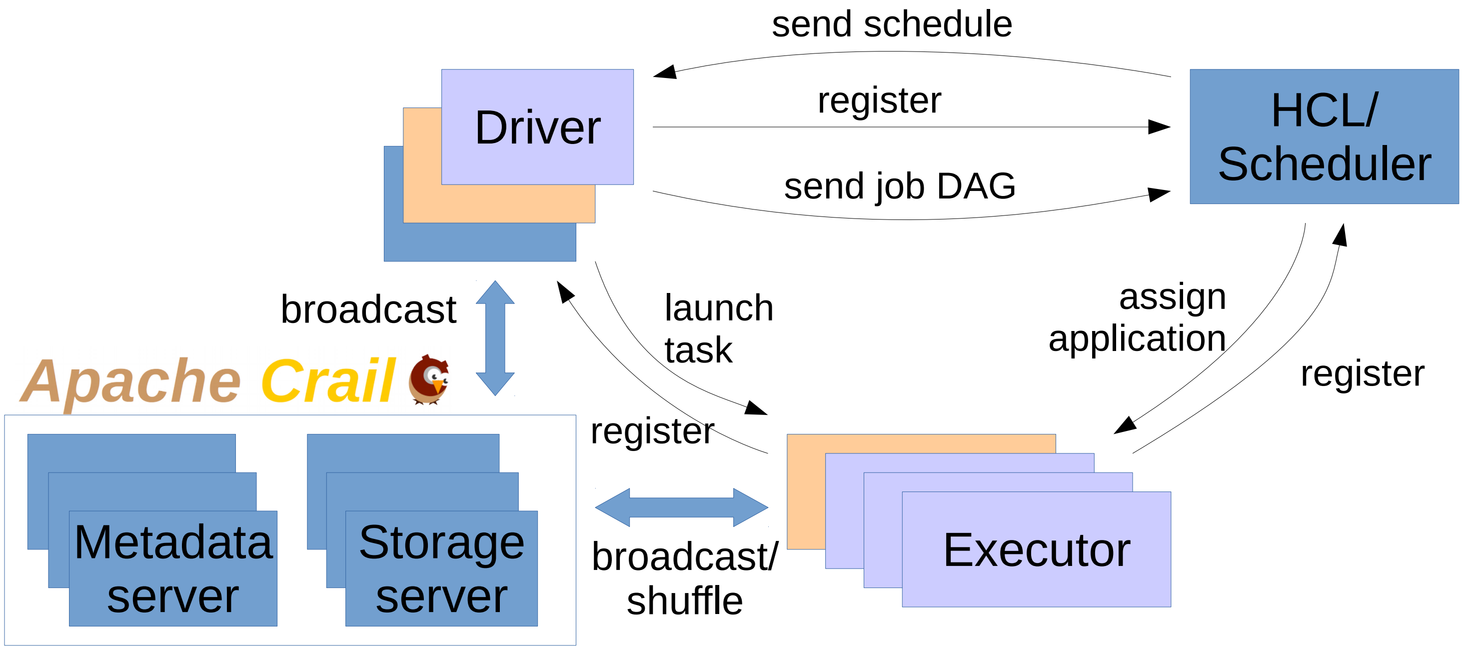

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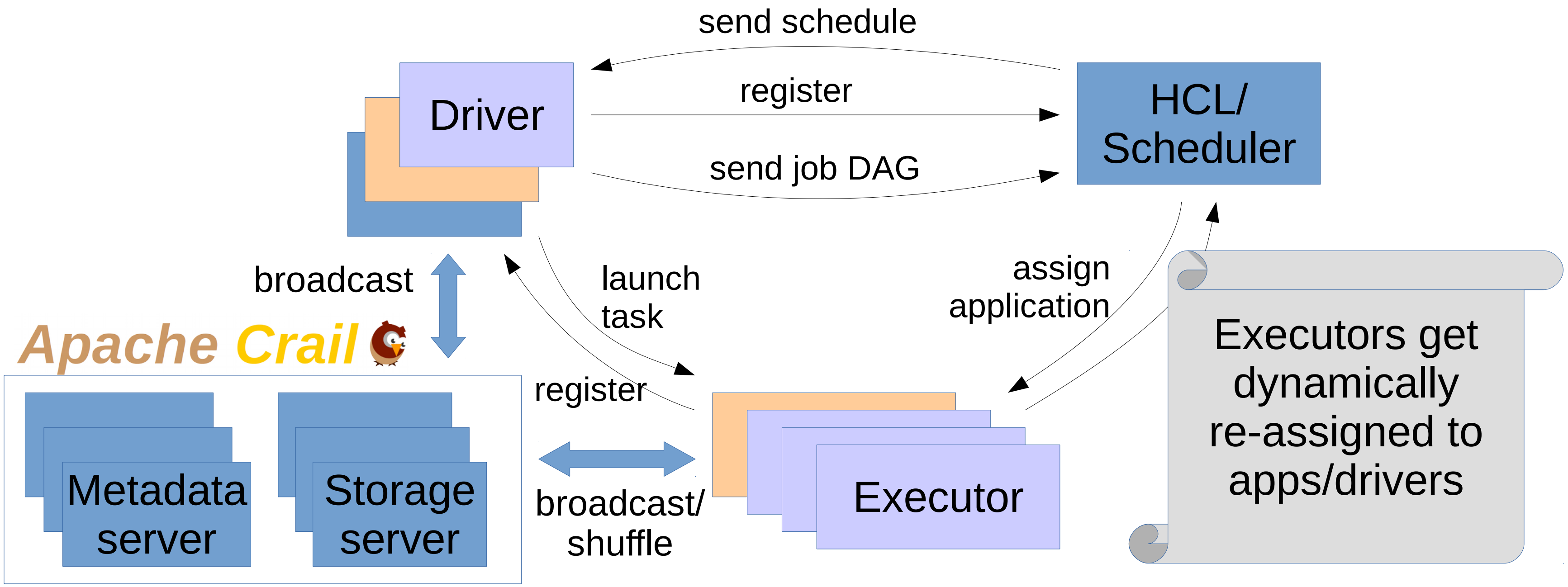
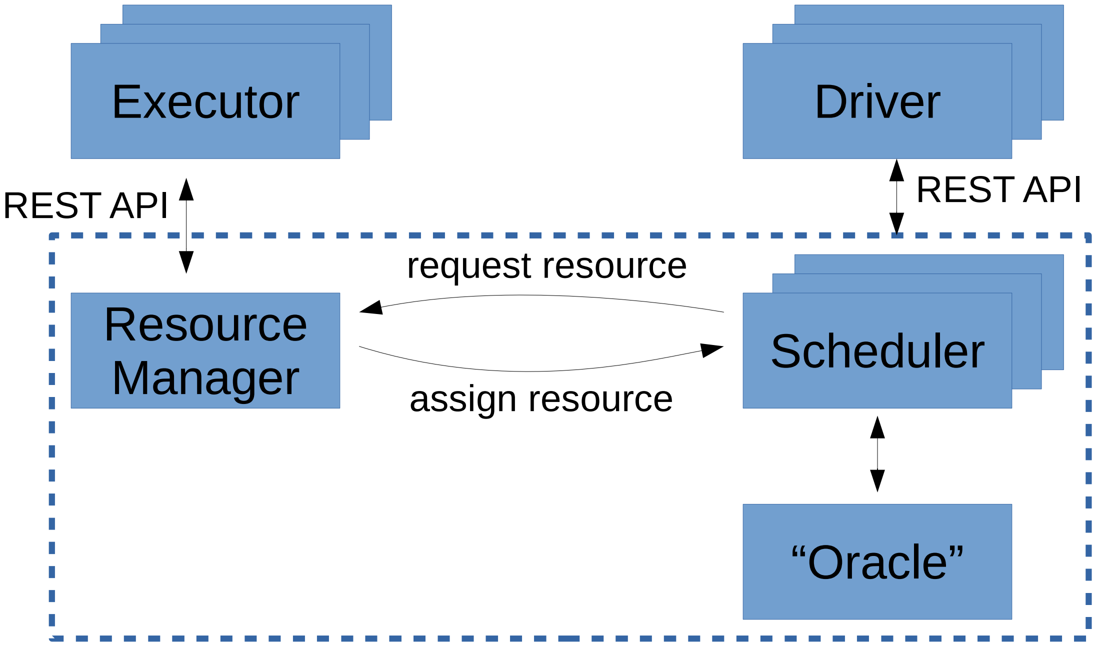


HCL Scheduler



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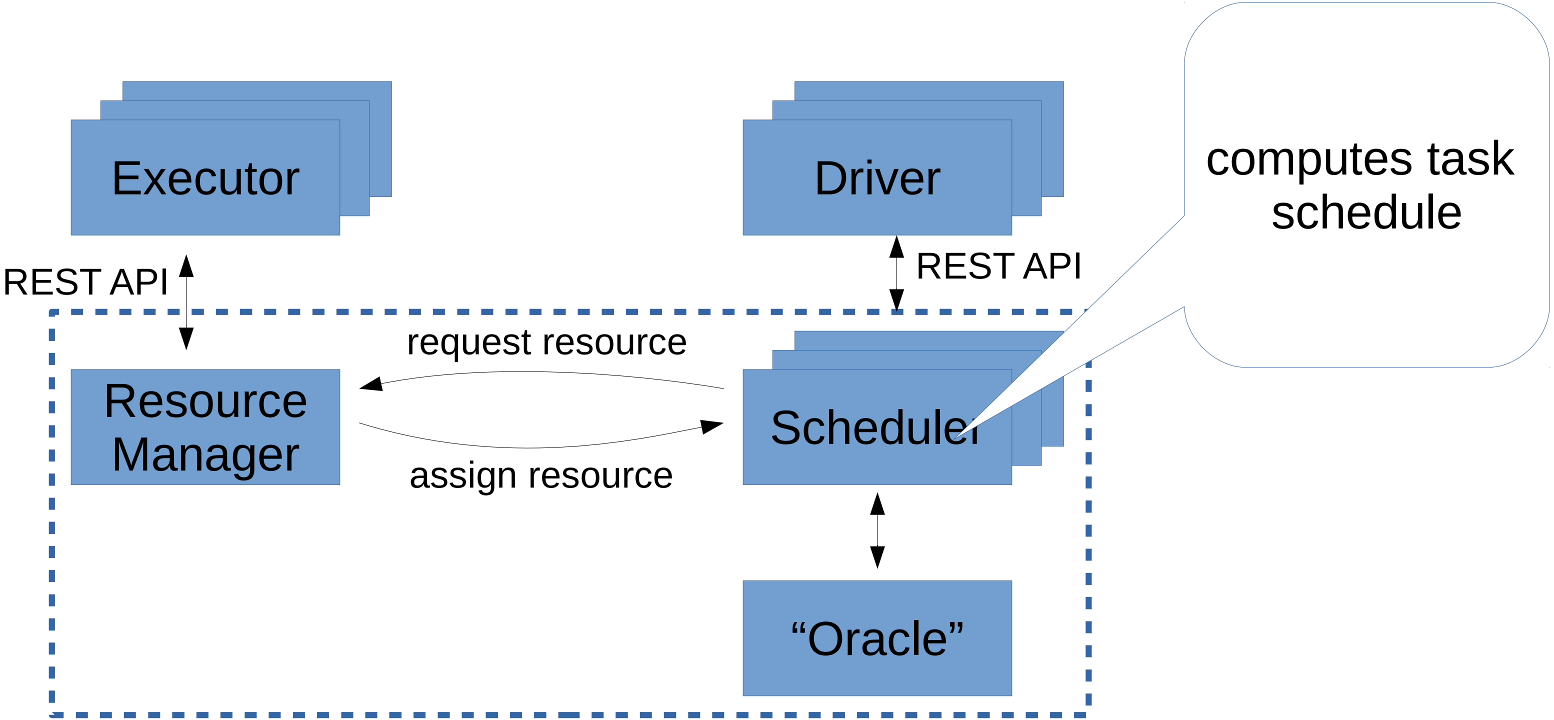

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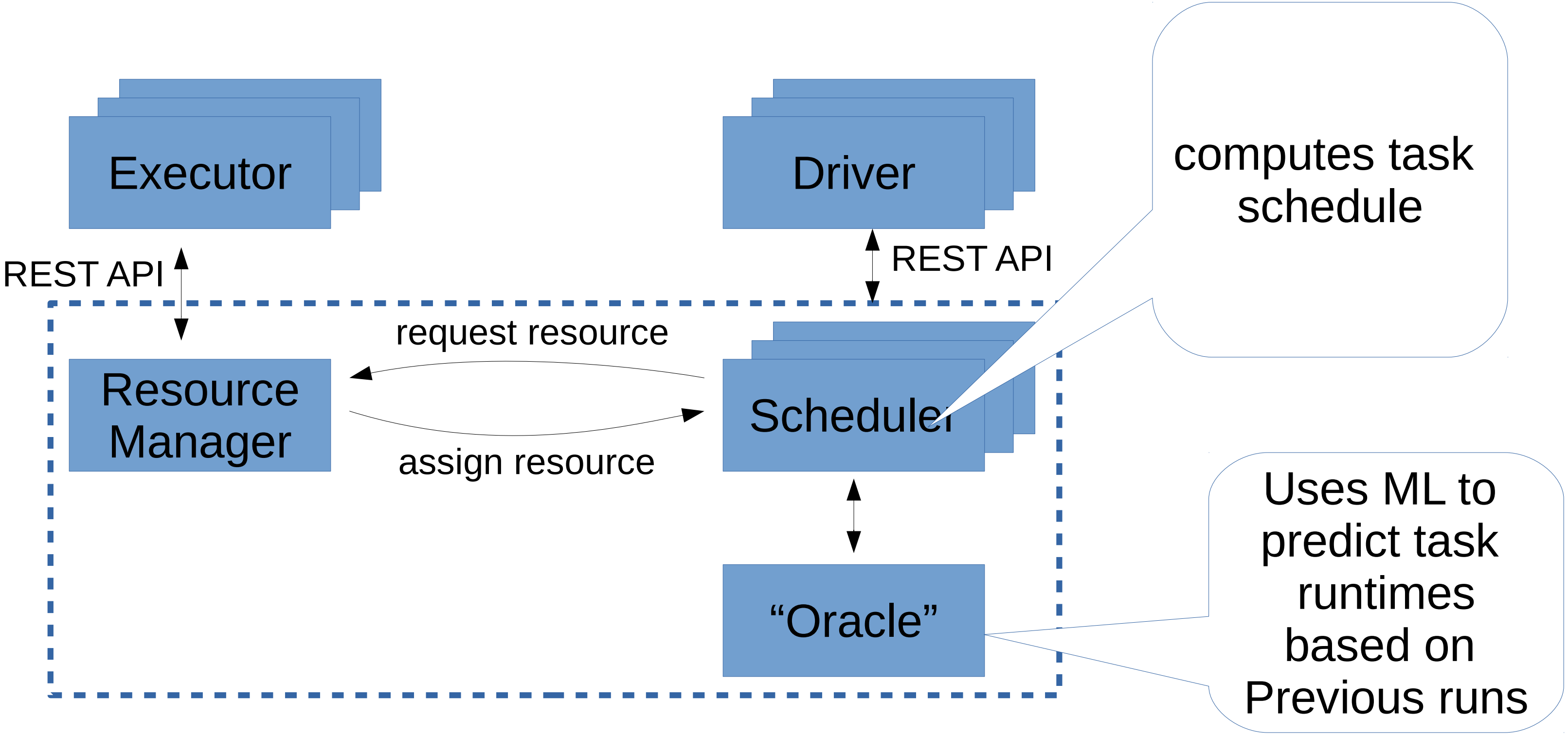

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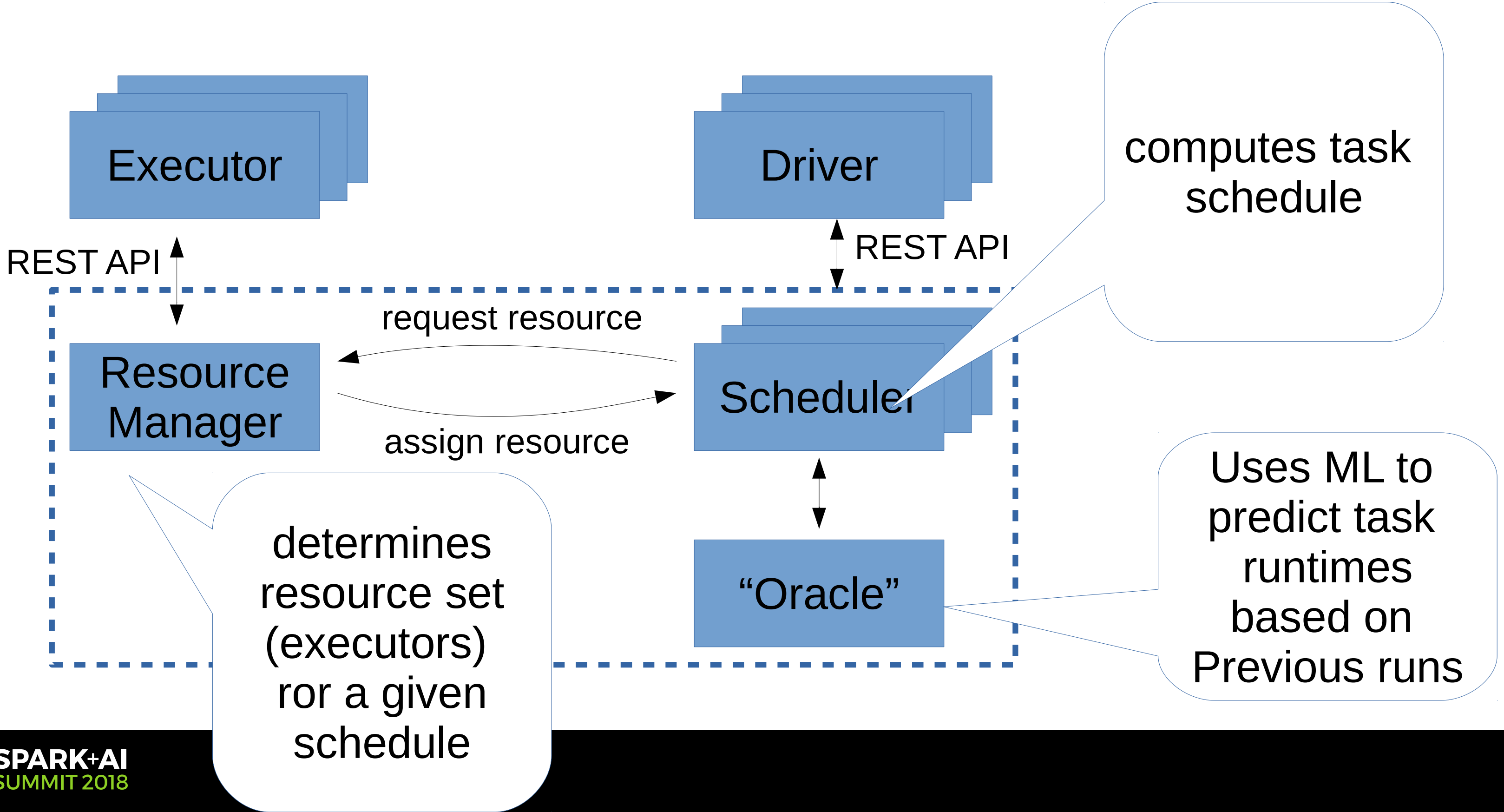

Example using ML and SQL

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