Serverless Machine Learning on Modern Hardware

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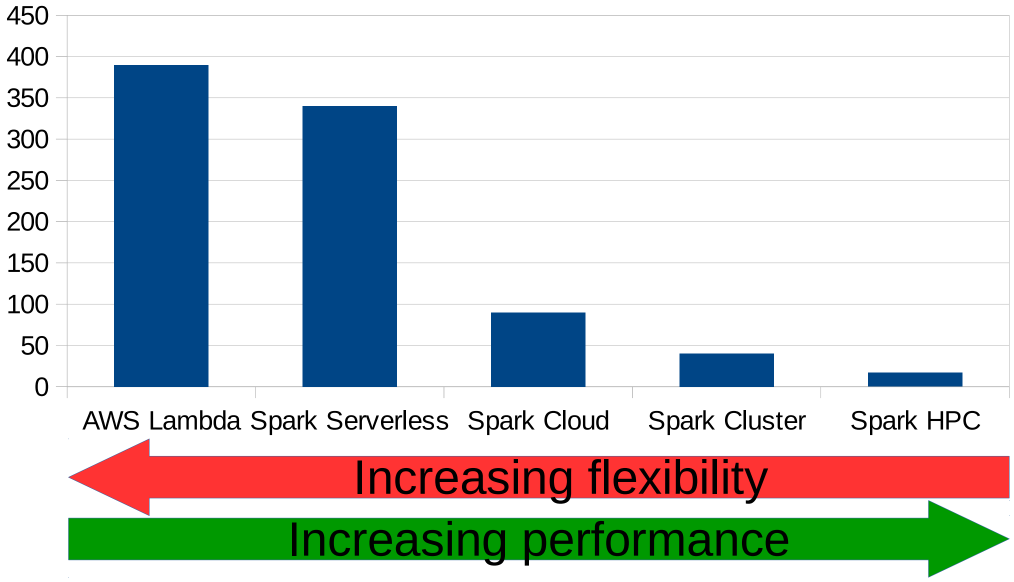
#Res6SAIS

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



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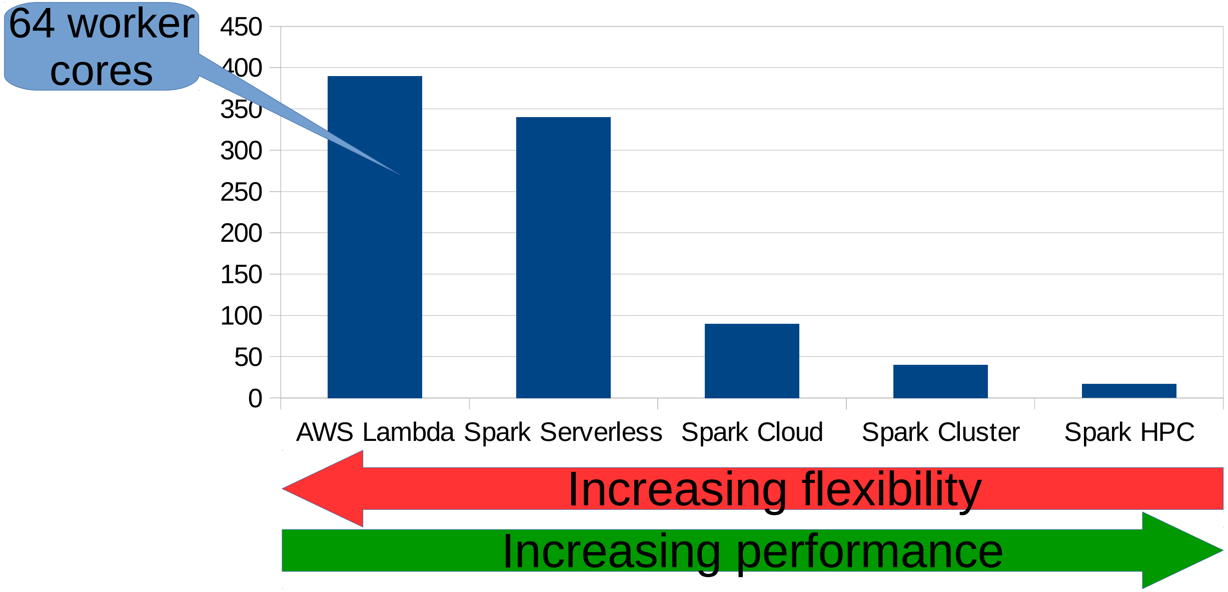

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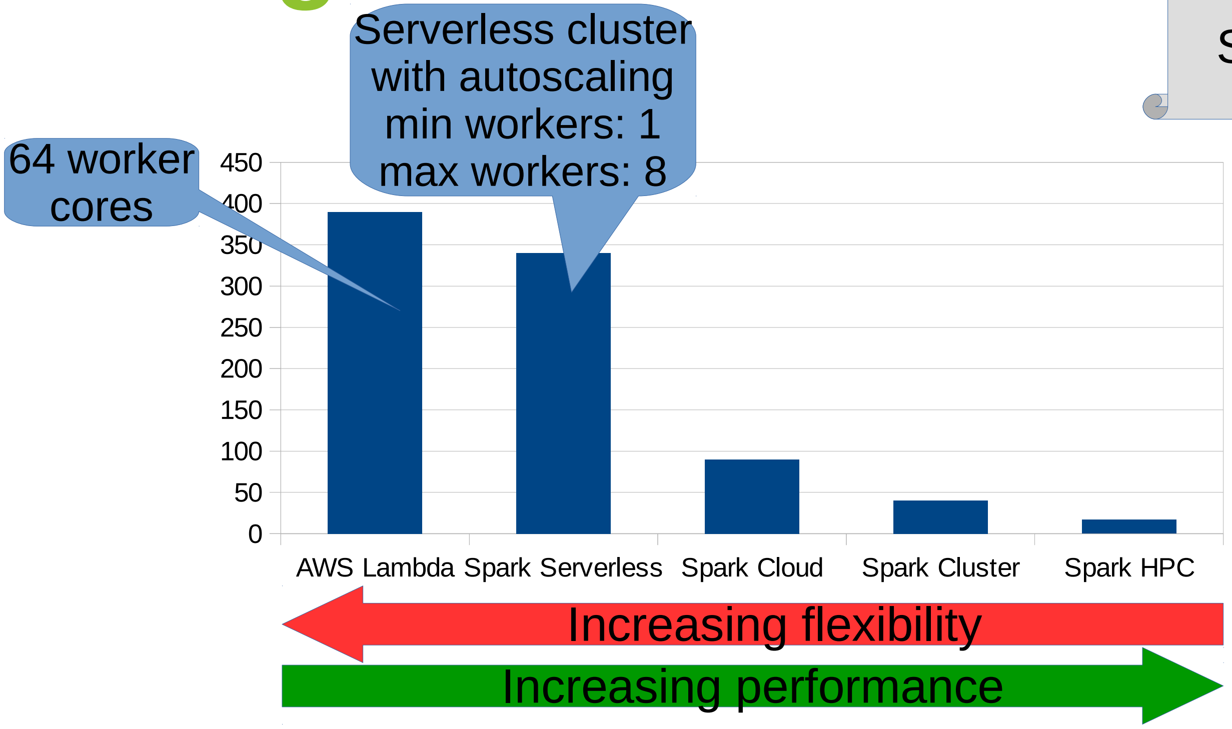

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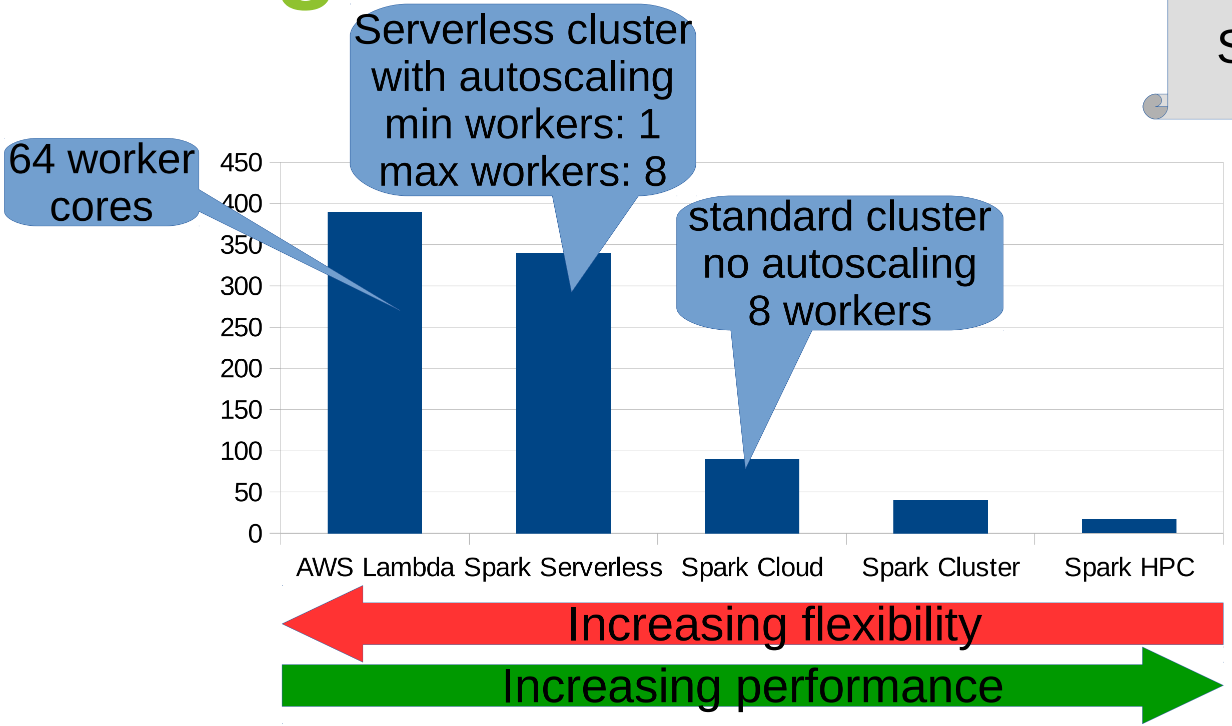

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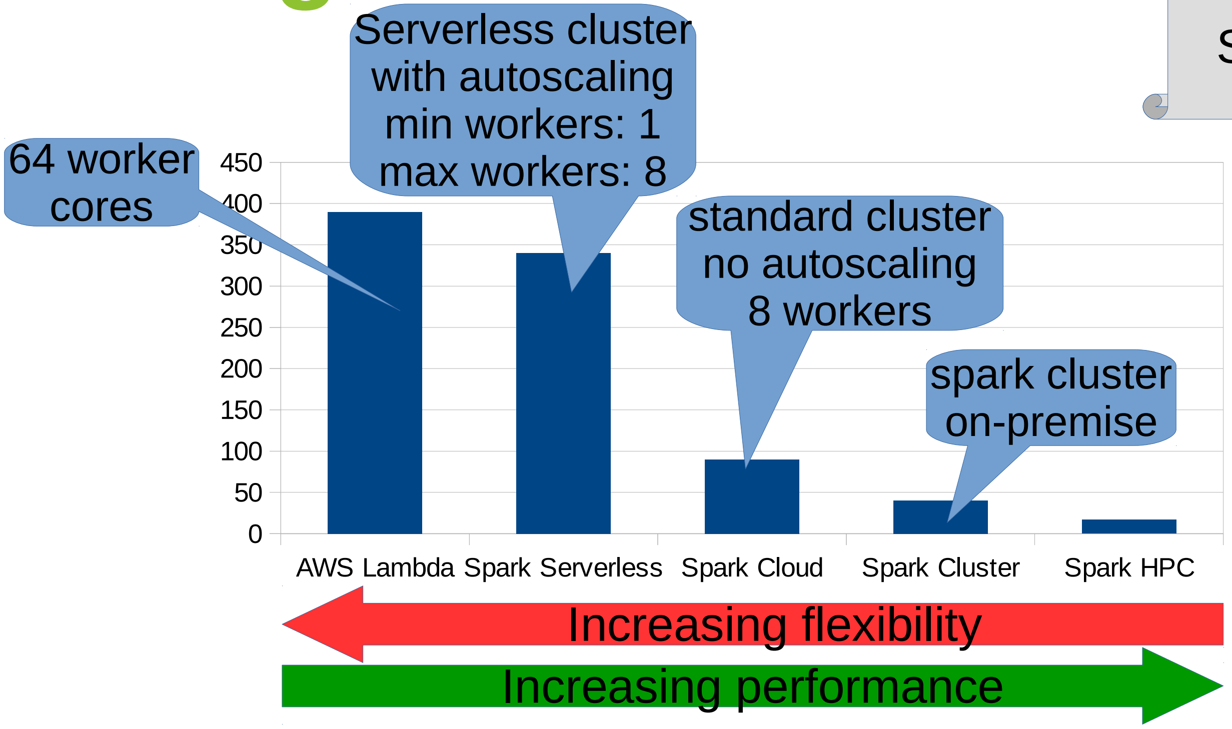

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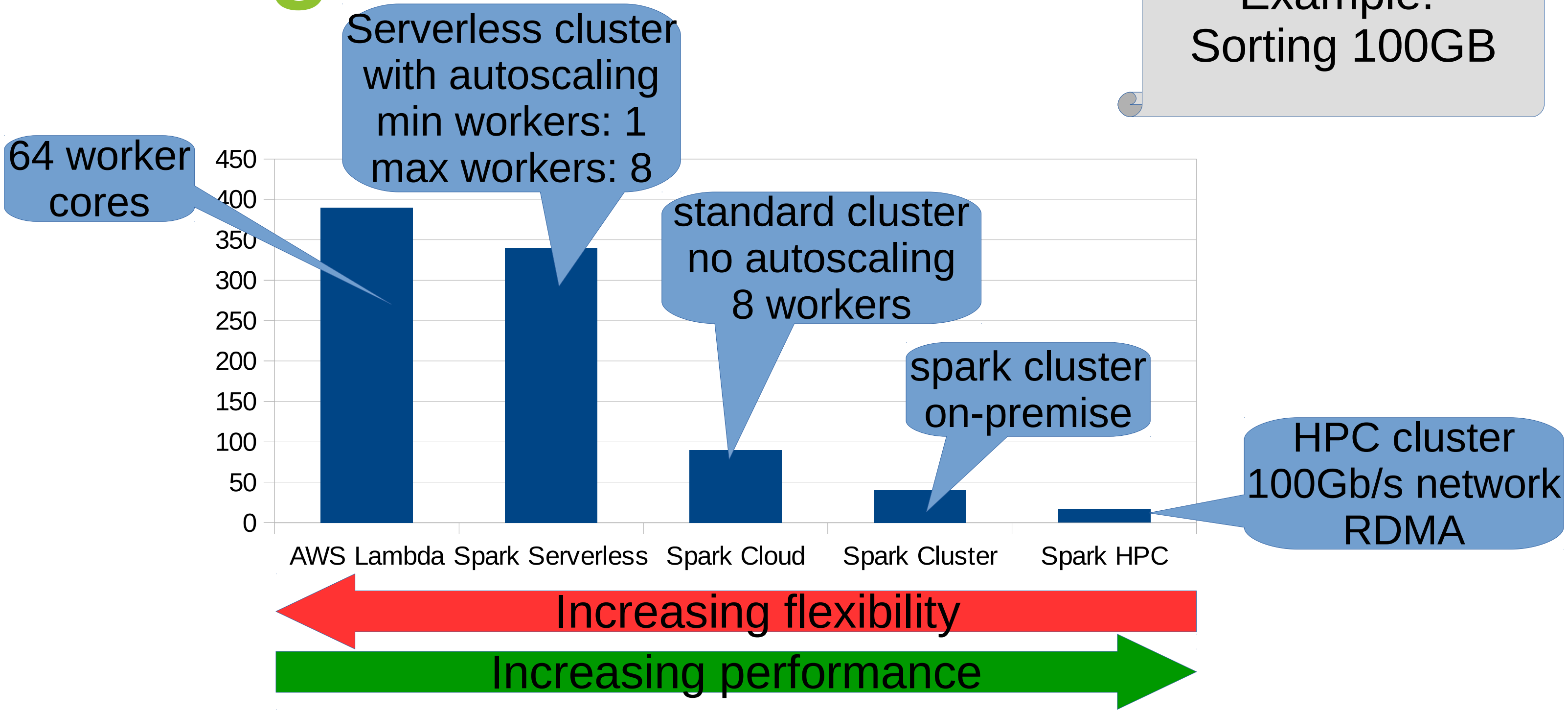

Why is it so hard?

- **Scheduler:** when to best add/remove resources?
- **Container startup:** may have to dynamically spin up containers 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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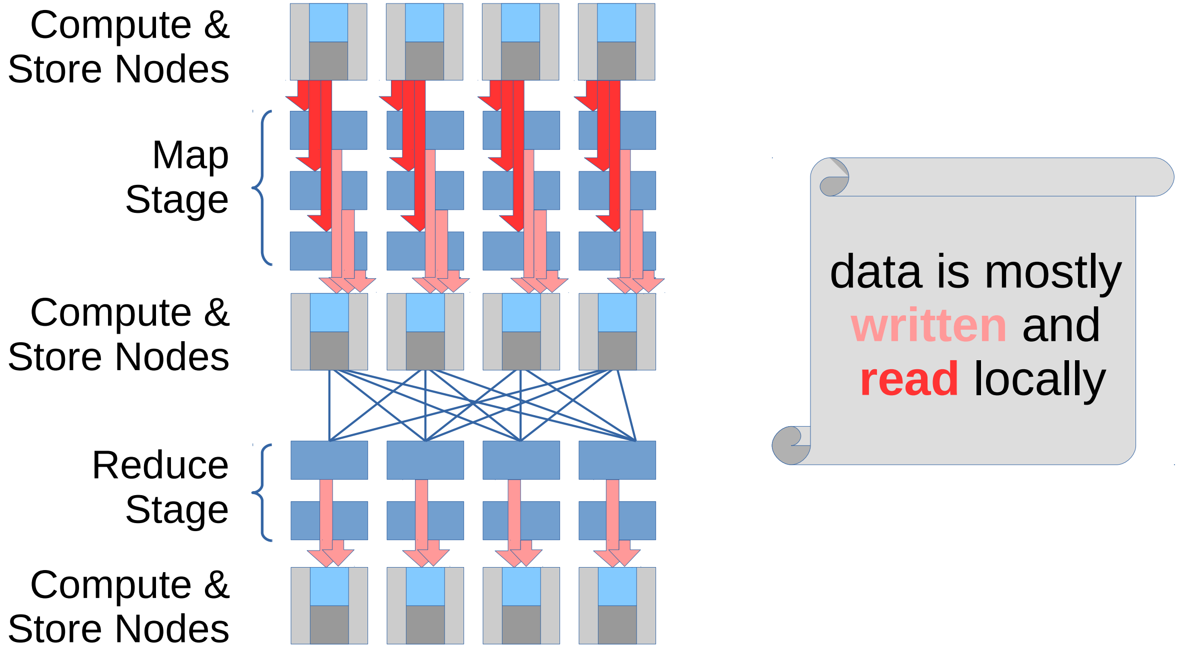
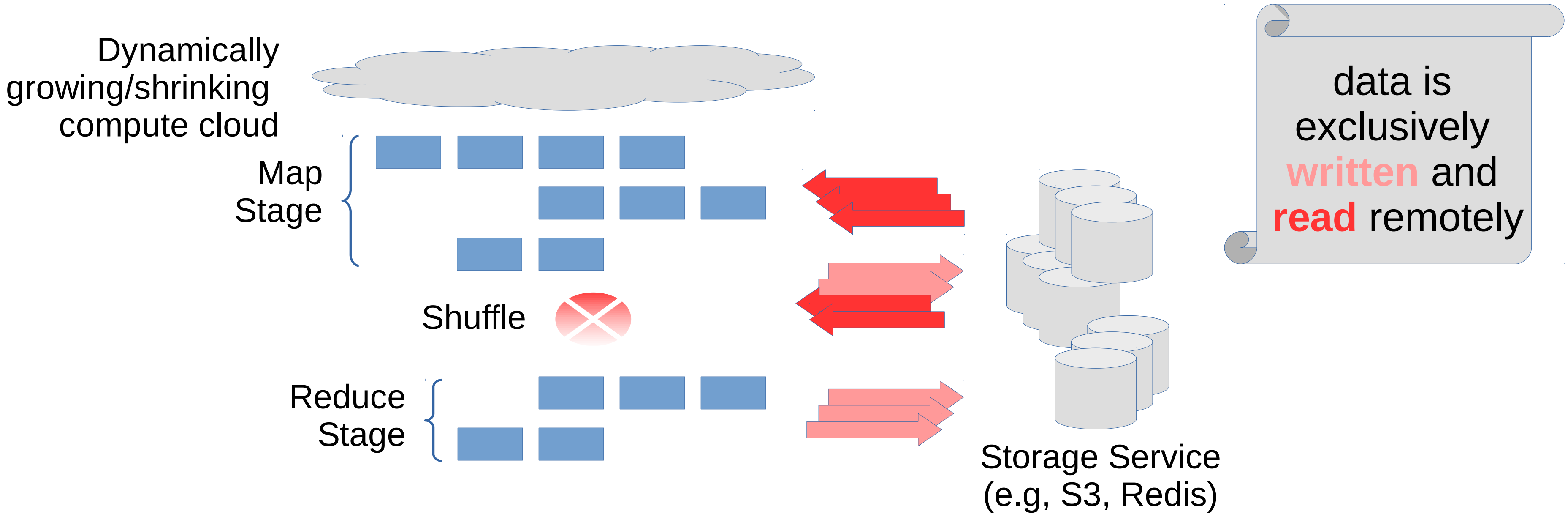
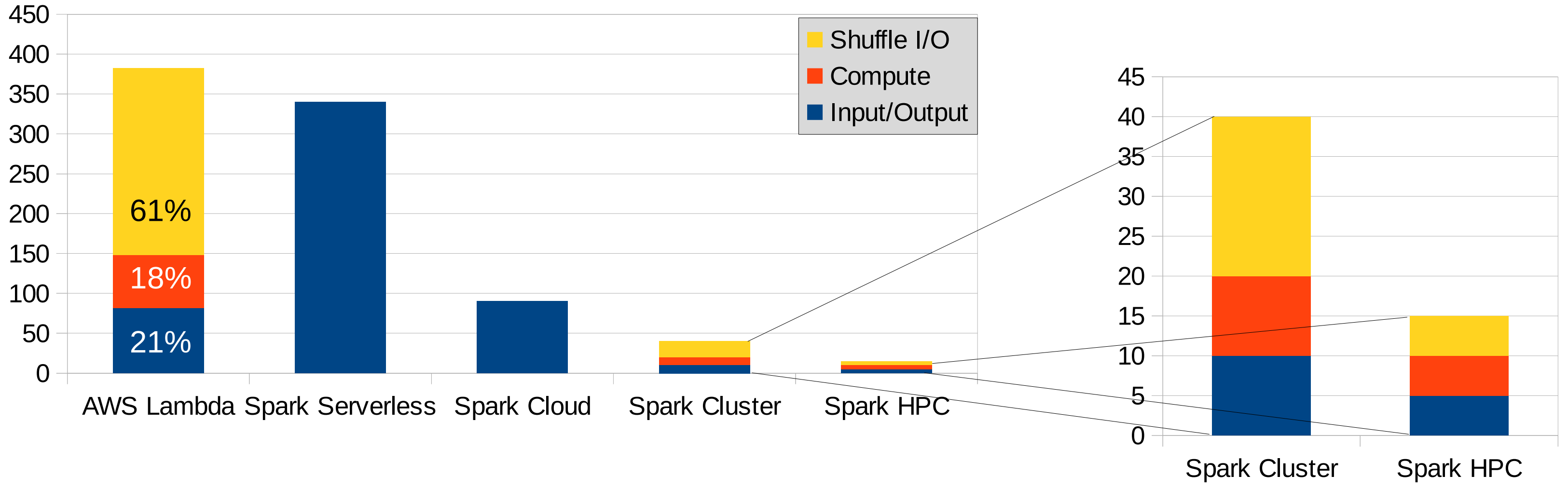
Example: MapReduce (Cluster)



Example: MapReduce (Serverless)



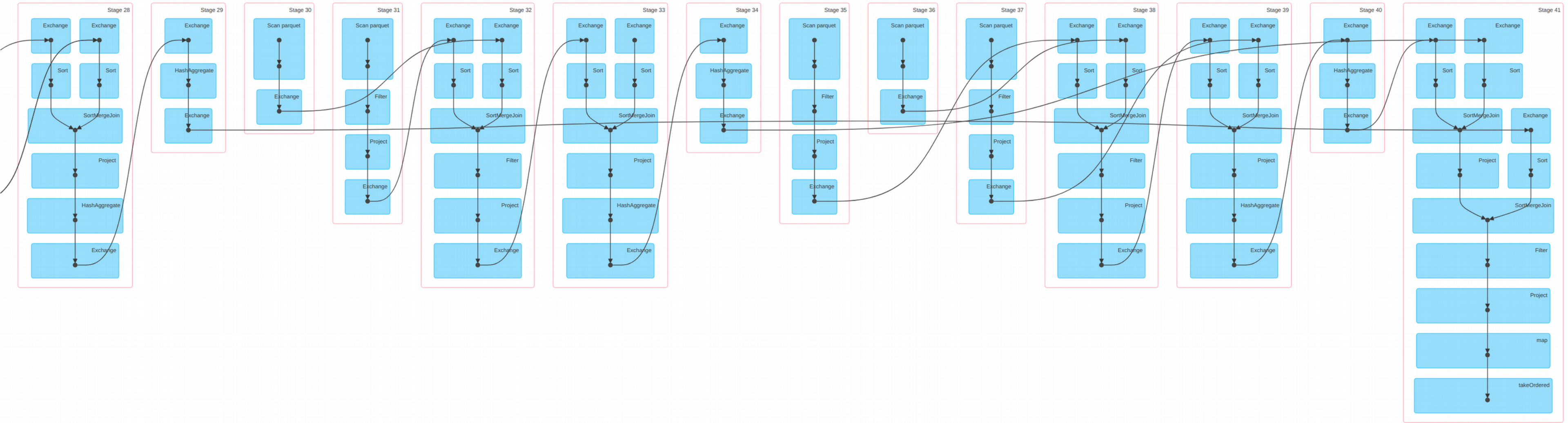
I/O Overhead: Sorting 100GB



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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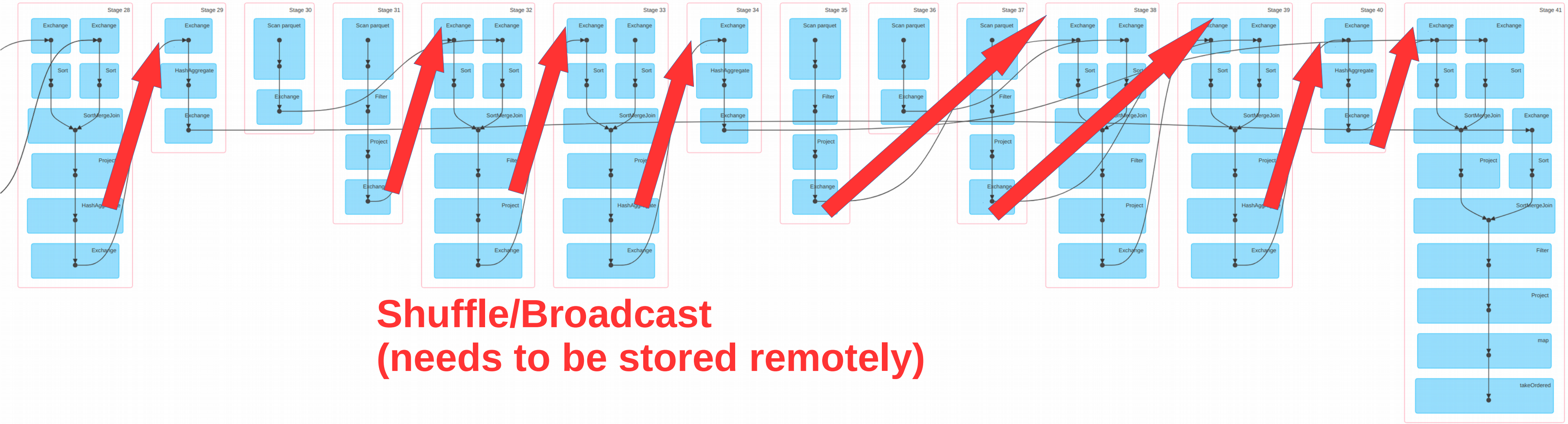
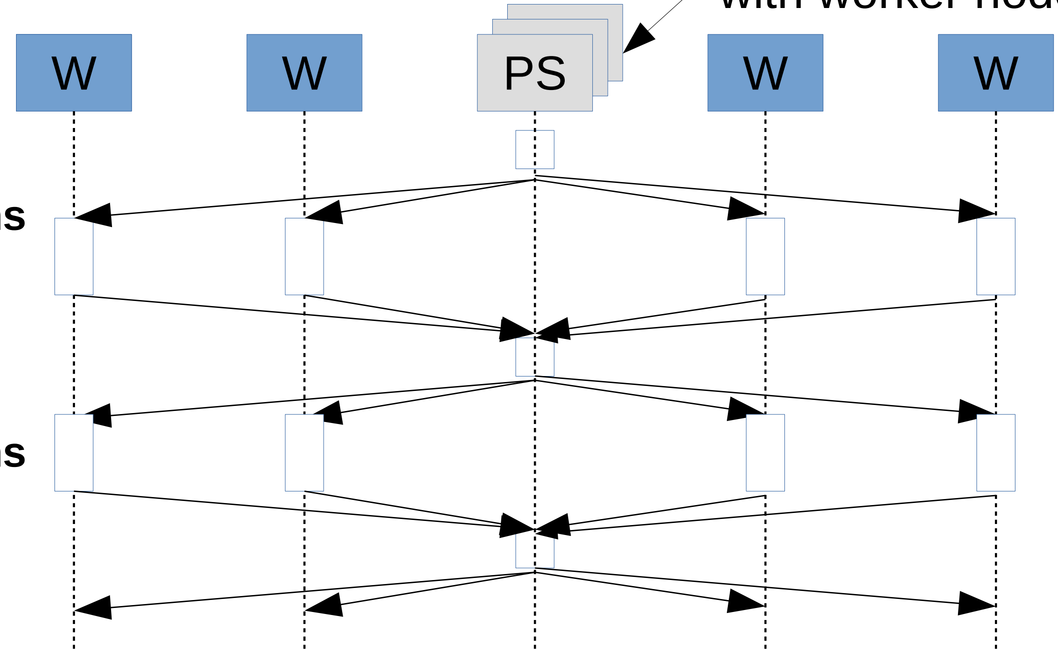


What about other workloads?

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

could be co-located
with worker nodes



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*) compute
*) update model

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What about other workloads?

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

*) read training data
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*) use cached data
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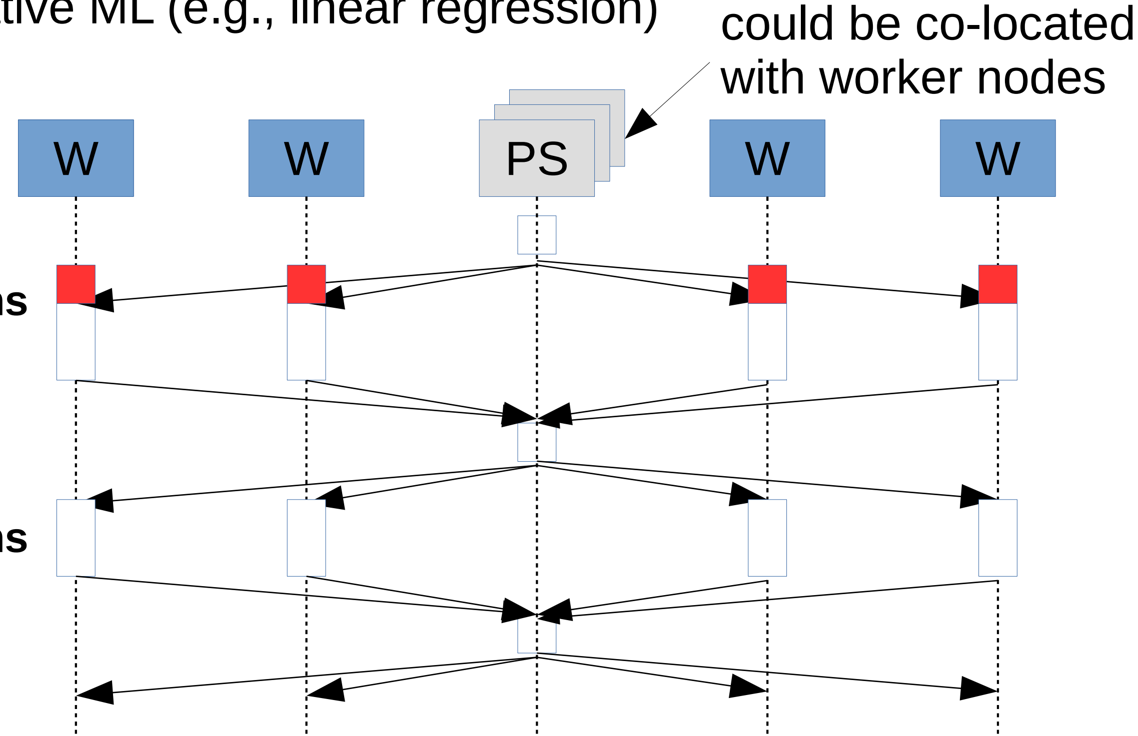

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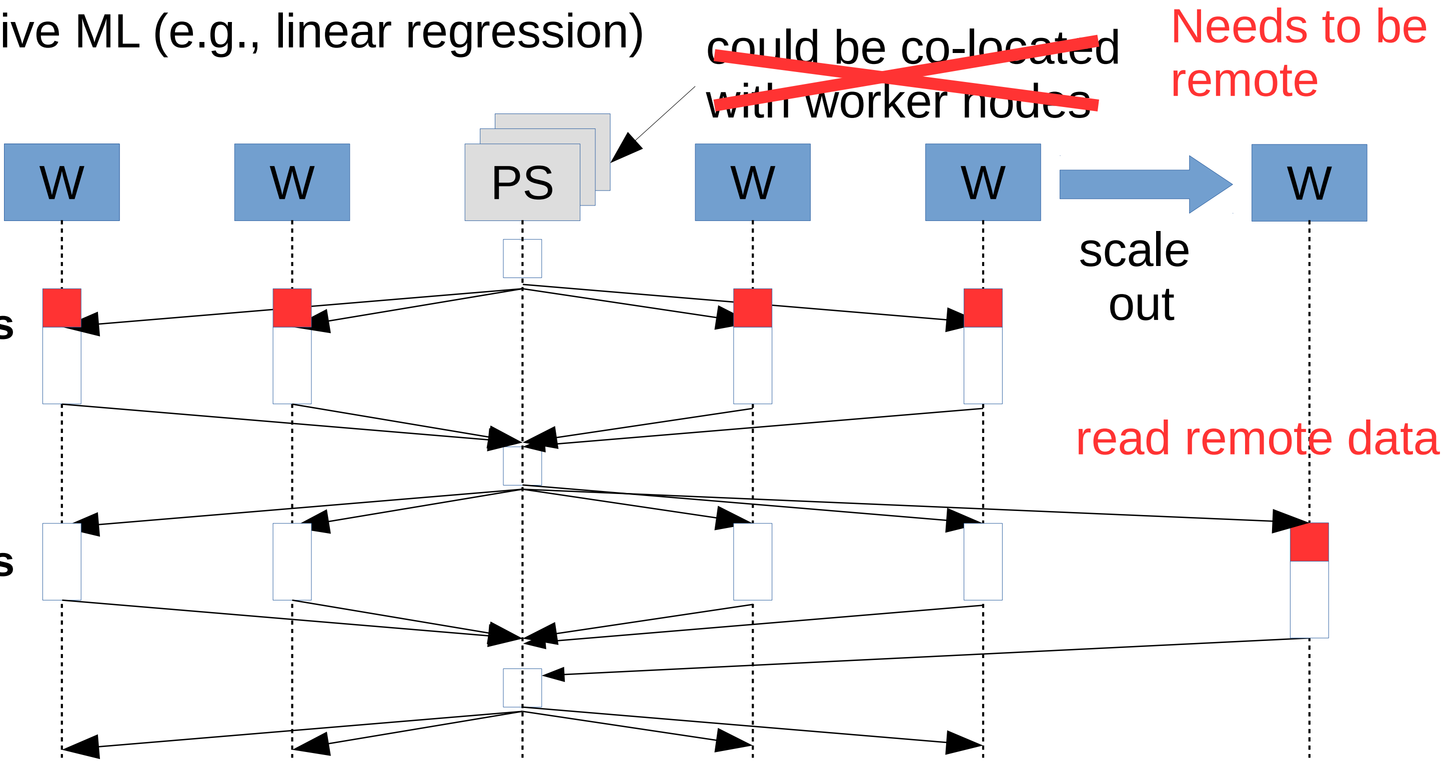

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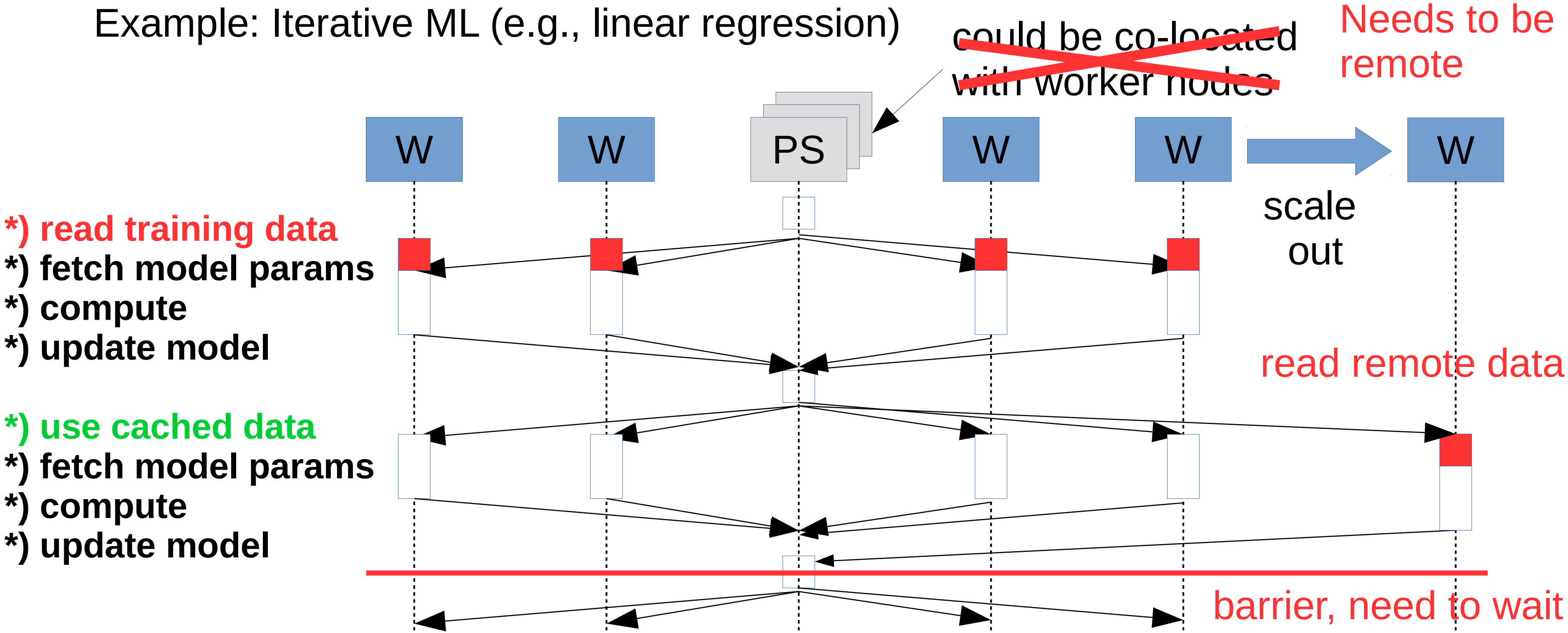

Can we..

- 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
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Complex!

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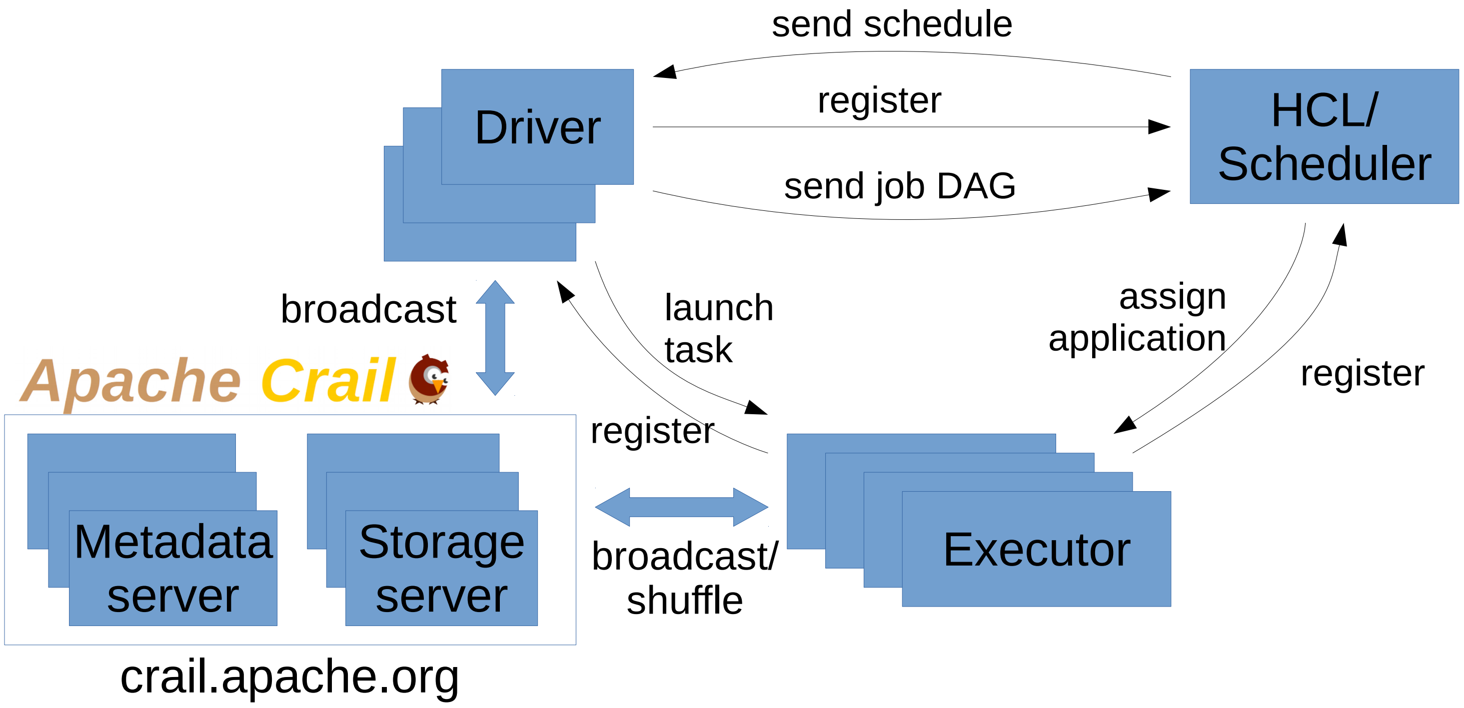
Architecture Overview



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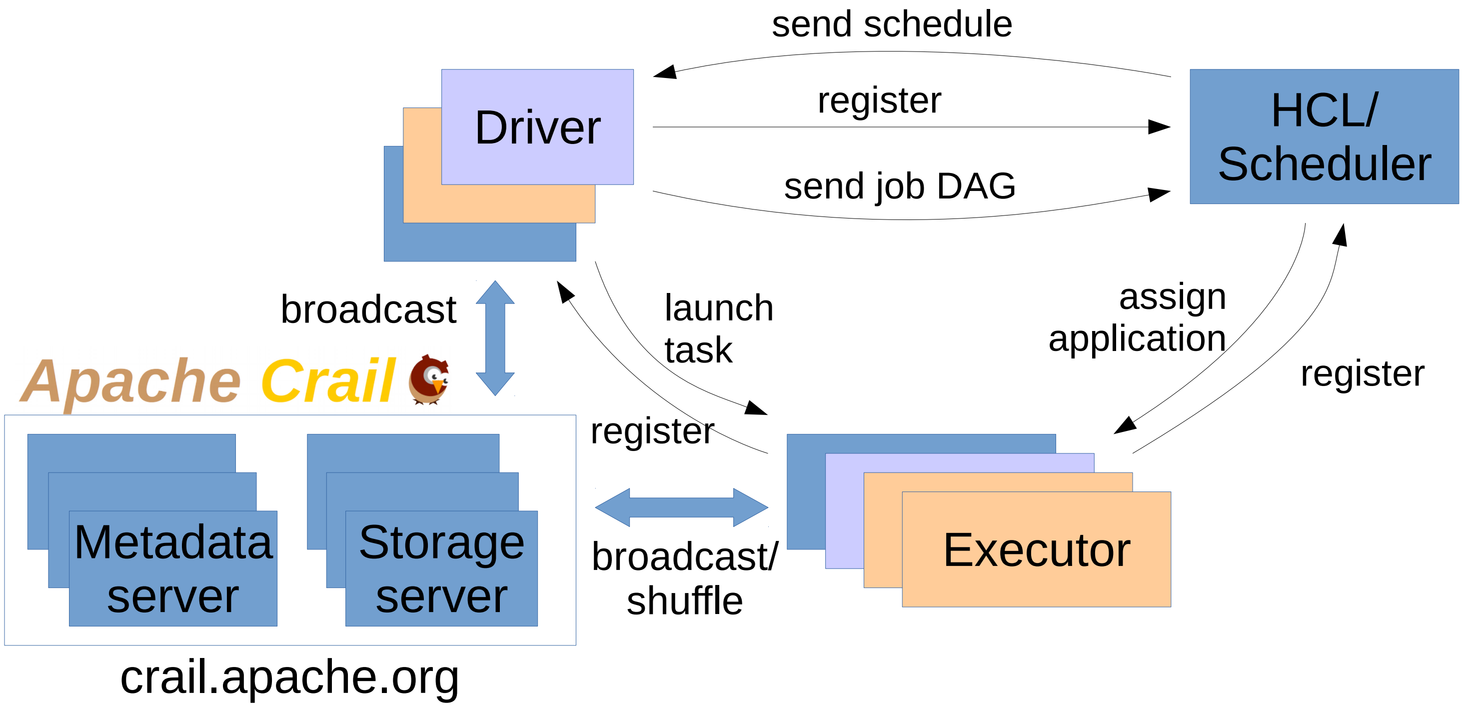

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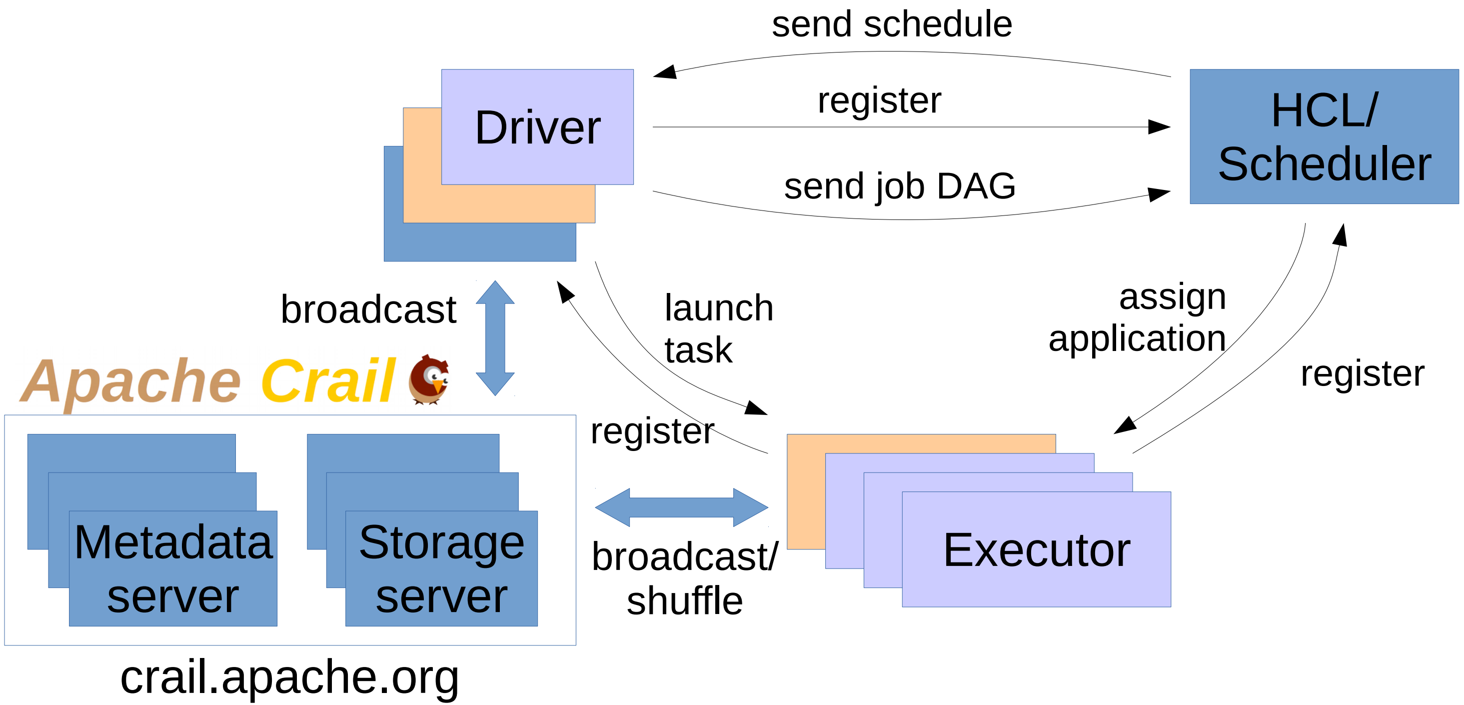

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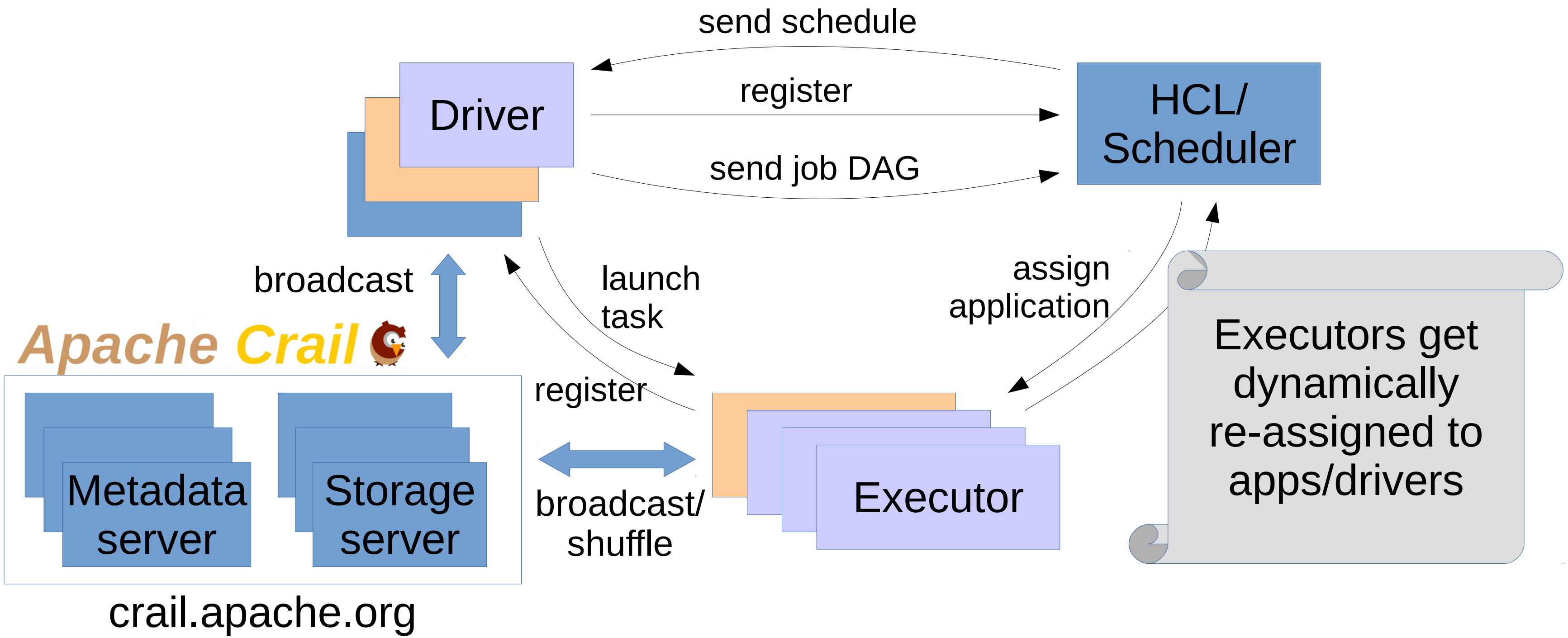
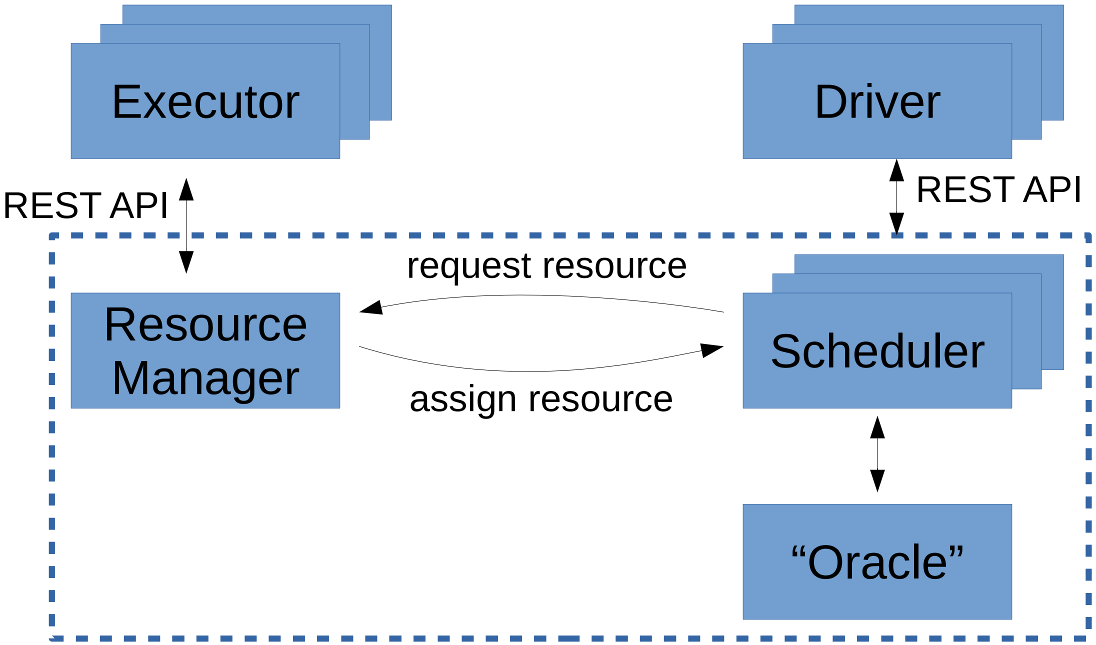


HCL Scheduler



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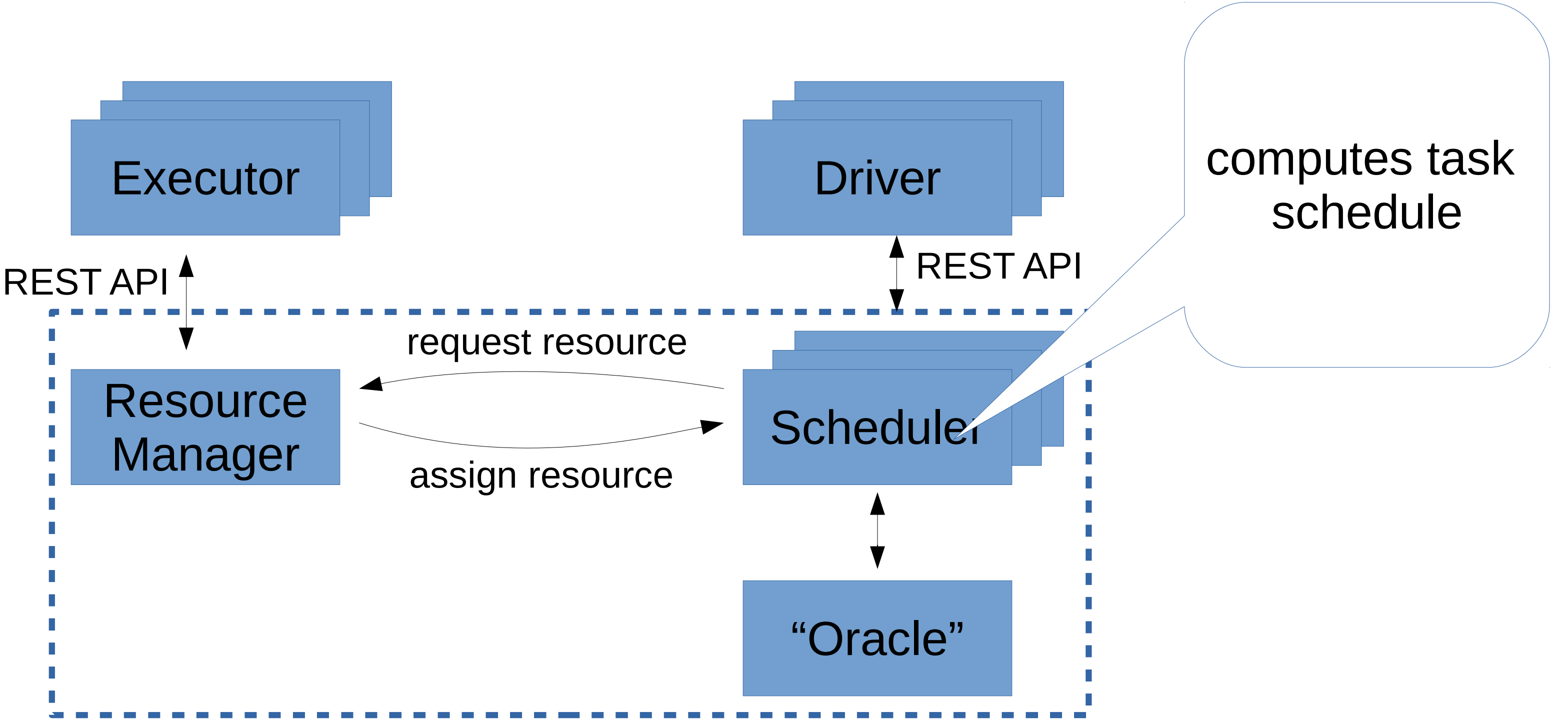

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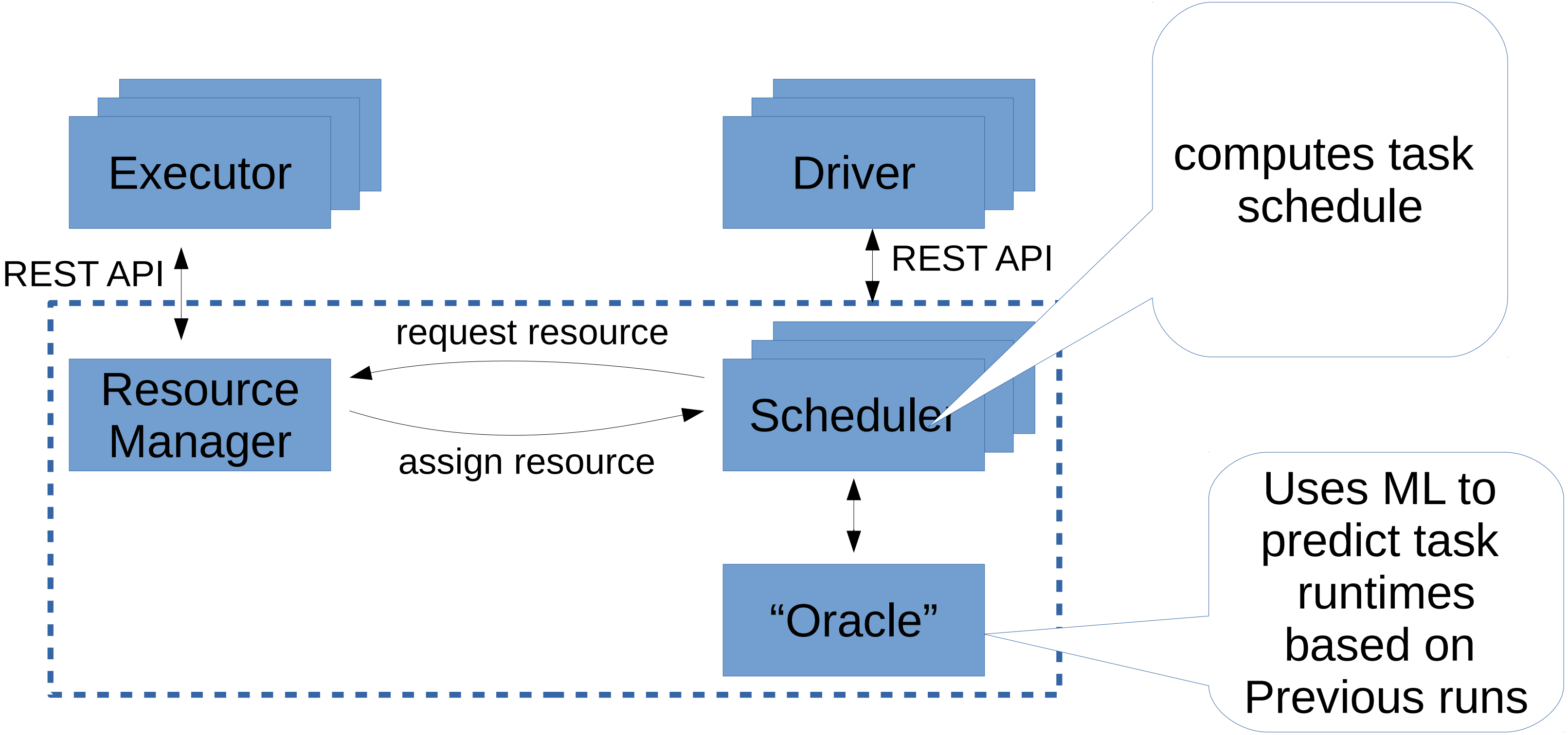

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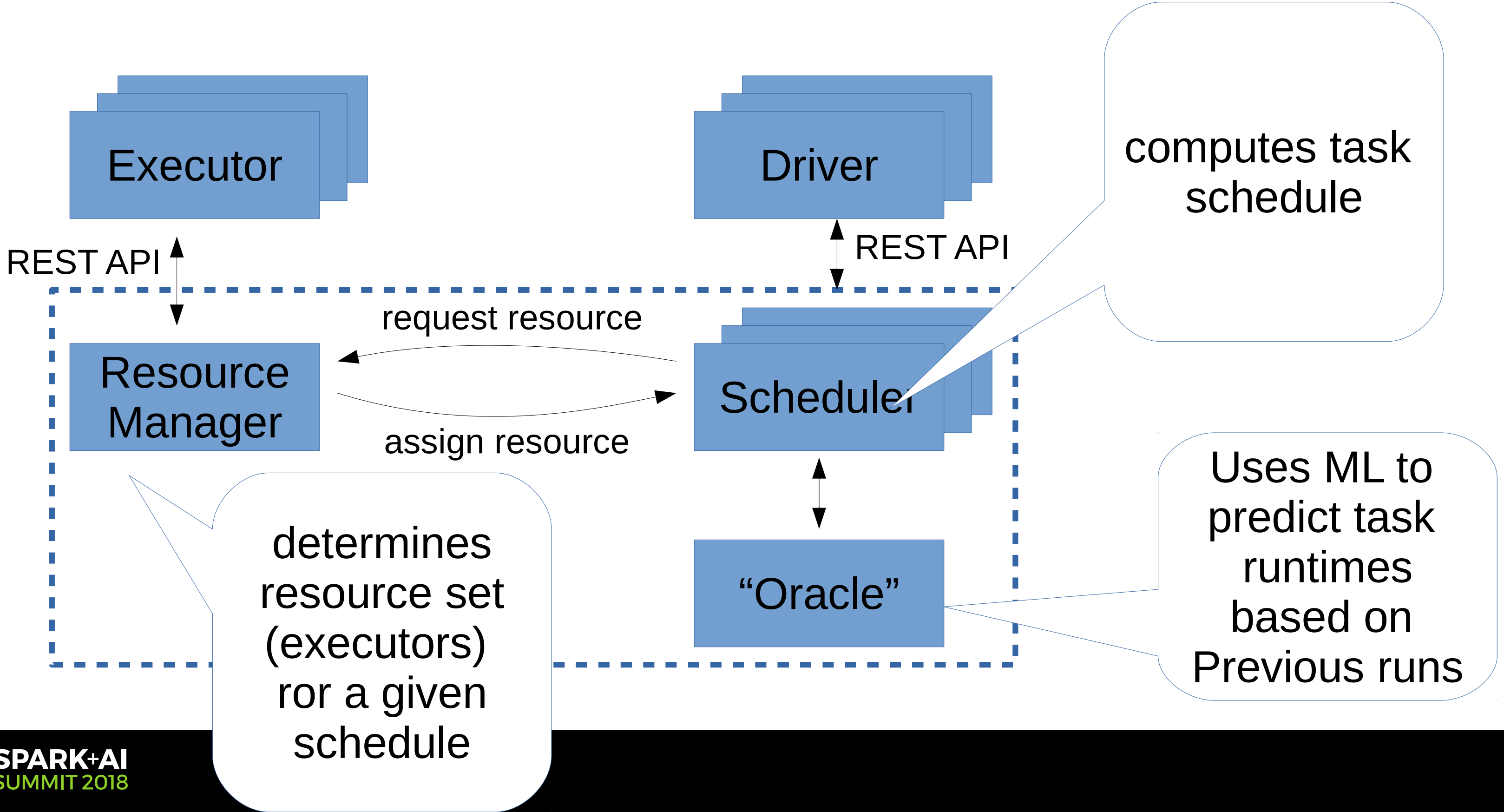
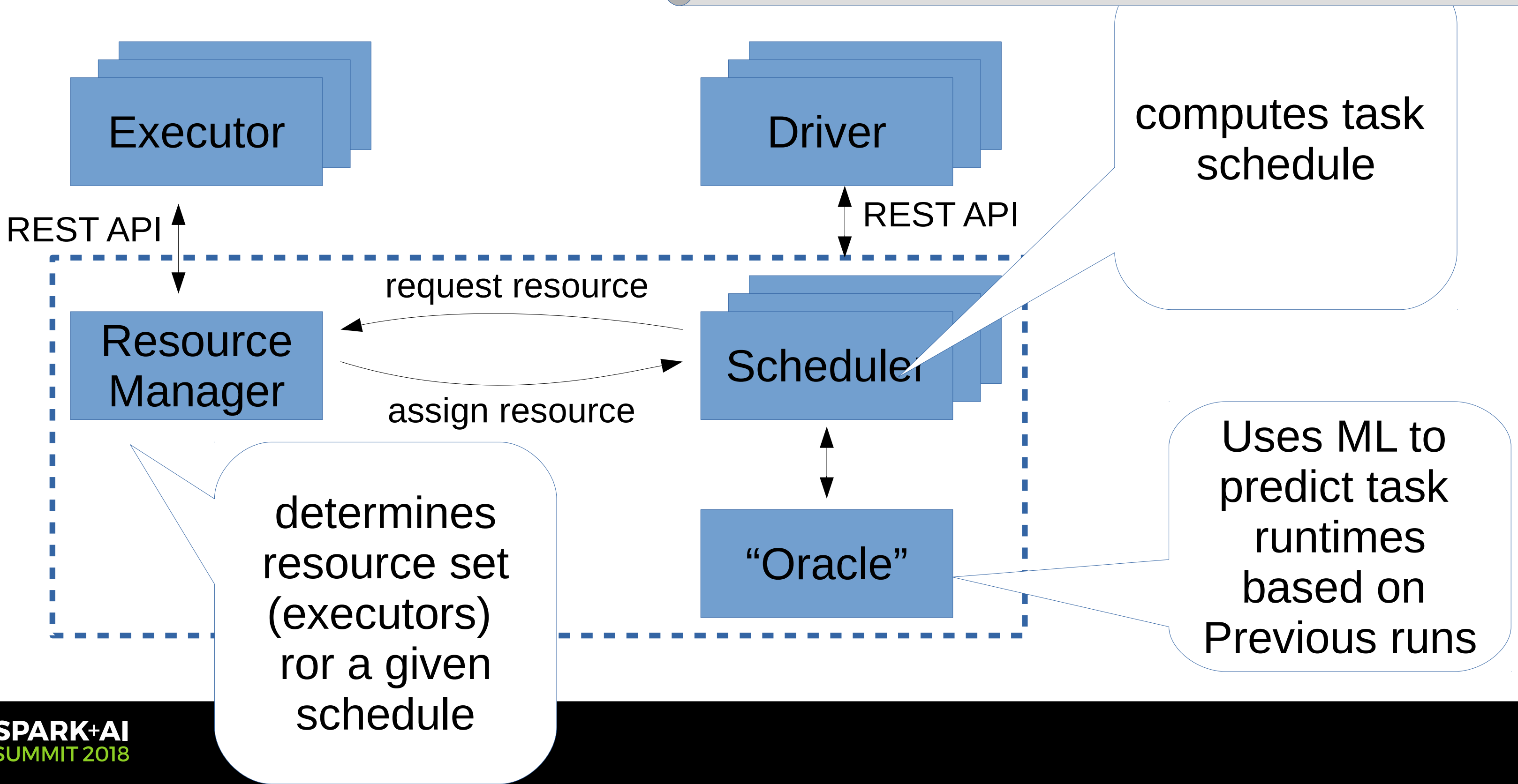


HCL Scheduler

“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

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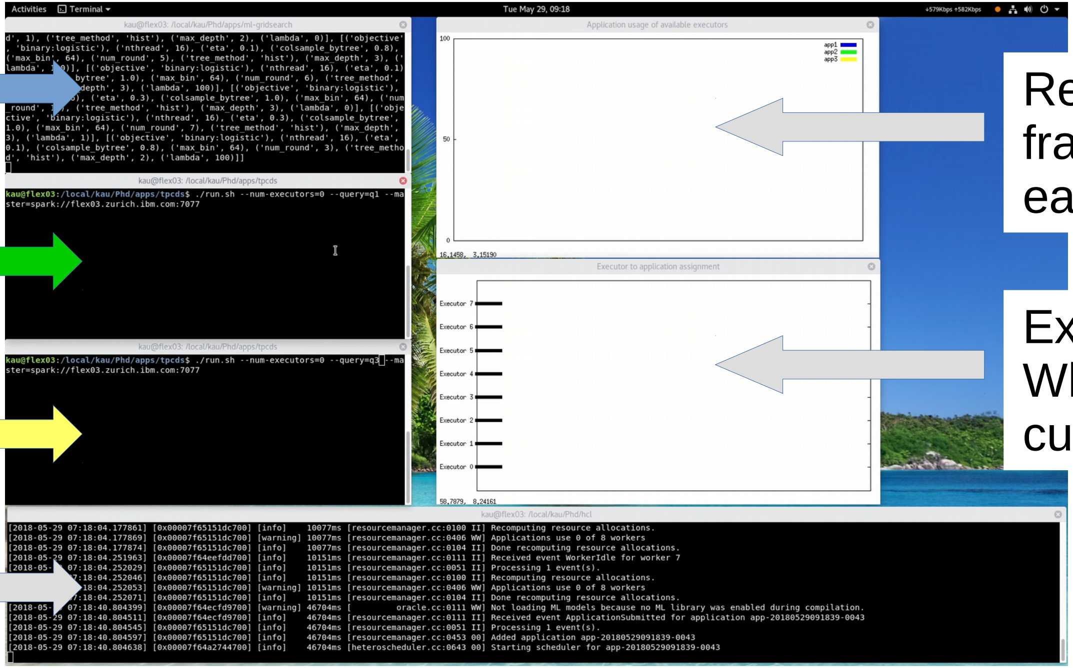
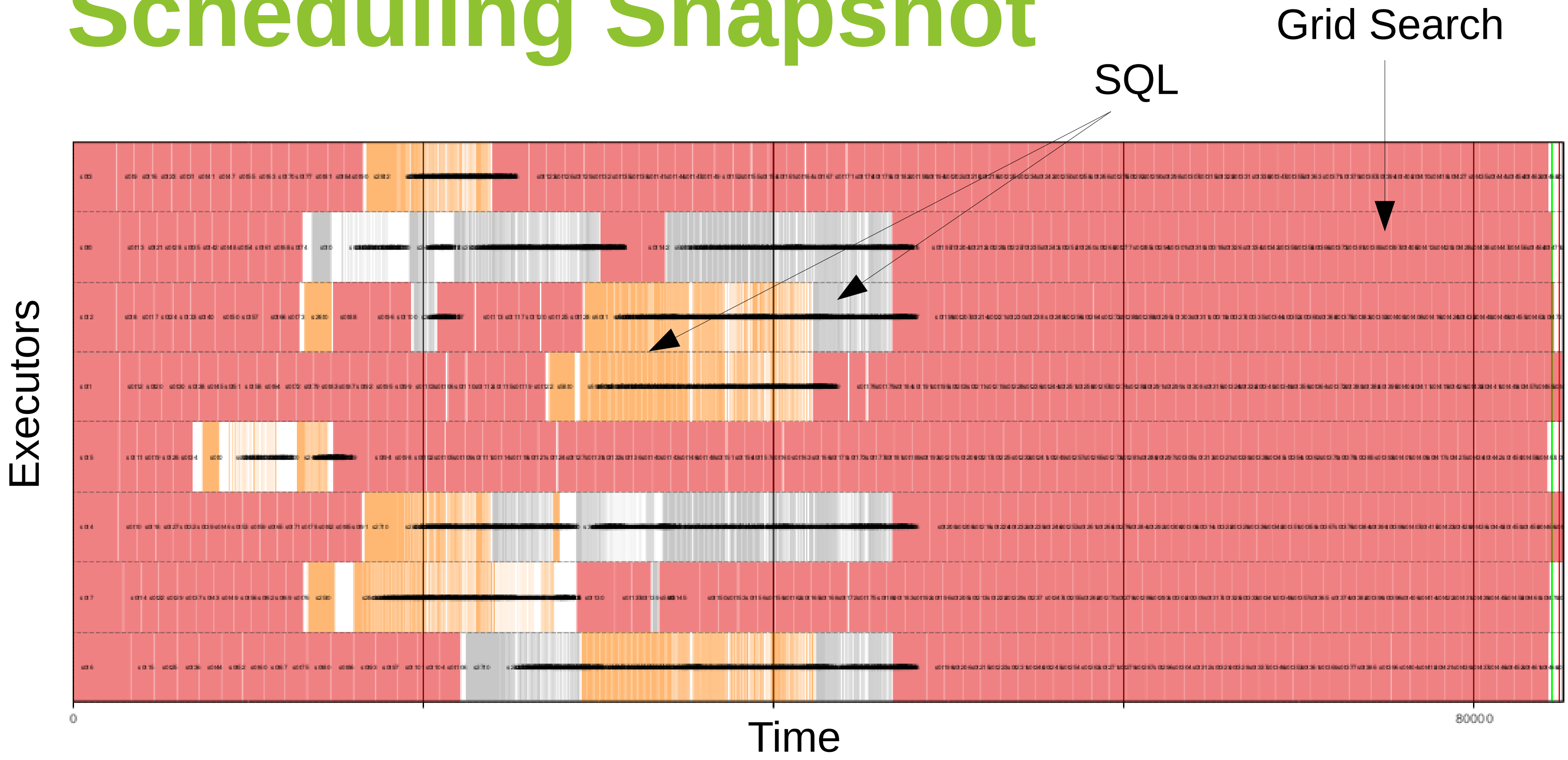


Resource view: fraction of resources each app consumes

Executor view: Which app an executor currently runs

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 ovherhad
  - 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