Serverless Machine Learning on Modern Hardware

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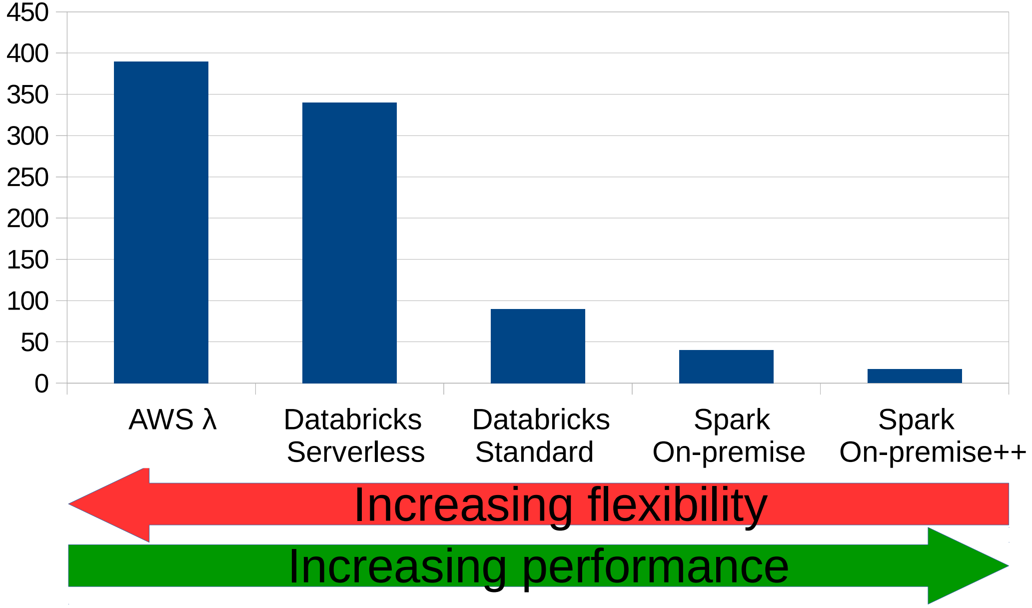
#Res6SAIS

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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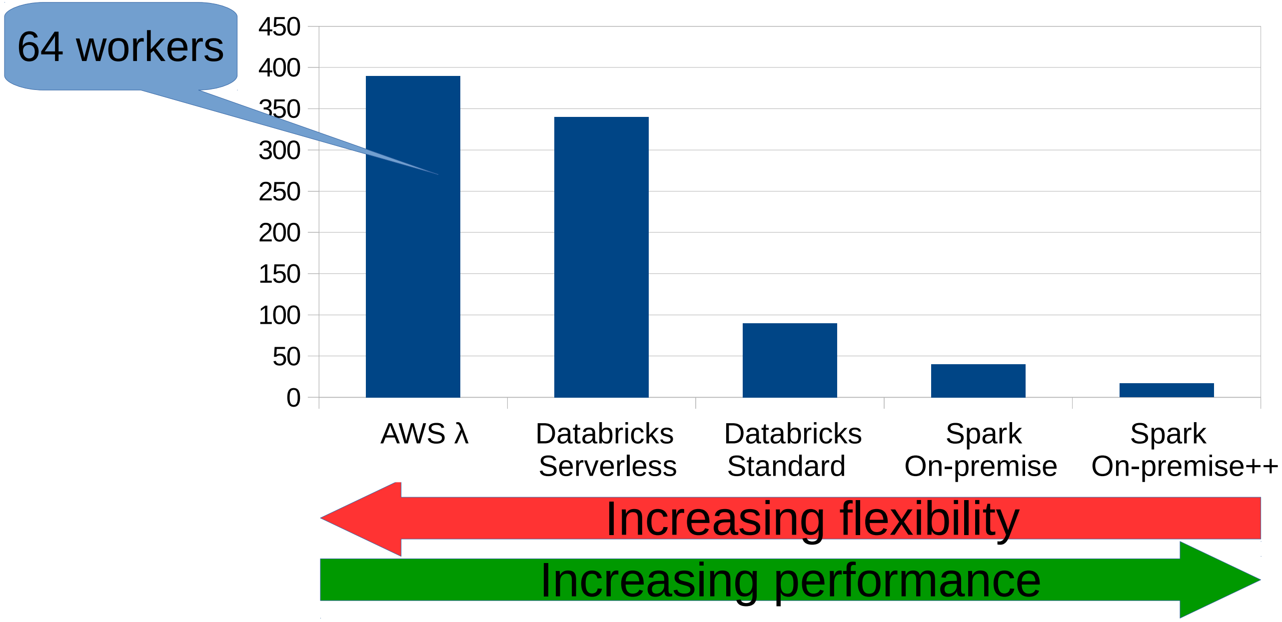

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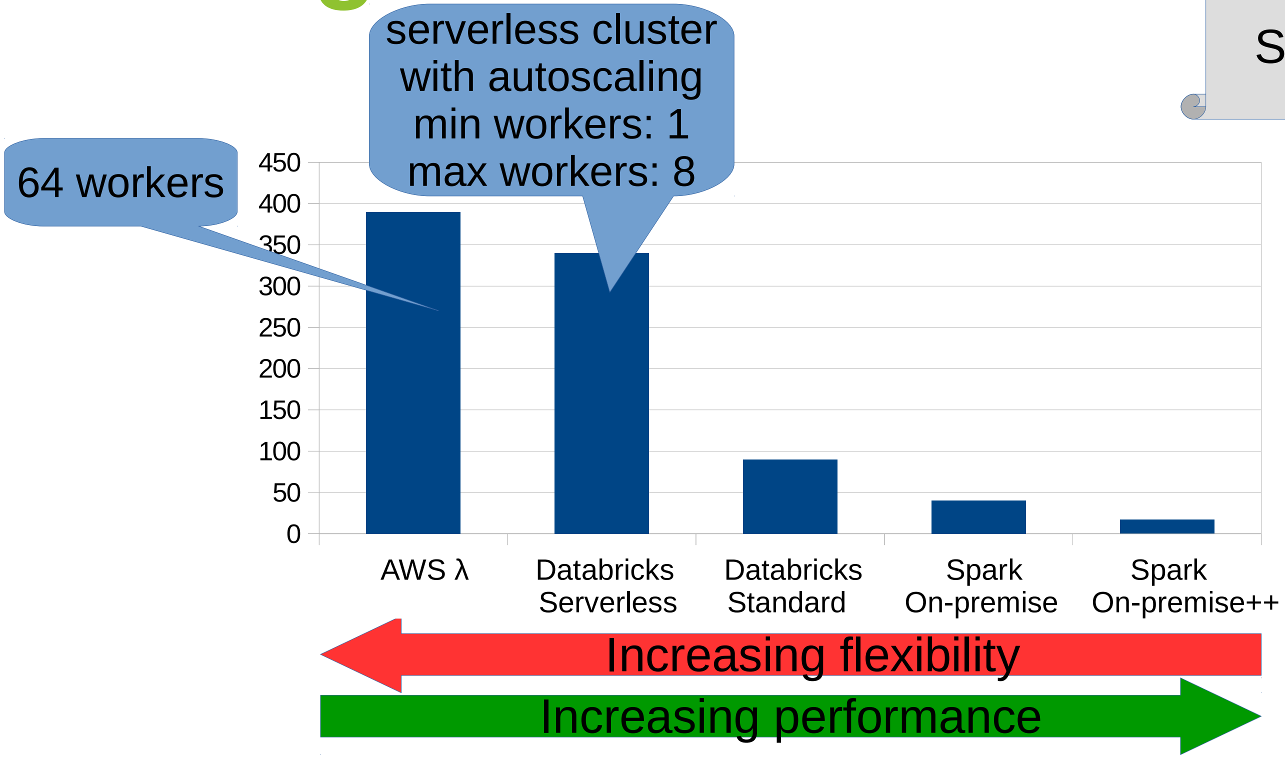

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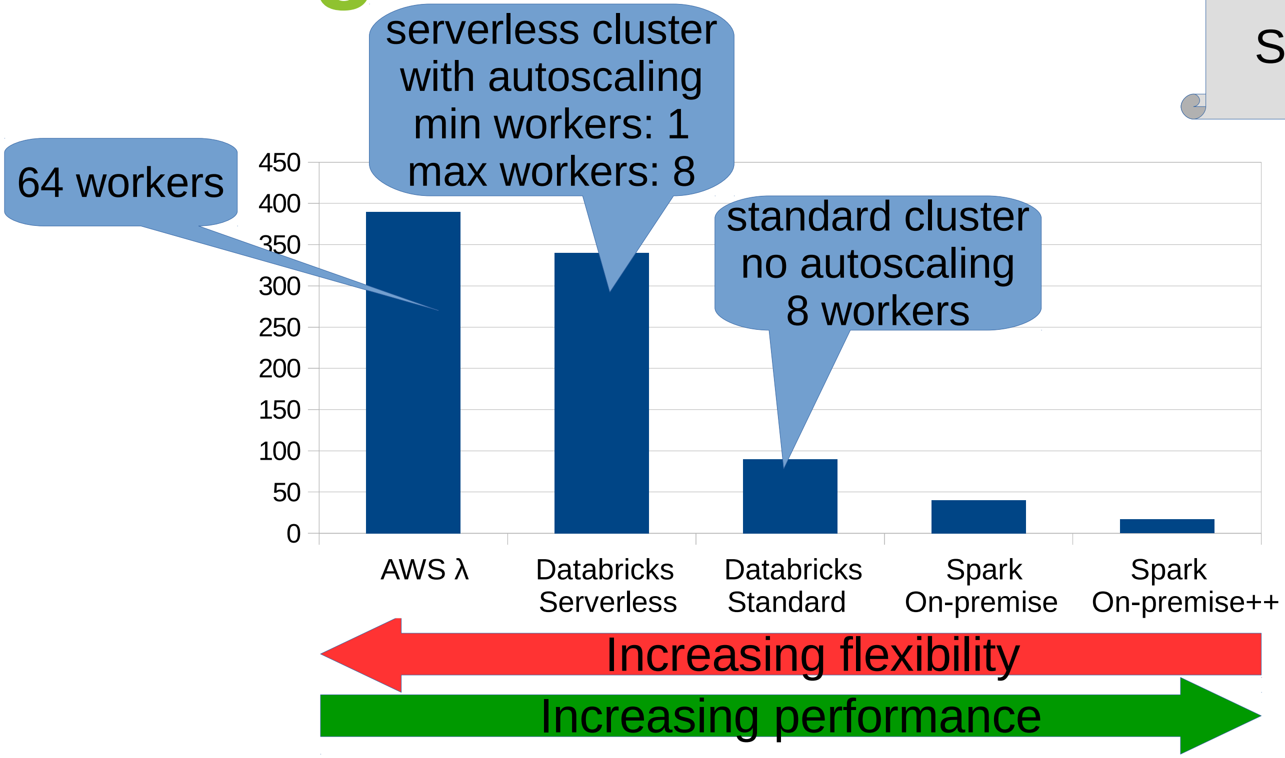

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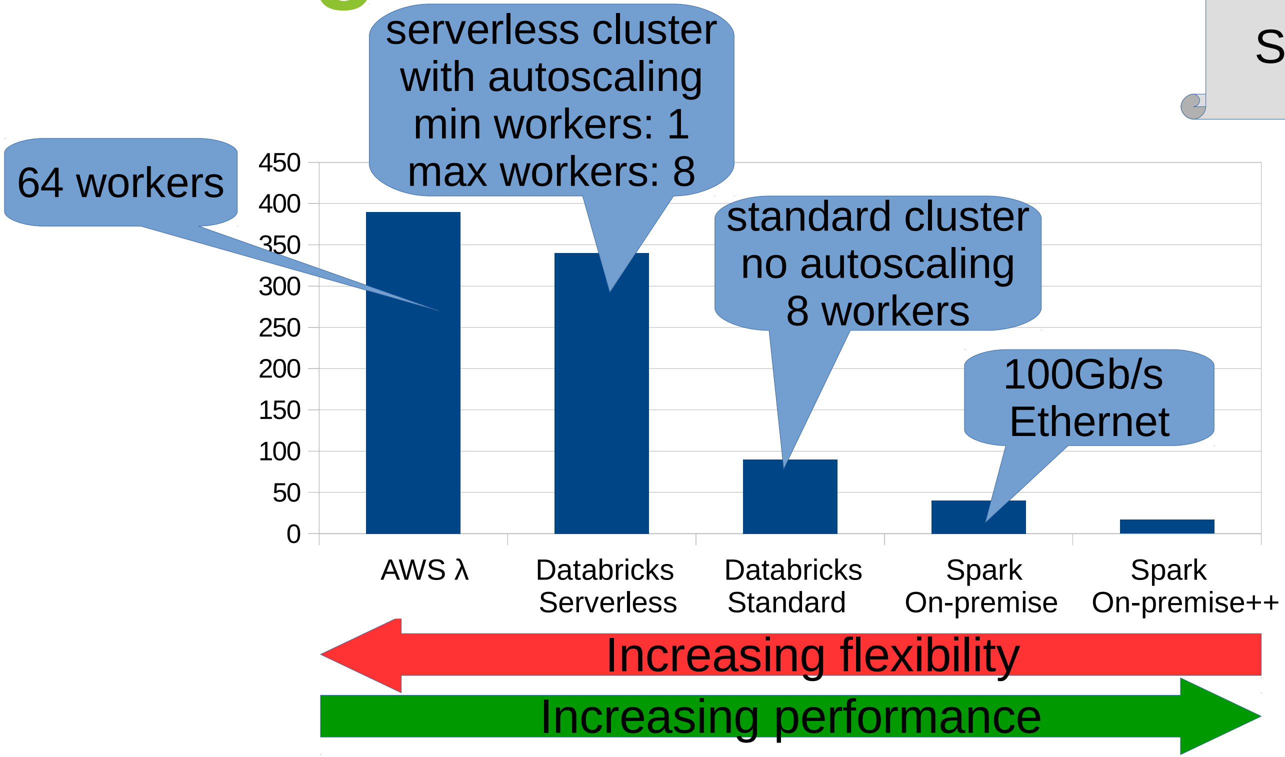

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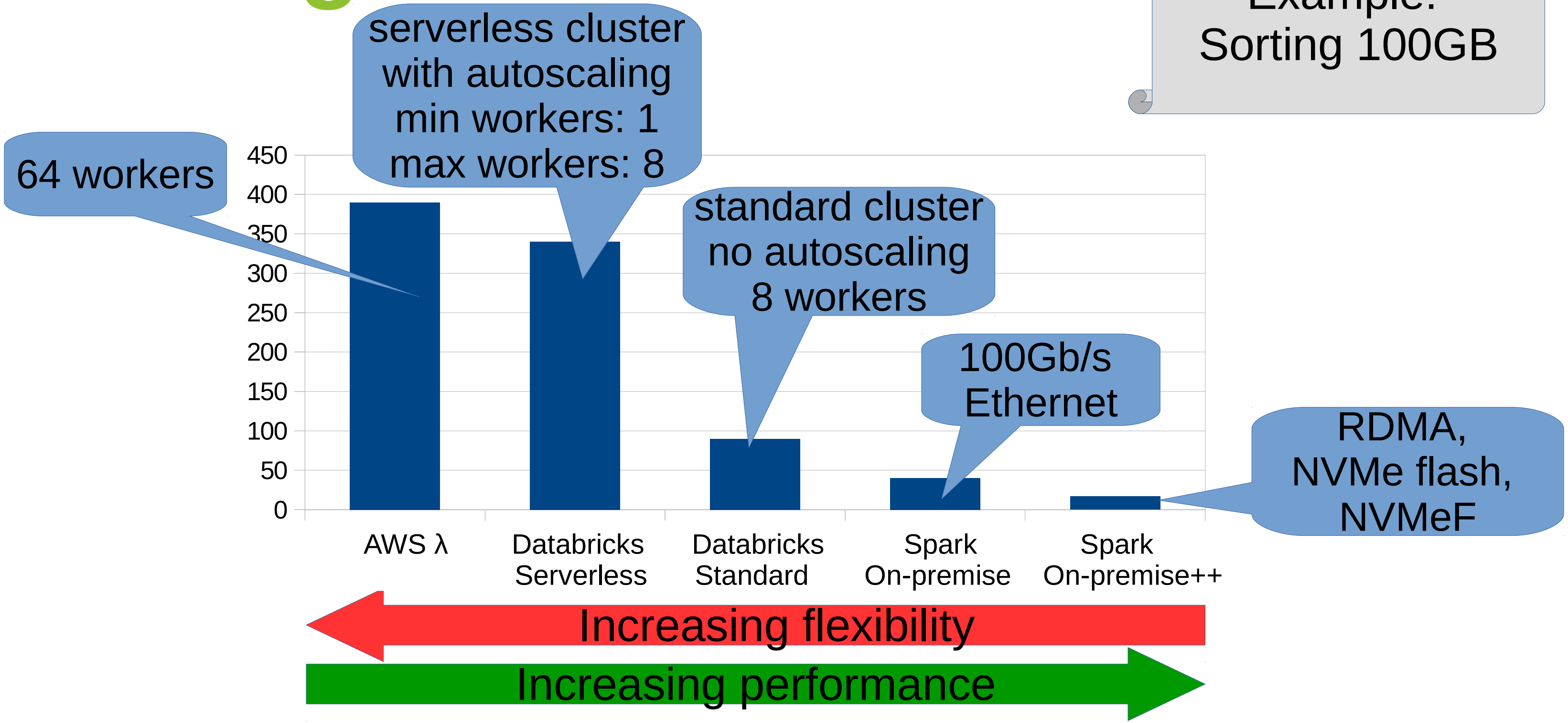

Why is it so hard?

- **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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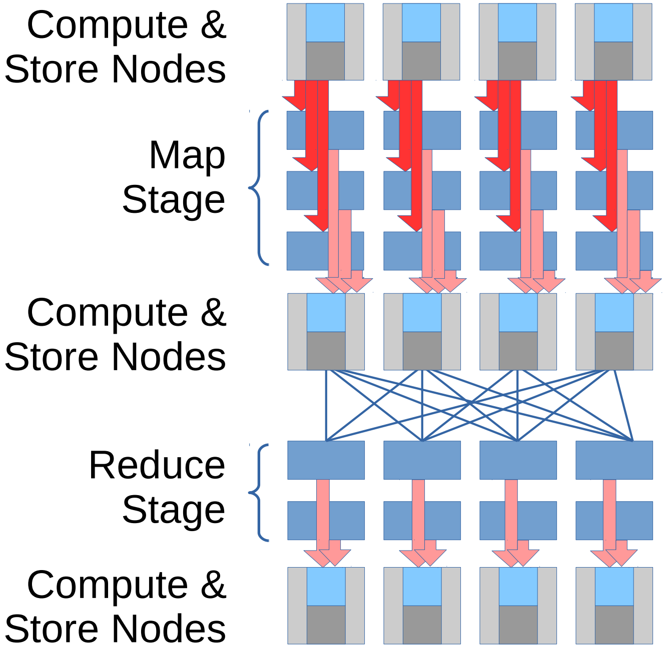
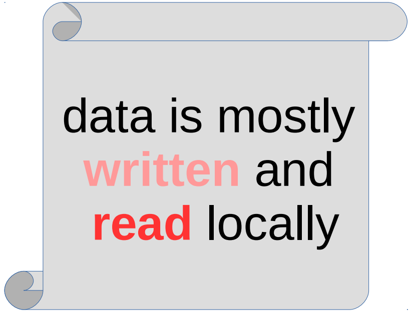
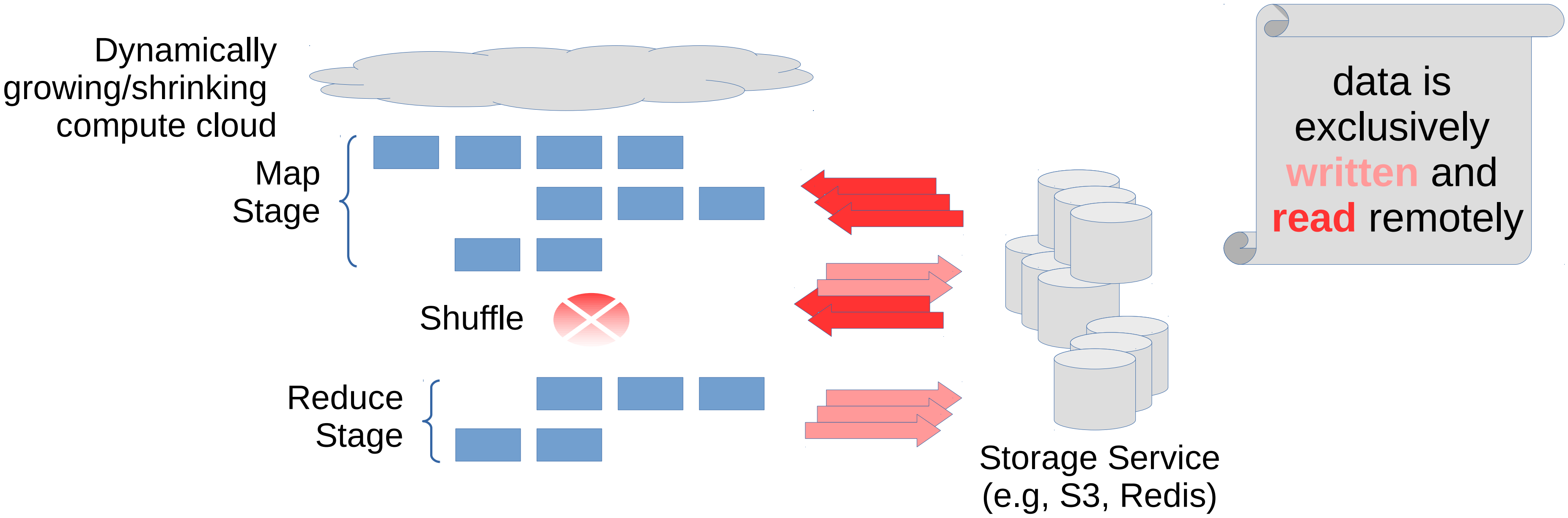
Example: MapReduce (Cluster)

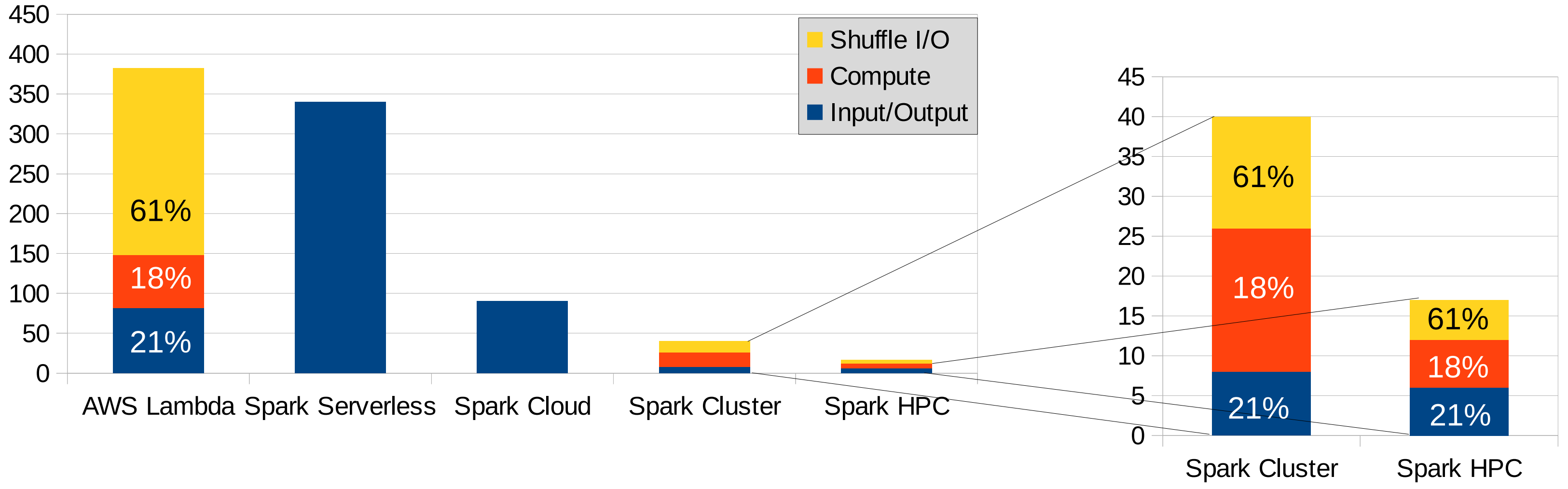




Example: MapReduce (Serverless)



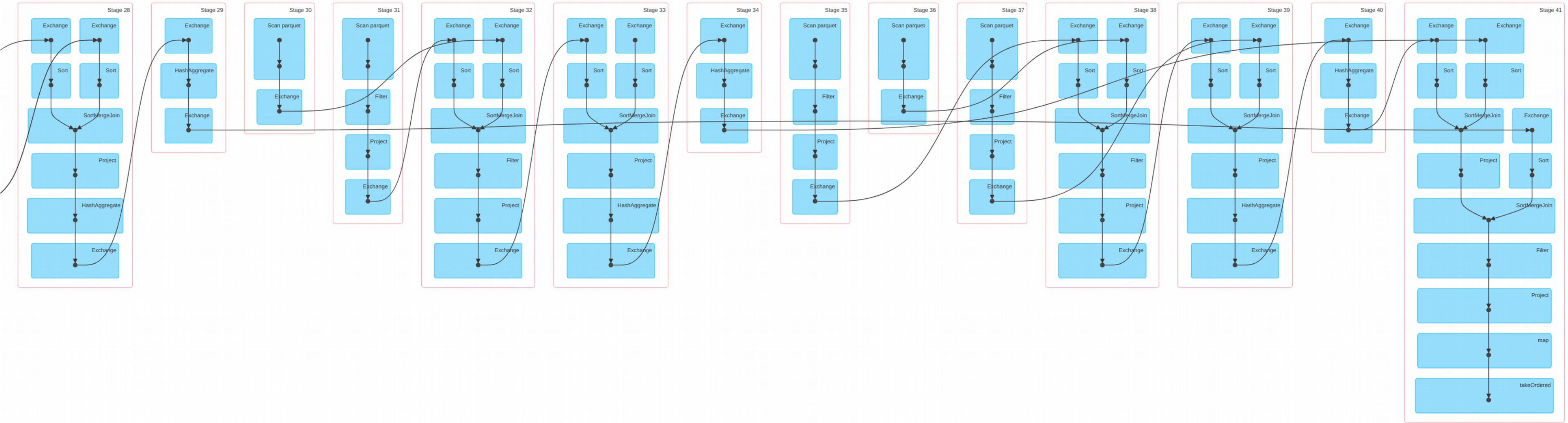
I/O Overhead: Sorting 100GB



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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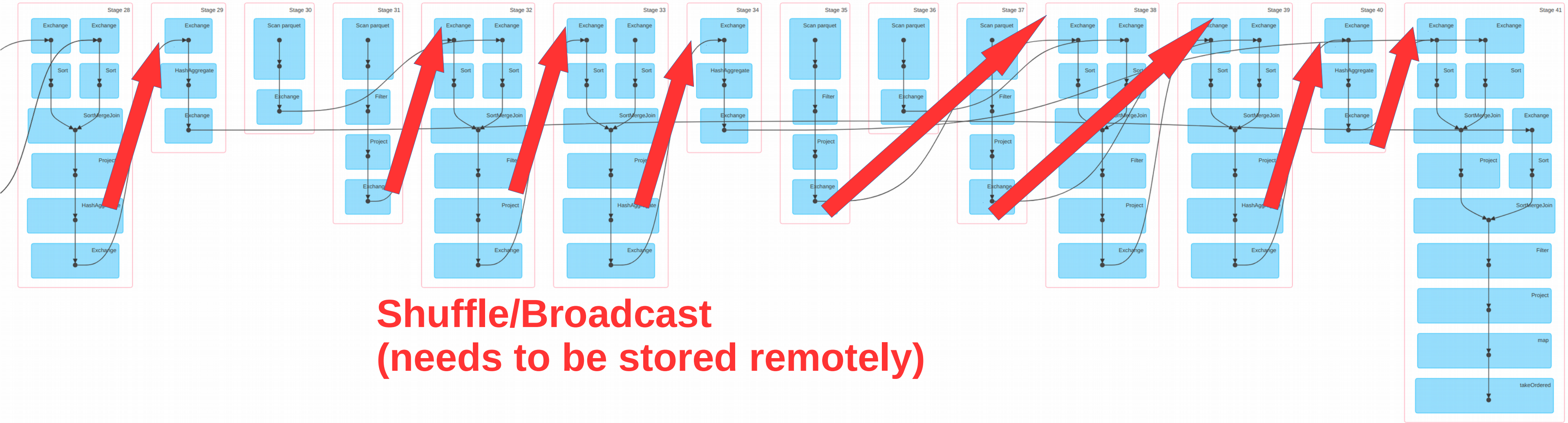

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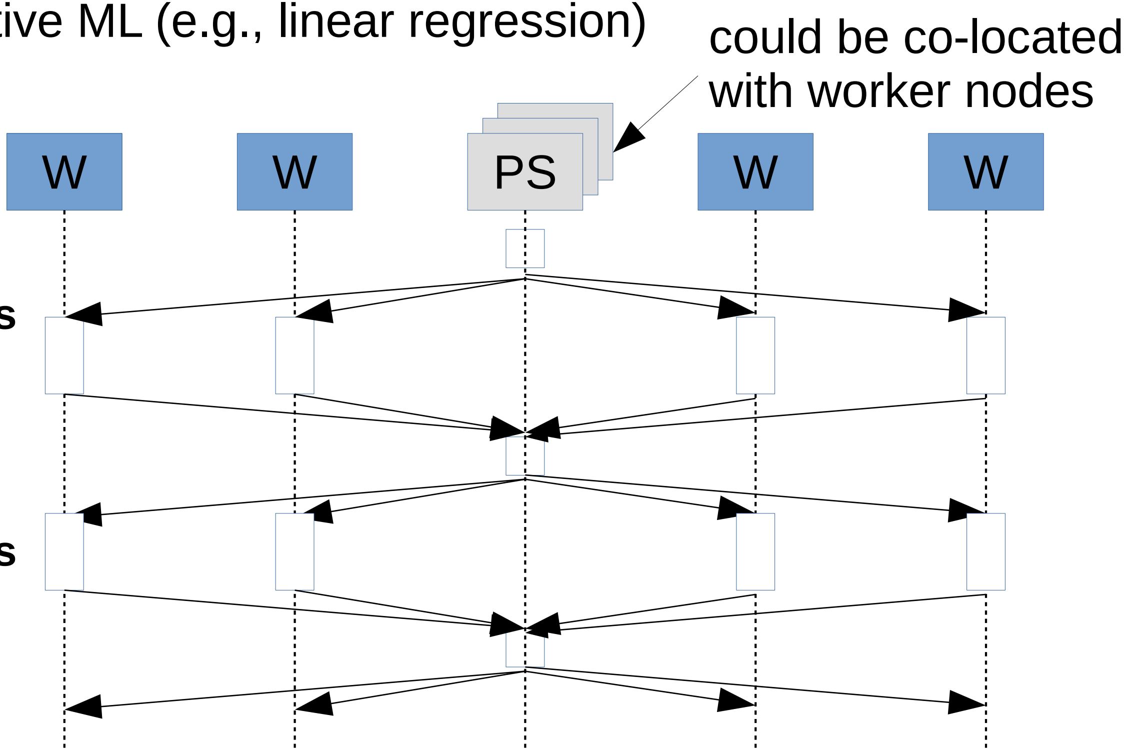
Example: Iterative ML (e.g., linear regression)



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

⋮

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

could be co-located
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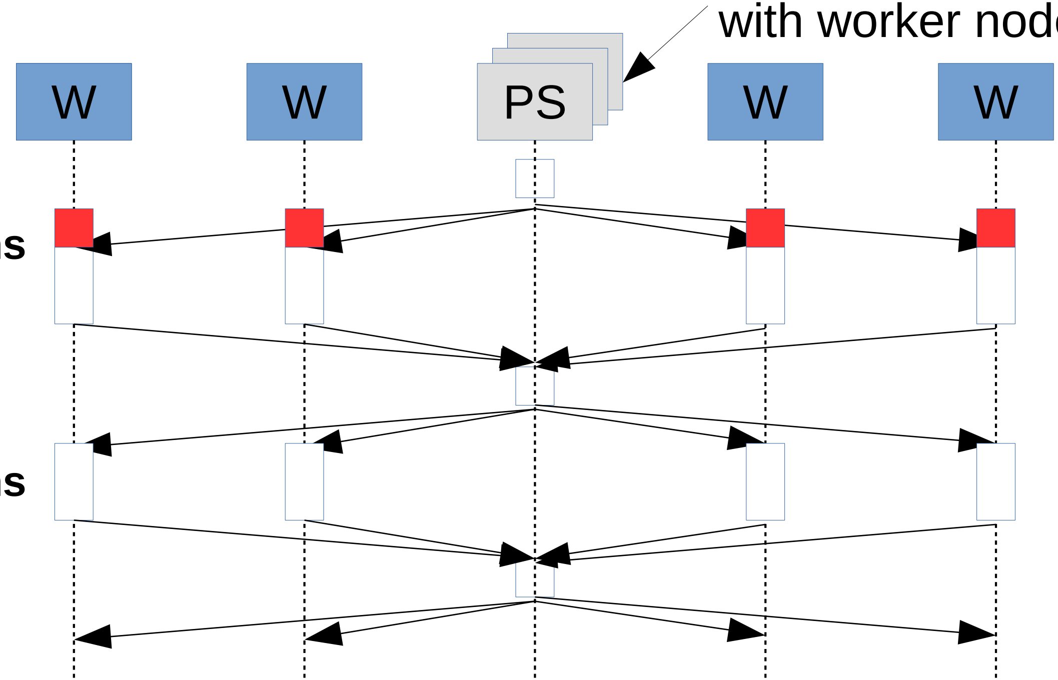

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~~could be co-located with worker nodes~~

Needs to be remote

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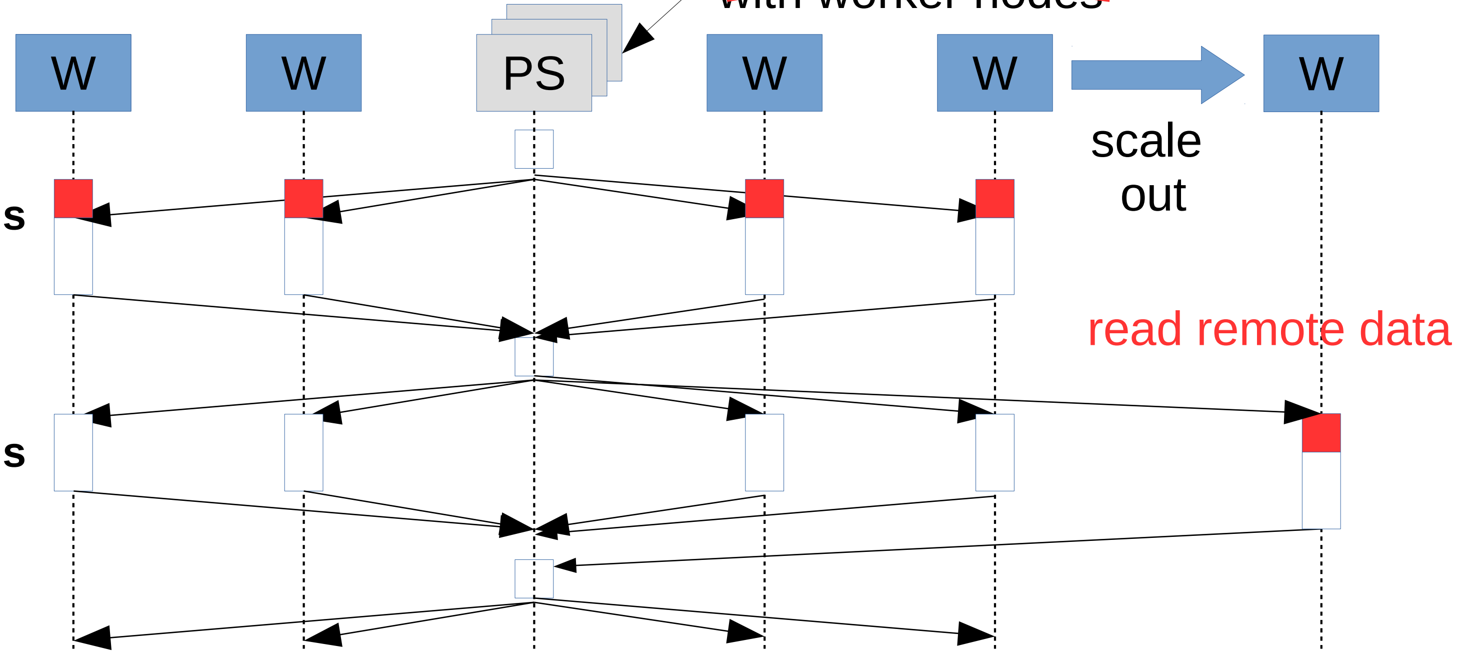

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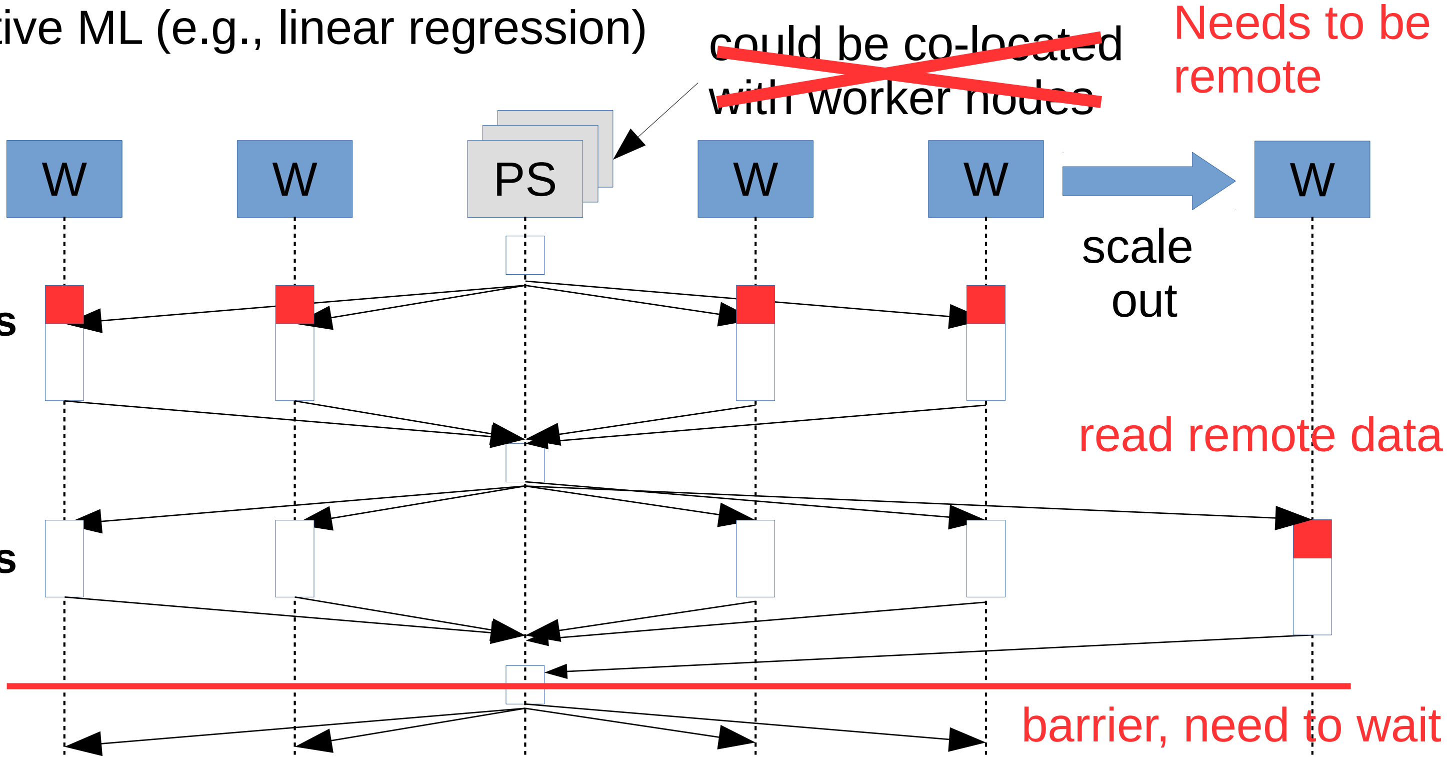

Can we..

- 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
- ..eliminate the performance overheads?

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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Complex!

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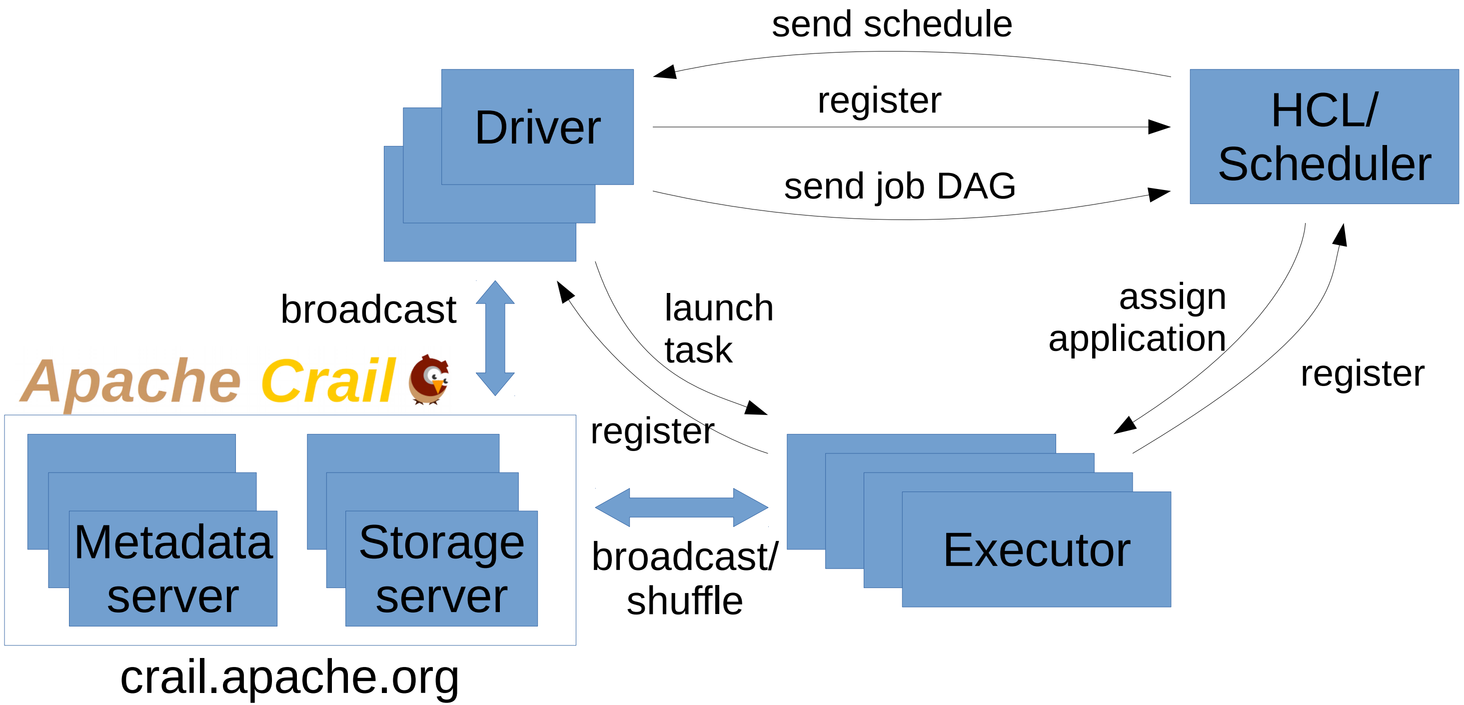
Architecture Overview



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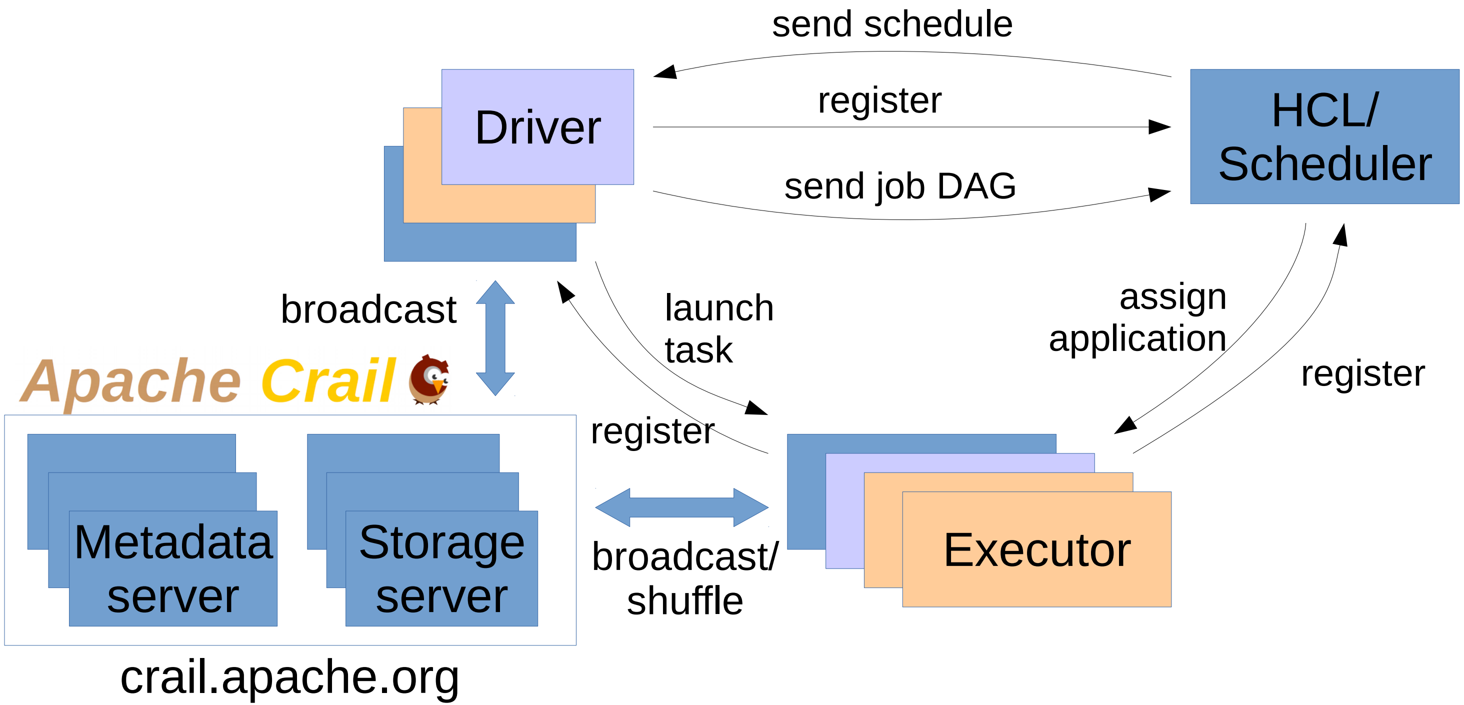

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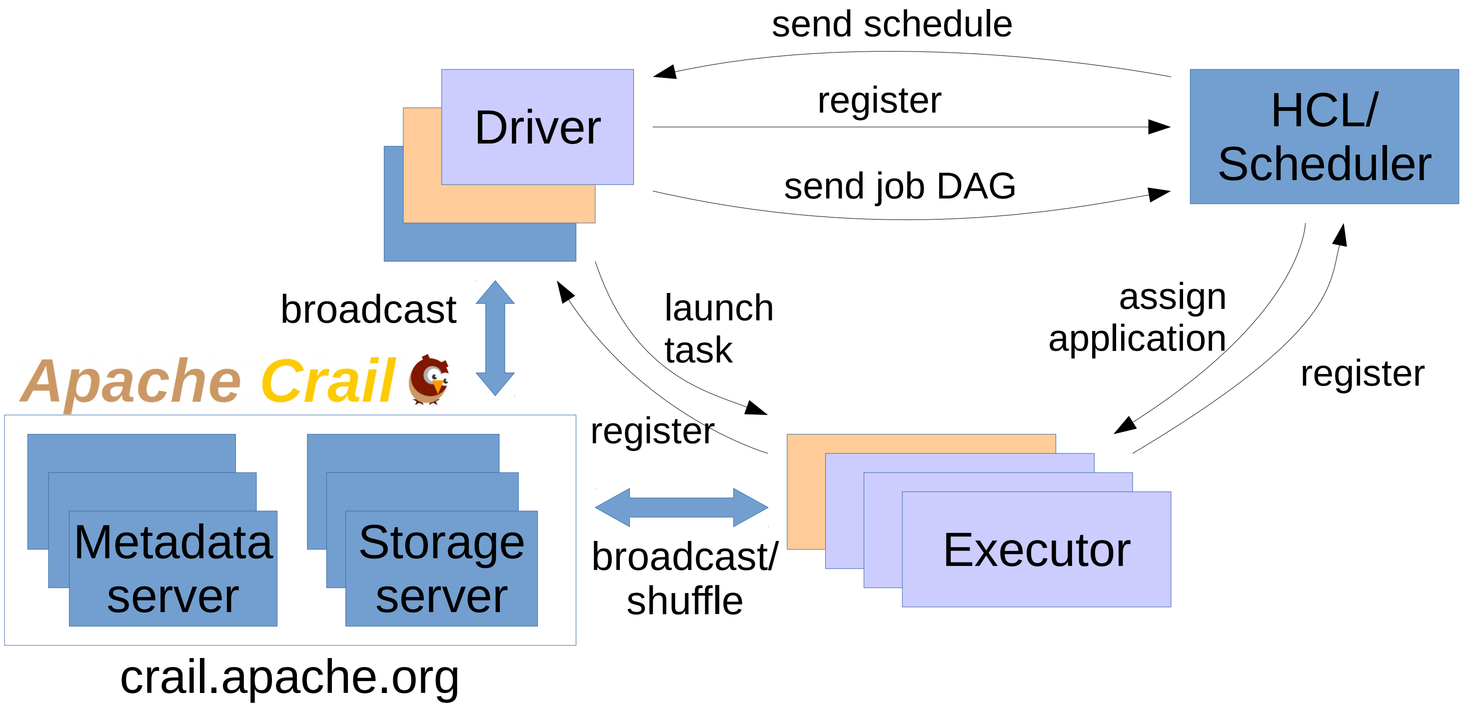

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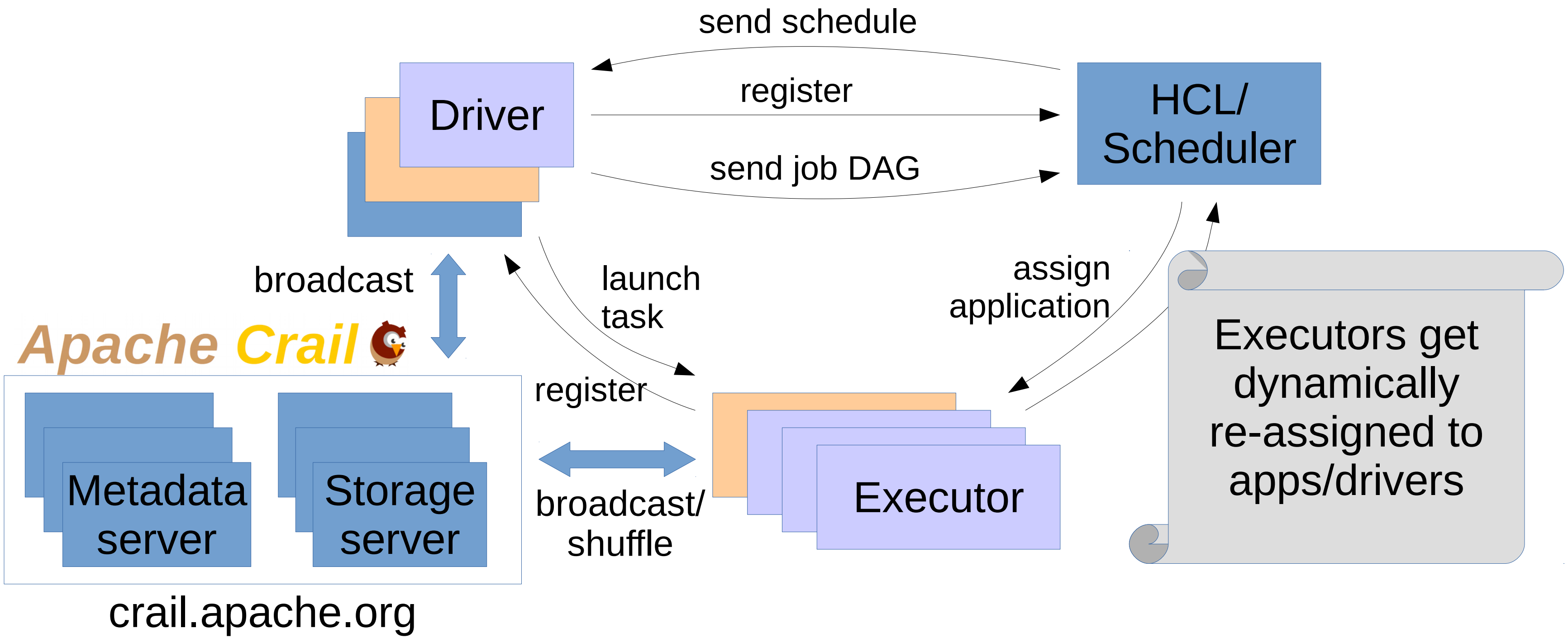
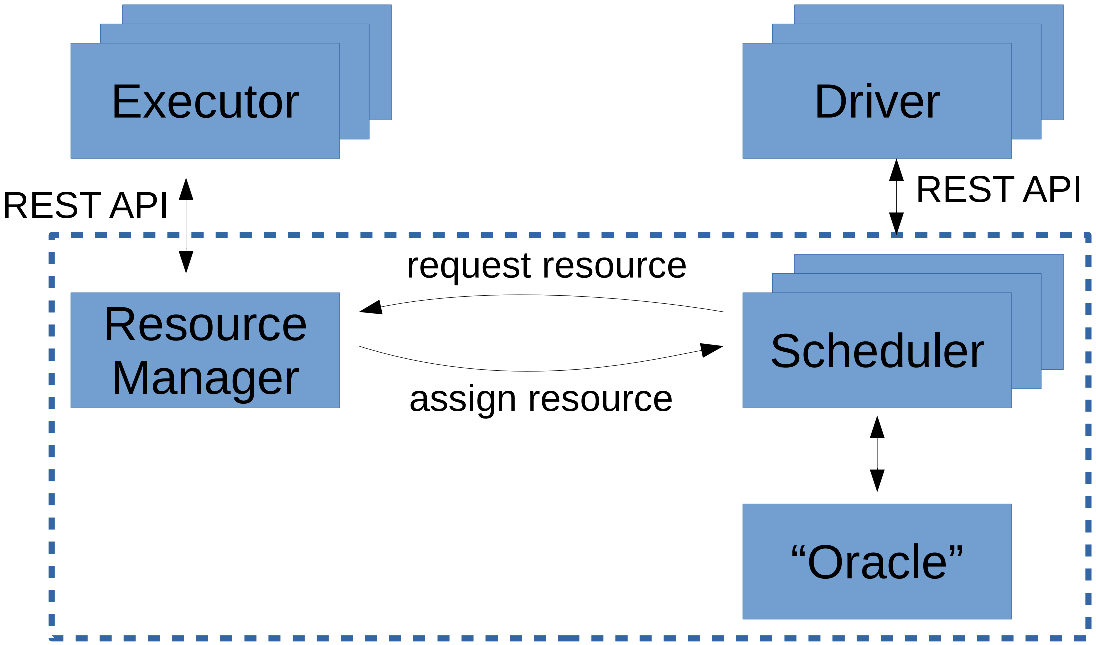


HCL Scheduler



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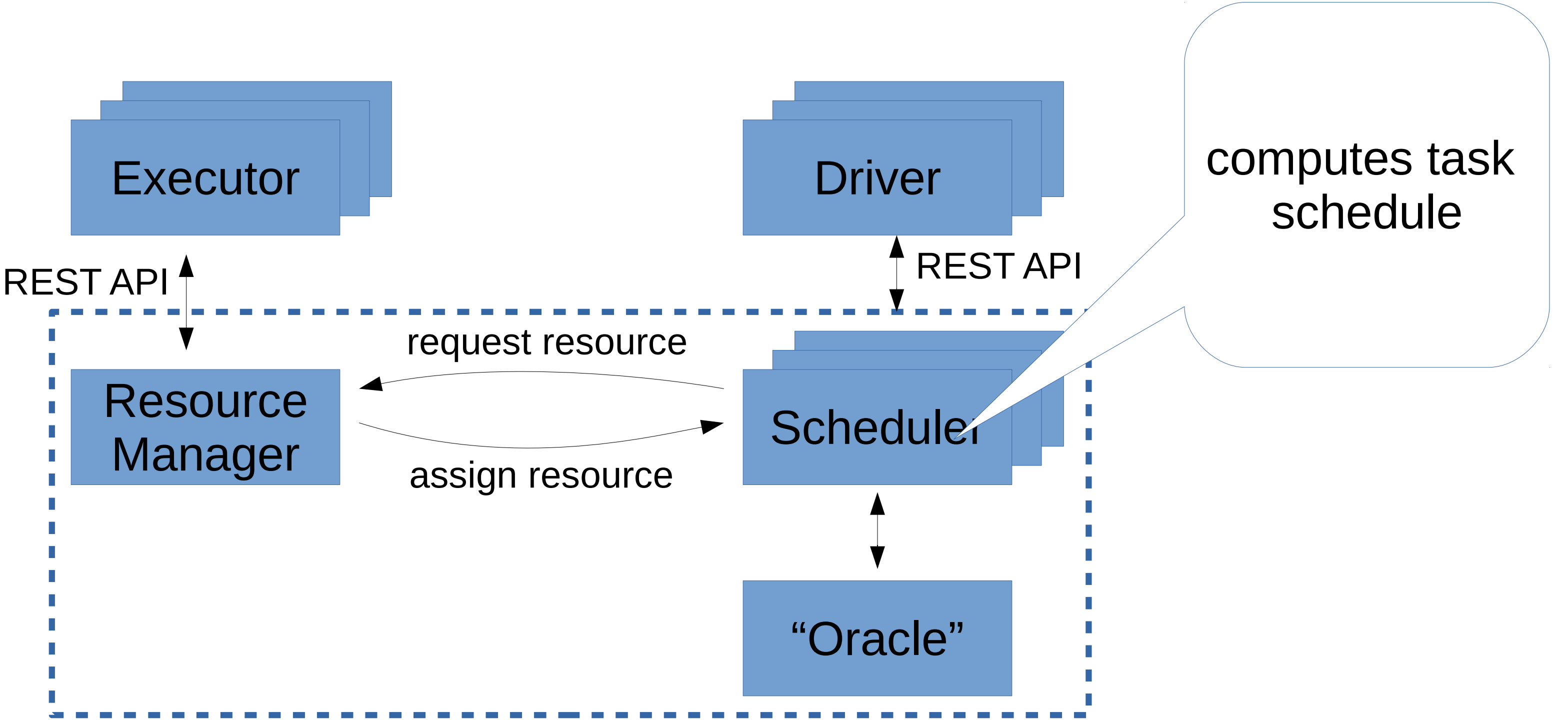

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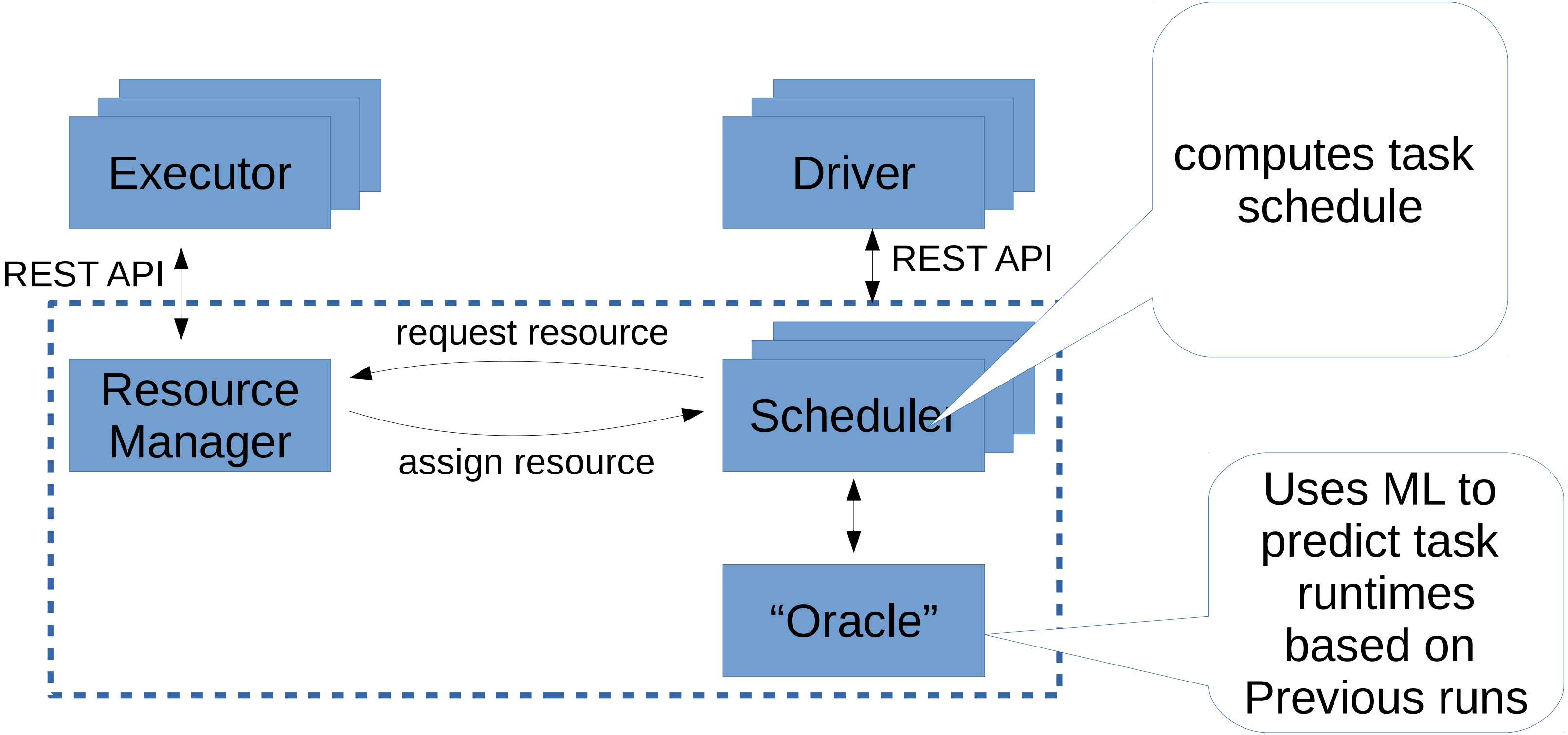

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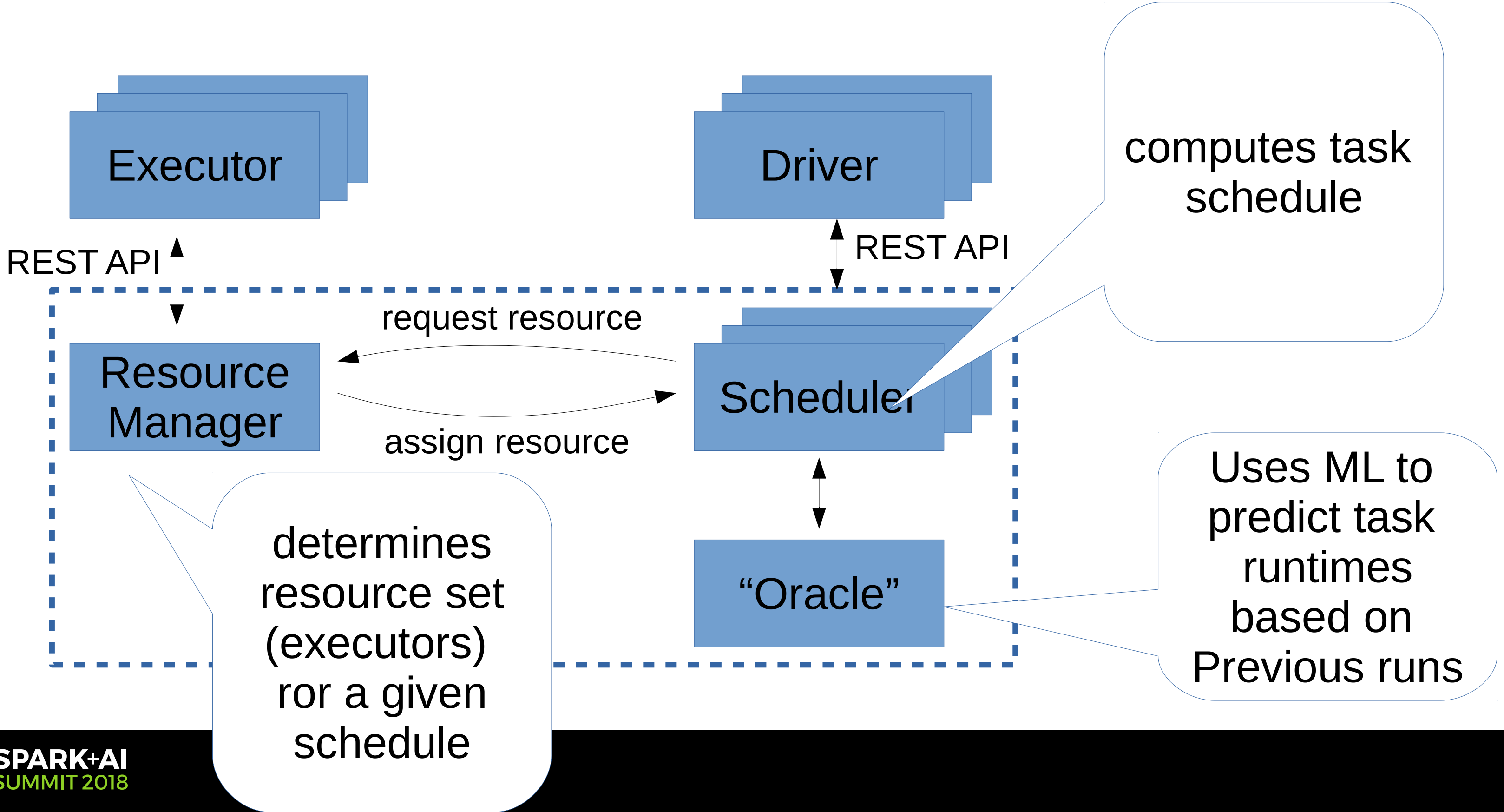
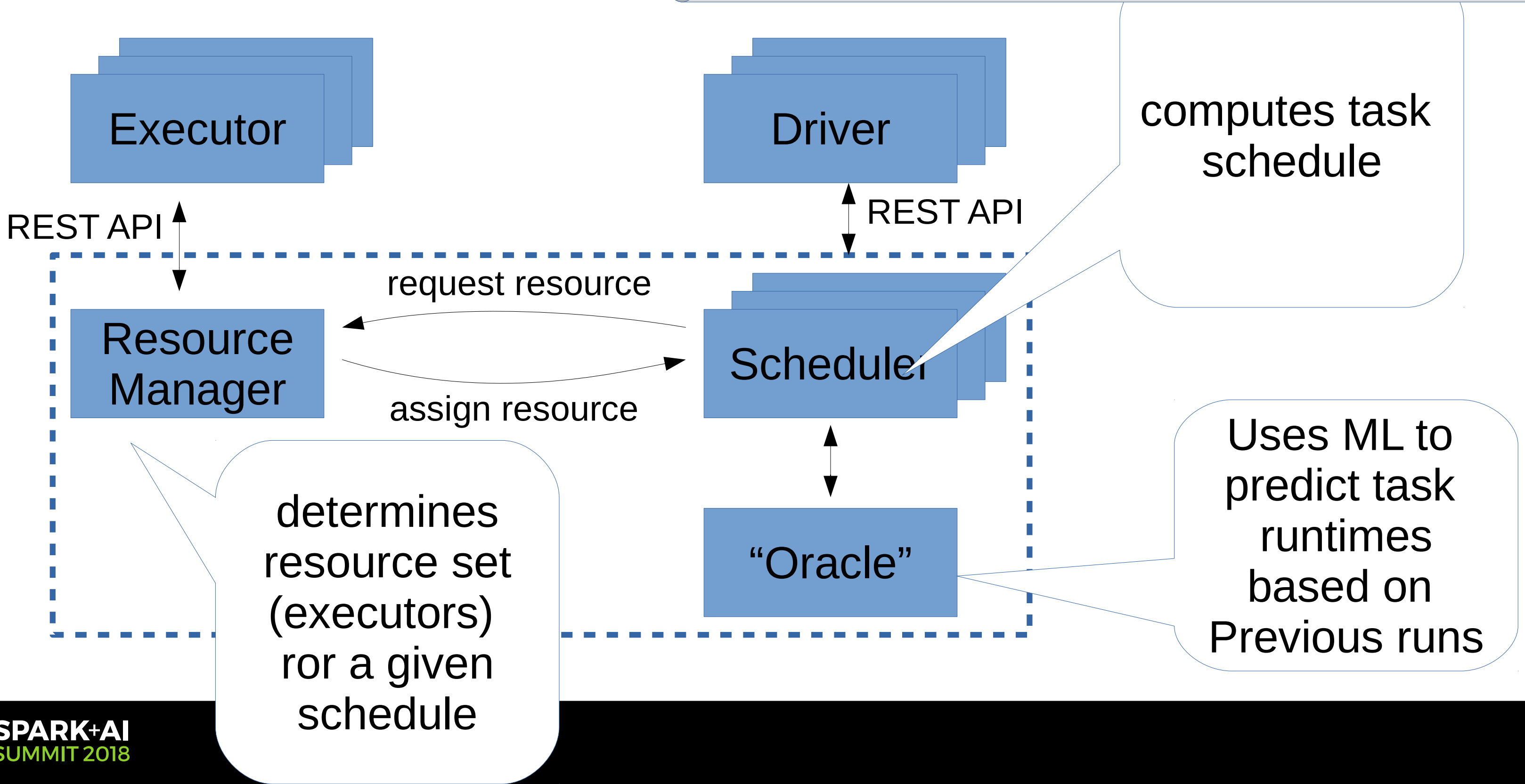


HCL Scheduler

"The HCl Scheduler:
Going all-in on Heterogeneity",
Michael Kaufmann et al., HotCloud'17



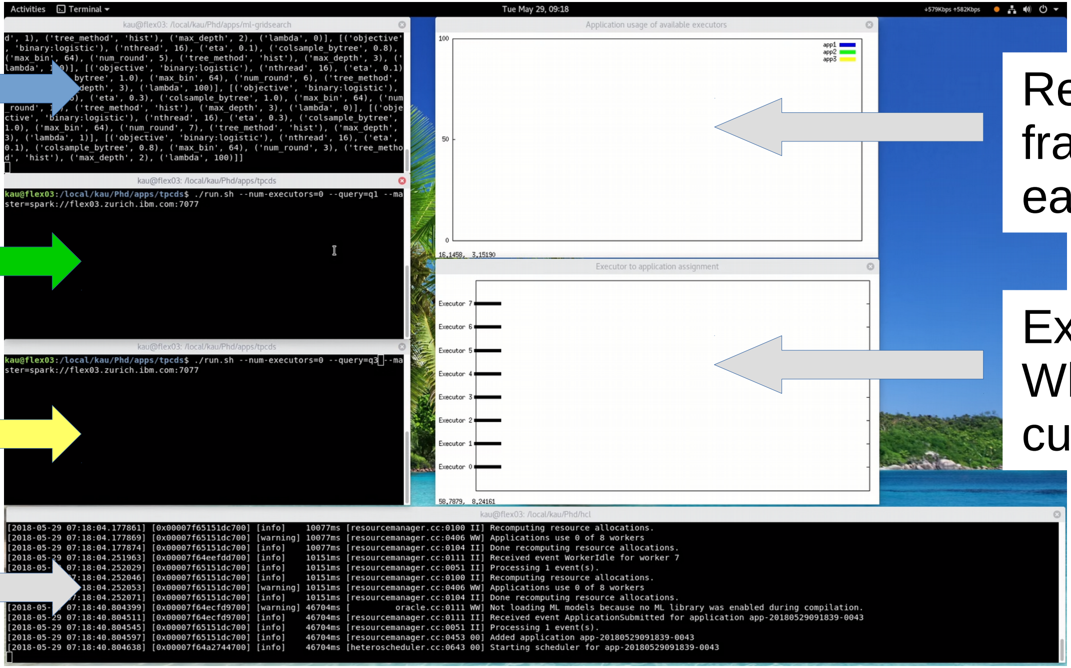
Video: Putting things together

Application 1:
GridSearch

Application 2:
SQL TPC-DS

Application 3:
SQL TPC-DS

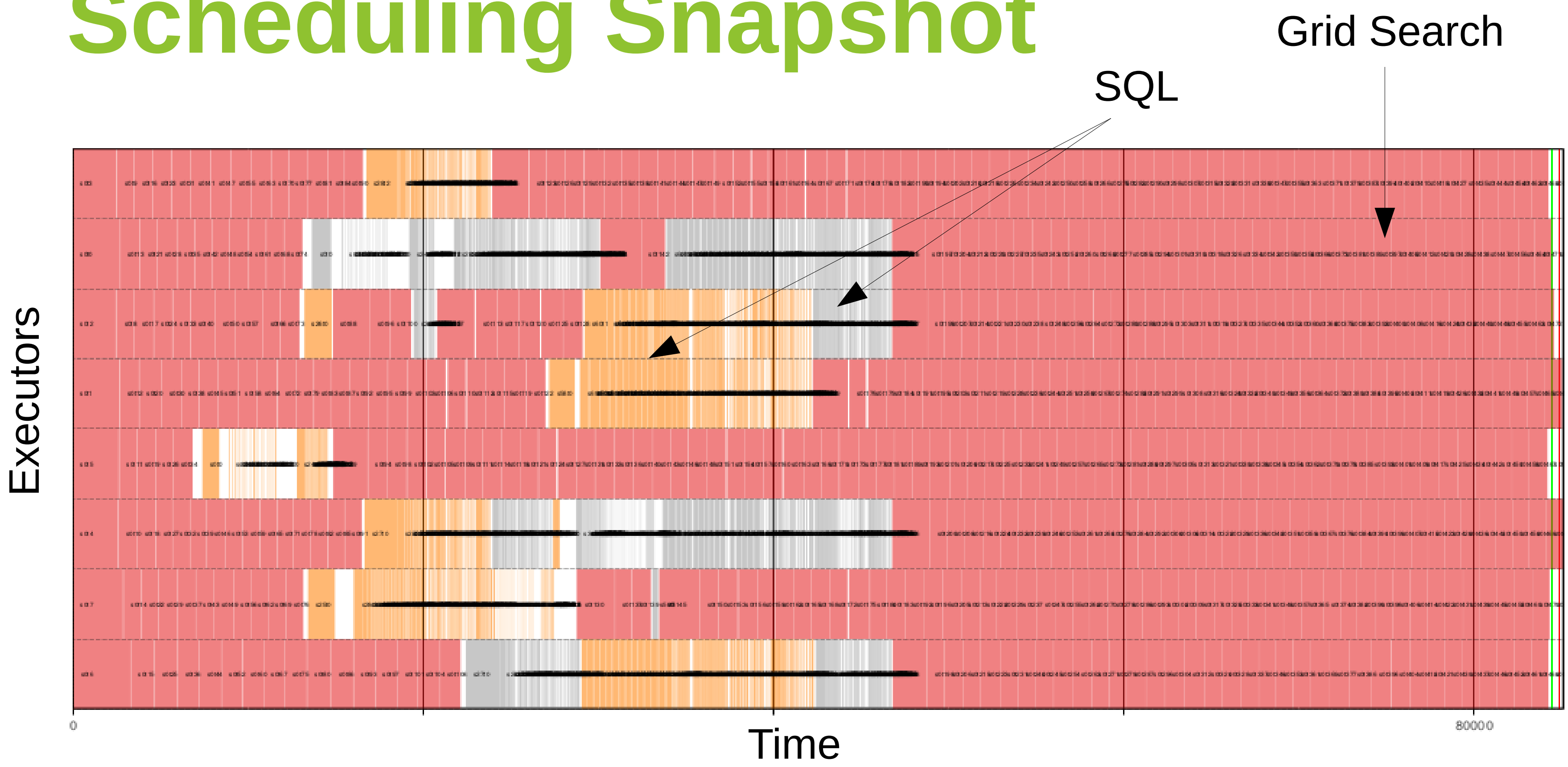
HCL
Scheduler



Resource view:
fraction of resources
each app consumes

Executor view:
Which app an executor
currently runs

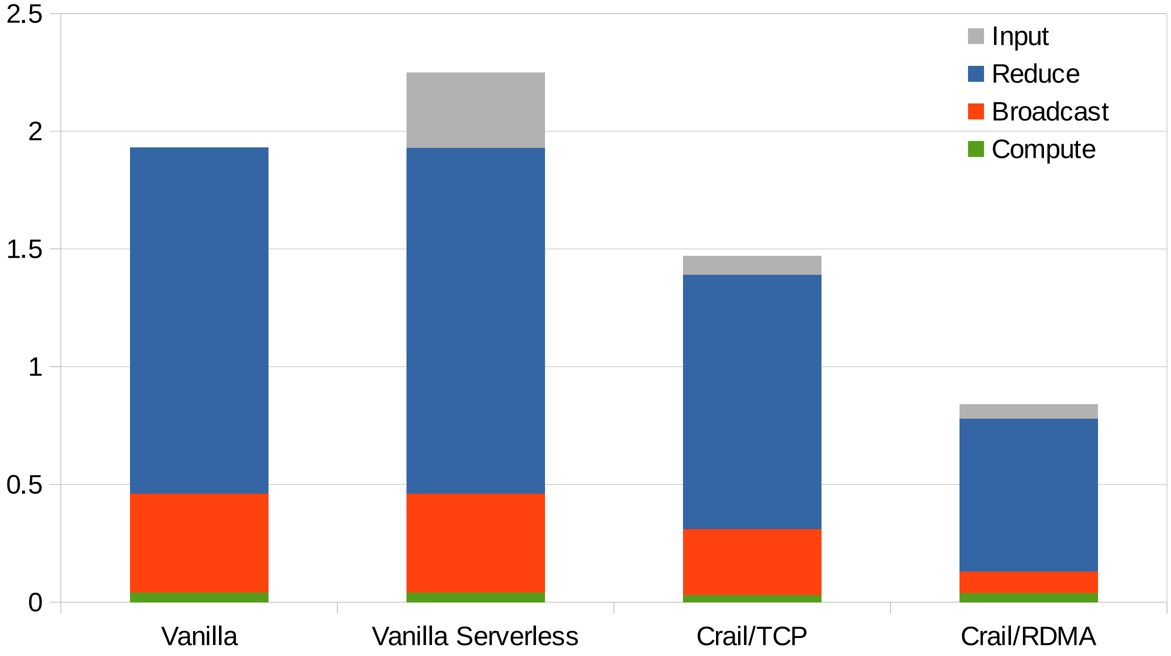
Scheduling Snapshot



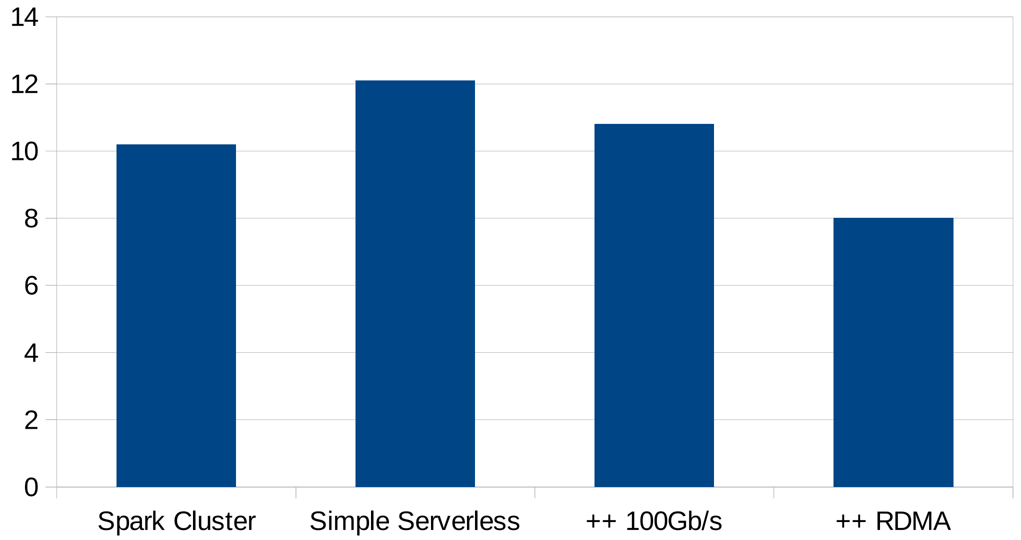
Let’s look at performance...

- Cluster size: 16 nodes
- Cluster hardware:
  - DRAM: 512 GB
  - Storage: 4x 1.2 TB NVMe SSD
  - Network: 10Gb/s Ethernert, 100Gb/s RoCE
- Workloads
  - ML: Logistic Regression using the CoCoa framework
  - SQL: TCP-DS

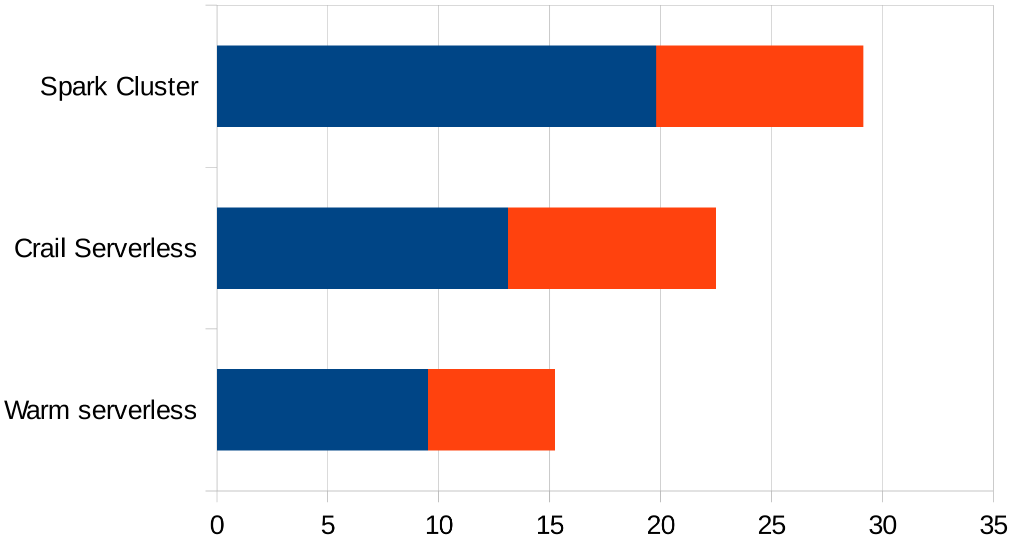
ML: Logistic Regression



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 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

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

Thanks to

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