# Serverless Machine Learning on Modern Hardware

IBM Research

#Res6SAIS

SPARK+AI SUMMIT 2018

# 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

- **Container startup:** may have to dynamically spin up containers per function call
  - Takes several 200-300 milliseconds for a “cold” container
- **Storage:** input data needs to be fetched from remote storage (e.g., S3 object store)
  - As opposed to compute-local storage, e.g., HDFS
- **Data sharing:** intermediate needs to be temporarily stored on remote storage (e.g. S3, Redis)
  - Becomes problematic as workloads get more complex
  - Affects operations like shuffle, broadcast, etc.,

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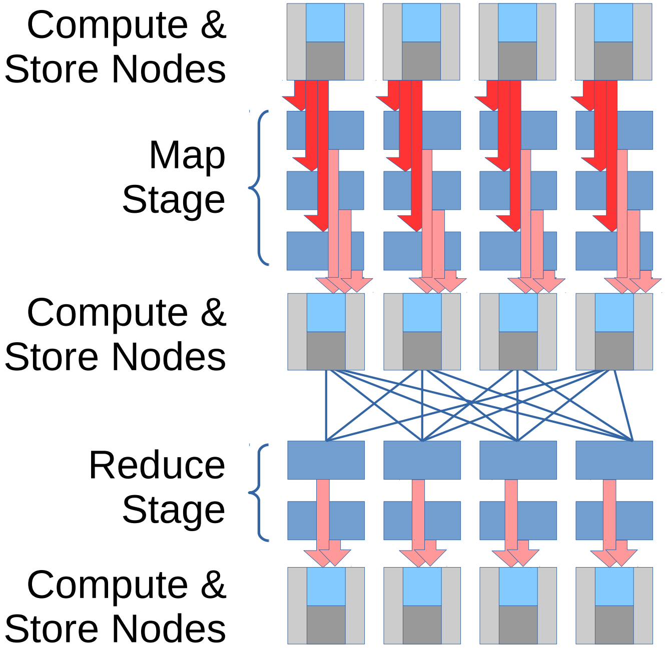
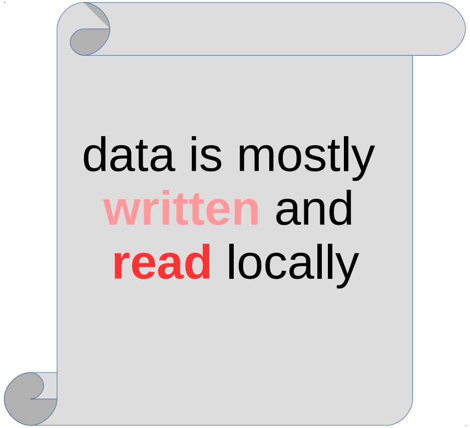
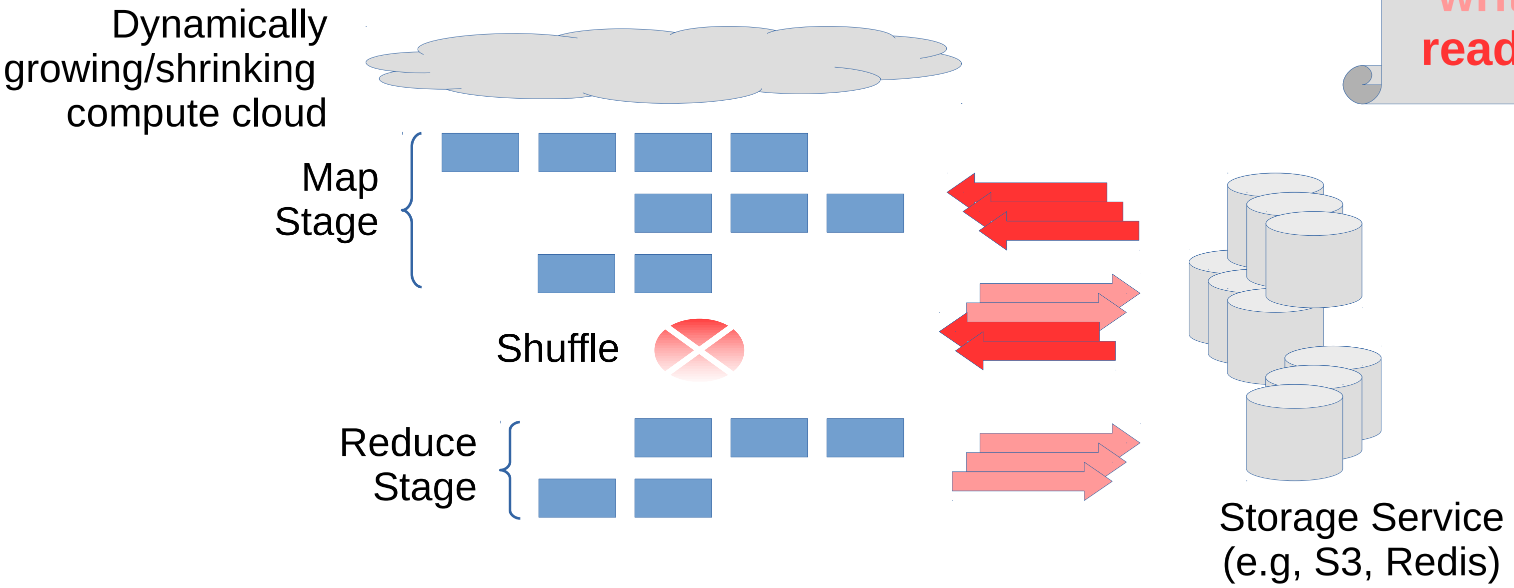
# Example: MapReduce (Cluster)



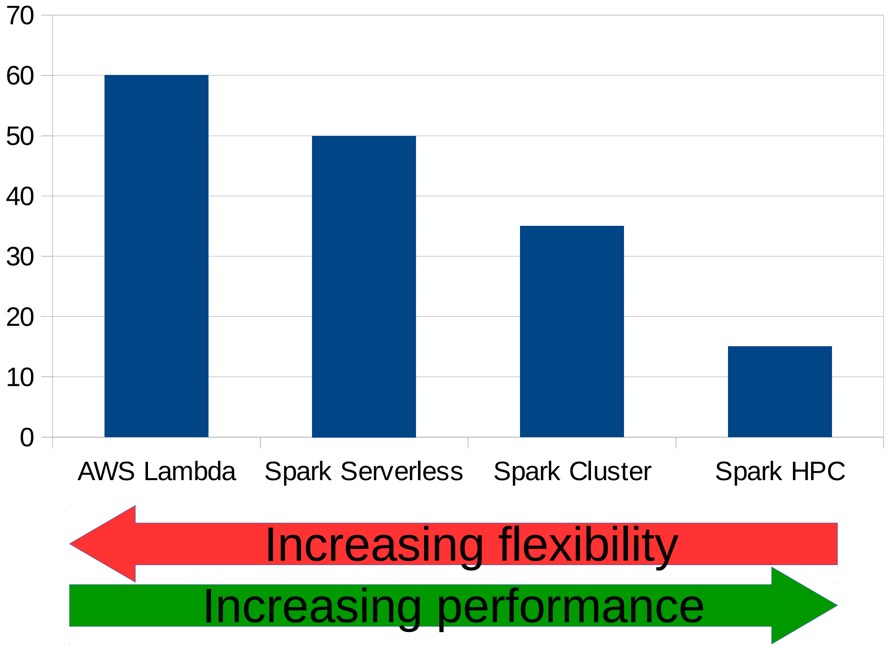



# Serverless MapReduce

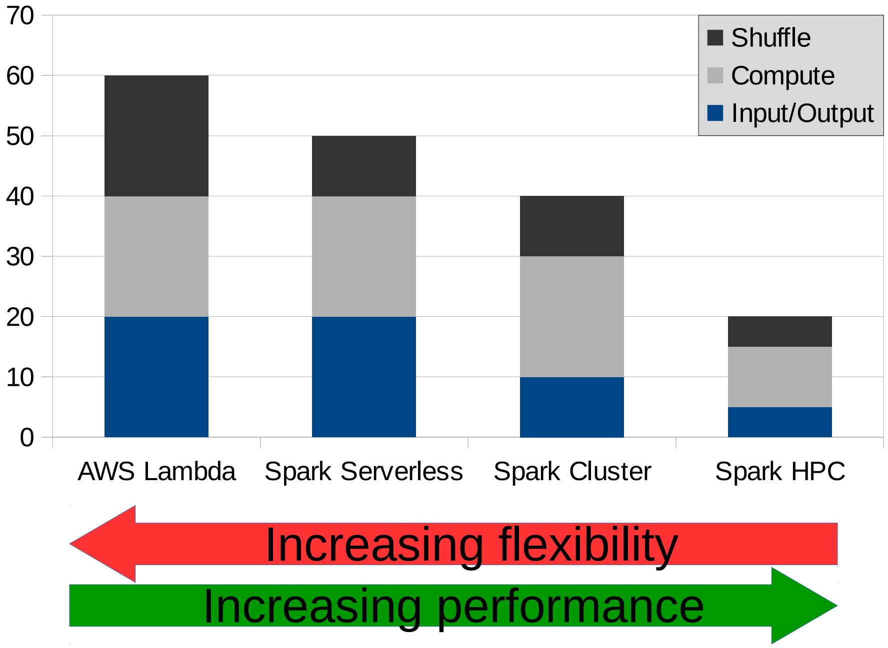



data is exclusively written and read remotely

# Sorting 100GB

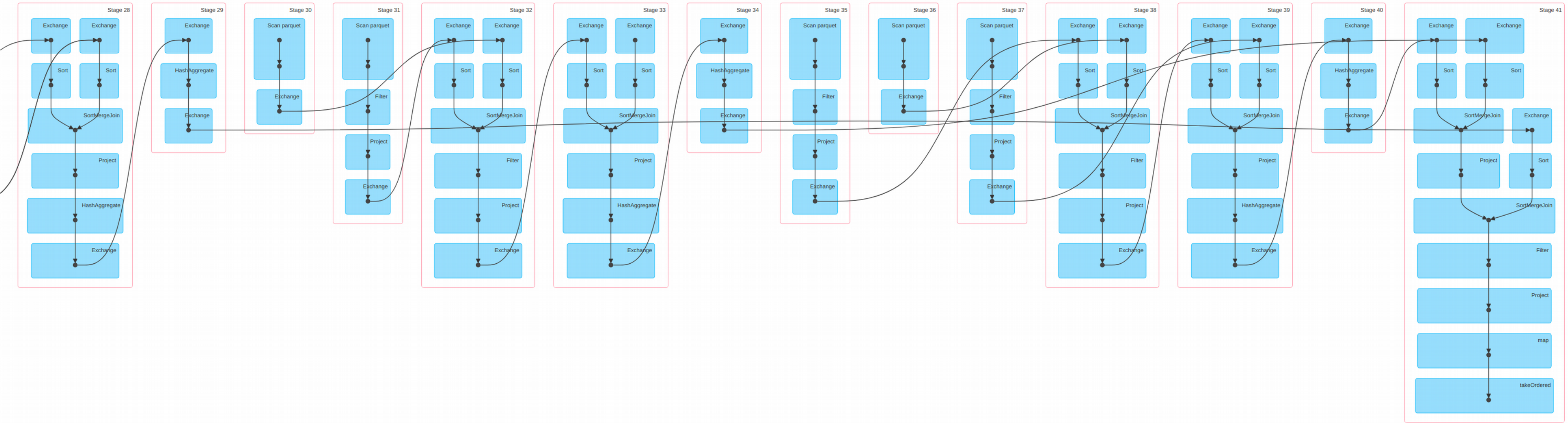


# Is I/O a problem?



# What about other workloads?

Example: SQL, Query 77 / TPC-DS benchmark



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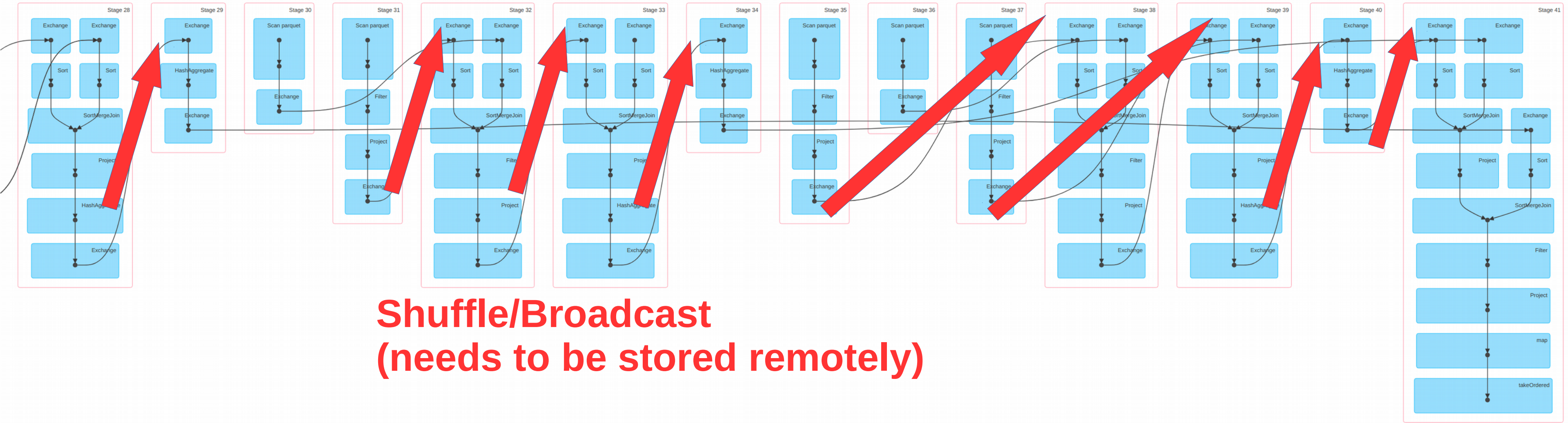
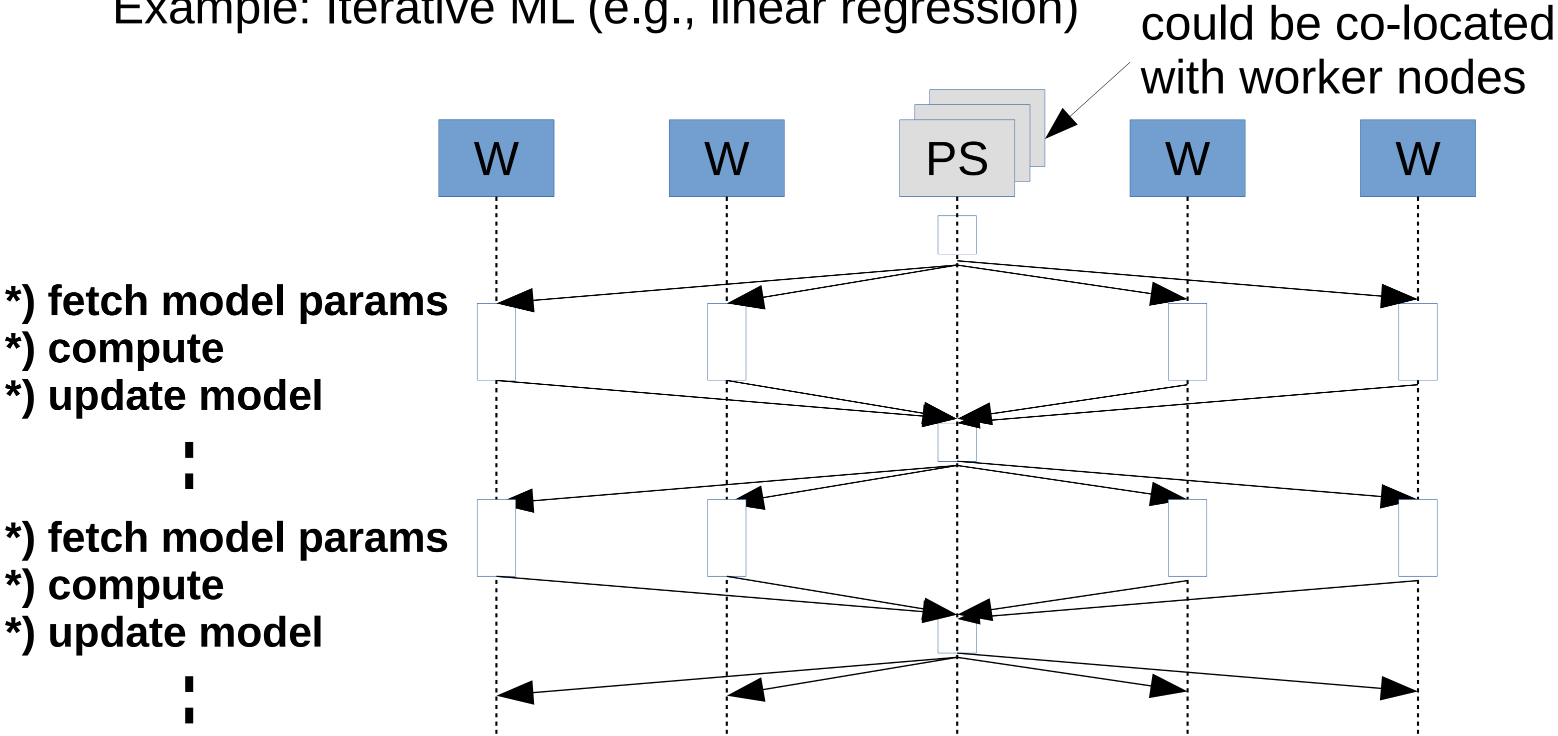



**Shuffle/Broadcast**
**(needs to be stored remotely)**

# What about other workloads?

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



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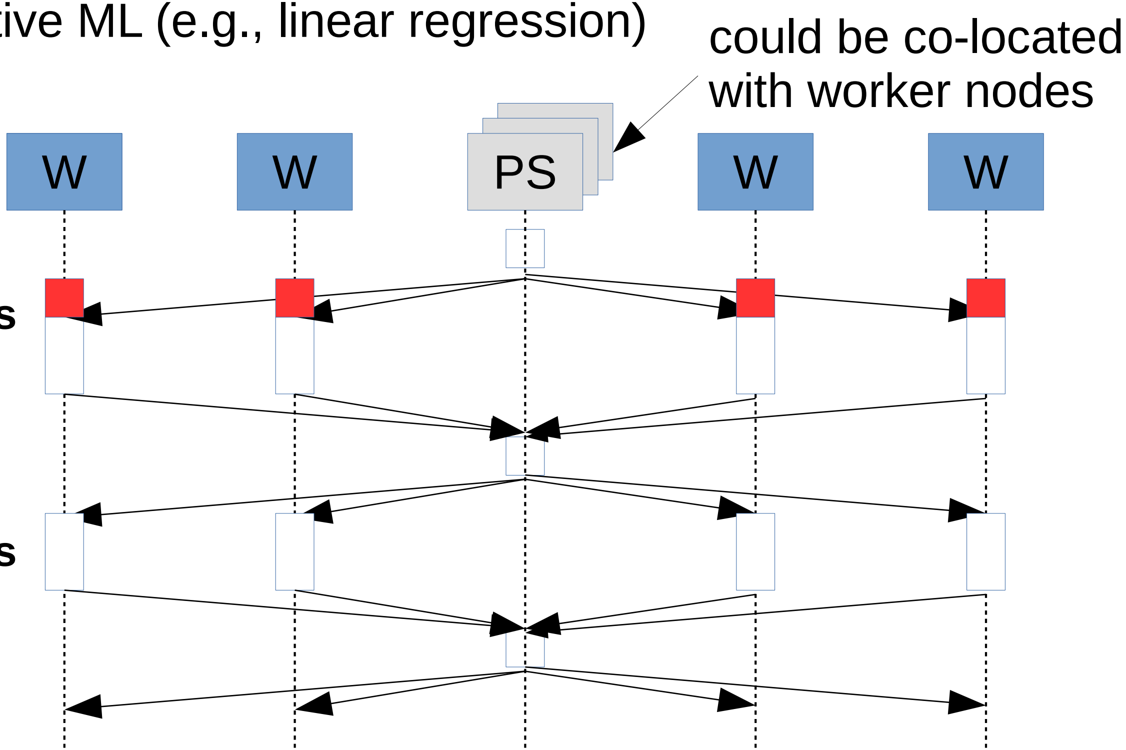


*) read training data
*) fetch model params
*) compute
*) update model

*) use cached data
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Example: Iterative ML (e.g., linear regression)

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

Needs to be remote

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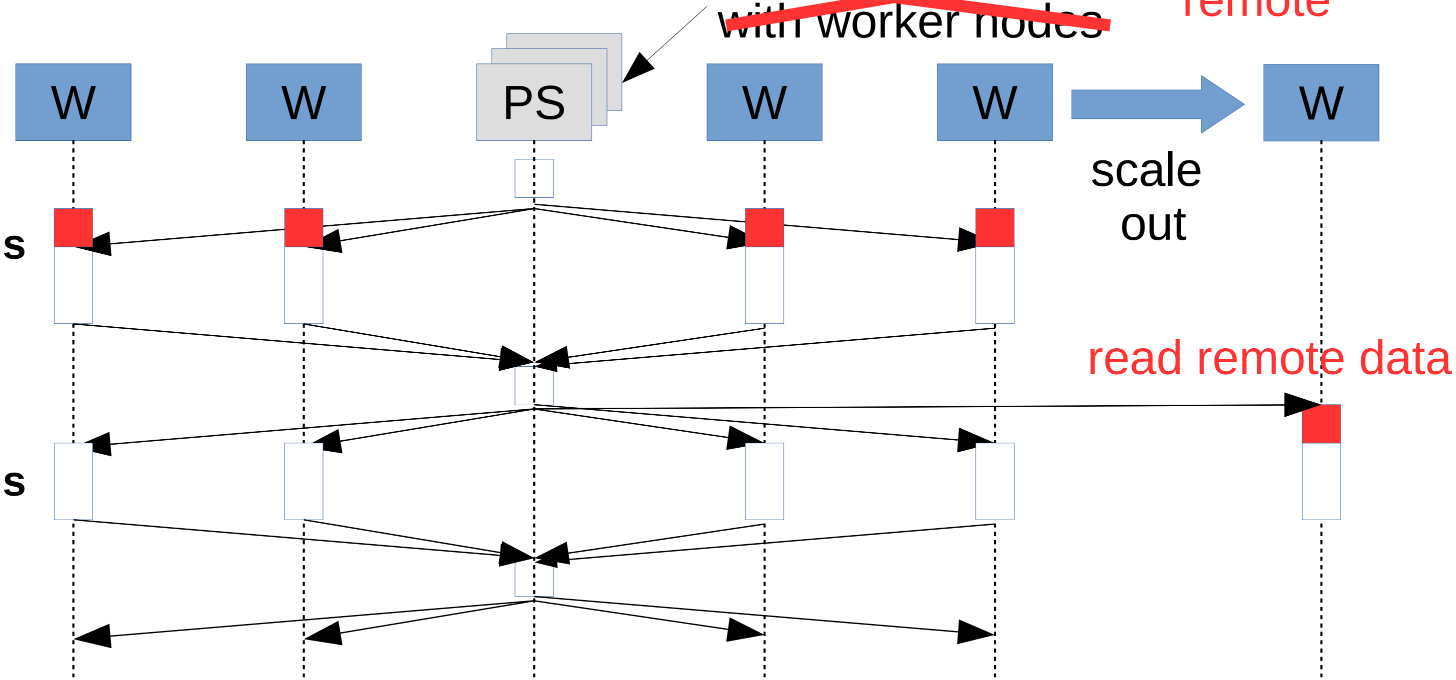

# Can we..

- ..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:**
  - 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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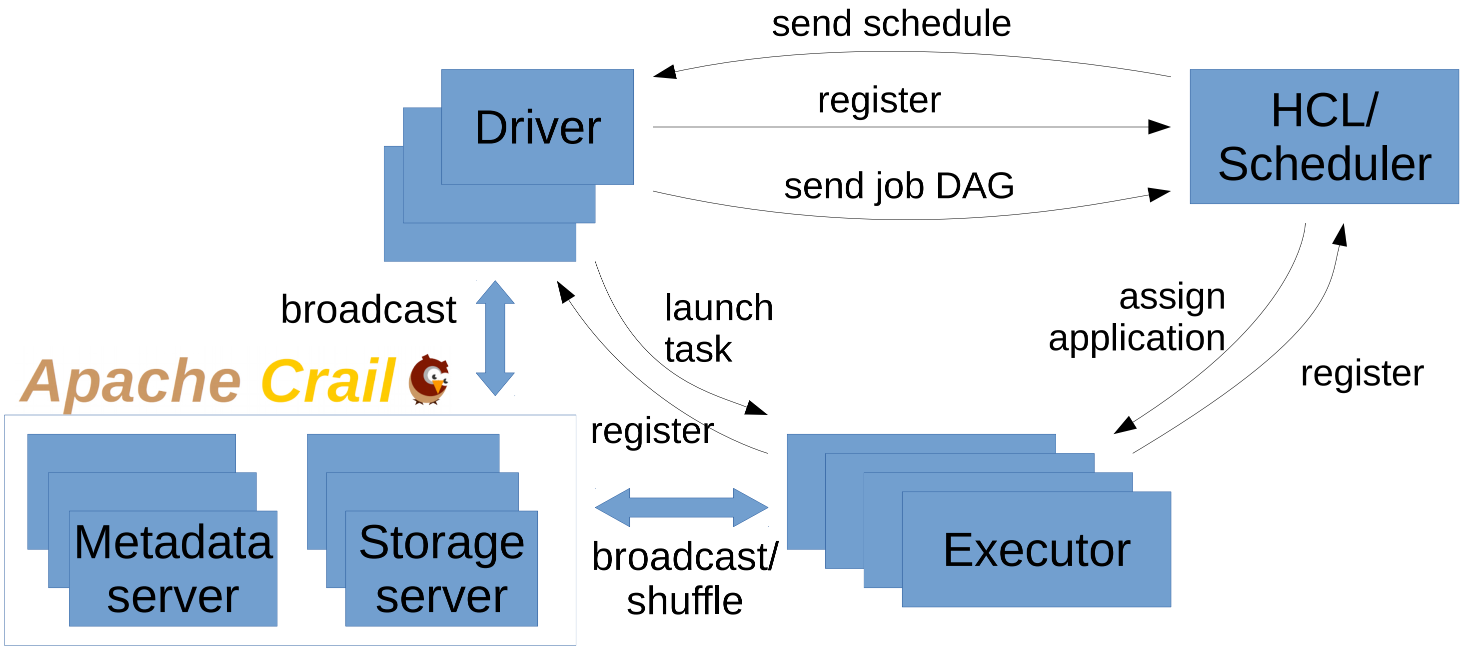
# Architecture Overview



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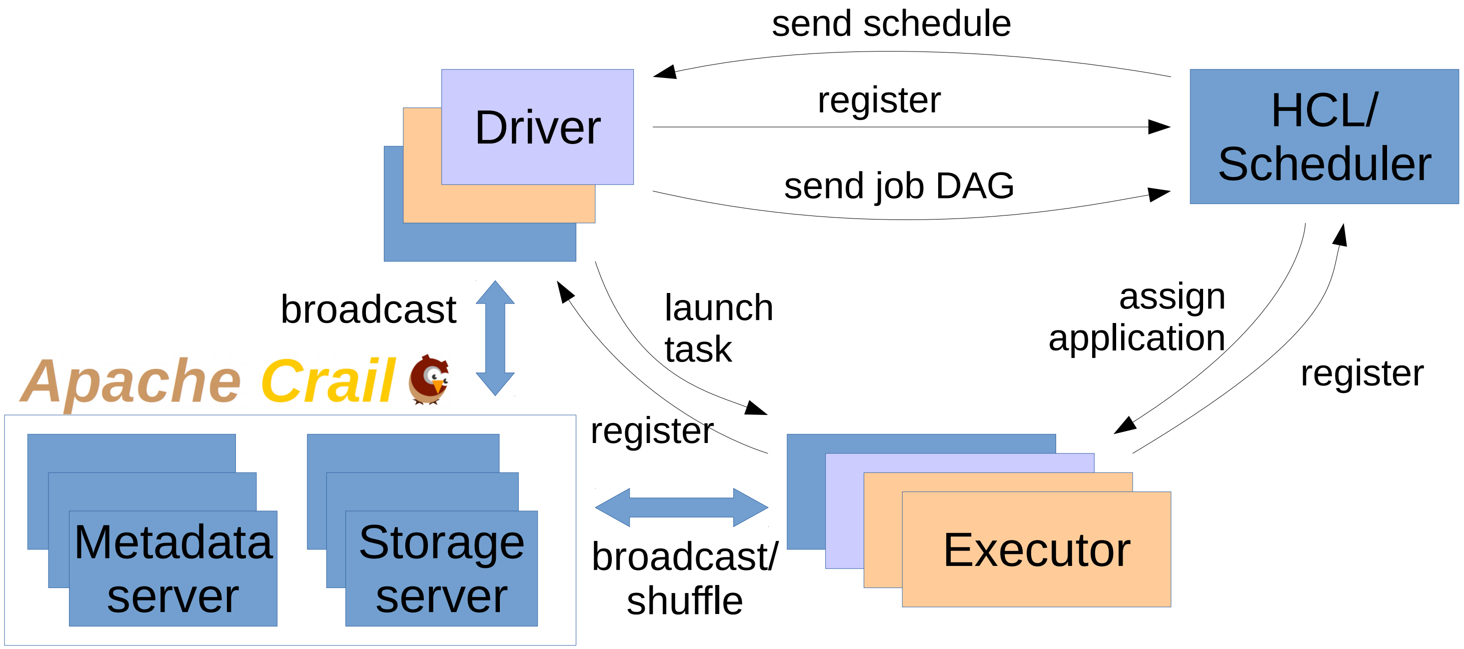

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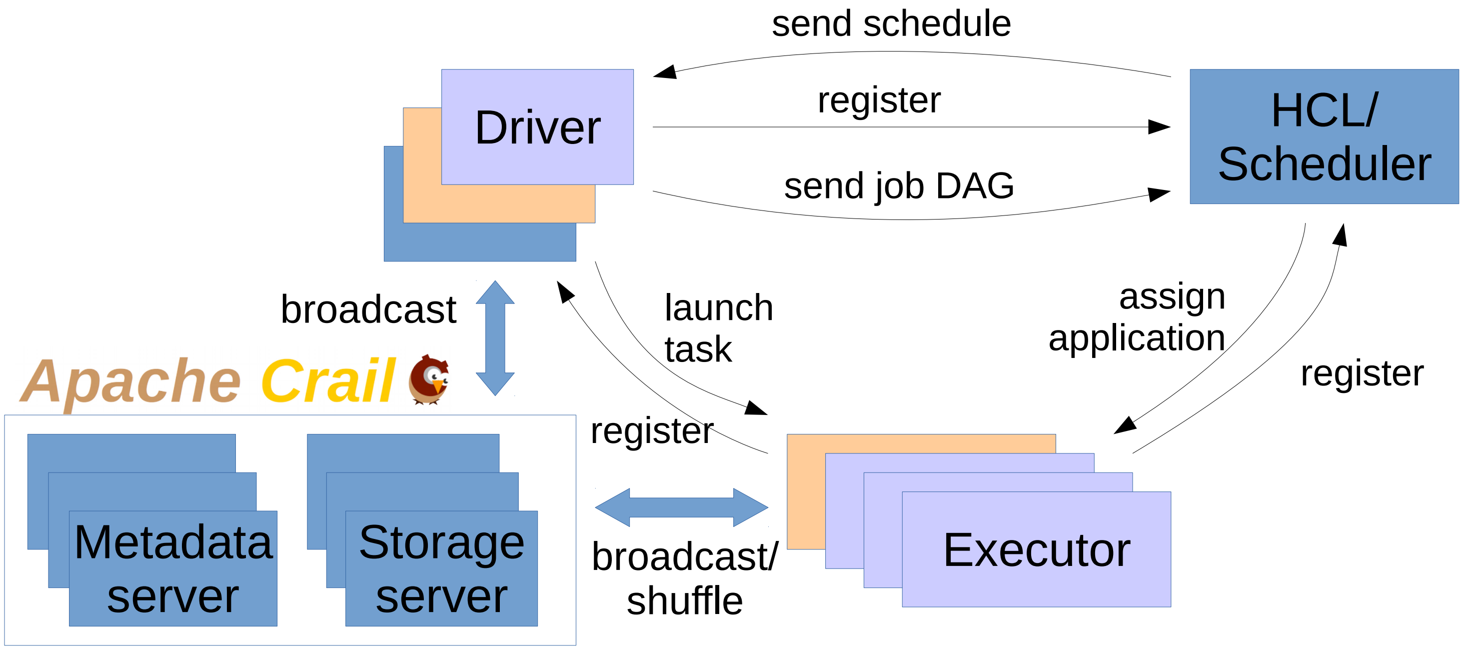

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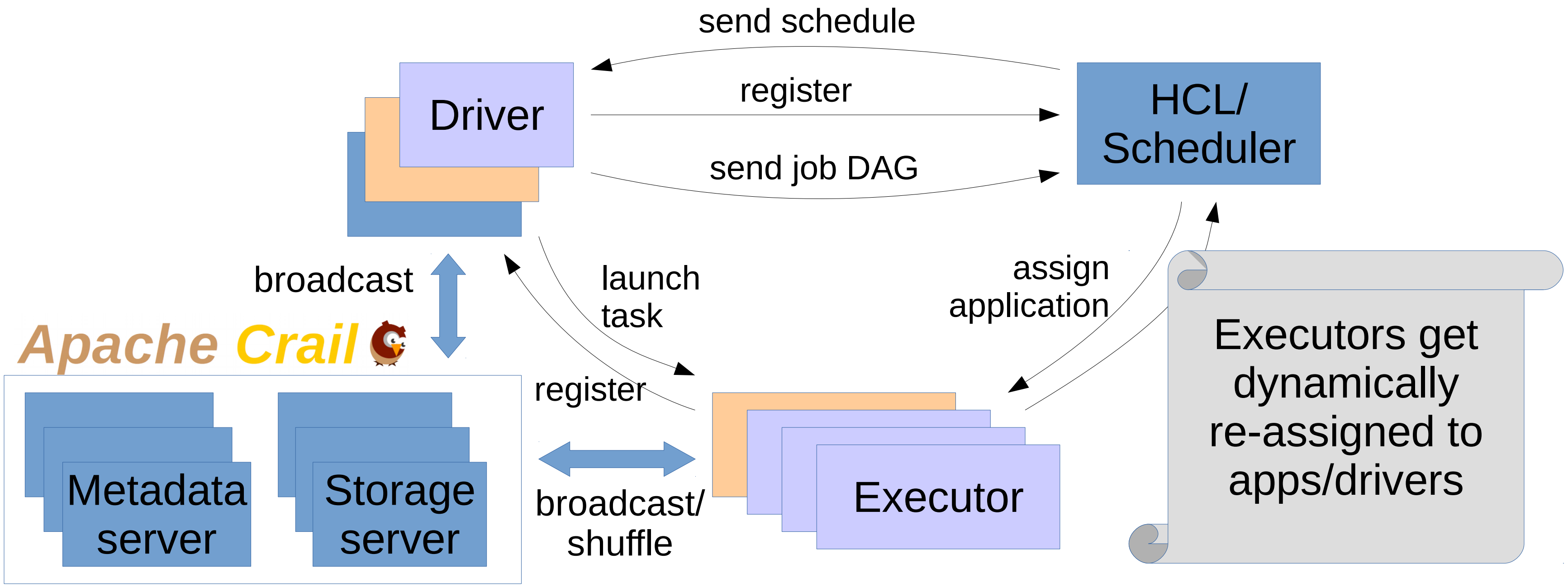

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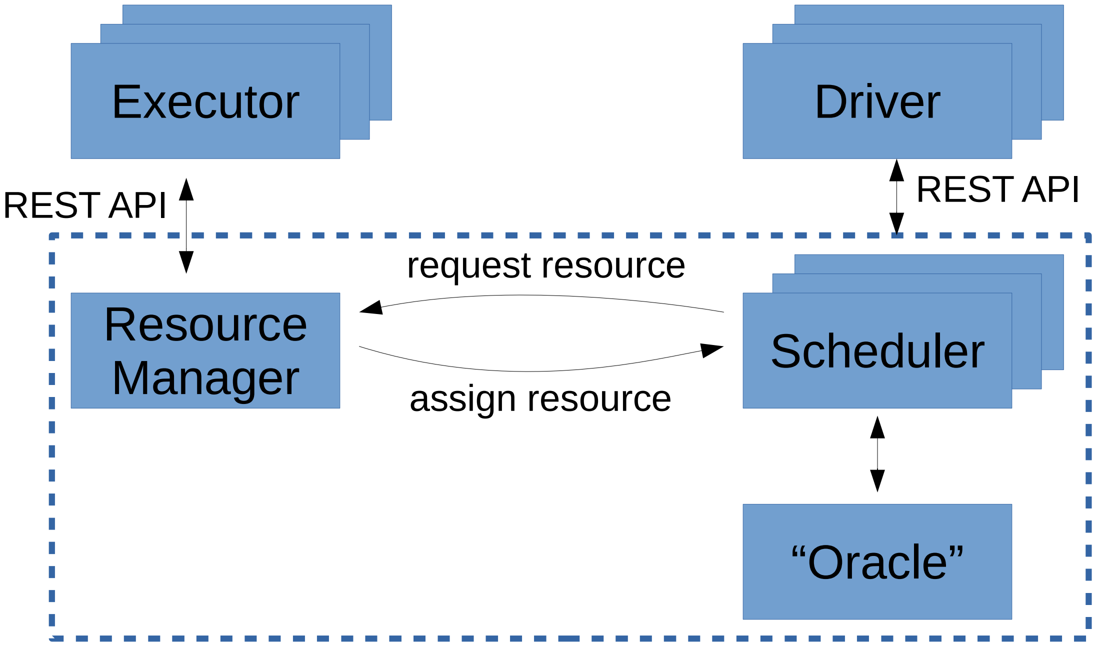

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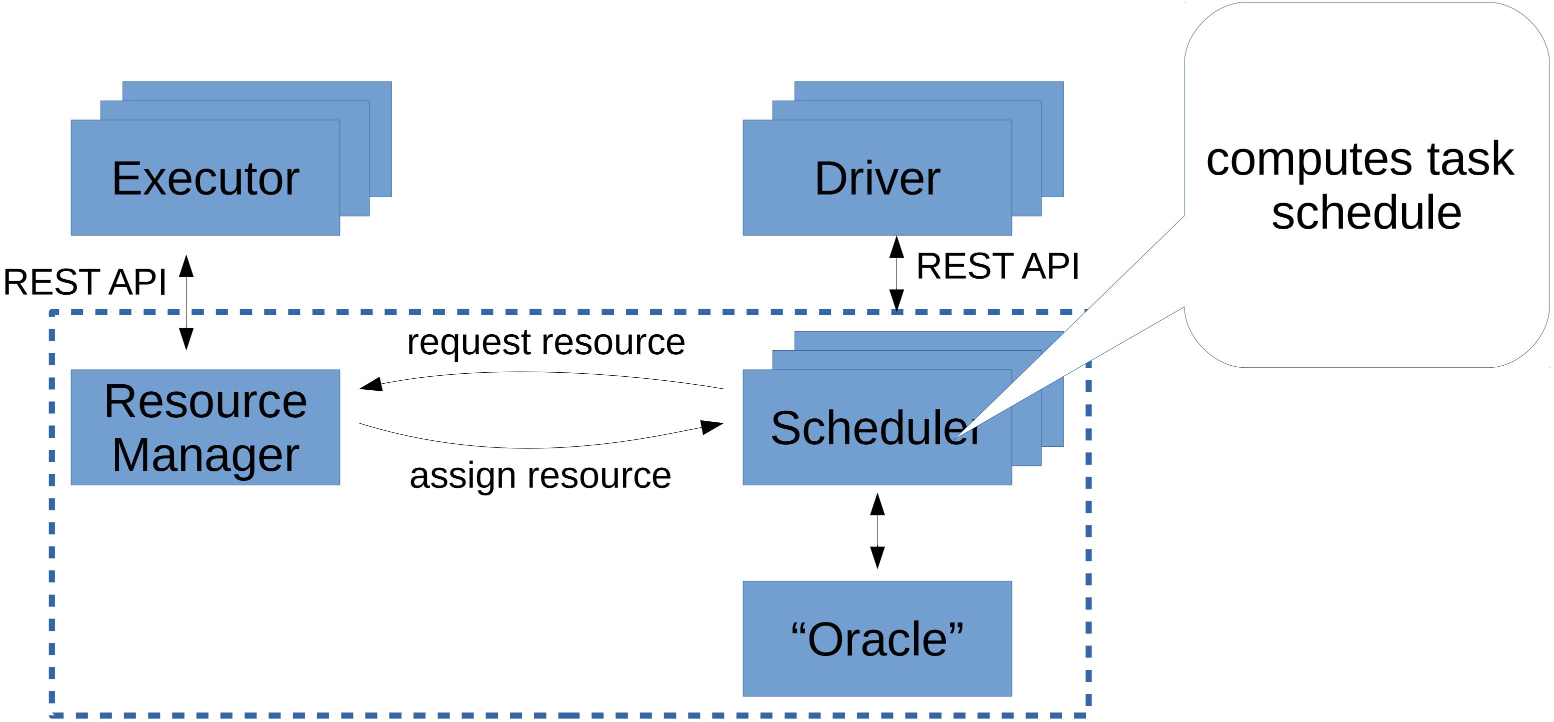

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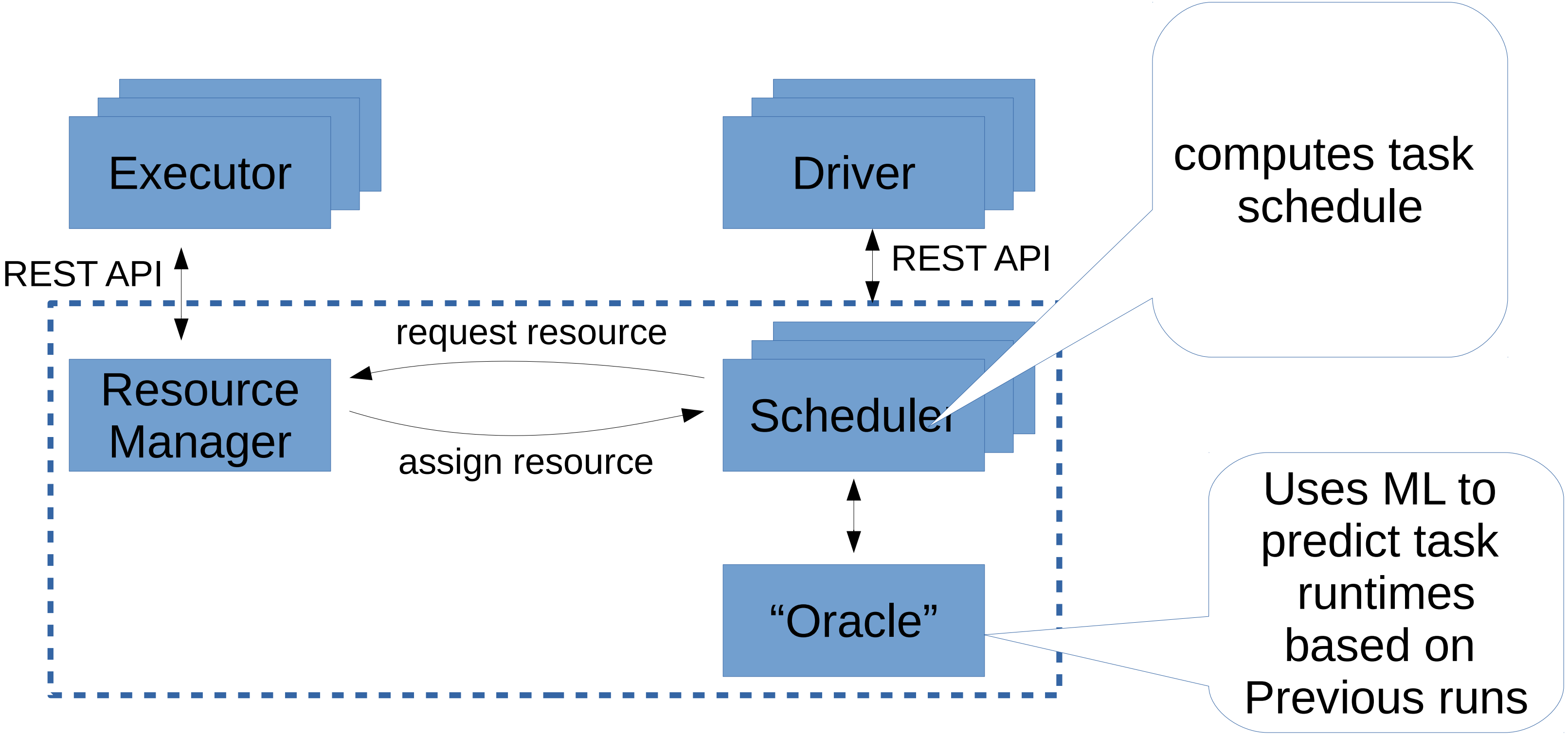

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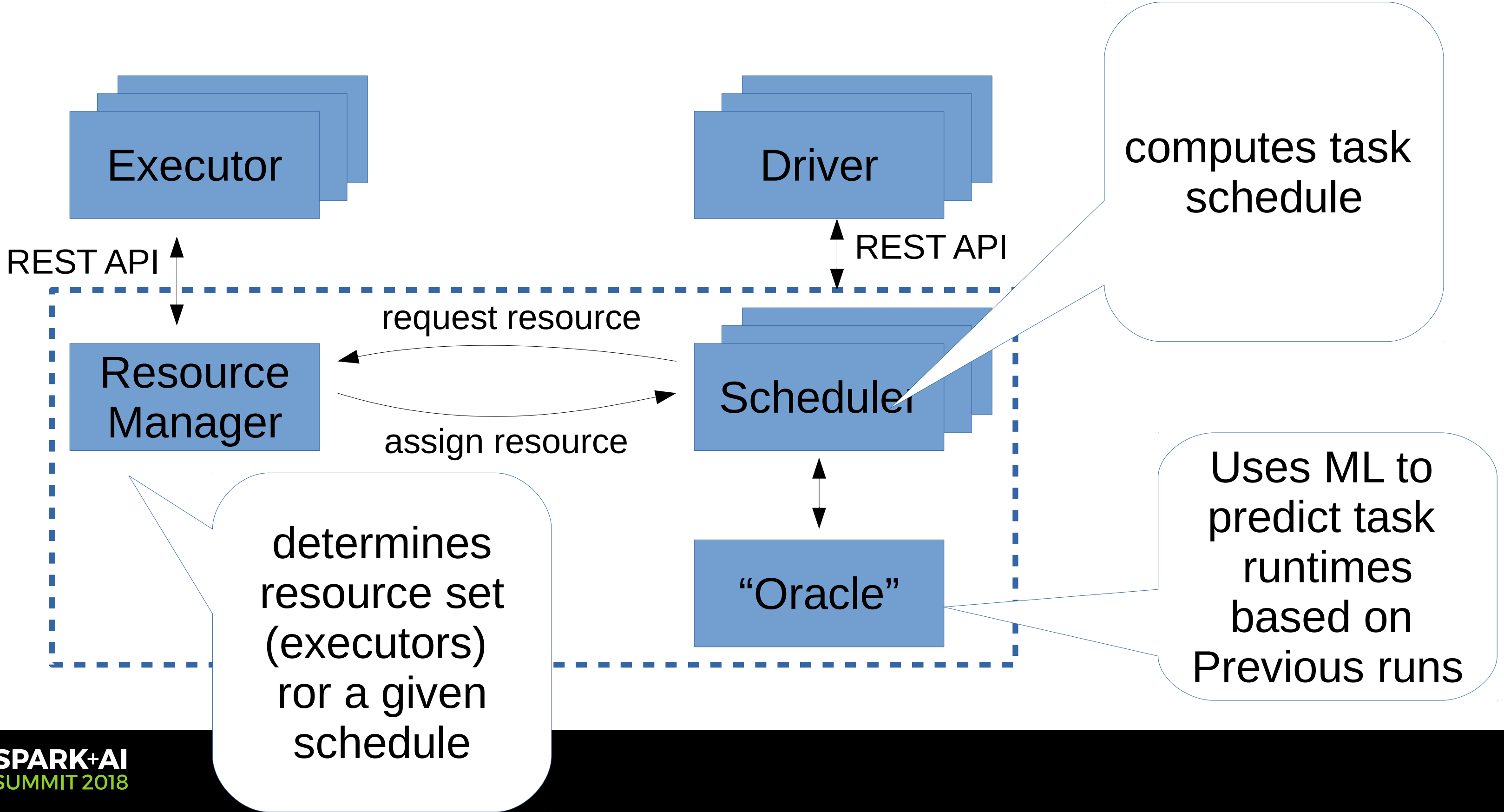


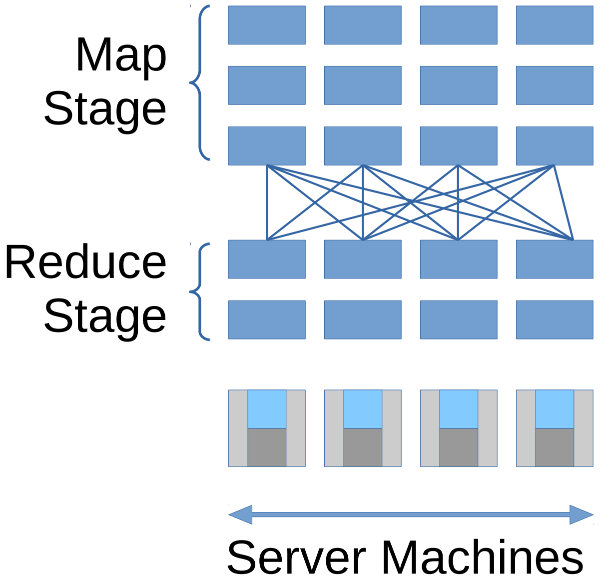
# Example using ML and SQL

# Backup

# Template Tite

- Template List
- Template List
  - Template item

# Example: MapReduce



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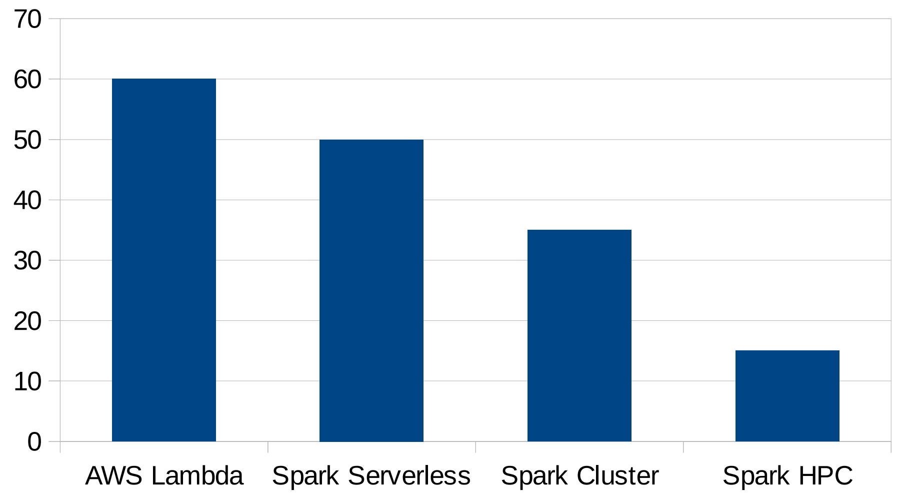


Serverless execution is 3-4x slower than an optimized cluster configuration

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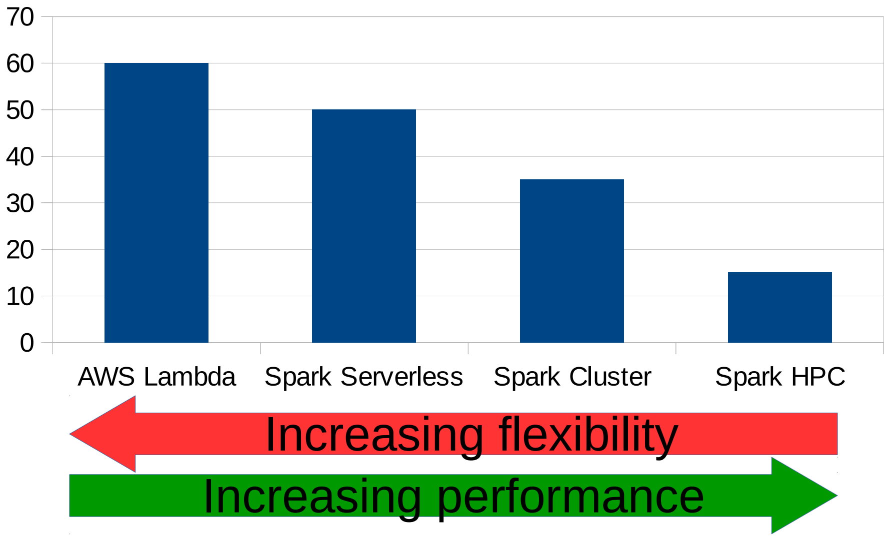


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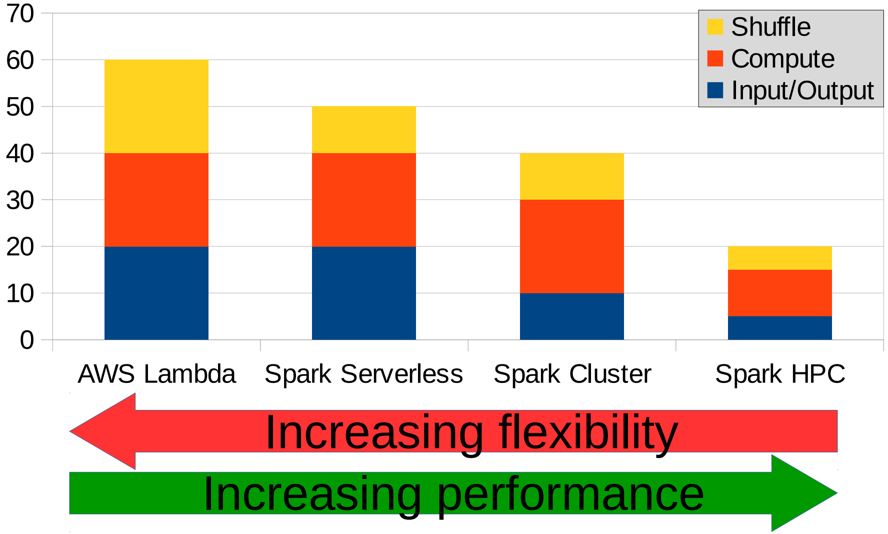


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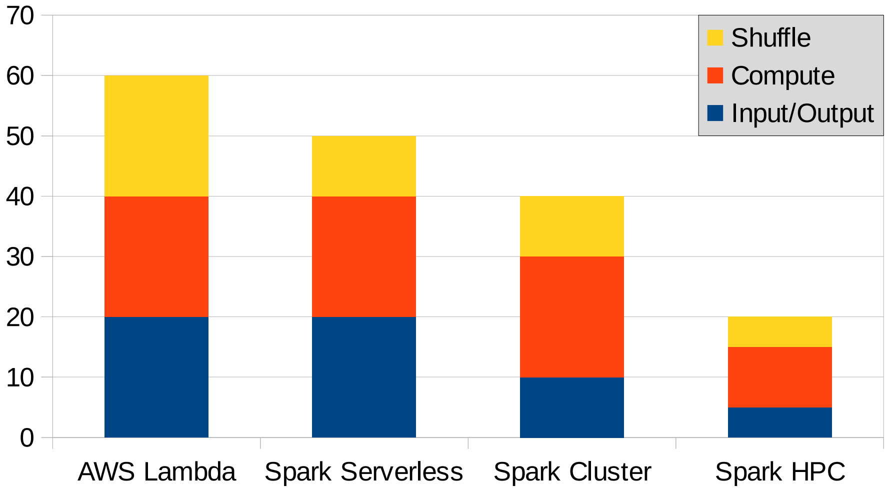


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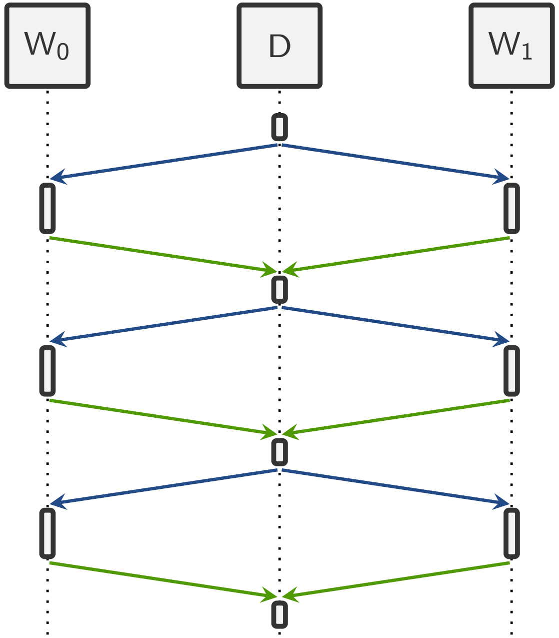

# Workloads and Frameworks

| | 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

# What about other workloads?

Example: RandomForest