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

- **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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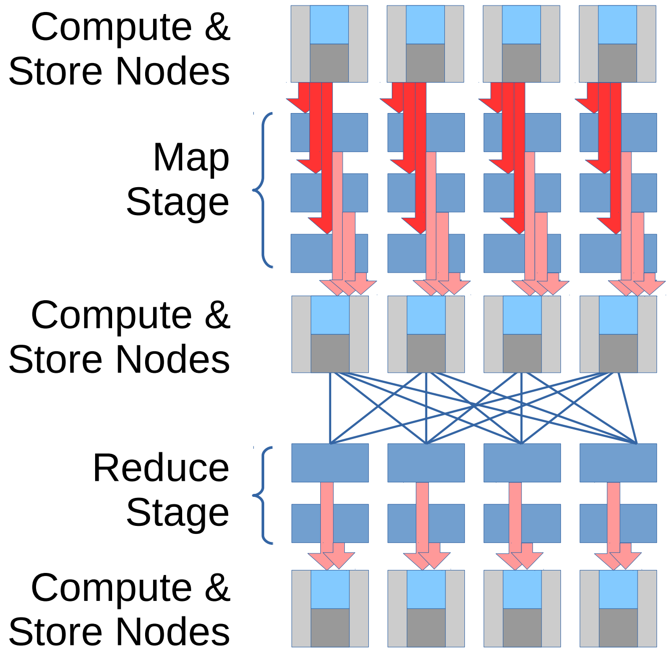
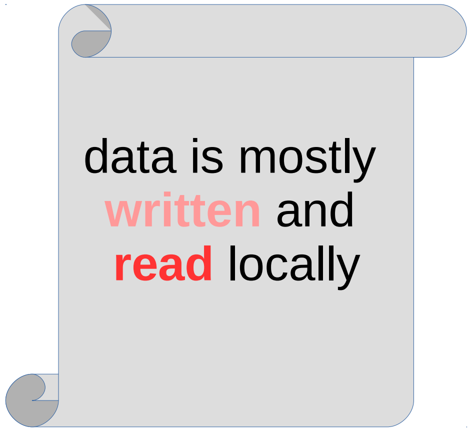
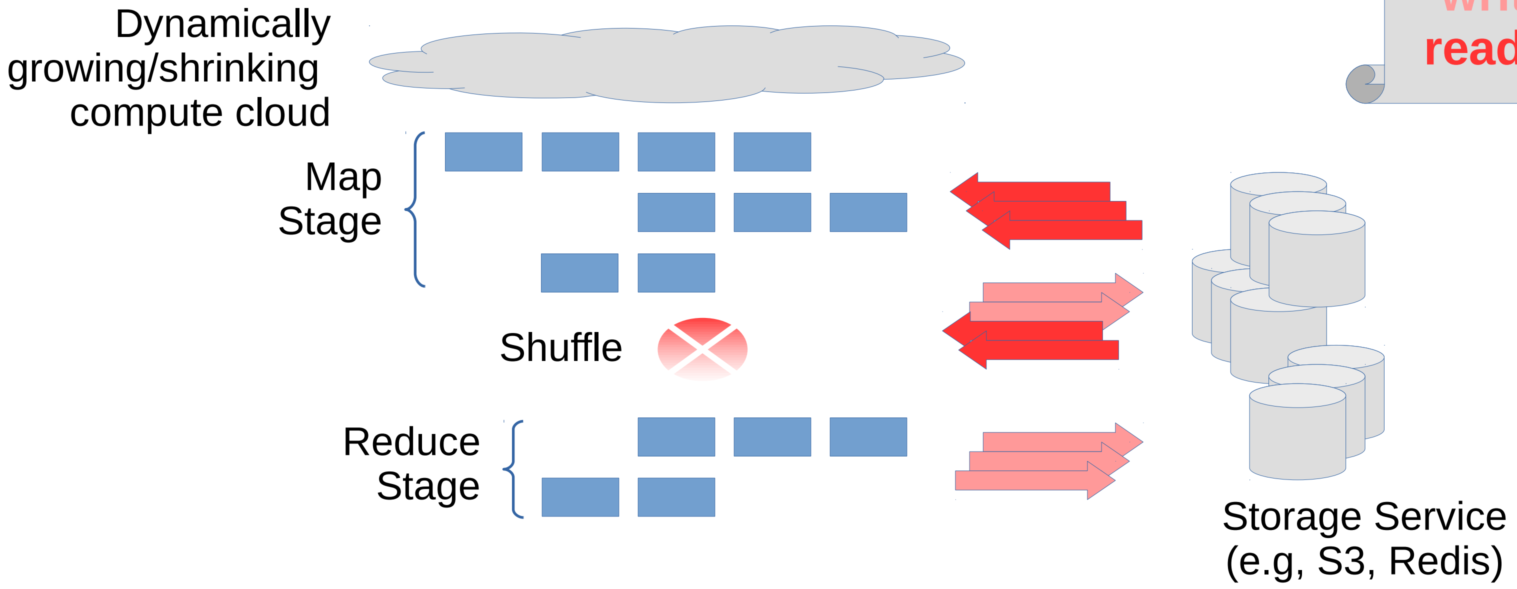
Example: MapReduce (Cluster)



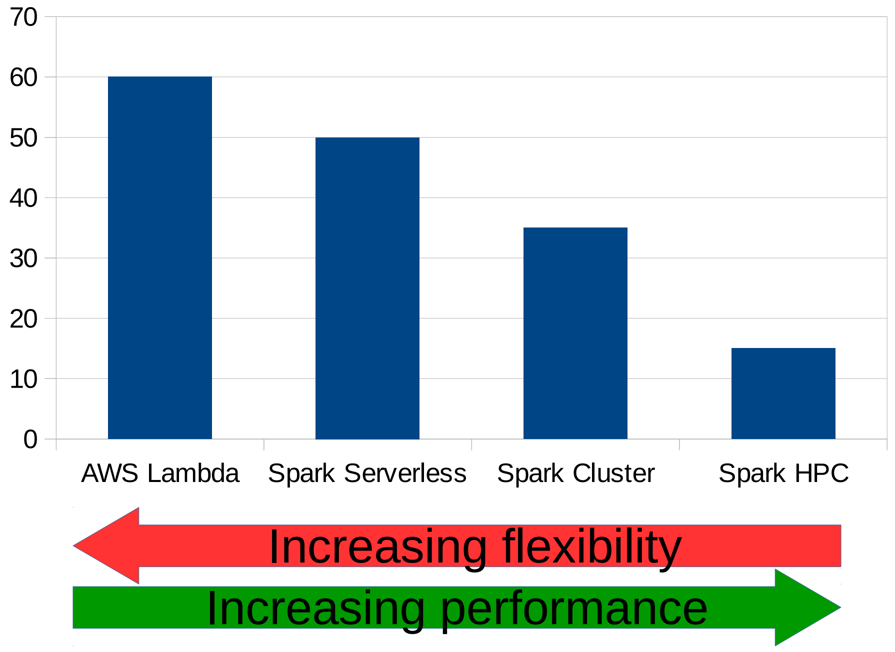

data is mostly **written** and **read** locally

Serverless MapReduce

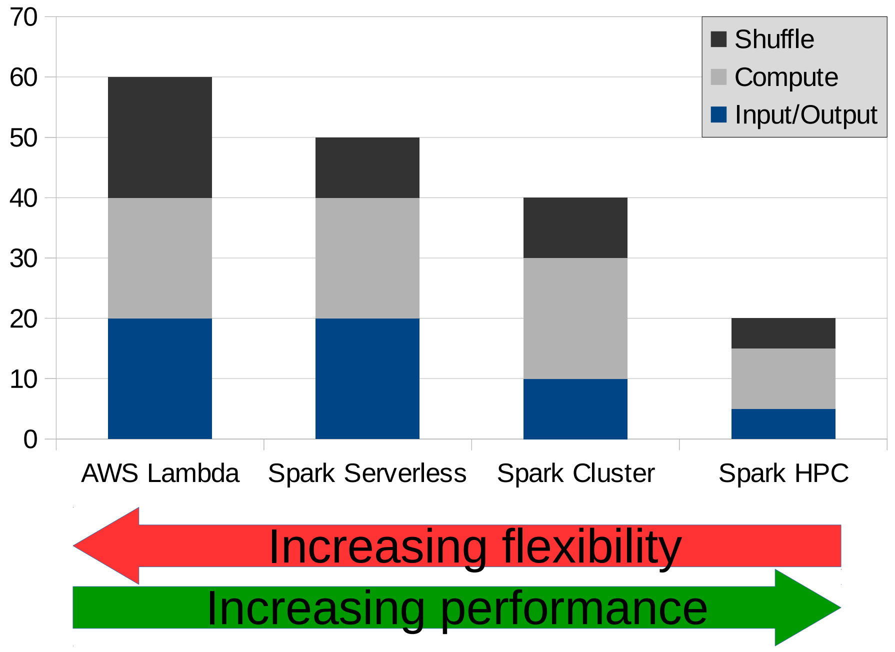

Dynamically growing/shrinking compute cloud
Map Stage
Shuffle
Reduce Stage
Storage Service (e.g, S3, Redis)

data is exclusively written and **read** remotely

Sorting 100GB

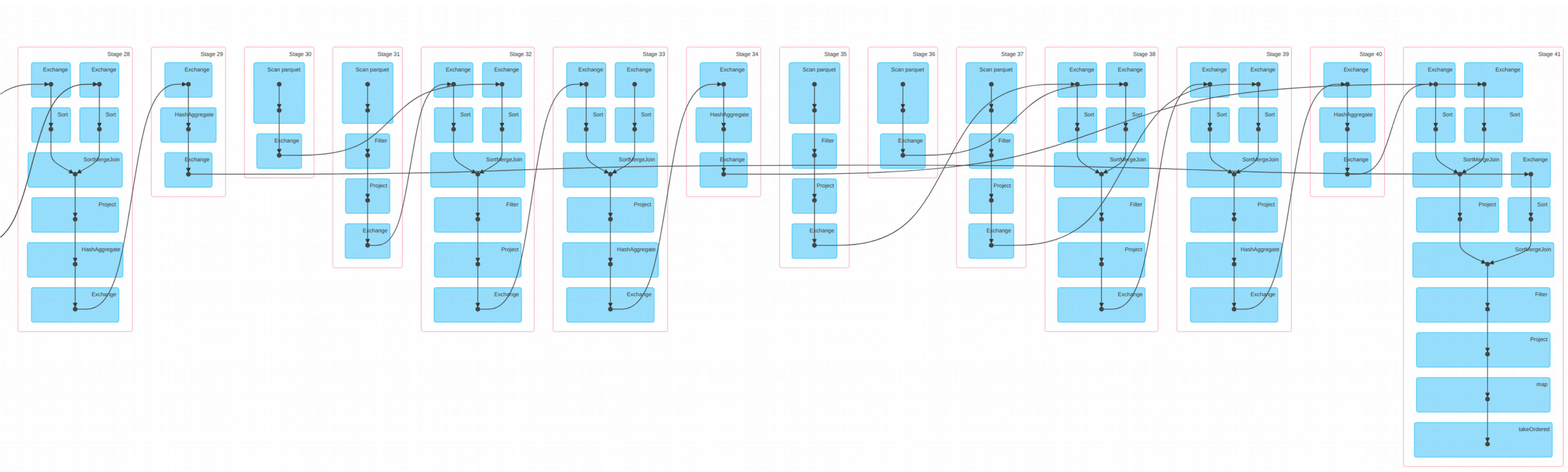


Is I/O a problem?



What about other workloads?

Example: SQL, Query 77 / TPC-DS benchmark



SPARK+AI SUMMIT 2018

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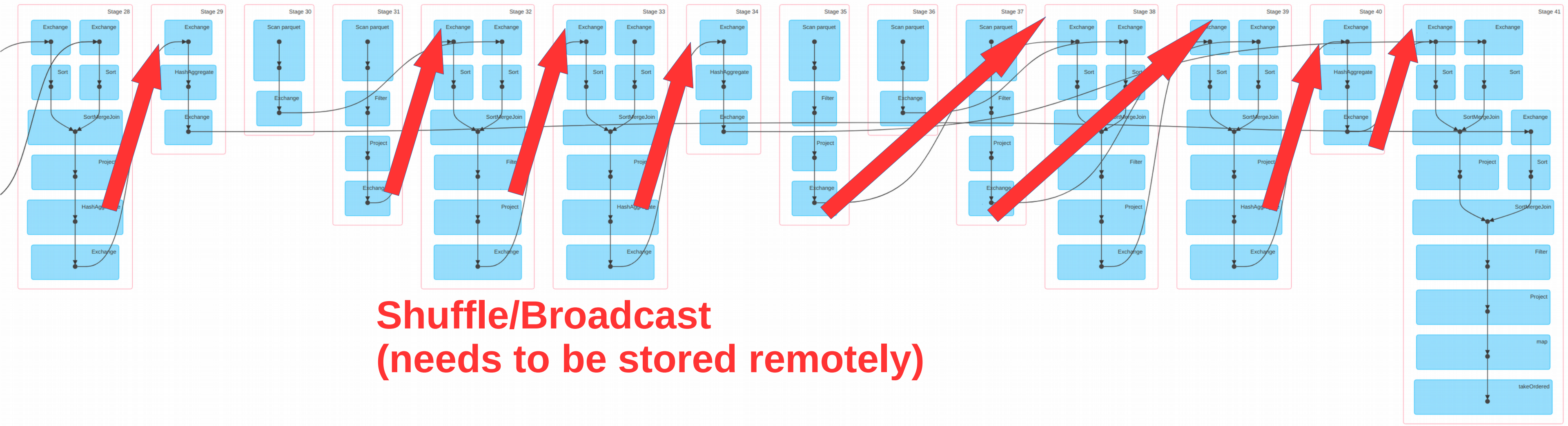
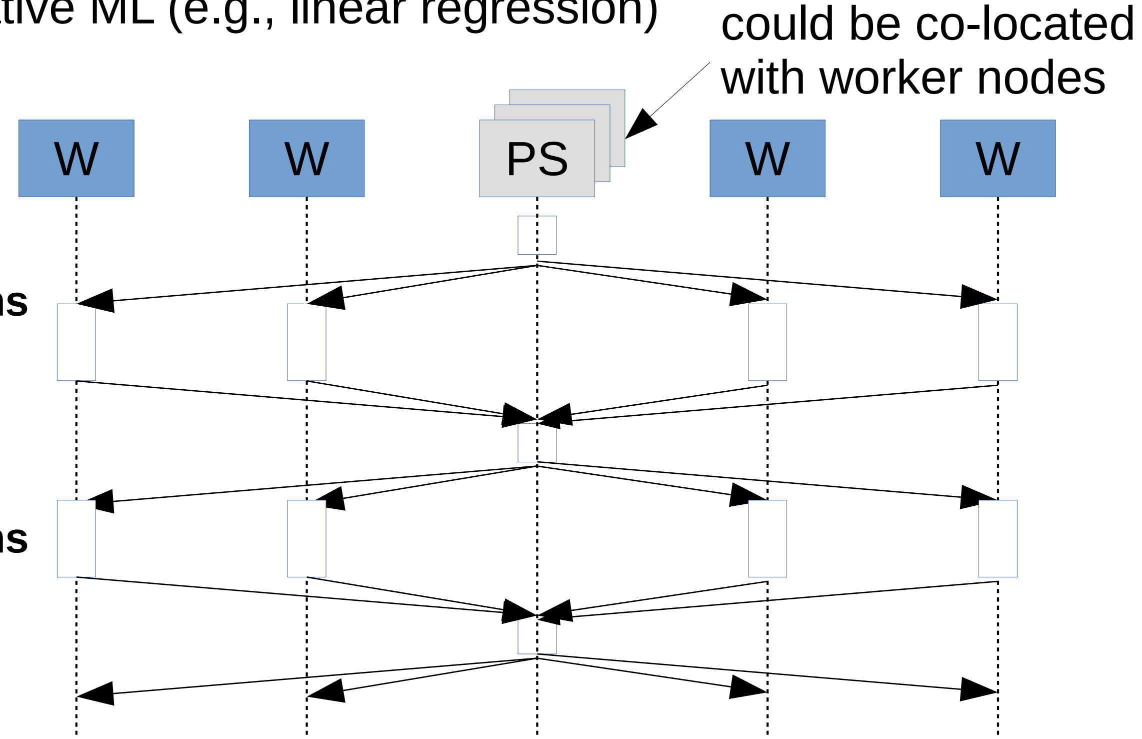


Shuffle/Broadcast
(needs to be stored remotely)

What about other workloads?

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



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

⋮

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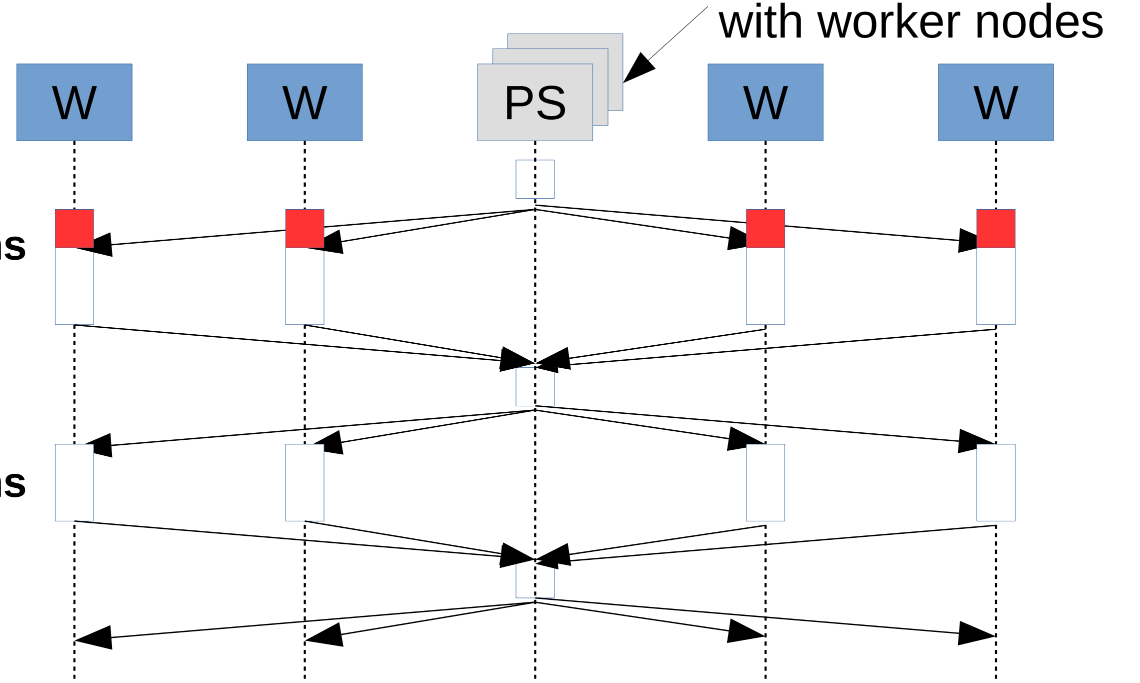

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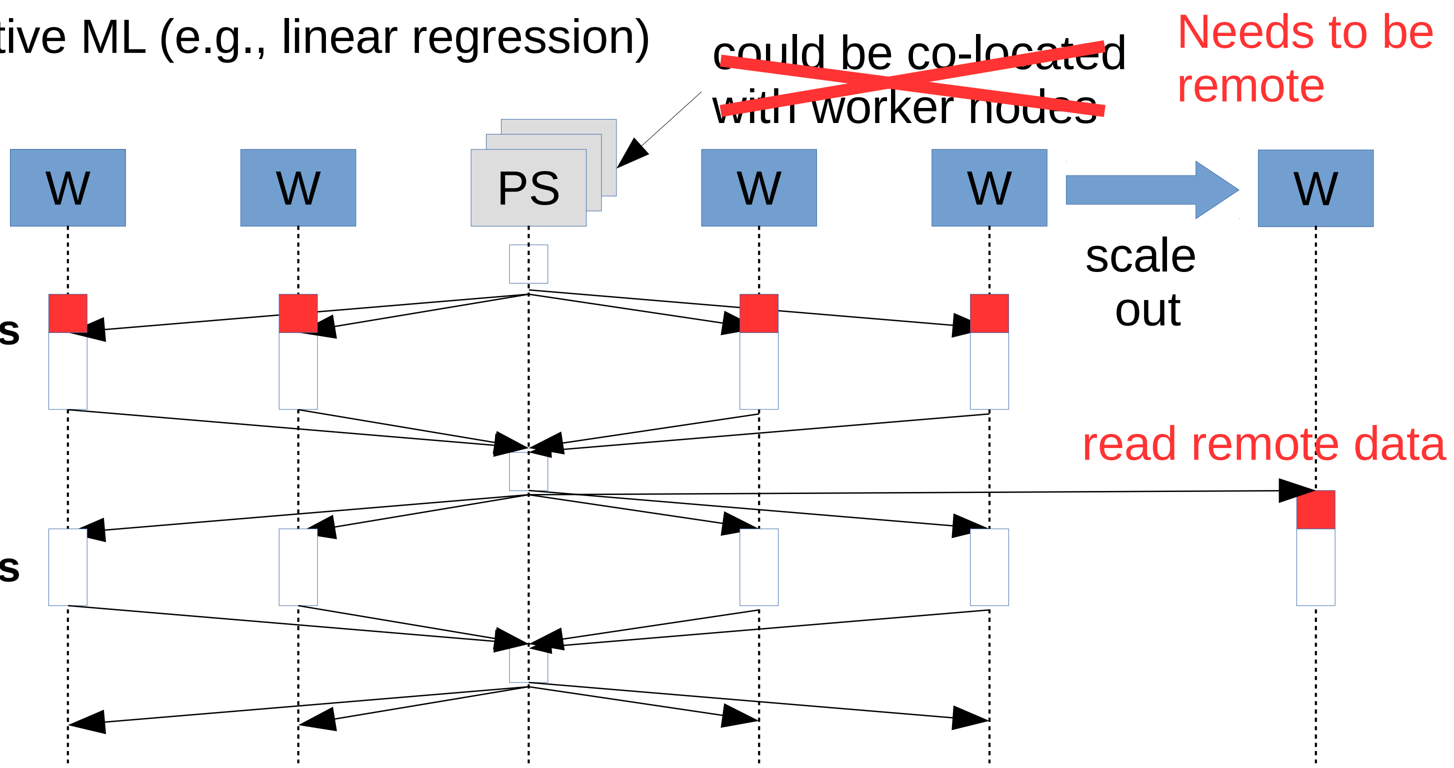

Can we..

- ..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:**
  - 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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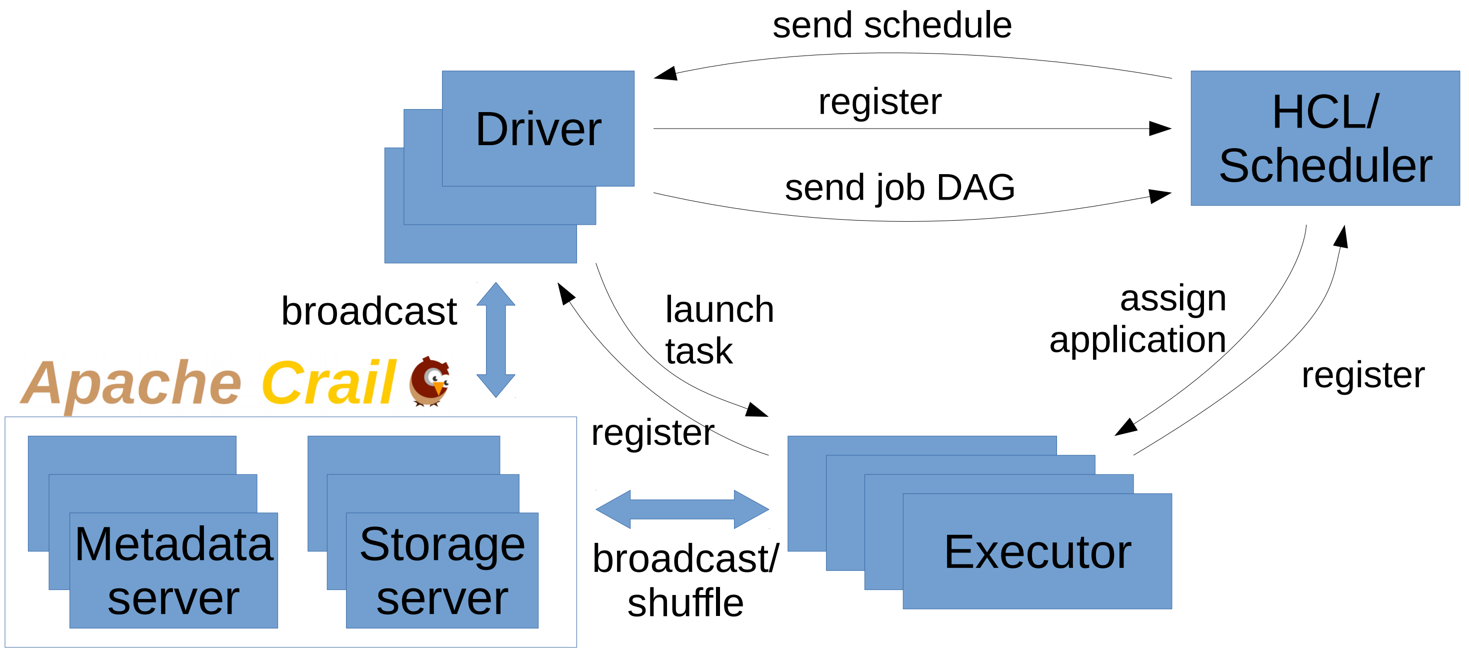
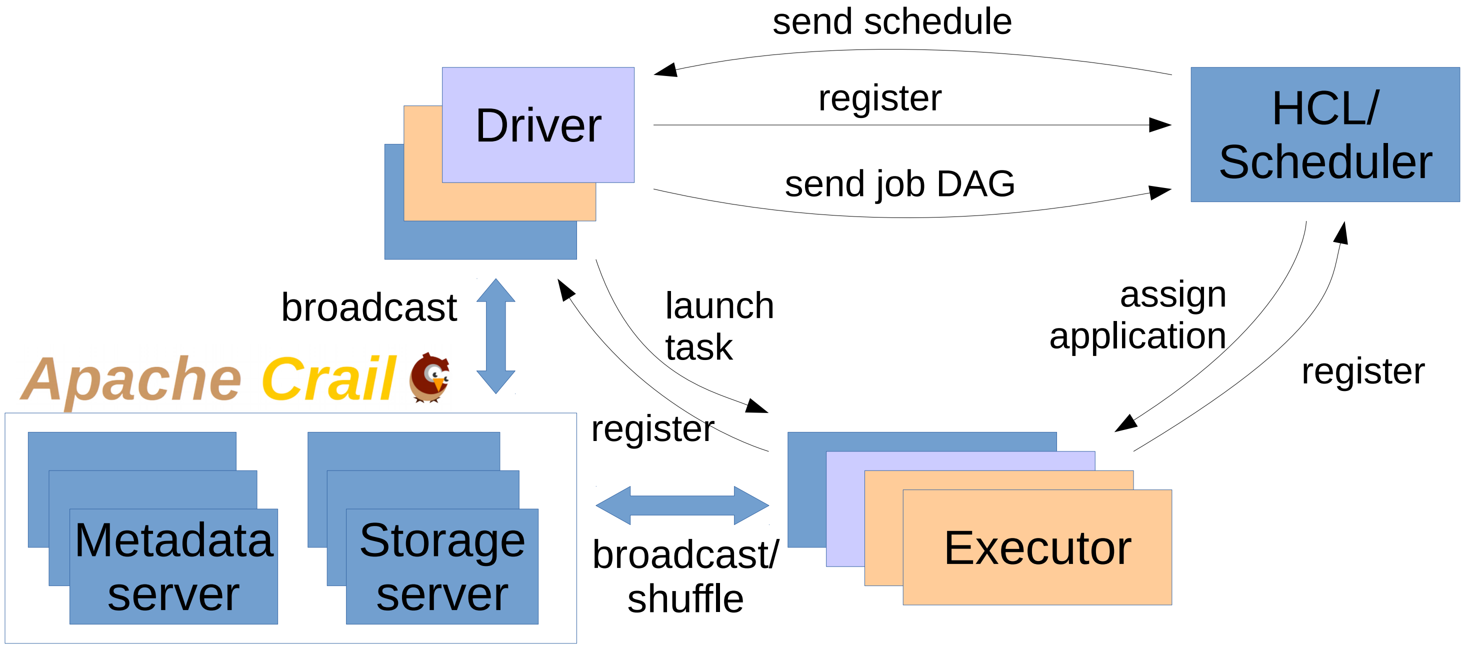
Architecture Overview



Architecture Overview



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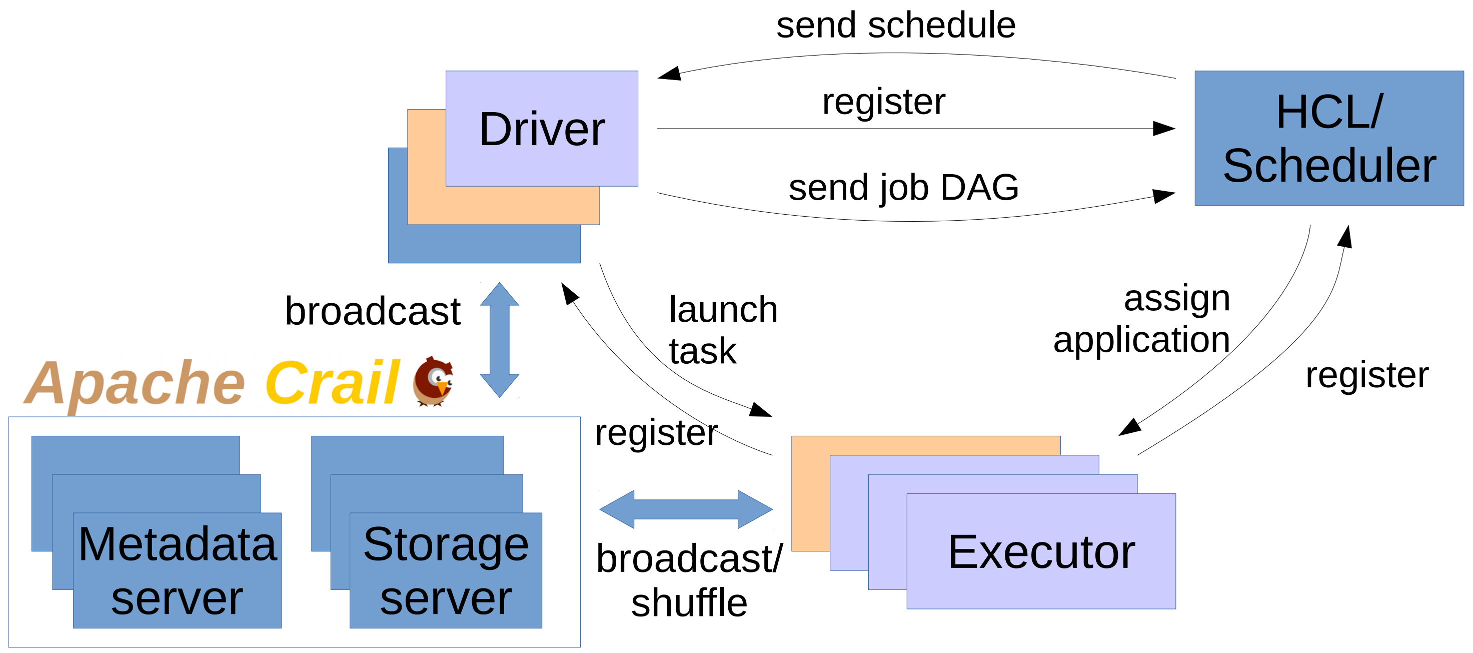

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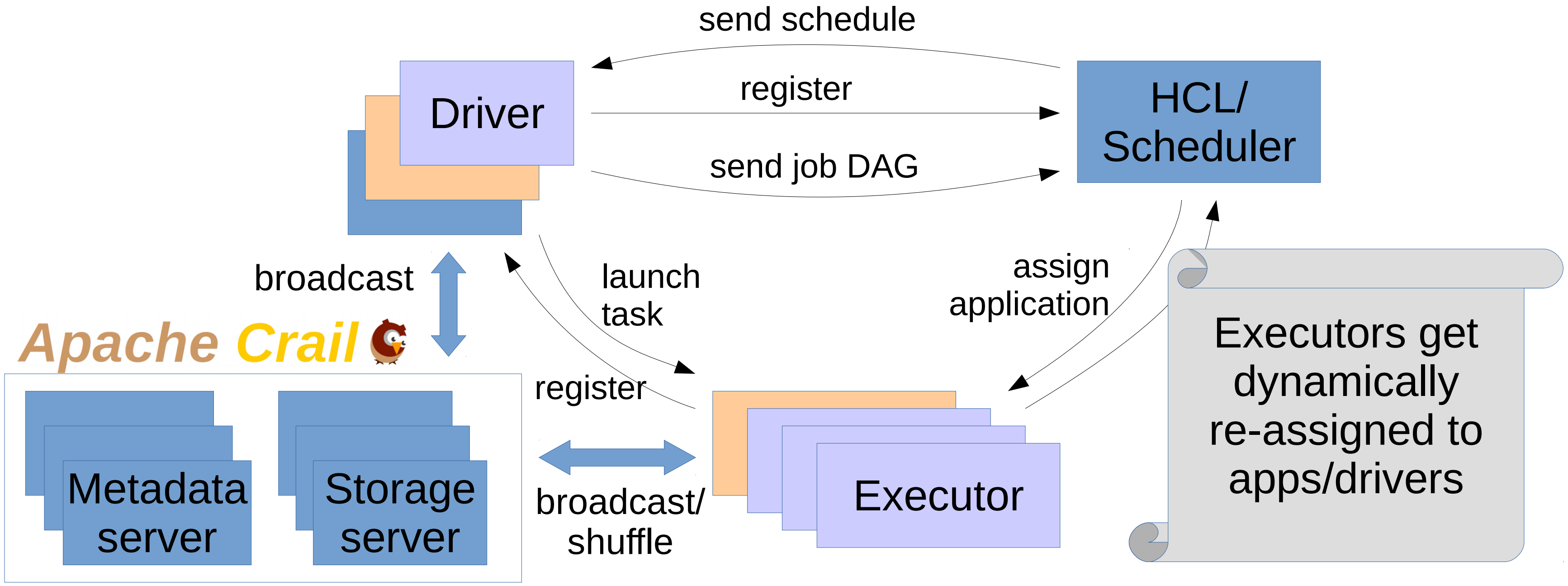


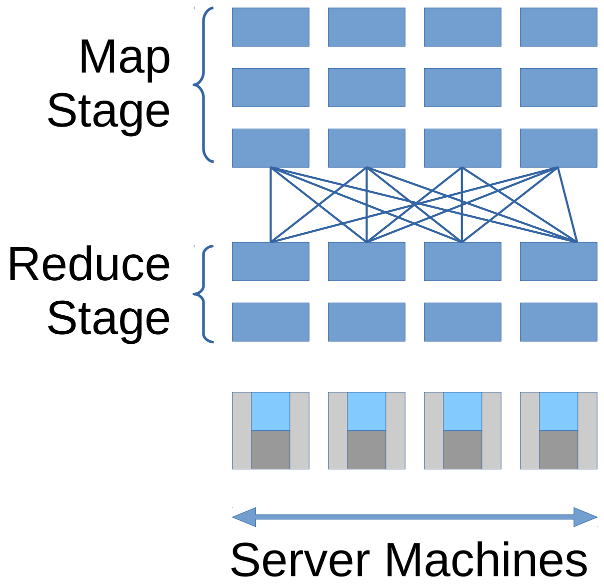
HCL Scheduler

Backup

Template Tite

- Template List
- Template List
  - Template item

Example: MapReduce



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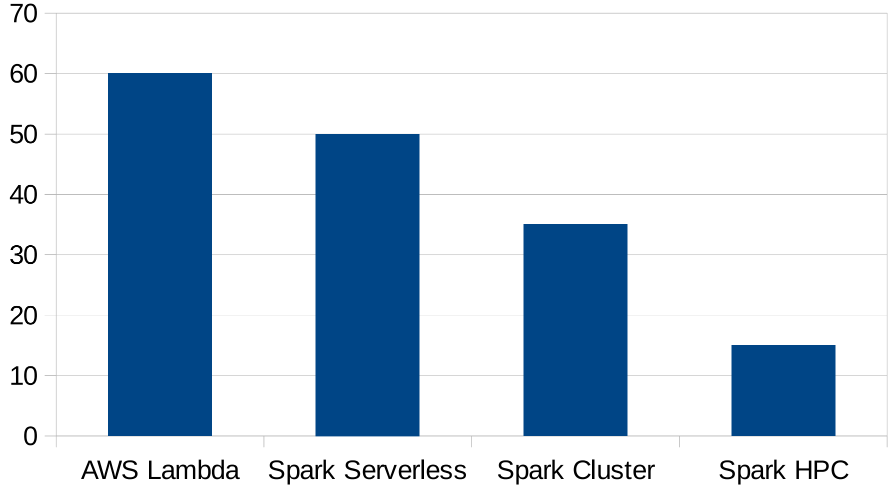

Serverless execution is 3-4x slower than an optimized cluster configuration

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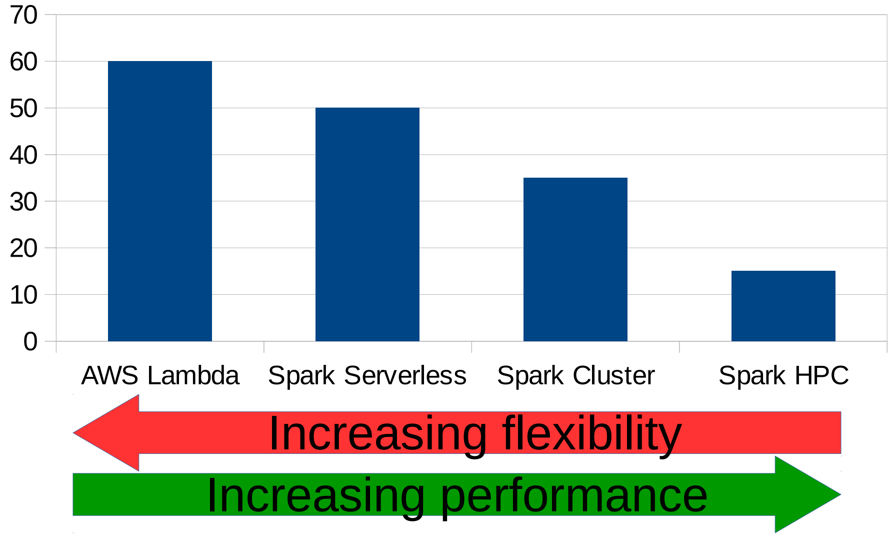

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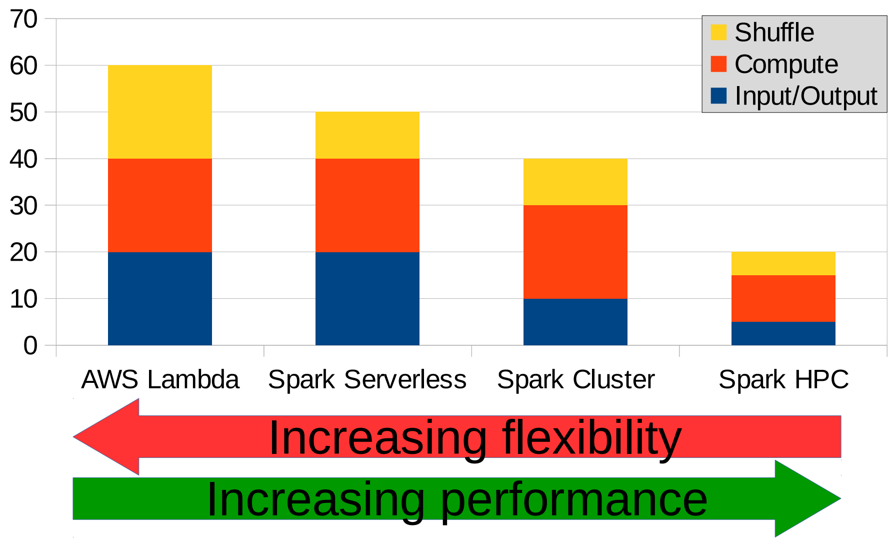

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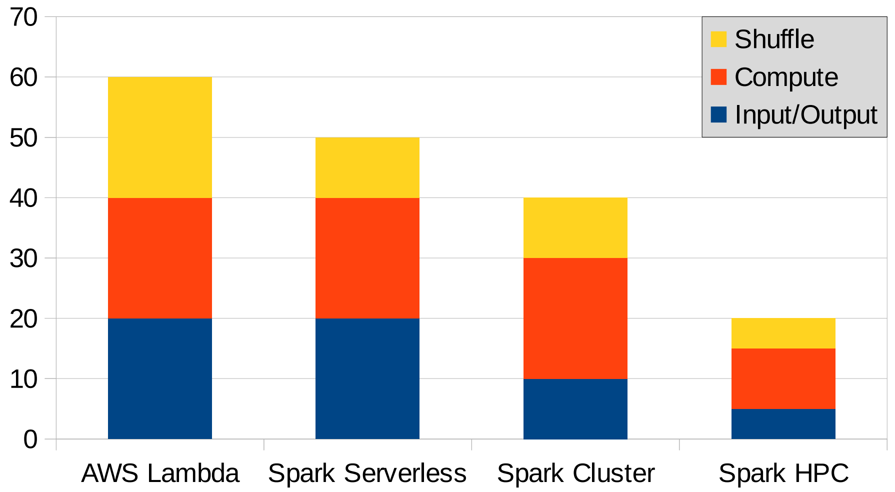

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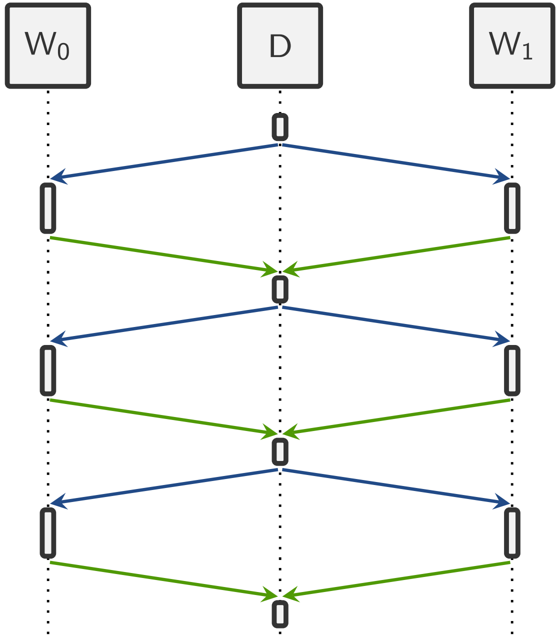


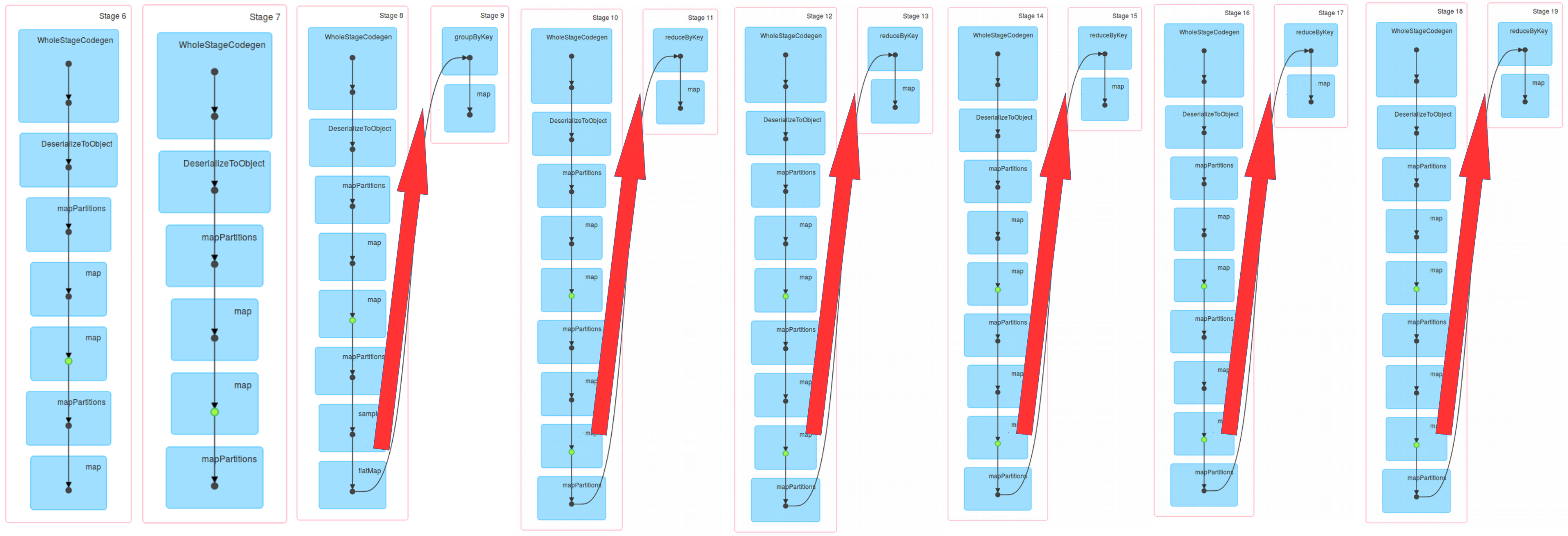
Workloads and Frameworks

	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


Stage 6
WholeStageCodegen
DeserializeToObject
mapPartitions
map
map
mapPartitions
map
Stage 7
WholeStageCodegen
DeserializeToObject
mapPartitions
map
map
mapPartitions
Stage 8
WholeStageCodegen
DeserializeToObject
mapPartitions
map
map
mapPartitions
flatMap
Stage 9
groupByKey
map
Stage 10
WholeStageCodegen
DeserializeToObject
mapPartitions
map
map
mapPartitions
map
mapPartitions
Stage 11
reduceByKey
map
Stage 12
WholeStageCodegen
DeserializeToObject
mapPartitions
map
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