Distributed computing with Spark and Python

A. Zonca - San Diego Supercomputer Center

What is Spark?

- A distributed computing framework

Connect to a spark cluster

Running on 4 instances of SDSC Cloud

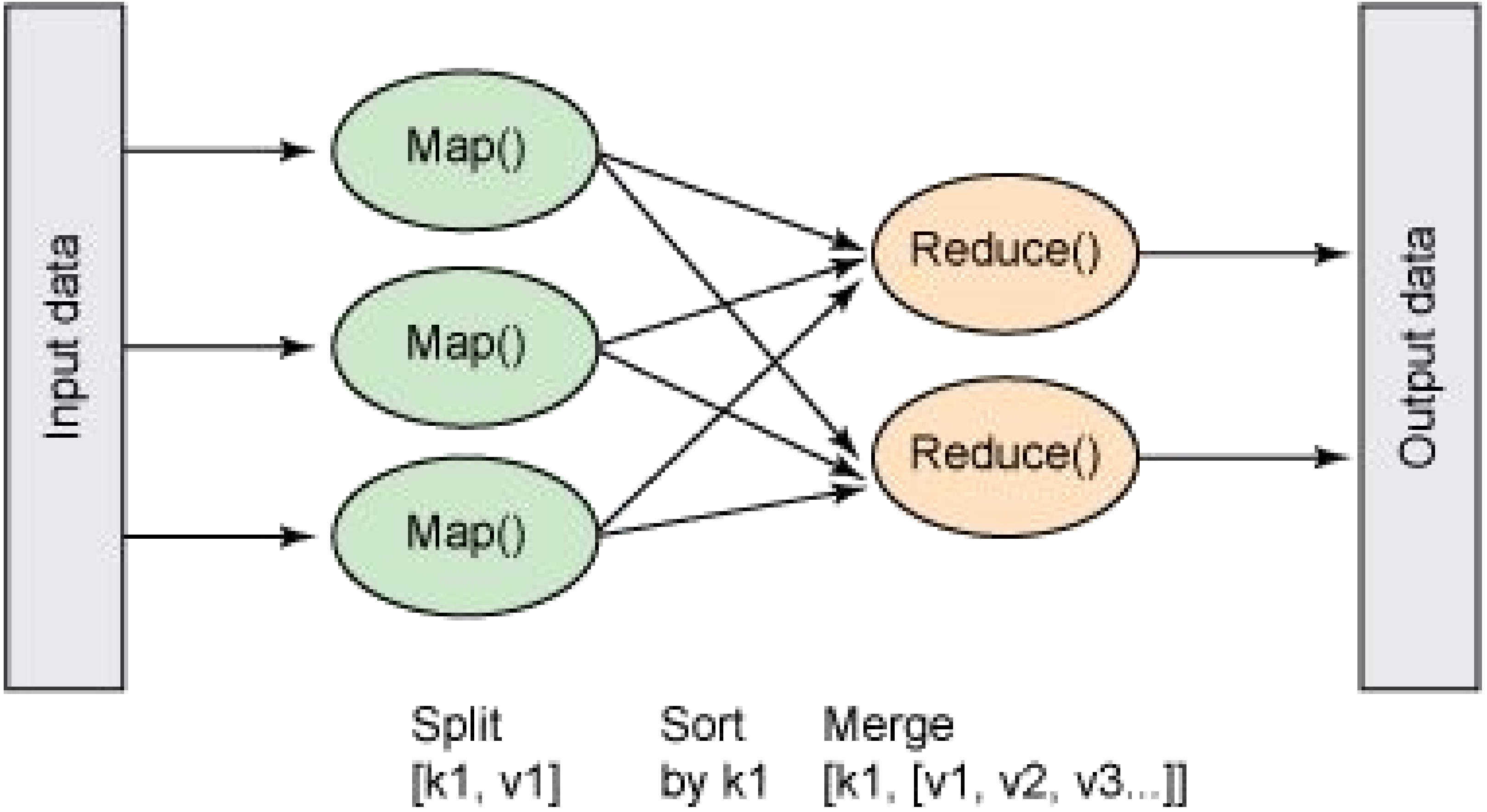
http://bit.ly/sparknotebook

password: acluster

ALWAYS COPY WITH YOUR NAME

House price example

see house_price.ipynb



map-reduce diagram

What's the point?

- write simple mapper and reducer
- framework scales to thousands of machines

Problem 1: Storage

- Big data
- Commodity hardware (Cloud)

Solution: Distributed File System

- redundant
- fault tolerant

Problem 2: Computation

- Slow to move data across network
- Computations fail

Solution: Hadoop Mapreduce / Spark

- Execute computation where data are located
- Rerun failed jobs

Problem 3: Communication

- Most of the times, need to summarize data to get a result
- Reduction phase in MapReduce
- Need data transfer across network

Solution: highly optimized Shuffle (All-to-All)

Spark and Hadoop

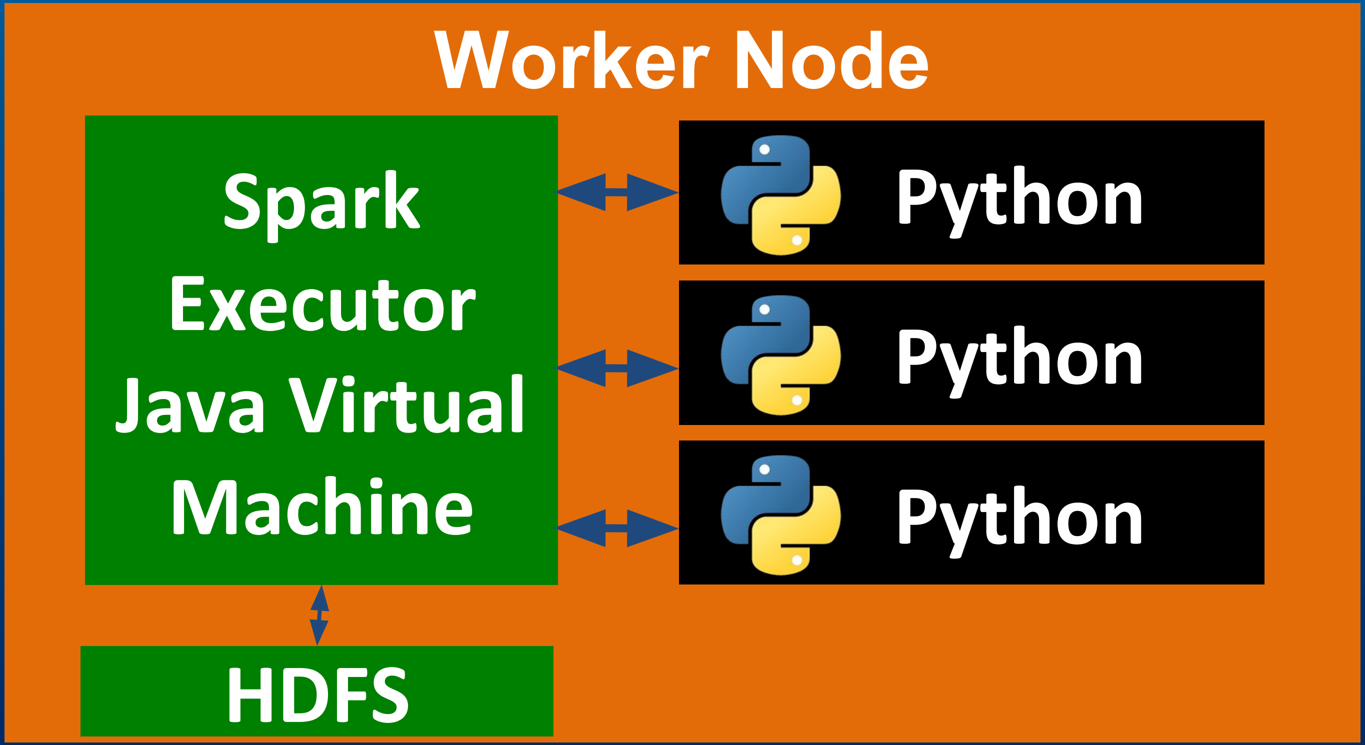
- Works within the Hadoop ecosystem
- Extends MapReduce
- Initially developed at UC Berkeley
- Now within the Apache Foundation
- ~400 and more developers

Key features of Spark

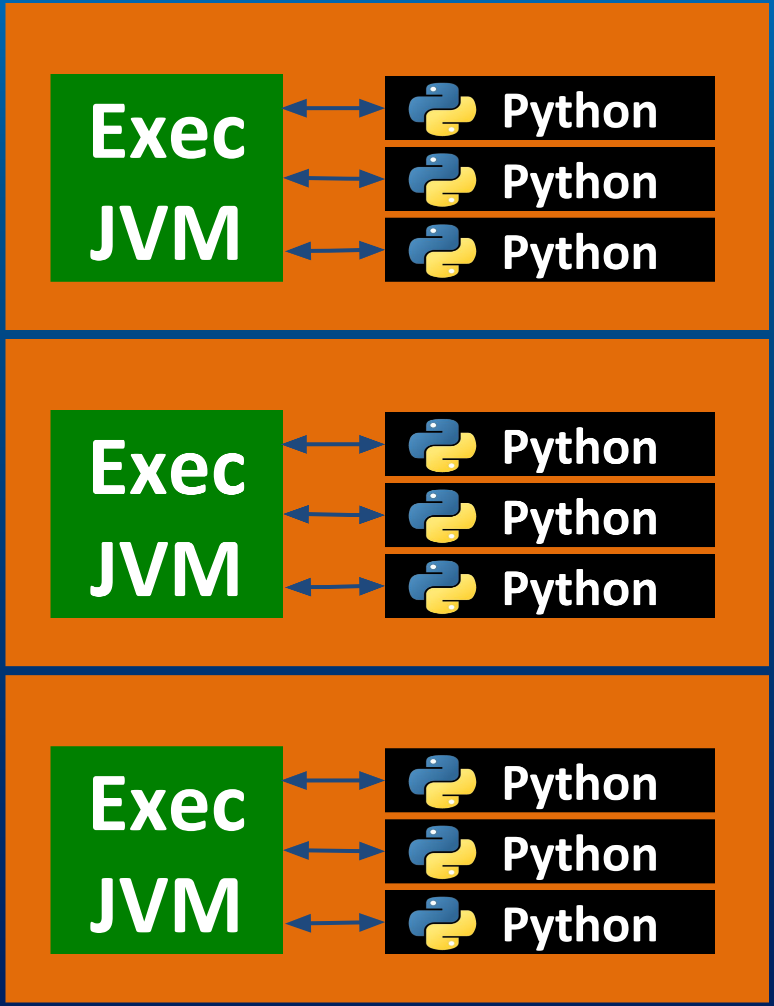
- **Resiliency**: tolerant to node failures
- **Speed**: supports in-memory caching
- **Ease of use**:
    - Python/Scala interfaces
    - interactive shells
    - many distributed primitives

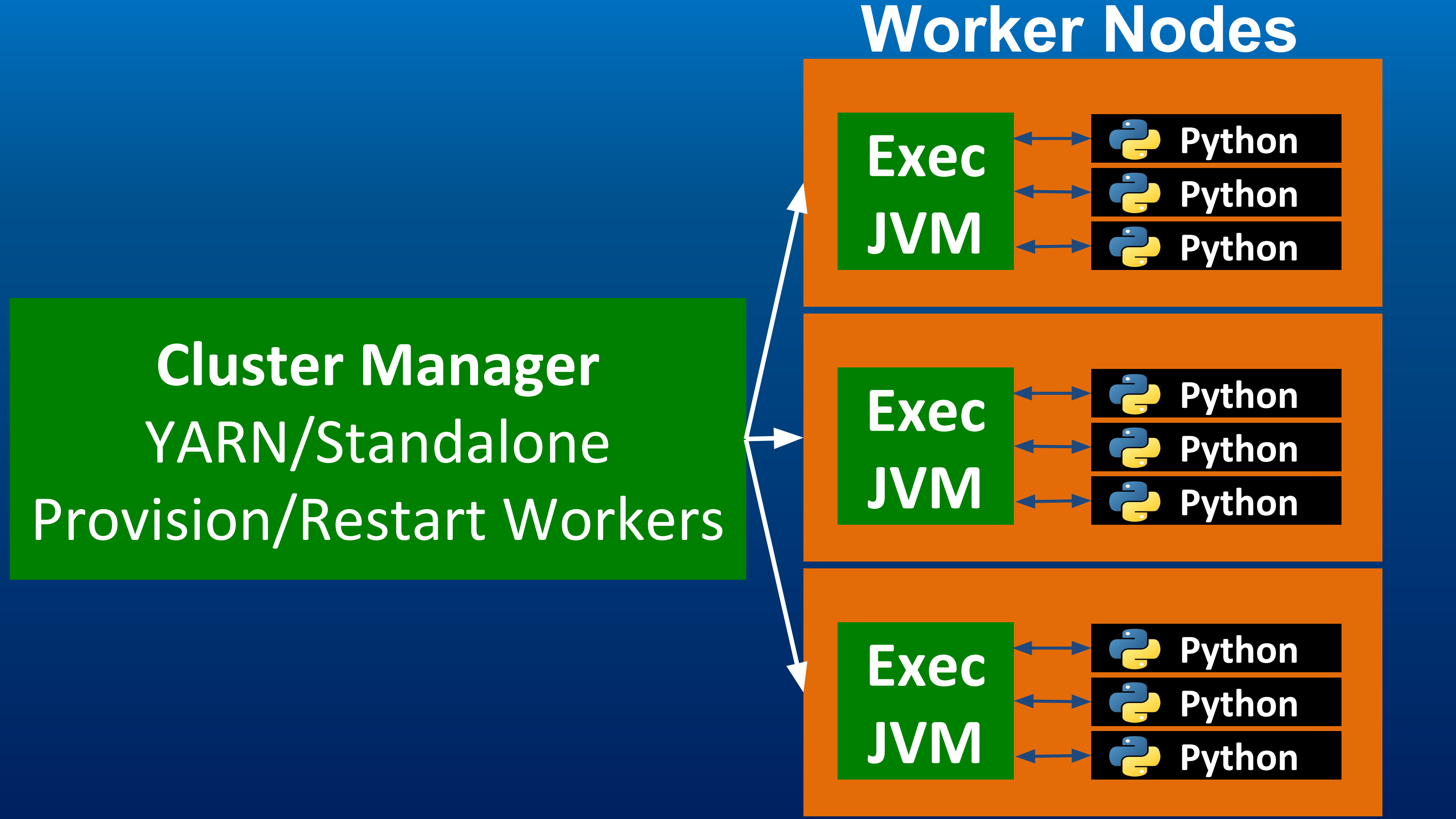
	Hadoop MR Record	**Spark Record**	**Spark 1 PB**
Data Size	102.5 TB	100 TB	1000 TB
Elapsed Time	72 mins	23 mins	234 mins
# Nodes	2100	206	190
# Cores	50400 physical	6592 virtualized	6080 virtualized
Cluster disk throughput	3150 GB/s (est.)	618 GB/s	570 GB/s
Sort Benchmark Daytona Rules	Yes	Yes	No
Network	dedicated data center, 10Gbps	virtualized (EC2) 10Gbps network	virtualized (EC2) 10Gbps network
Sort rate	**1.42 TB/min**	**4.27 TB/min**	**4.27 TB/min**
Sort rate/node	**0.67 GB/min**	**20.7 GB/min**	**22.5 GB/min**

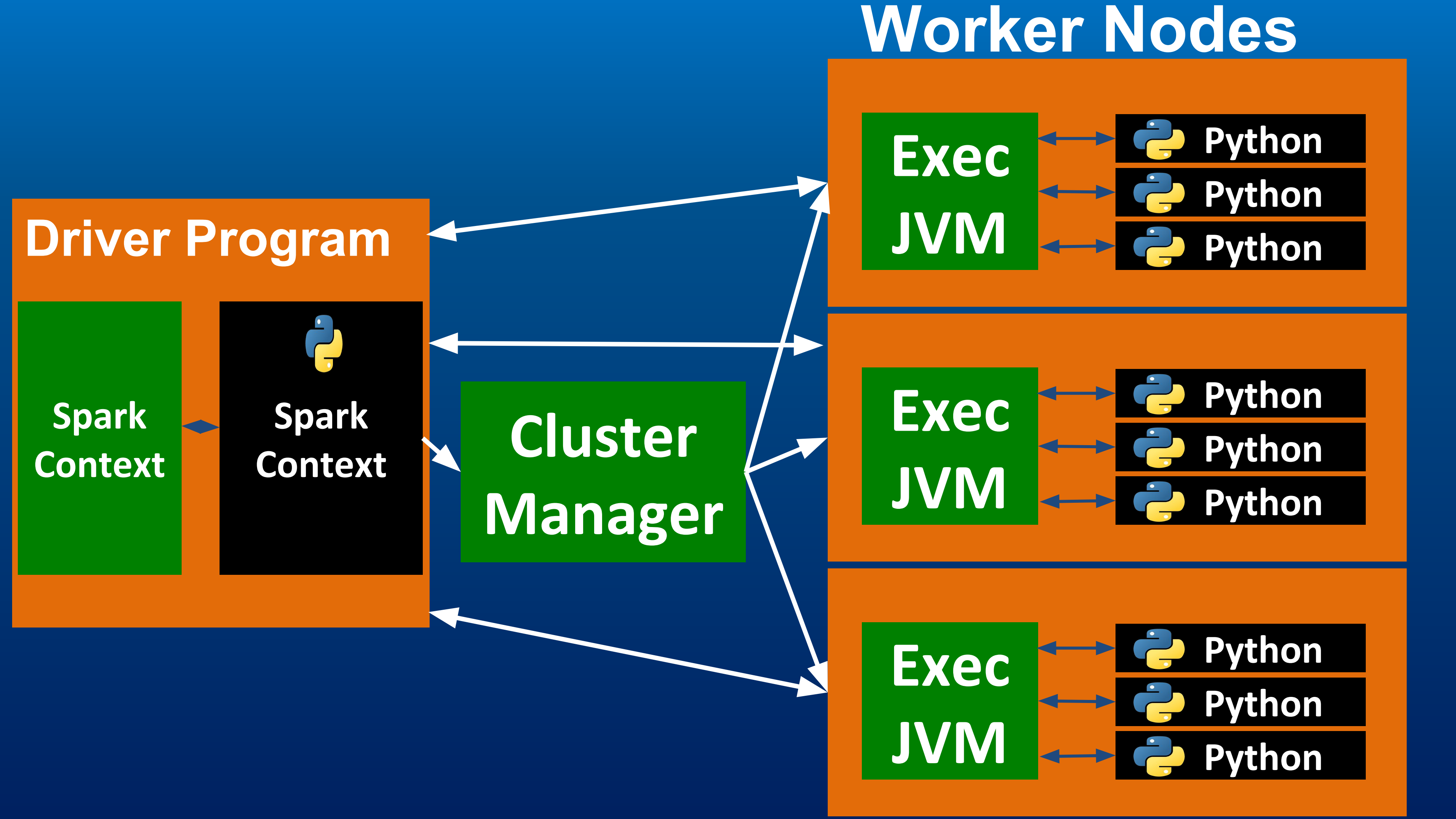
Spark 100TB benchmark


Worker Node
Spark Executor Java Virtual Machine
Python
Python
Python
HDFS

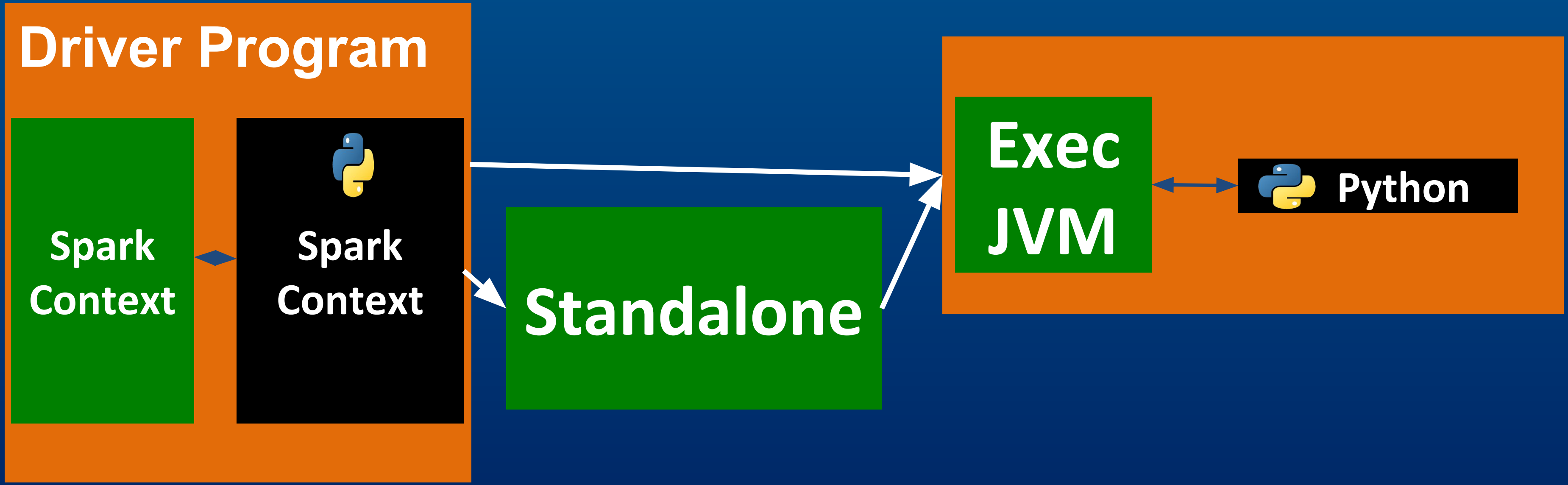
Worker Nodes




Worker Nodes
Cluster Manager
YARN/Standalone
Provision/Restart Workers
Exec
JVM
Python
Python
Python
Exec
JVM
Python
Python
Python
Exec
JVM
Python
Python
Python

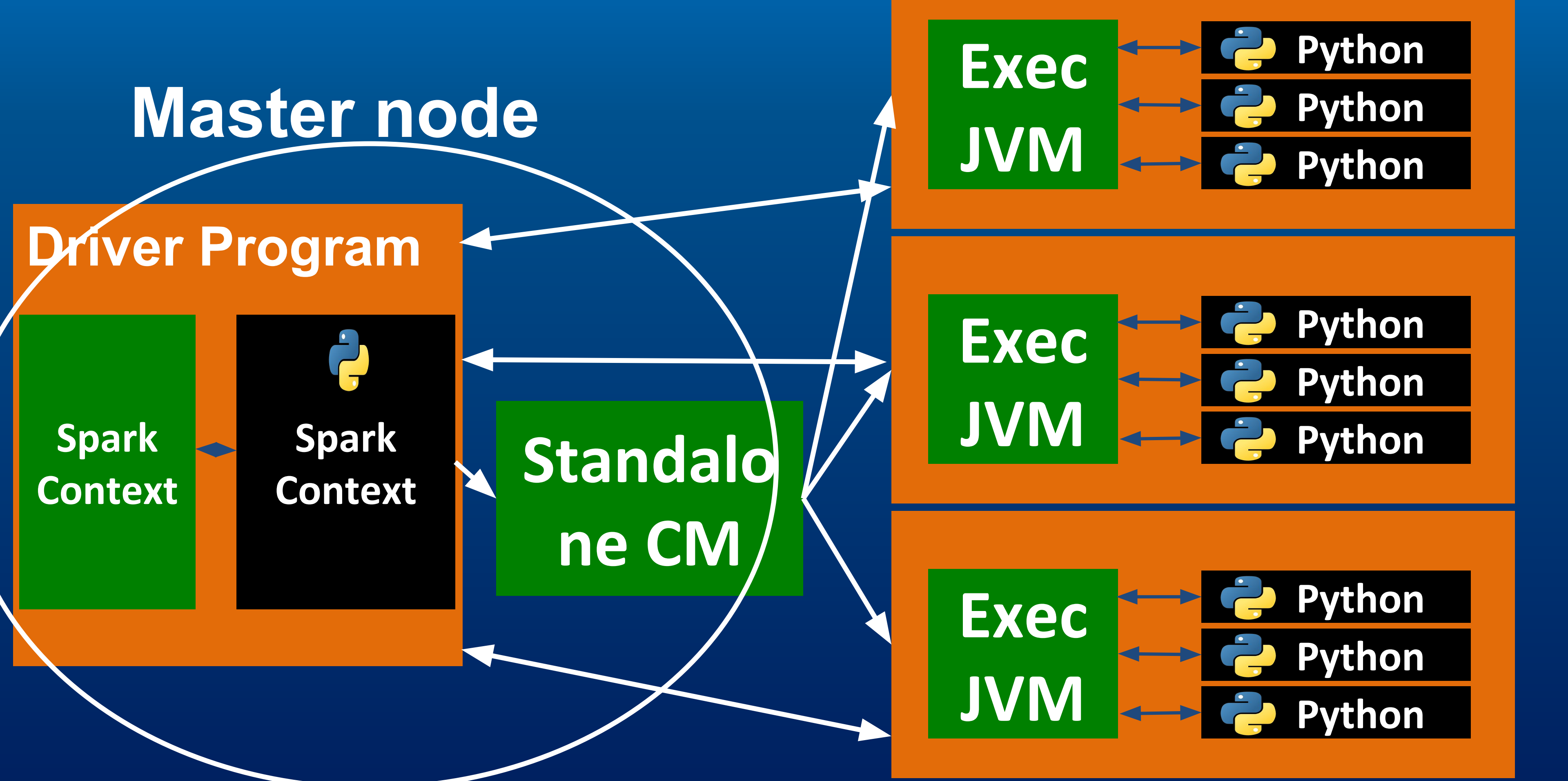

Worker Nodes
Driver Program
Spark Context
Spark Context
Cluster Manager
Exec JVM
Python
Python
Python
Exec JVM
Python
Python
Python
Exec JVM
Python
Python
Python

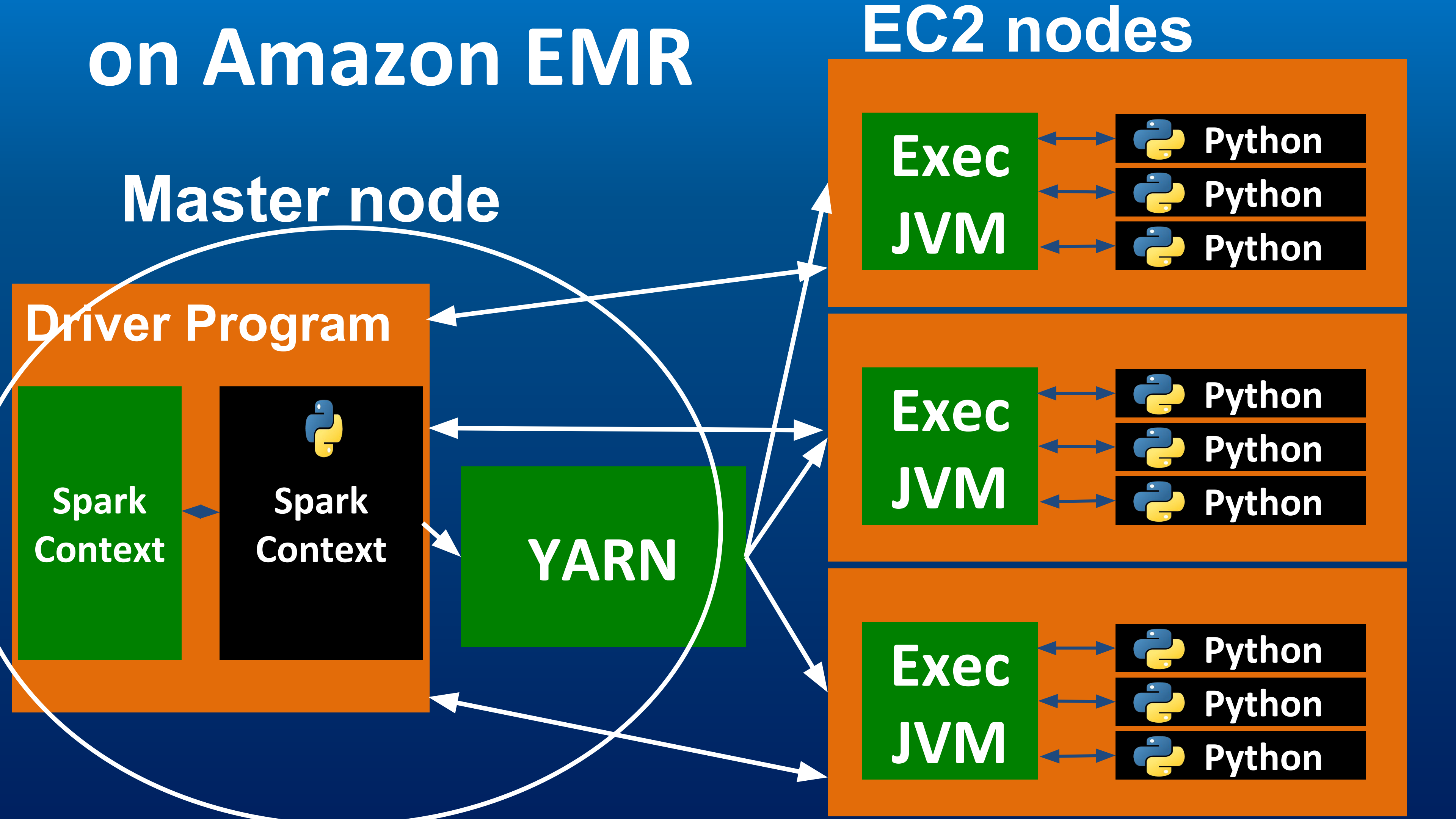
Spark Local

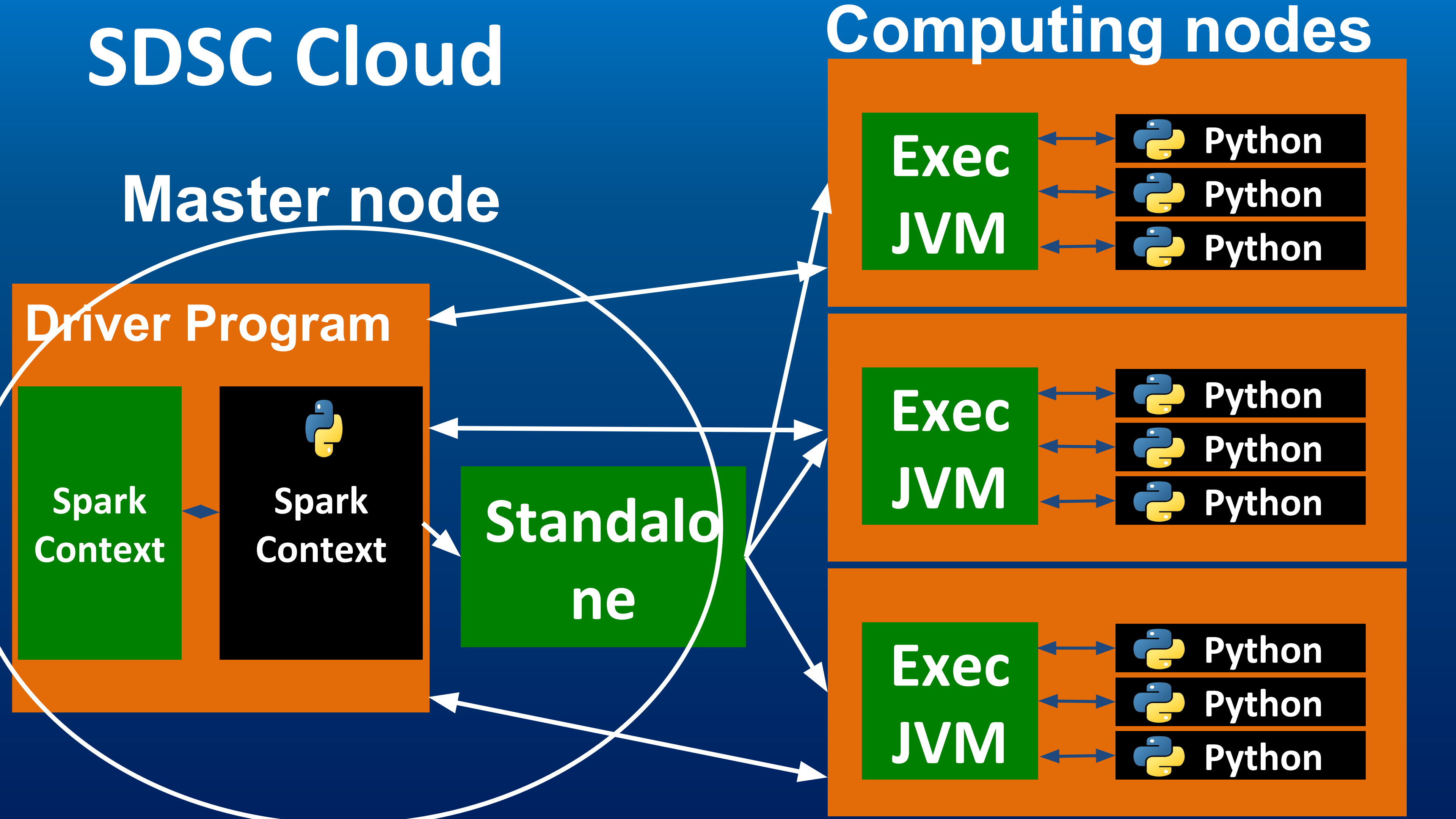


Driver Program
Spark Context
Spark Context
Standalone
Exec JVM
Python

on Comet


Computing Nodes
Master node
Driver Program
Spark
Context
Spark
Context
Standalo
ne CM
Exec
JVM
Python
Python
Python
Exec
JVM
Python
Python
Python
Exec
JVM
Python
Python
Python


on Amazon EMR
EC2 nodes
Master node
Driver Program
Spark
Context
Spark
Context
YARN
Exec
JVM
Python
Python
Python
Exec
JVM
Python
Python
Python
Exec
JVM
Python
Python
Python


SDSC Cloud
Computing nodes
Master node
Driver Program
Spark
Context
Spark
Context
Standalo
ne
Exec
JVM
Python
Python
Python
Exec
JVM
Python
Python
Python
Exec
JVM
Python
Python
Python

House price with HDFS

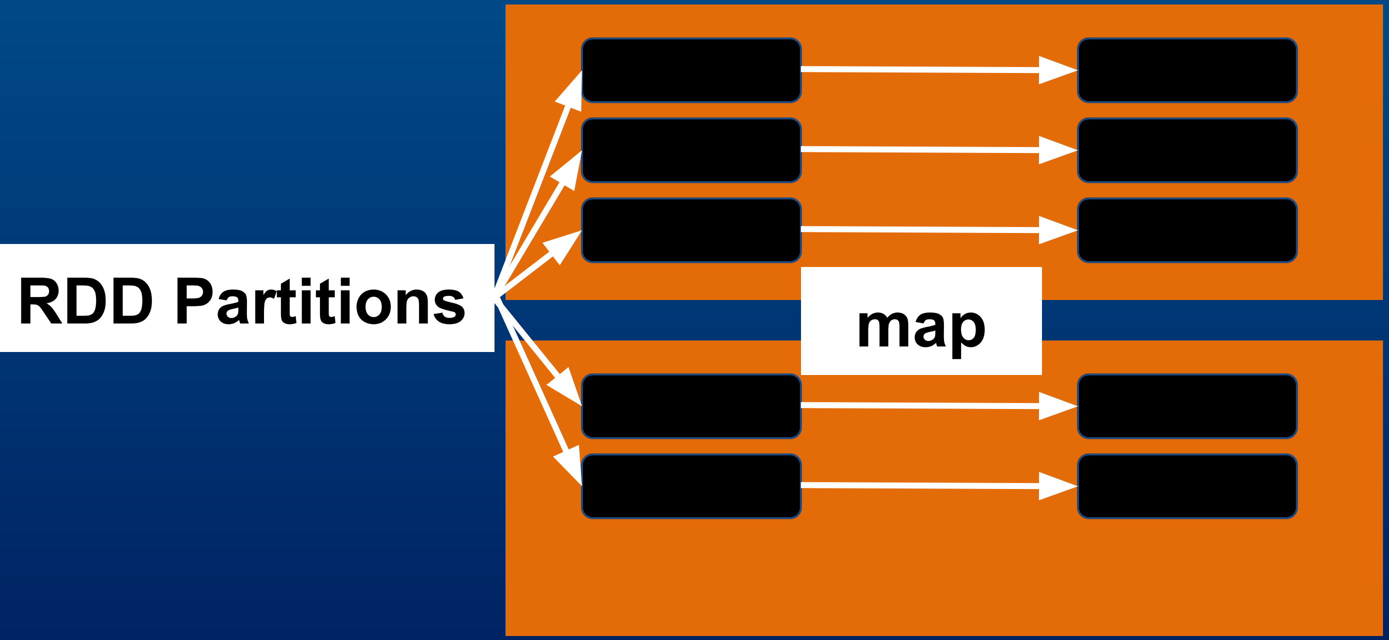
see house_price_hdfs.ipynb

Resilient Distributed Dataset

- Resilient: fault tolerant, lineage is saved, lost partitions can be recovered
- Distributed: partitions are automatically distributed across nodes
- Created from: HDFS, S3, HBase, Local file, Local hierarchy of folders

map

`map` : apply function to each element of RDD

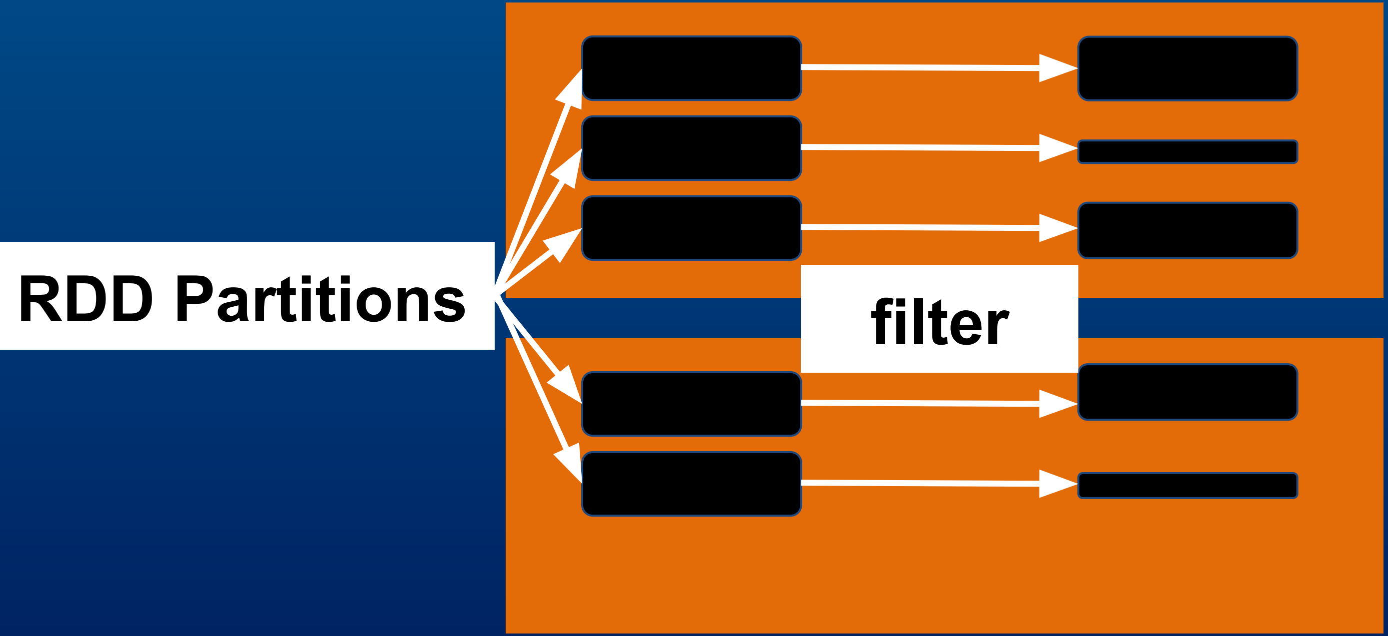


Other transformations

- filter(func) - keep only elements where func is true
- sample(withReplacement, fraction, seed) - get a random data fraction
- coalesce(numPartitions) - merge partitions to reduce them to numPartitions

filter

`filter` : keep only elements where func is true



coalesce

```
sc.parallelize(range(10), 4).glom().collect()
```

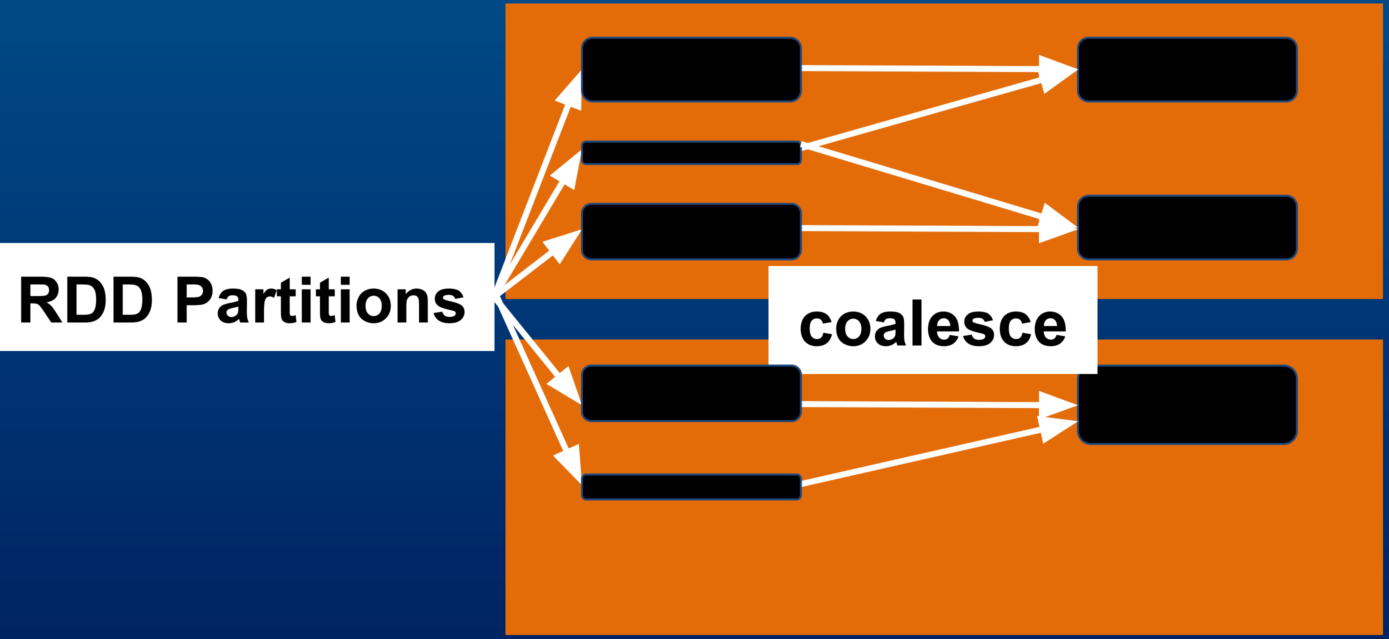
```
Out[]: [[0, 1], [2, 3], [4, 5], [6, 7, 8, 9]]
```

```
sc.parallelize(range(10), 4).coalesce(2).glom().collect()
```

```
Out[]: [[0, 1, 2, 3], [4, 5, 6, 7, 8, 9]]
```

coalesce

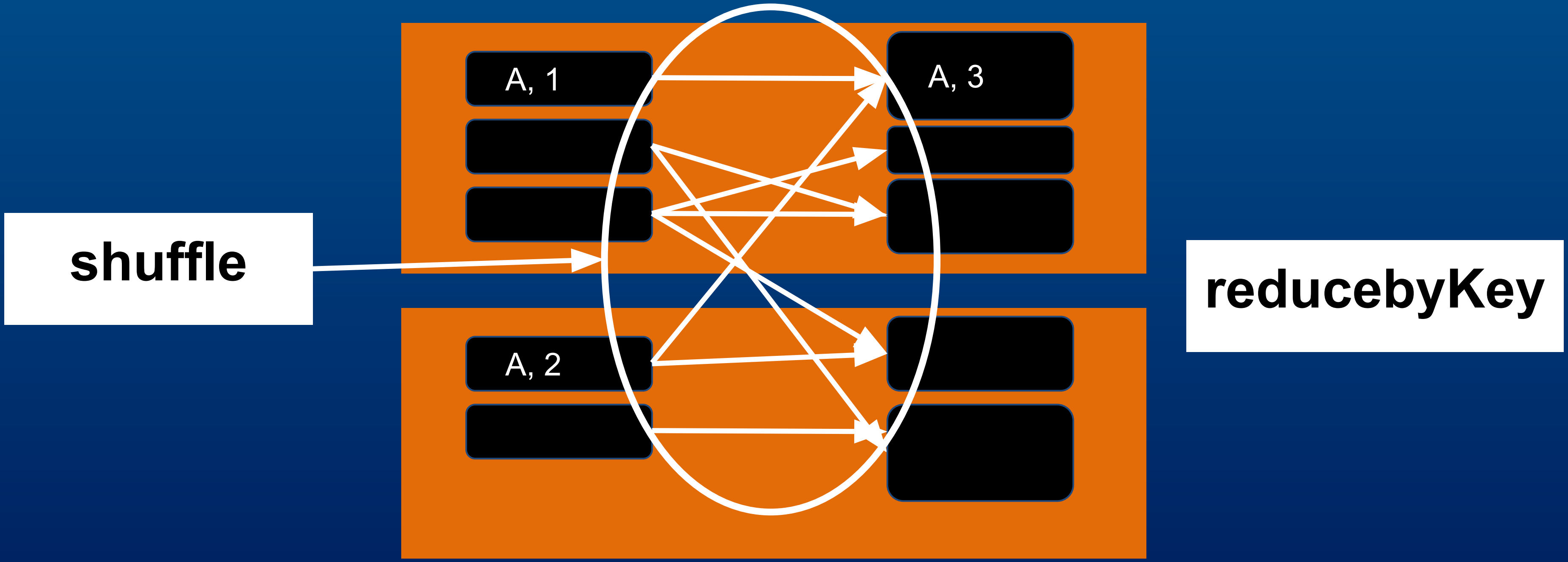
coalesce : reduce the number of partitions



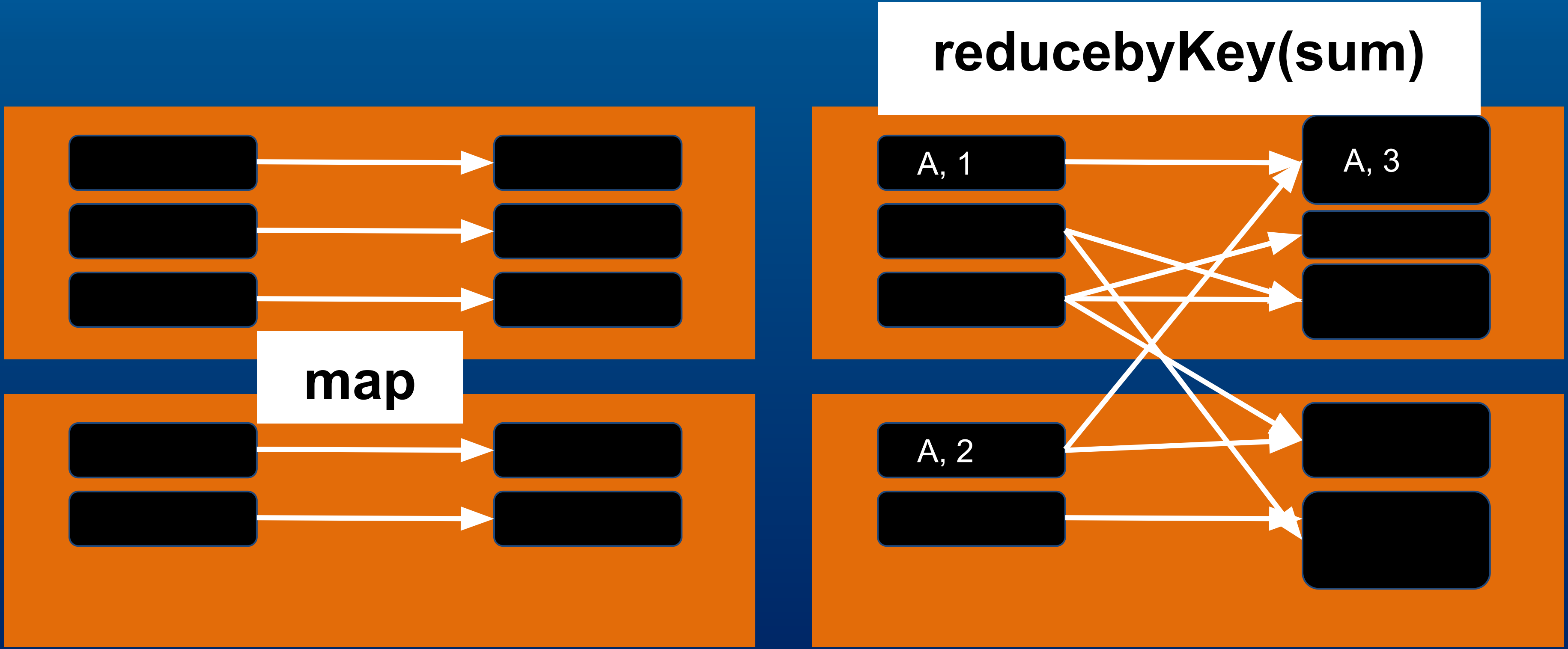
Wide transformations

reduceByKey(func)

(K, V) pairs => (K, reduce V with func)



Narrow vs Wide



Wide transformations

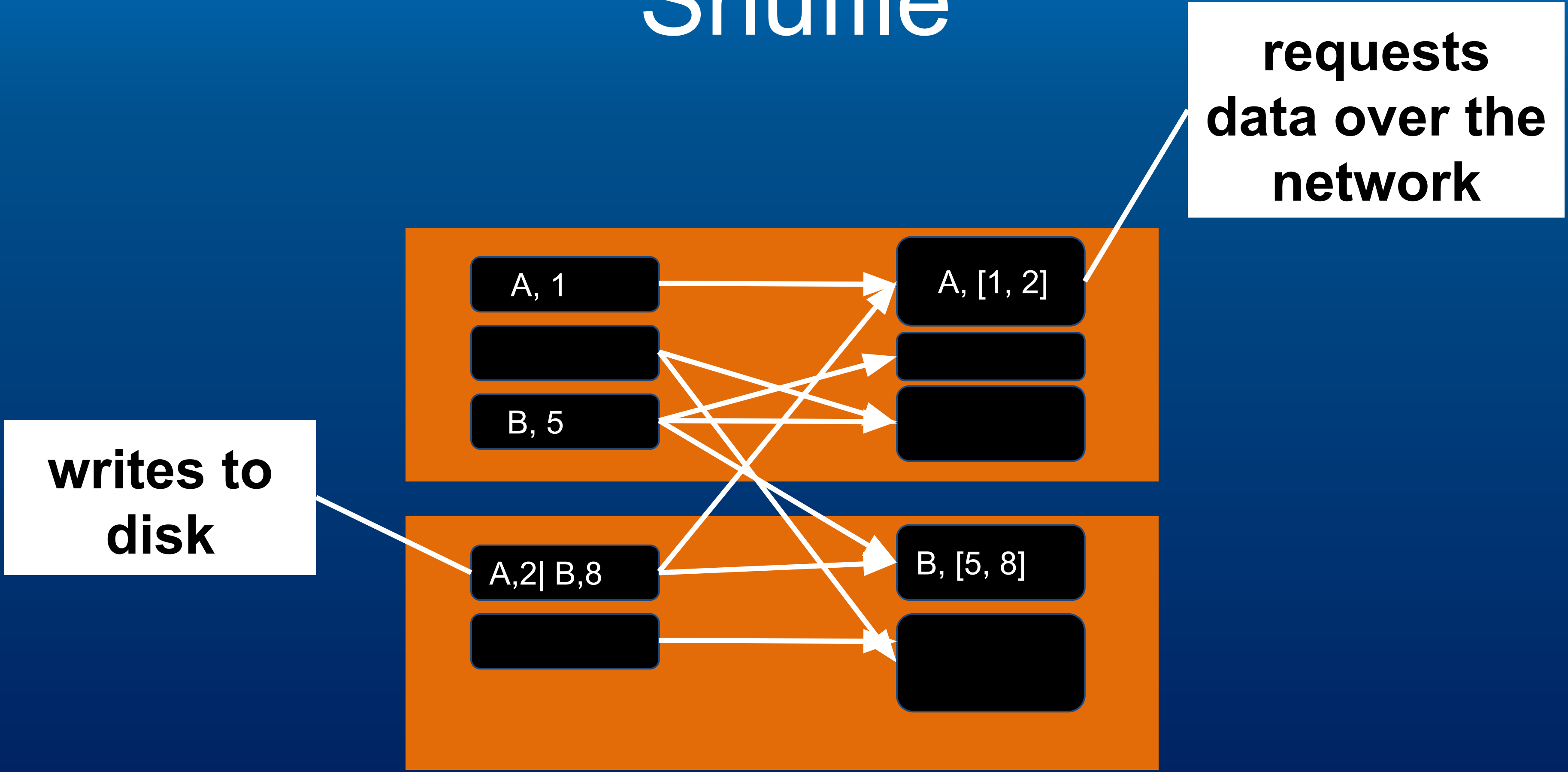
- groupByKey : (K, V) pairs => (K, iterable of all V)
- reduceByKey(func) : (K, V) pairs => (K, result of reduction by func on all V)
- repartition(numPartitions) : similar to coalesce, shuffles all data to increase or decrease number of partitions to numPartitions

Shuffle

Shuffle

- Global redistribution of data
- High impact on performance

Shuffle



requests data over the network
writes to disk
A, 1
B, 5
A,2| B,8
A, [1, 2]
B, [5, 8]

Know shuffle, avoid it

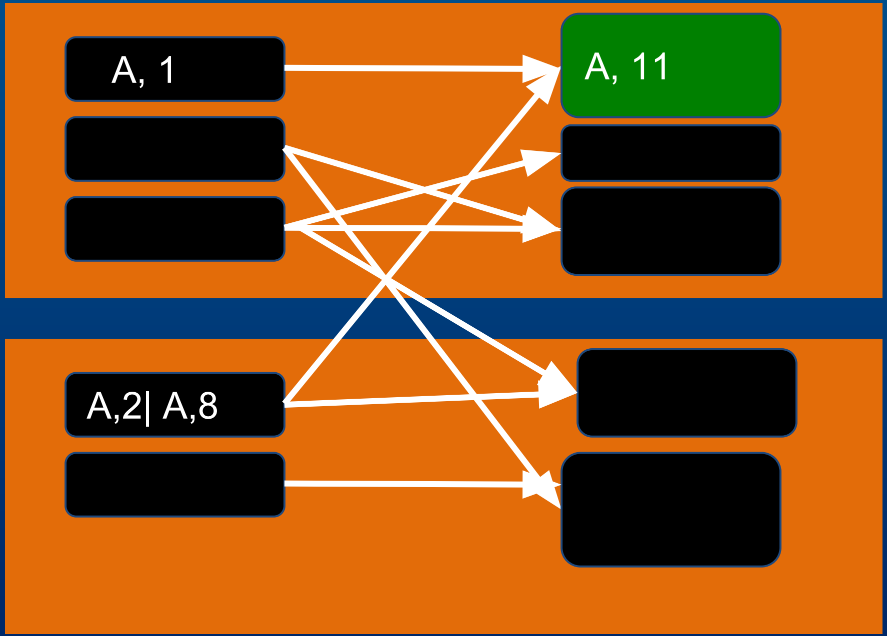
- Which operations cause it?
- Is it necessary?

Really need groupByKey?

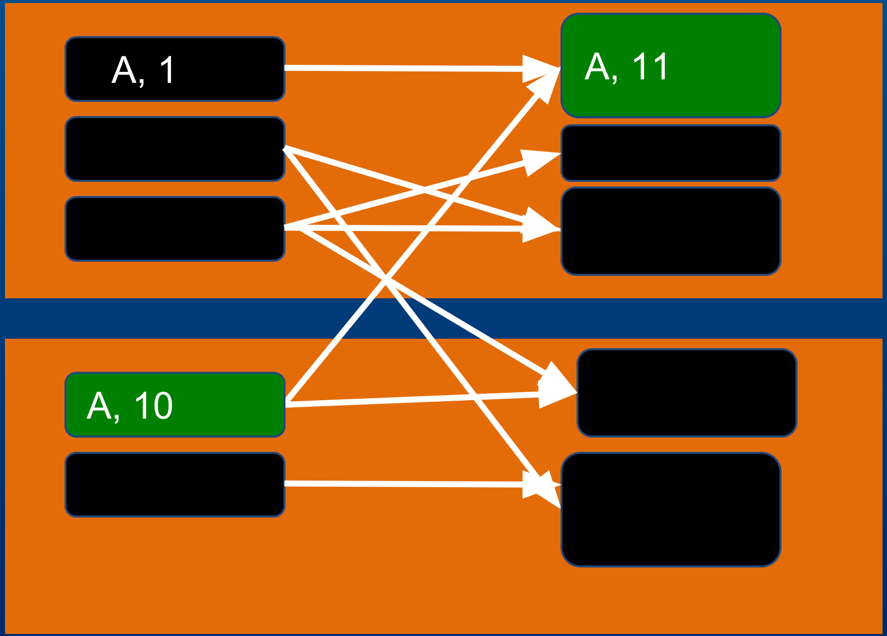
groupByKey: (K, V) pairs => (K, iterable of all V)

if you plan to call reduce later in the pipeline,
use reduceByKey instead.

groupByKey + reduce



reduceByKey



Extract data from RDD

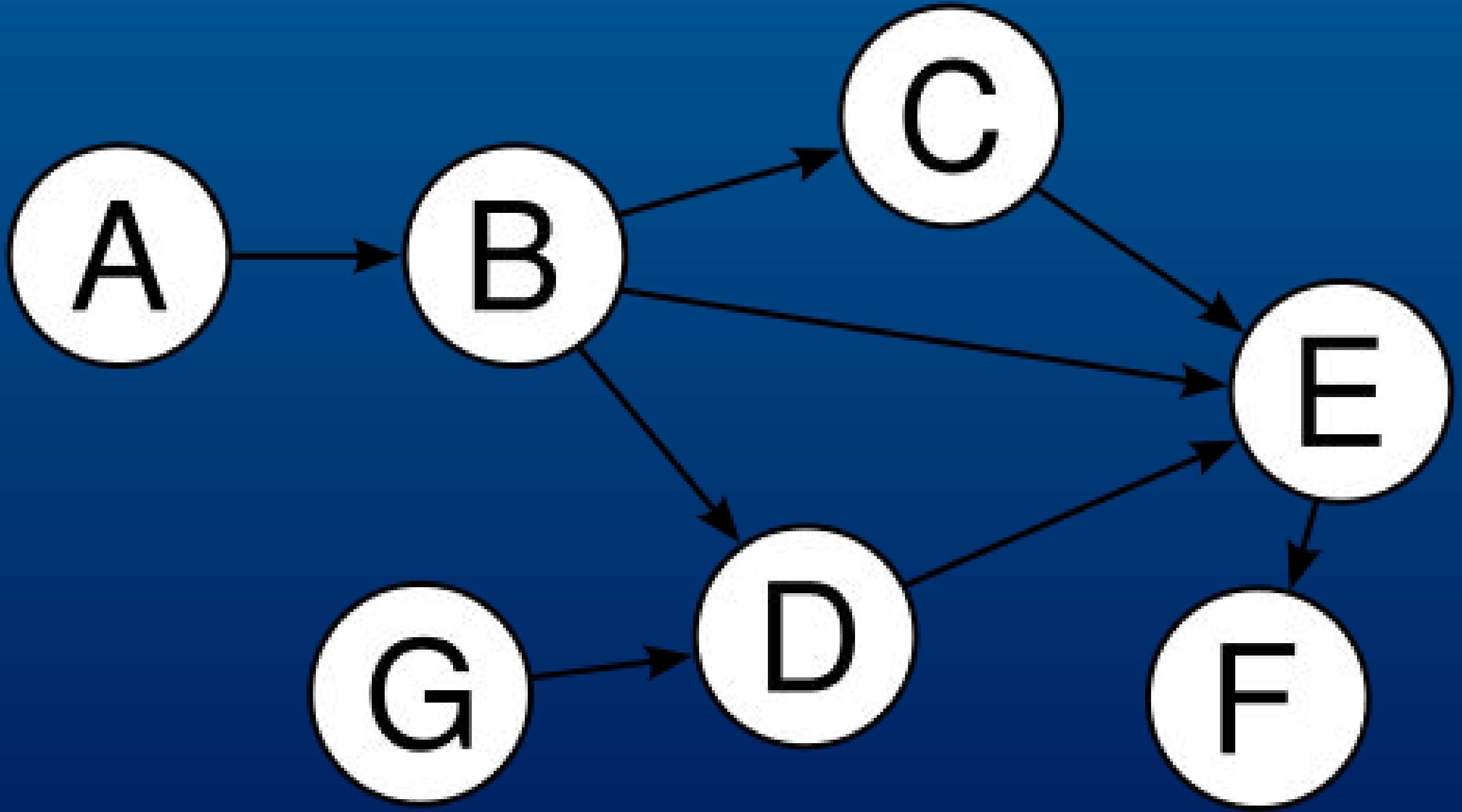
- collect() - copy all elements to the driver
- take(n) - copy first n elements
- saveAsTextFile(filename) - save to file
- reduce(func) - aggregate elements with func (takes 2 elements, returns 1)

Cached RDD

- Generally recommended after data cleaning
- Reusing cached data: 10x speedup
- Great for iterative algorithms
- If RDD too large, will only be partially cached in memory

Directed Acyclic Graph Scheduler

Directed Acyclic Graphs



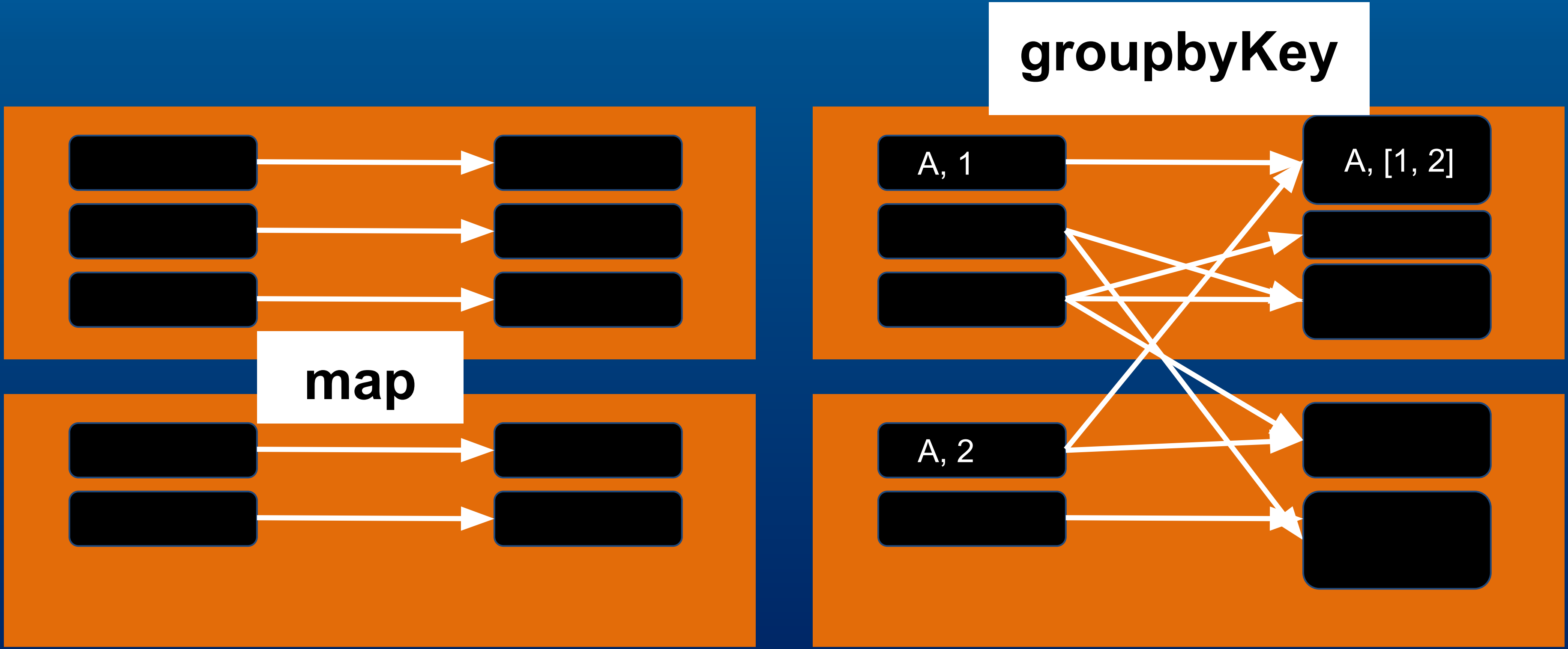
Directed Acyclic Graphs

Track **dependencies**!
(also known as lineage or provenance)

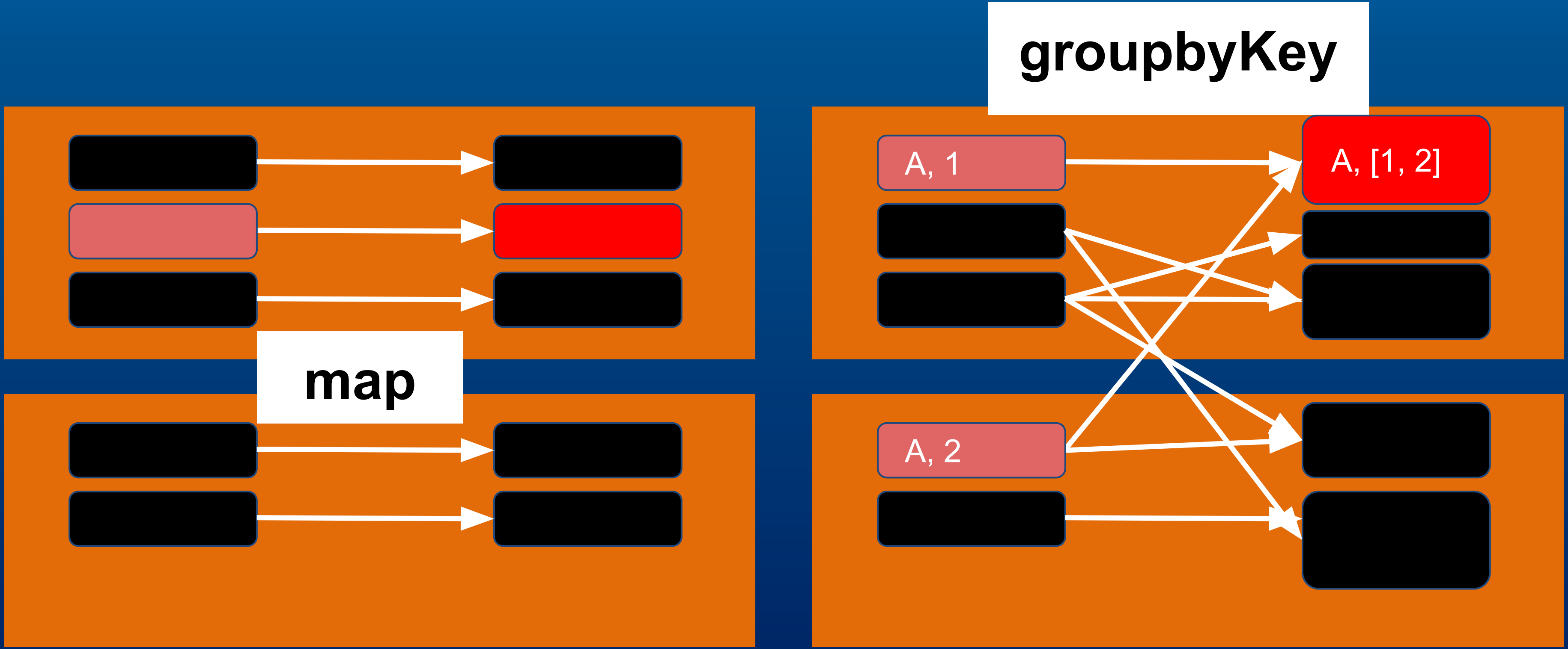
DAG in Spark

- nodes are RDDs
- arrows are Transformations

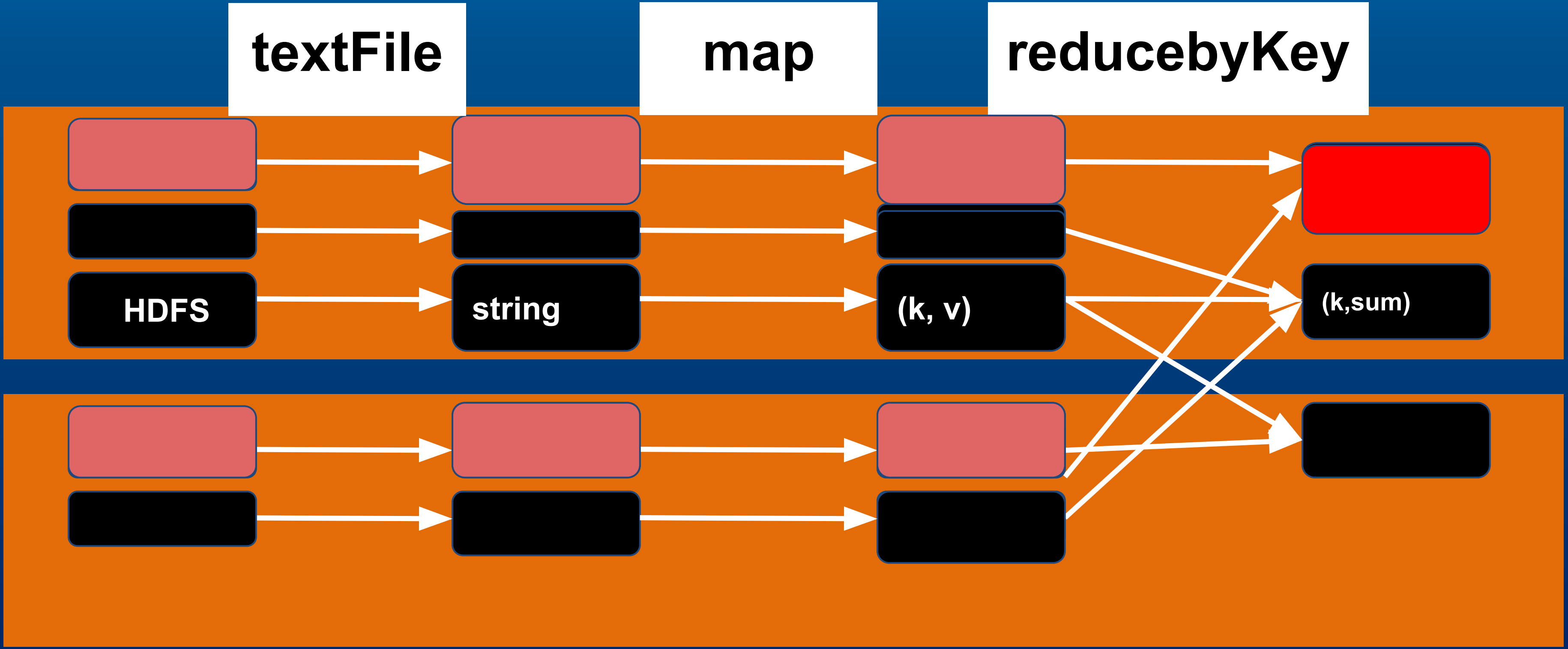
Narrow vs Wide

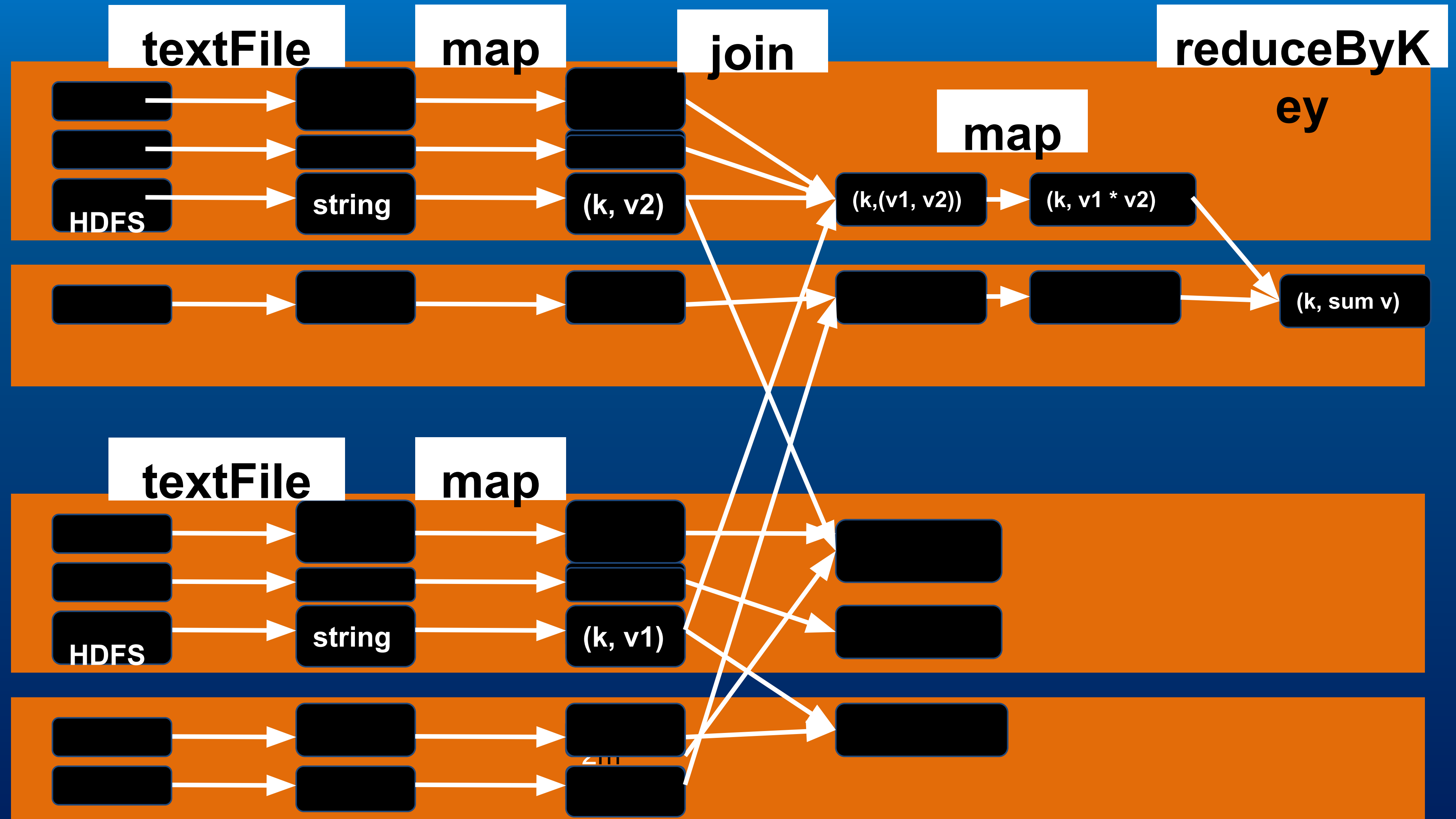


Narrow vs Wide



Spark DAG of transformations





textFile
map
join
reduceByK
ey
map
HDFS
string
(k, v2)
(k,(v1, v2))
(k, v1 * v2)
(k, sum v)
textFile
map
HDFS
string
(k, v1)

Thank you

zonca@sdsc.edu