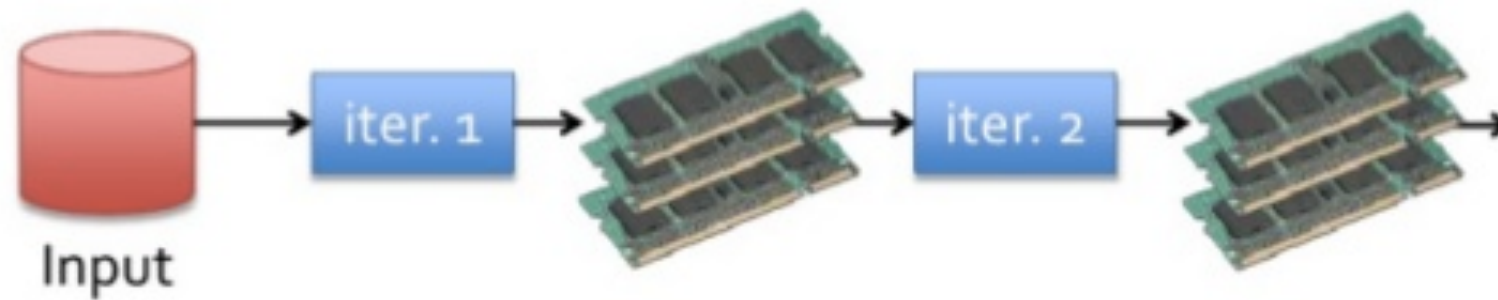
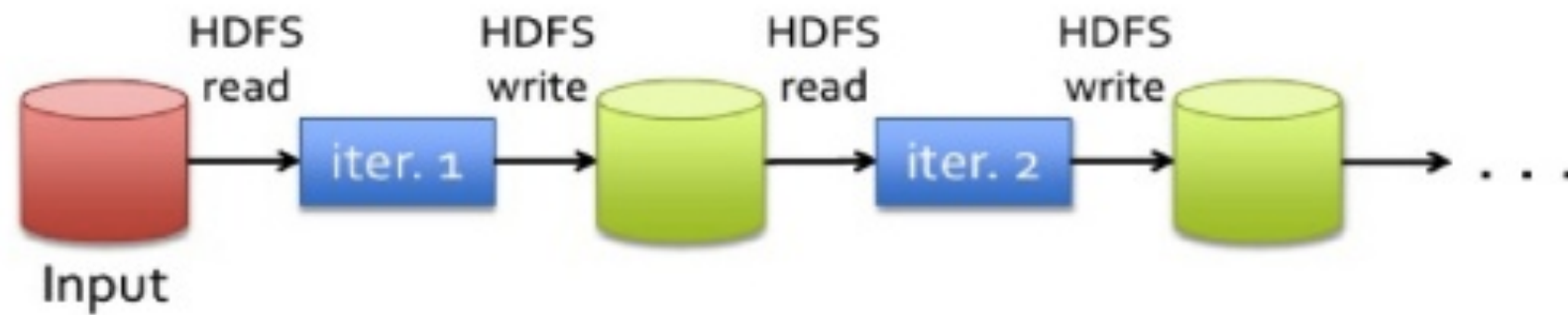
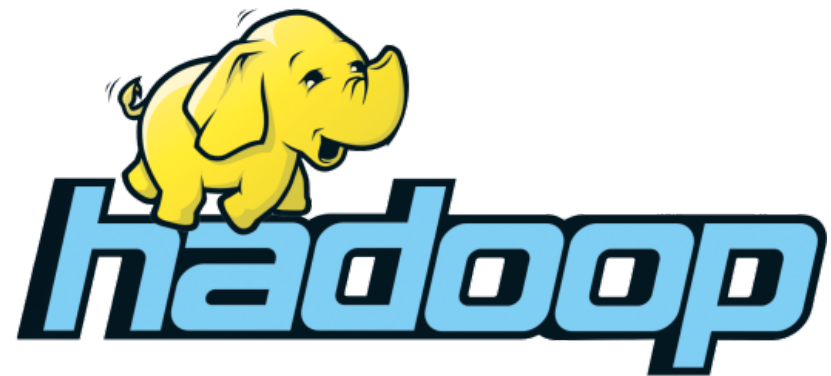




- Resilient Distributed Datasets (RDD)
- Transformations and Actions
- Building the Directed Acyclic Graph (DAG)
- Job, Stages, and Tasks
- Ways to Run Spark
- Spark DataFrames and SparkSQL
- Machine Learning on Spark
- Spark Tuning



Resilient Distributed Dataset (RDD)

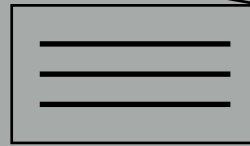
Dataset

```
1420589581, CEC023AA, 40712  
1436660661, 175AB332, 60813  
1469828518, 407BA6EF, 70179
```

...

...

...



5GB

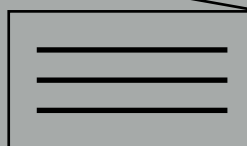
Dataset

```
1420589581, CEC023AA, 40712  
1436660661, 175AB332, 60813  
1469828518, 407BA6EF, 70179
```

...

...

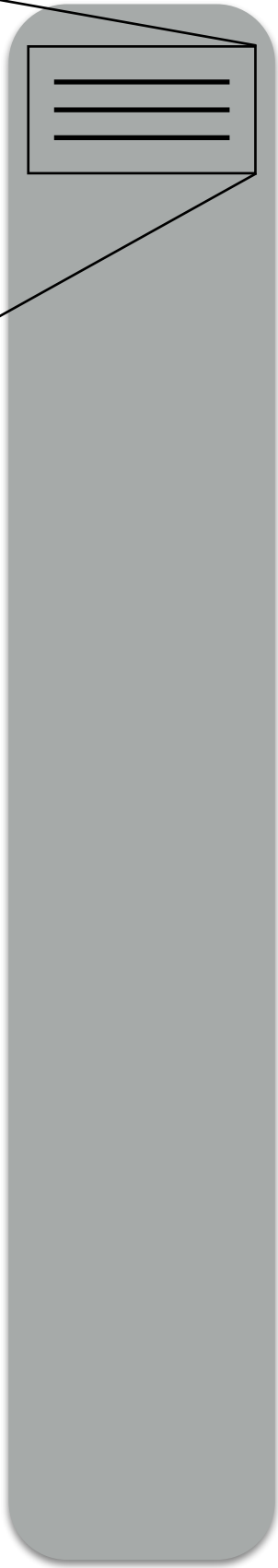
...



5GB

1420589581, CEC023AA, 40712
1436660661, 175AB332, 60813
1469828518, 407BA6EF, 70179
...
...
...

Dataset



RDD



1GB

1GB

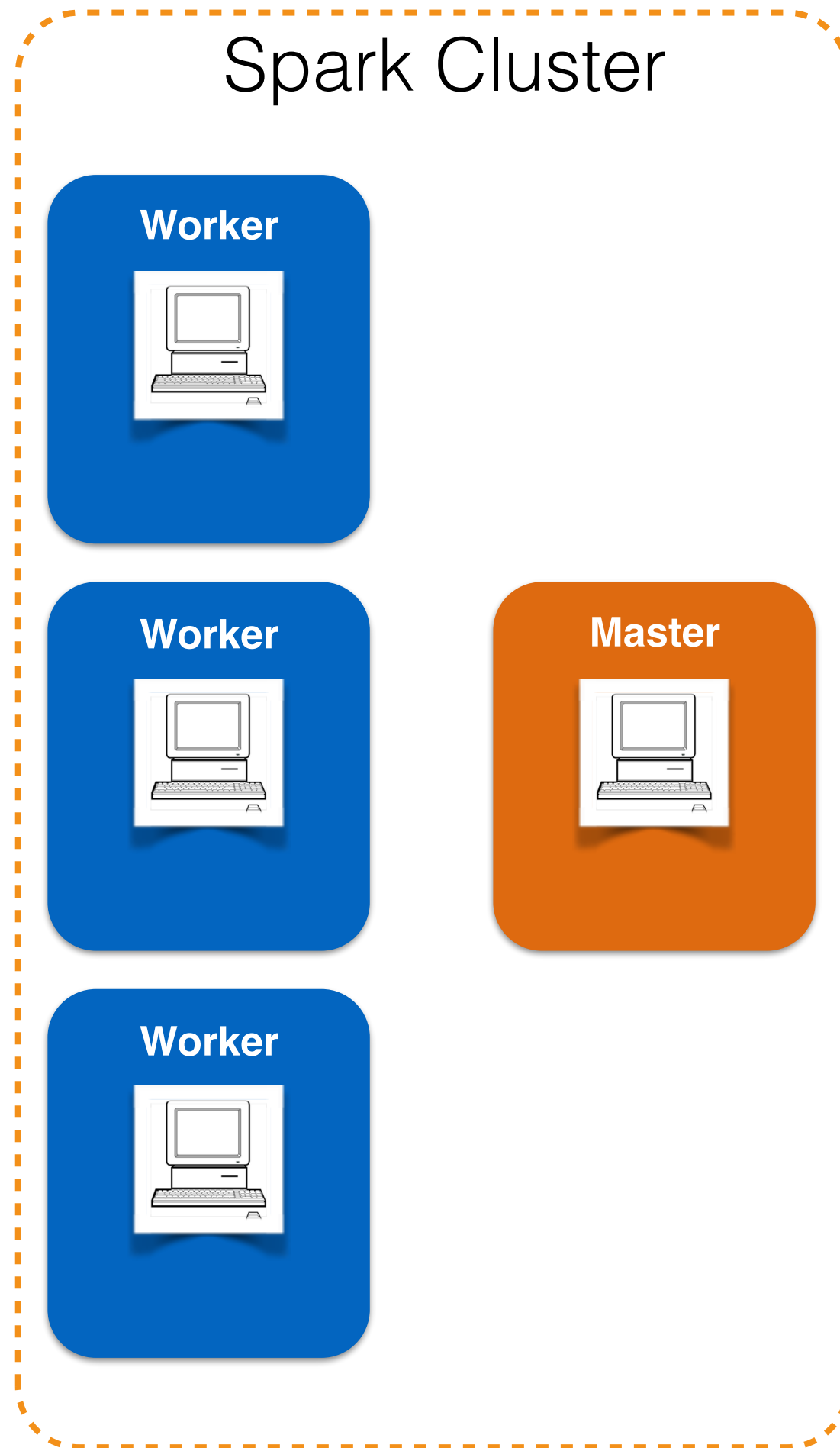
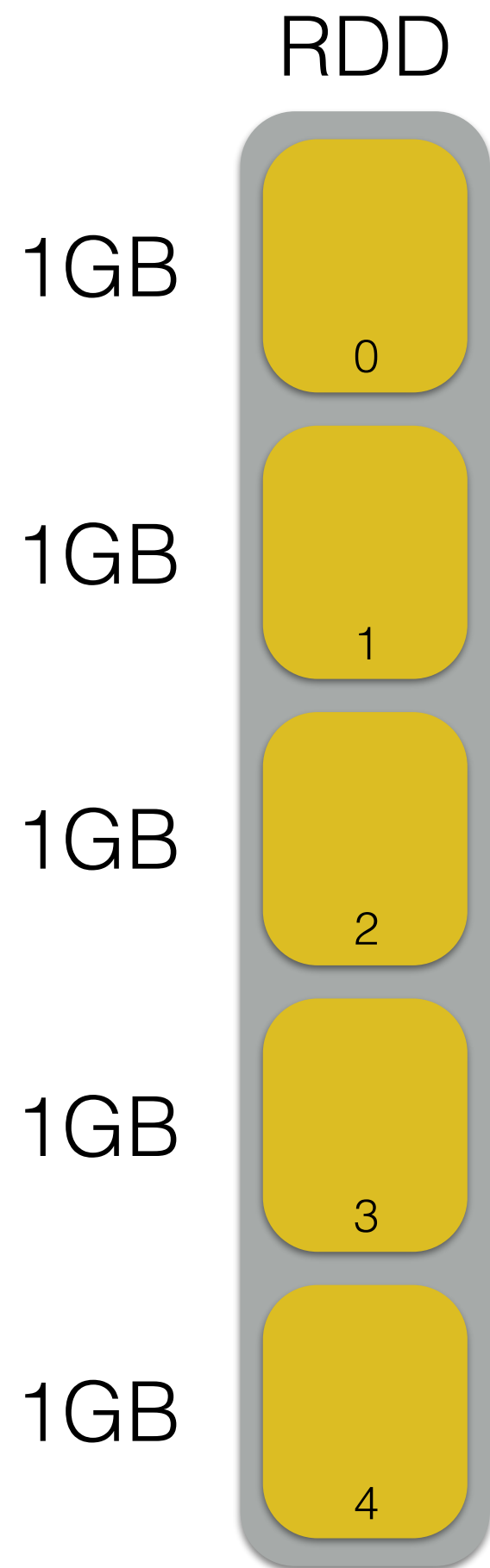
1GB

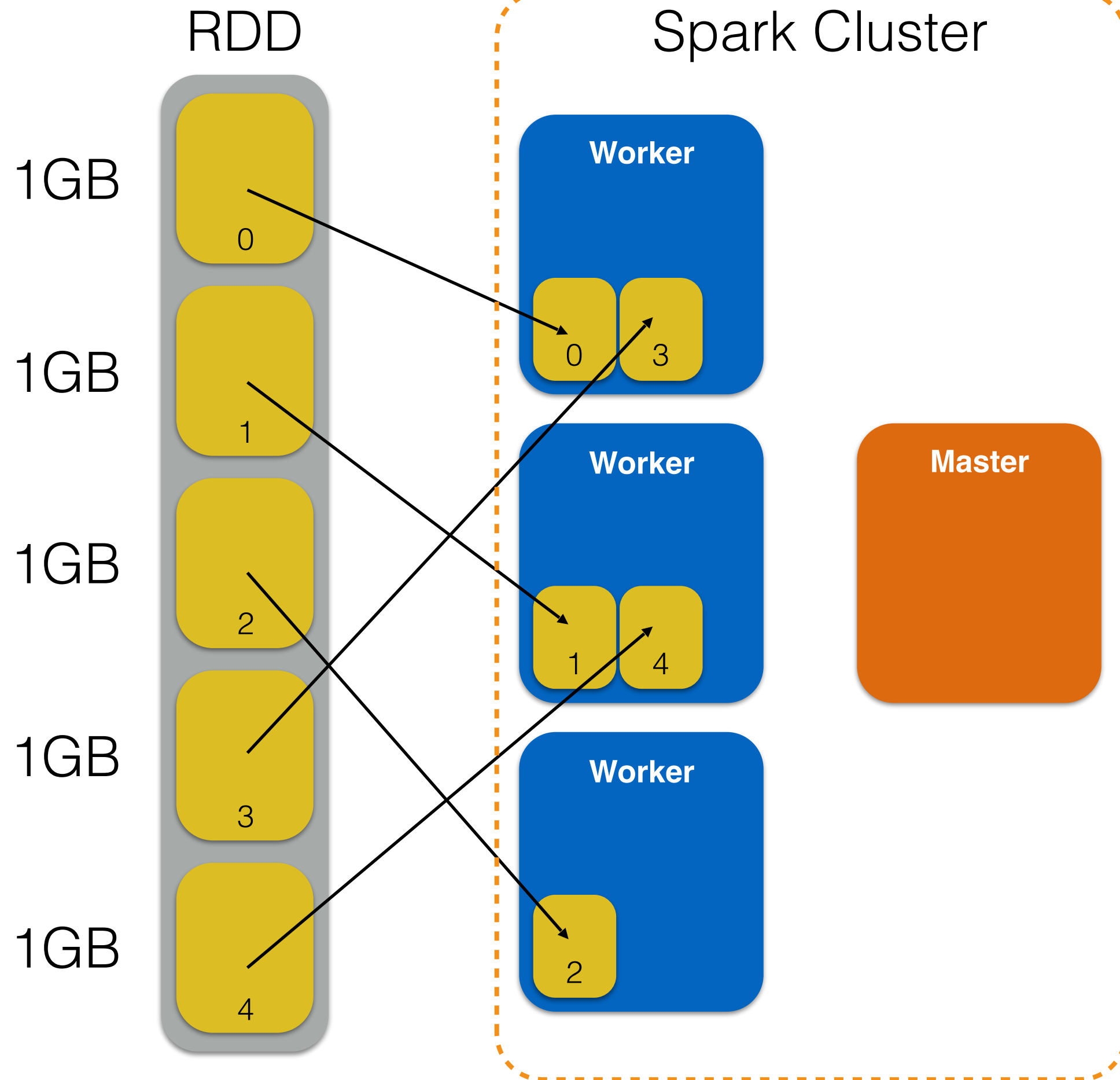
1GB

1GB

**Resilient
Distributed
Dataset**



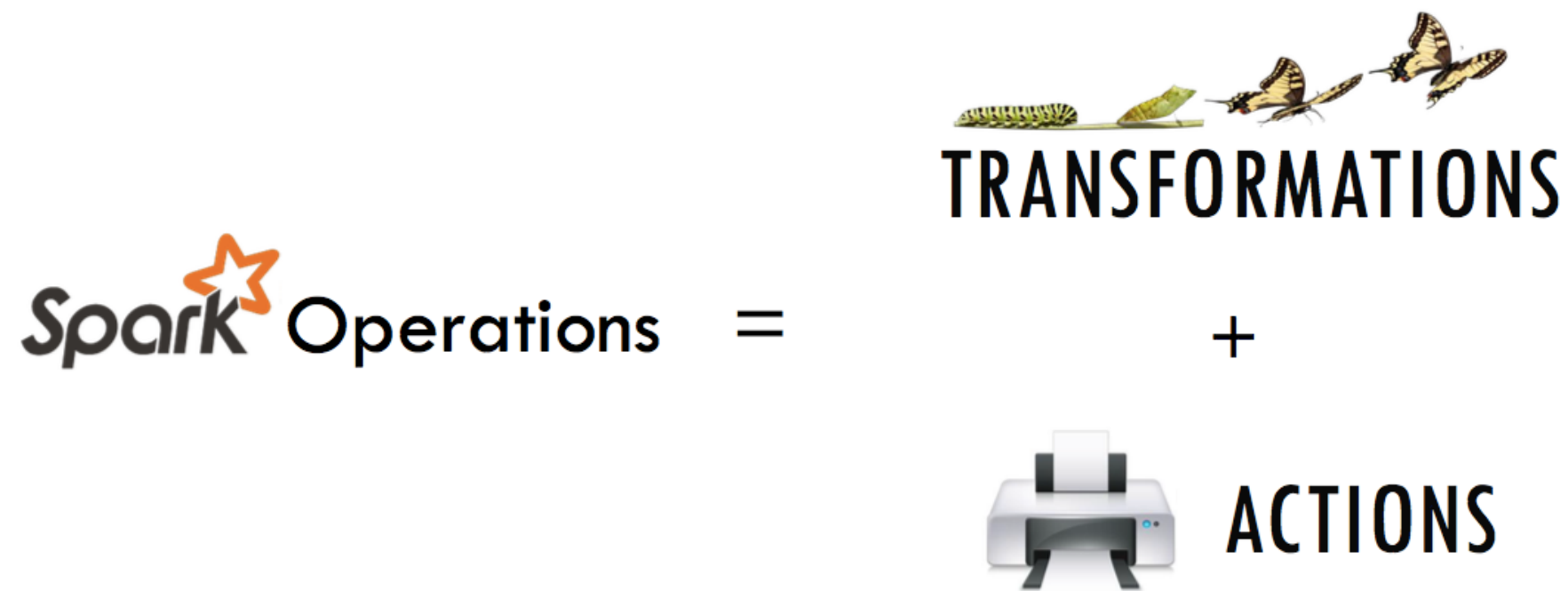




Transformations and Actions

Transformations and Actions

- Transformations are performed on RDDs
- Transformations are used to build a Directed Acyclic Graph (DAG)
- Actions trigger data to flow through the DAG



Transformations and Actions



.map
.filter
.groupByKey
.reduceByKey

.sortByKey
.flatMap
.repartition



.collect
.take
.first

.count
.takeSample
.reduce

Transformations and Actions



`.map`
`.filter`
`.groupByKey`
`.reduceByKey`

`.sortByKey`
`.flatMap`
`.repartition`

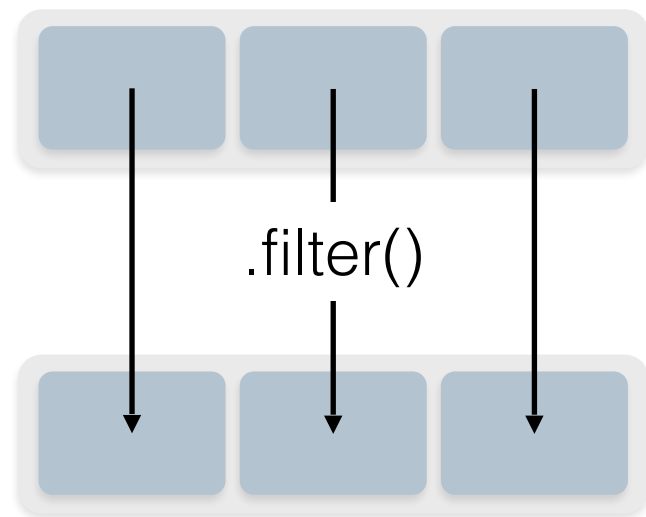


`.collect`
`.take`
`.first`

`.count`
`.takeSample`
`.reduce`

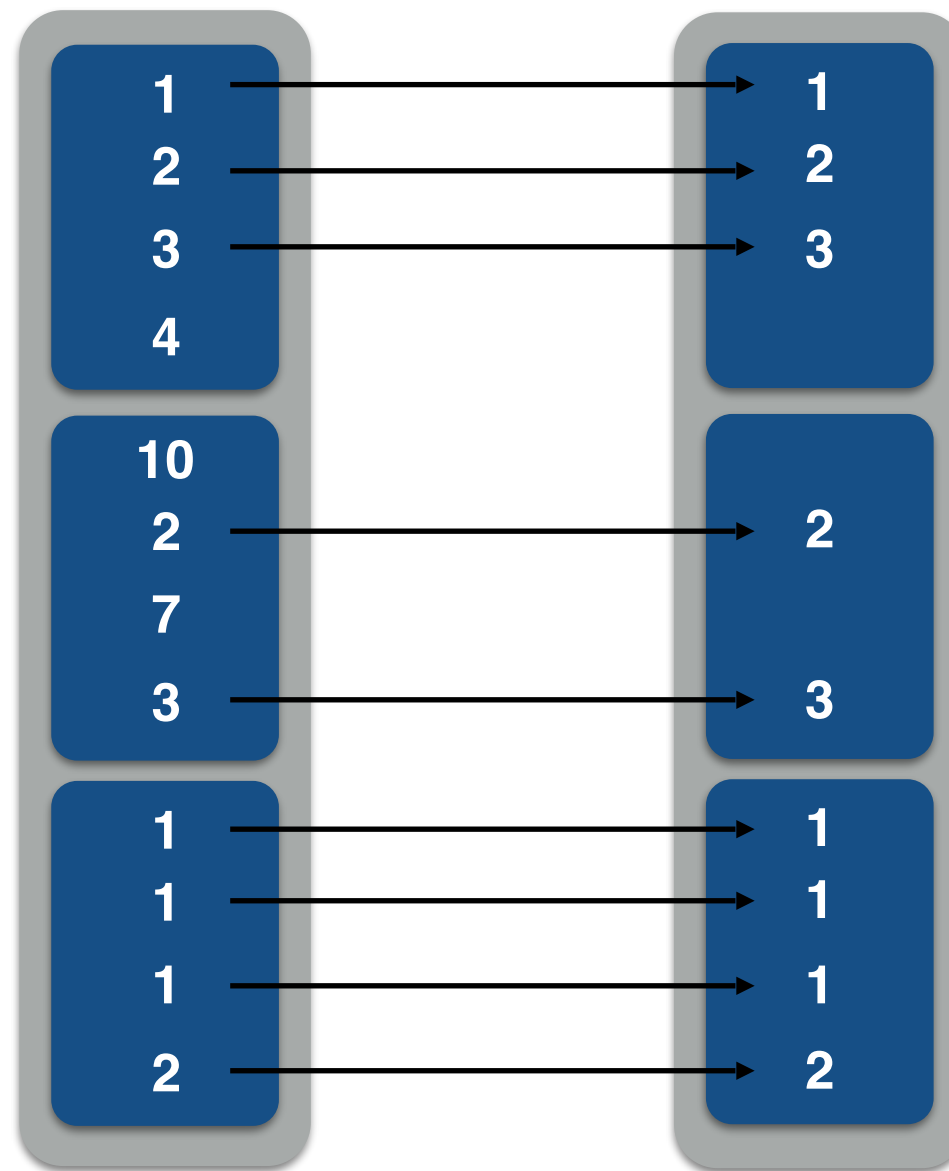
Basic Transformation Examples

`.filter(lambda r: r < 4)`



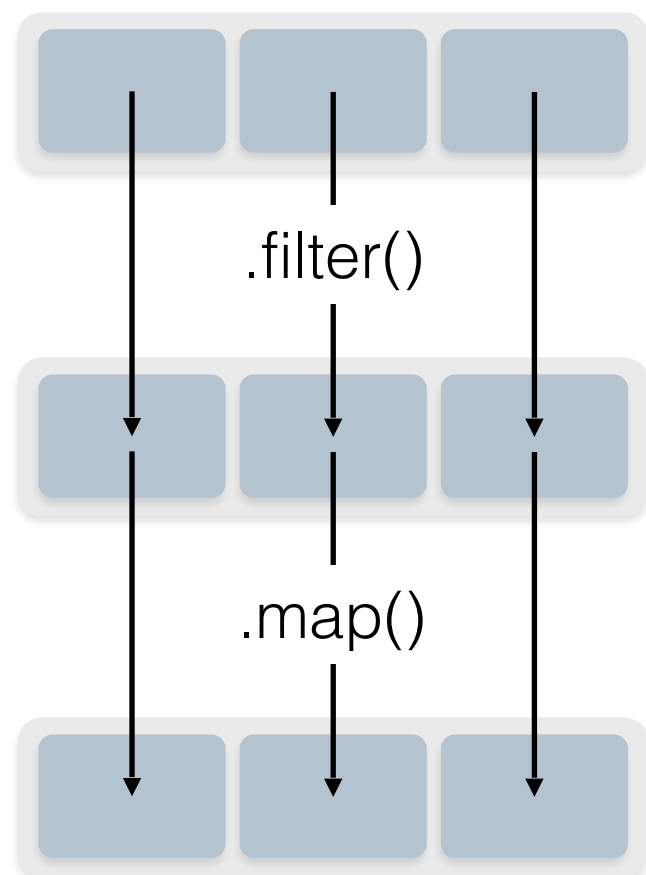
Parent RDD

Child RDD



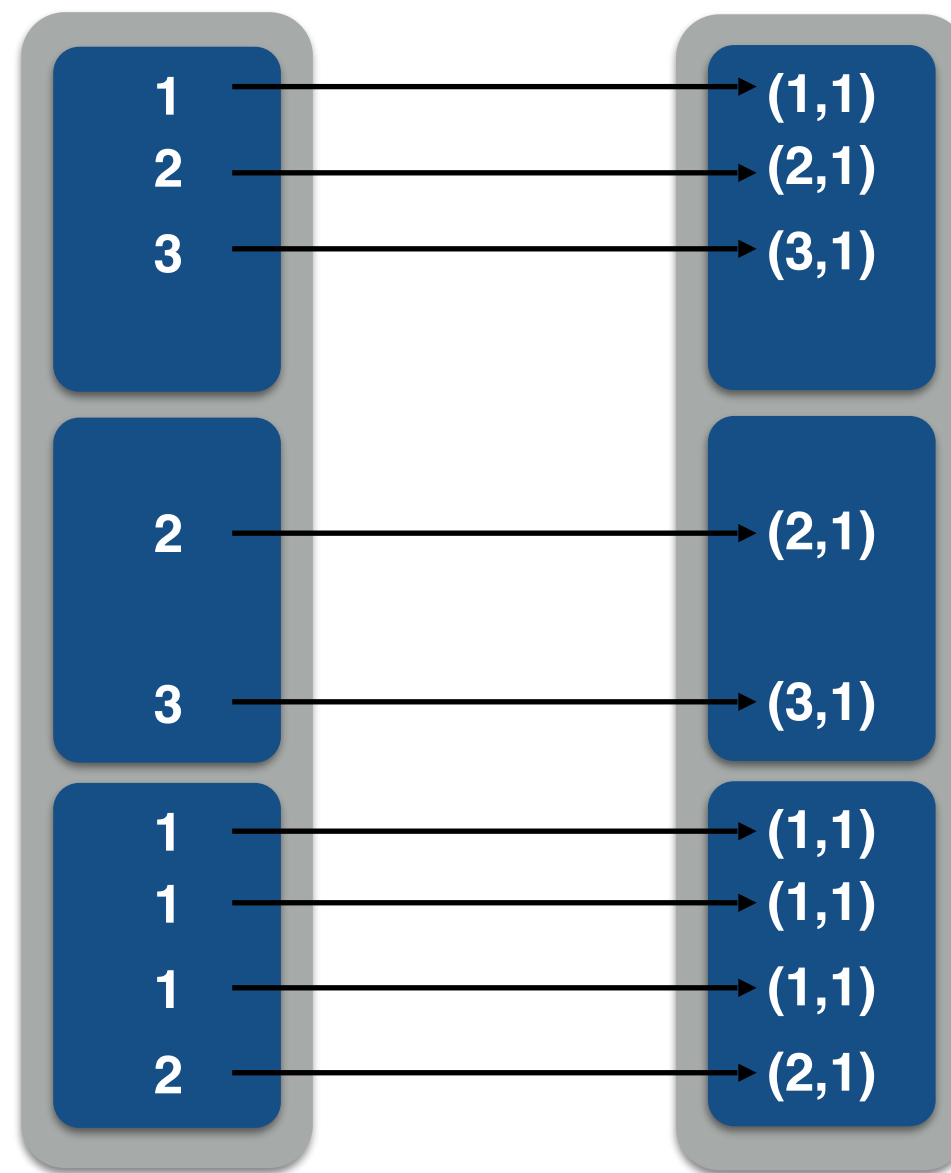
Basic Transformation Examples

`.map(lambda r: (r, 1))`



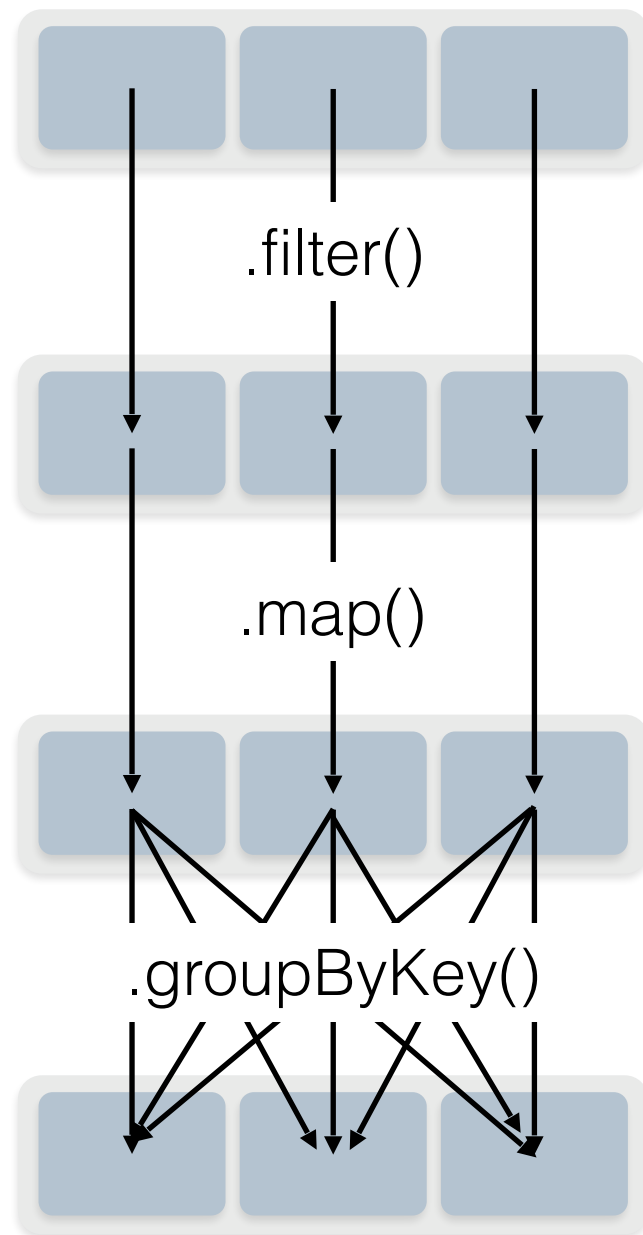
Parent RDD

Child RDD



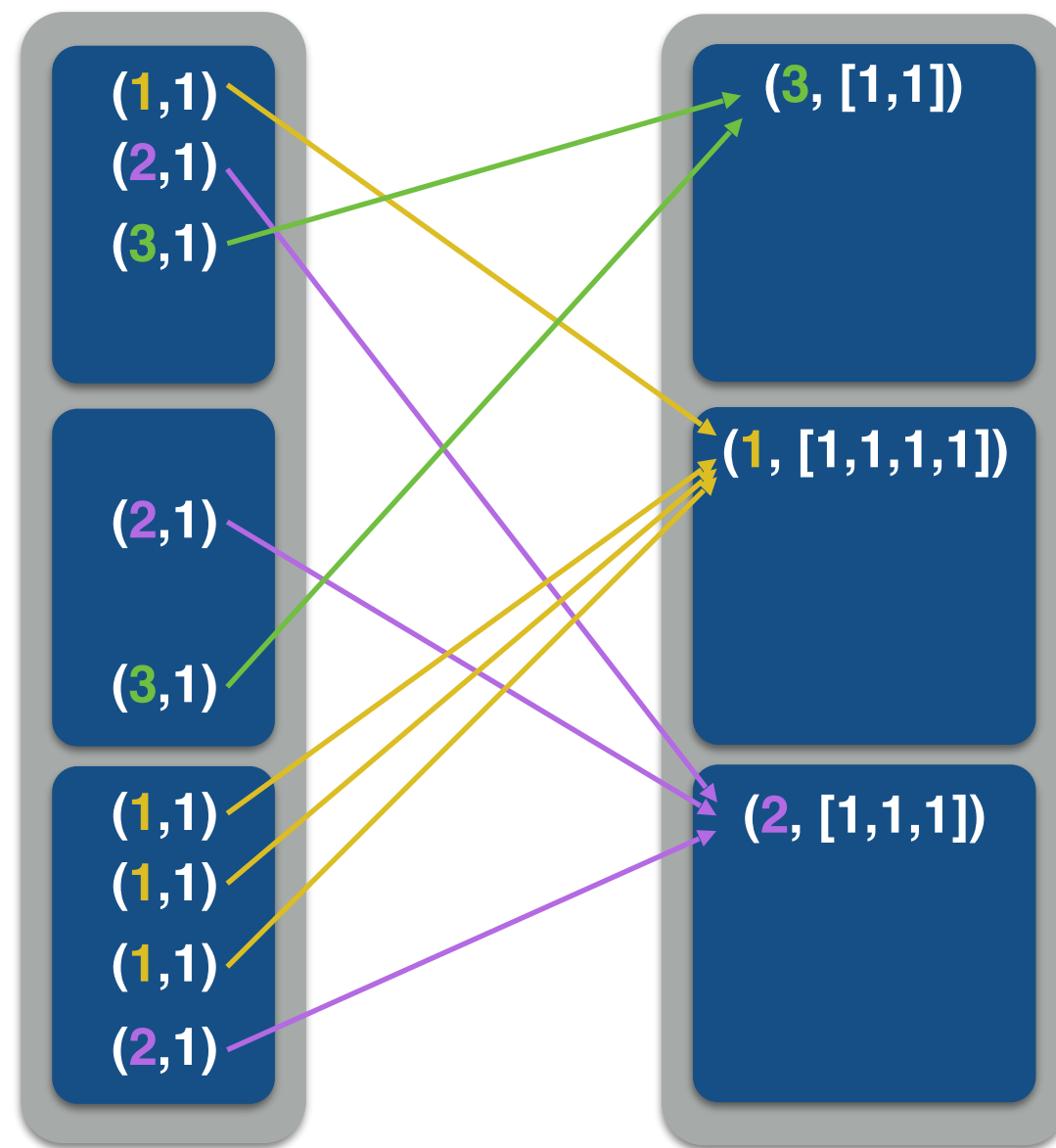
Basic Transformation Examples

`.groupByKey()`



Parent RDD

Child RDD



Basic Transformation Examples

Shuffle

Paired RDD $(_, _)$

↑
key



3



6dd28e9b



0

Child RDD



Narrow vs Wide Transformations



vs

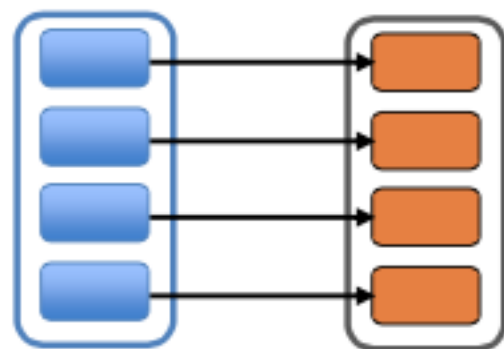


narrow

wide

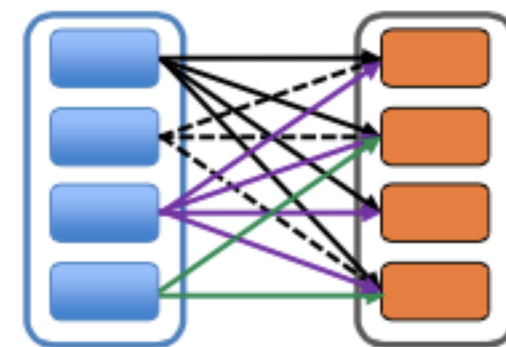
each partition of the parent RDD is used by at most one partition of the child RDD

multiple child RDD partitions may depend on a single parent RDD partition



Parent
RDD

Child
RDD



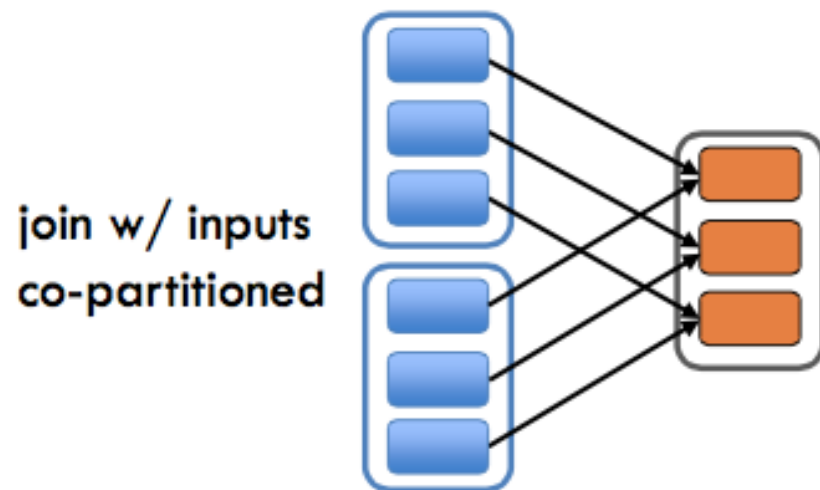
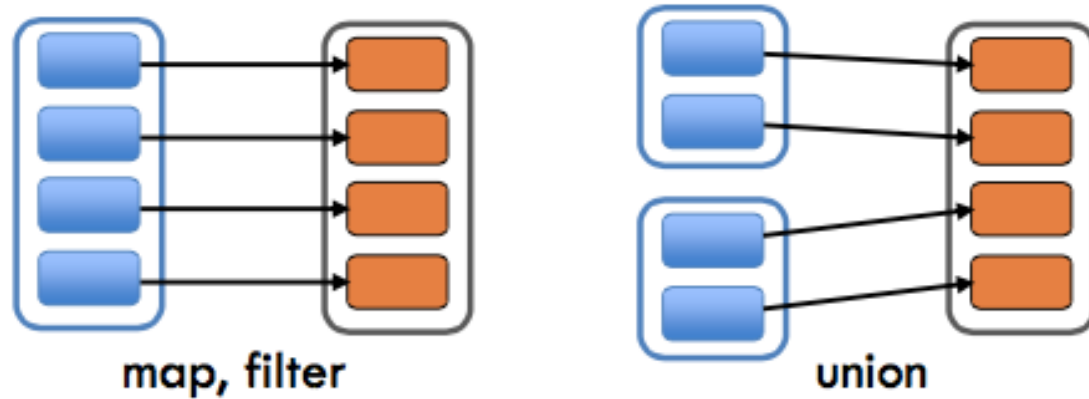
Parent
RDD

Child
RDD

Narrow vs Wide Transformations

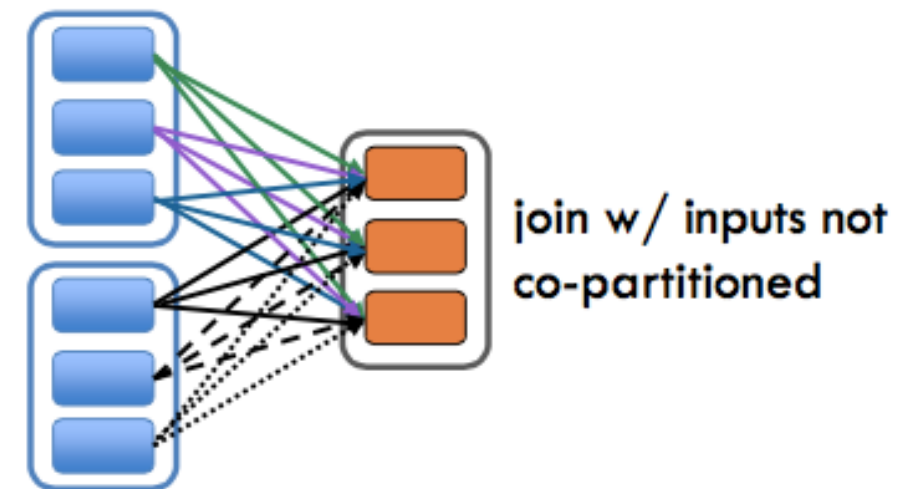
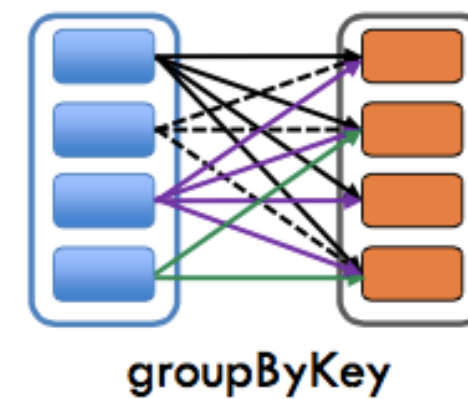
narrow

each partition of the parent RDD is used by at most one partition of the child RDD



wide

multiple child RDD partitions may depend on a single parent RDD partition



Transformations and Actions



.map
.filter
.groupByKey
.reduceByKey

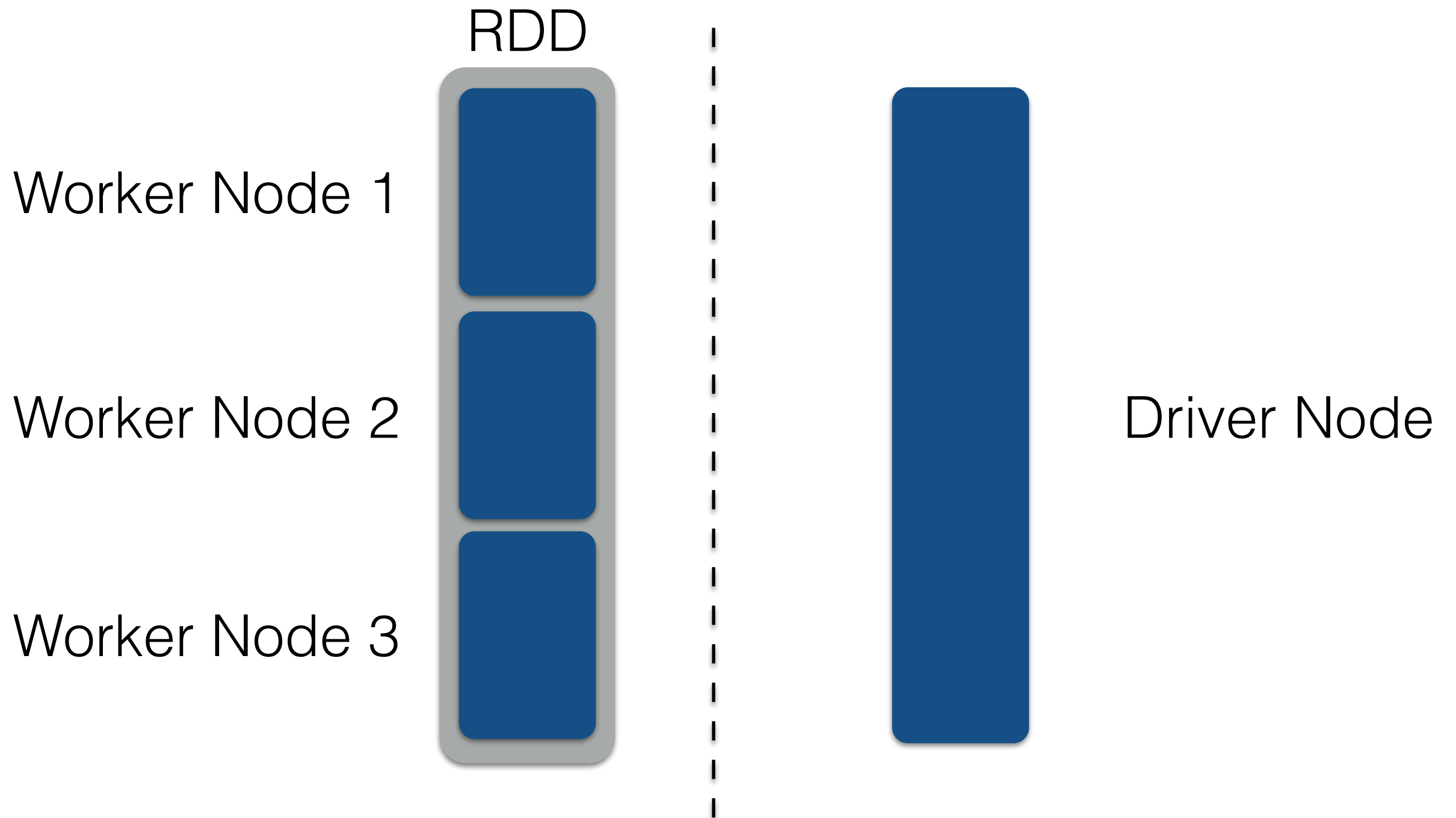
.sortByKey
.flatMap
.repartition



.collect
.take
.first

.count
.takeSample
.reduce

.collect()



All partitions must fit into memory on the driver node

Building the Directed Acyclic Graph (DAG)

Building the DAG

```
rdd1 = sc.textFile("dataset1.txt")  
rdd2 = sc.textFile("dataset2.txt")
```

```
reduced_rdd = rdd1.reduceByKey(...)  
filtered_rdd = rdd2.filter(...)
```

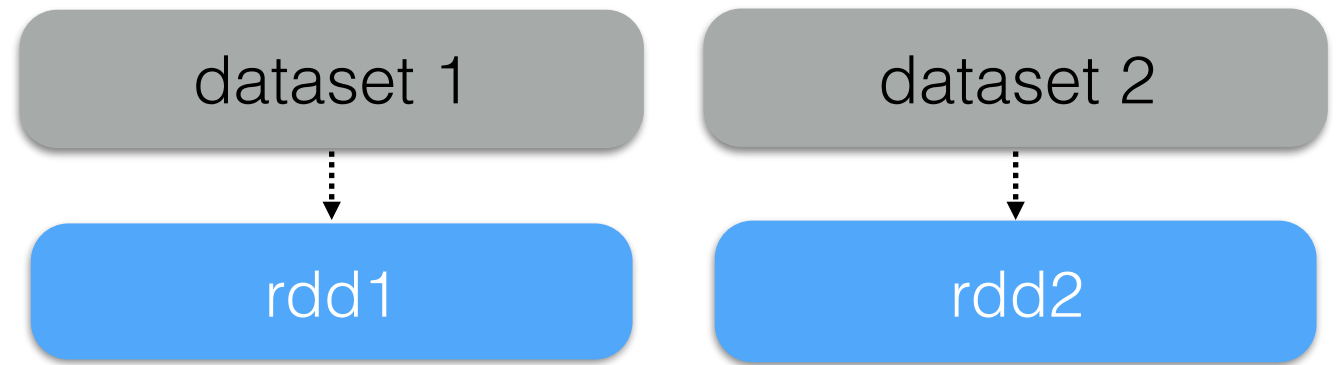
```
mapped_filtered_rdd = filtered_rdd.map(...)
```

```
joined_rdd = reduced_rdd.join(mapped_filtered_rdd)
```

```
mapped_joined_rdd = joined_rdd.map(...)
```

```
result = mapped_joined_rdd.collect()
```

Building the DAG



```
rdd1 = sc.textFile("dataset1.txt")  
rdd2 = sc.textFile("dataset2.txt")
```

```
reduced_rdd = rdd1.reduceByKey(...)
```

```
filtered_rdd = rdd2.filter(...)
```

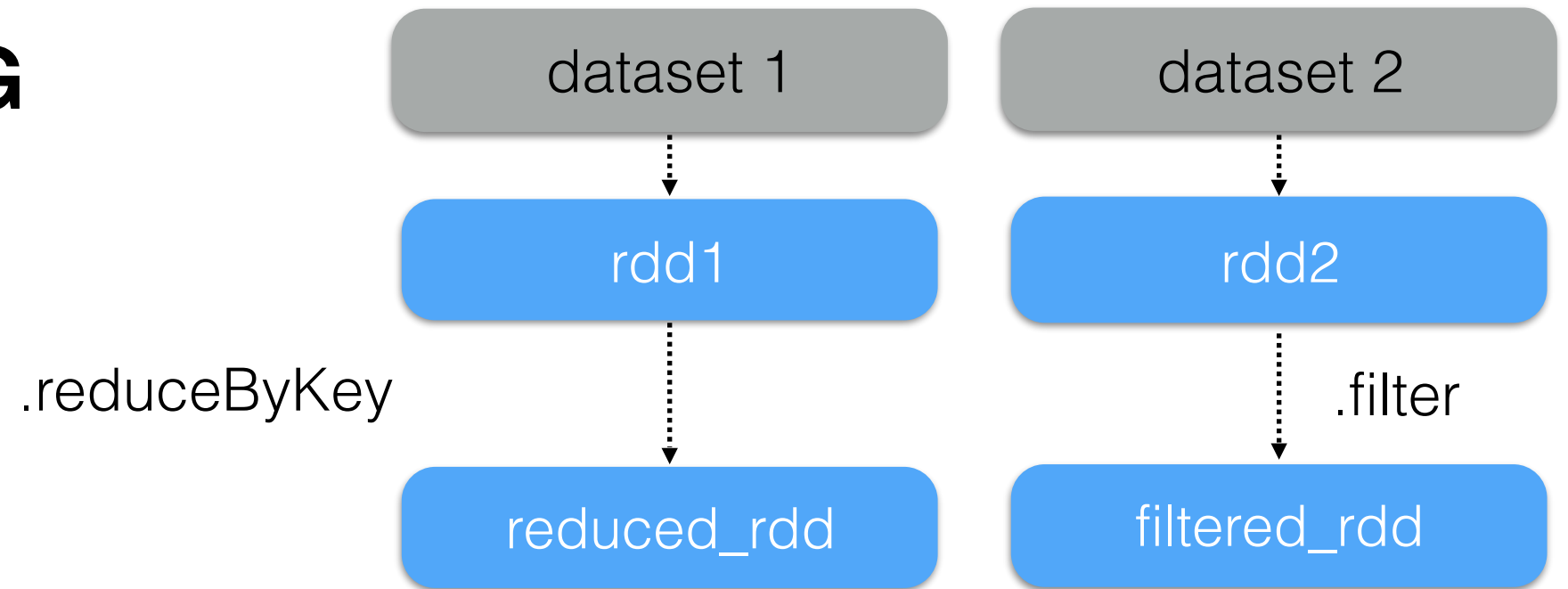
```
mapped_filtered_rdd = filtered_rdd.map(...)
```

```
joined_rdd = reduced_rdd.join(mapped_filtered_rdd)
```

```
mapped_joined_rdd = joined_rdd.map(...)
```

```
result = mapped_joined_rdd.collect()
```

Building the DAG



```
rdd1 = sc.textFile("dataset1.txt")  
rdd2 = sc.textFile("dataset2.txt")
```

```
reduced_rdd = rdd1.reduceByKey(...)  
filtered_rdd = rdd2.filter(...)
```

```
mapped_filtered_rdd = filtered_rdd.map(...)
```

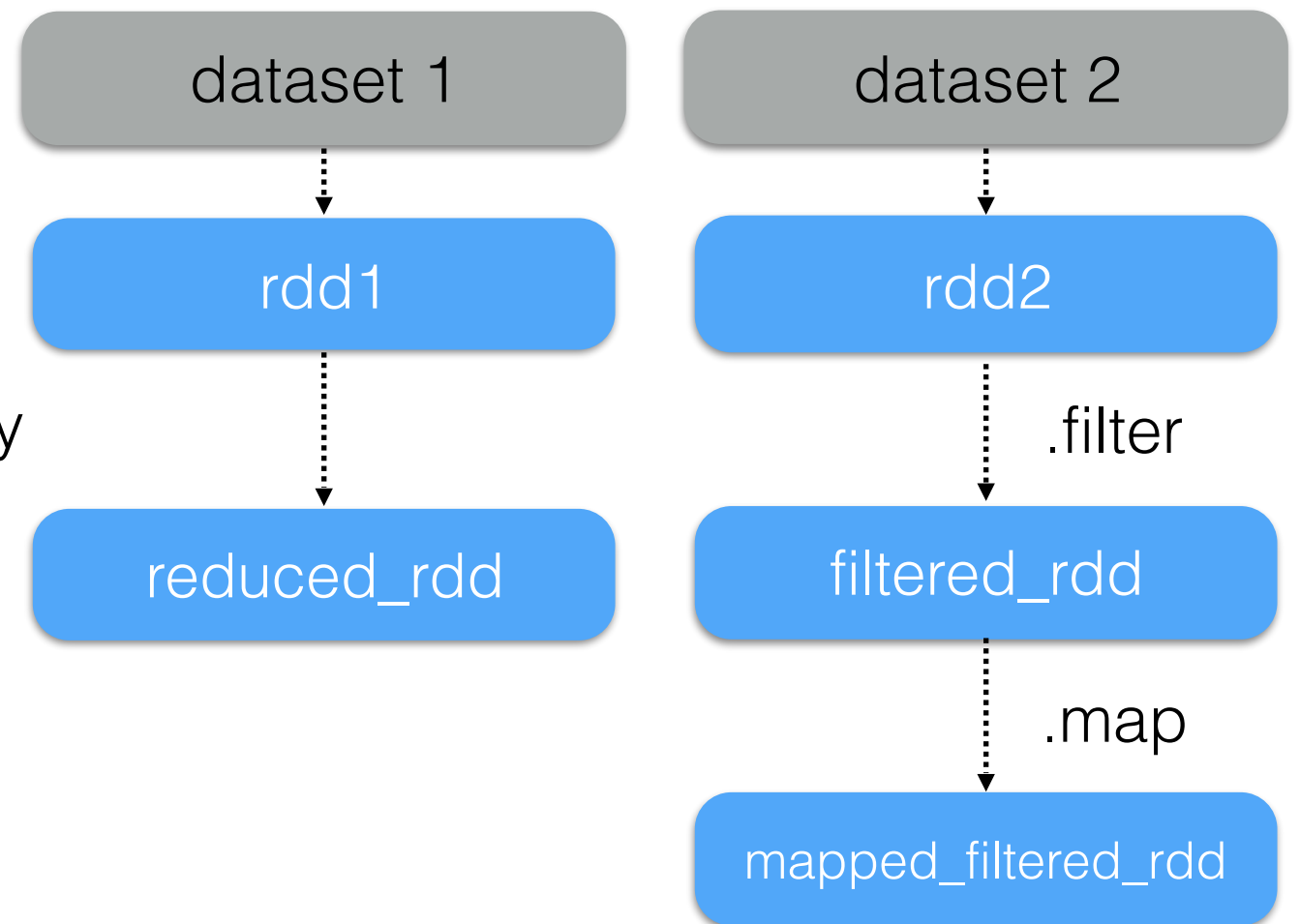
```
joined_rdd = reduced_rdd.join(mapped_filtered_rdd)
```

```
mapped_joined_rdd = joined_rdd.map(...)
```

```
result = mapped_joined_rdd.collect()
```


Building the DAG

.reduceByKey



```
rdd1 = sc.textFile("dataset1.txt")  
rdd2 = sc.textFile("dataset2.txt")
```

```
reduced_rdd = rdd1.reduceByKey(...)  
filtered_rdd = rdd2.filter(...)
```

```
mapped_filtered_rdd = filtered_rdd.map(...)
```

```
joined_rdd = reduced_rdd.join(mapped_filtered_rdd)
```

```
mapped_joined_rdd = joined_rdd.map(...)
```

```
result = mapped_joined_rdd.collect()
```

Building the DAG

.reduceByKey

.filter

.map

.join

```
rdd1 = sc.textFile("dataset1.txt")  
rdd2 = sc.textFile("dataset2.txt")
```

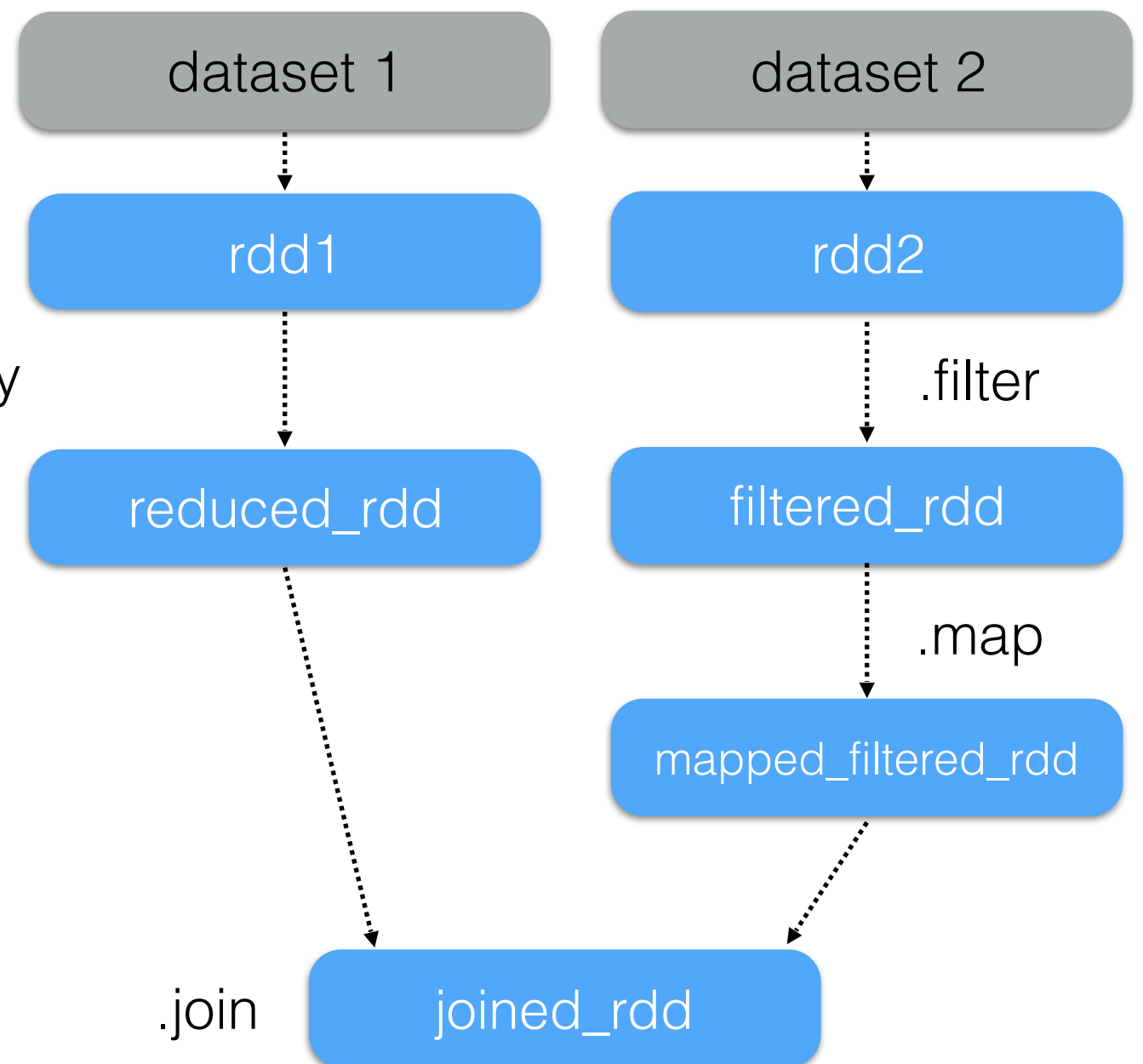
```
reduced_rdd = rdd1.reduceByKey(...)  
filtered_rdd = rdd2.filter(...)
```

```
mapped_filtered_rdd = filtered_rdd.map(...)
```

```
joined_rdd = reduced_rdd.join(mapped_filtered_rdd)
```

```
mapped_joined_rdd = joined_rdd.map(...)
```

```
result = mapped_joined_rdd.collect()
```



Building the DAG

```
rdd1 = sc.textFile("dataset1.txt")
rdd2 = sc.textFile("dataset2.txt")

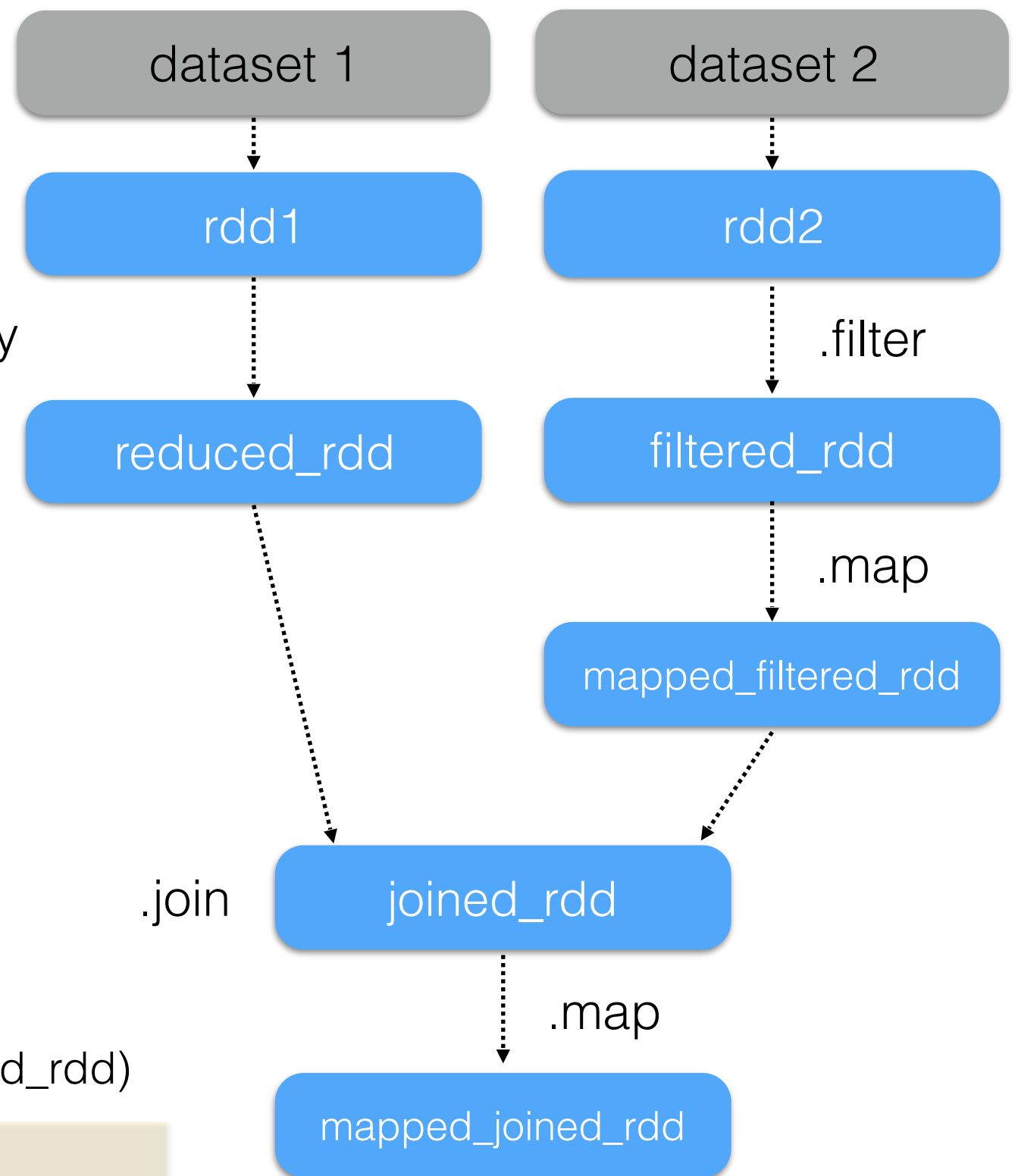
reduced_rdd = rdd1.reduceByKey(...)
filtered_rdd = rdd2.filter(...)

mapped_filtered_rdd = filtered_rdd.map(...)

joined_rdd = reduced_rdd.join(mapped_filtered_rdd)

mapped_joined_rdd = joined_rdd.map(...)

result = mapped_joined_rdd.collect()
```



Building the DAG

```
rdd1 = sc.textFile("dataset1.txt")
rdd2 = sc.textFile("dataset2.txt")

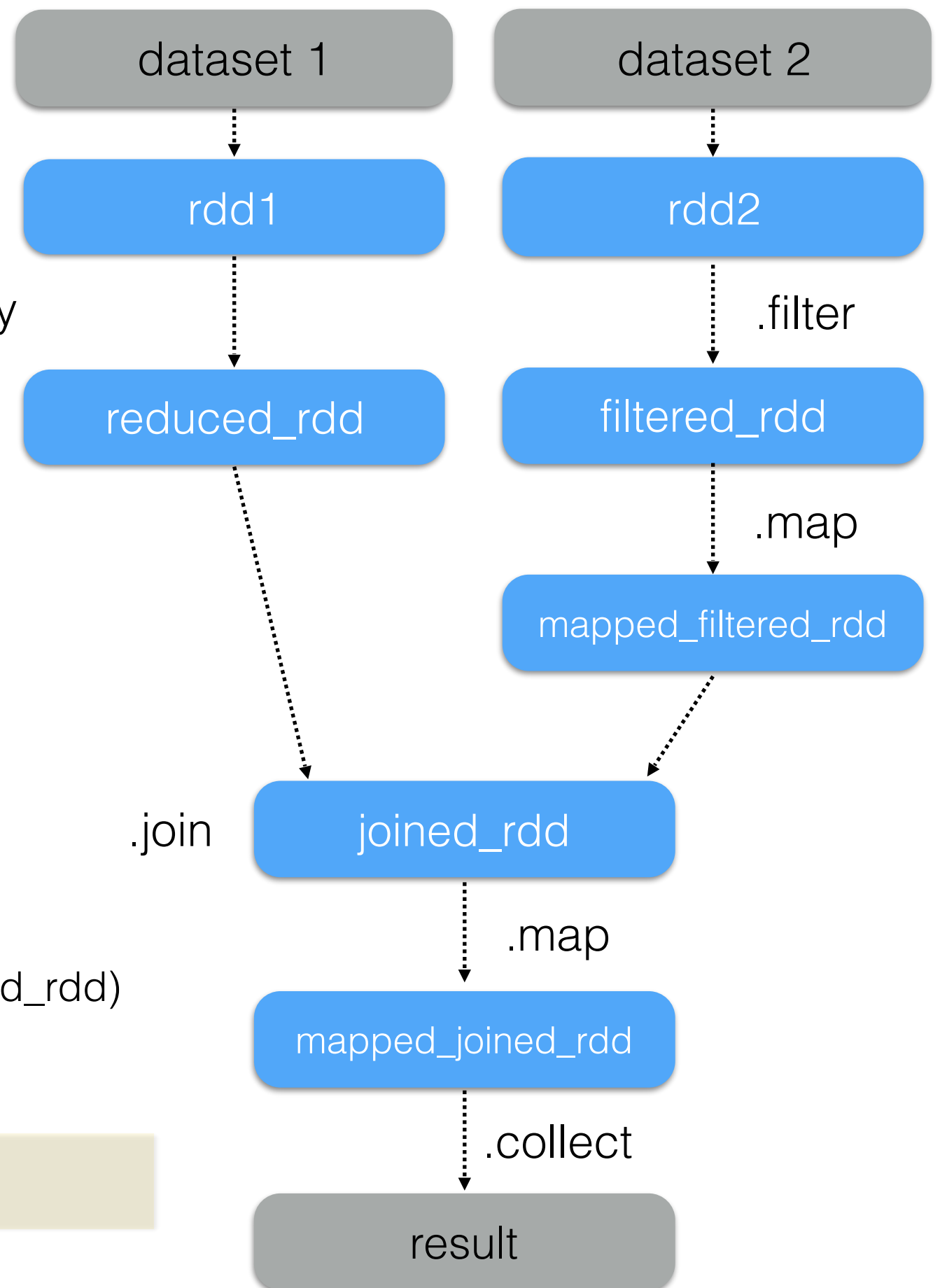
reduced_rdd = rdd1.reduceByKey(...)
filtered_rdd = rdd2.filter(...)

mapped_filtered_rdd = filtered_rdd.map(...)

joined_rdd = reduced_rdd.join(mapped_filtered_rdd)

mapped_joined_rdd = joined_rdd.map(...)

result = mapped_joined_rdd.collect()
```

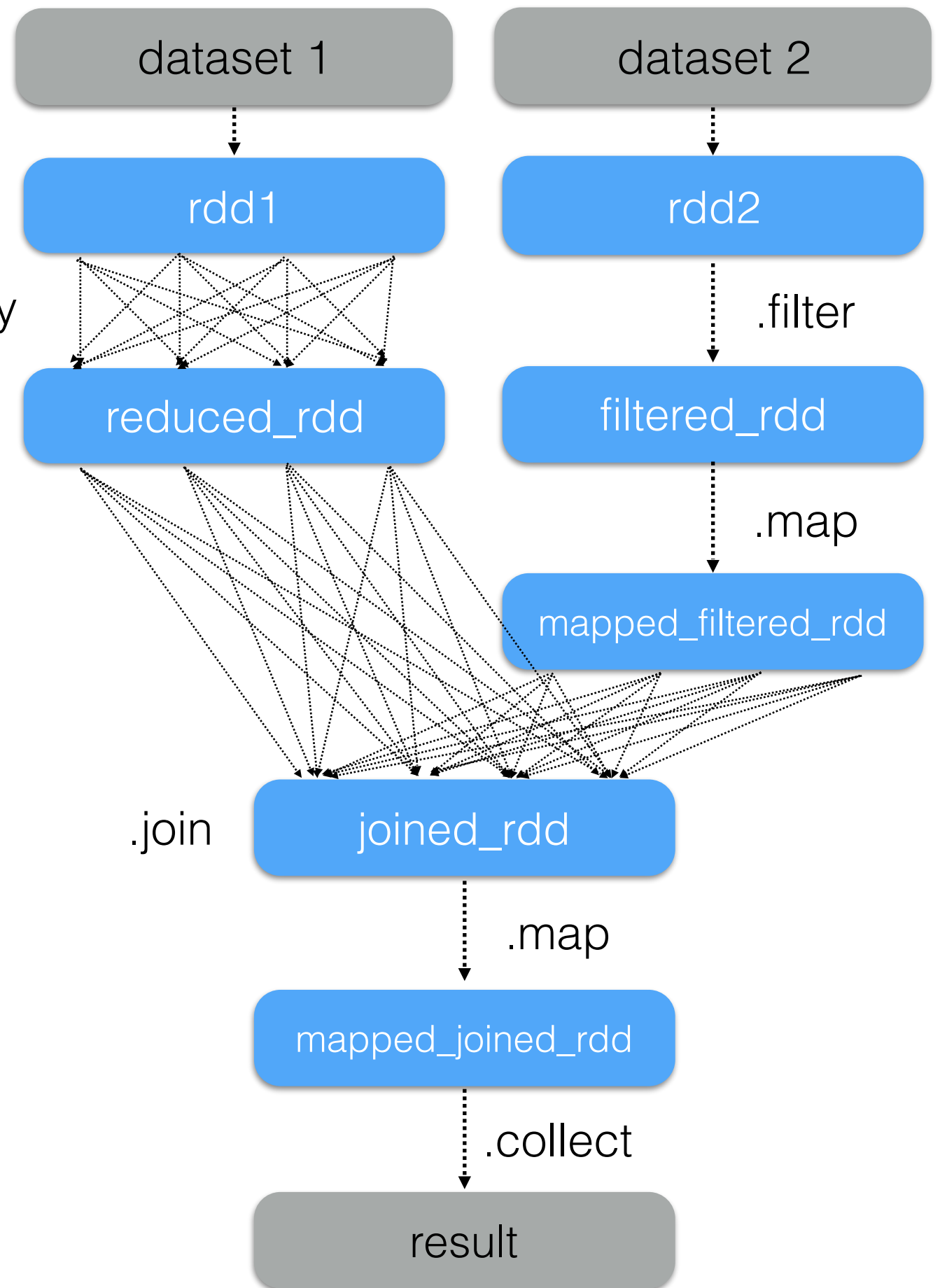


Determine Stages

Look for
Shuffle Boundaries



.reduceByKey

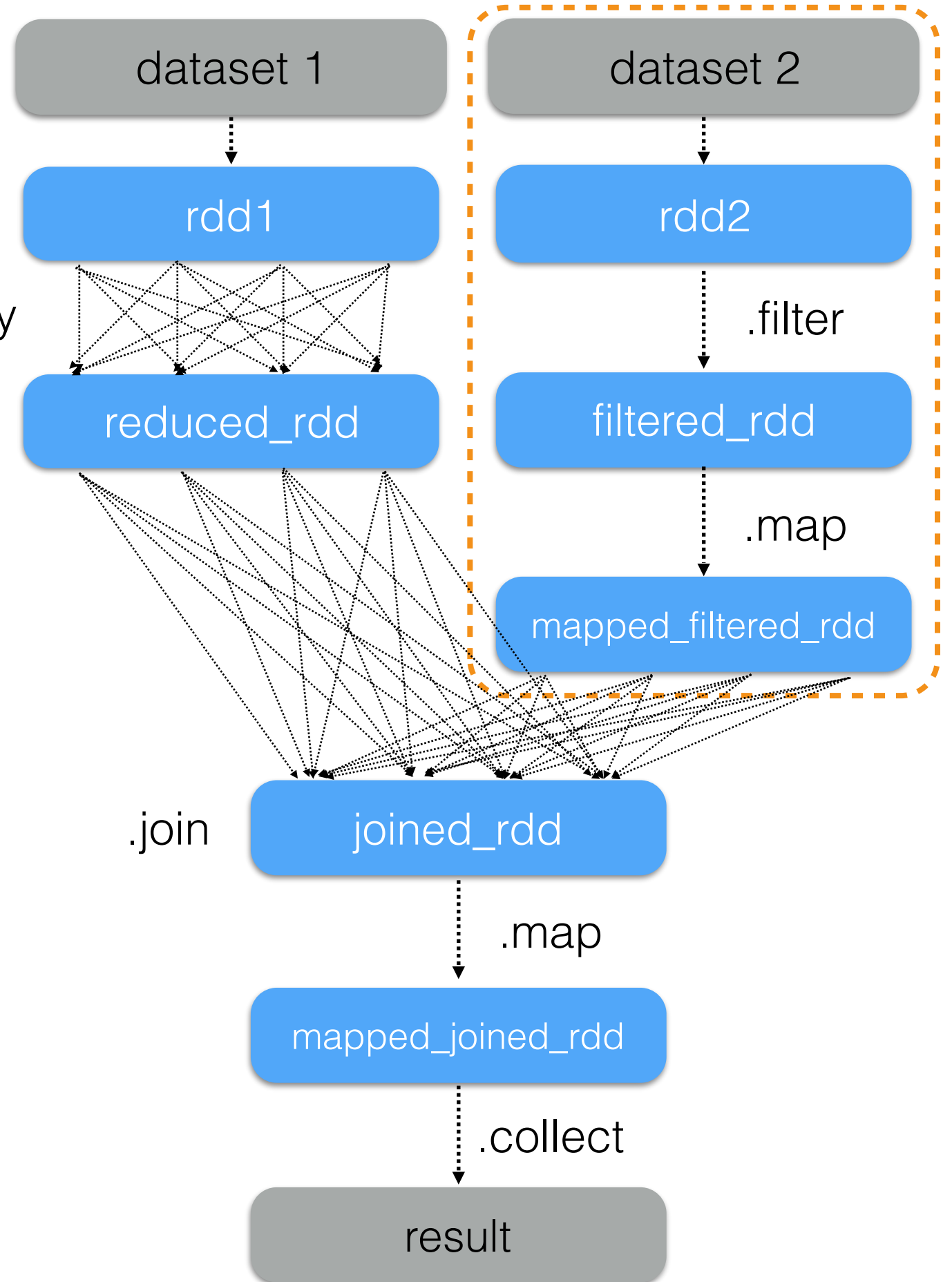


Determine Stages

Look for
Shuffle Boundaries



.reduceByKey

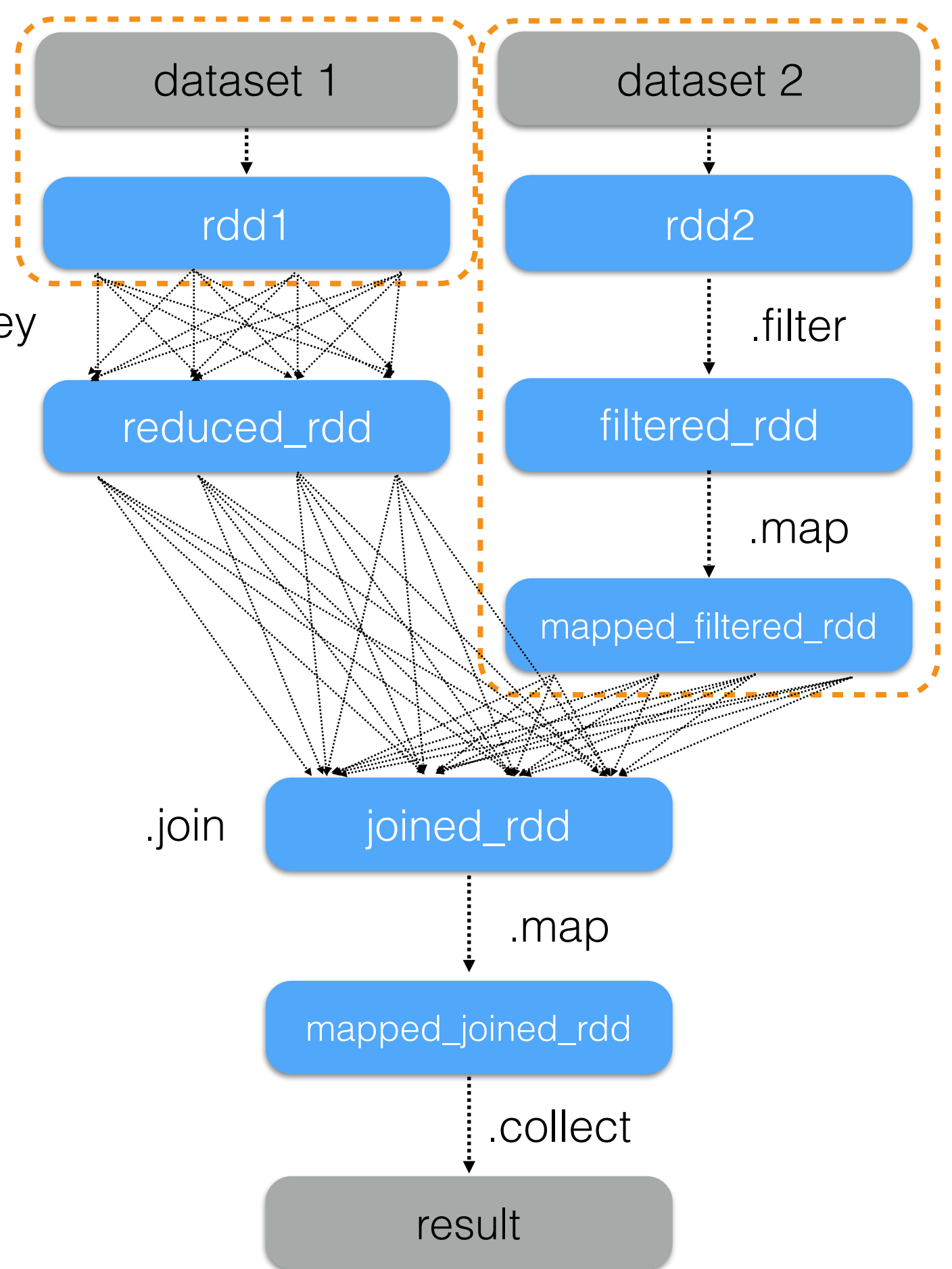


Determine Stages

Look for
Shuffle Boundaries



.reduceByKey

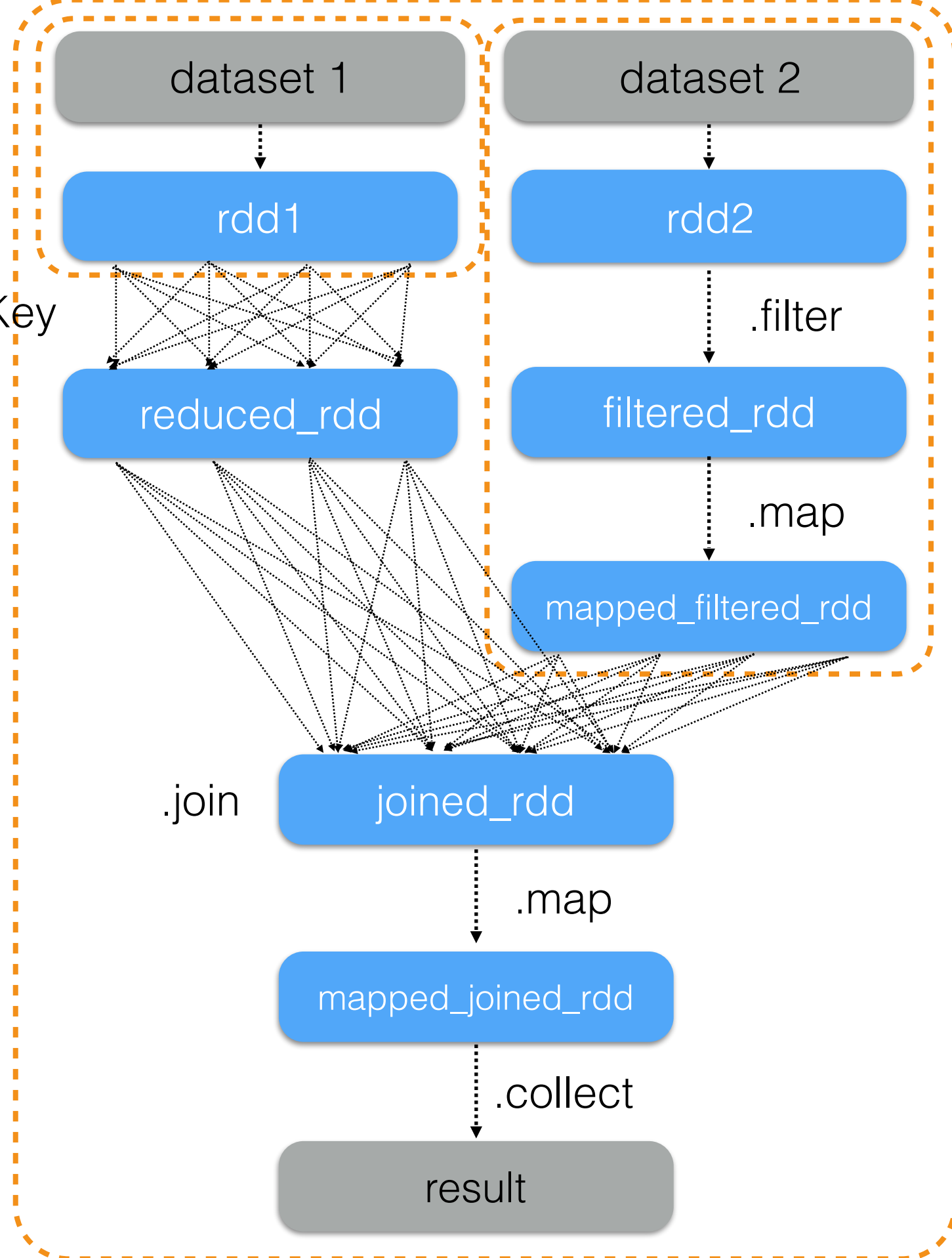


Determine Stages

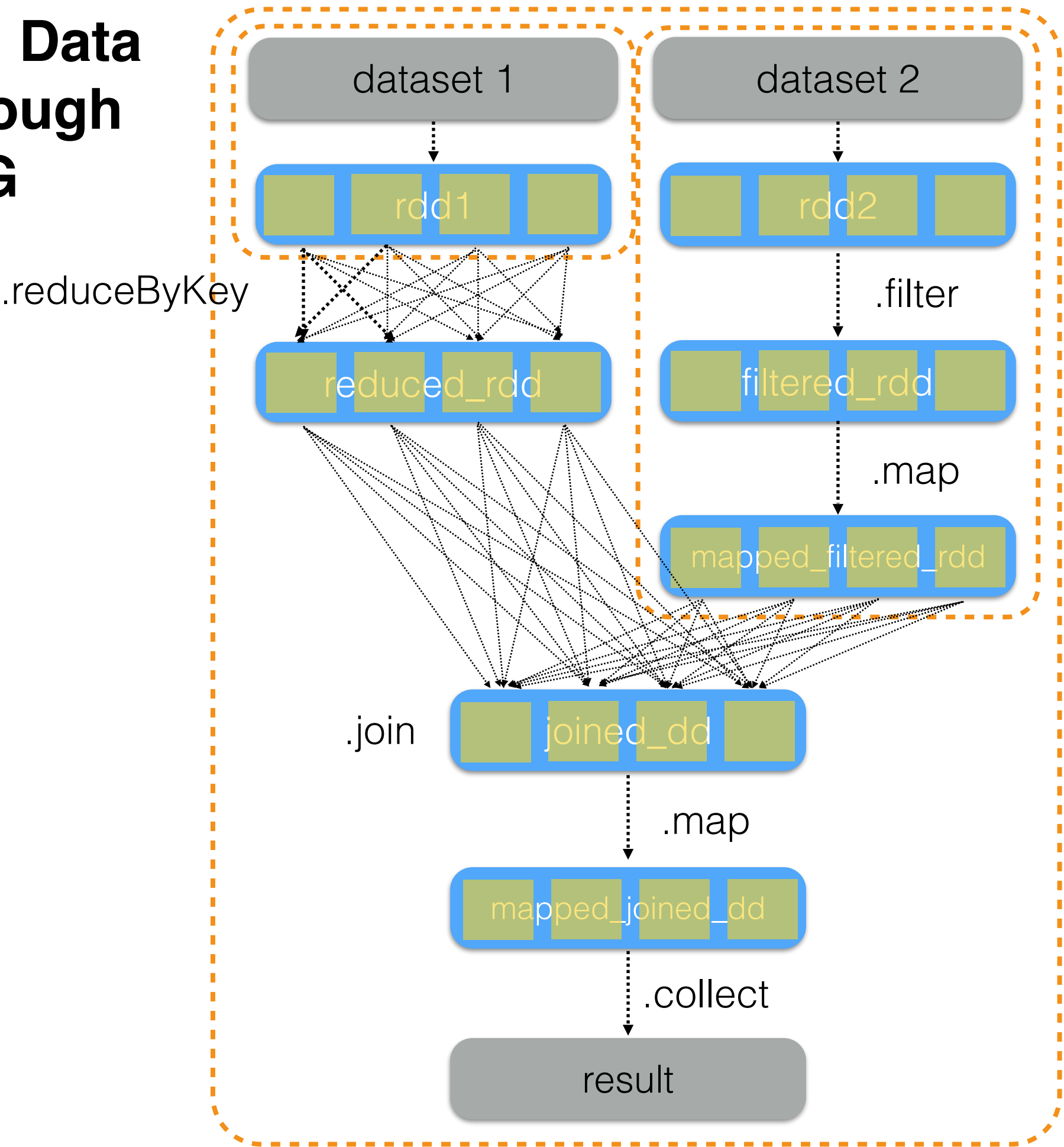
Look for
Shuffle Boundaries



.reduceByKey

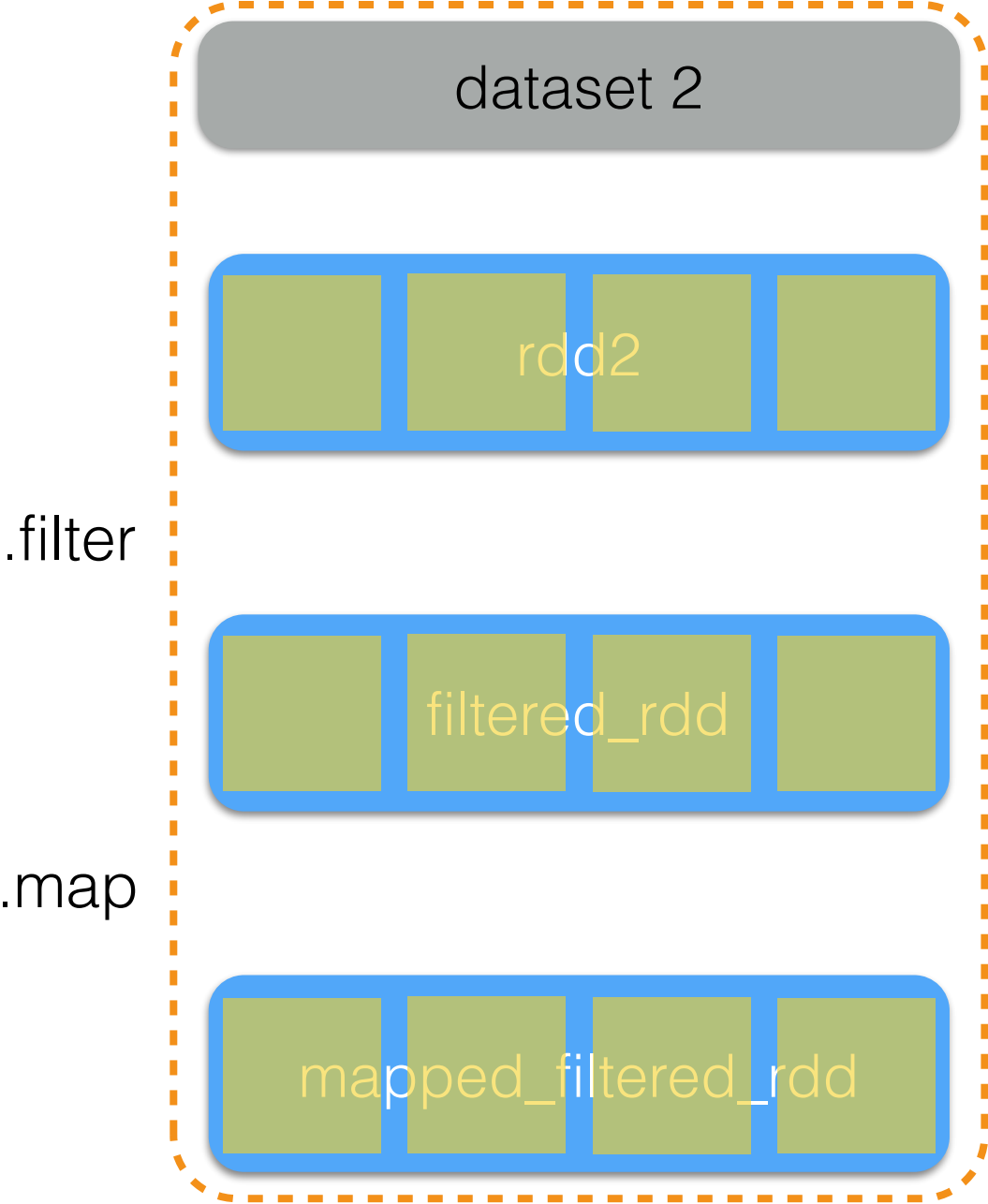


Run Data Through DAG



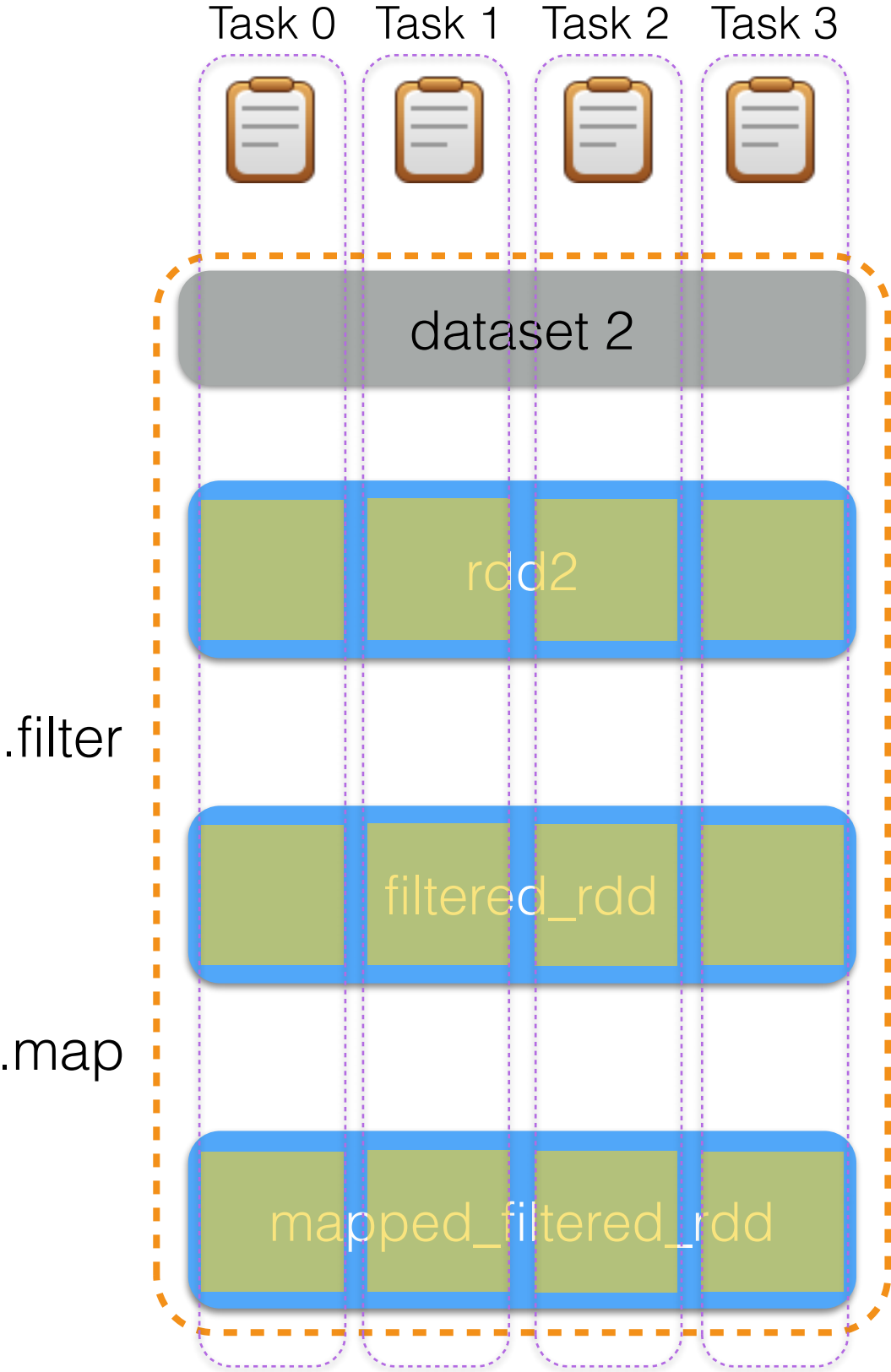
Data flow Through a Stage

Stage 0



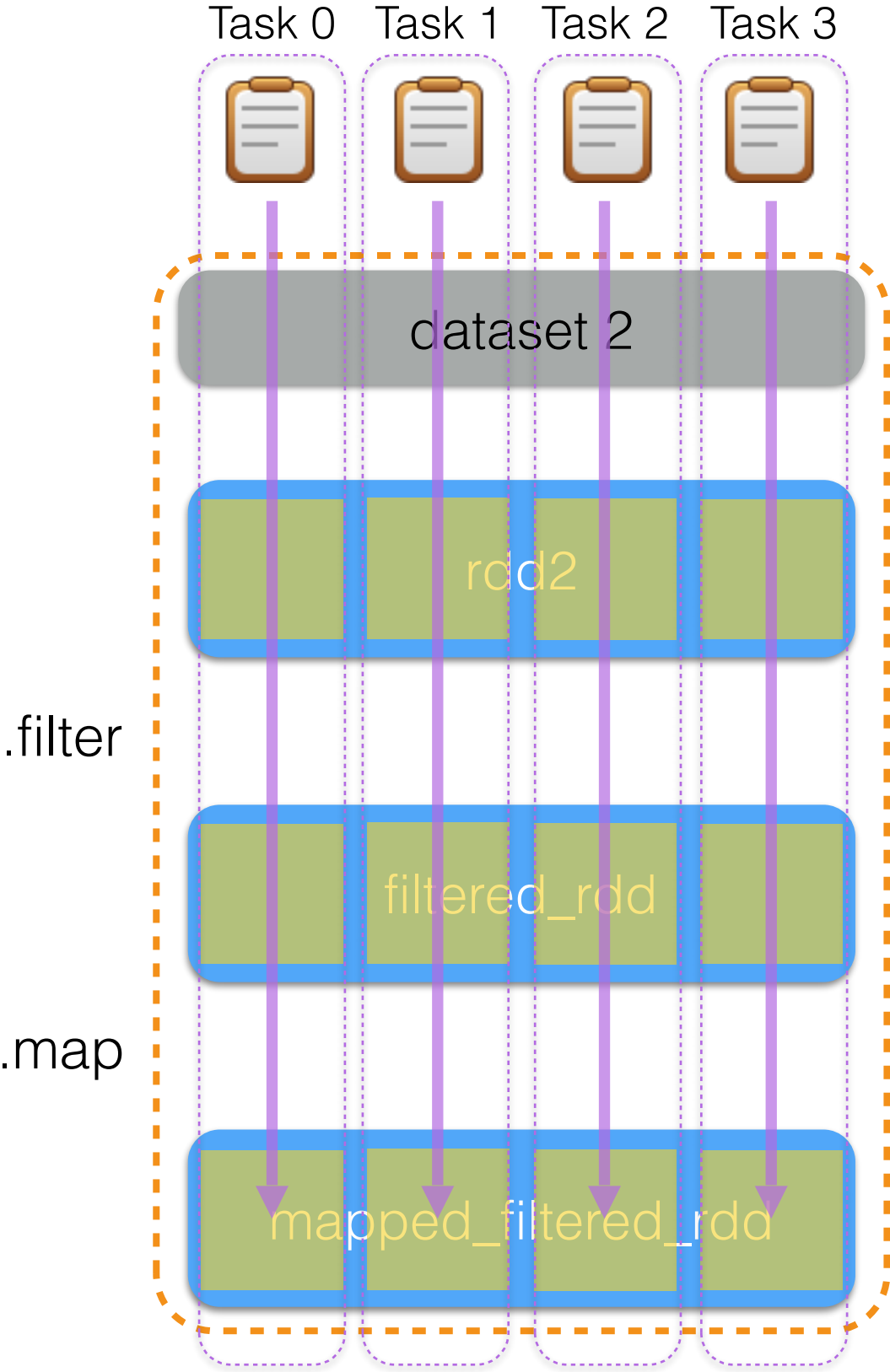
Data flow Through a Stage

Stage 0



Data flow Through a Stage

Stage 0



Jobs, Stages and Tasks

Jobs, Stages, Tasks

- Jobs are triggered by Actions
- Jobs are composed of one or more Stages
- Stages are composed of one or more Tasks

Jobs, Stages, Tasks

- Jobs are triggered by Actions
- Jobs are composed of one or more Stages
- Stages are composed of one or more Tasks

Job

ACTIONS

.collect()

.take()

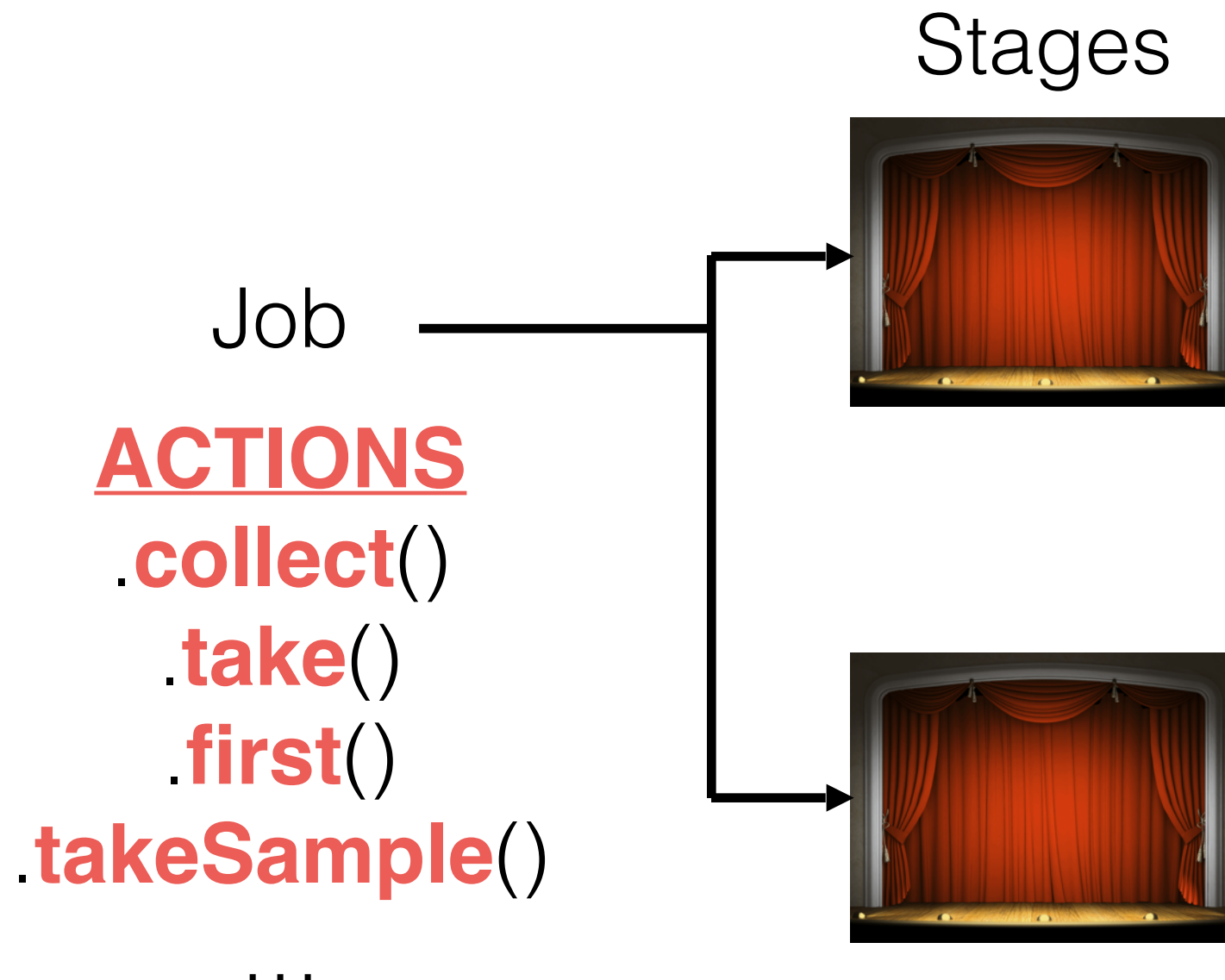
.first()

.takeSample()

...

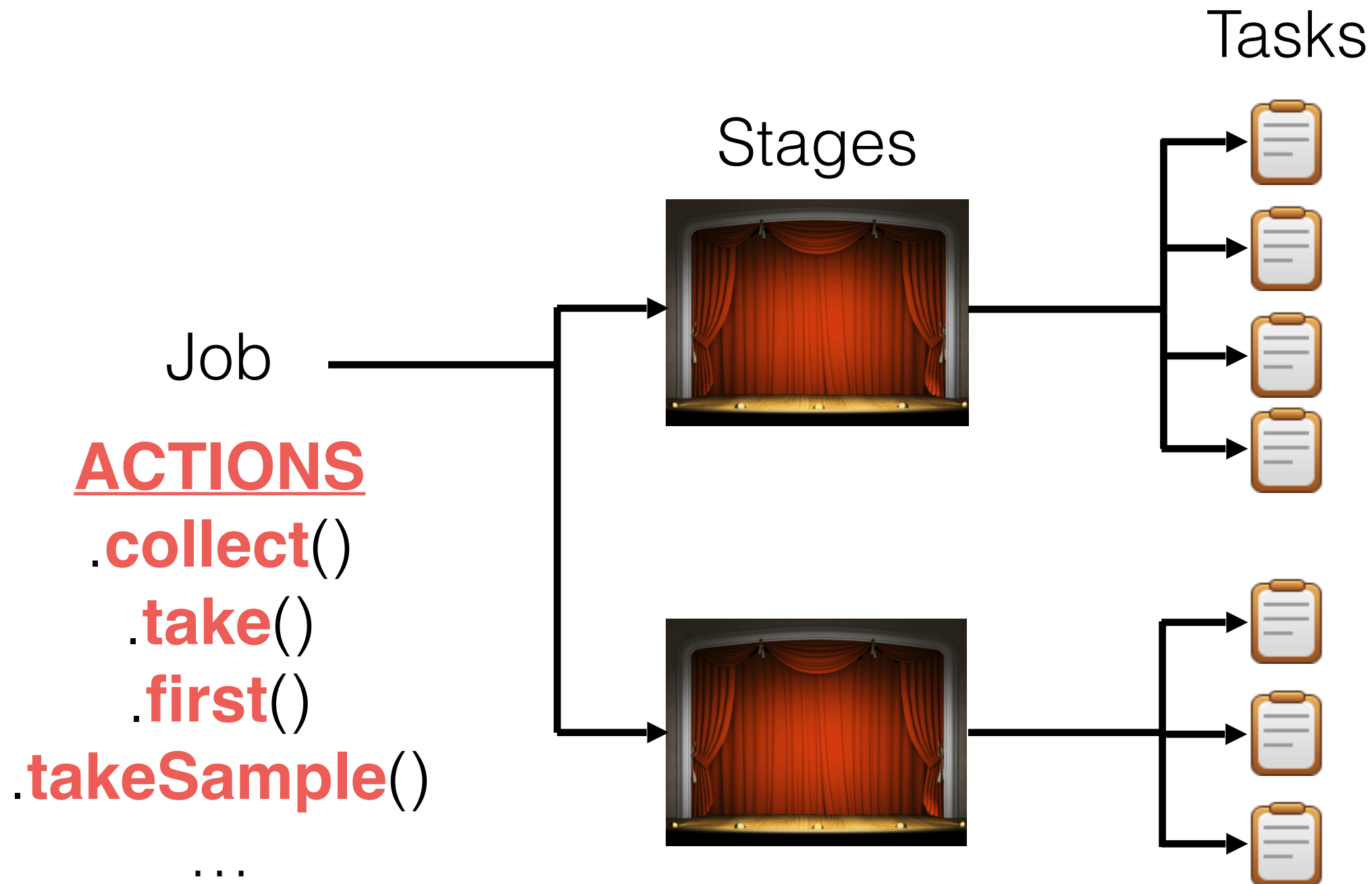
Jobs, Stages, Tasks

- Jobs are triggered by Actions
- Jobs are composed of one or more Stages
- Stages are composed of one or more Tasks



Jobs, Stages, Tasks

- Jobs are triggered by Actions
- Jobs are composed of one or more Stages
- Stages are composed of one or more Tasks



Ways to Run Spark

Local

Standalone

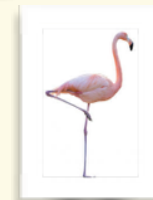
YARN

Mesos

Ways to Run Spark

Static
Resource
Management

Local
Standalone



YARN

Mesos

Dynamic
Resource
Management

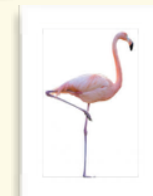
Ways to Run Spark

Static
Resource
Management

Local



Standalone



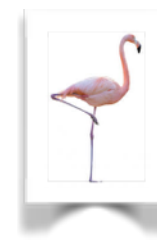
YARN



Mesos

Dynamic
Resource
Management

Standalone Mode



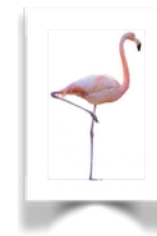
Master

Worker

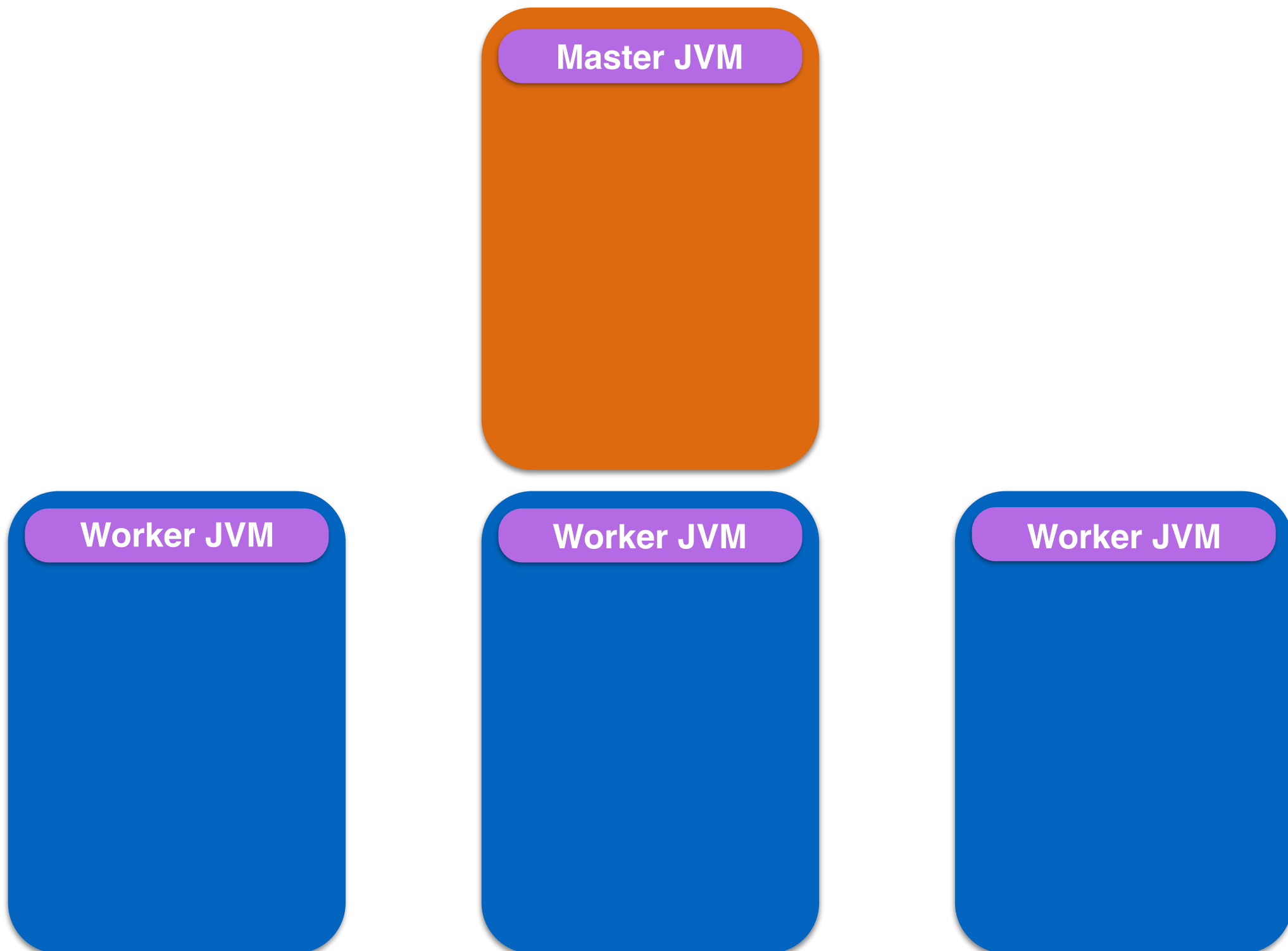
Worker

Worker

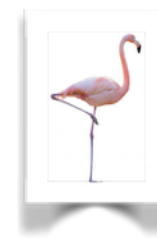
Standalone Mode



`$SPARK_HOME/sbin/start-all.sh`

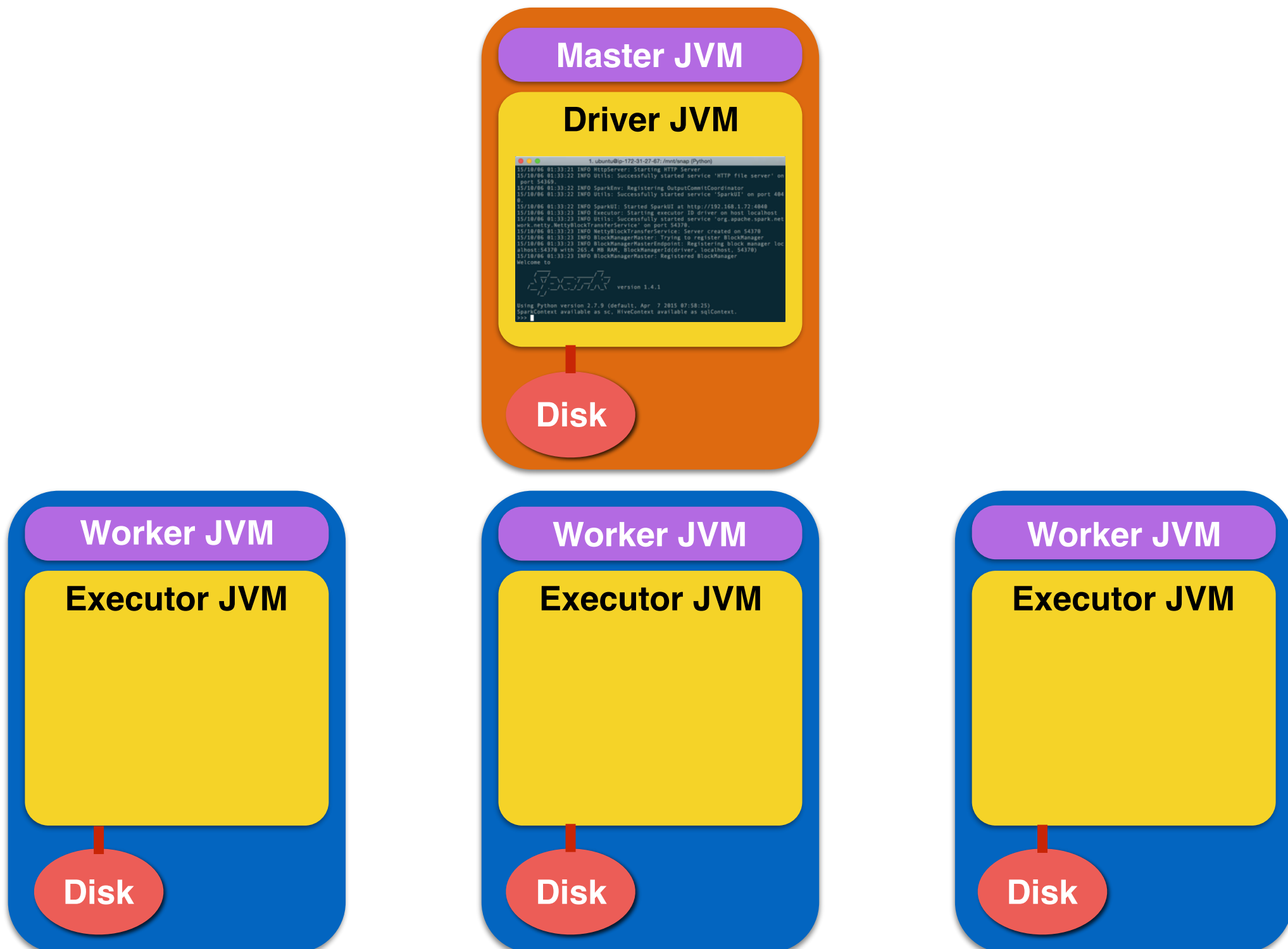


Standalone Mode

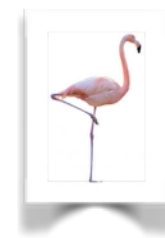


pyspark --master [spark://master_hostname:7077](#)

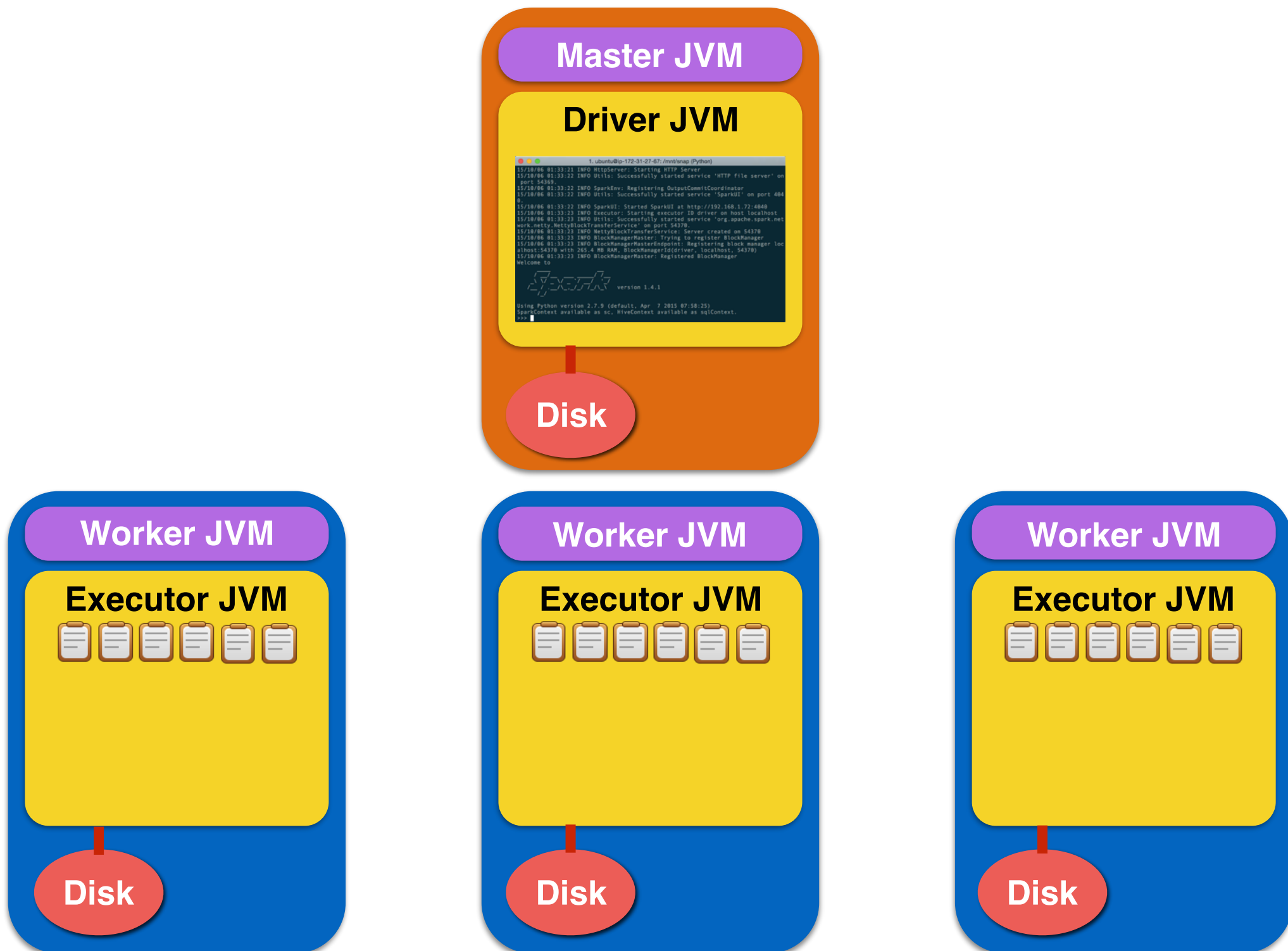
spark-shell --master [spark://master_hostname:7077](#)



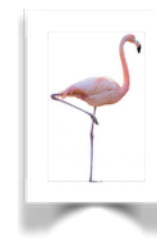
Standalone Mode



```
$SPARK_HOME/conf/spark-env.sh  
export SPARK_WORKER_CORES=6
```



Standalone Mode



Parallelism with multiple partitions in RDD



Spark DataFrames and Spark SQL

DataFrames and Spark SQL

RDD

```
(1420589581, CEC023AA, 40712)  
(1436660661, 175AB332, 60813)  
(1469828518, 407BA6EF, 70179)  
...
```

DataFrame

```
Row(timestamp=1420589581, uid=CEC023AA, zip=40712)  
Row(timestamp=1436660661, uid=175AB332, zip=60813)  
Row(timestamp=1469828518, uid=407BA6EF, zip=70179)  
...
```

DataFrames and Spark SQL

DataFrame

df

```
Row(timestamp=1420589581, uid=CEC023AA, zip=40712)
Row(timestamp=1436660661, uid=175AB332, zip=60813)
Row(timestamp=1469828518, uid=407BA6EF, zip=70179)
...
```

```
zip_grouped_DF = df.select("zip", "uid") \
    .distinct() \
    .groupBy("zip") \
    .count() \
    .withColumnRenamed("count", "unique_users") \
    .orderBy("unique_users")
```

DataFrames and Spark SQL

DataFrame

df

```
Row(timestamp=1420589581, uid=CEC023AA, zip=40712)
Row(timestamp=1436660661, uid=175AB332, zip=60813)
Row(timestamp=1469828518, uid=407BA6EF, zip=70179)
...
```

```
df.registerTempTable("my_table")

zip_grouped_DF = sqlContext.sql("""
    SELECT zip, COUNT(DISTINCT uid) as unique_users
    FROM my_table
    GROUP BY zip
    ORDER BY unique_users
    """)
```

Machine Learning on Spark

Differences between MLlib and ML Pipeline

MLlib

Inputs/Outputs
are
RDDs

Pros: Many available APIs for distributed ML processing

Cons: Must massage RDDs to fit specifically the input requirements of APIs

ML Pipeline

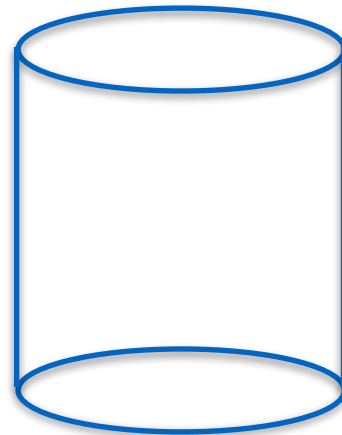
Inputs/Outputs
are
DataFrames

Pros: High level API to help with fast iterations on ML data processing

Cons: Can be less flexible in some cases

ML Pipeline Concepts

- **DataFrame**
- Transformer
- Estimator
- Pipeline



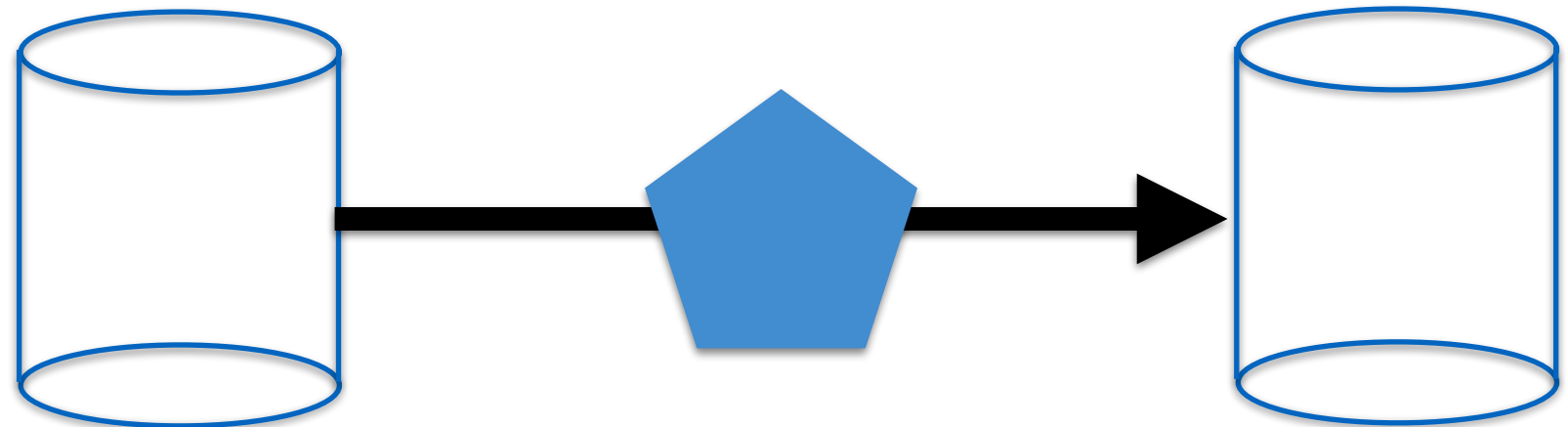
```
Row (f1=..., f2=..., f3=...)  
Row (f1=..., f2=..., f3=...)  
Row (f1=..., f2=..., f3=...)  
...
```

```
Row (f1=    f2=    f3= )
```


ML Pipeline Concepts

- DataFrame
- **Transformer**
- Estimator
- Pipeline

Transformer

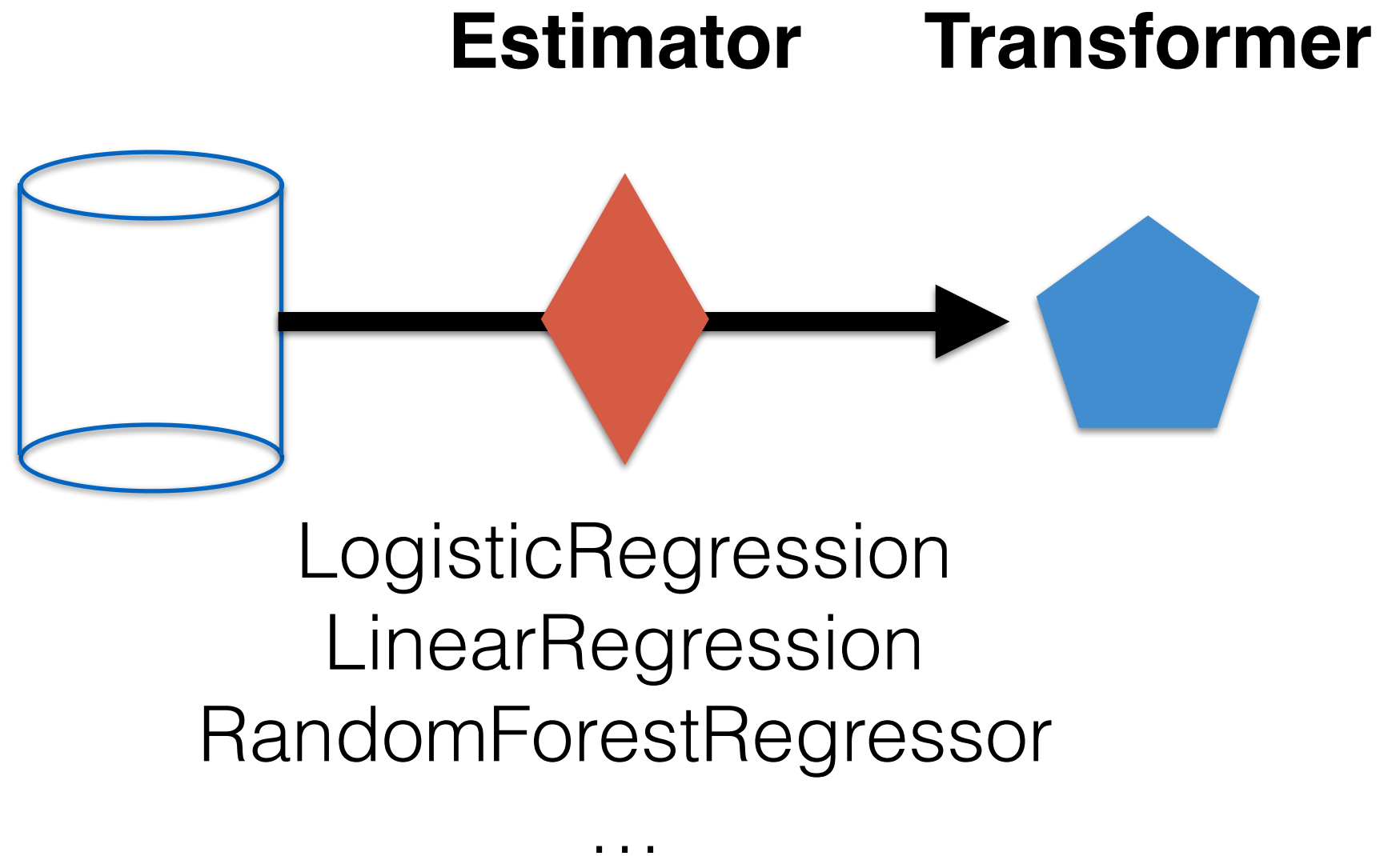


Tokenizer
Binarizer
Word2Vec

...

ML Pipeline Concepts




- DataFrame
- Transformer
- **Estimator**
- Pipeline



ML Pipeline Concepts

- DataFrame
- Transformer
- Estimator
- **Pipeline**

Pipeline is an Estimator 

pipeline = Pipeline([ ,  ,  **])**

Tokenizer 

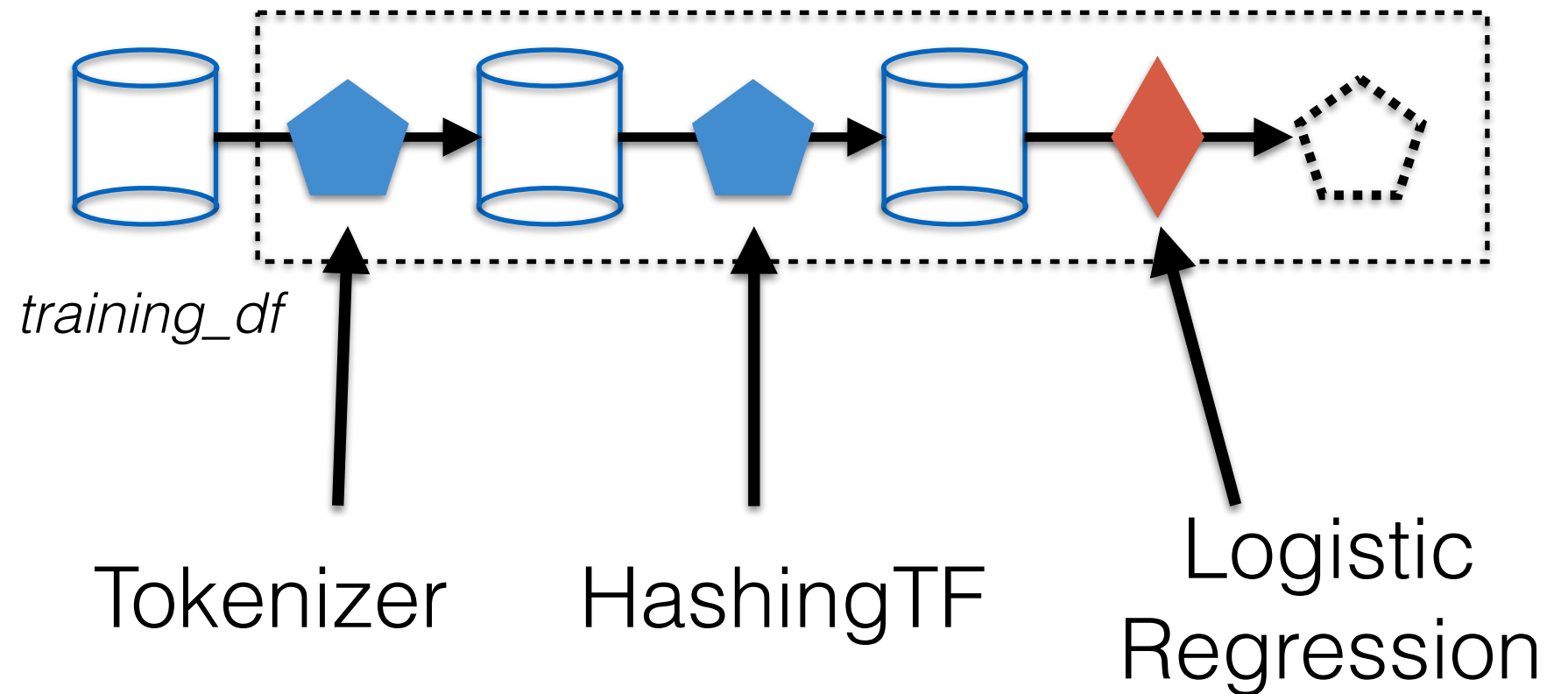
HashingTF 

Logistic
Regression 

ML Pipeline Concepts

- DataFrame
- Transformer
- Estimator
- **Pipeline**

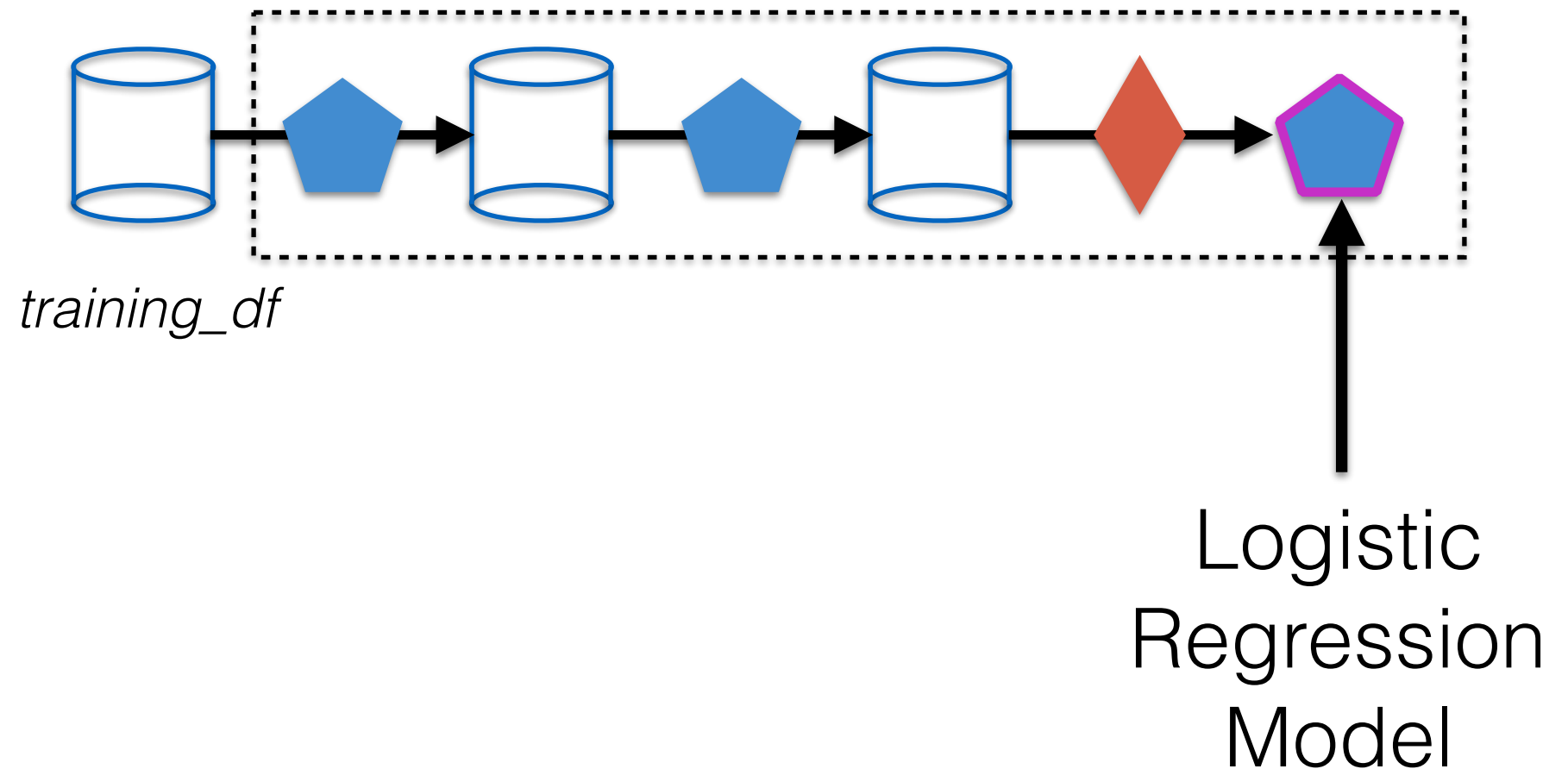
model = Pipeline.fit(training_df)



ML Pipeline Concepts

- DataFrame
- Transformer
- Estimator
- **Pipeline**

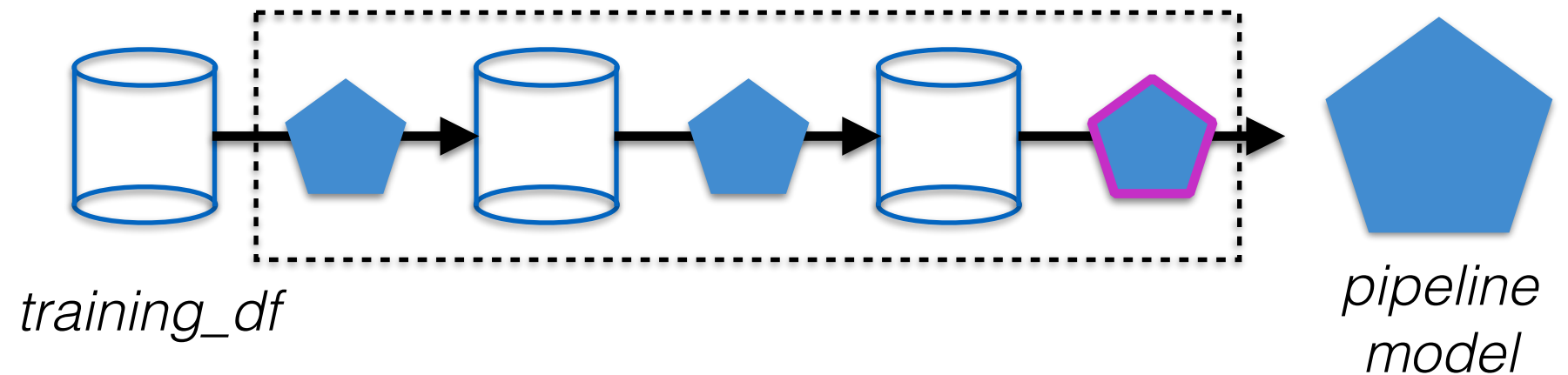
model = Pipeline.fit(training_df)



ML Pipeline Concepts

- DataFrame
- Transformer
- Estimator
- **Pipeline**

model = Pipeline.fit(training_df)



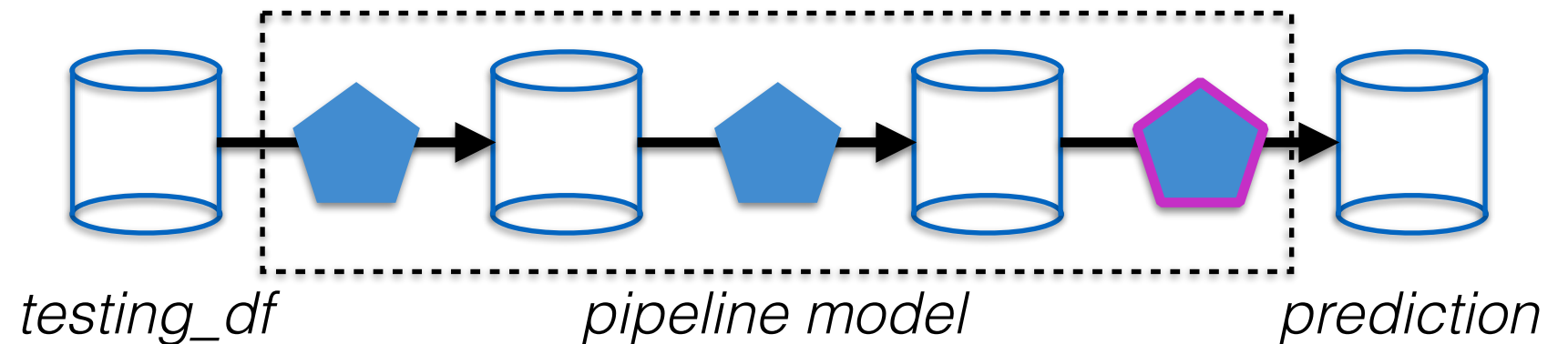
The output of the pipeline fit is a model which is a Transformer



ML Pipeline Concepts

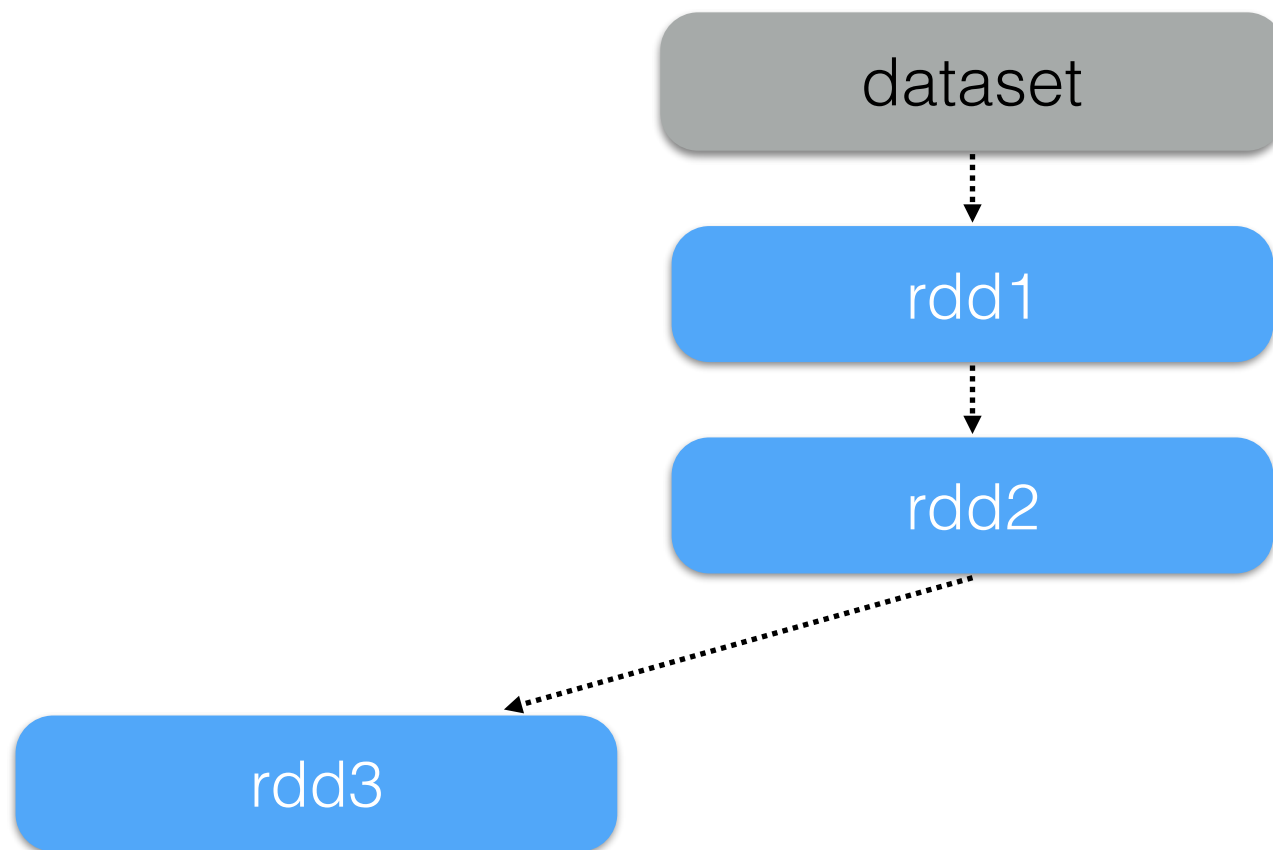
prediction = model.transform(testing_df)

- DataFrame
- Transformer
- Estimator
- **Pipeline**

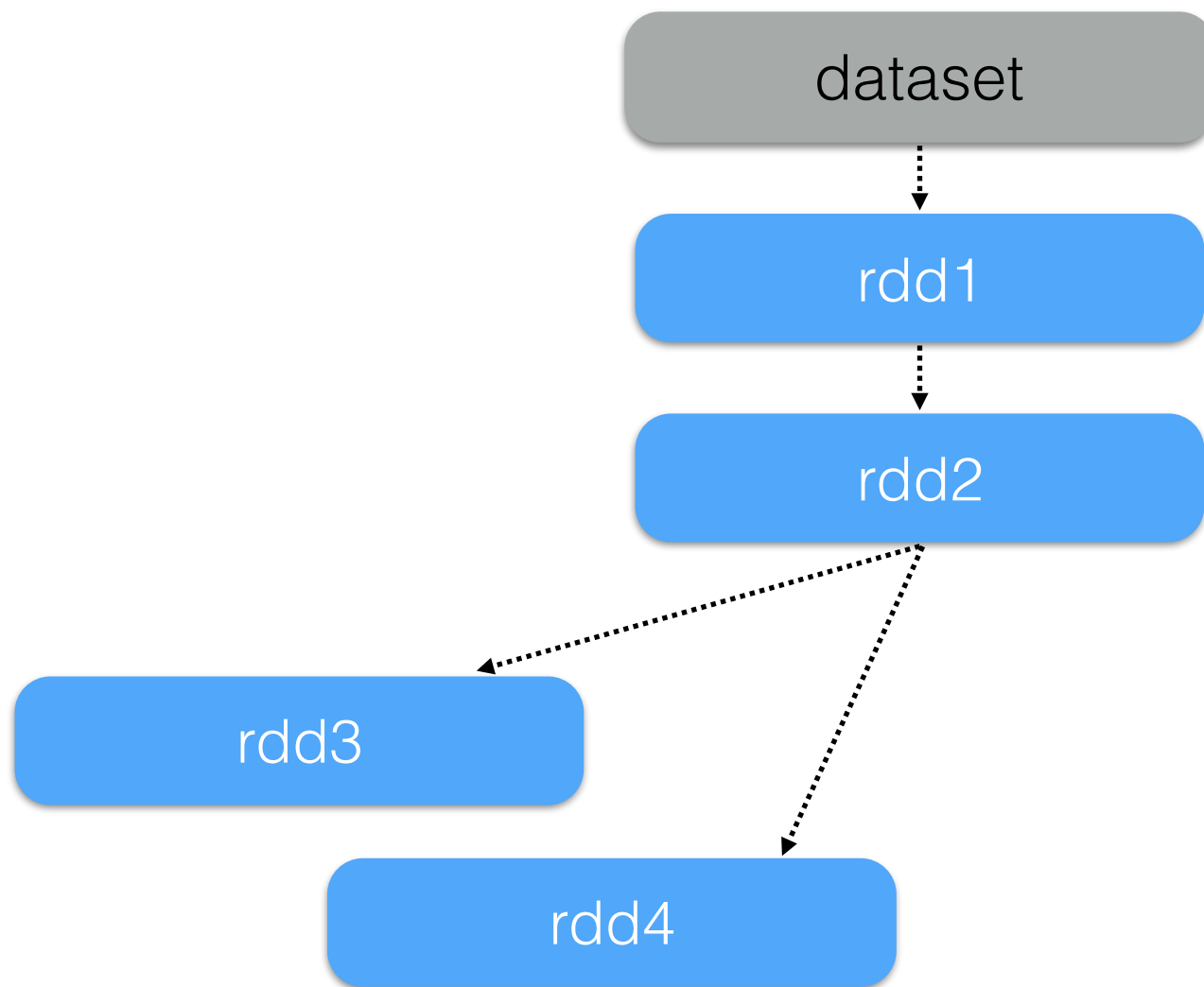


Spark Tuning

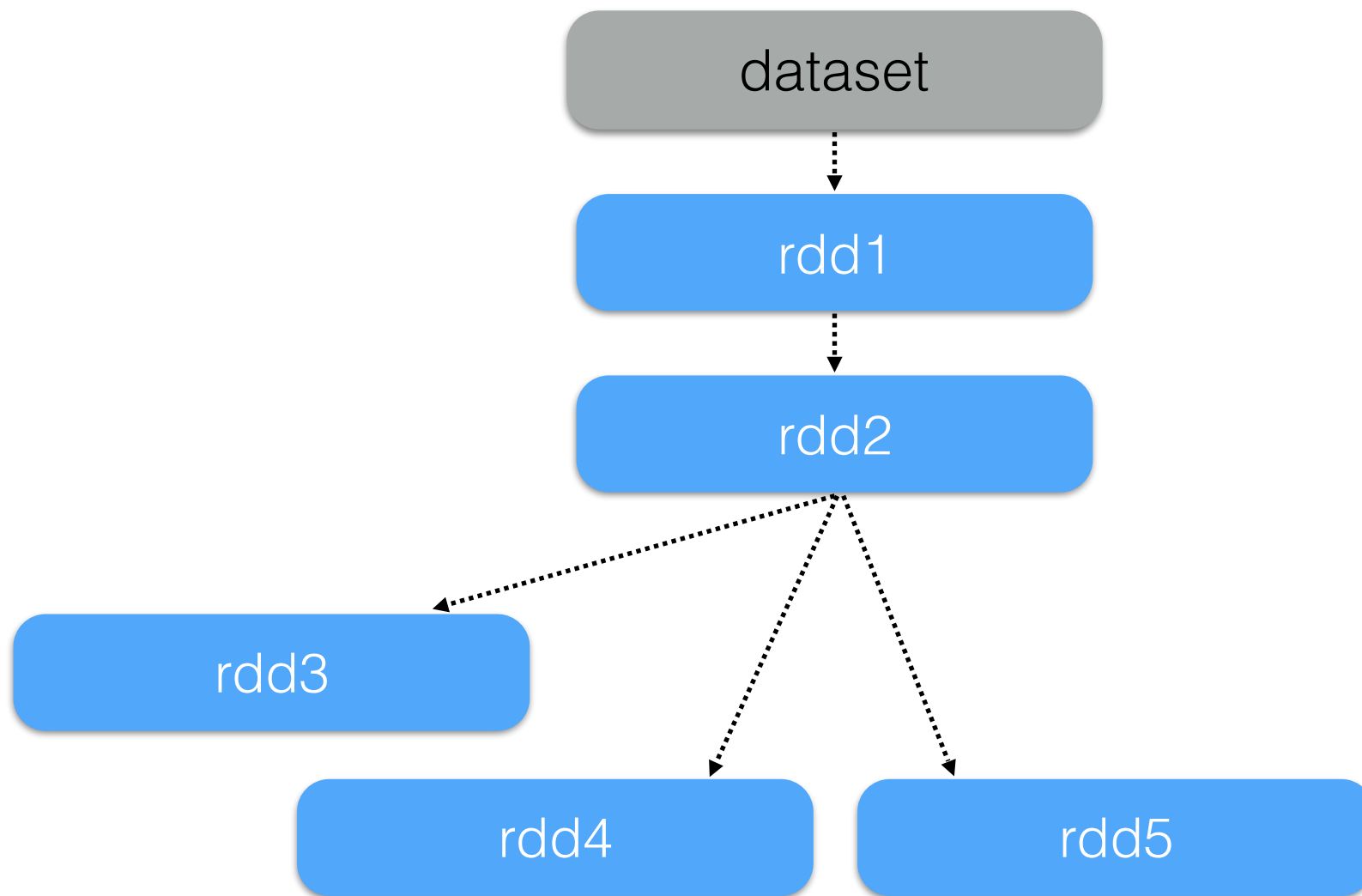
Persistence and Caching



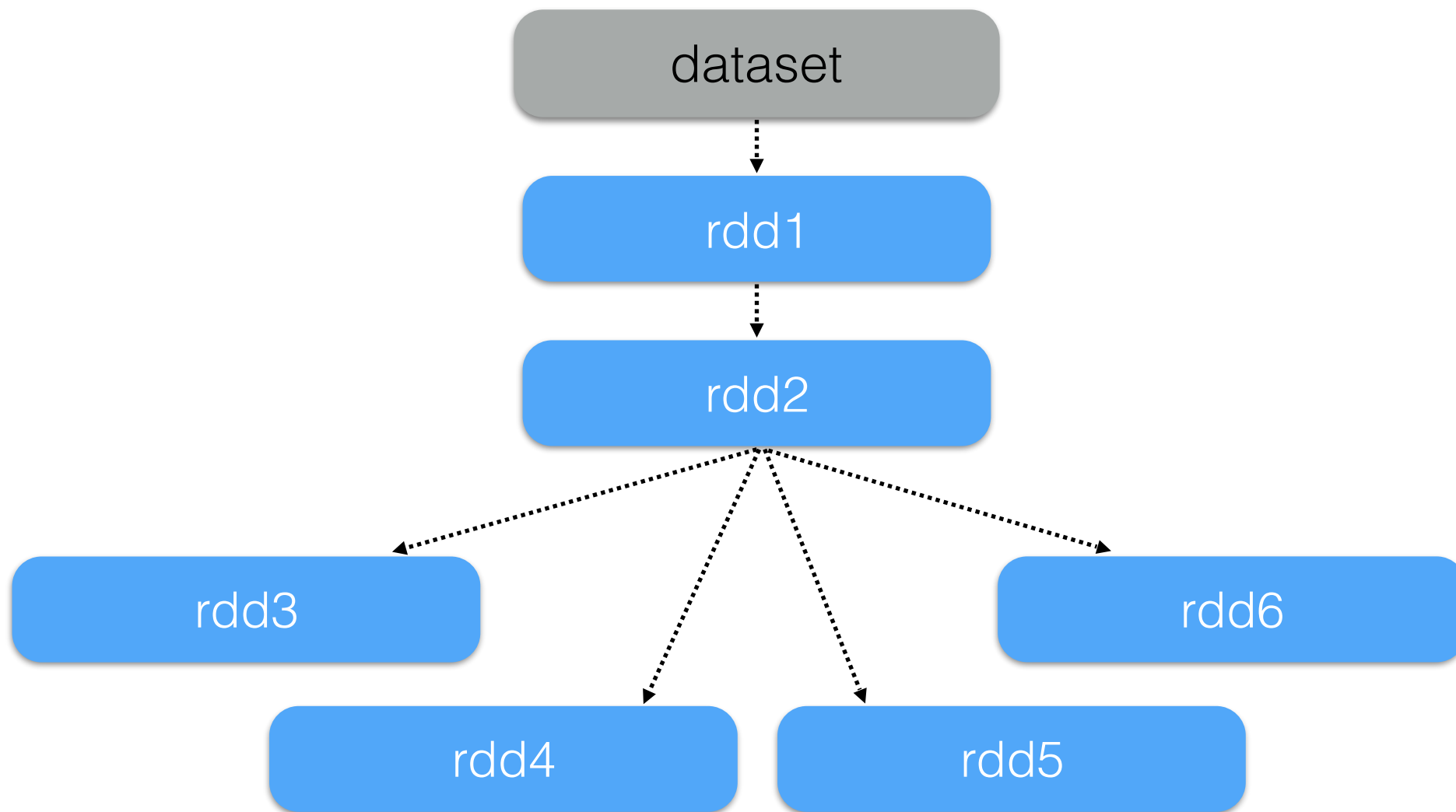
Persistence and Caching



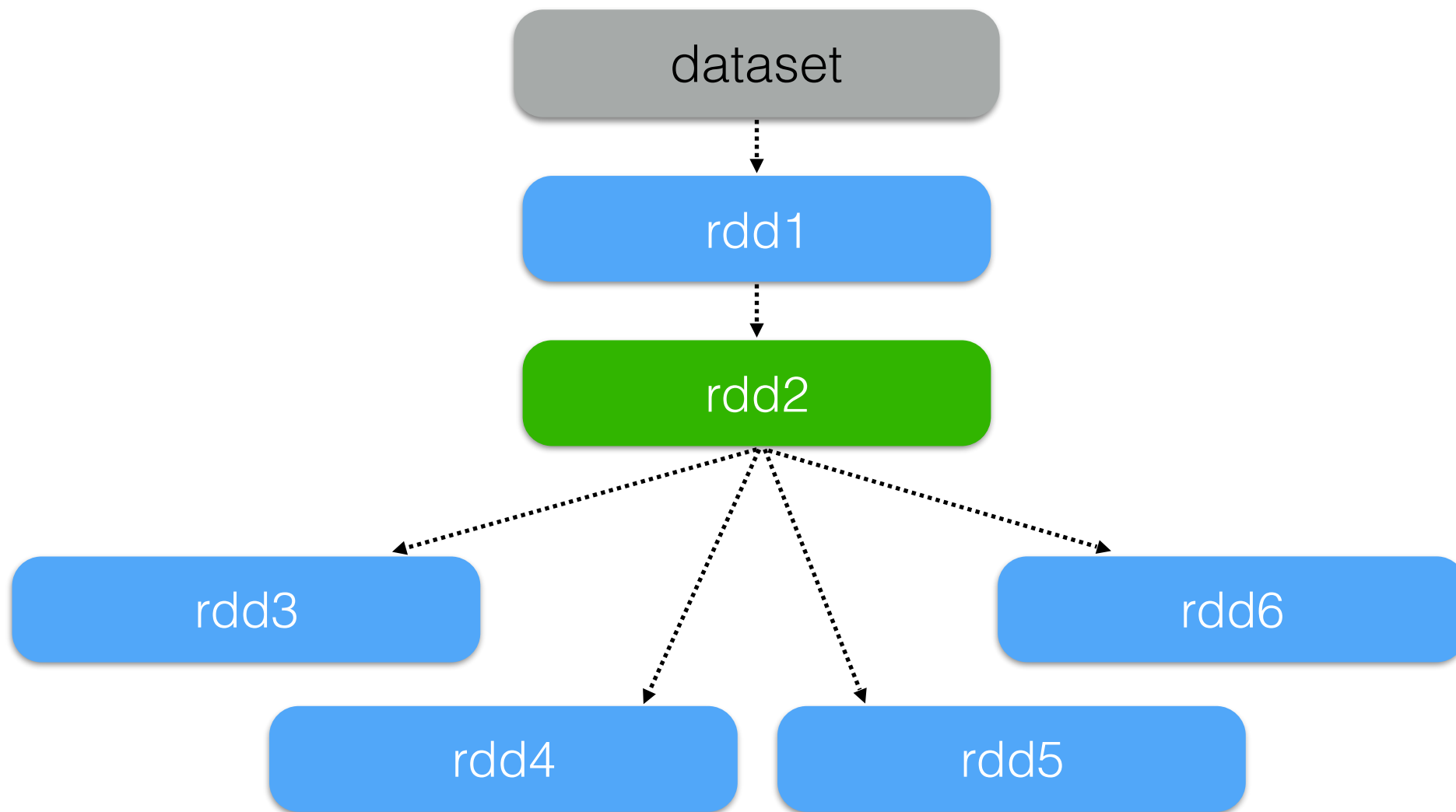
Persistence and Caching



Persistence and Caching



Persistence and Caching



Persistence and Caching

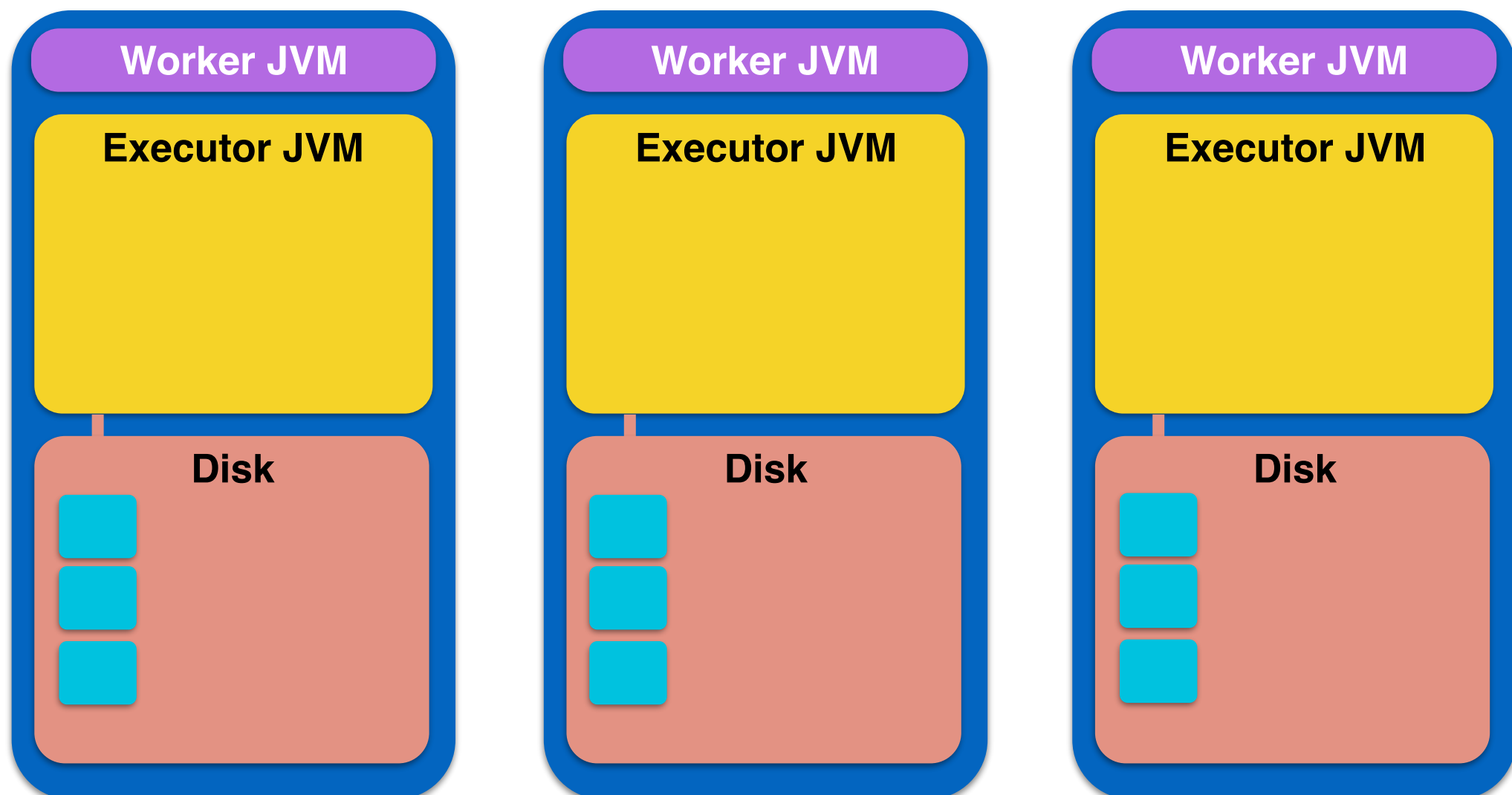
General Options for Persisting

disk only - Always Serialized
memory and disk - Spill to disk when memory is full Ser/De
memory only - Same as calling .cache() Ser/De
off heap - Tachyon Storage System

Persistence and Caching

General Options for Persisting

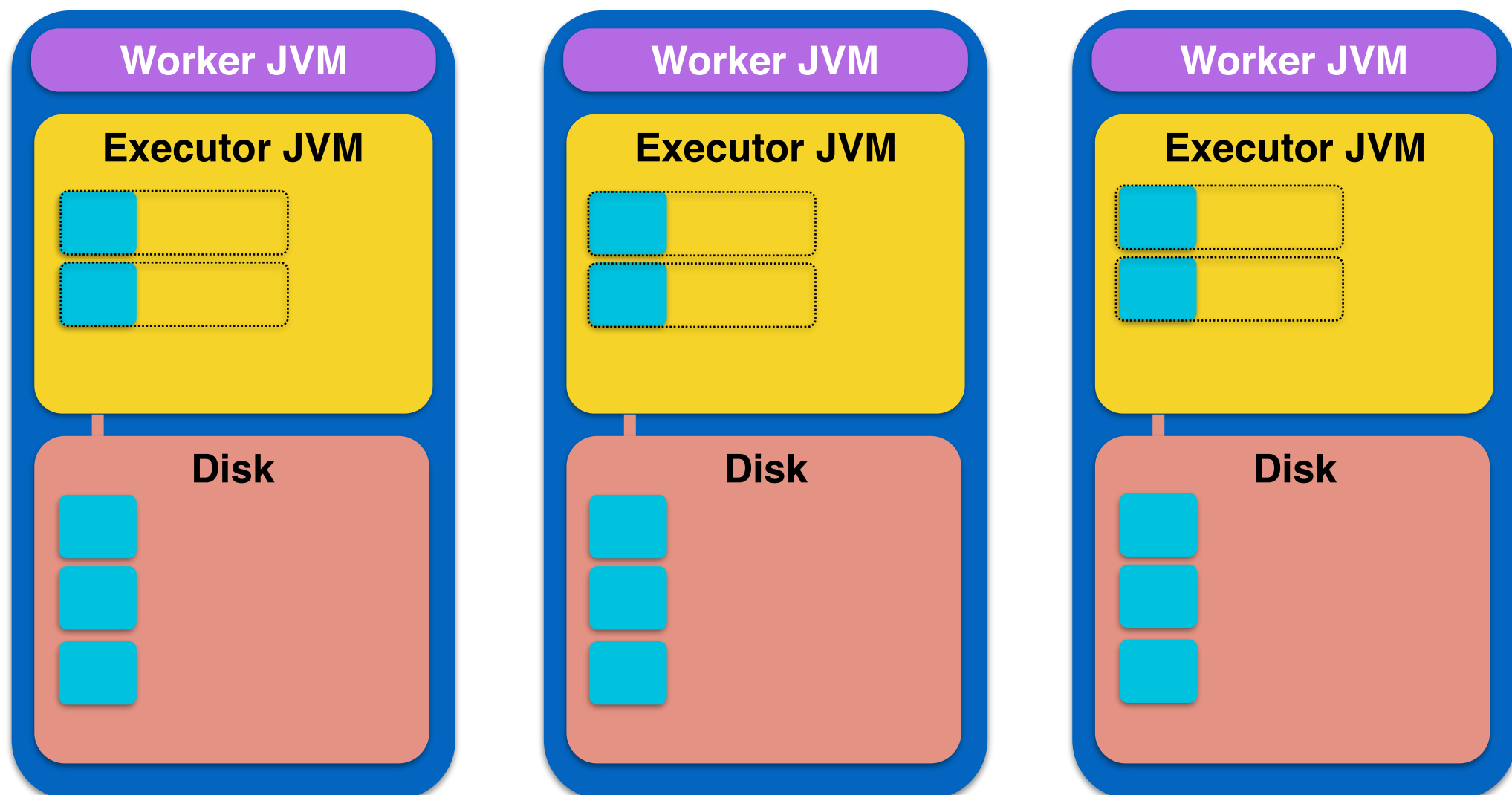
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Persistence and Caching

General Options for Persisting

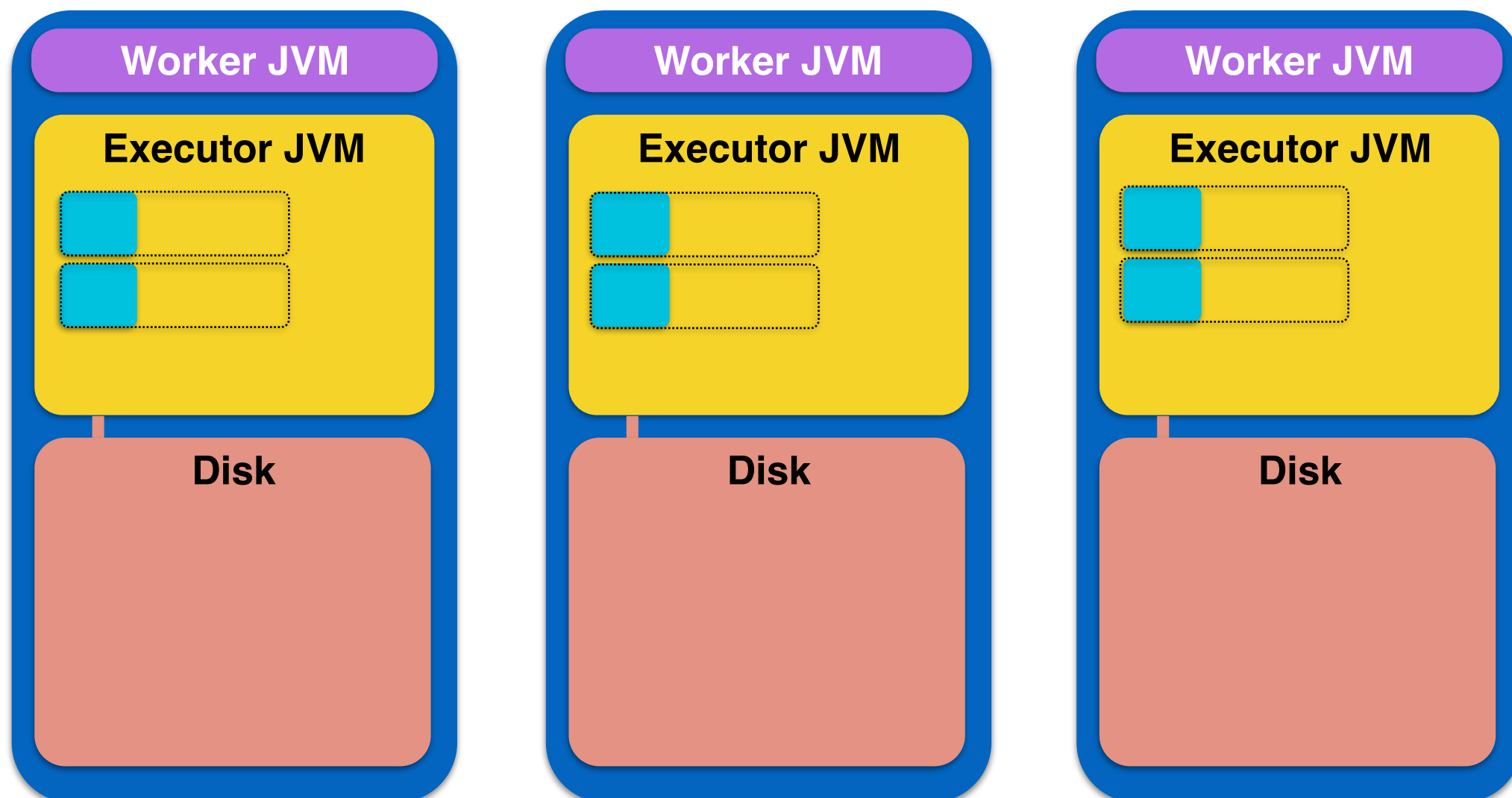
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Persistence and Caching

General Options for Persisting

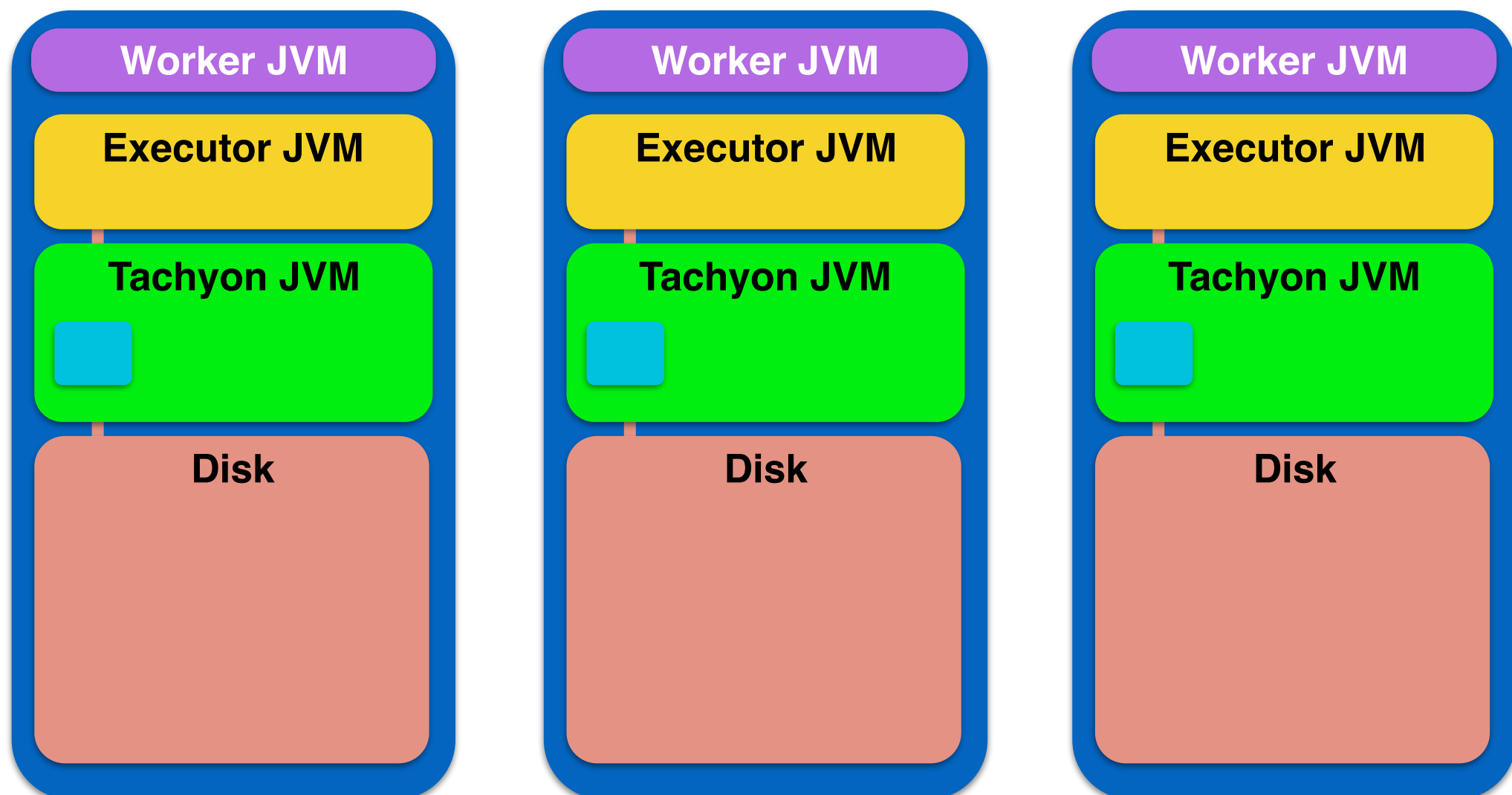
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Persistence and Caching

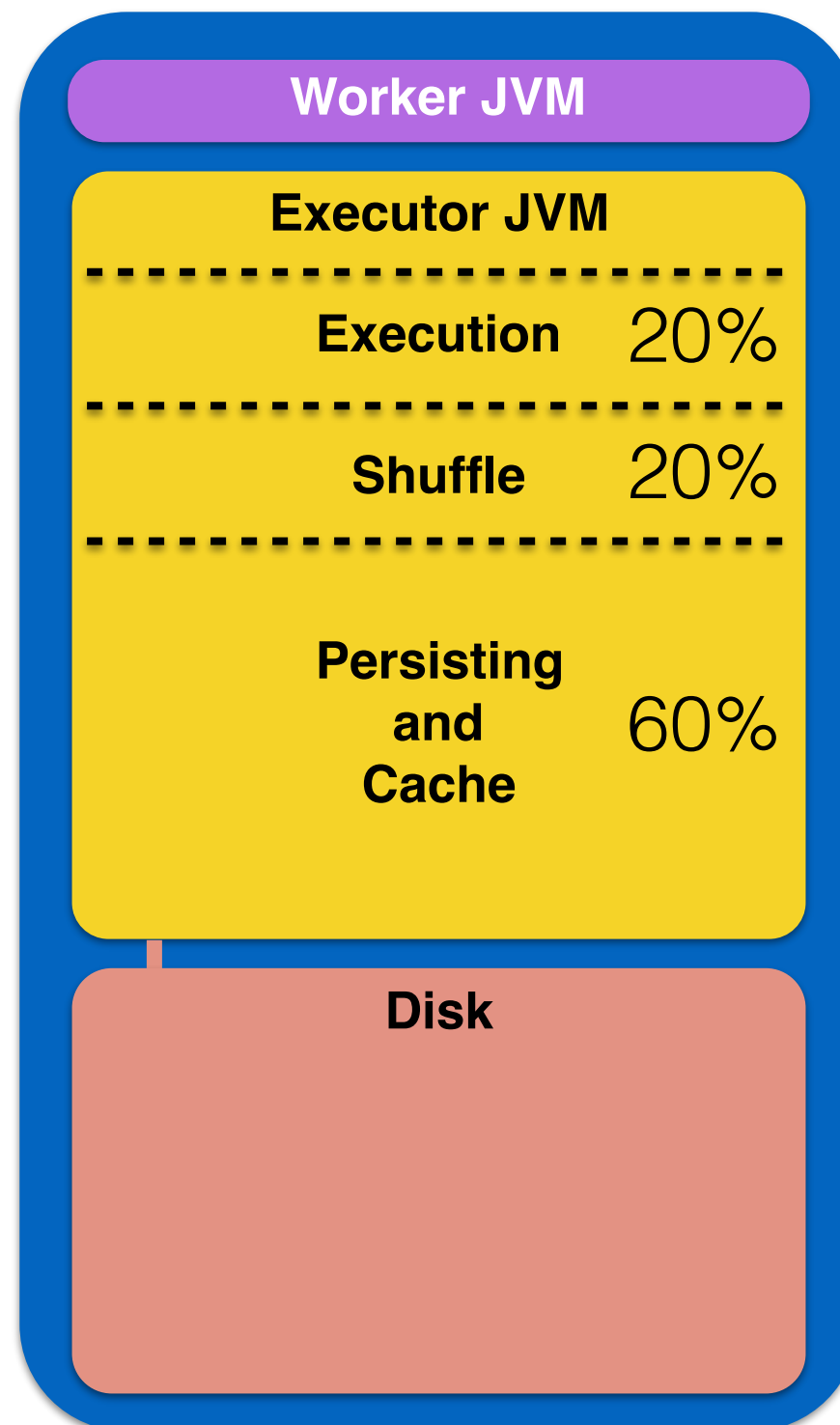
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Persistence and Caching

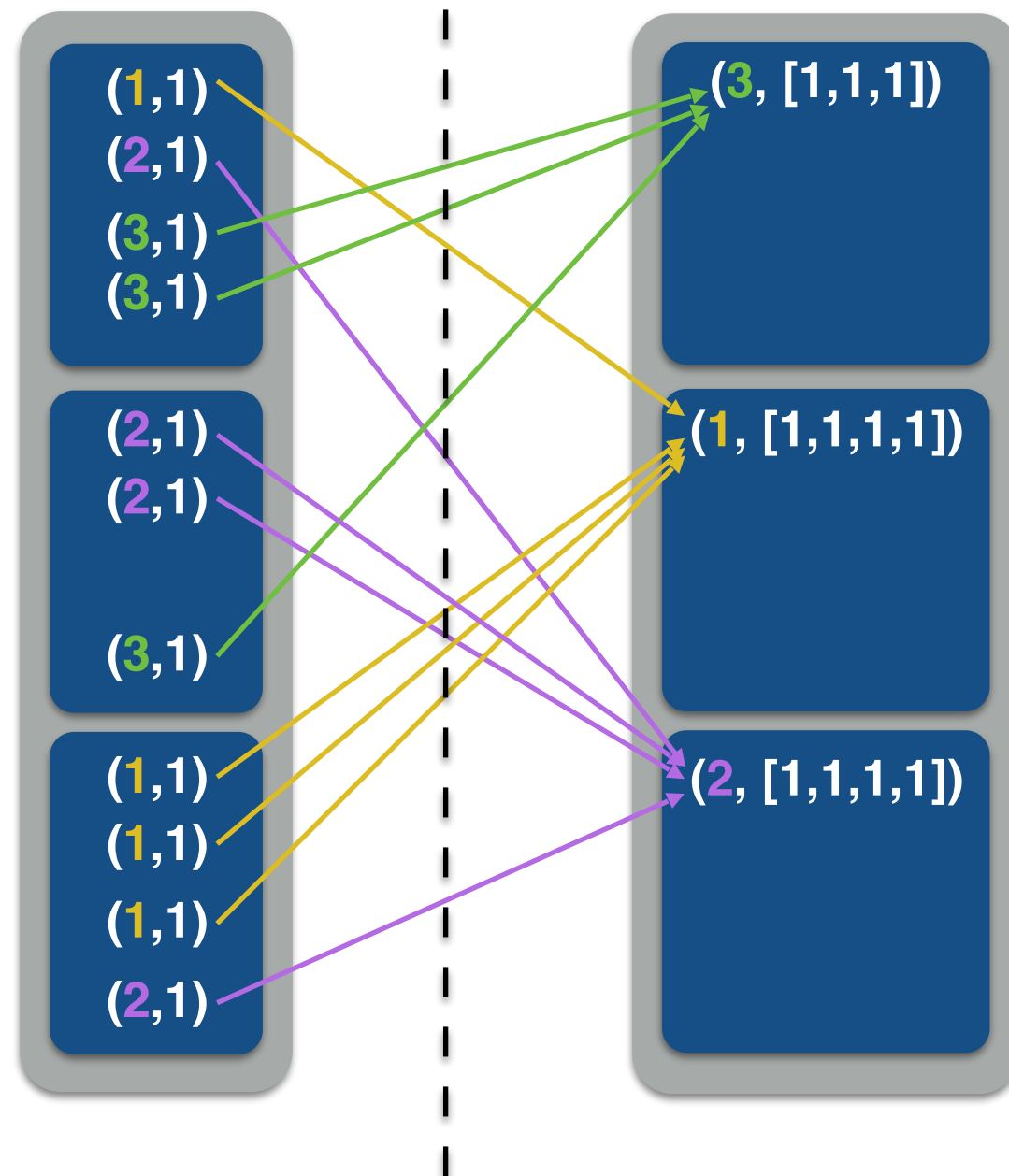
Default Split of the Executor JVM



reduceByKey vs groupByKey

.groupByKey()

Parent RDD Child RDD

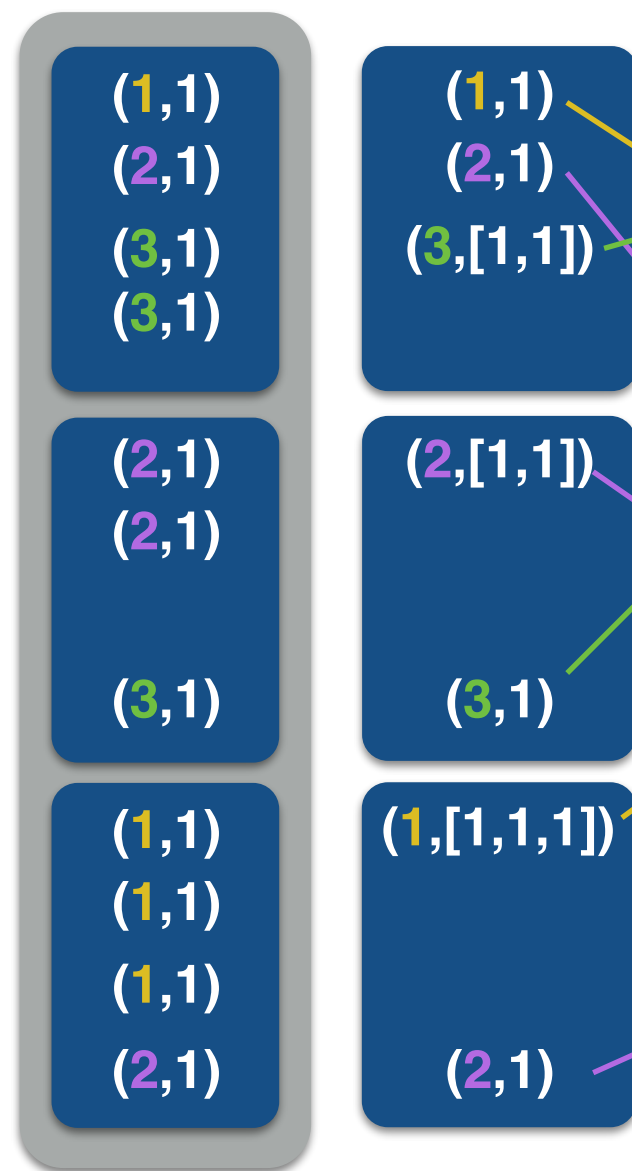


11 records
shuffled
across
network

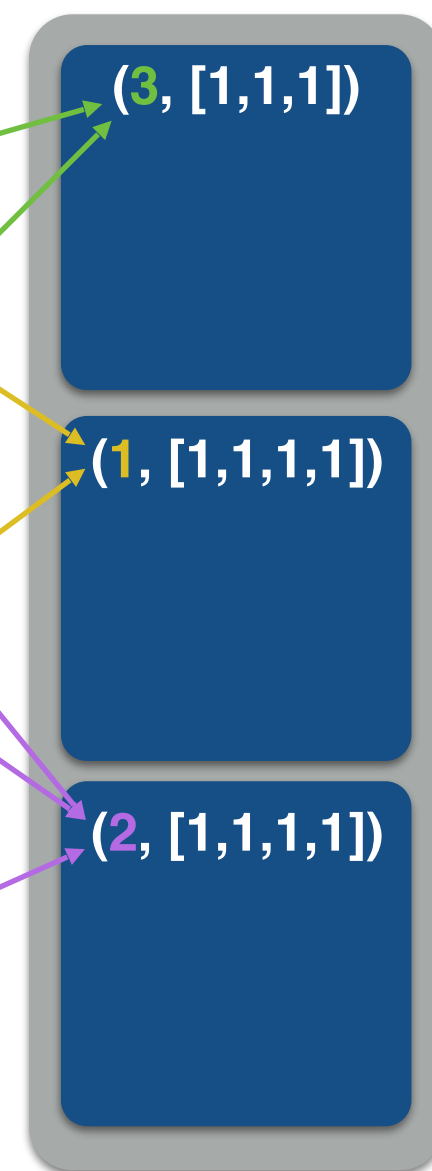
reduceByKey vs groupByKey

.reduceByKey()

Parent RDD



Child RDD



7 records
shuffled
across
network