RDD (I)

- A **resilient distributed dataset** (RDD) is a distributed memory abstraction
- Immutable collection of objects spread across the cluster

RDD (I)

- A **resilient distributed dataset** (RDD) is a distributed memory abstraction
- Immutable collection of objects spread across the cluster

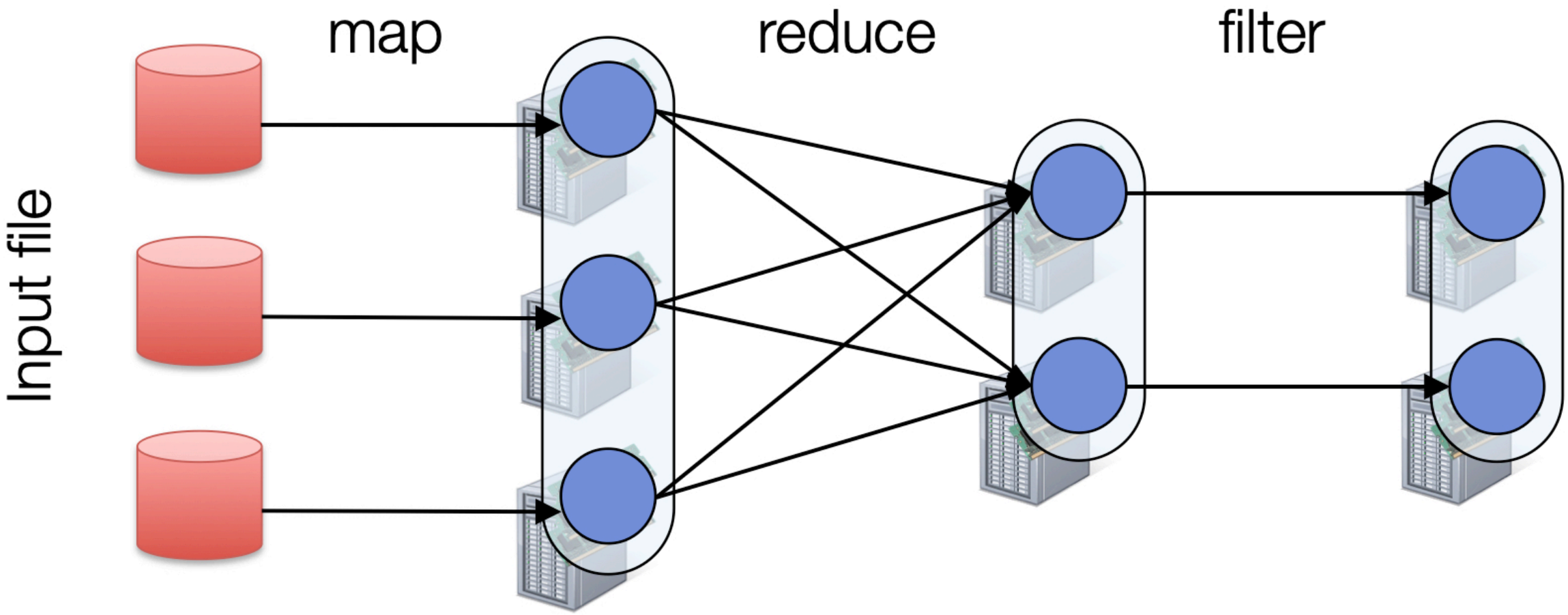
- An RDD is divided into a number of **partitions**, which are atomic pieces of information
- Partitions of an RDD can be stored on different nodes of a cluster

RDD (II)

- Collections of objects across a cluster with **user controlled partitioning & storage** (memory, disk, ...)
- Built via **parallel transformations** (`map`, `filter`, ...)
- The world only lets you make make RDDs such that **they can be automatically rebuilt on failure**

Lineage

```
file.map(lambda rec: (rec.type, 1))
    .reduceByKey(lambda x, y: x + y)
    .filter(lambda (type, count): count > 10)
```



- RDDs track **lineage** info to rebuild lost data

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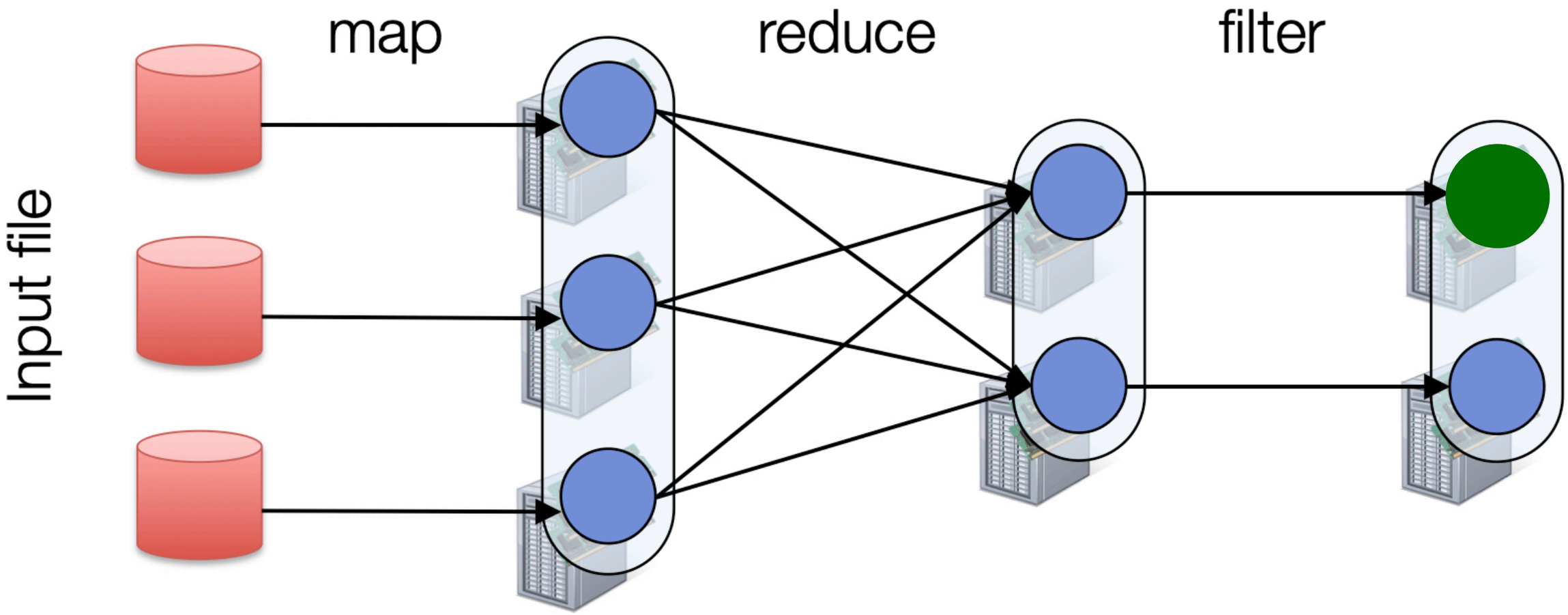

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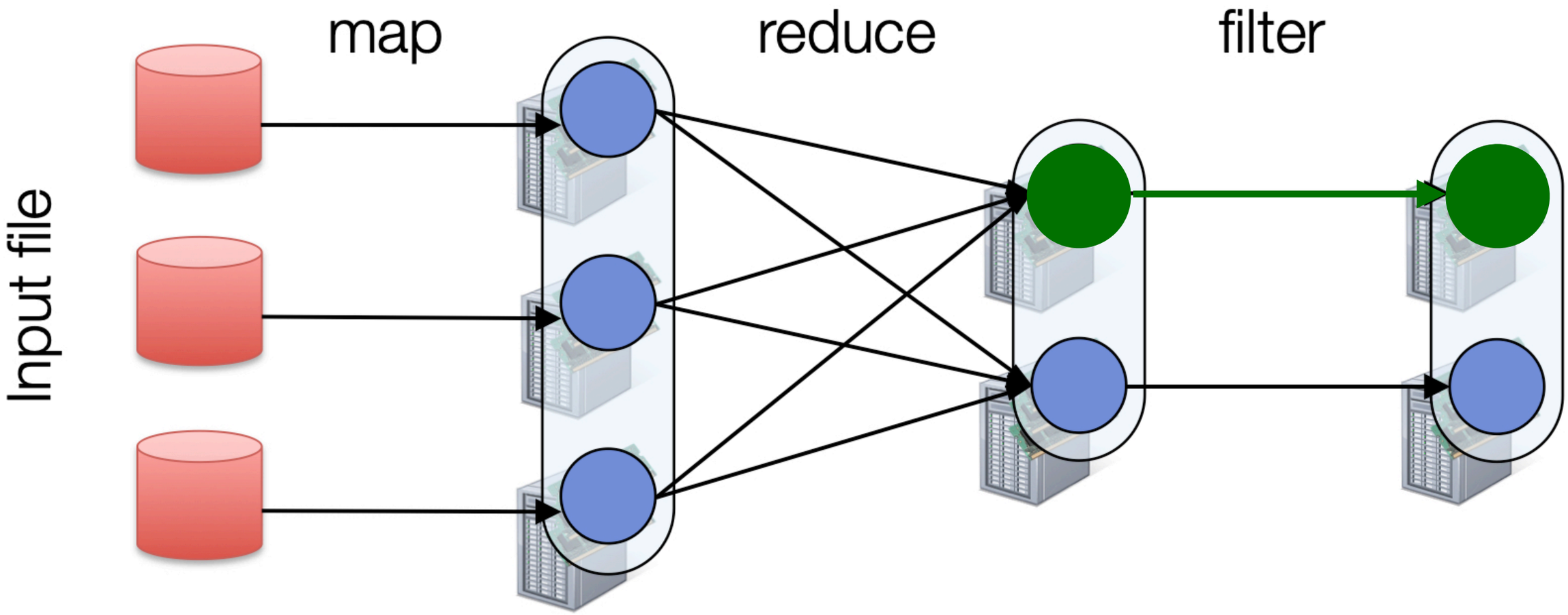

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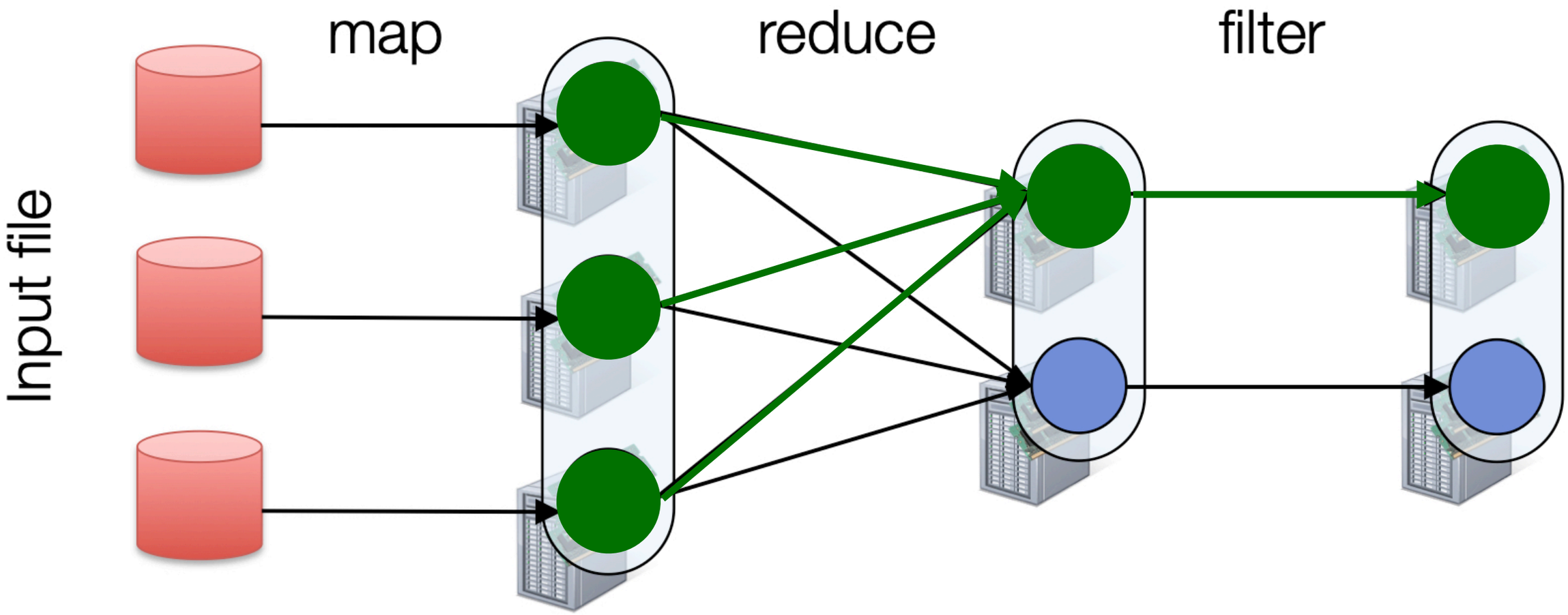

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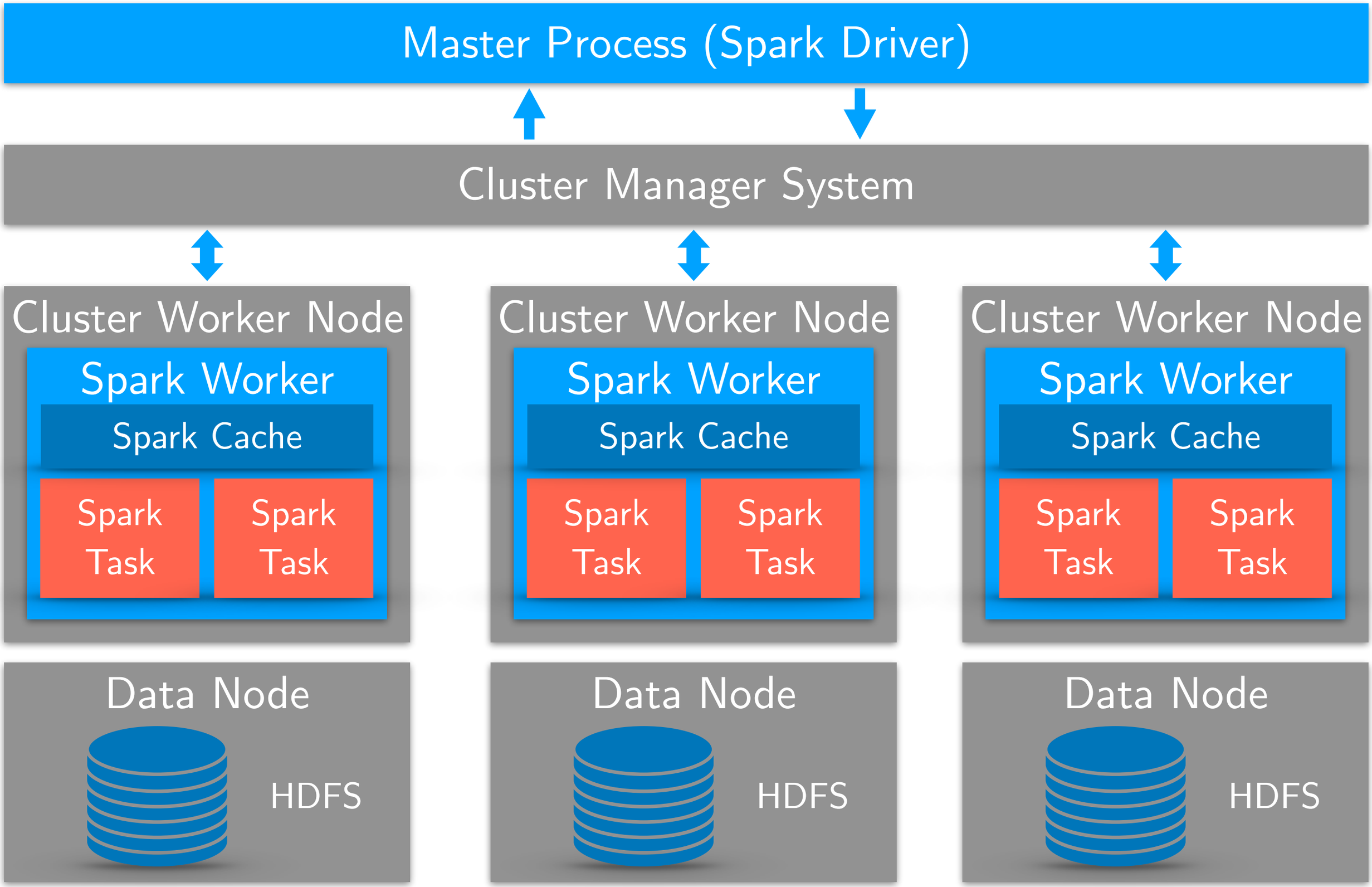
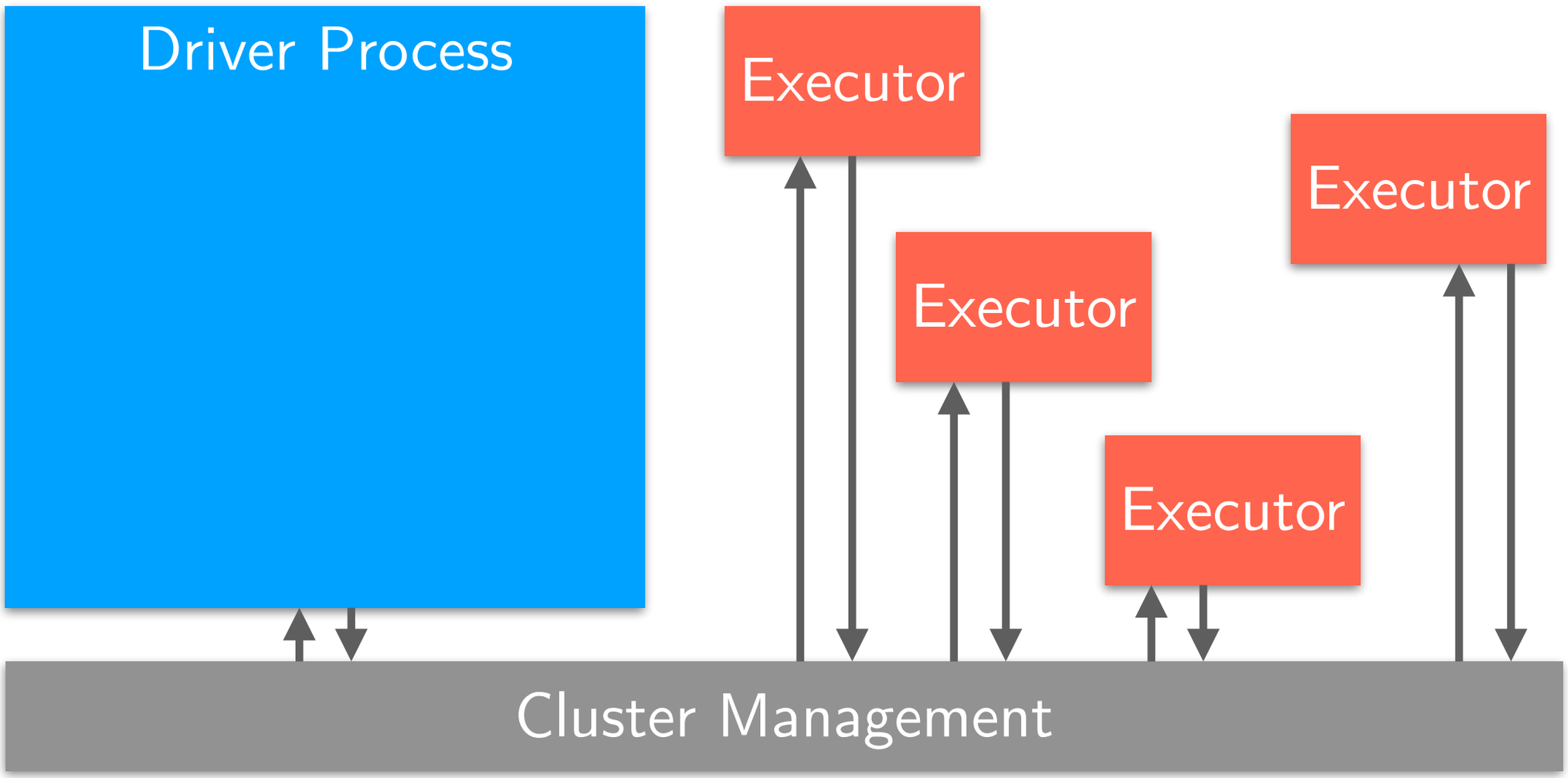
Spark Architecture



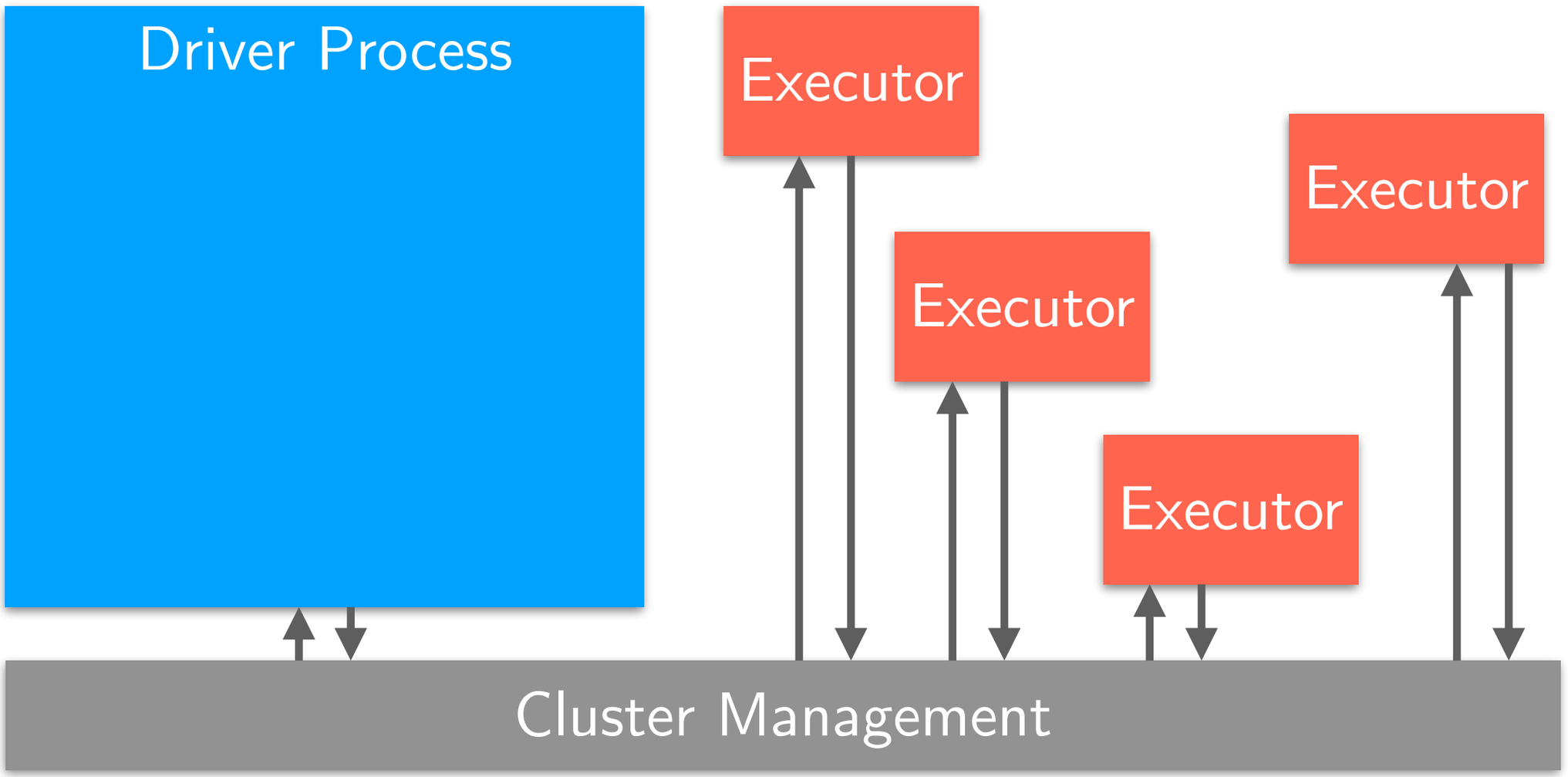
Spark Applications Architecture

- A **Spark application** consists of
  - a **driver** process
  - a **set of executor** processes



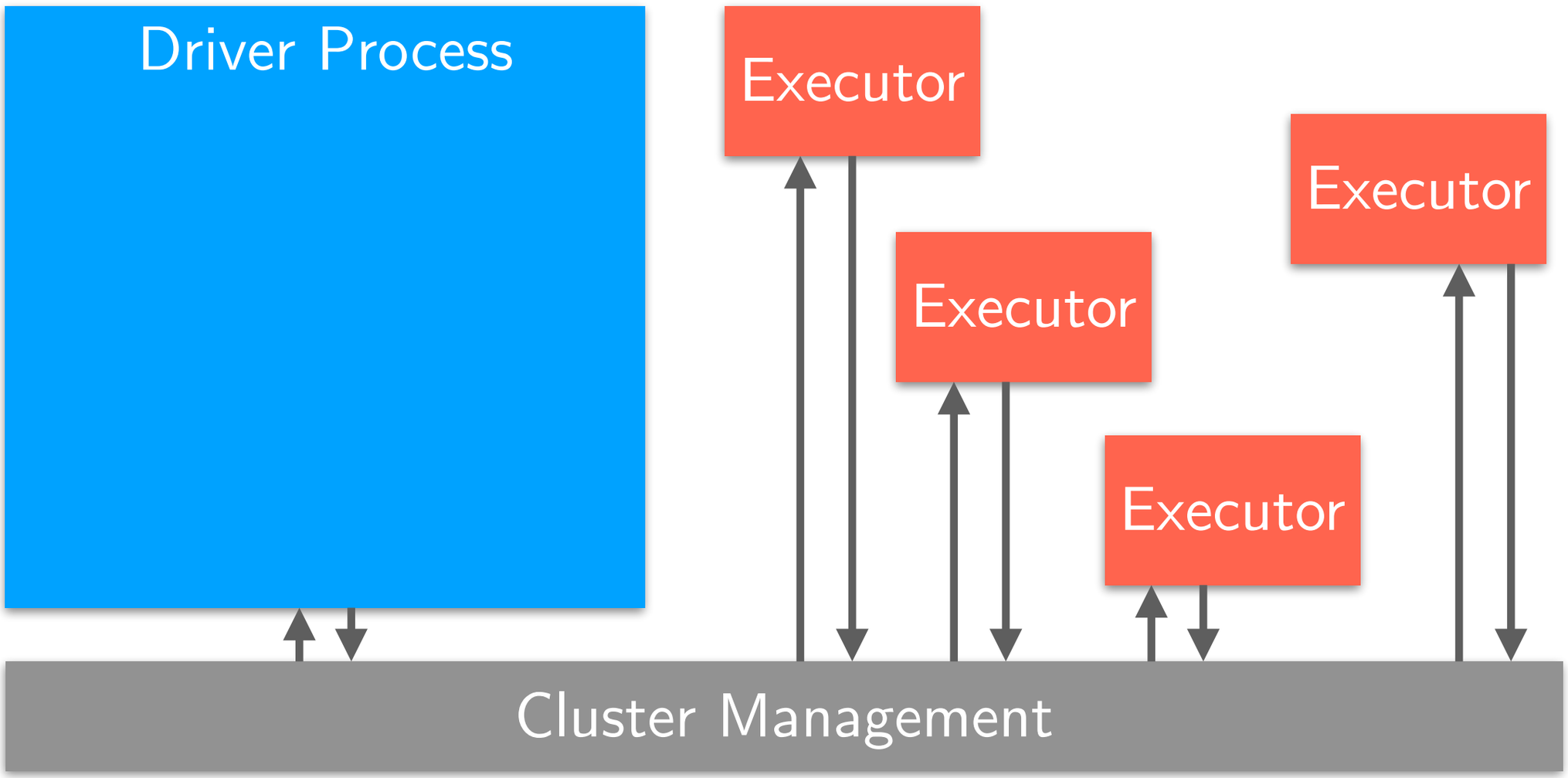
Spark Driver

- The driver process is
  - the heart of a Spark application
  - runs in a node of the cluster
  - runs the `main()` function



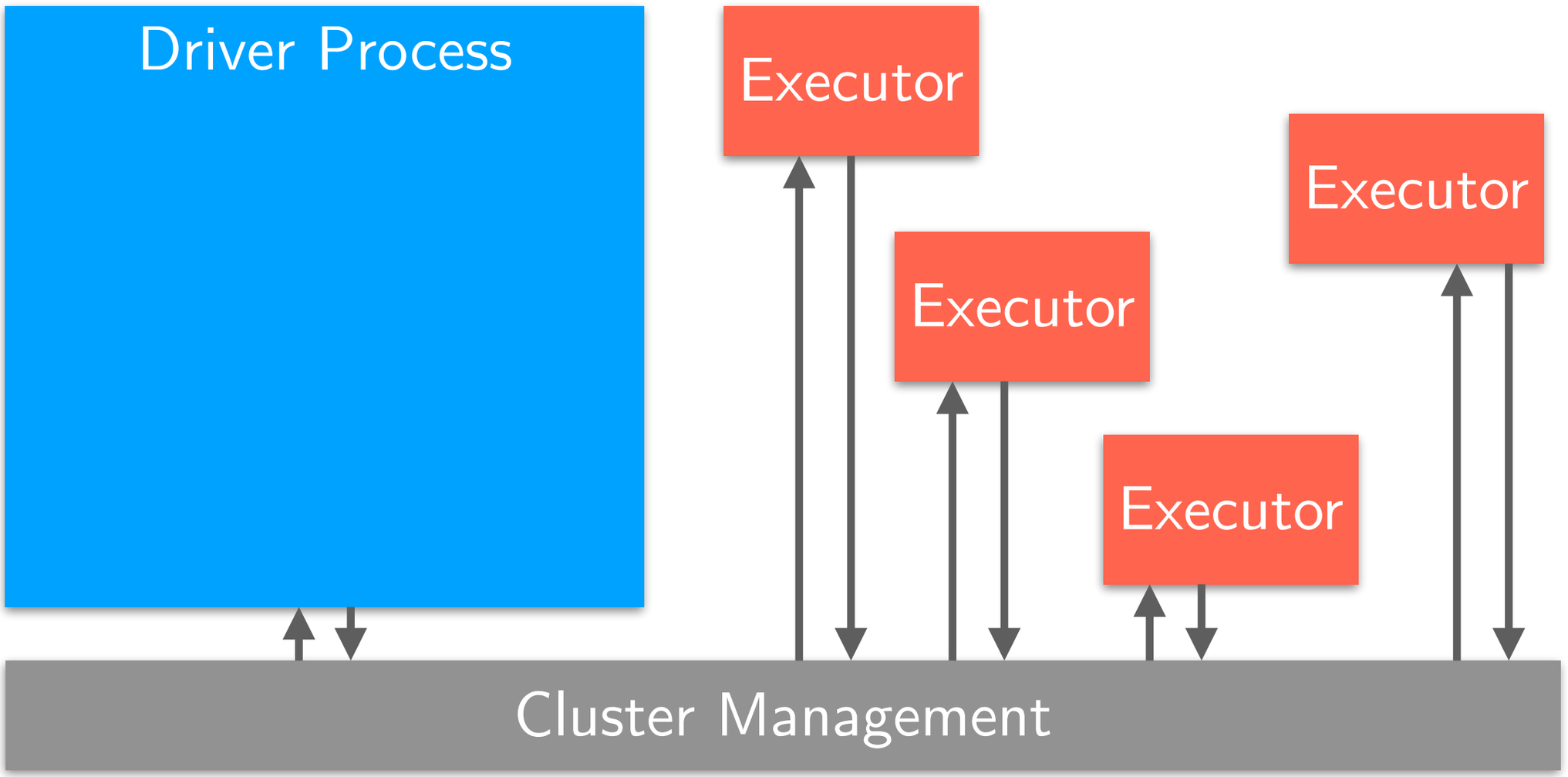
Spark Driver

- Responsible for three things:
  1. **Maintaining information** about the Spark application
  2. **Interacting** with the user
  3. **Analyzing, distributing and scheduling** work across the executors



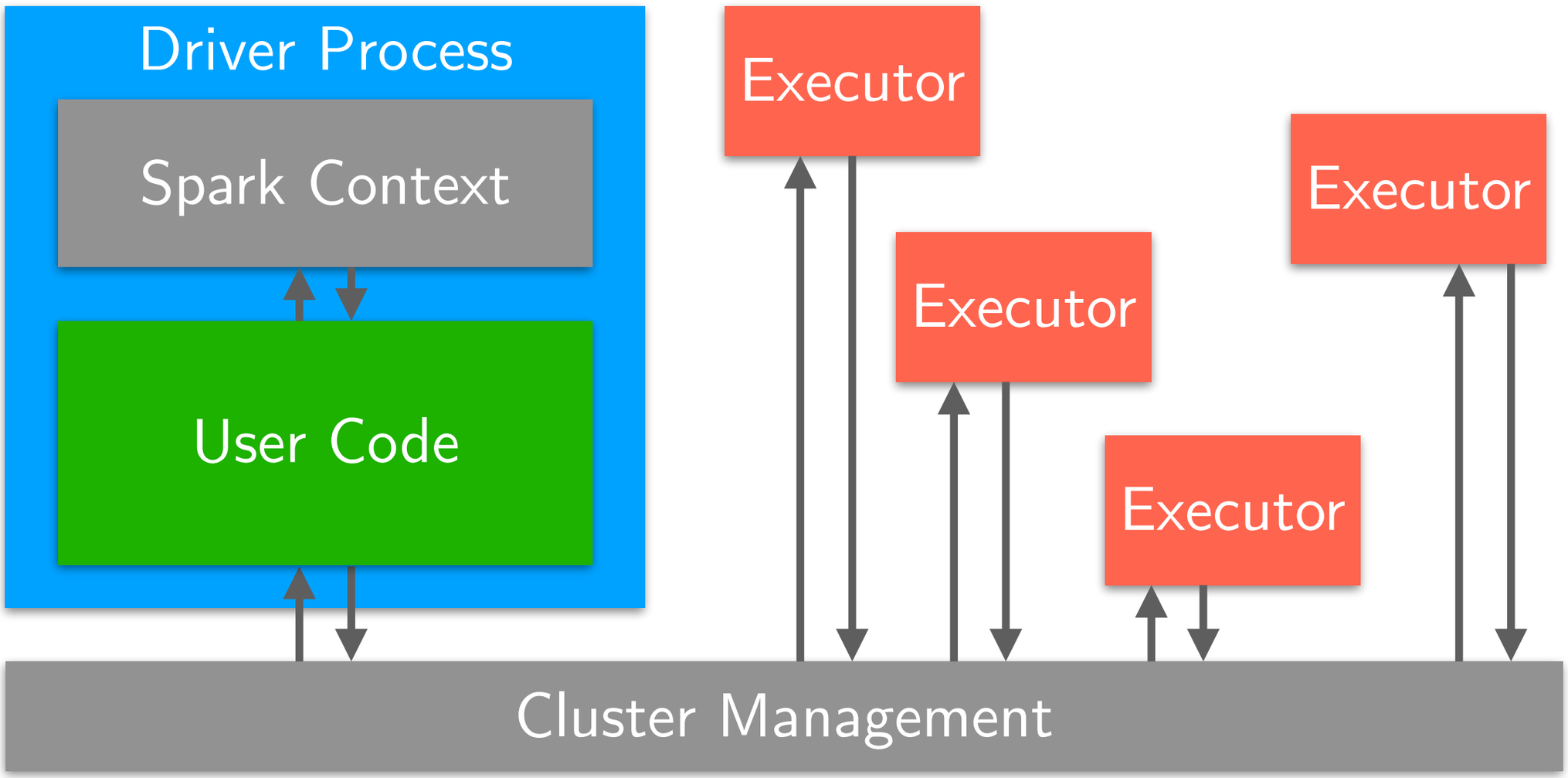
Spark Executors

- Responsible for two things:
  1. **Executing code** assigned to it by the driver
  2. **Reporting the state** of the computation on that executor back to the driver



Spark Context

- The driver process is composed by:
  - A **spark context**
  - A **user code**



Spark Context (I)

- The `SparkContext` object represents a connection with the cluster system.
- In the **`pyspark`** shell
  - a `SparkContext` is created automatically on start
  - It is accessible through the variable `sc`
- In a Python script including a Spark application you need to create it as soon as necessary

```
# import spark
from pyspark import SparkContext

# initialize a new Spark Context to use for the execution of the script
sc = SparkContext(appName="MY-APP-NAME", master="local[*]")
```

Spark Context (I)

- The `master` argument can assume different values, e.g.:
  - `local`: run in local mode with a single core
  - `local[N]`: run in local mode with `N` cores
  - `local[*]`: run in local mode and use as many cores as the machine has
  - **`yarn`**: connect to a YARN cluster
- Spark provides a single tool for submitting jobs across all cluster managers, called **`spark-submit`**
- We can use the **`--master`** flag to specify the execution mode of the Spark application.

Creating an RDD

- Use the parallelize method on a `SparkContext` object `sc`
- Turns a single node collection into a parallel collection.
- You can also explicitly state the number of partitions.

```
numbers = [1,2,3,4,5]
rdd_numbers = sc.parallelize(numbers)
print(rdd_numbers)

words = "i love spark".split(" ")
rdd_words = sc.parallelize(words, 2)
print(rdd_words)
```

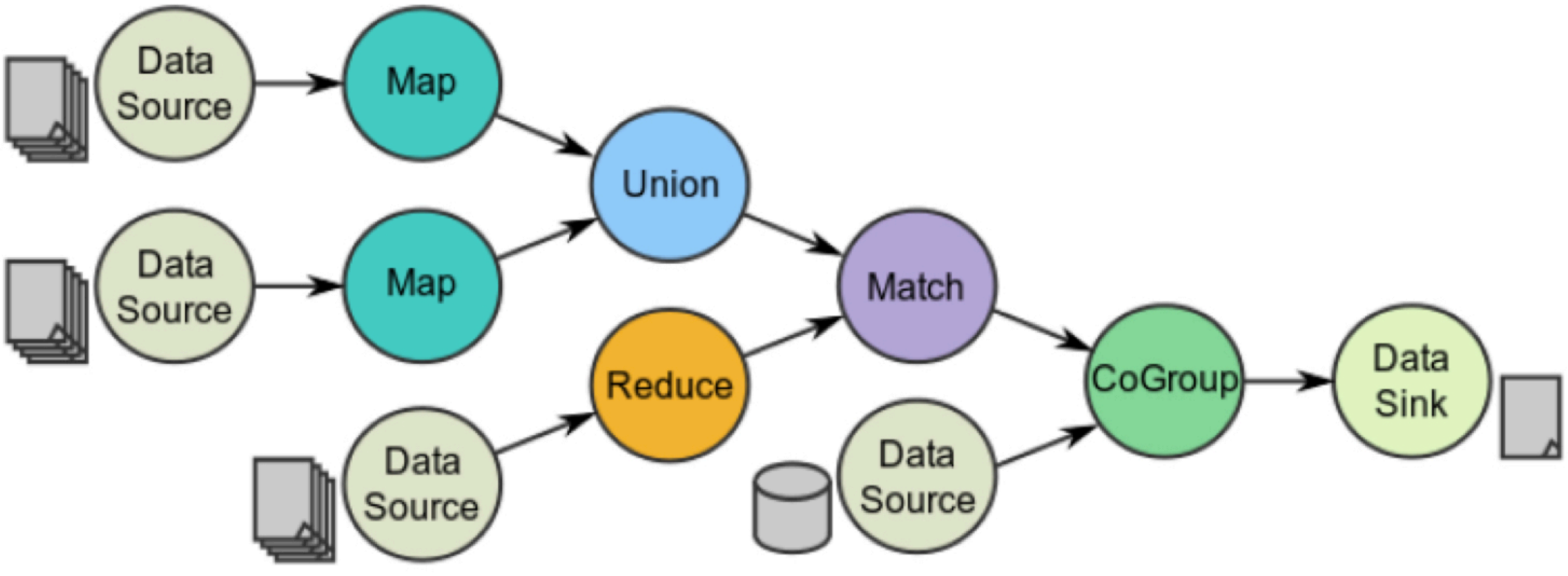
Creating an RDD

- RDDs can be created from external storage
  - Local disk, HDFS, Amazon S3, ...
- Text file RDDs can be created using the `textFile()` method

```
rdd_file = sc.textFile("file.txt")
rdd_hdfs = sc.textFile("hdfs://namenode:9000/path/to/file")
shakespeare_rdd = sc.textFile("hdfs://172.16.0.1/user/hadoop/
shakespeare.txt")
```

Spark Programming Model

- Based on **parallelizable operators**, i.e., **higher-order functions** that execute **user-defined functions** in **parallel**
- **Data flow** is composed of any number of data sources, operators, and data sinks by connecting their inputs and outputs
- Job description based on **directed acyclic graph** (DAG)



RDD Operations

- RDDs support **two types** of operations:
  1. **Transformations**: allow us to build the logical plan
  2. **Actions**: allow us to trigger the computation
- **Transformations** create a **new RDD** from an **existing RDD**.
  - **Not compute** their results right away (**lazy**).
  - **Remember** the transformations applied to the base dataset.
    - They are only computed when an action requires a result to be returned to the driver program.
- **Actions** **trigger** the computation.
  - Instruct Spark to **compute a result** from a series of transformations.
  - There are **three** kinds of actions:
    - Actions to **view data** in the console
    - Actions to **collect data** to native objects in the respective language
    - Actions to **write to output** data sources

RDD Actions

- `collect` returns all the elements of the RDD as an **array** at the driver
- `first` returns the first **value** in the RDD
- `take` returns an **array** with the first ***n*** elements of the RDD
  - Variations on this function: `takeOrdered` and `takeSample`
- `count` returns the **number** of elements in the dataset
- `max` and `min` return the **maximum** and **minimum** values, respectively.
- `reduce` aggregates the elements of the dataset using a given **function**.
  - The given function should be **commutative** and **associative** so that it can be computed correctly in parallel.
- `saveAsTextFile` writes the elements of an RDD as a **text file**.
  - Local filesystem, HDFS or any other Hadoop-supported file system.

RDD Actions Examples

```
numbers = sc.parallelize([1, 2, 2, 2, 1, 1, 4, 3, 3, 5, 5])
numbers.collect() # triggers execution on ALL elements, takes time
# list [1, 2, 2, 2, 1, 1, 4, 3, 3, 5, 5]
numbers.first()
# int 1
numbers.take(4) # triggers execution on 4 elements, good for debug
# list [1, 2, 2, 2]
numbers.takeOrdered(4)
# list [1, 1, 1, 2]
numbers.takeOrdered(4)
# list [1, 1, 1, 2]
withReplacement = True
numberToTake = 4
randomSeed = 123456
numbers.takeSample(withReplacement, numberToTake, randomSeed)
# list [1, 5, 2, 5]
```

RDD Actions Examples

```
numbers = sc.parallelize([1, 2, 2, 2, 1, 1, 4, 3, 3, 5, 5])
numbers.count()
# int 11
numbers.countByValue()
# defaultdict(int, {1: 3, 2: 3, 4: 1, 3: 2, 5: 2})
numbers.max()
# int 5
numbers.min()
# int 1
numbers.reduce(lambda x, y: x + y)
# int 29
numbers.saveAsTextFile('numbers.txt')
# exit pyspark check contents of file 'numbers.txt'
# ls -ltrh snumbers.txt
```

Generic RDD Transformations

- `distinct` removes duplicates from the RDD
- `filter` returns the RDD records that match some **predicate function**

```
numbers = sc.parallelize([1,2,2,2,3,3,4,5,5,5,5])
distinct_numbers = numbers.distinct()
print(distinct_numbers.collect()) # this is an action
[2, 4, 1, 3, 5]
even_numbers = distinct_numbers.filter(lambda x: x % 2 == 0)
print(even_numbers.collect()) # this is an action
[2, 4]
```

- `sample` draws a random sample of the data, with or without replacement

```
data = sc.parallelize(range(20))
sampled_data = data.sample(withReplacement = False, fraction = 0.20)
print(sampled_data.collect()) # this is an action
[5, 13, 14, 16]
```

Generic RDD Transformations

- `map` and `flatMap` apply a given function to each RDD element **independently**
- `map` transforms an RDD of **length *n*** into another RDD of **length *n***.
- `flatMap` allows returning **0, 1 or more elements** from map function.

```
data = sc.parallelize(range(10))
squared_data = data.map(lambda x: x * x)
print(squared_data.collect()) # this is an action
[0, 1, 4, 9, 16, 25, 36, 49, 64, 81]

squared_cubed_data_1 = data.map(lambda x: ( x * x, x * x * x))
print(squared_cubed_data_1.collect()) # this is an action
[(0, 0), (1, 1), (4, 8), (9, 27), (16, 64), (25, 125), (36, 216), (49, 343),
(64, 512), (81, 729)]

squared_cubed_data_2 = data.flatMap(lambda x: ( x * x, x * x * x))
print(squared_cubed_data_2.collect()) # this is an action
[0, 0, 1, 1, 4, 8, 9, 27, 16, 64, 25, 125, 36, 216, 49, 343, 64, 512, 81,
729]
```

Generic RDD Transformations

- `sortBy` sorts an RDD
- `union` performs the **merging** of RDDs
- `intersection` performs the **set intersection** of RDD

```
words = sc.parallelize("nel mezzo del cammin di nostra vita".split(" "))
sorted_words = words.sortBy(lambda w: len(w))
print(sorted_words.collect()) # this is an action
['di', 'nel', 'del', 'vita', 'mezzo', 'cammin', 'nostra']

data1 = sc.parallelize(range(0,7))
data2 = sc.parallelize(range(3,10))
union = data1.union(data2)
print(union.collect()) # this is an action
[0, 1, 2, 3, 4, 5, 6, 3, 4, 5, 6, 7, 8, 9]

intersection = data1.intersection(data2)
print(intersection.collect()) # this is an action
[3, 4, 5, 6]
```

Key-Value RDD Transformations

- In a `(k,v)` pair, `k` is the **key**, and `v` is the **value**
- To create a key-value RDD:
  - `map` over your current RDD to a basic key-value structure.
  - Use the `keyBy` to create a key from the current value.
  - Use the `zip` to zip together two RDD.

```
words = sc.parallelize("nel mezzo del cammin di nostra vita".split(" "))
keywords1 = words.map(lambda w: (w.upper(), 1))
print(keywords1.collect()) # this is an action
[('NEL', 1), ('MEZZO', 1), ('DEL', 1), ('CAMMIN', 1), ('DI', 1), ('NOSTRA', 1), ('VITA',
1)]

keywords2 = words.keyBy(lambda w: w[0].upper())
print(keywords2.collect()) # this is an action
[('N', 'nel'), ('M', 'mezzo'), ('D', 'del'), ('C', 'cammin'), ('D', 'di'), ('N', 'nostra'),
('V', 'vita')]

numbers = sc.parallelize(range(7))
keywords3 = words.zip(numbers)
print(keywords3.collect()) # this is an action
[('nel', 0), ('mezzo', 1), ('del', 2), ('cammin', 3), ('di', 4), ('nostra', 5), ('vita',
6)]
```

Key-Value RDD Transformations

- `keys` and `values` extract keys and values from the RDD, respectively
- `lookup` looks up the **list of values** for a particular key in an RDD

```
words = sc.parallelize("nel mezzo del cammin di nostra vita".split(" "))
keywords = words.keyBy(lambda w: w[0])
# [('n', 'nel'), ('m', 'mezzo'), ('d', 'del'), ('c', 'cammin'), ('d', 'di'), ('n',
'nostra'), ('v', 'vita')]
k = keywords.keys()
# ['n', 'm', 'd', 'c', 'd', 'n', 'v']
v = keywords.values()
# ['nel', 'mezzo', 'del', 'cammin', 'di', 'nostra', 'vita']
look = keywords.lookup("n")
print(look)
['nel', 'nostra']
```

Key-Value RDD Transformations

- `reduceByKey` combines values with the same key
  - Takes a **function** as input and uses it to **combine values** of the same key
- `sortByKey` returns an RDD sorted by the key

```
words = sc.parallelize("fare o non fare non esiste provare".split(" "))
wordcount = words.map(lambda w: (w, 1)).reduceByKey(lambda x, y: x + y)
print(wordcount.collect()) # this is an action
[('provare', 1), ('fare', 2), ('non', 2), ('esiste', 1), ('o', 1)]

sorted_wordcount = wordcount.sortByKey()
print(sorted_wordcount.collect()) # this is an action
[('esiste', 1), ('fare', 2), ('non', 2), ('o', 1), ('provare', 1)]
```

Key-Value RDD Transformations

- `join` performs an inner-join on the key
- Other types of join:
  - `fullOuterJoin`
  - `leftOuterJoin, rightOuterJoin`
  - `cartesian`

```
cars = sc.parallelize(["Ferrari", "Porsche", "Mercedes"])
colors = sc.parallelize(["red", "black", "pink"])
joined = cars.cartesian(colors)
print(joined.collect())
[('Ferrari', 'red'), ('Ferrari', 'black'), ('Ferrari', 'pink'), ('Porsche',
'red'), ('Porsche', 'black'), ('Porsche', 'pink'), ('Mercedes', 'red'),
('Mercedes', 'black'), ('Mercedes', 'pink')]

cars = sc.parallelize([(1,"Ferrari"), (1, "Porsche"), (2, "Mercedes")])
colors = sc.parallelize([(1, "red"), (2, "black"), (3, "pink")])
joined = cars.join(colors)
 print(joined.collect())
[(1, ('Ferrari', 'red')), (1, ('Porsche', 'red')), (2, ('Mercedes', 'black'))]
```

RDD High Order Functions Summary

Transformations	$map(f : \mathrm{T} \Rightarrow \mathrm{U})$	:	$\mathrm{RDD[T]} \Rightarrow \mathrm{RDD[U]}$
	$filter(f : \mathrm{T} \Rightarrow \mathrm{Bool})$	:	$\mathrm{RDD[T]} \Rightarrow \mathrm{RDD[T]}$
	$flatMap(f : \mathrm{T} \Rightarrow \mathrm{Seq[U]})$	:	$\mathrm{RDD[T]} \Rightarrow \mathrm{RDD[U]}$
	$sample(fraction : \mathrm{Float})$	:	$\mathrm{RDD[T]} \Rightarrow \mathrm{RDD[T]}$ (Deterministic sampling)
	$groupByKey()$	:	$\mathrm{RDD[(K, V)]} \Rightarrow \mathrm{RDD[(K, Seq[V])]}$
	$reduceByKey(f : (\mathrm{V}, \mathrm{V}) \Rightarrow \mathrm{V})$	:	$\mathrm{RDD[(K, V)]} \Rightarrow \mathrm{RDD[(K, V)]}$
	$union()$	:	$(\mathrm{RDD[T]}, \mathrm{RDD[T]}) \Rightarrow \mathrm{RDD[T]}$
	$join()$	:	$(\mathrm{RDD[(K, V)]}, \mathrm{RDD[(K, W)]}) \Rightarrow \mathrm{RDD[(K, (V, W))]}$
	$cogroup()$	:	$(\mathrm{RDD[(K, V)]}, \mathrm{RDD[(K, W)]}) \Rightarrow \mathrm{RDD[(K, (Seq[V], Seq[W]))]}$
	$crossProduct()$	:	$(\mathrm{RDD[T]}, \mathrm{RDD[U]}) \Rightarrow \mathrm{RDD[(T, U)]}$
	$mapValues(f : \mathrm{V} \Rightarrow \mathrm{W})$	:	$\mathrm{RDD[(K, V)]} \Rightarrow \mathrm{RDD[(K, W)]}$ (Preserves partitioning)
	$sort(c : \mathrm{Comparator[K]})$	:	$\mathrm{RDD[(K, V)]} \Rightarrow \mathrm{RDD[(K, V)]}$
	$partitionBy(p : \mathrm{Partitioner[K]})$	:	$\mathrm{RDD[(K, V)]} \Rightarrow \mathrm{RDD[(K, V)]}$
Actions	$count()$	:	$\mathrm{RDD[T]} \Rightarrow \mathrm{Long}$
	$collect()$	:	$\mathrm{RDD[T]} \Rightarrow \mathrm{Seq[T]}$
	$reduce(f : (\mathrm{T}, \mathrm{T}) \Rightarrow \mathrm{T})$	:	$\mathrm{RDD[T]} \Rightarrow \mathrm{T}$
	$lookup(k : \mathrm{K})$	:	$\mathrm{RDD[(K, V)]} \Rightarrow \mathrm{Seq[V]}$ (On hash/range partitioned RDDs)
	$save(path : \mathrm{String})$	:	Outputs RDD to a storage system, *e.g.*, HDFS

Word Count (I)

1. Load "`comedies.txt`" text file into Spark
2. Transform the lines RDD into a words RDD
3. Transform each `word` into a `(word, 1)` pair
4. Reduce words by key to sum up word occurrences
5. Save results as text file

Word Count (II)

```
text    = sc.textFile("data/comedies.txt")
words   = text.flatMap(lambda x: x.split(" "))
ones    = words.map(lambda w: ( w, 1 ))
counts = ones.reduceByKey(lambda x, y: x + y)
counts.saveAsTextFile("data/comedies_wordcount.txt")
```

Word Count (III)

```
import sys

from pyspark import SparkContext


if __name__ == "__main__":

    master = "local"

    if len(sys.argv) == 2:

        master = sys.argv[1]

    sc = SparkContext(master, "WordCount")

    lines = sc.parallelize(["pandas", "i like pandas"])

    result = lines.flatMap(lambda x: x.split(" ")).countByValue()

    for key, value in result.items():

        print("%s %i" % (key, value))
```

Bigram Count (I)

1. Define a function extracting all bigrams from a string of words.
2. Load "`comedies.txt`" text file into Spark
3. Transform the lines RDD into a bigrams RDD
4. Transform each bigram into a (bigram, 1) pair
5. Reduce bigrams by key to sum up bigram occurrences
6. Save results as text file

Bigram Count (II)

```
def create_bigrams(line):
    pairs = []
    words = line.lower().split()
    for i in range(len(words) -1):
        pairs.append(words[i] + "_" + words[i + 1])
    return pairs

text = sc.textFile("data/comedies.txt")
bigrams = text.flatMap(create_bigrams)
ones = bigrams.map(lambda b: ( b, 1 ))
counts = ones.reduceByKey(lambda x, y: x + y)
counts.saveAsTextFile("data/comedies_bigramscount.txt")
```

RDD Persistence (I)

- By default, each transformed RDD may be **recomputed** each time an action is run on it
- Spark also supports the **persistence** (or **caching**) of RDDs in memory across operations for rapid reuse
  - When RDD is persisted, each node stores any partitions of it that it computes in memory and reuses them in other actions on that dataset (or datasets derived from it)
  - This allows future actions to be **much faster** (even 100x)
  - To persist RDD, use `persist()` or `cache()` methods on it
  - Spark's cache is **fault-tolerant**: a lost RDD partition is automatically recomputed using the transformations that originally created it
- Key tool for **iterative algorithms** and fast **interactive use**

RDD Persistence (II)

- Using `persist()` you can specify the storage level for persisting an RDD
- Storage levels for `persist()`: `MEMORY_ONLY`, `MEMORY_AND_DISK`, `DISK_ONLY`, ...
- Calling `cache()` is the same , as calling `persist()` with the default storage level (`MEMORY_ONLY`)
- Which storage level is **best**? Few things to consider:
  - Try to **keep in-memory as much as possible**
  - **Serialization** make the objects **much more space-efficient**
    - But select a fast serialization library
  - **Try not to spill to disk** unless the functions that computed your datasets are expensive (e.g., filter a large amount of the data)
  - Use replicated storage levels only if you want **fast fault recovery**

Some issues

- Iterative or single jobs with large global variables
  - Sending a large lookup table to workers
  - Sending a large feature vector in a ML algorithm to workers
- Counting events that occur during job execution
  - How many input lines were blank?
  - How many input records were corrupt?
- Problems
  - Closure are (re-)sent with every job
  - Inefficient to send large data to each worker
  - Closures are one-way: from driver to workers

Distributed Shared Variables

- In addition to the Resilient Distributed Dataset (RDD) interface, in Spark there are **two** types of **distributed shared variables**:
  - **broadcast variables**: let you save a value on all the worker nodes and reuse it across many Spark actions without re-sending it to the cluster
  - **accumulators**: let you add together data from all the tasks into a shared result
- These are variables you can use in your user-defined functions (e.g., in a map function on an RDD) that have special properties when running on a cluster

Broadcast Variables

- Efficiently send large, read-only values to all workers
  - Saved at workers for use in one or more Spark operations
  - Like sending a large, read-only lookup table to all workers
- Keep read-only variables cached on workers
  - Ship to each worker only once instead with every task

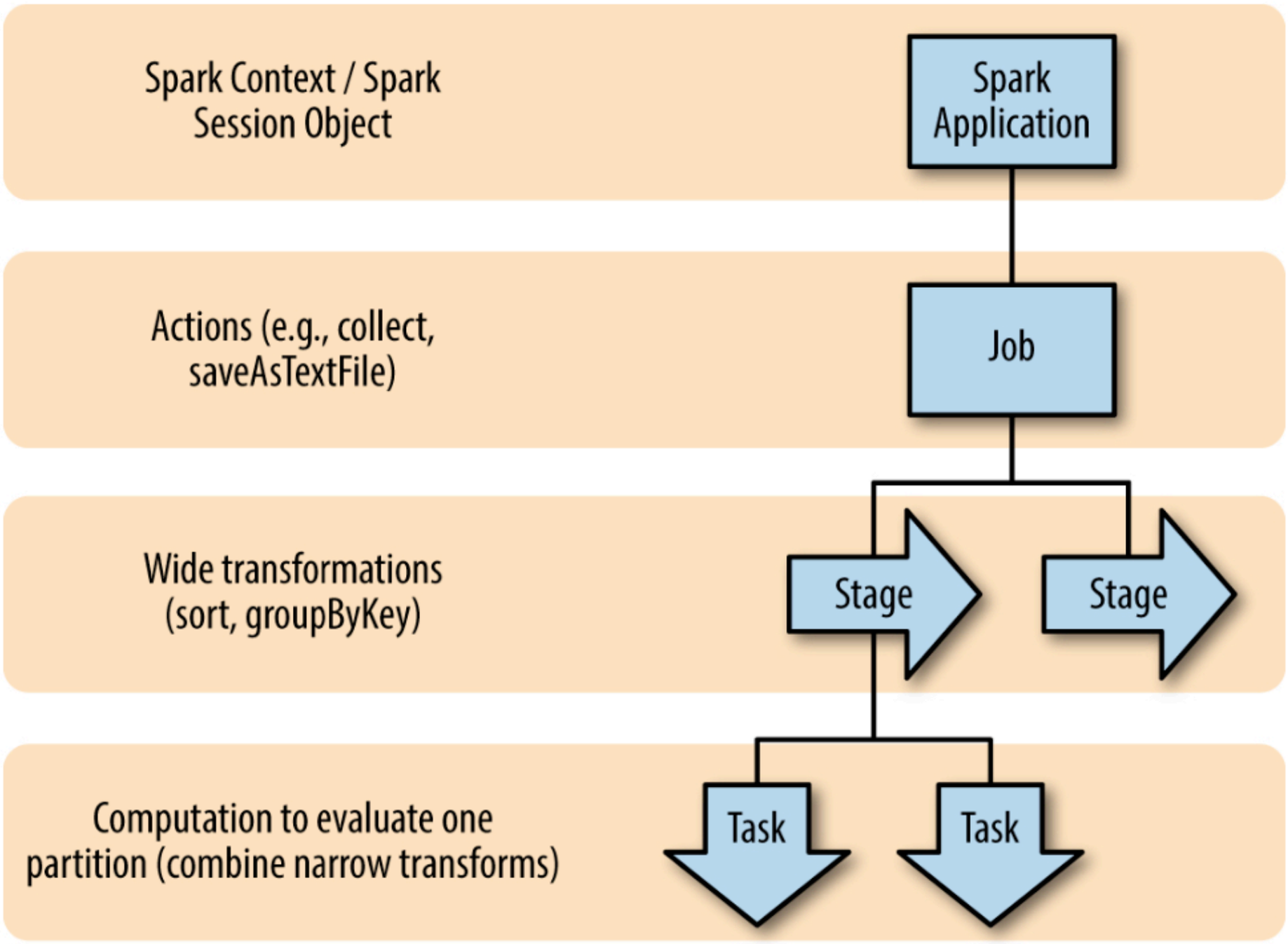
```
# At driver

broadcastVar = sc.broadcast([1, 2, 3])

# At workers (in a closure)

print(broadcastVar.value)

>> [1, 2, 3]
```

Accumulators

- Update a value inside of a variety of transformations and propagating that value to the driver node in an **efficient** and **fault-tolerant** way.
- Accumulators are variables that are "added" to only through an **associative** and **commutative** operation and can therefore be efficiently supported in parallel.
- **Updated only once** that RDD is **actually computed** (lazy evaluation in transformations)
- Tasks at workers see accumulators as **write-only variables**

```
# At driver

accumulator = spark.sparkContext.accumulator(0)

# At workers (in a closure)

accumulator.add(3)

# At driver

print(accumulator.value)

>> 3
```

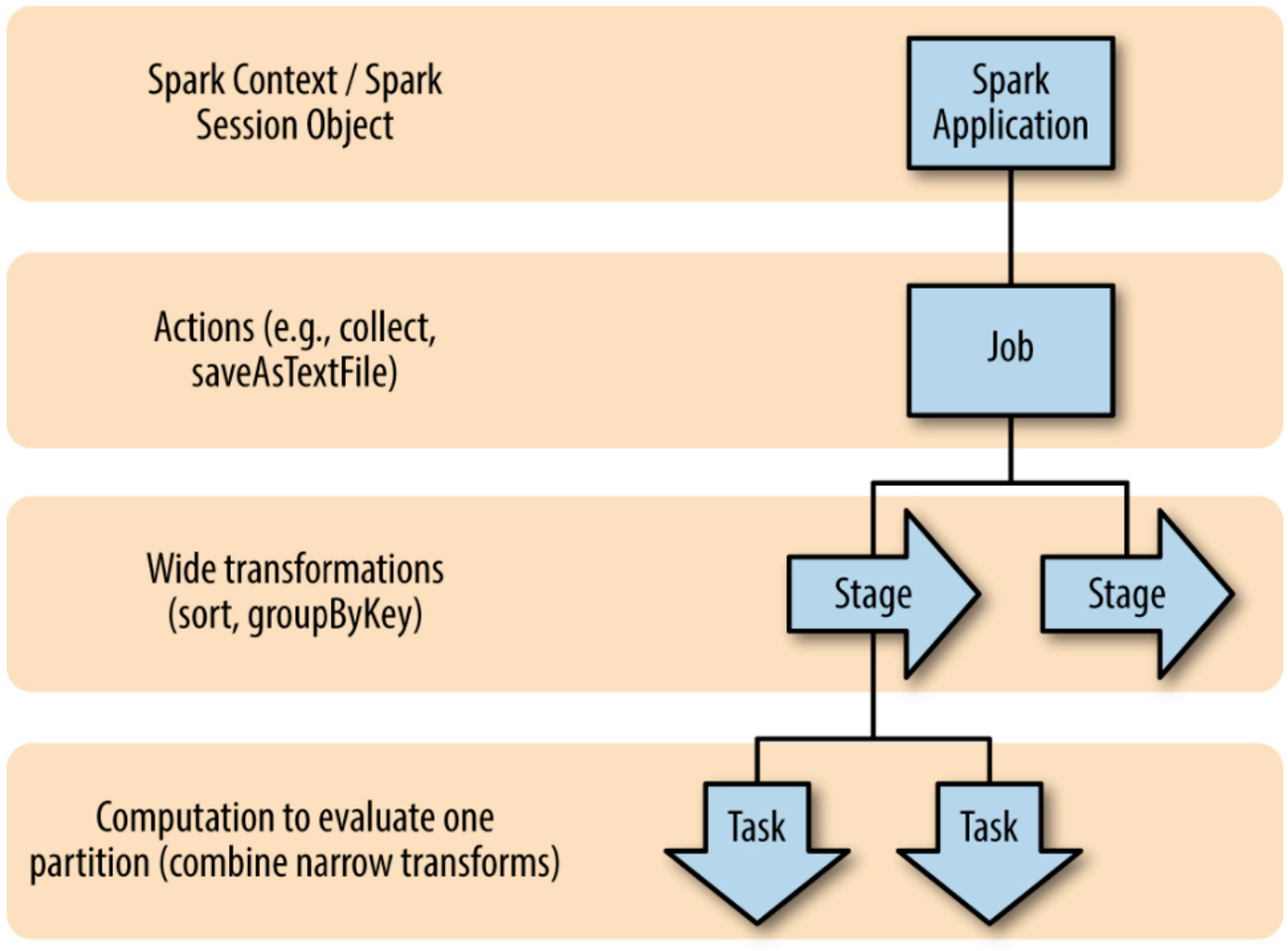
Anatomy of a Spark Job



Source: Karau et al., "High Performance Spark", O'Reilly, 2017

Spark application

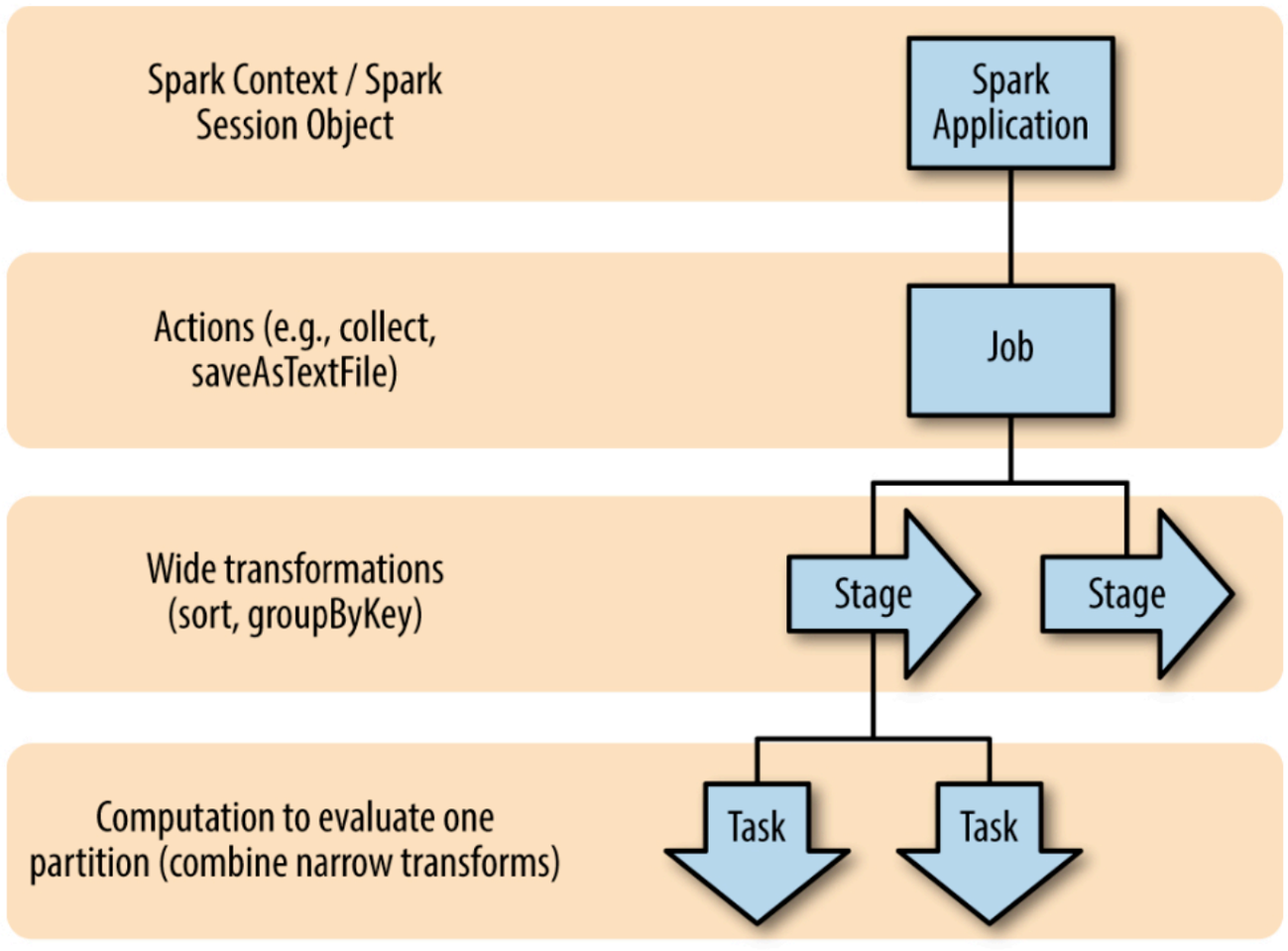
- A **Spark application** doesn't "do anything" until the driver program calls an action (**lazy evaluation**)



Source: Karau et al., "High Performance Spark", O'Reilly, 2017

Spark Job

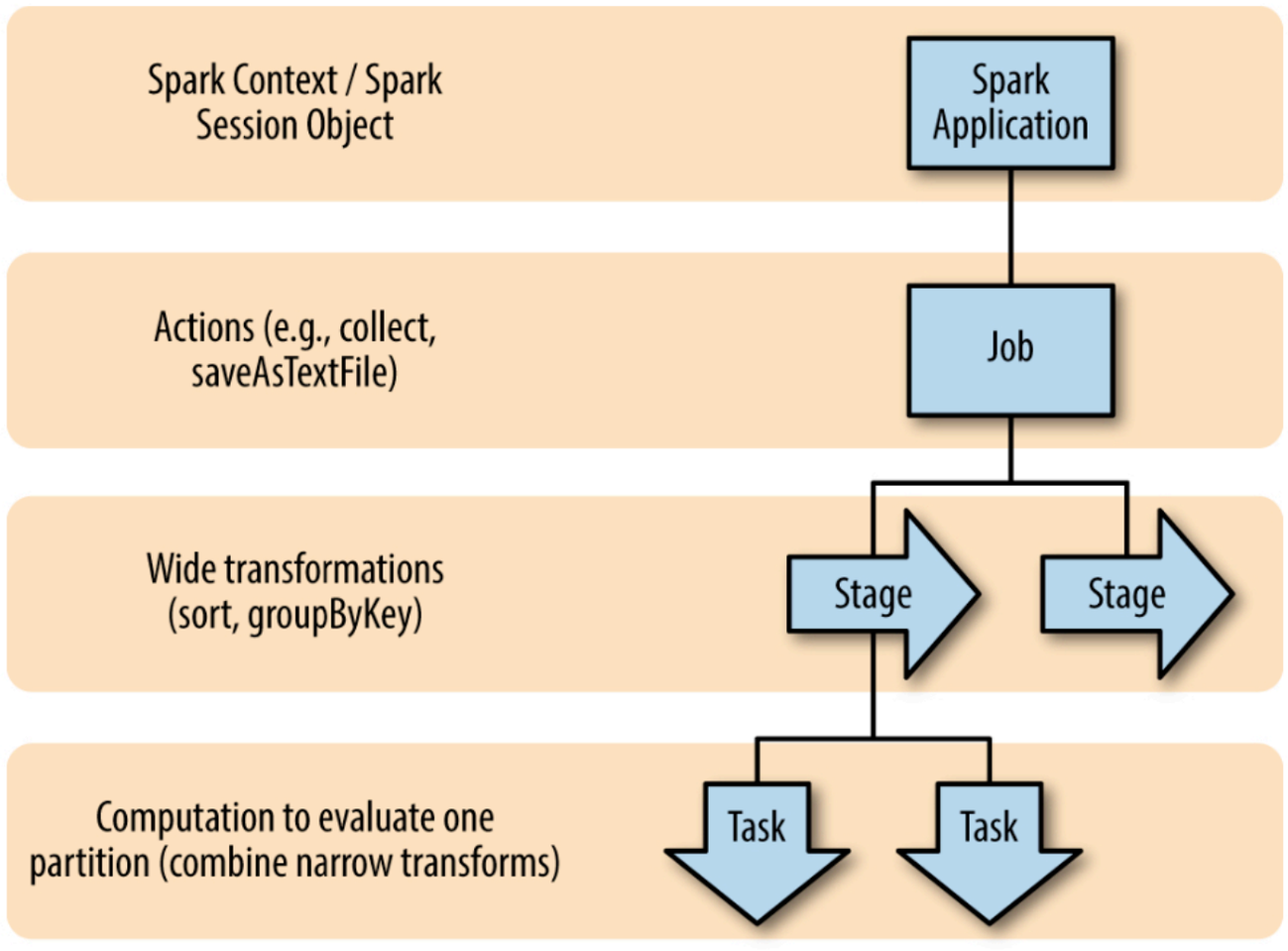
- A **Spark job** is the highest element of Spark's execution hierarchy
  - Each Spark job corresponds to **one action**
  - Each **action** is called by the **driver** program of a Spark application



Source: Karau et al., "High Performance Spark", O'Reilly, 2017

Spark Stage

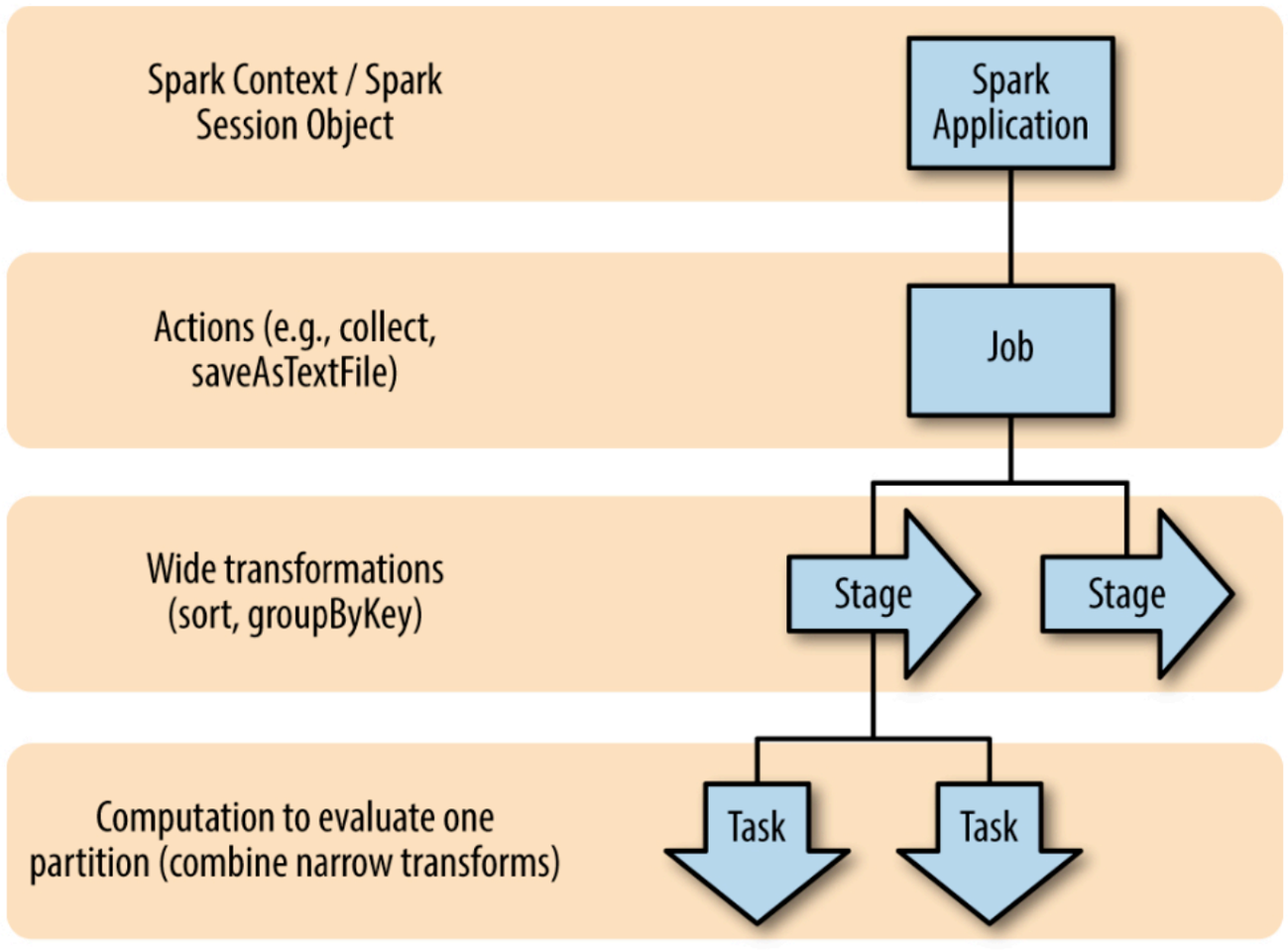
- Each **job** breaks down into a **series of stages**
  - Stages in Spark represent **groups of tasks** that can be executed **together**
  - **Wide transformations** define the breakdown of jobs into stages



Source: Karau et al., "High Performance Spark", O'Reilly, 2017

Spark Task

- A **stage** consists of **tasks**, which are the **smallest execution unit**
  - Each task represents **one local computation**
  - All of the tasks in one stage execute the **same code** on a **different piece of the data**



Source: Karau et al., "High Performance Spark", O'Reilly, 2017

Wide and Narrow Transformations

- Transformations fall into **two categories**: transformations with narrow dependencies and transformations with wide dependencies
- **Narrow transformations**
  - Dependencies can be determined at **design time**, irrespective of the values of the records in the parent partitions, and if **each parent has at most one child partition**
  - Can be executed on an arbitrary subset of the data without any information about the other partitions.
- **Wide transformations (shuffle)**
  - Cannot be executed on arbitrary rows and instead **require the data to be partitioned in a particular way**, e.g., according the value of their key