THE DATA SCIENCE LAB

Introduction to the Spark Runtime Architecture

COM 490 – Spring 2021

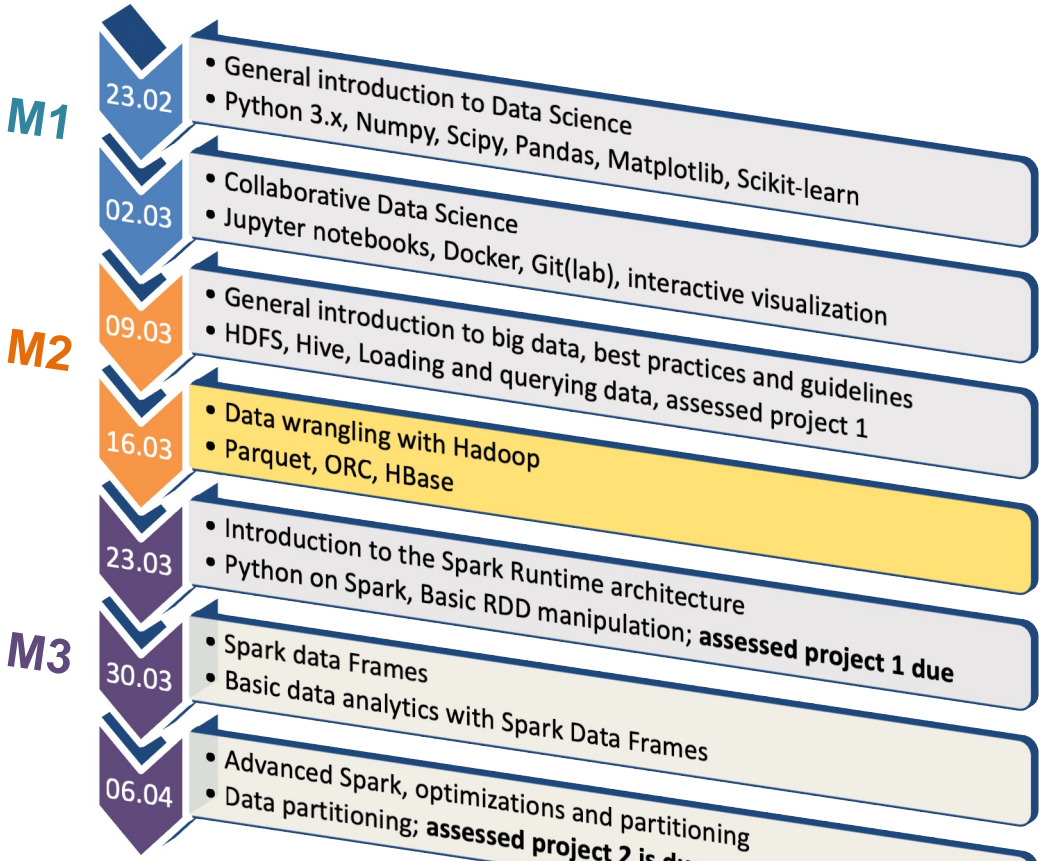
Week 5

THIS CLASS WILL BE RECORDED

EPFL

Week 4 – Questions?

Agenda Spring 2022



*Details on Moodle

Today's Agenda

- Introduction to Spark
- Spark architecture overview
- RDDs
- Getting started with Spark
- Introduction to this week's exercises
- Homework 2

Introduction to Spark

Getting started with

What is Spark?

Yet another- distributed computation framework

> **Apache Spark™** is a unified analytics engine for large-scale data processing.

KEY FEATURES

- Interactive data exploration
- In-memory data
- Fault-tolerance, parallelism

USED BY

- Internet applications (recommendation engines, usage analysis)
- Classic big data use cases e.g. text analysis
- Some academia, notably neuroscience

A bit of history

- MapReduce OSDI 2004
- Hadoop 2006, open source MR
- Many applications & frameworks!
- Mesos NSDI 2011
- Spark NSDI 2012
- Yarn SOCC 2013

NSDI '12 Home
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Resilient Distributed Datasets: A Fault-Tolerant Abstraction for In-Memory Cluster Computing

connect with us

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Awarded Best Paper!

Awarded Community Award Honorable Mention!

Abstract:

We present Resilient Distributed Datasets (RDDs), a distributed memory abstraction that lets programmers perform in-memory computations on large clusters in a fault-tolerant manner. RDDs are motivated by two types of applications that current computing frameworks handle inefficiently: iterative algorithms and interactive data mining tools. In both cases, keeping data in memory can improve performance by an order of magnitude. To achieve fault tolerance efficiently, RDDs provide a restricted form of shared memory, based on coarse-grained transformations rather than fine-grained updates to shared state. However, we show that RDDs are expressive enough to capture a wide class of computations, including recent specialized programming models for iterative jobs, such as Pregel, and new applications that these models do not capture. We have implemented RDDs in a system called Spark, which we evaluate through a variety of user applications and benchmarks.

A bit of stats

- Language: Scala
- Since 2009, more than 1200 developers have contributed to Spark!
- The project's committers come from more than 25 organizations.

Why Spark?

Spark is just one solution that facilitates analysis on large data.

Other options:

- using the Message Passing Interface (MPI) library
- similar frameworks e.g. Apache Flink (more streaming-specific)
- Python-specific Dask (nice abstraction for scaling python-native applications)

Flexibility

Spark's flexibility is what makes it so popular.

The spark runtime can be deployed on:

- a single machine (local)
- a set of pre-defined machines (stand-alone)
- a dedicated Hadoop-aware scheduler (YARN/Mesos)
- "cloud", e.g. Amazon EC2
- Kubernetes

Incremental, interactive development

Deployment workflow: start small (local) and scale up to one of the other solutions, depending on needs and resources.

In addition, you can run applications on any of these platforms either

- interactively through a shell (or a Jupyter notebook as we'll see)
- batch mode

No code changes to go between these methods of deployment!

Spark's flexibility

Supported languages

- Scala
- Java
- R
- Python
- .NET
- Julia

Specialized libraries

- SparkSQL
- SparkStreaming
- MLlib
- GraphX

Supported data storage

- Cassandra
- HDFS
- Alluxio
- Hbase
- Hive

Spark Architecture Overview

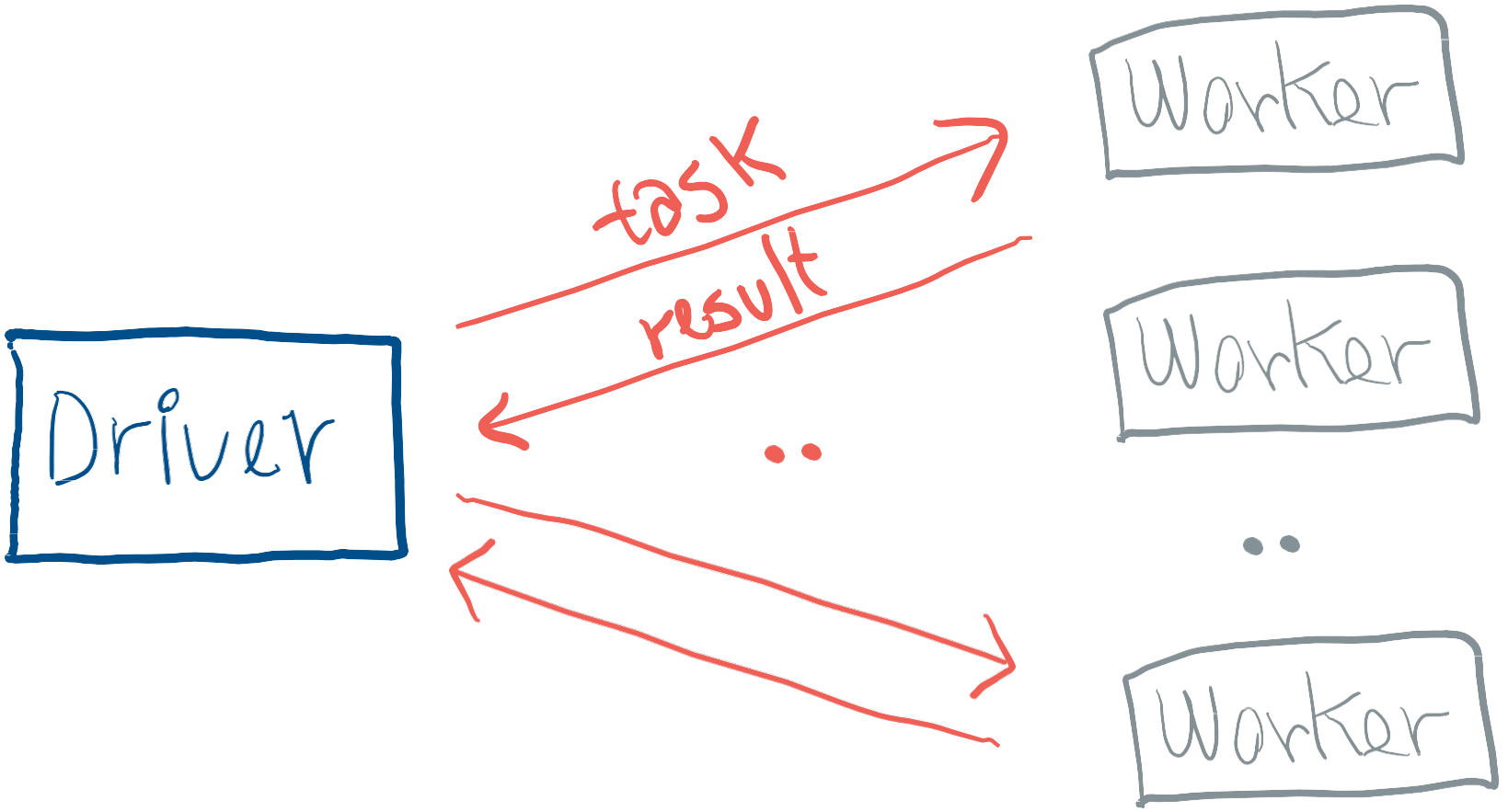
Distributed computing framework

- Revisit

1. Distribute work
2. Orchestrate task execution
3. Collect results

- Fault-tolerant
- Efficient

Spark architecture



Driver

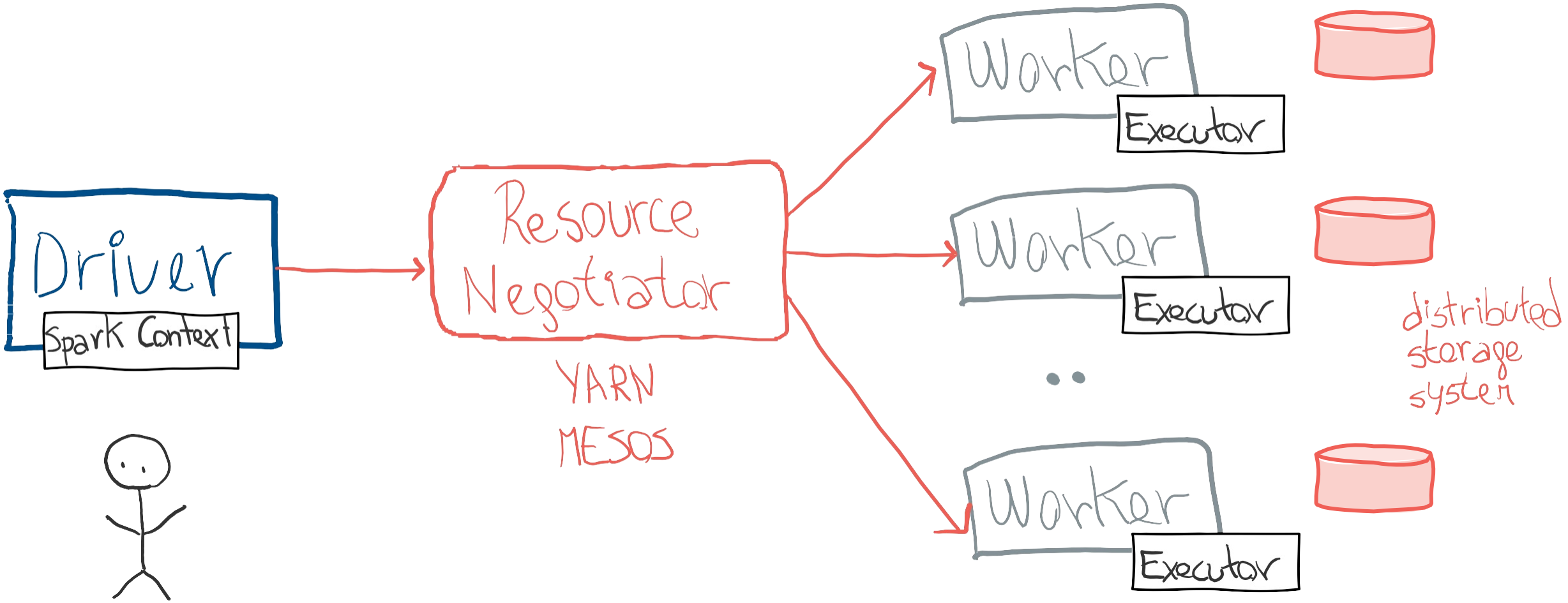
- coordinates the work to be done
- keeps track of tasks
- collects metrics about the tasks (disk IO, memory, etc.)
- communicates with the workers (and the user)

Worker

- receive tasks to be done from the driver
- store data in memory or on disk
- perform calculations
- return results to the driver

The user's access point to this Spark universe is the **Spark Context** which provides an interface to generate RDDs.

Spark architecture



Resilient Distributed Dataset

Basic Data Abstraction

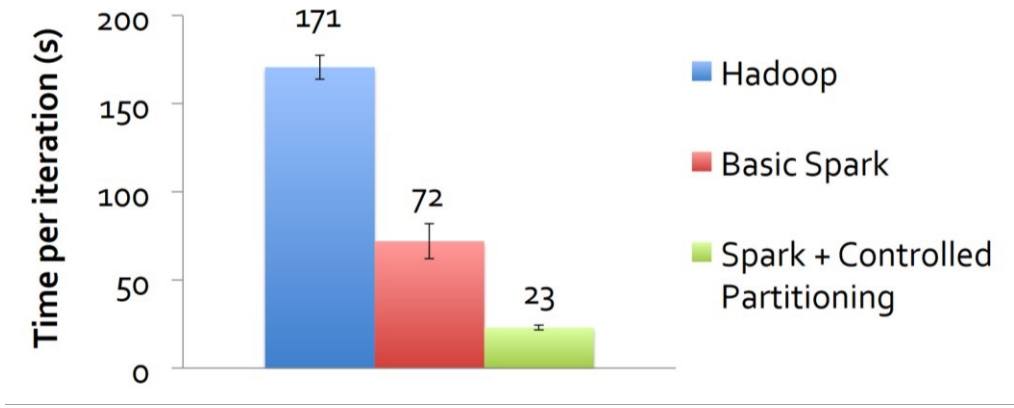
RDD: primary interface of every Spark application

- keeps track of data distribution across the workers
- provides an interface to the user to access and operate on the data
- fault-tolerant and efficient for iterative algorithms

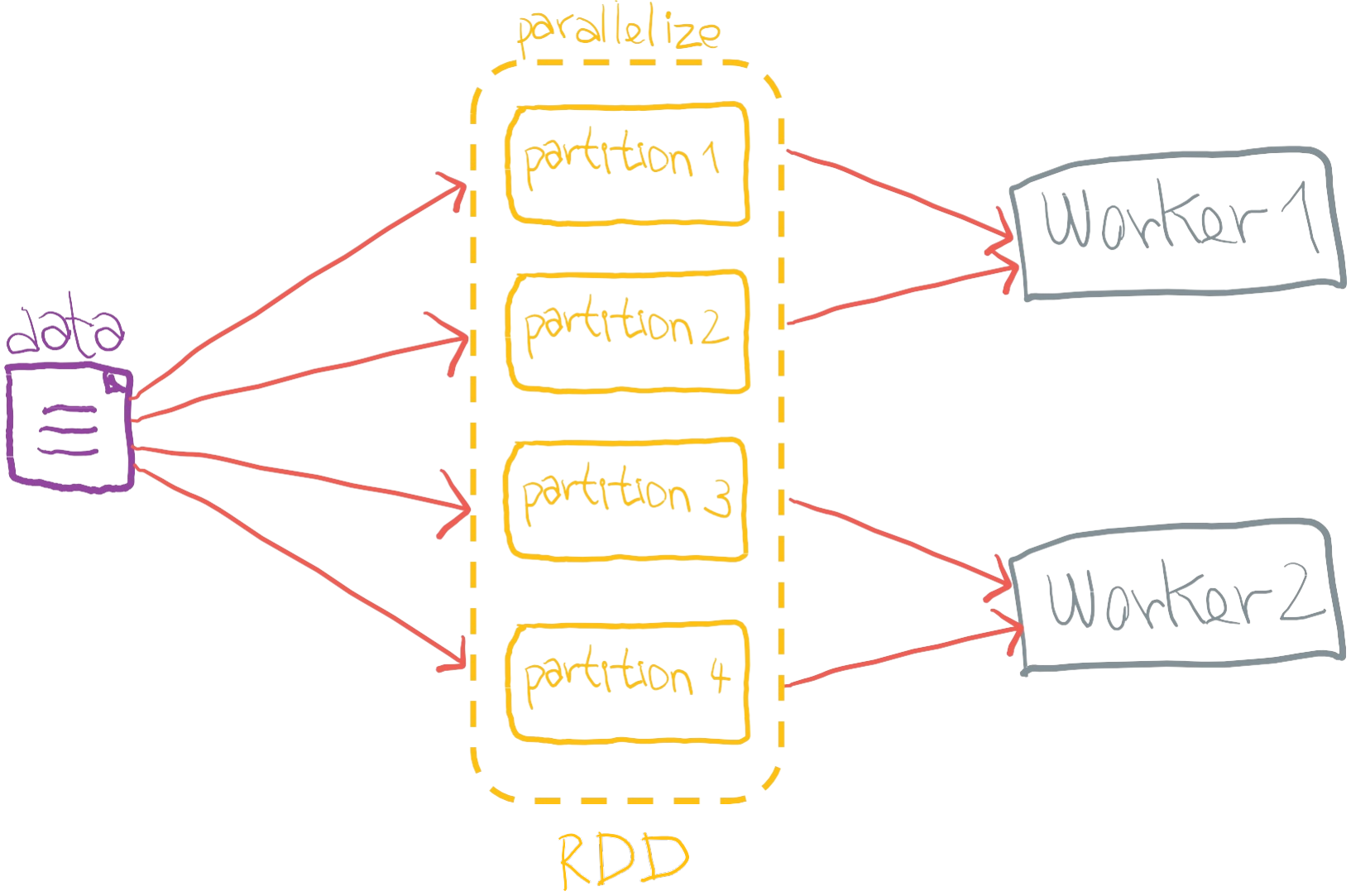
As a Spark user, you write applications that feed data into RDDs and subsequently transform them into something useful

Why RDDs?

- Use case: iterative algorithms ML, graph, ad-hoc queries
- Hadoop MapReduce: stable storage
  - HDFS, disk, replication (disk I/O)
  - for every stage!
- RDD keep data in memory
  - Faster BUT
  - expensive fault-tolerance
- RDD lineage
  - state can be rebuilt with lineage (cheap to replicate)
  - limit operations: immutable, coarse-grained actions



RDDs


parallelize
data
partition 1
partition 2
partition 3
partition 4
Worker 1
Worker 2
RDD

RDD operations

Once an RDD is created, it is **immutable** - it can only be transformed into a new RDD via a transformation.

A transformation, however, does not trigger any computation, only updates the DAG.

Calculations are triggered by actions.

Transformations

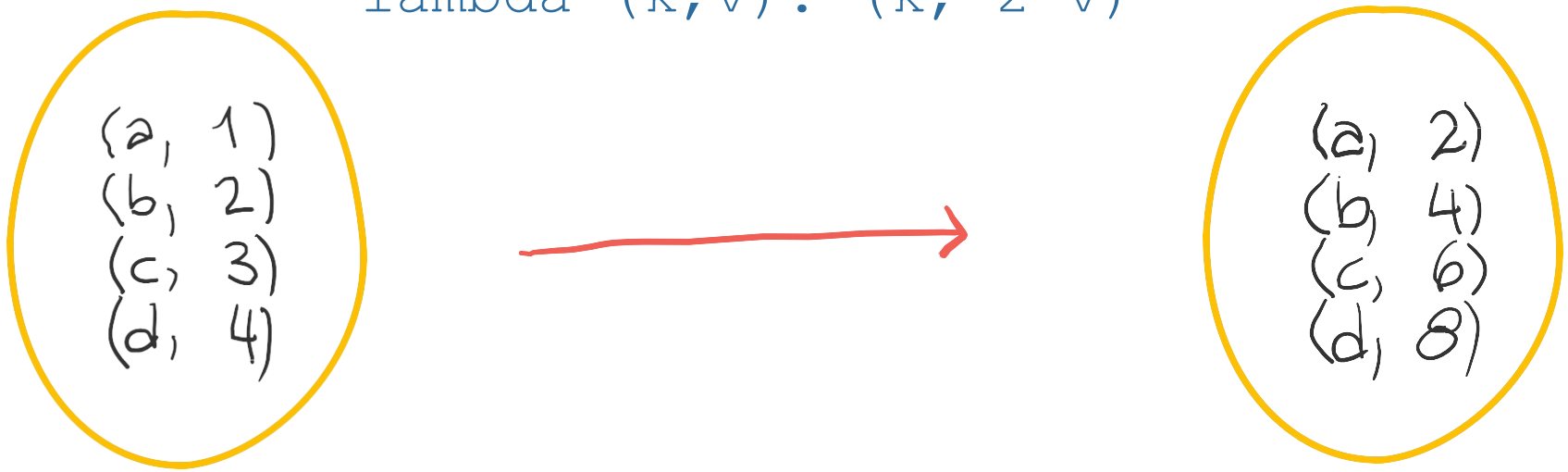
Name	Use
`map(func)`	the most basic transformation with 1:1 correspondence to original data
`filter(func)`	only keep those elements for which the filter function evaluates to True
`mapPartitions(func)`	similar to map but done on a per-partition basis (requires a generator function)
`flatMap(func)`	similar to map but each element can be mapped to more than one corresponding item (func returns a Seq)
`distinct([numPartitions])`	only retain the unique elements of the entire RDD
`reduceByKey(func, [numPartitions])`	group elements by key and keep the data distributed
`groupByKey([numPartitions])`	sort elements based on keys K, where K implements Ordered

Transformations are evaluated "lazily" - only executed once an action is performed.

Transformations: map

map

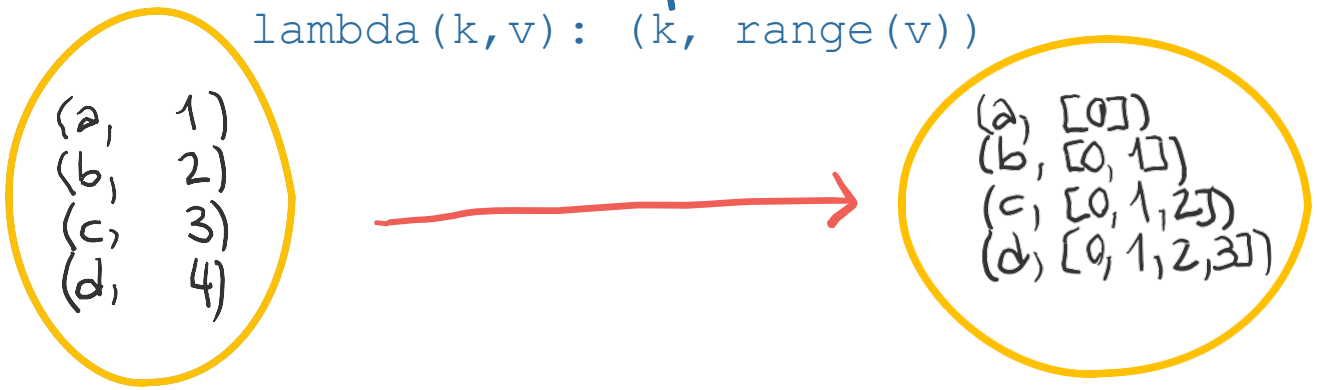
```
lambda (k,v): (k, 2*v)
```



Transformations: flatMap

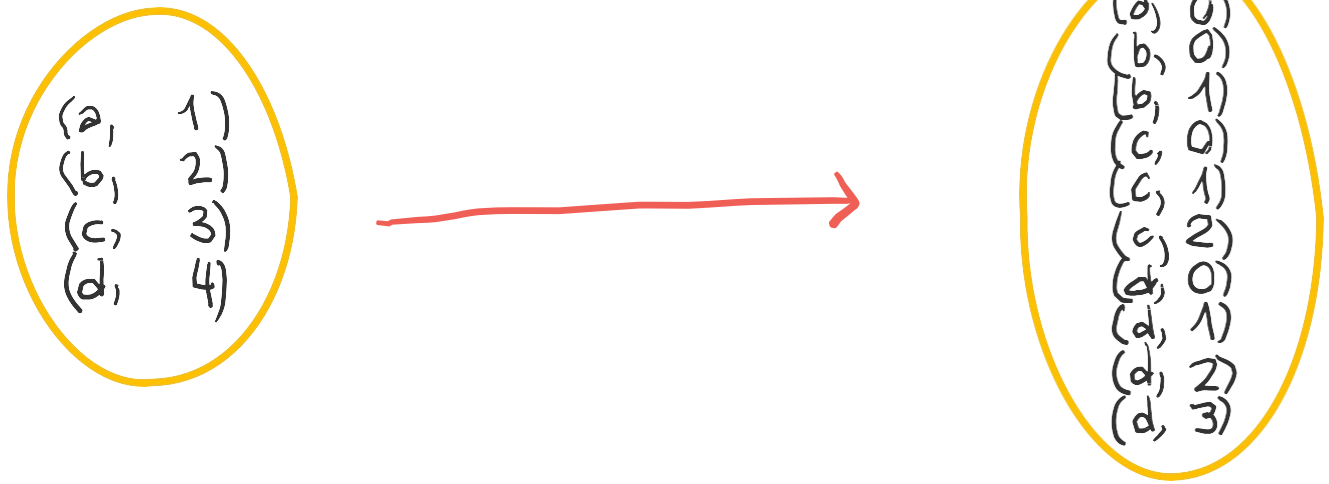
map

```
lambda(k,v): (k, range(v))
```



flatMap

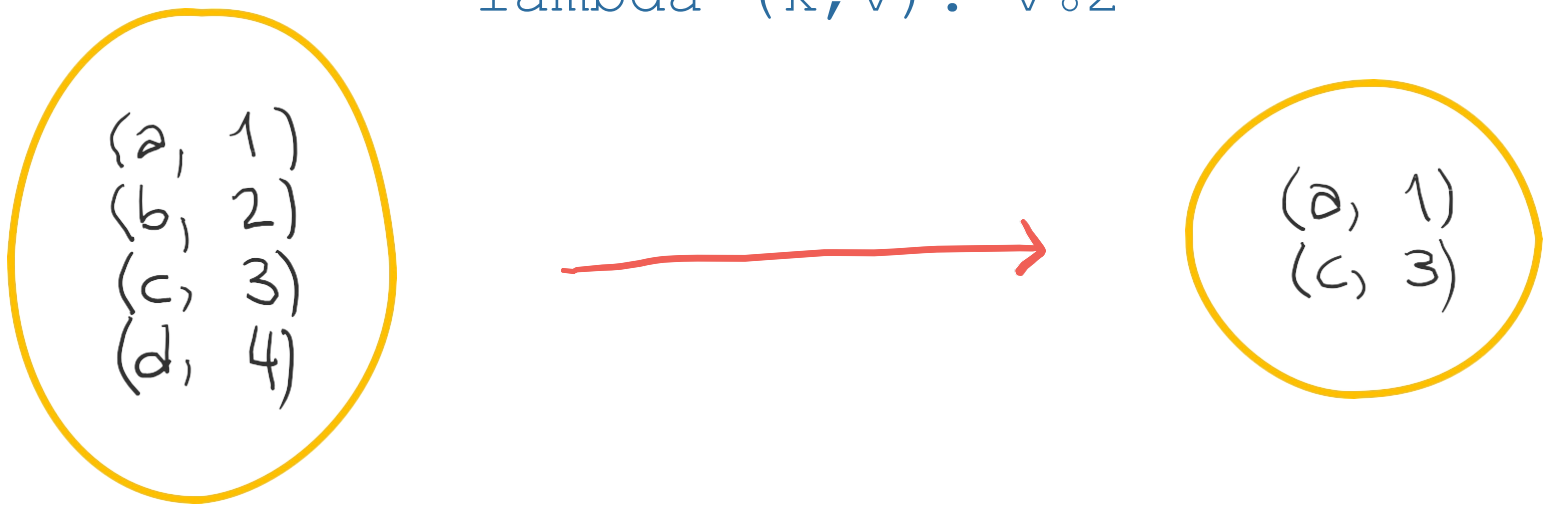
```
lambda(k,v): [(k,v) for v in range(v))]
```



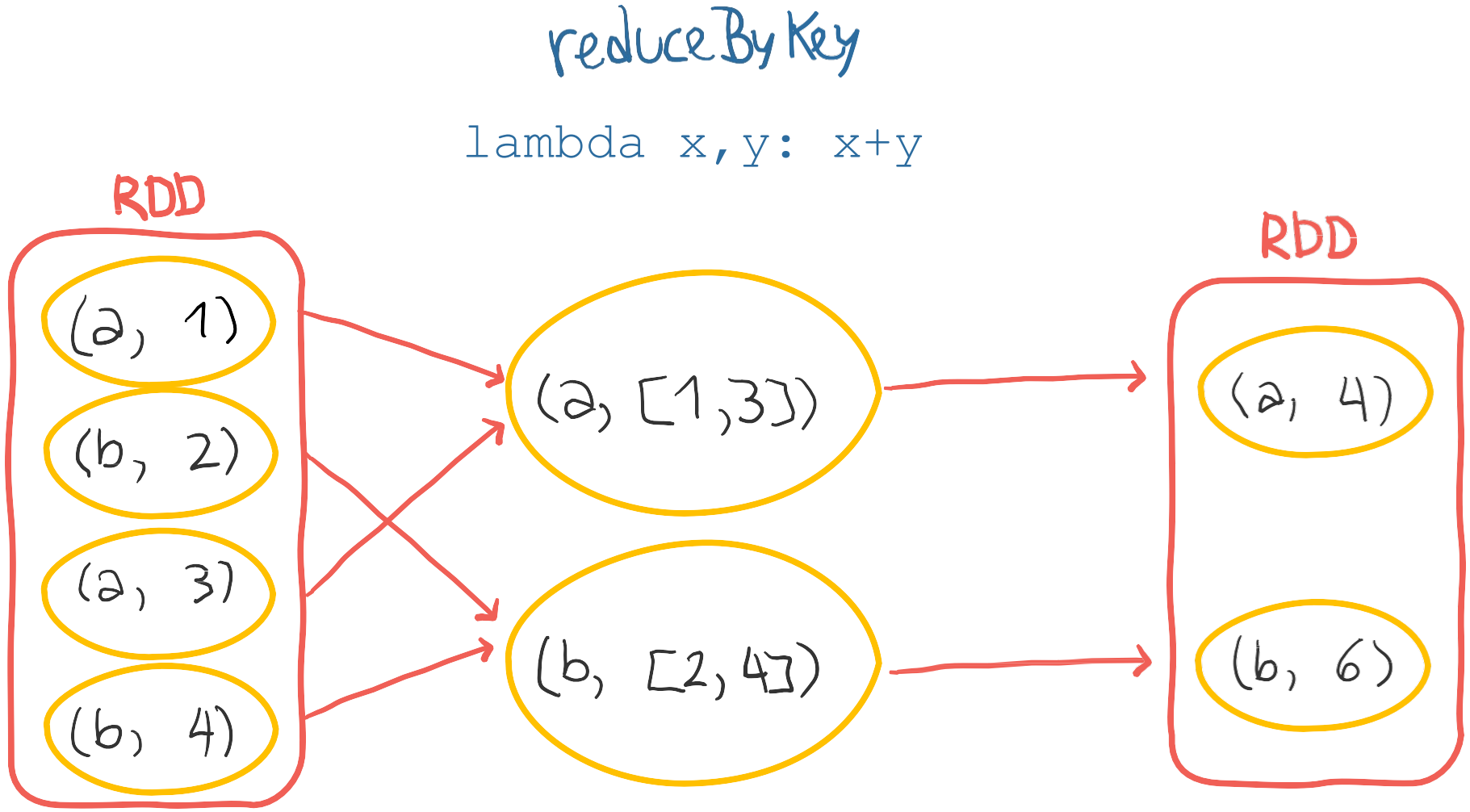
Transformations: filter

filter

```
lambda (k,v): v%2
```



Transformations: reduceByKey



Actions

Name	Use
`reduce(func)`	reduces the entire RDD to a single value
`collect()`	pulls all elements of the RDD to the driver (often a bad idea!!)
`first()`	returns the first element of the RDD to the driver
`take(n)`	yields a desired number of items to the driver
`countByKey()`	yields a hashmap of (K, Int) pairs with the count of each key

Don't worry, you will soon get to practice with most of these!

Lineage

- When an RDD is transformed, this transformation is not automatically carried out.
- Instead, the system remembers how to get from one RDD to another and only executes whatever is needed for the action that is being done.
- this allows one to build up a complex "pipeline" and easily tweak/rerun it in its entirety

Getting started with Spark

Initializing Spark

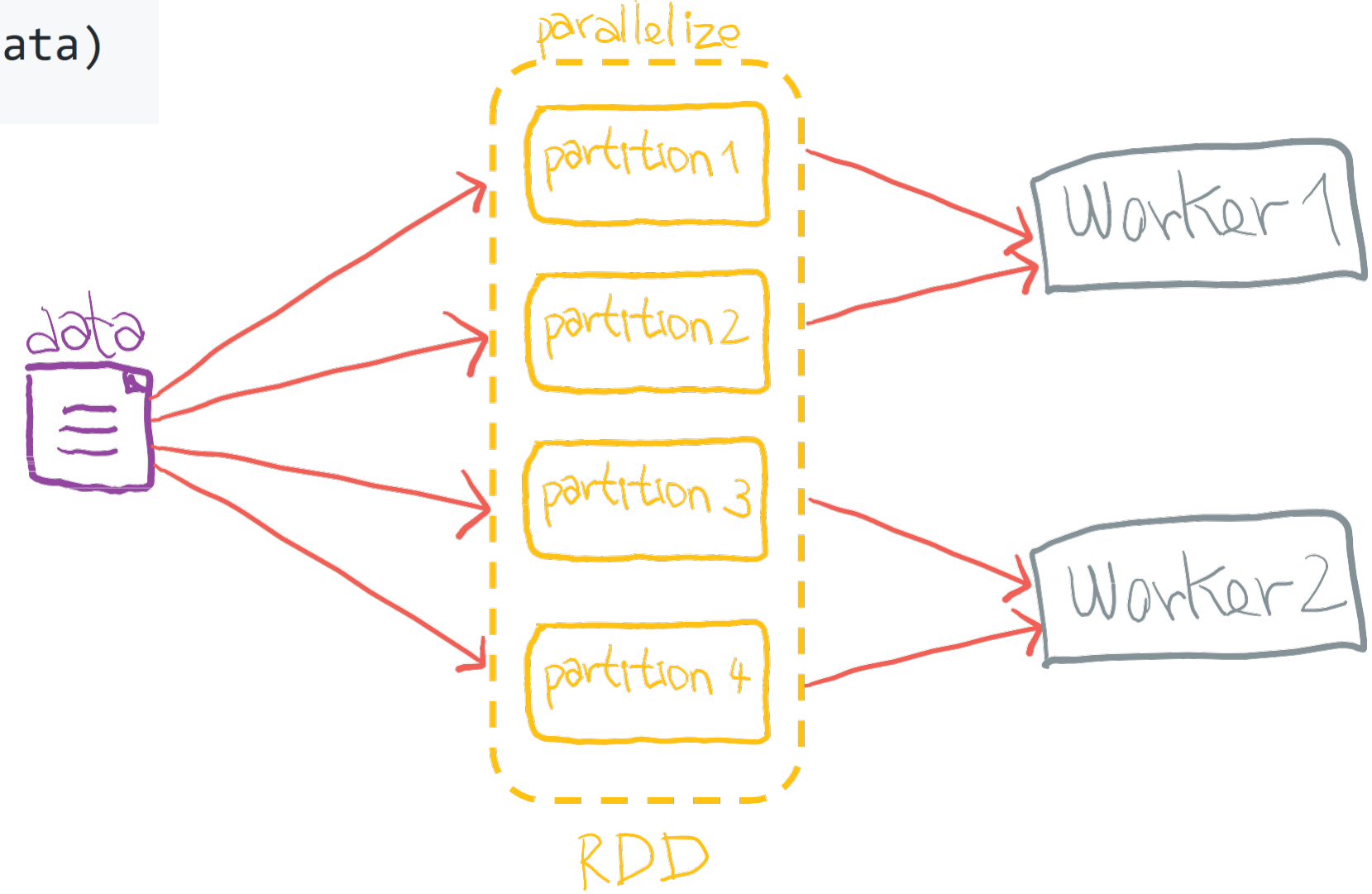
```
import pyspark

sc = pyspark.SparkContext()
```

Launches the Spark runtime and connects the application to the master.

This creates a driver which can now be used to dispatch work to the resources allocated for the application.

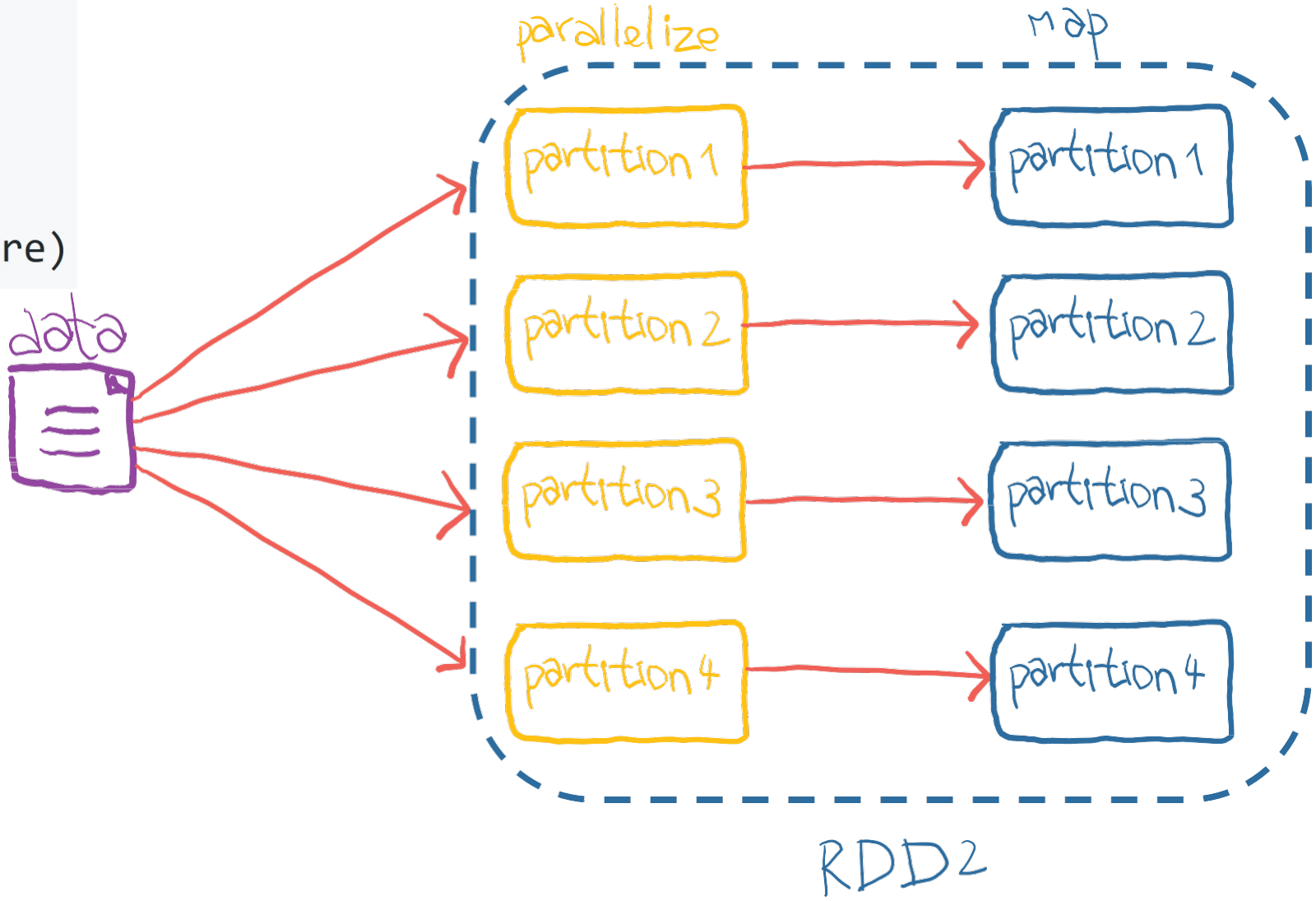
Create an RDD: parallelize

```
rdd = sc.parallelize(data)
```



Transform an RDD: map

```
def square(x):
    return x*x

rdd = sc.parallelize(data)
rdd_squared = rdd.map(square)
```

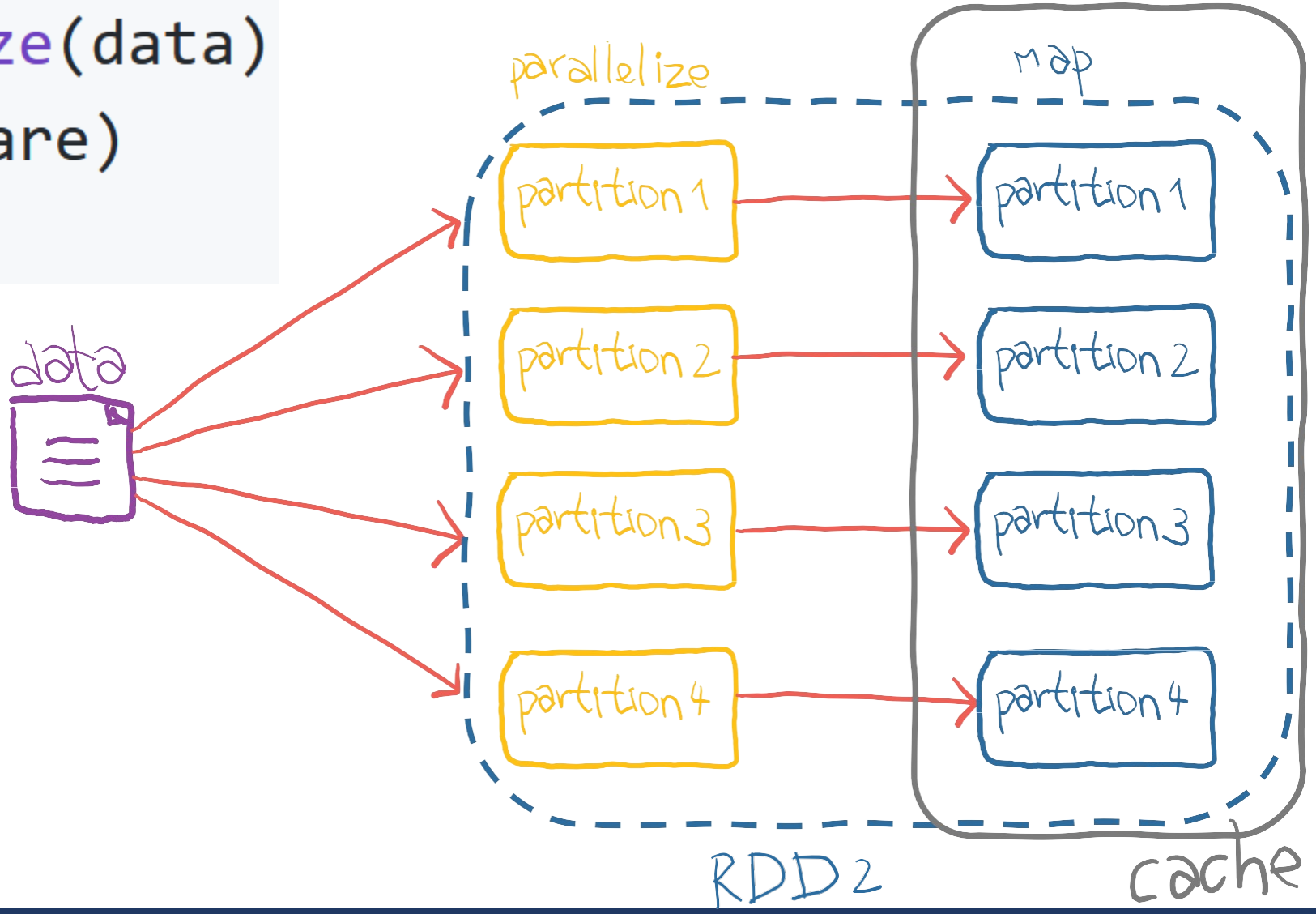


Caching

- RDD evalutations are *lazy*
- whenever an action is performed, the entire lineage graph is recalculated
- unless! an intermediate RDD is cached -- then it is only calculated once and reused from memory each subsequent time
- this allows for good performance when iterating on an RDD is required

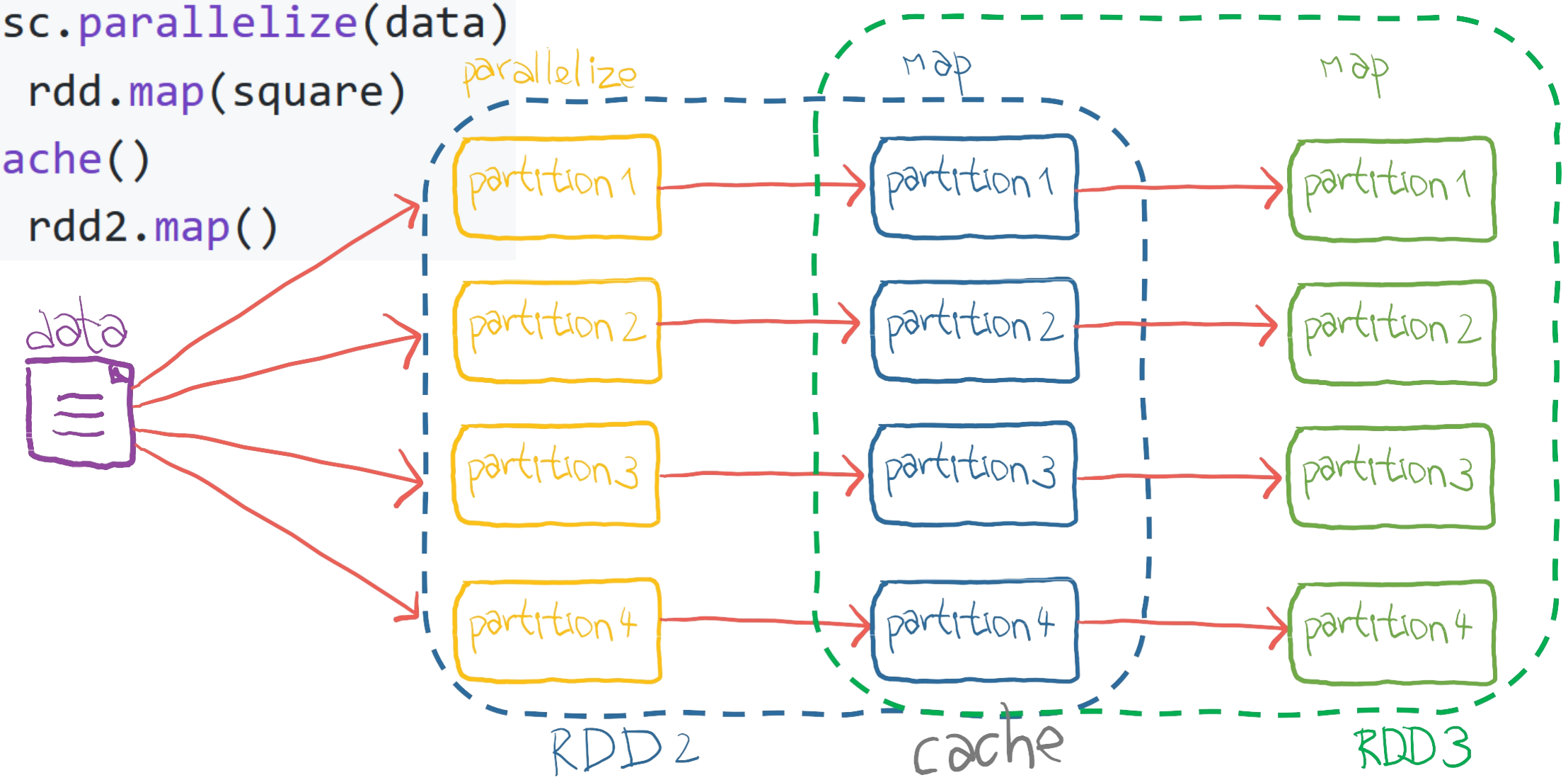
Caching

```
rdd = sc.parallelize(data)
rdd2 = rdd.map(square)
rdd2.cache()
```



Caching example

```
rdd = sc.parallelize(data)
rdd2 = rdd.map(square)
rdd2.cache()
rdd3 = rdd2.map()
```

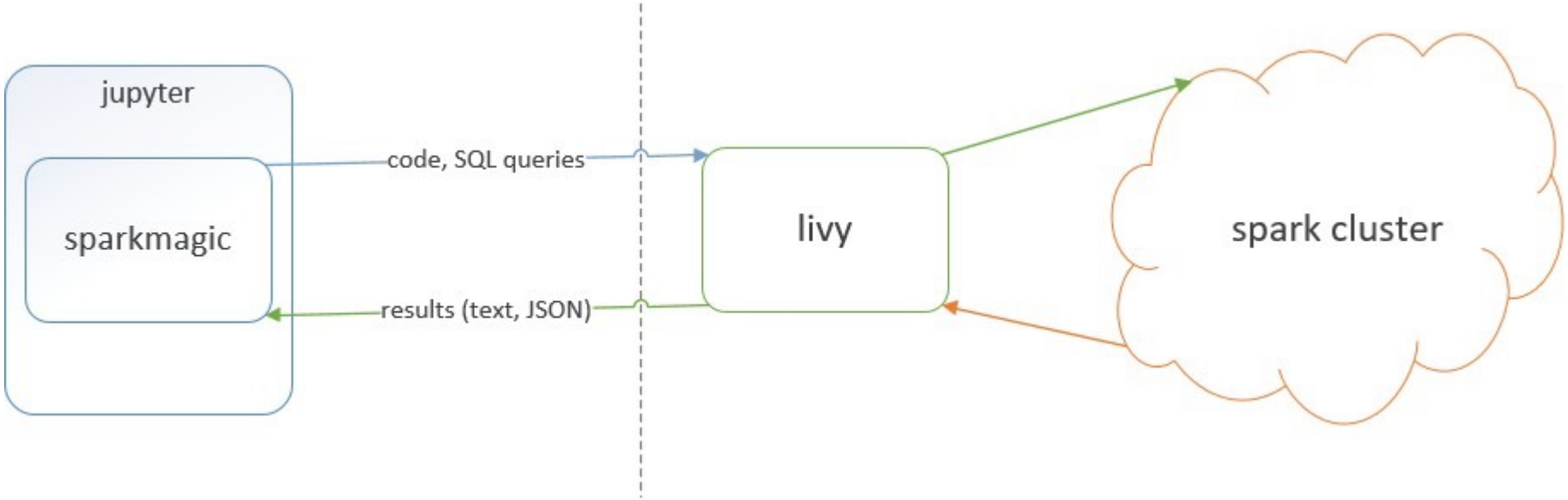


Partitioning

- data of each RDD is partitioned and each partition is assigned to an executor
- each partition in a transformation results in a task
- there may be many more tasks than cores in the system, which allows for good utilization by fine-graining the overall load.

Exercises & homework: Spark magic

We will be using Sparkmagic client to interact remotely with the Spark cluster from within a jupyter notebook



https://github.com/jupyter-incubator/sparkmagic

References

- Spark official website https://spark.apache.org/
- Spark RDD documentation https://spark.apache.org/docs/latest/rdd-programming-guide.html
- Spark RDD paper https://www.usenix.org/system/files/conference/nsdi12/nsdi12-final138.pdf
- Spark github repository https://github.com/apache/spark/

- MapReduce paper https://dl.acm.org/doi/abs/10.1145/1327452.1327492
- Yarn paper https://dl.acm.org/doi/10.1145/2523616.2523633

Start your engines

https://dslab2021-renku.epfl.ch/projects/com490-pub/w5-exercises

Time for the basic Spark tutorial!

- Head to the gitlab repo for this week:
- https://dslab2022-renku.epfl.ch/projects/com490/lab-course/
- Make sure you have the right commit and follow the instructions in the README.md to get set up in week5 folder.

Analyzing the Gutenberg corpus

- The Gutenberg Project is a large free repository of books and other media in different languages (but primarily English)
- We will use it to do some basic text analysis using key/value PairRDDs in Spark.

The data

- We have pre-processed the data already and created an RDD for you to use. The RDD consisting of (ID, text) key-value pairs can be found in

- HDFS /data/gutenberg/rdd

- This RDD will form the basis of the work in the notebook.

The goal

- The eventual goal is to produce something like the Google NGram viewer, but for the Gutenberg corpus.

- Because the notebook is quite long, the last part of the notebook is already filled in, but feel free to run it!