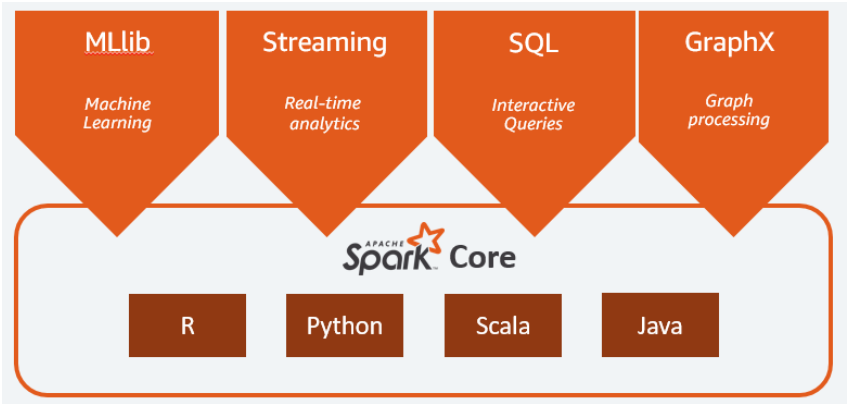
Apache Spark Fundamentals

OUTLINE

Introduction

- Spark is an open-source framework for developing and running applications on clusters. (Devised at *UC Berkeley* in 2009 and later donated to *Apache Software Foundation*).
- Spark provides
  - Unified computing engine (Spark Core) ← Orchestrates the computation
  - Programming interface usable with Scala, Java, Python, R
  - APIs for data analysis: Spark SQL (structured data) MLlib (machine learning), GraphX (graph analytics), Spark Streaming (streaming analytics). Spark is written in Scala.



- Spark runs on the Java Virtual Machine (JVM)

Introduction

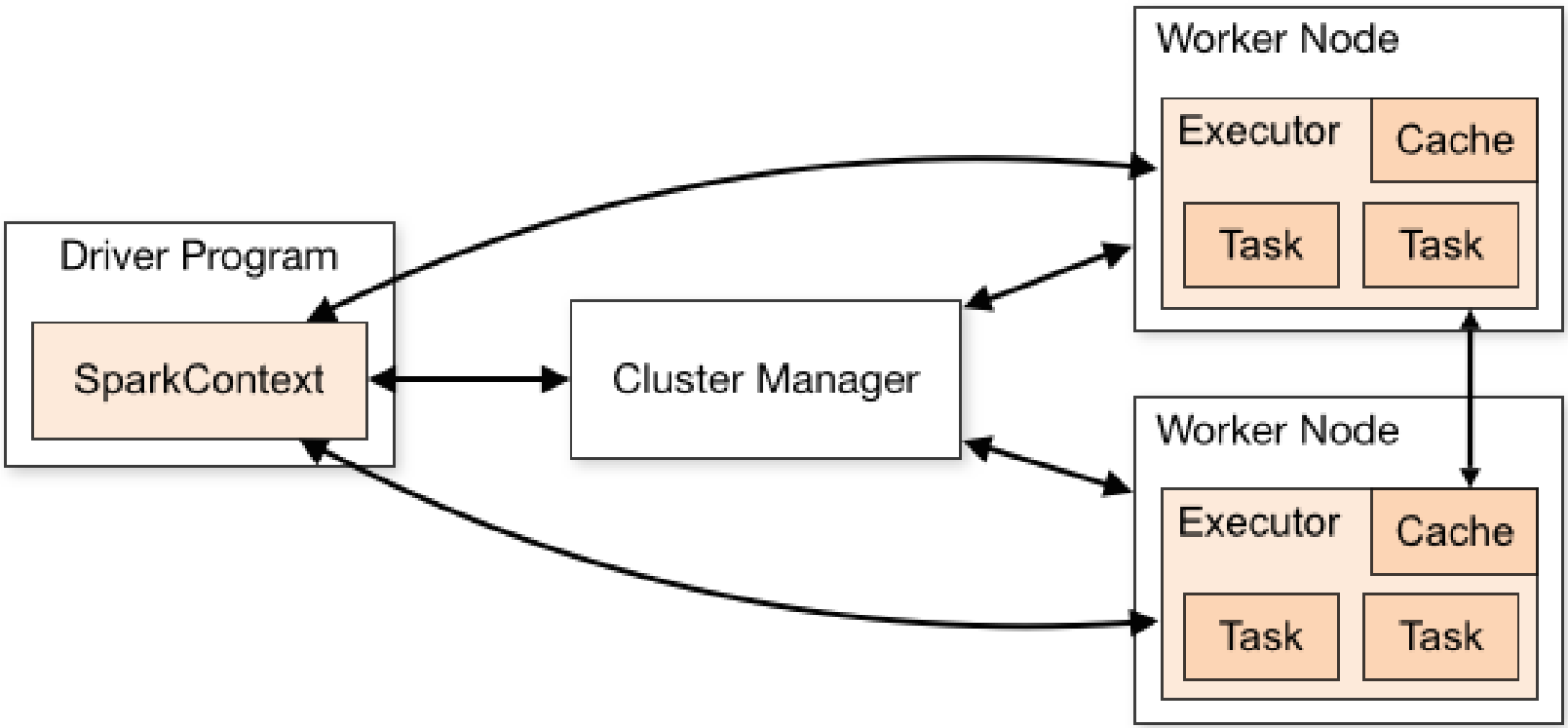
- Spark does not come with a storage system (unlike Hadoop) but can run on the *Hadoop Distributed File System* (HDFS) as well as on other systems (e.g., Amazon S3, Cassandra, HIVE, Relational DBMS).
- Spark's features:
  - Fault tolerance.
  - In-memory caching, which enables efficient execution of multiround algorithms, with a substantial performance improvement w.r.t. Hadoop.
- Spark can run:
  - On a single machine in the so called local mode. This is what we do in Homeworks 1 and 2.
  - On a cluster managed by a cluster manager such as Spark's Standalone, YARN, Mesos. For Homework 3 we will use the YARN cluster manager on CloudVeneto.

Why do we need a framework like Spark?

* To process big data efficiently at moderate costs we need to pool power and resources of several (inexpensive) machines into one platform
* Spark manages and coordinates the execution of big data jobs on such a distributed platform

Without a careful management and coordination the potential of the platform is likely to be wasted

Spark Application



Spark Application

- Driver (a.k.a. master): it is the heart of the application, and
  - Creates the Spark Context, an object which can be regarded as a channel to access all Spark functionalities.

    Obs.: Spark 2.0.0 introduced a Spark Session object which encapsulates the Spark Context and provides more functionalities.
  - Distributes tasks to the executors.
  - Monitors the status of the execution.

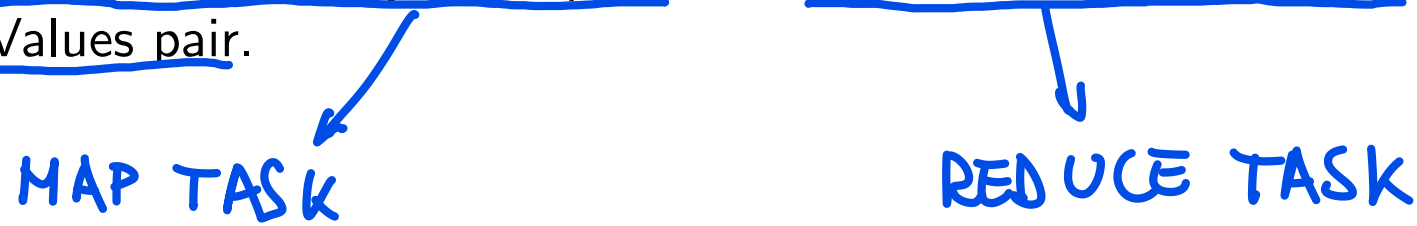
  The driver runs Java/Python/Scala code through the Spark's API.
- Executors (a.k.a. workers): execute the tasks assigned (through Scala code) by the driver, and report their status to the driver.

Spark Application

- Cluster manager: when the application is run on a distributed platform, the cluster manager controls the physical machines (i.e., compute nodes) and allocates resources to applications.

EXECUTION: when the application is run on a single machine (i.e., local mode) both driver and executors run on that machine as threads. If instead the application is run on a distributed platform (i.e., cluster mode) driver and executors can run on different machine

MAP REDUCE TASKS: if the application implements a MapReduce computation, a task assigned to an executor typically comprises running a map function on several key-value pairs or a reduce function on several key-listOfValues pair.

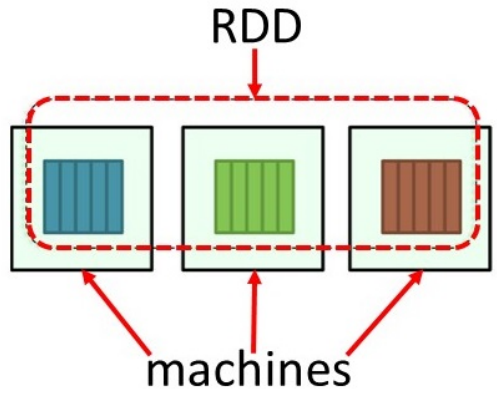


Observation: Even if a Map Task or a Reduce Task assigned to an executor requires the application of a map or reduce function to several inputs, the inputs will be processed one after the other in sequential fashion

Spark tries to assemble map and reduce tasks so to minimize data movement and to exploit caching

Resilient Distributed Dataset (RDD)

- Fundamental abstraction in Spark. An RDD is a collection of elements of the same type, partitioned and distributed across several machines (if available).



- An RDD provides an interface based on coarse-grained transformations.
- RDDs ensure fault-tolerance. (self recovery)

RDD: Main characteristics

- RDDs are created
  - from data in stable storage (e.g., HDFS), or
  - from other RDDs, through transformations.
- RDDs are immutable (i.e., read-only).
- RDDs are materialized only when needed (lazy evaluation).
- Spark maintains the *lineage* of each RDD, namely the sequence of transformations that generate it, which enable to materialize it or reconstruct it after a failure, starting from data in stable storage.

Because of the lazy evaluation, time measurements require care

RDD: Partitioning

- Key ingredient for efficiency: each RDD is broken into chunks called partitions which are distributed among the available machines.
- A program can specify the number of partitions for each RDD (if not, Spark will choose one).
- Partitions are created by default (using a HashPartitioner, based on objects' hash codes) or through a custom partitioner.
- Typical number of partitions: is 2x/3x the number of cores, which helps *balancing the work*.
- Partitioning enables:
  - Parallelism. Some data transformations can be applied to the partitions in parallel, thus exploiting the parallelism offered by the underlying platform.
  - Data reuse. In multi-round applications, the same partitioning can be exploited in consecutive rounds, so each partition remains stored in the same machine and, possibly, in RAM.

RDD: Operations

The following types of operations can be performed on an RDD A

- TRANSFORMATIONS. A transformation generates a new RDD B starting from the data in A. We distinguish between:
  - Narrow transformation. Each partition of A contributes to (at most) one partition of B, which is stored in the same machine. No shuffling of data across machines is needed ($\Rightarrow$ maximum parallelism). E.g., the *map* method.
  - Wide transformation. Each partition of A may contribute to many partitions of B. Hence, shuffling of data across machines may be required. E.g., the *groupByKey* method.

RDD: Operations

- ACTIONS. An action is a computation on the elements of A which returns a value to the application. E.g., the *count* method.

  LAZY EVALUATION: RDD A is materialized only when an action is performed.

- Persistence. Methods like persist or cache will save the RDD data in memory after the subsequent action.

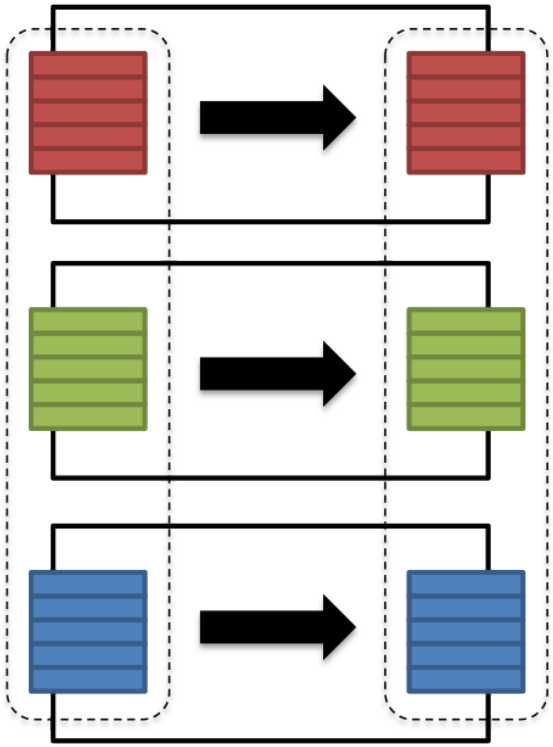
CACHE() ⇒ data will be stored in the RAMs of the executors. Those that do not fit in RAM will be recomputed

PERSIST(..) ⇒ receives as argument the type of storage for the data (e.g. RAM + disk)

RDD: Operations

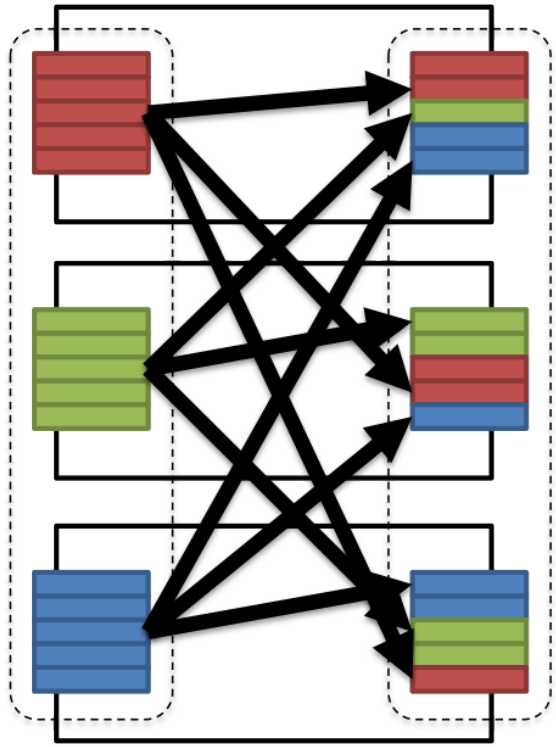
Narrow transformation

- Input and output stays in same partition
- No data movement is needed



Wide transformation

- Input from other partitions are required
- Data shuffling is needed before processing



Implementing MapReduce algorithms in Spark

The homeworks will provide you first-hand experience on how to implement MapReduce algorithms using Spark.

Summarized here are key points to keep in mind about this issue.

- Spark enables the implementation of MapReduce algorithms but offers a much richer set of processing methods.
- Spark (and MapReduce) exploits a core idea of functional programming: *functions can be argument to other functions*.
- A program which implements a MapReduce algorithm typically comprises
  - Spark configuration steps (e.g., creation of the context);
  - Definitions of global variables and data structures;
  - Reading of input data into one or more RDDs;
  - Code for the various rounds.

Implementing a MapReduce round in Spark

RDD X: input of the round

↓ MAP PHASE

RDD X': intermediate pairs

↓ REDUCE PHASE

RDD Y: output of the round

Observations on X, X', Y:

* distinct RDDs that will be materialized only if an action on Y is executed
* contain (key, value) pairs (NOT a STRINGENT REQUIREMENT)

Implementing a MapReduce round in Spark

- **Map Phase:** on the input RDD X invoke one of map methods offered by Spark (*narrow transformation*) passing the desired map function as argument.
- **Reduce Phase:** on the RDD X' resulting from the Map Phase:
  - invoke one of grouping methods offered by Spark (*wide transformation*) to group the key-value pairs into *key-ListOfValues* pairs;
  - invoke one of map methods offered by Spark to apply the desired *reduce function* to each *key-ListOfValues* pair.

  The reduceByKey method allows you to do both steps at once.

DataFrames and Datasets

- RDDs represent the most basic data model in Spark: it is low-level and schema-less.
- On top of RDDs, the Spark SQL module provides APIs to operate on the following structured data (similar to tables in Relational DB):
  - DataFrame: distributed collection of data organized into named columns
  - Dataset: extension of DataFrame (available only in Java and Scala) with type-safe, object-oriented programming interface.

In the course we use RDDs only!

Summary

- Spark features
- Spark Application: driver process, executor processors, cluster manager.
- Resilient Distributed Dataset (RDD)
  - Main characteristics
  - Partitioning
  - Operations: transformations, actions, persistence.
- Implementing MapReduce algorithms in Spark.
- DataFrames and Datasets.

References

AS-1 Spark's Web Site: `spark.apache.org`

AS-2 Spark's RDD Programming guide:
`spark.apache.org/docs/latest/rdd-programming-guide.html`

CZ18 A Gentle Introduction to Apache Spark. From B. Chambers, M. Zaharia. *Spark: The Definite Guide*, Databricks 2018.

Z+12 M. Zaharia et al. Resilient Distributed Datasets: A Fault-Tolerant Abstraction for In-Memory Cluster Computing. NSDI 2012: 15-28.