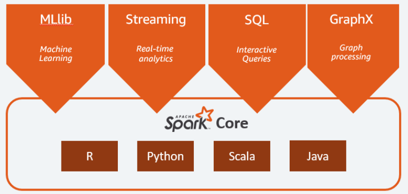
Apache Spark Fundamentals

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)
    - 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.



easy to write
long to execute

- Spark runs on the Java Virtual Machine (JVM)

Introduction

NO DFS

- 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.
  - On a cluster managed by a cluster manager such as Spark's Standalone, YARN, Mesos.

In the homeworks, you will have the opportunity to use Spark on your machine as well as on a cluster through CloudVeneto (using YARN).

Why do we need a framework like Spark?

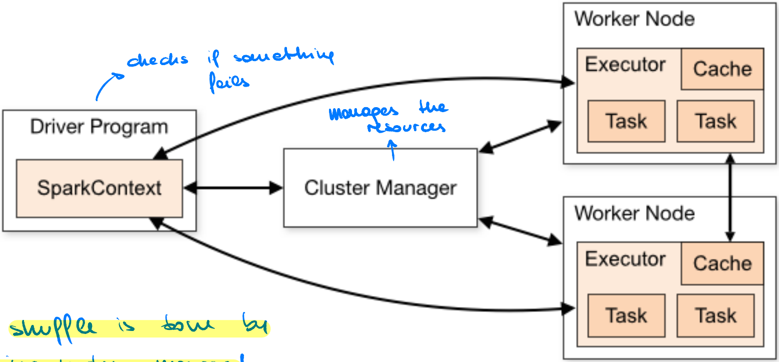
- Processing big data
- Hide low level details
- Easier to write BD algorithms
- Data-driven approach

functional approach

Spark Application

checks if something fails

manages the resources



map / redu

The shuffle is done by working nodes, managed by the driver program

(nodes move data where the driver program tell them where to send data)

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/R 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

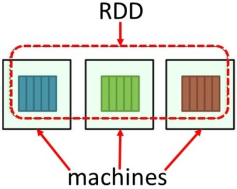
- Cluster manager: when the application is run on a distributed platform, the cluster manager controls the physical machines (i.e., compute nodes) and allocates resources to applications.

EXECUTION: when the application is run on a single machine (i.e., local mode), 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 machines

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.

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.

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.

$R_1 \rightarrow R_2 = R_1.\text{transform} \ldots \rightarrow R_{n+1} = R_n.\text{transform}.$

new one

If I lose R_{n+1} I don't need to start over but I just need to do R_n.transform

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 is exploited to enhance performance:
  - Spark creates map tasks so to make each executor apply the map function on data from a locally stored partition (if possible).
  - To implement algorithms that require partitioning, the programmer can explicitly access RDD partitions (e.g., *mapPartition* method).
  - RDD partitions are explioited implicitly by some ready-made Spark aggregation primitives (e.g., *reduceByKey* method).

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., *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., *groupByKey* method.

RDD: Operations

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

  LAZY EVALUATION: RDD A is materialized only when an action is performed. *This must be carefully taken into account when measuring running times*

- Persistence. Methods like cache() or persist() will save the RDD data in memory after the subsequent action.
  - cache(): data are stored asin RAM (if they fit). Data that do not fit are recomputed when needed.
  - persist(): data are stored as instructed. There are several options, e.g., MEMORY_AND_DISK (RAM+Disk).

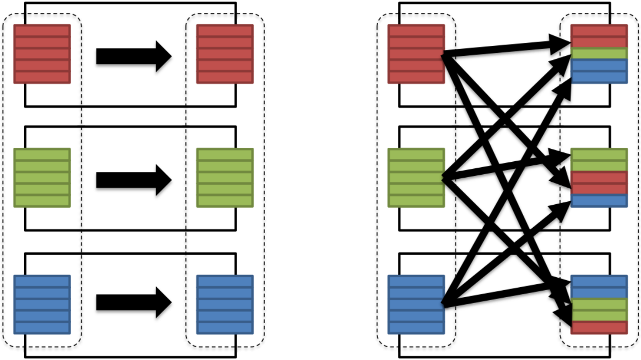
RDD: Operations

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 (typically, in the driver's memory);
  - Reading of input data into one or more RDDs;
  - Code for the various rounds.

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.

Alternatively, one can use one of the ready-made reduce primitives offered by Spark (e.g., reduceByKey).

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!