Parallel Data with MapReduce and Spark (Part 2, Spark)

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Lecture 11.1.2 (v1.0.1)

Signposting

- Block 11 on **parallel infrastructure** is paired with Block 10 on **parallel algorithms**.
- This week we cover **parallel data frameworks**, which use parallel algorithms on distributed datasets.
- Lecture 11.1 covers all the abstract content, whilst the workshop 11.2 focusses on practicalities.
- This is 11.1.2, which covers:
  - Spark overview
  - Resilient Distributed Datasets
  - Spark

Spark

- Like Hadoop, Spark accesses data stored on HDFS via YARN. It offers many additional features, including:
  - **Data abstractions**, both data table and graph-based;
  - Interactive, **stateful** data representations;
  - Interfaces for multiple programming languages (Scala, Python, Java);
  - MLlib, a distributed machine learning toolkit.
- We'll focus on **pyspark**.
  - This means that we access the features of Spark through python code.
  - It is still necessary to learn the **concepts** of Spark.
  - The code that we write will be python, though the setup of a Spark session involves very specific commands.

Resilient Distributed Dataset (RDD)

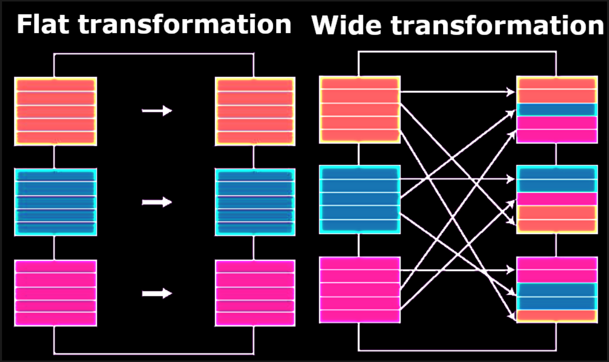
- The core concept of Spark is the RDD.
- RDDs are **immutable**, **distributed** collection of elements of your data that can be **stored in memory or disk**.
- They should be thought of as a new type of data frame, e.g. numpy, pandas, RDD.
- Interacting with them is mostly just learning new notation...
- With the exception that it operates through:
  - **transformations**, which create a new dataset from an existing one,
  - **actions**, which return a value.
- As in Hadoop, Spark also makes strong use of key/value pairs.

Transformations

- Transformations [1] are **lazy**, i.e. they are not evaluated until the answer is required. This means that they can be efficiently compiled into complex batch operations.
- Transformations can **persist**, i.e. be retained in the memory of each worker node.
- Naive use of transformations can be inefficient, due to data duplication. This is why they are batched together.
- Behind the scenes, **computational graphs** are being exploited to ensure **parallelisation** and lazy, i.e. efficient **evaluation**.
- Chaining multiple transformations allow only the RDD at the start and end of the operation is (explicitly) stored.

[1] Spark RDD Transformations

Transformation types



- Transformations can be thought of in two key types.
  - **Narrow transformations**: which operate locally on data (embarrassingly parallel),
  - **Wide transformations**: which operate on the whole of the data.

Actions

- Actions are simpler concepts than transformations: they return a value.
- They return a “value”, i.e. a not an RDD, either to the interface or to disk.
- They trigger the evaluation of transformations.

RDD Examples

- Which of these are narrow transformations? Which are wide? Which are actions?
  - Collect: Collects data to the interface.
  - Map: Map as in MapReduce.
  - Intersection: Compute the intersection data in multiple RDDs.
  - Distinct: Obtain only distinct elements, discarding duplicates.
  - Filter: Remove elements satisfying some criterion.
  - First: Get the first few elements.
  - Sample: Get a sample of elements.
  - Union: Combine two RDDs.
  - ReduceByKey: Reduce an RDD by key.
  - Take: Get specific elements.
  - Join: Merge two RDDs.

RDD Examples - Answers

- Narrow Transformations:
  - Map
  - Filter
  - Sample
  - Union
- Wide Transformations:
  - Intersection
  - Distinct
  - ReduceByKey
  - Join
- Actions:
  - Collect
  - First
  - Take

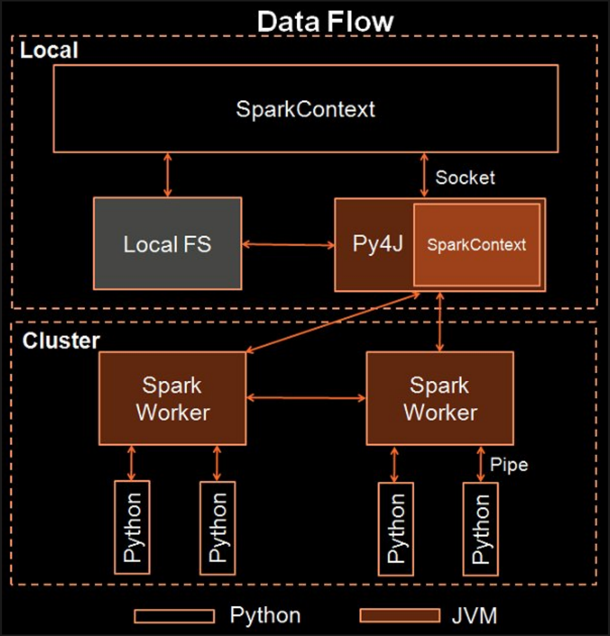
Pyspark

- Interacting with RDDs requires learning the new schema associated with them.
- Apart from interacting with RDDs, **pyspark can use standard python functions** to perform calculations.
- This means that you can use standard “boiler plate” RDD manipulation (copied from the internet),
- And write your own dedicated analysis in a familiar language.

The Spark Context

- Spark is really a **framework** running in Java, by which compute processes communicate.
- On the **head** machine ("Local") you create a **SparkContext** instance, which sets up **Spark Worker** instances on (typically remote) compute nodes.
- These will operate on RDDs seamlessly for you as the user.
- Users can:
  - interact with the local file system,
  - distribute data via RDDs,
  - distribute variables via direct communication,
- All seamlessly, **as if the data were stored on their local instance**.

The Spark Context



Passing functions to Spark

```
def myFunc(s):
    words = s.split(" ")
    return len(words)
sc = SparkContext(...)
sc.textFile("file.txt").map(myFunc)
```

Sharing data across nodes

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

- Any communication that can occur via RDDs should do so, as this is computationally efficient.
- However, Spark supports **communication between nodes** in a number of ways.
  - One is the **broadcast**, which shares results with all other nodes.
- This is a way to share common information.

Important transformations

- See the Spark RDD guide for many more transformations:
- Map/Reduce:
  - **map**: as we know from map/reduce.
  - **reduceByKey**: as we know from map/reduce, but with flexible key specification.
- Database:
  - **join**: merge datasets by a key.
  - **filter**: selection of items by feature.
  - **sortByKey**: sorting by key, as from map/sort/reduce.
  - **aggregateByKey**: aggregate/combine the data into a new type.
- Data management:
  - **sample**: random selection of items (as an RDD).
  - **repartition**: reshuffle the data across the nodes.

Accumulate example

```
accum = sc.accumulator(0)
sc.parallelize([1, 2, 3, 4]).foreach(lambda x: accum.add(x))
accum.value
## 10
```

- As in Python Map/Reduce, **Reducing** is called many things.
- Just like Python, each does a slightly different thing. One key distinction is whether the reduce is a transformation, or an action.
- An **Accumulator** is the main **Action** for reducing.
- You can of course run a **reduceByKey** followed by a **collect** to achieve a similar thing.

Summary

- Parallel computing with Spark provides a transparent way to scale to **big data**, too large to fit on one machine.
- It requires a paradigm shift to its concept of RDDs, and their associated **transformations** and **actions**.
- There are some simple (enough) commands to create the required infrastructure.
- Beyond this, everything is vanilla python (with **pyspark**) or indeed vanilla R (with **SparkR**).

Reflection

- What are the key properties of an RDD?
- Why do we use transformations and actions?
- What advantages does Spark offer over Hadoop? How is it related?
- How are RDDs related to the Map/Reduce concepts?
- By the end of the course you should:
    - Be able to work with RDDs,
    - Understand Spark at a high level,
    - Be able to work with Big Data by coding in a Distributed Dataset programming environment.

Signposting

- In the workshop we will explore Hadoop and pyspark in a toy context.
- Note that the University doesn't support genuine HDFS deployment.
- We'll apply the ideas above into code.
- The final Block 12 is about being a "well rounded data scientist" - covering ethics, privacy, and deployment.
- References:
  - Spark RDD guide
  - pyspark
  - Spark RDD Transformations