Overview of Spark

Let’s learn something!

PIERIAN DATA

Python and Spark

- Before we begin the setup and coding with Python and Spark, let’s discuss what Spark is in the context of Big Data.
- We’ll begin with a general explanation of what Big Data is and related technologies.

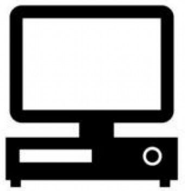
Big Data Overview

- What is “Big Data”?
- Explanation of Hadoop, MapReduce,and Spark
- Local versus Distributed Systems
- Overview of Hadoop Ecosystem
- Overview of Spark

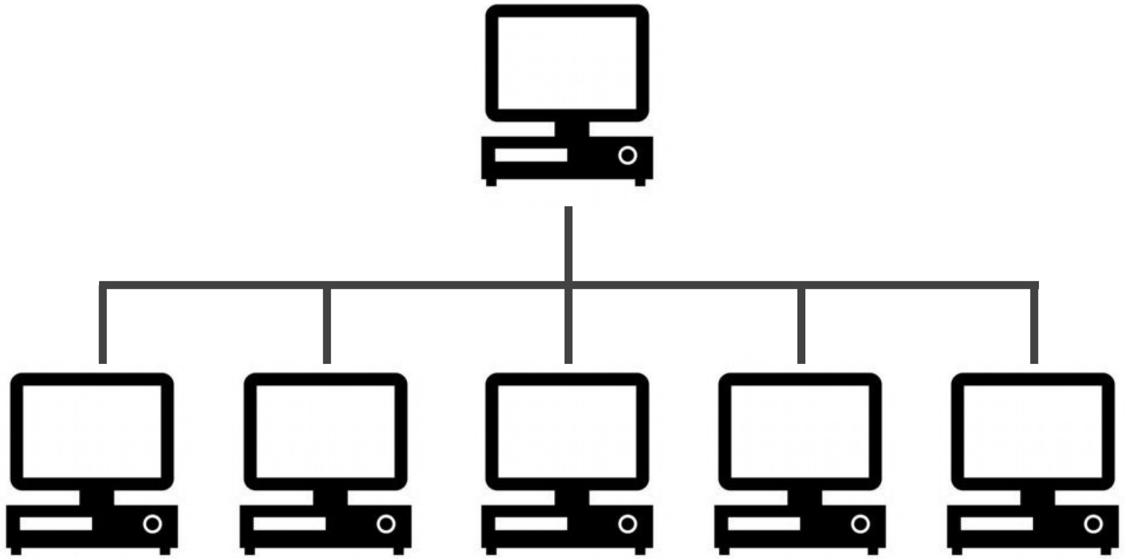
Big Data

- Data that can fit on a local computer, in the scale of 0-32 GB depending on RAM.
- But what can we do if we have a larger set of data?
  - Try using a SQL database to move storage onto hard drive instead of RAM
  - Or use a distributed system, that distributes the data to multiple machines/computer.

Local versus Distributed



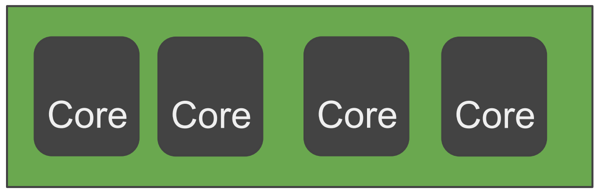
Local



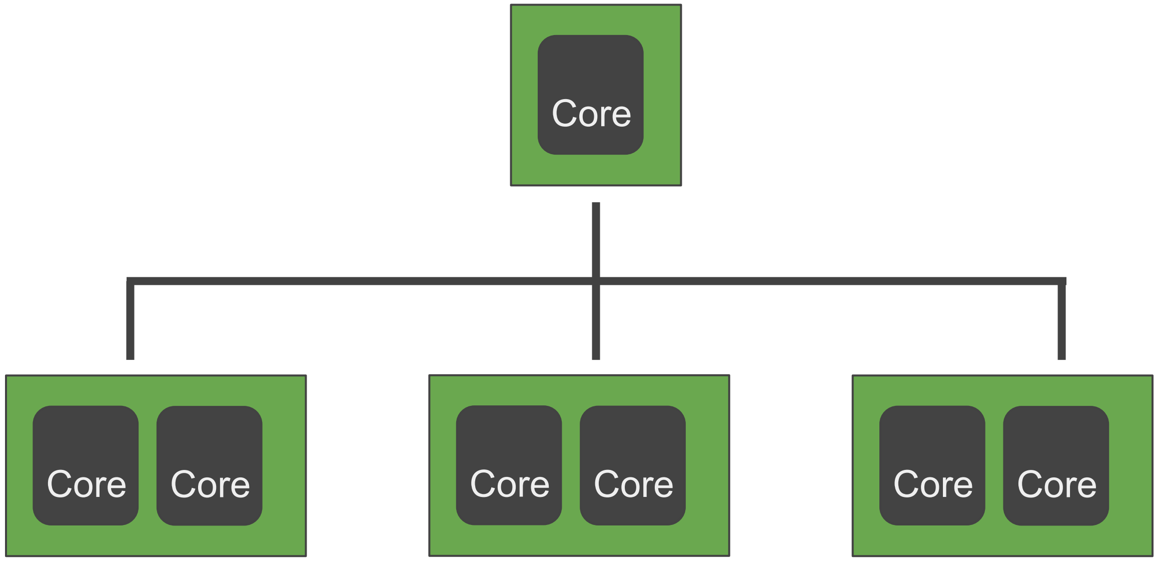
Distributed

PIERIAN DATA

Local versus Distributed



Local



Distributed

Big Data

- A local process will use the computation resources of a single machine
- A distributed process has access to the computational resources across a number of machines connected through a network

Big Data

- After a certain point, it is easier to scale out to many lower CPU machines, than to try to scale up to a single machine with a high CPU.
- Distributed machines also have the advantage of easily scaling, you can just add more machines

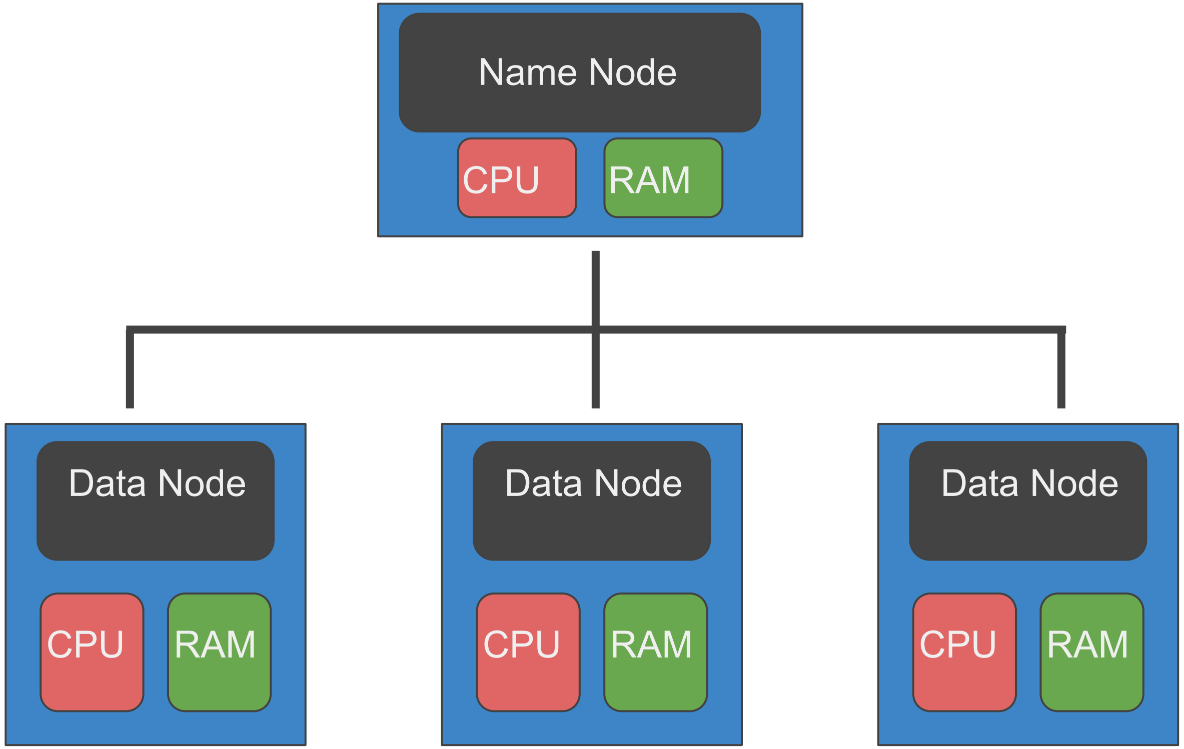
Big Data

- They also include fault tolerance, if one machine fails, the whole network can still go on.
- Let’s discuss the typical format of a distributed architecture that uses Hadoop

Hadoop

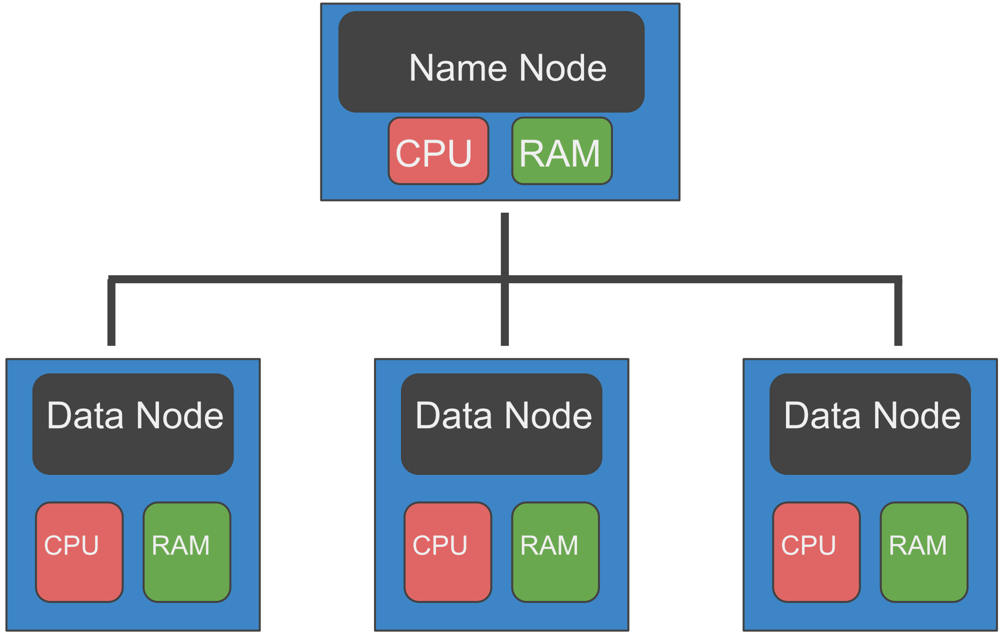
- Hadoop is a way to distribute very large files across multiple machines.
- It uses the Hadoop Distributed File System (HDFS)
- HDFS allows a user to work with large data sets
- HDFS also duplicates blocks of data for fault tolerance
- It also then uses MapReduce
- MapReduce allows computations on that data

Distributed Storage - HDFS



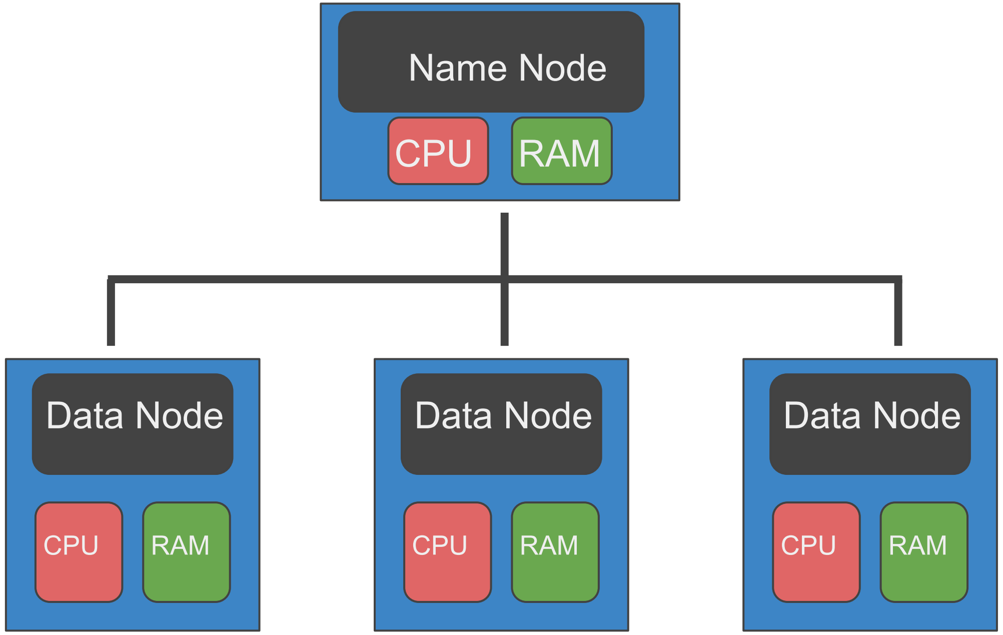
Distributed Storage - HDFS

- HDFS will use blocks of data, with a size of 128 MB by default
- Each of these blocks is replicated 3 times
- The blocks are distributed in a way to support fault tolerance



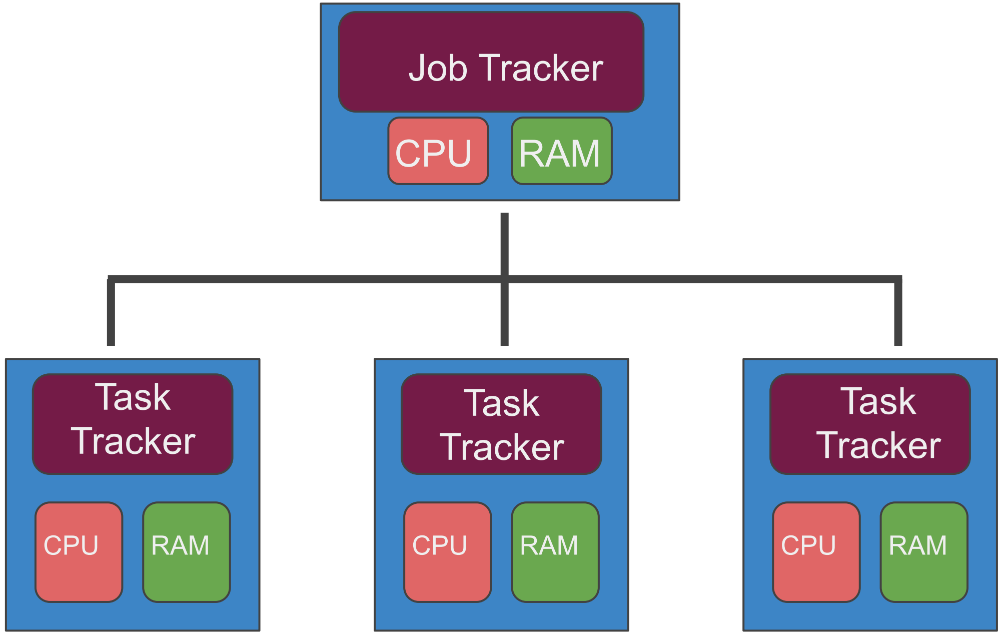
Distributed Storage - HDFS

- Smaller blocks provide more parallelization during processing
- Multiple copies of a block prevent loss of data due to a failure of a node



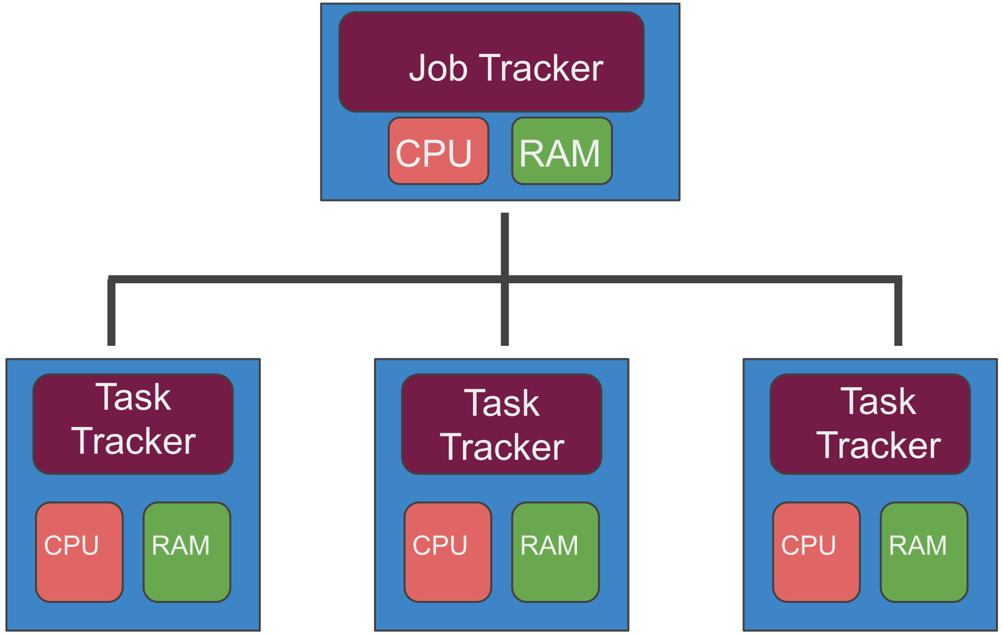
MapReduce

- MapReduce is a way of splitting a computation task to a distributed set of files (such as HDFS)
- It consists of a Job Tracker and multiple Task Trackers



MapReduce

- The Job Tracker sends code to run on the Task Trackers
- The Task trackers allocate CPU and memory for the tasks and monitor the tasks on the worker nodes



Big Data

- What we covered can be thought of in two distinct parts:
  - Using HDFS to distribute large data sets
  - Using MapReduce to distribute a computational task to a distributed data set
- Next we will learn about the latest technology in this space known as Spark.
- Spark improves on the concepts of using distribution

Spark

- This lecture will be an abstract overview, we will discuss:
    - Spark
    - Spark vs MapReduce
    - Spark RDDs
    - Spark DataFrames

Spark

- Spark is one of the latest technologies being used to quickly and easily handle Big Data
- It is an open source project on Apache
- It was first released in February 2013 and has exploded in popularity due to it’s ease of use and speed
- It was created at the AMPLab at UC Berkeley

Spark

- You can think of Spark as a flexible alternative to MapReduce
- Spark can use data stored in a variety of formats
    - Cassandra
    - AWS S3
    - HDFS
    - And more

Spark vs MapReduce

- MapReduce requires files to be stored in HDFS, Spark does not!
- Spark also can perform operations up to 100x faster than MapReduce
- So how does it achieve this speed?

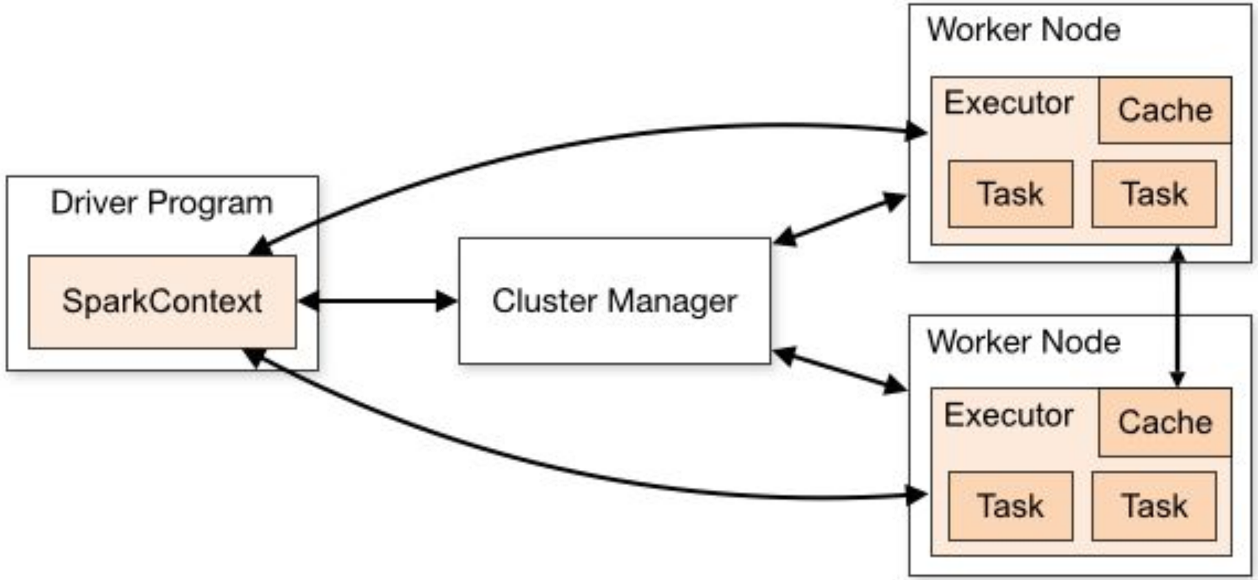
Spark vs MapReduce

- MapReduce writes most data to disk after each map and reduce operation
- Spark keeps most of the data in memory after each transformation
- Spark can spill over to disk if the memory is filled

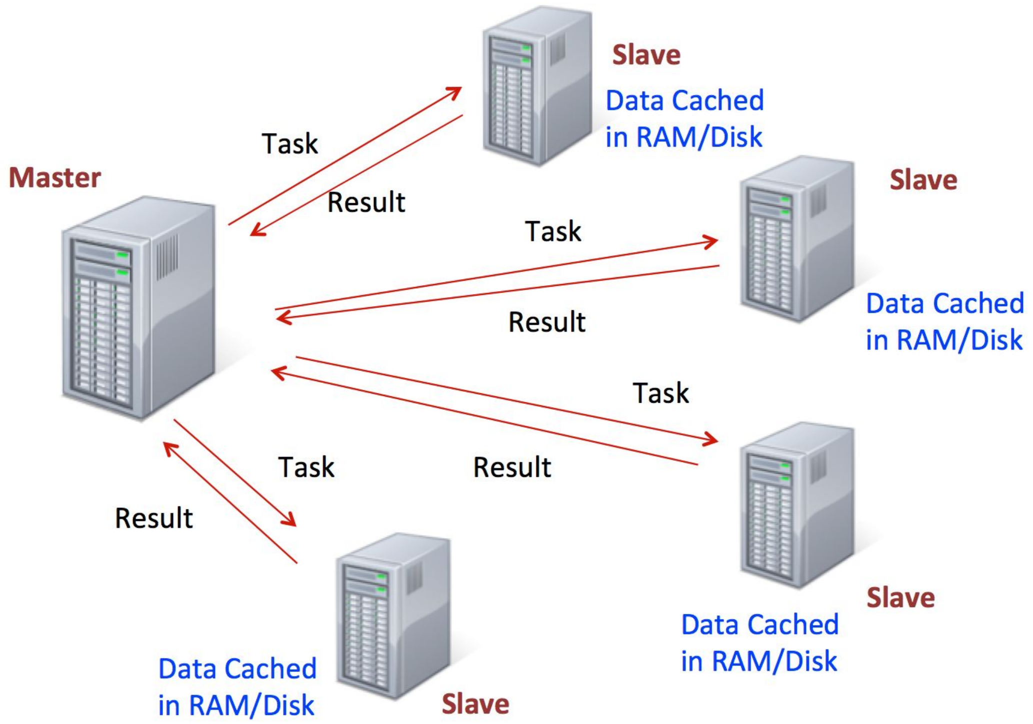
Spark RDDs

- At the core of Spark is the idea of a Resilient Distributed Dataset (RDD)
- Resilient Distributed Dataset (RDD) has 4 main features:
    - Distributed Collection of Data
    - Fault-tolerant
    - Parallel operation - partioned
    - Ability to use many data sources

Spark RDDs


Driver Program
SparkContext
Cluster Manager
Worker Node
Executor
Cache
Task
Task
Worker Node
Executor
Cache
Task
Task

Spark RDDs


Slave
Data Cached in RAM/Disk
Task
Result
Master
Slave
Task
Data Cached in RAM/Disk
Result
Task
Task
Result
Result
Slave
Data Cached in RAM/Disk
Data Cached in RAM/Disk
Slave

Spark RDDs

- RDDs are immutable, lazily evaluated, and cacheable
- There are two types of Spark operations:
  - Transformations
  - Actions
- Transformations are basically a recipe to follow.
- Actions actually perform what the recipe says to do and returns something back.

Spark RDDs

- This behaviour carries over to the syntax when coding.
- A lot of times you will write a method call, but won’t see anything as a result until you call the action.
- This makes sense because with a large dataset, you don’t want to calculate all the transformations until you are sure you want to perform them!

Spark RDDs

- When discussing Spark syntax you will see RDD versus DataFrame syntax show up.
- With the release of Spark 2.0, Spark is moving towards a DataFrame based syntax, but keep in mind that the way files are being distributed can still be thought of as RDDs, it is just the typed out syntax that is changing

Spark RDDs

- We’ve covered a lot!
- Don’t worry if you didn’t memorize all these details, a lot of this will be covered again as we learn about how to actually code out and utilize these ideas!

Spark DataFrames

- Spark DataFrames are also now the standard way of using Spark’s Machine Learning Capabilities.
- Spark DataFrame documentation is still pretty new and can be sparse.
- Let’s get a brief tour of the documentation!

http://spark.apache.org/

Python and Spark

PIERIAN DATA