DB Management Systems
Distributed: Spark

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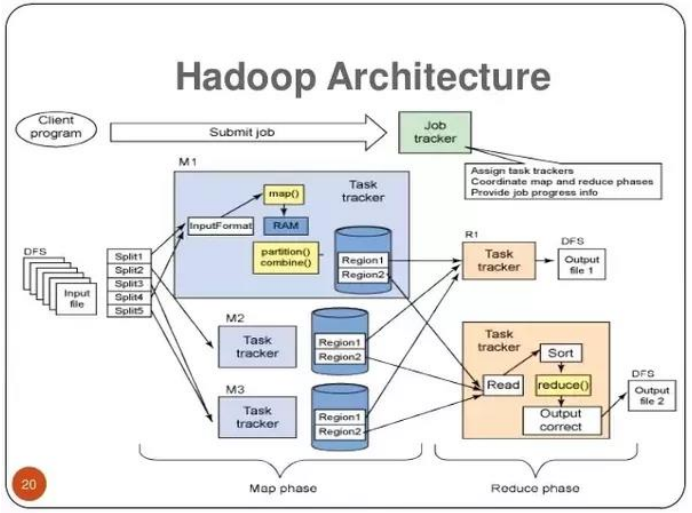
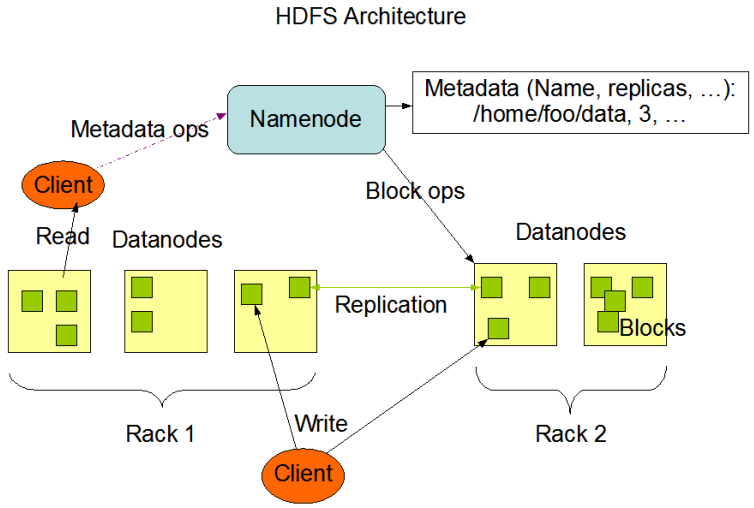
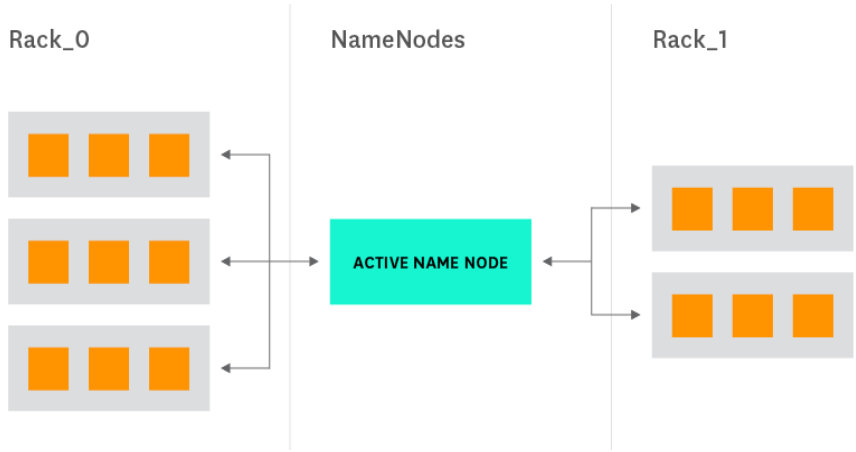
Spark Architecture

Spark? Architectural Diagram

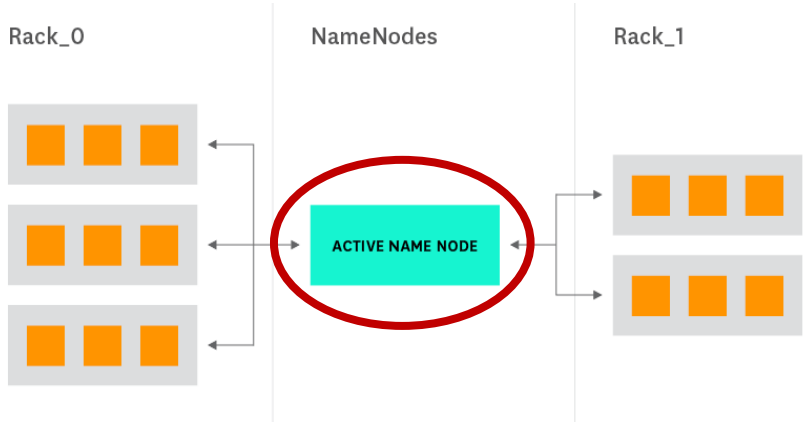
Complex → **Simple**





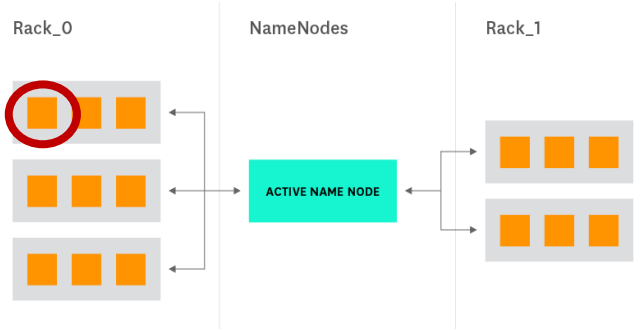


NameNode (Spark Driver)



- Think of this as the master node.
- It is the node a user actually interfaces with to input commands/configuration
- It doesn’t need to necessarily be a crazy machine (specs wise) as it doesn’t do any of the heavy lifting

DataNode (Worker/Executor)



- DataNode's represent the true brute force behind Spark.
- They are the nodes that both store and process (in memory) the data used by Sparks acyclic graph transformations
  - Executors can load data through a number of different sources
    - S3, FTP, local filesystem, Azure, Swift(??)
  - Executors load the data into memory, rather than locally on disk
- These machines are usually beefier than the NameNode, as they need to be able to process large amounts of data quickly
  - These machines typically need more RAM since spark operates entirely in memory

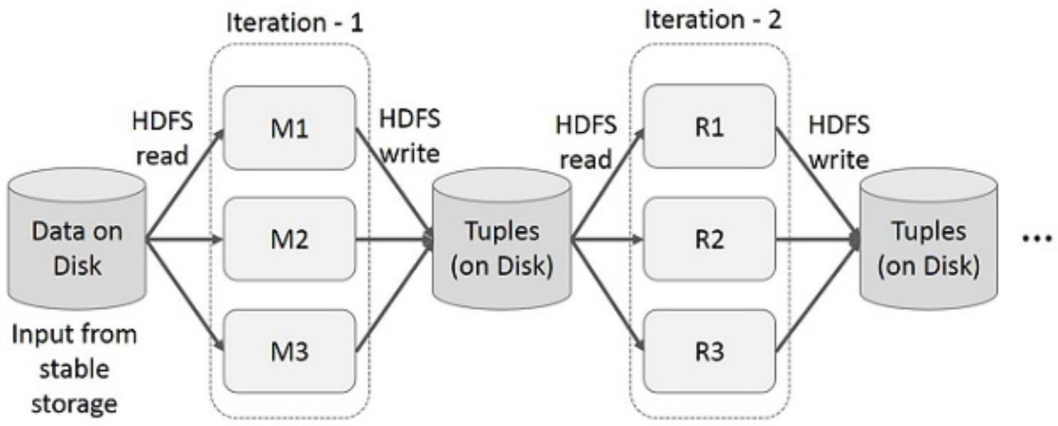
Resilient Distributed Dataset

- RDD's are essentially like Series in Spark, designed for parallelized and distributed operations.
  - They are a collection of objects storing data
  - Some key traits are:
    - Immutability – once created they can not be changed
    - Partitioned – the dataframes are split amongst a number of executors
    - Typed – each record is statically typed (RDD[Long], RDD[String, Int, etc.])
- RDD's can only be manipulated via transformations
  - **map**, flatmap, **filter**, **reduceByKey**, join, cogroup

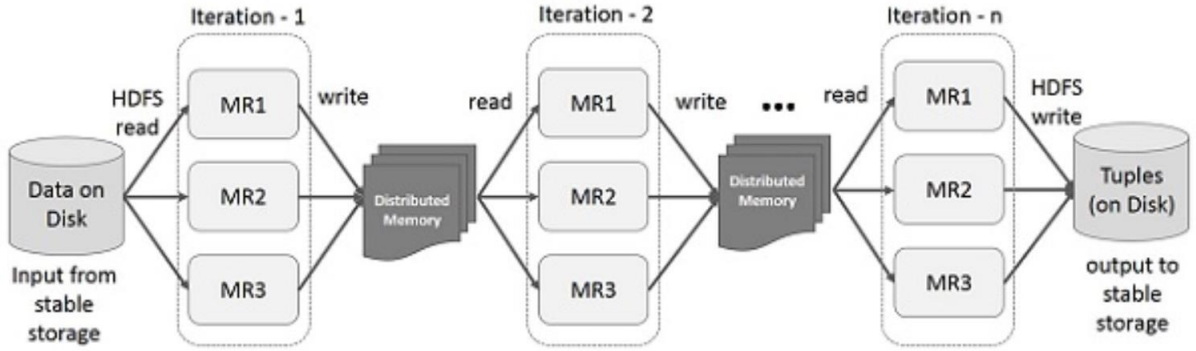
Directed Acyclic Graph (DAG)

- DAG is Sparks version of MapReduce. It is essentially a more verbose implementation.
  - Essentially it is the process of altering an RDD through a series of transformations (as mentioned earlier)

Hadoop MapReduce



Spark DAG



MapReduce

- Always two operations in order
  1. Map
  2. Reduce
- Information is read from disk and saved out to disk during each intermediary step
- Great for batch processing

DAG

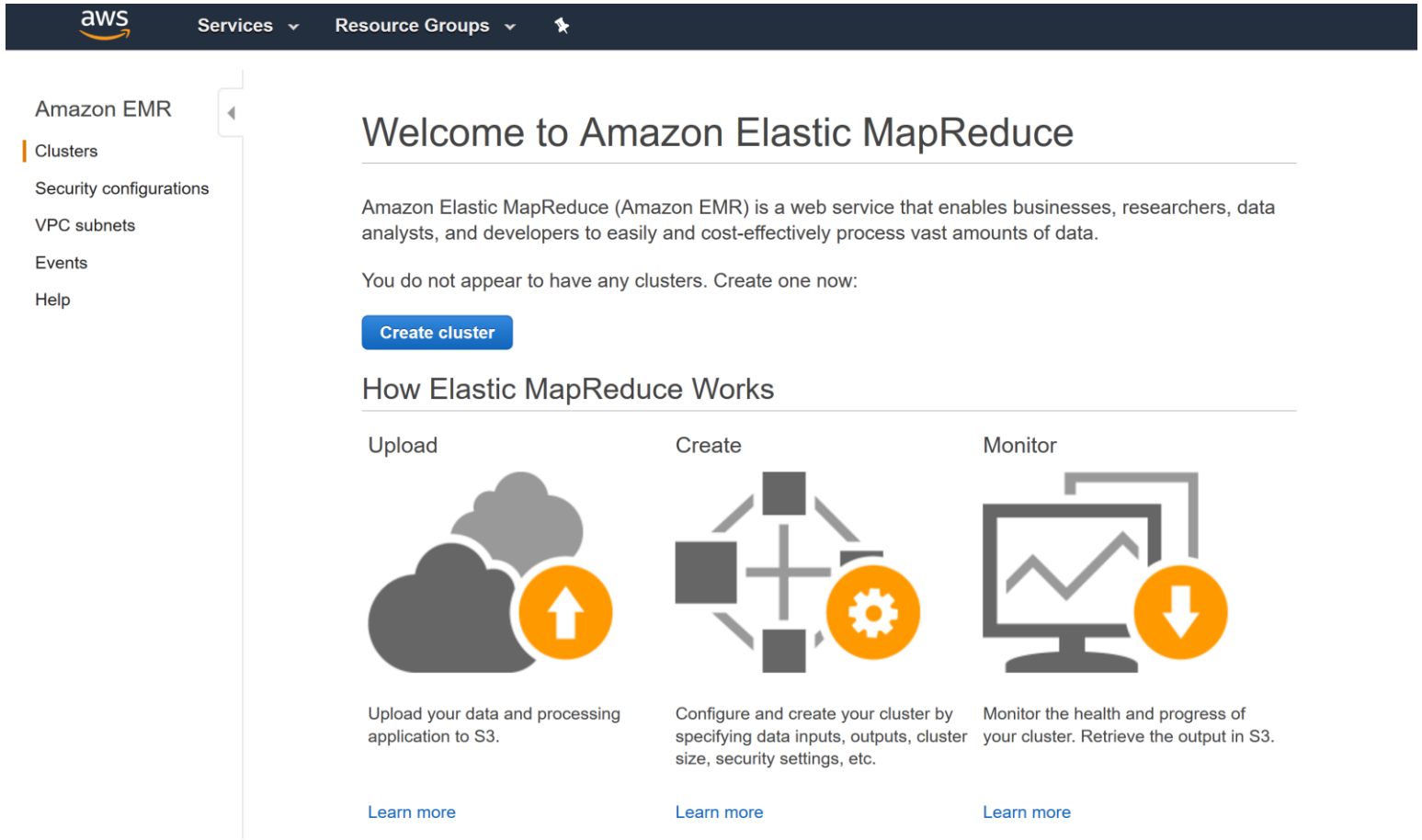
- Can perform any combination of transformations between RDD states
  - MapReduce can be one of these transformation processes
- Initial data is read from disk, but all further transformations take place solely in-memory
- Great for real-time processing and fast iterative processes (training ML algorithms)

Programming in Spark

- One of the main reasons for the recent surge in Spark is due to its ease of use through flexible API's
- These API's have SDKs for the following programming languages (there may be more):
  - Scala
  - Java
  - Python
  - SQL
  - R

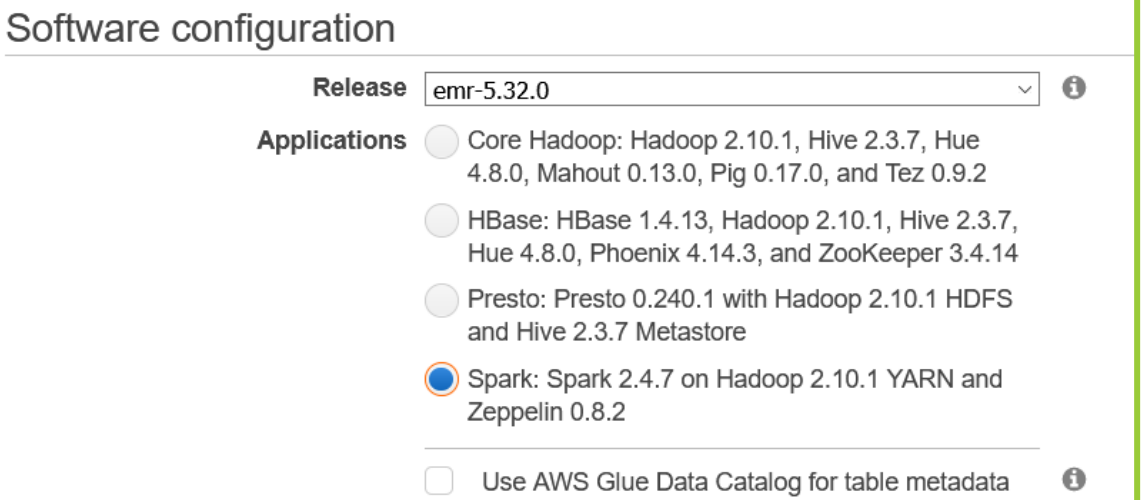
Spark on AWS

EMR (Elastic Map Reduce)



Enabling EMR Notebooks

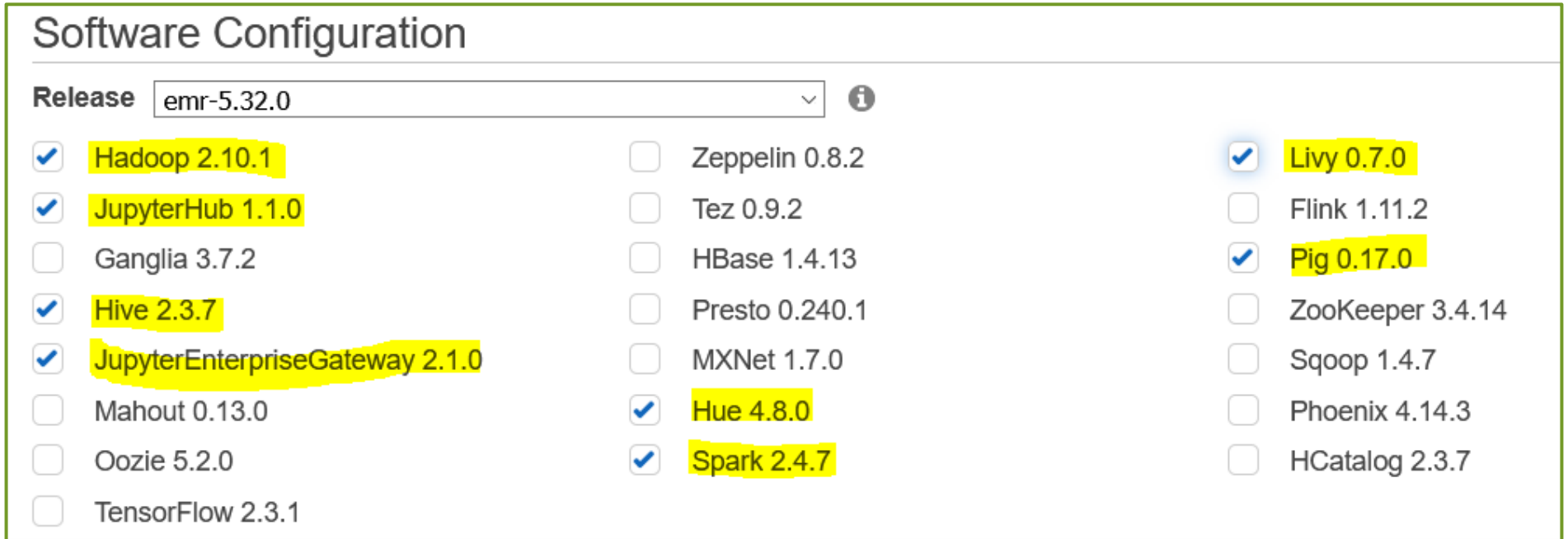
- Normally we could simply instantiate the spark cluster using a default software configuration



- However, to make things easier for us, we're going to setup Spark so it can connect to an AWS hosted Jupyter notebook or EMR Notebook

Custom Configuration Software

- For **EMR Notebooks** to work we need to configure a custom selection of software for things to work.
  - We can also enable **Hive** so we can take a second look at it's use cases

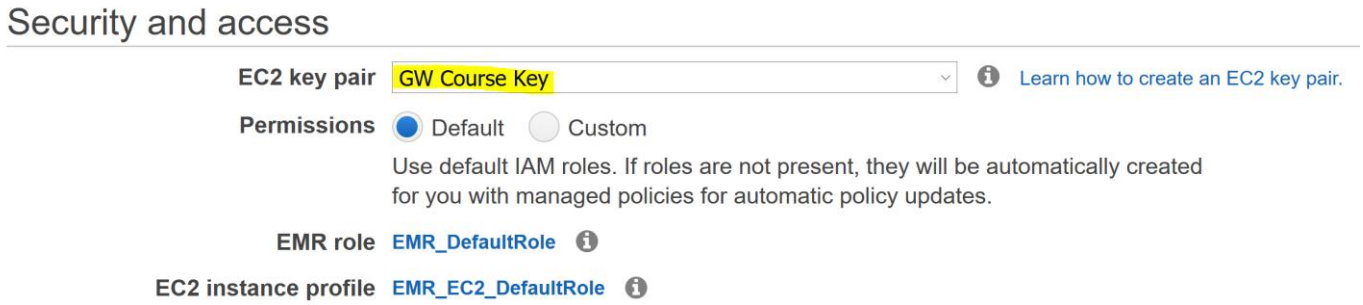


Reason for Custom Configuration

- There are a couple of reasons why we need to modify the configuration
  - Adding JupyterHub and JupyterEnterpriseGateway enable us to connect via JupyterNotebooks
    - JupyterHub is a webserver-based version of Jupyter
    - JupyterEnterpriseGateway enables JupyterHub to spin up notebooks on a cluster of machines
  - Adding Livy provides a REST driven API for spark that makes handling concurrent asynchronous requests easier (basically makes the notebook interactions work from the EMR perspective)

Creating an EMR Cluster cont.

- Defining Security:
  - We'll still setup the EC2 key pair, so we can connect directly to the master node

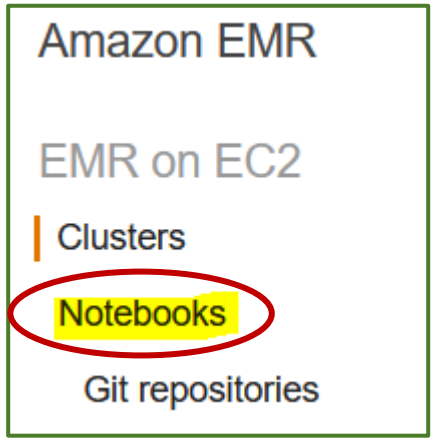


- Waiting:
  - This shouldn't take any longer than last time, but we still do need to wait

Accessing Our EMR

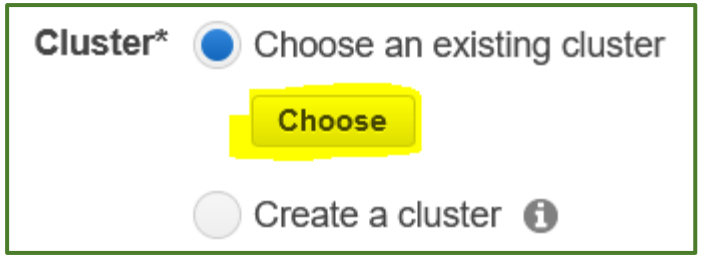
EMR Notebooks

- From the EMR service page, there is an option to setup an **EMR Notebook**, we'll be using that to connect to our cluster



- From here we can Create notebook

- The only thing we need to define (beyond providing a name), is the existing cluster for the notebook to connect

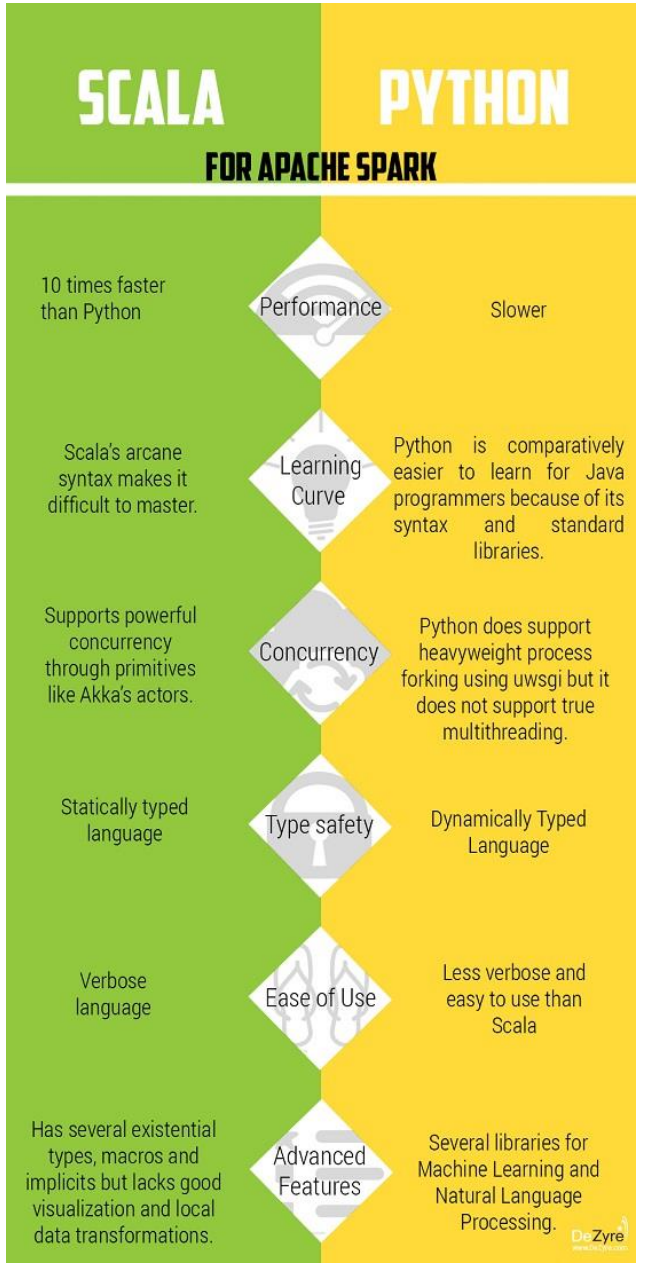


PySpark

PySpark

- PySpark is the name of the python specific interface for python programming in Spark
- One of its main benefits is ability to seamlessly leverage python for distributed programming
- PySpark also heavily utilizes Dataframes an abstraction of RDD's
  - PySpark Dataframes work a lot like pandas dataframes, but have some unique interfaces

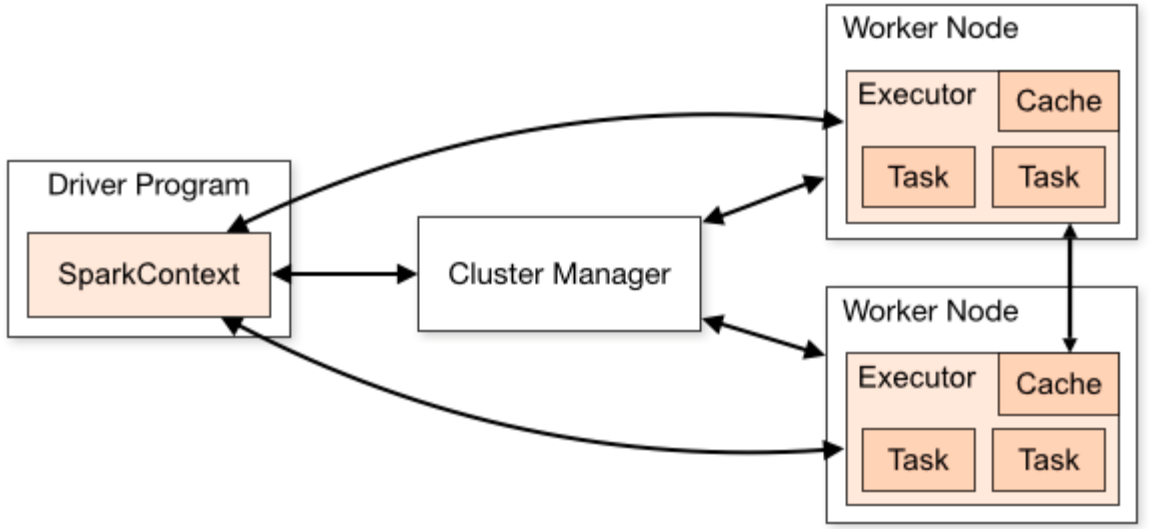
Python vs Scala



Working with PySpark

Spark Session

- The **spark session** is the primary interface for working with Spark's API
  - This means that we need an active spark session to do anything within spark
  - Creating the EMR Notebooks provides us an easy mechanism to hook into the spark session



Source: hadoopsters.com/2020/10/26/spark-starter-guide-4-2-how-to-create-a-spark-session/

Working with a Spark Session

- Normally we need to build a spark session (which can require some complex networking for custom environments)
  - spark = SparkSession.builder.appName("Python Spark SQL basic example").config("spark.some.config.option", "some-value").getOrCreate()
  - With the **EMR Notebook** we can simply call spark directly

Creating a spark Dataframe

- To create a spark Dataframe we need to tell spark to read in data from a data source. This can be accomplished through several different commands, like Hadoop:

- For our case, we'll read in the same data from s3 from last class:
  - spark.read.json("s3a://{s3_bucket}/ratebeer/*.json")

- Most datawarehousing applications use file types like parquet and avro

Alternative File Formats - Parquet and Avro

- Parquet and Avro are file types that emulate many of the compression techniques provided by databases and archiving (think .zip or .targz)
  - This means that unlike json and csv, these file types are focused around data optimization
- Parquet is a columnar storage format, meaning that it focuses on storing columns of data (compared to csv which is row focused)
- Avro is essentially a serialized version of JSON and has similarities to protobuf
  - Field names are abstracted away and data is stored in binary formatting

PySpark Lazy Evaluation

- RDD's, and thus Dataframes, are lazily evaluated. This means that transformations on the dataframe won't be evaluated until actually requested.

- This also means that only necessary transformations actually occur (to an extent). This is part of the advantage to columnar data, as the entire file/dataset may not need to be processed, but only a single column.

PySpark Streaming and SQL API

SQL in PySpark

- In addition to working with data loaded straight into a dataframe, we can also query our data leveraging SQL through Spark's SQL API

- To accomplish this we need to simply create a temporary view of our data the we can query against
  - df.createOrReplaceTempView("beer_table")

- Now all we need to do is create a new Dataframe by querying our existing information
  - sql_table = spark.sql("SELECT * from beer_table LIMIT 10")

End Slide

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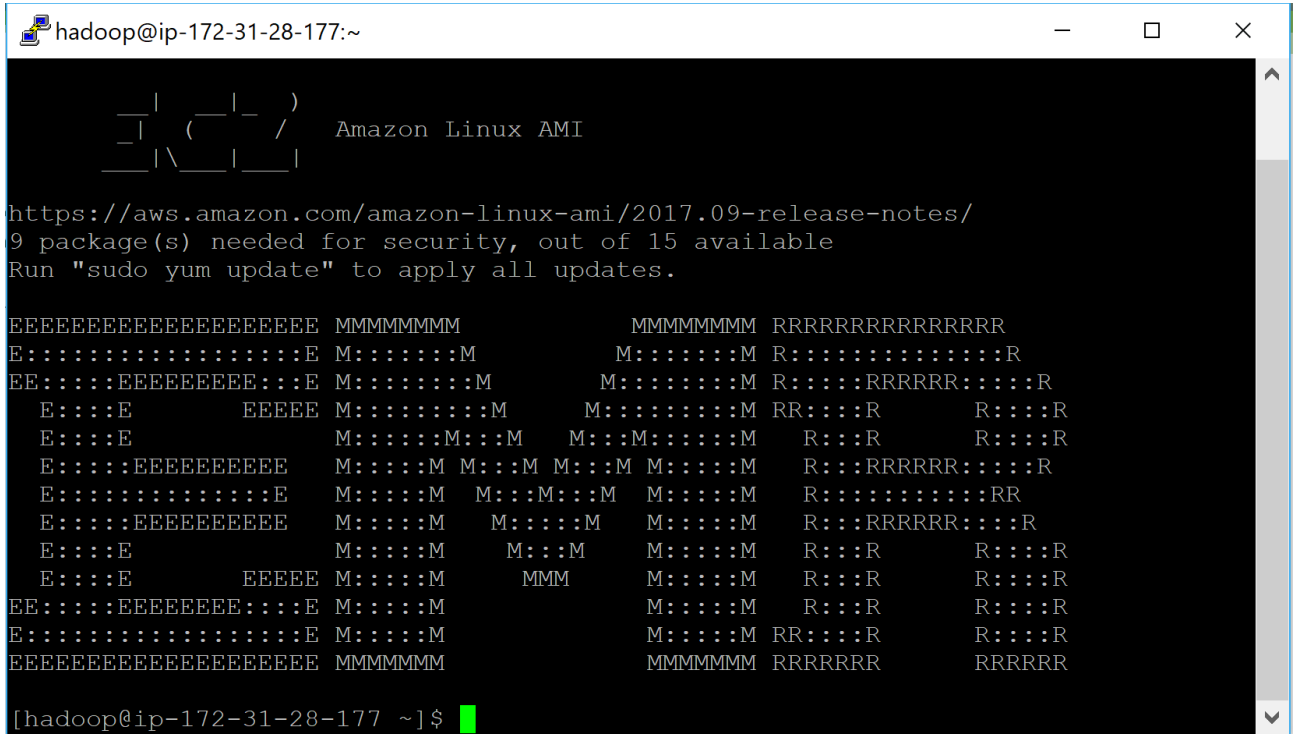
PySpark Terminal (If Using SSH)

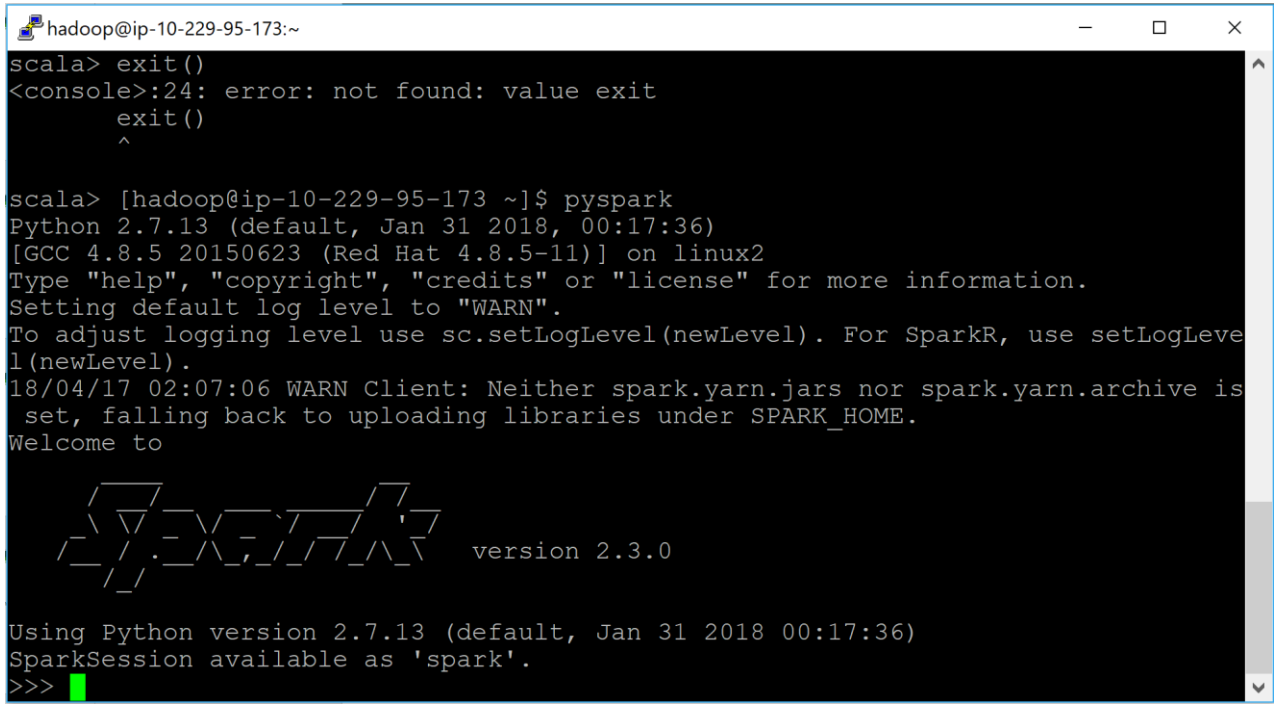
Once Connected Via SSH

- If everything was done correctly, we should be met with the following:



Connecting to PySpark

- From the terminal, we are actually very easily able to connect to hive
  - We simply run: $ pyspark
  - This should produce the hive interface: >>>



Spark REPL

- REPL stands for Read-Eval-Print-Loop
- The pyspark repl is effectively a python console
  - This means that all generic python will run in the pyspark repl
- The key difference between pyspark repl and a generic python console is the ability to leverage DAG operations to process RDD's
  - You can see when spark is being leveraged when you see the following in the console: