"It's difficult to imagine the power that you're going to have when so many different sorts of data are available"

Tim Berners-Lee, WWW Inventor, 2007

Lecture C2 Dataflow Processing

CS205: Computing Foundations for Computational Science
Dr. Ignacio M. Llorente
Spring Term 2020





Before We Start

Where We Are

Computing Foundations for Computational and Data Science

How to use modern computing platforms in solving scientific problems

Intro: Large-Scale Computational and Data Science

- A. Parallel Processing Fundamentals
- B. Parallel Computing
- C. Parallel Data Processing
 - C1. Batch Data Processing
 - **C2. Dataflow Processing**
 - C3. Stream Data Processing

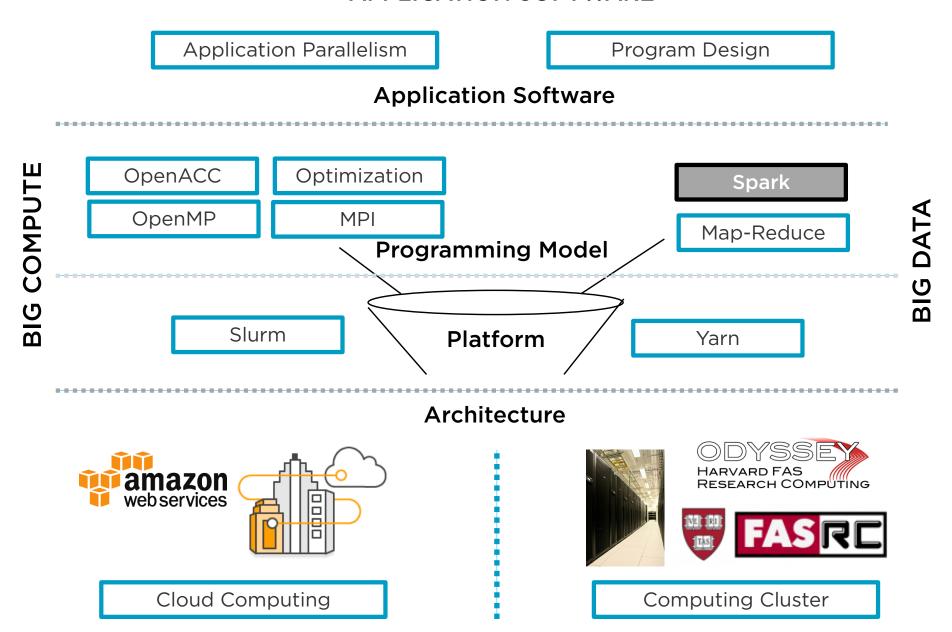
Wrap-Up: Advanced Topics





CS205: Contents

APPLICATION SOFTWARE







Before We Start

Where We Are



Week 9: **Batch Data Processing** => MapReduce

3/23	3/24 Lecture C1	3/25 Lab 18	3/26 Hands-on H4	3/27
	Batch Data Processing	MapReduce Hadoop Cluster	MapReduce Programming	
	(Quiz & Reading)			

Week 10: Dataflow Processing => Spark

3/30	3/31 Lecture C2	4/1 Lab l9	4/2 Hands-on H5	4/3
	Dataflow Processing	Spark Single Node	Spark Programming	
	(Quiz & Reading)			





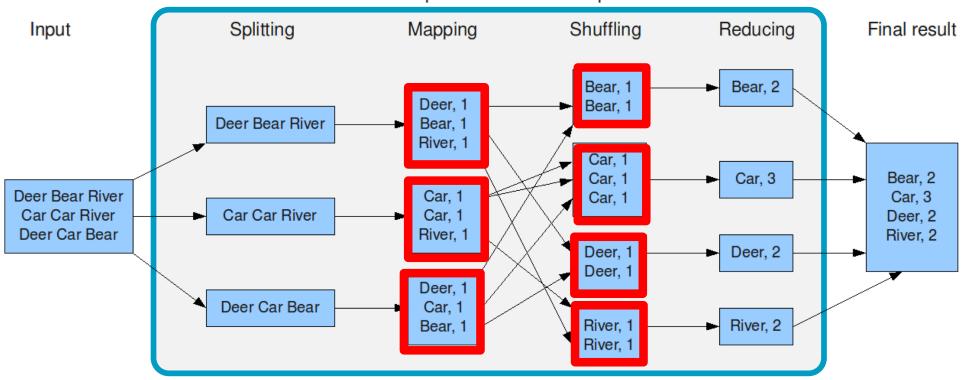
Context

The MapReduce Programming Model

JOB DESCRIPTION (map / reduce)



The overall MapReduce word count process

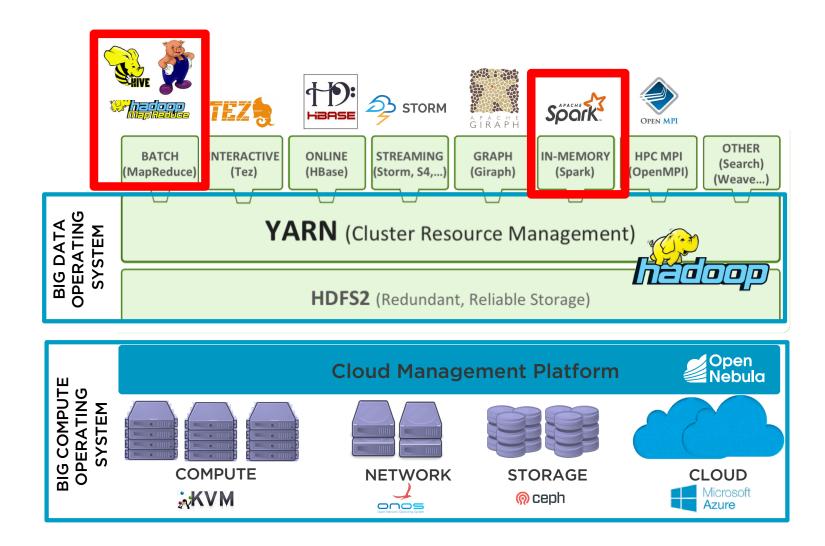






Context

The Hadoop Platform







Roadmap

Dataflow Processing

MapReduce Limitations The Spark Execution Engine The Spark Programming Model The Spark Ecosystem

Lecture C2. Dataflow Processing



Hadoop Limitations

First Impressions about MapReduce?



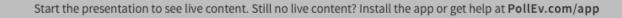
What are your first impressions about MapReduce?

https://PollEv.com/ignaciomarti376





What are your first impressions about MapReduce?



MapReduce Limitations

MapReduce Is for One-Pass Computations of Large Data Sets

Suitability of the Programming Model

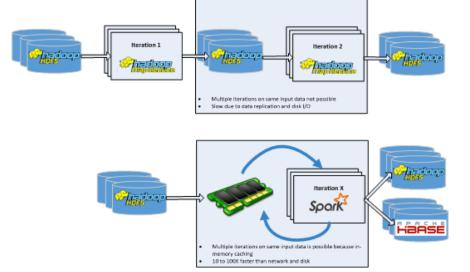
- Any use case should be converted into MapReduce pattern where each step in the data processing workflow requires one Map phase and one Reduce phase
- Work **from/to disk**, which is too slow for small data, interactive queries, iterative jobs, streaming...

Complex Deployment

- MapReduce **always requires clusters** that are hard to set up and manage, and the integration of several tools for different big data use cases
- Separate modules require separate administration

Inefficient Multi-pass Computations

• The output data between each step has to be stored in the DFS before the next step can begin, which is slow due to replication & disk storage







In-Memory Cluster Computing



Overcoming MapReduce Limitations

- In-memory data sharing across DAGs, so that different jobs can work with the same data
- Develop complex, multi-step data pipelines using DAG patterns
- Simple deployment and management

Complements Hadoop

Not a modified version of Hadoop Can work standalone or on Hadoop common Supports Scala, Python and Java

MapReduce is special-purpose Big Dataflow Processing

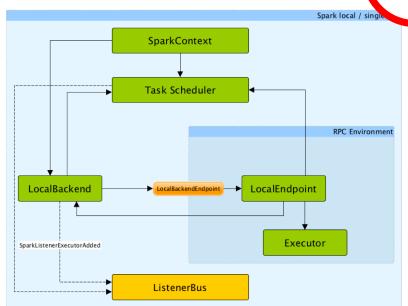
Spark is general-purpose Big Dataflow Processing





Deployment Models



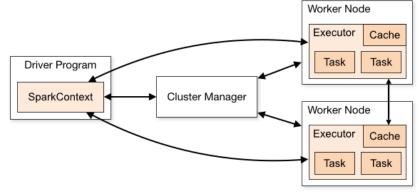


Sources: https://jaceklaskowski.gitbooks.io/mastering-apache-spark/spark-local.html

- Non-distributed single-node deployment mode, Spark spawns all the execution components in the same single node.
- Multi-core!

Cluster

l10



Sources: https://spark.apache.org/docs/latest/cluster-overview.html

- Standalone Simple cluster manager included with Spark that makes it easy to set up a cluster
- Apache Mesos General cluster manager that can also run Hadoop MapReduce and service applications.
- Hadoop YARN Resource manager in Hadoop 2.
- Multi-core and multi-node!



Functional Programming



Functional Parallel Programming

• Application decomposed into a set of connections (functions/transformations) as Directed Acyclic Graphs (DAG), with emphasis on "data flow" between the nodes

Computation of Distributed Collections of Data

- •Resilient Distributed Datasets (RDD). The environment only lets you make a collection of immutable data sets that are distributed across a cluster such that they can be automatically re-built upon node failure.
- •Coarse-grained transformations. A program is a set of parallel transformations (e.g, map, filter, join, \cdots ,) that compute on RDDs.

Declarative Definition of Computations

- Functions: Mathematically, like mapping from set A (domain) to set B (codomain), and computationally, transformation of input into output
- •Composition (pipelining) of functions: Written $f \cdot g(x)$ and interpreted as g(f(x)) i.e, apply the function f to x, and then apply g to the the result of f(x)

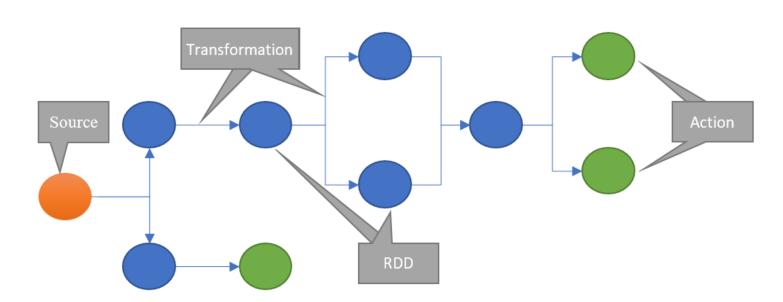




DAG Parallelism

A Parallel Program is Modelled as a DAG

- Vertices (nodes) representing RDDs
- Edges (arrows) representing functions that are either
 - Transformations : RDD => RDD (eg. map, filter, groupBy, join)
 - Actions : RDD => result (eg., count, reduce)



Sources: medium.com/towards-data-science/apache-spark-101-3f961c89b8c5



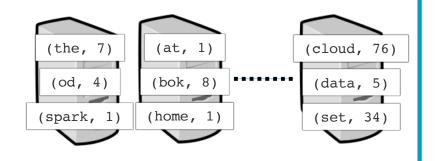


The Basics

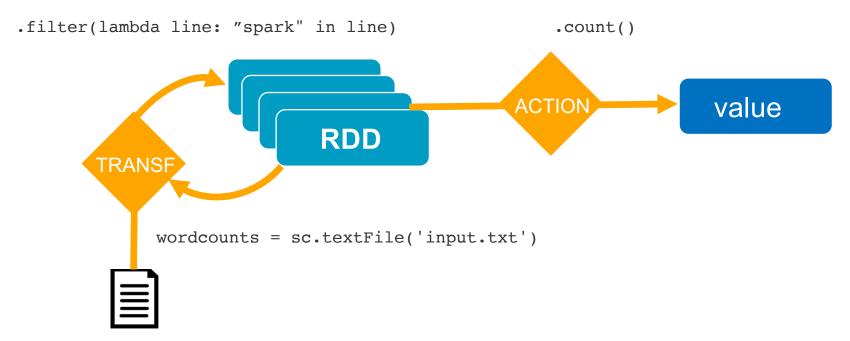
The Fundamental Data Structure - Resilient Distributed Dataset

- Resilient: Fault-tolerant
- **Distributed:** Multiple-node
- Dataset: Collection of partitioned

data organized in records



Operations: Transformations and Actions









The WordCount Example with Spark

A Pipeline of Transformations



wordcounts = sc.textFile('input.txt')

'The Project Gutenberg EBook of Moby Dick; or The Whale, by Herman' 'Melville. This eBook is for the use of anyone anywhere at no cost and'



```
.map(lambda x: x.replace(',',' ').replace('.',' '). lower())
```

'the project gutenberg eBook of moby dick or the whale by herman' melville this eBook is for the use of anyone anywhere at no cost and'



.flatMap(lambda x: x.split())

'the' 'project' 'gutenberg' 'eBook' 'of' 'moby' 'dick' 'or' 'the 'whale'
'by' 'herman' 'melville' 'this' 'eBook' 'is' 'for' 'the' 'use' 'of'



.map(lambda x: (x, 1))

```
'(the, 1)' '(project ,1)' '(gutenberg, 1)' '(eBook, 1)' '(of, 1)' '(moby , 1)' '(dick, 1)' '(or, 1)' '(the, 1)' '(whale, 1)' '(by, 1)'
```



.reduceByKey(lambda x,y:x+y)

```
'(the, 11)' '(project ,10)' '(gutenberg, 9)' '(eBook, 37)' '(of, 15)' '(moby , 5)' '(dick, 7)' '(or, 9)' '(the, 9)' '(whale, 123)' '(by, 98)'
```





The WordCount Example with Spark

```
from pyspark import SparkConf, SparkContext
import string
conf = SparkConf().setMaster('local').setAppName('WordCount')
sc = SparkContext(conf = conf)
RDDvar = sc.textFile("input.txt")
words = RDDvar.flatMap(lambda line: line.split())
result = words.map(lambda word:
(str(word.lower()).translate(None, string.punctua
tion),1))
aggreg1 = result.reduceByKey(lambda a, b: a+b)
aggreg1.saveAsTextFile("output.txt")
```





Parallel Execution

NUMBER OF TASKS CREATED BY SPARK TO PROCESS IN PARALLEL EACH RDD



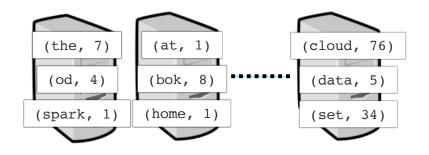
NUMBER OF NODES AND THREADS PER NODE



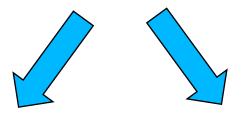
Parallel Execution

Application Parallelism

- •RDD partitions given by the programmer (parallelize) for new created data, determined by the parent RDD, or defined by the underlying file system
- A task is created to process each partition



ratings.csv is 709 MB



Local FS 709/32 = 22 partitions

HDFS 709/128 = 6partitions



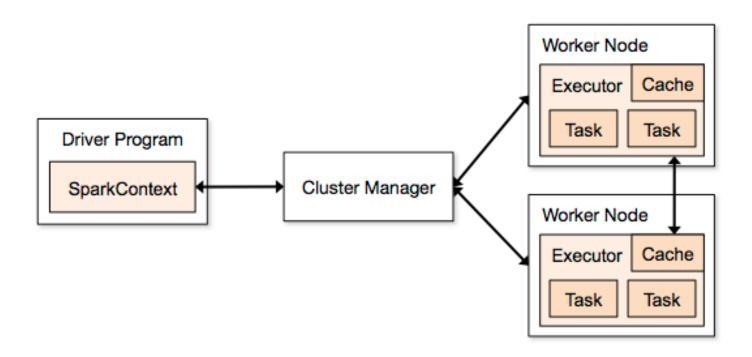


Parallel Execution

System Parallelism

- In local mode setMaster in the SparkConf
- •In **cluster mode**, determined by the executors (one per node) and the threads (cores) per executor

--num-executors --executor-cores in spark-submit





Parallel Execution

Compute PI Number with Spark

```
from pyspark import SparkConf, SparkContext
import string

conf = SparkConf().setMaster('local[2]').setAppName('Pi')
sc = SparkContext(conf = conf)

N = 10000000
delta_x = 1.0 / N
print sc.parallelize( xrange (N),4 ).map( lambda i: (i +0.5) *
delta_x ).map( lambda x: 4 / (1 + x **2) ).reduce ( lambda a, b: a+b) * delta_x
```

Execute with different number of partitions and threads, and compare number of tasks and execution time





Spark Ecosystem

Spark SQL

Data abstraction that provides support for structured and semistructured data

Spark Streaming

Fast scheduling capability to perform streaming analytics

MLlib

Distributed machine learning framework

GraphX

Distributed graphprocessing framework

Spark Core Engine

Standalone Scheduler

Hadoop Common

HDFS

Distributes & replicates data across machines

YARN

Distributes & monitors tasks





DataFrames

Higher Level Abstraction that Gives a Tabular View of Data

- Like an RDD, a DataFrame is an immutable distributed collection of data.
- Unlike an RDD, data is organized into a tabular format, a two-dimensional array-like structure.
- Makes large data sets processing easier, and allows Spark to run certain optimizations on the finalized query or processing operation.

```
df = spark.read.json("examples/src/main/resources/people.json")
```

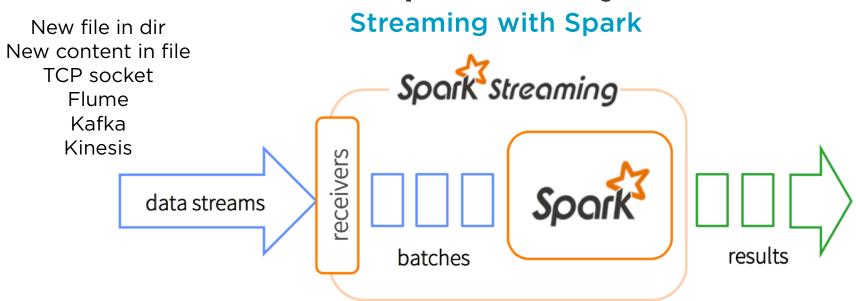
```
# Displays the content
df.show()
# +----+
# | age| name |
# +----+
# |null|Michael|
# | 30| Andy|
# | 19| Justin|
# +----+
```

```
# Select a Column
df.select("name").show()
# +----+
# | name |
# +----+
# |Michael|
# | Andy|
# | Justin|
# +-----+
```

```
# Select people older
df.filter(df['age'] > 21).show()
# +---+
# | age| name |
# +---+
# | 30| Andy|
# +---+
```

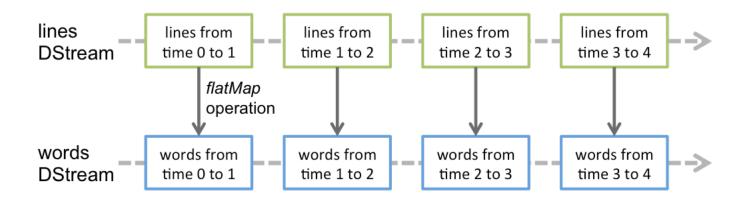






DStream (micro-batching)

• A continuous data stream is discretized into a continuous series of RDD







Machine Learning with Spark

Supervised learning

Training data contains both input vector and desired output. We also called it as labeled data.

Classification:

- Naive Bayes
- SVM
- Random Decision Forests

Regression:

- Linear Regression
- Logistic Regression

Unsupervised learning

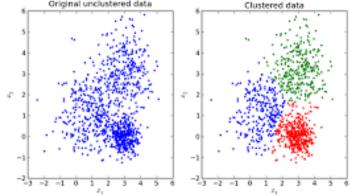
Training data sets without labels.

Clustering:

K-means clustering

Dimensionality reduction

- Principal component analysis
- SVD







Next Steps

- Get ready for next lab:
 19. Install Spark in Local Mode (Wednesday 4/1)
- Get ready for next hands-on:
 H6. Spark Programming (Thursday 4/2)

Questions

Dataflow Processing

http://piazza.com/harvard/spring2020/cs205/home

