Mining Massive Datasets

Lecture 1

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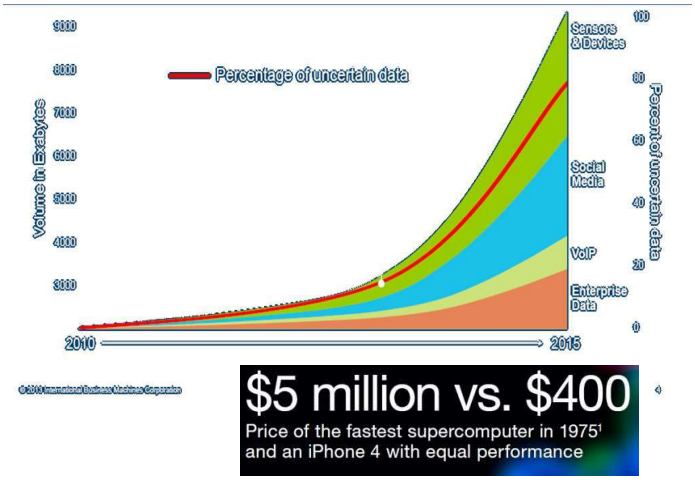
Note on Slides

A substantial part of these slides come (either verbatim or in a modified form) from the book Mining of Massive Datasets by Jure Leskovec, Anand Rajaraman, Jeff Ullman (Stanford University).
For more information, see the website accompanying the book: http://www.mmds.org.

Motivation and Course Contents

Lot of Data, Lot of Computing Power



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Data ≠ Knowledge

- To extract the knowledge from data it needs to be
  - Stored
  - Managed
  - Processed
  - And Analyzed

} This course

Data Mining ≈ Big Data ≈ Predictive Analytics ≈ Data Science

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Data Mining Tasks

- Descriptive methods
  - Find human-interpretable patterns that describe the data
    - **Example:** Clustering
- Predictive methods
  - Use some variables to predict unknown or future values of other variables
    - **Example:** Recommender systems

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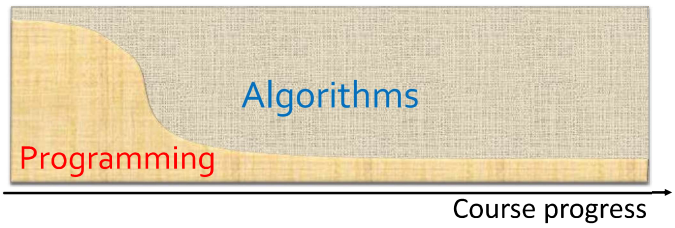
Programming vs. Algorithms

- You need programming to analyze (esp. large) data
  - E.g. Wikipedia text corpus is stored as XML, to extract text you need to write scripts
- In the first part of this course, we will learn programming to process and analyze large data
- Later we will use this to implement algorithms



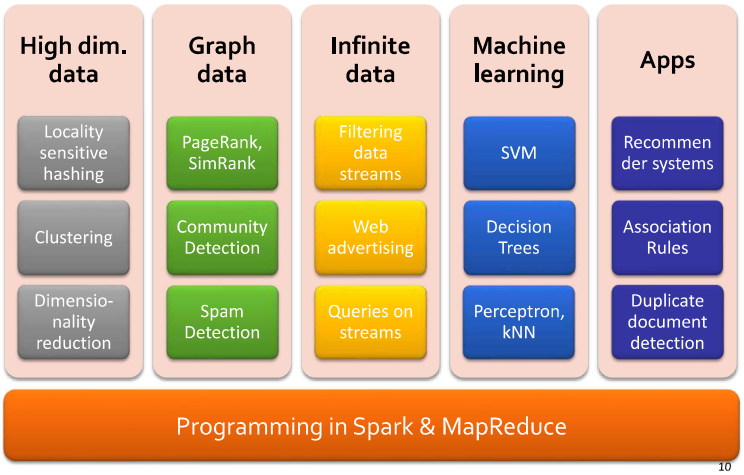
What will we learn?

- **We learn paradigms & tools for programming**
  - Spark & related libs (Shark, GraphX, MLlib, …)
  - Hadoop MapReduce & related frameworks (Apache Mahout, Pig, …)
  - … and a bit of Python
- **We learn to mine different types of data**
  - Data is high dimensional
  - Data is a graph
  - Data is infinite/never-ending
  - Data is labeled

What will we learn?

- **We will learn to solve real-world problems**
  - Recommender systems
  - Spam detection
  - Duplicate document detection
- **We will learn various algorithmic "tools"**
  - Linear algebra (e.g. SVD)
  - Optimization (stochastic gradient descent)
  - Dynamic programming
  - Hashing (e.g. locality-sensitive hashing, LSH)

Overview (Superset)



Questionnaire

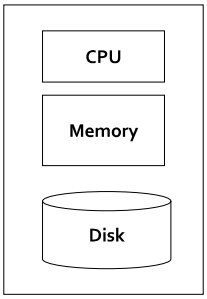
- Who have heard about MapReduce?
- … about Spark? 25 / 7
- … about Hive? 3

- Who have used Apache Hadoop? 6

- Who has programmed in Python? all
- … in Java? 25
- … in Scala?
- … in C++?

Distributed Processing: Motivation

Single Node Architecture



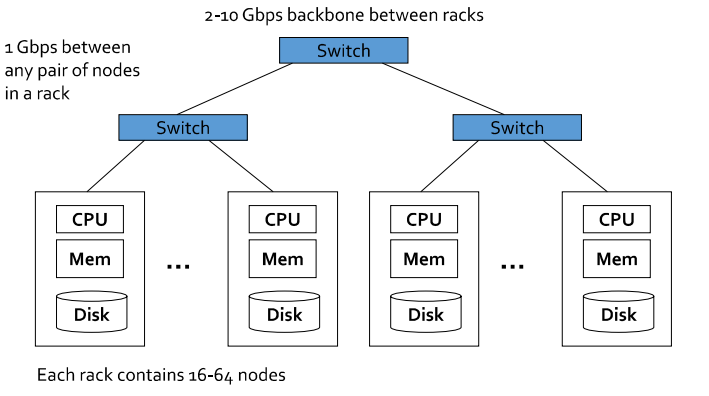
Machine Learning, Statistics

"Classical" Data Mining

Motivation: Google Example

- 20+ billion web pages x 20KB = 400+ TB
- 1 computer reads 30-35 MB/sec from disk
  - ~4 months to read the web
- ~1,000 hard drives to store the web
- Takes even more to **do** something useful with the data!
- **Today, a standard architecture for such problems is emerging:**
  - Cluster of commodity Linux nodes
  - Commodity network (ethernet) to connect them

Cluster Architecture



In 2011 it was guestimated that Google had 1M machines, http://bit.ly/Shh0RO

Large-scale Computing

- Large-scale computing for data mining problems on commodity hardware
- **Challenges:**
  - How do you distribute computation?
  - How can we make it easy to write distributed programs?
  - Dependability - machines fail:
    - One server may stay up 3 years (1,000 days)
    - If you have 1,000 servers, expect to loose 1/day
    - People estimated Google had ~1M machines in 2011
      - 1,000 machines fail every day!

Storage Infrastructure

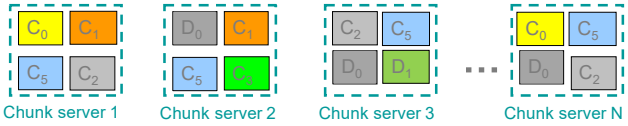
- **Problem:**
  - If nodes fail, how to store data persistently?
- **Answer:**
  - **Distributed File System:**
    - Provides global file namespace
    - Google GFS; Hadoop HDFS;
- **Typical usage pattern**
  - Huge files (100s of GB to TB)
  - Data is rarely updated in place
  - Reads and appends are common

Distributed File System

- **Chunk servers**
  - File is split into contiguous chunks
  - Typically each chunk is 16-64MB
  - Each chunk replicated (usually 2x or 3x)
  - Try to keep replicas in different racks
- **Master node**
  - a.k.a. Name Node in Hadoop's HDFS
  - Stores metadata about where files are stored
  - Might be replicated
- **Client library for file access**
  - Talks to master to find chunk servers
  - Connects directly to chunk servers to access data

Distributed File System

- **Reliable distributed file system**
- Data kept in "chunks" spread across machines
- Each chunk replicated on different machines
  - Seamless recovery from disk or machine failure



Chunk servers also serve as compute servers

Using HDFS – Various Ways

- Via shell commands, e.g.
  - bin/hadoop dfs -mkdir <hdfs-dir>
  - bin/hadoop dfs -put <local-dir> <hdfs-dir>
  - bin/hadoop dfs -get <hdfs-dir> <local-dir>
- By mounting HDFS like a local file system
  - http://wiki.apache.org/hadoop/MountableHDFS
- Programmatically: Java, MapReduce, Spark, ….
  - https://developer.yahoo.com/hadoop/tutorial/module2.html
- Watch video "Hadoop Tutorial: Intro to HDFS"
  - https://www.youtube.com/watch?v=ziqx2hJY8Hg

Implementations

- **Google File System** (GFS)
  - Not available outside Google
  - More info: Wikipedia, paper (2003)
- **Hadoop Distributed File System** (HDFS)
  - An open-source implementation in Java
  - A de-facto standard for storing large data
  - Download: http://lucene.apache.org/hadoop/
- Other distributed file systems
  - Lustre (for HPC), Fossil (for HPC), GPFS (IBM), Ceph (Red Hat), XtreemFS (EU Project),…

Programming Paradigms

What Is Apache Hadoop?

- "The Apache™ Hadoop® project develops open-source software for reliable, scalable, distributed computing.
- … Modules:
  - **Hadoop Common**
  - **Hadoop Distributed File System** (**HDFS**)
  - **Hadoop YARN**
  - **Hadoop MapReduce**"
- Other Hadoop-related projects at Apache:
  - Ambari™
  - Avro™
  - Cassandra™
  - Chukwa™
  - HBase™
  - Hive™
  - Mahout™
  - Pig™
  - Spark™
  - Tez™
  - ZooKeeper™

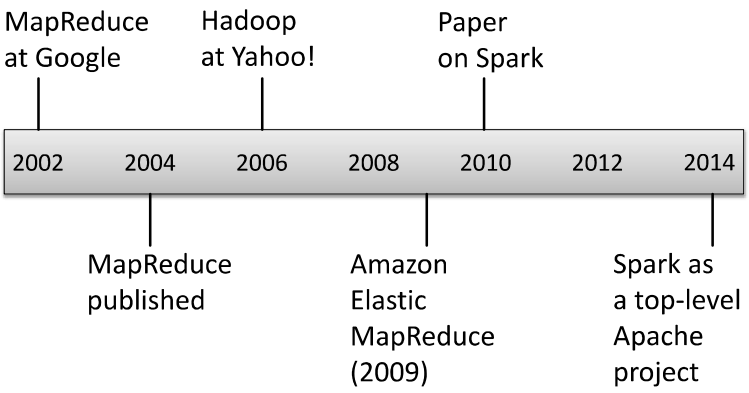
Large-Scale Data Processing

- Our focus: How to perform large scale computing for data processing & analysis?
- **Challenges**:
  - How to distribute computation?
  - How to make programming less difficult?
  - How to deal with high rate of component failures?

Efficient Frameworks Needed

- Issues: Copying data costs time / Nodes fails
- Ideas:
  - Store files multiple times for reliability
  - Bring computation close to the data
- **Solutions:**
  - Fault-tolerant storage infrastructure (file system)
    - **Hadoop Distributed File System** (HDFS)
  - Programming models (selection)
    - **Hadoop Map-Reduce**: older, but still most widely used
    - Apache **Spark**: richer set of operators & faster

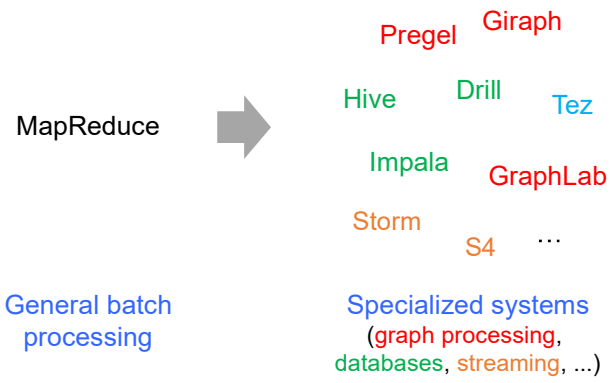
A Brief History



MapReduce Problems

- Difficulty of programming
- Performance bottlenecks
  - Esp. for iterative jobs or "multi-MR" jobs
- MapReduce is not an ideal paradigm for large applications (with multiple processing phases)
- => A lot of specialized systems were created as workarounds

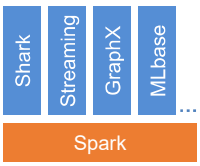
MapReduce Problems



From: The State of Spark, and Where We're Going Next
Matei Zaharia, Spark Summit (2013)

Spark's Approach

- Instead of specializing, *generalize* MapReduce to support new apps in same engine
- Two changes (general task DAG & data sharing) are enough to express previous models!
- Unification has big benefits
  - For the engine
  - For users



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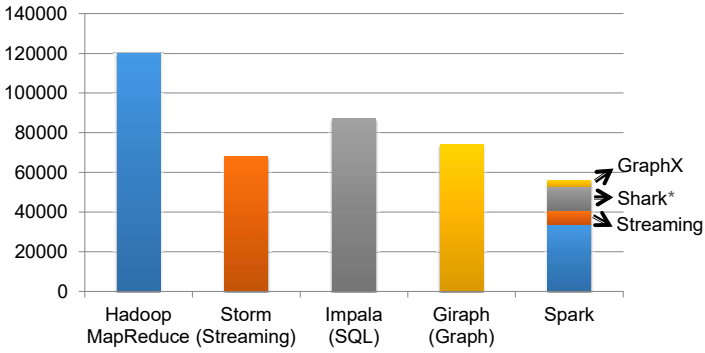
Code Size: Spark vs. Others

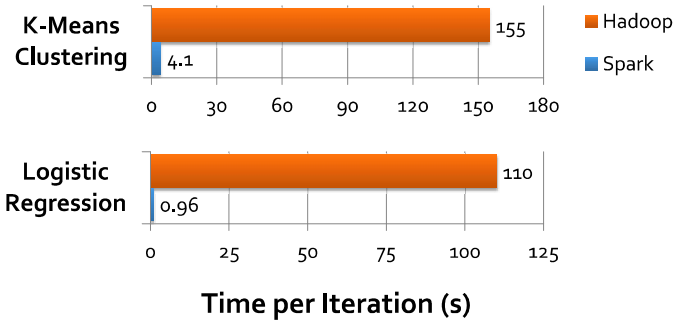


non-test, non-example source lines

* also calls into Hive

From: The State of Spark, and Where We're Going Next
Matei Zaharia, Spark Summit (2013)

Performance: Iterative Algorithms



From: *Parallel Programming with Spark*, **Matei Zaharia**, AmpCamp 2013

MapReduce is Being Replaced

*Website of **Mahout**, a library for large-scale machine learning algorithms (as of 10 Oct 2014)*

25 April 2014 - Goodbye MapReduce

The Mahout community decided to move its codebase onto modern data processing systems that offer a richer programming model and more efficient execution than Hadoop MapReduce. **Mahout will therefore reject new MapReduce algorithm implementations from now on.**
…
We are building our future implementations on top of a DSL for linear algebraic operations which has been developed over the last months. Programs written in this DSL are automatically optimized and executed in parallel on Apache Spark.

Spark Programming: Introduction

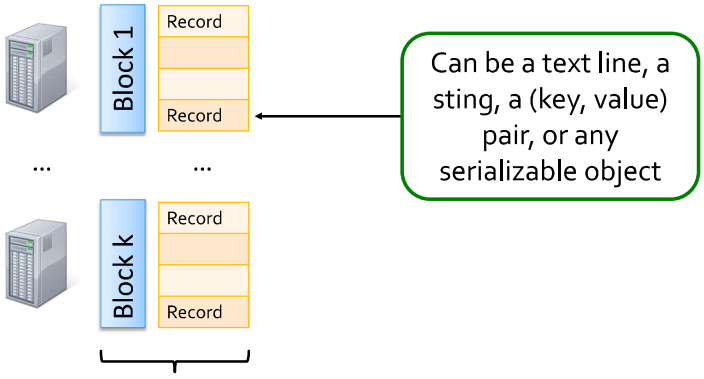
Virtual Machine with Spark

- We have prepared a virtual machine with Spark (under Oracle VirtualBox)
- Available on a USB stick
- Using Spark:
  - Most convenient: included Intellij IDEA IDE with a starter project in Python
  - For freaks via a Spark shell:
    - Python: pyspark, Scala: spark-shell

Key Idea and Data Structure

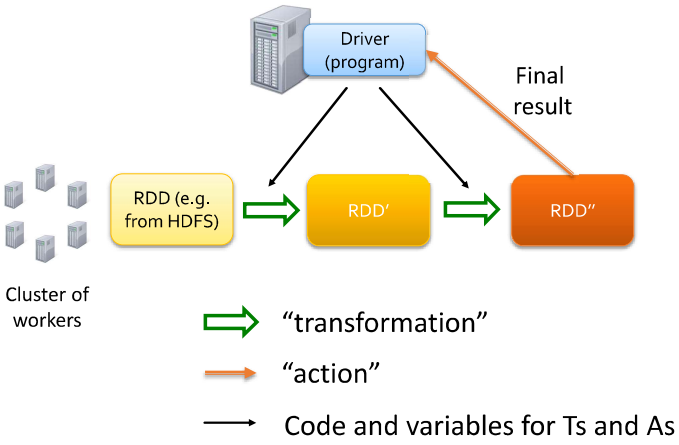
- **Write programs in terms of transformations on distributed datasets**
- Main data structure: **resilient distributed dataset (RDD)**
  - Collections of records spread across a cluster

Resilient Distributed Dataset (RDD)



A RDD; accessible in code via a single "variable"

Computations with RDDs



Operations

- **Transformations** (e.g. map, filter, groupBy)
  - Lazy operations to build RDDs from other RDDs
- **Actions** (e.g. count, collect, save)
  - Return a result or write it to storage

From: *Parallel Programming with Spark*, **Matei Zaharia**, AmpCamp 2013

Creating RDDs (Python)

SparkContext is the "entry point" to Spark functionality, here referenced by variable `sc`

```
# Turn a Python list [1, 2, 3] into an RDD
sc.parallelize([1, 2, 3])

# Load text file from local FS (file/dir) or HDFS
sc.textFile("file.txt")
sc.textFile("directory/*.txt")
sc.textFile("hdfs://namenode:9000/path/file")
```

From: *Parallel Programming with Spark*, **Matei Zaharia**, AmpCamp 2013

Interlude: Lambdas in Python

- We need to pass code to Ts and As
  - Handle code like variables
- Convenient: **anonymous functions**, or inline functions; in Python: lambda functions
- Syntax: `lambda <params> : expression`
- Example – computing x^2
  - g = **lambda** x: x**2; same as def g(x): return x**2
- What is this doing?
  - **lambda** x, y: x**2 + y**2 <= 1.0

Basic Transformations

```
nums = sc.parallelize([1, 2, 3])

# Pass each element through a function
squares = nums.map(lambda x: x*x)   // {1, 4, 9}

# Keep elements passing a predicate
even = squares.filter(lambda x: x % 2 == 0) // {4}

# Map each element to zero or more others
flats = nums.flatMap(lambda x: [x, -x, x*x])
    # => {1, -1, 1, 2, -2, 4, 3, -3, 9}
```

From: *Parallel Programming with Spark*, **Matei Zaharia**, AmpCamp 2013

Basic Actions

```
nums = sc.parallelize([1, 2, 3])

# Retrieve RDD contents as a local collection
nums.collect() # => [1, 2, 3]

# Return first K elements
nums.take(2)   # => [1, 2]

# Count number of elements
nums.count()   # => 3

# Merge elements with an associative function
nums.reduce(lambda x, y: x + y)  # => 6

# Write elements to a text file
nums.saveAsTextFile("hdfs://file.txt")
```

From: *Parallel Programming with Spark*, **Matei Zaharia**, AmpCamp 2013

Working with Key-Value Pairs

- Spark's "distributed reduce" transformations operate on RDDs of key-value pairs
- Python:

```
pair = (a, b)
pair[0] # => a
pair[1] # => b
```

- Scala:

```
val pair = (a, b)
pair._1 // => a
pair._2 // => b
```

- Java:

```
Tuple2 pair = new Tuple2(a, b);
pair._1 // => a
pair._2 // => b
```


Setting the Level of Parallelism

- All the pair RDD operations take an optional second parameter p for number of tasks

```
words.reduceByKey(lambda x, y: x + y, 5)
words.groupByKey(5)
```


Some Key-Value Operations

```
pets = sc.parallelize(
  [("cat", 1), ("dog", 1), ("cat", 2)])

pets.reduceByKey(lambda x, y: x + y)
                  # => {(cat, 3), (dog, 1)}

pets.groupByKey() # => {(cat, [1, 2]), (dog, [1])}
pets.sortByKey()  # => {(cat, 1), (cat, 2), (dog, 1)}
```


Using Local Variables

Essentially, piece of code executed by a transformation or action

- Any external variables you use in a closure will automatically be shipped to the cluster:

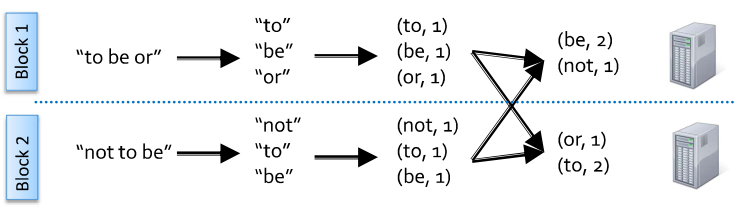
```
query = sys.stdin.readline()
pages.filter(lambda x: query in x).count()
```

- Some caveats:
  - Each task gets a new copy (no updates sent back)
  - Variable must be Serializable / Pickle-able
  - Don't use fields of an outer object (ships all of it!)

There are also shared variables: broadcasts, accumulators

Example: Word Count

```
lines = sc.textFile("hamlet.txt")
counts = lines.flatMap(lambda line: line.split(" "))
              .map(lambda word : (word, 1))
              .reduceByKey(lambda x, y: x + y)
```



Fault Recovery

RDDs track *lineage* information that can be used to efficiently recompute lost data

Ex:

```
msgs = textFile.filter(lambda s: s.startsWith("ERROR"))
               .map(lambda s: s.split("\t")[2])
```

Other RDD Operators

- `map`
- `filter`
- `groupBy`
- `sort`
- `union`
- `join`
- `leftOuterJoin`
- `rightOuterJoin`
- `reduce`
- `count`
- `fold`
- `reduceByKey`
- `groupByKey`
- `cogroup`
- `cross`
- `zip`
- `sample`
- `take`
- `first`
- `partitionBy`
- `mapWith`
- `pipe`
- `save`
- `...`

More details: spark-project.org/docs/latest/

From: *Parallel Programming with Spark*, **Matei Zaharia**, AmpCamp 2013

More Resources

- Sanjay Ghemawat, Howard Gobioff, and Shun-Tak Leung: The Google File System
  - http://labs.google.com/papers/gfs.html
- Hadoop Wiki
  - Introduction: http://wiki.apache.org/lucene-hadoop/
  - Getting Started: http://wiki.apache.org/lucene-hadoop/GettingStartedWithHadoop
  - Map/Reduce Overview
    - http://wiki.apache.org/lucene-hadoop/HadoopMapReduce
    - http://wiki.apache.org/lucene-hadoop/HadoopMapRedClasses

Recommended Videos on Spark

- Introduction tutorials on Spark
  - Parallel programming with Spark Presented by Matei Zaharia UC Berkeley AmpLab 2013
  - https://www.youtube.com/watch?v=e-56inQL5hQ&t=30s
  - Parallel Programming with Spark (Part 1 & 2) by Matei Zaharia (2012)
  - https://www.youtube.com/watch?v=7k4yDKBYOcw
- Coursera
  - Big Data Analysis with Scala and Spark
  - https://www.coursera.org/learn/scala-spark-big-data
  - Enroll -> Audit, then for free!

Thank you.

Questions?

Reading Materials on Spark

- Free Materials:
  - Spark Programming Guide
    - https://spark.apache.org/docs/latest/rdd-programming-guide.html
  - Apache Spark Tutorial: ML with PySpark
    - https://goo.gl/u4RjeB
  - Cheat Sheet PySpark-RDD Basics, https://goo.gl/UF5zVr
  - Jacek Laskowski, Mastering Apache Spark 2, GitBook.com, https://goo.gl/yFYRYm
- Books
  - Matthew Rathbone: 10+ Great Books for Apache Spark
    - https://blog.matthewrathbone.com/2017/01/13/spark-books.html