



Learning Apache Spark with Python

Release v1.0

Wenqiang Feng

September 28, 2017

CONTENTS

| | |
|-------------------------------------------------|-----------|
| 1 Preface | 3 |
| 1.1 About | 3 |
| 1.2 Motivation for this tutorial | 4 |
| 1.3 Acknowledgement | 4 |
| 1.4 Feedback and suggestions | 4 |
| 2 Why Spark with Python ? | 5 |
| 2.1 Why Spark? | 5 |
| 2.2 Why Spark with Python (PySpark)? | 7 |
| 3 Configure Running Platform | 9 |
| 3.1 Run on Databricks Community Cloud | 9 |
| 3.2 Configure Spark on Mac and Ubuntu | 14 |
| 3.3 Configure Spark on Windows | 17 |
| 3.4 PySpark With Text Editor or IDE | 17 |
| 3.5 Set up Spark on Cloud | 19 |
| 3.6 Demo Code in this Section | 21 |
| 4 An Introduction to Apache Spark | 23 |
| 4.1 Core Concepts | 23 |
| 4.2 Spark Components | 23 |
| 4.3 Architecture | 26 |
| 4.4 How Spark Works? | 26 |
| 5 Programming with RDDs | 27 |
| 5.1 Create RDD | 27 |
| 5.2 Spark Transformations | 30 |
| 5.3 Spark Actions | 30 |
| 6 Statistics Preliminary | 31 |
| 6.1 Notations | 31 |
| 6.2 Measurement Formula | 31 |
| 7 Regression | 33 |
| 7.1 Linear Regression | 33 |
| 7.2 Generalized linear regression | 39 |

| | | |
|-----------|----------------------------------------------------|------------|
| 7.3 | Decision tree Regression | 45 |
| 7.4 | Random Forest Regression | 49 |
| 7.5 | Gradient-boosted tree regression | 50 |
| 8 | Classification | 51 |
| 8.1 | Logistic regression | 51 |
| 8.2 | Decision tree Classification | 51 |
| 8.3 | Random forest Classification | 58 |
| 8.4 | Gradient-boosted tree Classification | 65 |
| 8.5 | Naive Bayes Classification | 65 |
| 9 | Clustering | 67 |
| 9.1 | K-Means Model | 67 |
| 10 | Text Mining | 69 |
| 10.1 | Text Collection | 69 |
| 10.2 | Text Preprocessing | 76 |
| 10.3 | Text Classification | 78 |
| 10.4 | Sentiment analysis | 84 |
| 10.5 | N-grams and Correlations | 90 |
| 10.6 | Topic Model: Latent Dirichlet Allocation | 90 |
| 11 | Social Network Analysis | 103 |
| 11.1 | Co-occurrence Network | 103 |
| 11.2 | Correlation Network | 108 |
| 12 | Neural Network | 109 |
| 12.1 | Feedforward Neural Network | 109 |
| 13 | Main Reference | 113 |
| | Bibliography | 115 |
| | Index | 117 |



Welcome to our **Learning Apache Spark with Python** note! In these note, you will learn a wide array of concepts about **PySpark** in Data Mining, Text Mining, Machine Learning and Deep Learning. The PDF version can be downloaded from [HERE](#).

CHAPTER ONE

PREFACE

1.1 About

1.1.1 About this note

This is a shared repository for Learning Apache Spark Notes. The first version was posted on Github in [\[Feng2017\]](#). This shared repository mainly contains the self-learning and self-teaching notes from Wenqiang during his [IMA Data Science Fellowship](#).

In this repository, I try to use the detailed demo code and examples to show how to use each main functions. If you find your work wasn't cited in this note, please feel free to let me know.

Although I am by no means an data mining programming and Big Data expert, I decided that it would be useful for me to share what I learned about PySpark programming in the form of easy tutorials with detailed example. I hope those tutorials will be a valuable tool for your studies.

The tutorials assume that the reader has a preliminary knowledge of programing and Linux. And this document is generated automatically by using [sphinx](#).

1.1.2 About the authors

- **Wenqiang Feng**

- Data Scientist and Phd in Mathematics
- University of Tennessee at Knoxville
- Email: wfeng1@utk.edu

- **Biography**

Wenqiang Feng is Data Scientist within DST's Applied Analytics Group. Dr. Feng's responsibilities include providing DST clients with access to cutting-edge skills and technologies, including Big Data analytic solutions, advanced analytic and data enhancement techniques and modeling.

Dr. Feng has deep analytic expertise in data mining, analytic systems, machine learning algorithms, business intelligence, and applying Big Data tools to strategically solve industry problems in a cross-functional business. Before joining DST, Dr. Feng was an IMA Data Science Fellow at The Institute for Mathematics and its Applications (IMA) at the University of Minnesota. While there, he helped startup companies make marketing decisions based on deep predictive analytics.

Dr. Feng graduated from University of Tennessee, Knoxville, with Ph.D. in Computational Mathematics and Master's degree in Statistics. He also holds Master's degree in Computational Mathematics from Missouri University of Science and Technology (MST) and Master's degree in Applied Mathematics from the University of Science and Technology of China (USTC).

- **Declaration**

The work of Wenqiang Feng was supported by the IMA, while working at IMA. However, any opinion, finding, and conclusions or recommendations expressed in this material are those of the author and do not necessarily reflect the views of the IMA, UTK and DST.

1.2 Motivation for this tutorial

I was motivated by the [IMA Data Science Fellowship](#) project to learn PySpark. After that I was impressed and attracted by the PySpark. And I foud that:

1. It is no exaggeration to say that Spark is the most powerful Bigdata tool.
2. However, I still found that learning Spark was a difficult process. I have to Google it and identify which one is true. And it was hard to find detailed examples which I can easily learned the full process in one file.
3. Good sources are expensive for a graduate student.

1.3 Acknowledgement

At here, I would like to thank Ming Chen, Jian Sun and Zhongbo Li at the University of Tennessee at Knoxville for the valuable dissussion and thank the generous anonymous authors for providing the detailed solutions and source code on the internet. Without those help, this repository would not have been possible to be made. Wenqiang also would like to thank the [Institute for Mathematics and Its Applications \(IMA\)](#) at [University of Minnesota, Twin Cities](#) for support during his IMA Data Scientist Fellow visit.

1.4 Feedback and suggestions

Your comments and suggestions are highly appreciated. I am more than happy to receive corrections, suggestions or feedbacks through email (wfeng1@utk.edu) for improvements.

WHY SPARK WITH PYTHON ?

Note: Sharpening the knife longer can make it easier to hack the firewood – old Chinese proverb

I want to answer this question from the following two parts:

2.1 Why Spark?

I think the following four main reasons from Apache Spark™ official website are good enough to convince you to use Spark.

1. Speed

Run programs up to 100x faster than Hadoop MapReduce in memory, or 10x faster on disk.

Apache Spark has an advanced DAG execution engine that supports acyclic data flow and in-memory computing.

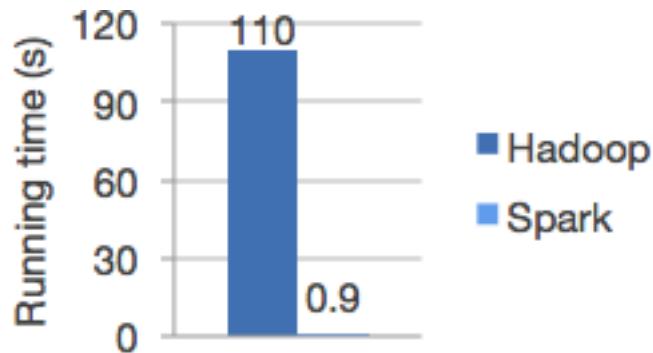


Figure 2.1: Logistic regression in Hadoop and Spark

2. Ease of Use

Write applications quickly in Java, Scala, Python, R.

Spark offers over 80 high-level operators that make it easy to build parallel apps. And you can use it interactively from the Scala, Python and R shells.

3. Generality

Combine SQL, streaming, and complex analytics.

Spark powers a stack of libraries including SQL and DataFrames, MLlib for machine learning, GraphX, and Spark Streaming. You can combine these libraries seamlessly in the same application.

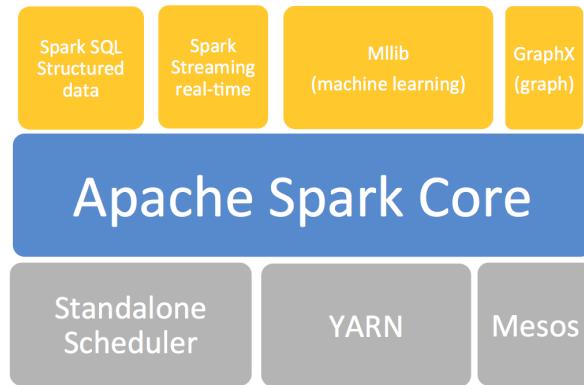


Figure 2.2: The Spark stack

4. Runs Everywhere

Spark runs on Hadoop, Mesos, standalone, or in the cloud. It can access diverse data sources including HDFS, Cassandra, HBase, and S3.



Figure 2.3: The Spark platform

2.2 Why Spark with Python (PySpark)?

No matter you like it or not, Python has been one of the most popular programming languages.

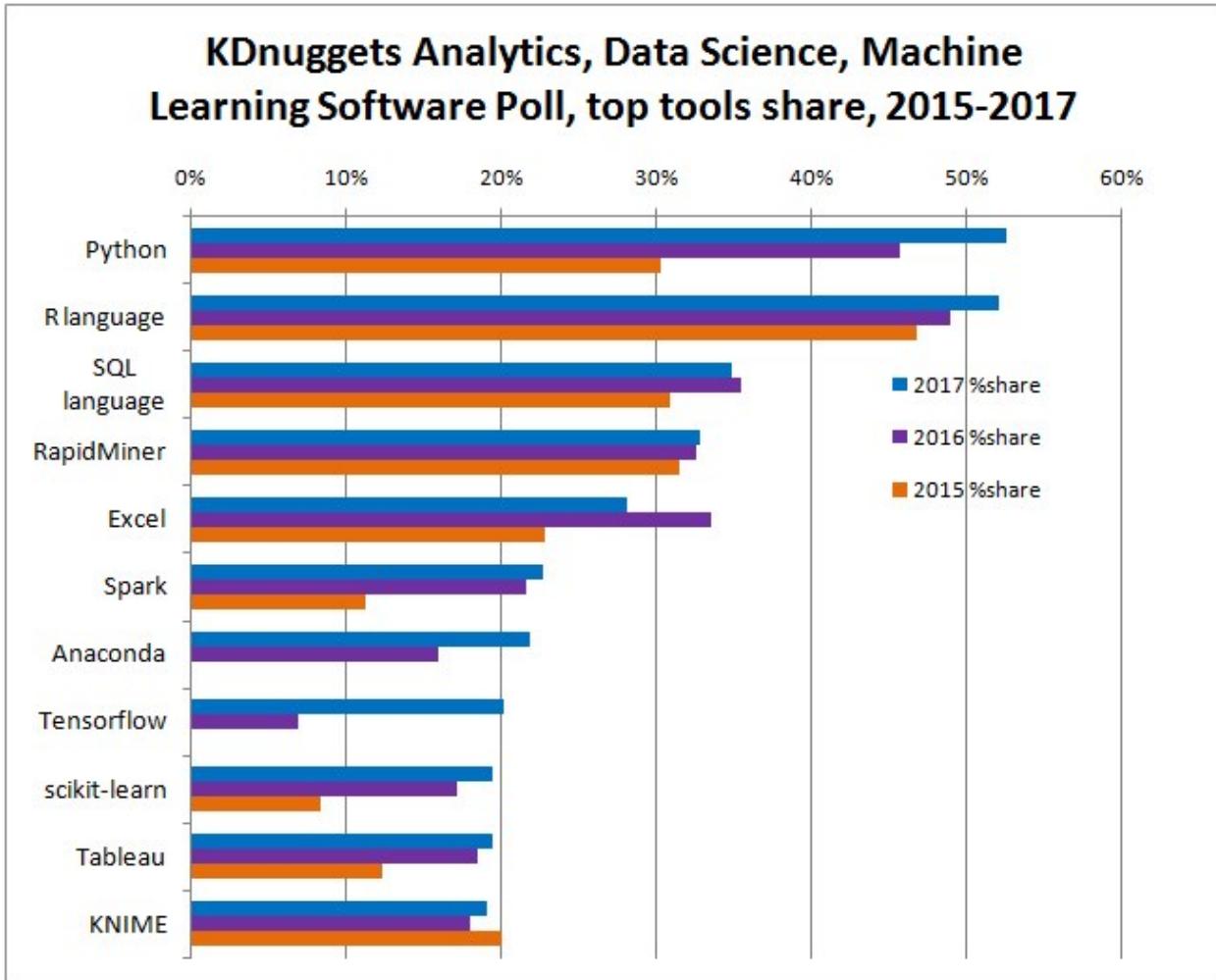


Figure 2.4: KDnuggets Analytics/Data Science 2017 Software Poll from [kdnnuggets](#).

**CHAPTER
THREE**

CONFIGURE RUNNING PLATFORM

Note: Good tools are prerequisite to the successful execution of a job. – old Chinese proverb

A good programming platform can save you lots of troubles and time. Herein I will only present how to install my favorite programming platform and only show the easiest way which I know to set it up on Linux system. If you want to install on the other operator system, you can Google it. In this section, you may learn how to set up Pyspark on the corresponding programming platform and package.

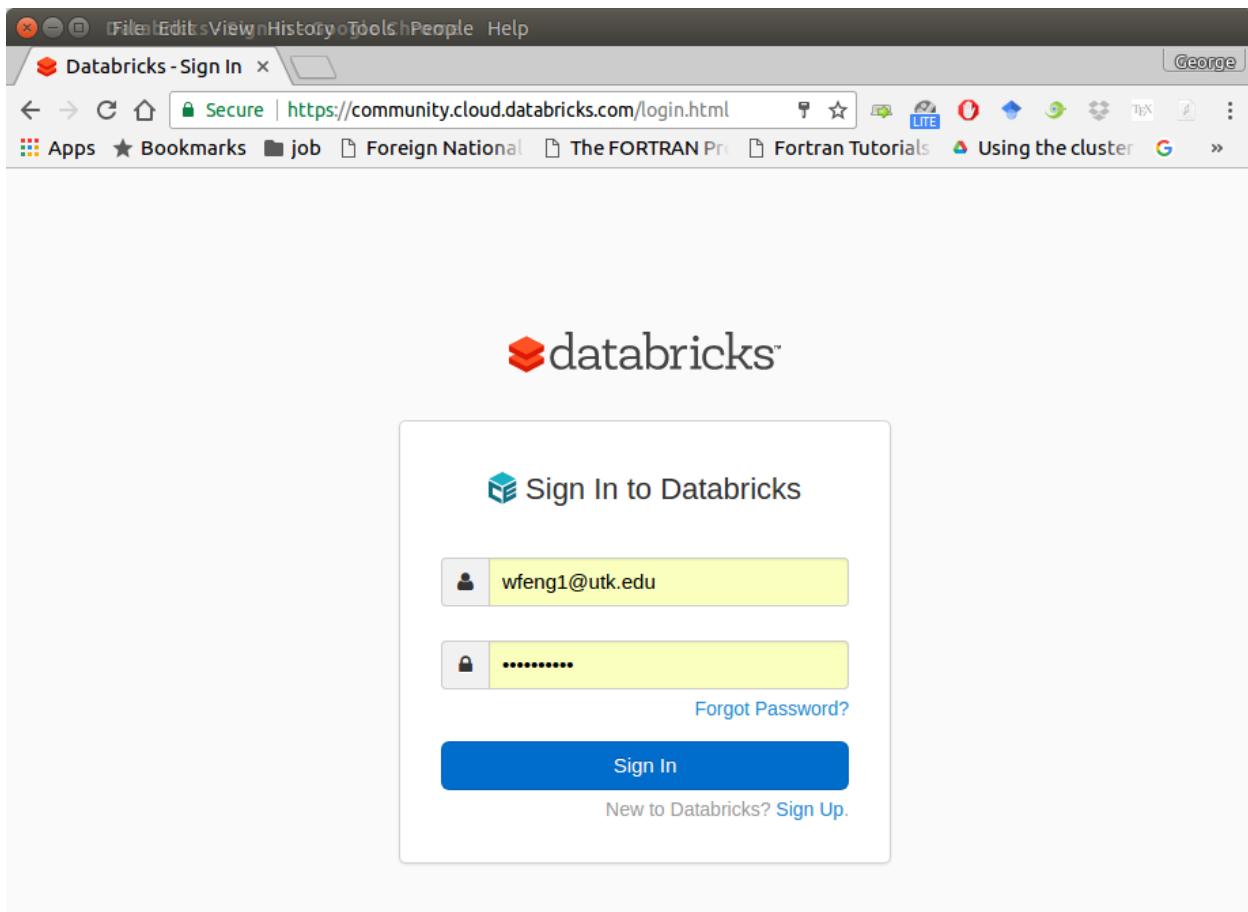
3.1 Run on Databricks Community Cloud

If you don't have any experience with Linux or Unix operator system, I would love to recommend you to use Spark on Databricks Community Cloud. Since you do not need to setup the Spark and it's totally **free** for Community Edition. Please follow the steps listed below.

1. Sign up a account at: <https://community.cloud.databricks.com/login.html>
2. Sign in with your account, then you can creat your cluster(machine), table(dataset) and notebook(code).
3. Create your cluster where your code will run
4. Import your dataset

Note: You need to save the path which appears at Uploaded to DBFS: /File-Store/tables/05rmhuqv1489687378010/. Since we will use this path to load the dataset.

5. Creat your notebook



Welcome to **databricks™**

Featured Notebooks

- Introduction to Apache Spark on Databricks
- Databricks for Data Scientists
- Introduction to Structured Streaming

New

- Notebook
- Job
- Cluster
- Table
- Library

Documentation

- Databricks Guide
- Python, R, Scala, SQL
- Importing Data

Open Recent

- Databricks for Data Scientists
- linearRegression

What's new?

- Automatic termination of clusters
- Autoscaling local storage with EBS volumes (*beta*)

Latest release notes

Send Feedback

Create Cluster

New Cluster

Create Cluster

0 Workers: 0.0 GB Memory, 0 Cores, 0 DBU
1 Driver: 6.0 GB Memory, 0.88 Cores, 1 DBU

Cluster Name: MLmachine

DataBricks Runtime Version: Spark 2.1 (Auto-updating, Scala 2.10)

Instance: Free 6GB Memory: As a Community Edition user, your cluster will automatically terminate after an idle period of two hours.
For more configuration options, please upgrade your Databricks subscription.

AWS Spark

Availability Zone: us-west-2c

Send Feedback

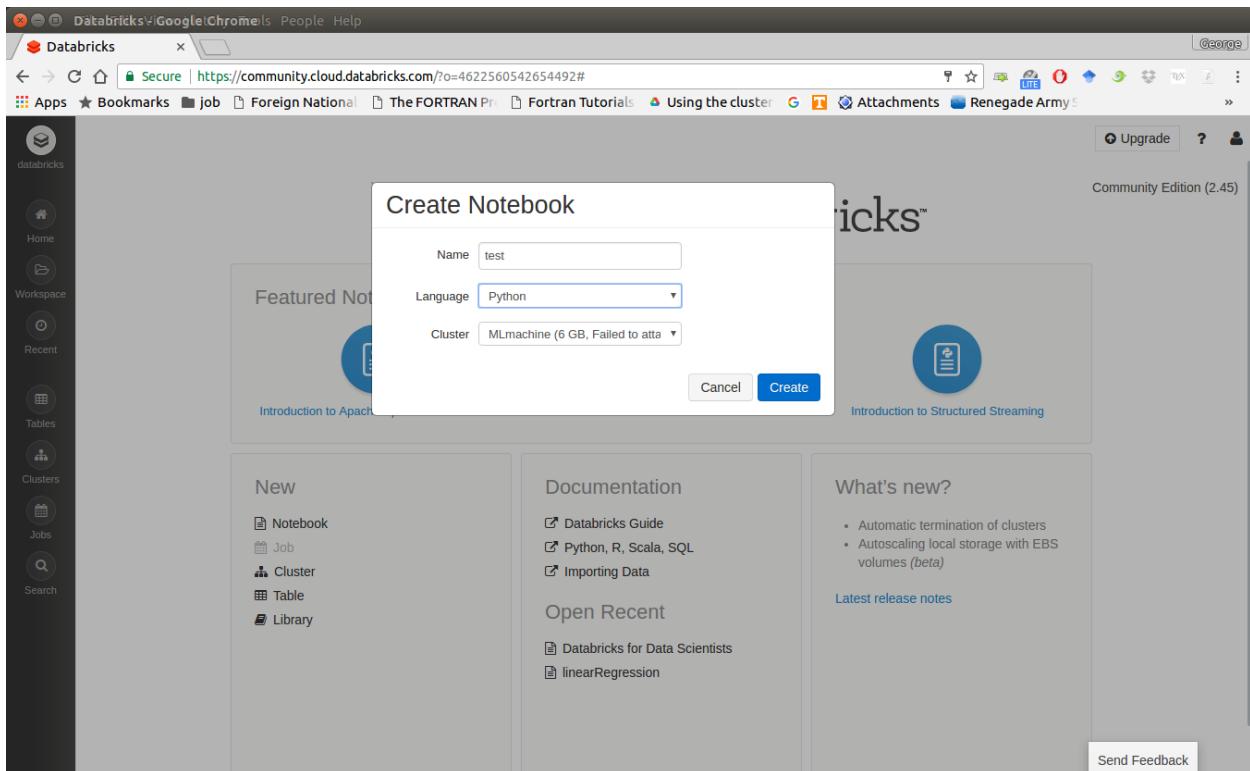
Learning Apache Spark with Python, Release v1.0

The screenshot shows the 'Create Table' interface in Databricks. On the left is a sidebar with icons for Home, Workspace, Recent, Tables, Clusters, Jobs, and Search. The main area has a title 'Create Table' and a sub-section 'Data Import'. It shows a dropdown 'Data Source' set to 'File' and a large input field labeled 'File(s)' with a placeholder 'Drop file or click here to upload'. A 'Send Feedback' button is at the bottom right.

The screenshot shows the 'Create Table' interface after a file has been uploaded. The 'File(s)' section now displays 'Heart (1).csv' with a size of '19.9 KB' and a 'Remove file' link. Below this, it says 'Uploaded to DBFS' and shows the path '/FileStore/tables/nlqogm7b1495157186117/Heart__1_-466d4.csv'. A 'Preview Table' button is visible. The 'Table Details' section on the left shows 'Table name: heart', 'File type: CSV', and 'Column Delimiter: ,'. The 'First row is header' checkbox is checked. A preview table grid shows two rows of data:

| | _c0 | Age | Sex | ChestPain | RestBP |
|---|-----|-----|--------|--------------|--------|
| 1 | 39 | 160 | Male | typical | 145 |
| 2 | 63 | 100 | Female | asymptomatic | 160 |

A 'Create Table' button is at the bottom of the 'Table Details' section. A 'Send Feedback' button is at the bottom right.



1. Linear Regression with PySpark on Databricks

Author: Wenqiang Feng

Set up SparkSession

```

Cmd 1
1 from pyspark.sql import SparkSession
2
3 spark = SparkSession \
4     .builder \
5     .appName("Python Spark Linear Regression Example") \
6     .config("spark.some.config.option", "some-value") \
7     .getOrCreate()

```

Command took 0.16 seconds -- by wfeng1@utk.edu at 4/2/2017, 11:12:21 PM on MLmachine

2. Load dataset

```

Cmd 5
1 df = spark.read.format('com.databricks.spark.csv') \
2     .options(header='true', \
3             inferSchema='true') \
4     .load("/FileStore/tables/05rmhuqv1489687378010/", header= True)

```

After finishing the above 5 steps, you are ready to run your Spark code on Databricks Community Cloud. I will run all the following demos on Databricks Community Cloud. Hopefully, when you run the demo code, you will get the following results:

```
+---+-----+-----+-----+-----+
|_c0|    TV|Radio|Newspaper|Sales|
+---+-----+-----+-----+-----+
|  1|230.1| 37.8|    69.2| 22.1|
|  2| 44.5| 39.3|    45.1| 10.4|
|  3| 17.2| 45.9|    69.3|  9.3|
|  4|151.5| 41.3|    58.5| 18.5|
|  5|180.8| 10.8|    58.4| 12.9|
+---+-----+-----+-----+
only showing top 5 rows

root
|-- _c0: integer (nullable = true)
|-- TV: double (nullable = true)
|-- Radio: double (nullable = true)
|-- Newspaper: double (nullable = true)
|-- Sales: double (nullable = true)
```

3.2 Configure Spark on Mac and Ubuntu

3.2.1 Installing Prerequisites

I will strongly recommend you to install Anaconda, since it contains most of the prerequisites and support multiple Operator Systems.

1. Install Python

Go to Ubuntu Software Center and follow the following steps:

1. Open Ubuntu Software Center
2. Search for python
3. And click Install

Or Open your terminal and using the following command:

```
sudo apt-get install build-essential checkinstall
sudo apt-get install libreadline-gplv2-dev libncursesw5-dev libssl-dev
                  libsqlite3-dev tk-dev libgdbm-dev libc6-dev libbz2-dev
sudo apt-get install python
sudo easy_install pip
sudo pip install ipython
```

3.2.2 Install Java

Java is used by many other softwares. So it is quite possible that you have already installed it. You can by using the following command in Command Prompt:

```
java -version
```

Otherwise, you can follow the steps in [How do I install Java for my Mac?](#) to install java on Mac and use the following command in Command Prompt to install on Ubuntu:

```
sudo apt-add-repository ppa:webupd8team/java
sudo apt-get update
sudo apt-get install oracle-java8-installer
```

3.2.3 Install Java SE Runtime Environment

I installed ORACLE Java JDK.

Warning: Installing Java and Java SE Runtime Environment steps are very important, since Spark is a domain-specific language written in Java.

You can check if your Java is available and find it's version by using the following command in Command Prompt:

```
java -version
```

If your Java is installed successfully, you will get the similar results as follows:

```
java version "1.8.0_131"
Java(TM) SE Runtime Environment (build 1.8.0_131-b11)
Java HotSpot(TM) 64-Bit Server VM (build 25.131-b11, mixed mode)
```

3.2.4 Install Apache Spark

Actually, the Pre-build version doesn't need installation. You can use it when you unpack it.

1. Download: You can get the Pre-built Apache Spark™ from [Download Apache Spark™](#).
2. Unpack: Unpack the Apache Spark™ to the path where you want to install the Spark.
3. Test: Test the Prerequisites: change the direction
`spark-#.#.#-bin-hadoop#.#/bin` and run

```
./pyspark
```

```
Python 2.7.13 |Anaconda 4.4.0 (x86_64)| (default, Dec 20 2016, 23:05:08)
[GCC 4.2.1 Compatible Apple LLVM 6.0 (clang-600.0.57)] on darwin
Type "help", "copyright", "credits" or "license" for more information.
Anaconda is brought to you by Continuum Analytics.
Please check out: http://continuum.io/thanks and https://anaconda.org
Using Spark's default log4j profile: org/apache/spark/log4j-defaults.properties
```

```
Setting default log level to "WARN".  
To adjust logging level use sc.setLogLevel(newLevel). For SparkR,  
use setLogLevel(newLevel).  
17/08/30 13:30:12 WARN NativeCodeLoader: Unable to load native-hadoop  
library for your platform... using builtin-java classes where applicable  
17/08/30 13:30:17 WARN ObjectStore: Failed to get database global_temp,  
returning NoSuchObjectException  
Welcome to
```

Using Python version 2.7.13 (default, Dec 20 2016 23:05:08)
SparkSession available as 'spark'.

3.2.5 Configure the Spark

- 1. Mac Operator System:** open your bash_profile in Terminal

```
vim ~/.bash_profile
```

And add the following lines to your `bash_profile` (remember to change the path)

```
# add for spark
export SPARK_HOME=your_spark_installation_path
export PATH=$PATH:$SPARK_HOME/bin:$SPARK_HOME/sbin
export PATH=$PATH:$SPARK_HOME/bin
export PYSPARK_DRIVER_PYTHON="jupyter"
export PYSPARK_DRIVER_PYTHON_OPTS="notebook"
```

At last, remember to source your bash profile

```
source ~/.bash_profile
```

2. **Ubuntu Operator Sysytem:** open your bashrc in Terminal

```
vim ~/.bashrc
```

And add the following lines to your bashrc (remember to change the path)

```
# add for spark
export SPARK_HOME=your_spark_installation_path
export PATH=$PATH:$SPARK_HOME/bin:$SPARK_HOME/sbin
export PATH=$PATH:$SPARK_HOME/bin
export PYSPARK_DRIVER_PYTHON="jupyter"
export PYSPARK_DRIVER_PYTHON_OPTS="notebook"
```

At last, remember to source your bashrc

```
source ~/.bashrc
```

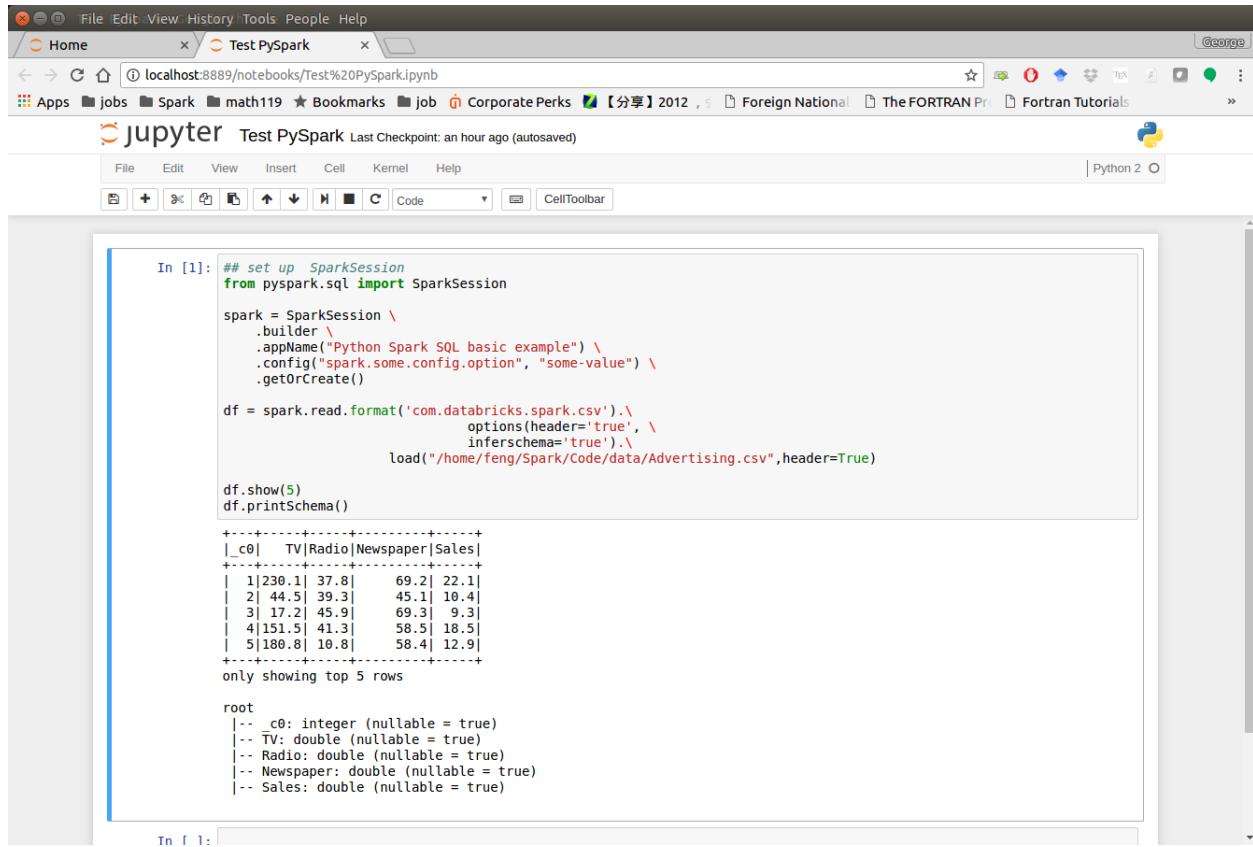
3.3 Configure Spark on Windows

Installing open source software on Windows is always a nightmare for me. Thanks for Deelesh Mandloi. You can follow the detailed procedures in the blog [Getting Started with PySpark on Windows](#) to install the Apache Spark™ on your Windows Operator System.

3.4 PySpark With Text Editor or IDE

3.4.1 PySpark With Jupyter Notebook

After you finishing the above setup steps in [Configure Spark on Mac and Ubuntu](#), then you should be good to write and run your PySpark Code in Jupyter notebook.



```
In [1]: ## set up SparkSession
from pyspark.sql import SparkSession

spark = SparkSession \
    .builder \
    .appName("Python Spark SQL basic example") \
    .config("spark.some.config.option", "some-value") \
    .getOrCreate()

df = spark.read.format('com.databricks.spark.csv') \
    .options(header='true', \
            inferSchema='true') \
    .load("/home/feng/Spark/Code/data/Advertising.csv",header=True)

df.show(5)
df.printSchema()

+---+---+---+---+
|_c0| TV|Radio|Newspaper|Sales|
+---+---+---+---+
| 1|230.1| 37.8|   69.2| 22.1|
| 2| 44.5| 39.3|   45.1| 10.4|
| 3| 17.2| 45.9|   69.3|  9.3|
| 4|151.5| 41.3|   58.5| 18.5|
| 5|180.8| 10.8|   58.4| 12.9|
+---+---+---+---+
only showing top 5 rows

root
 |-- _c0: integer (nullable = true)
 |-- TV: double (nullable = true)
 |-- Radio: double (nullable = true)
 |-- Newspaper: double (nullable = true)
 |-- Sales: double (nullable = true)
```

3.4.2 PySpark With Apache Zeppelin

After you finishing the above setup steps in [Configure Spark on Mac and Ubuntu](#), then you should be good to write and run your PySpark Code in Apache Zeppelin.

The screenshot shows a Zeppelin Notebook interface with several cells and visualizations:

- Cell 1:** PySpark code to load a CSV file into a DataFrame.
- Cell 2:** PySpark code to show the top 4 rows of the DataFrame.
- Cell 3:** PySpark code to register the DataFrame as a temporary table named "bank".
- Cell 4:** SQL query to find the maximum age in the bank table.
- Cell 5:** SQL query to count the number of people in each age group where age is less than 30.
- Cell 6:** SQL query to count the number of people in each marital status.
- Visualizations:**
 - A pie chart showing the distribution of ages from 19 to 29.
 - A pie chart showing the distribution of marital statuses: single, married, divorced, and separated.
 - A histogram showing the distribution of age.

3.4.3 PySpark With Sublime Text

After you finishing the above setup steps in [Configure Spark on Mac and Ubuntu](#), then you should be good to use Sublime Text to write your PySpark Code and run your code as a normal python code in Terminal.

```
python test_pyspark.py
```

Then you should get the output results in your terminal.

The screenshot shows a Sublime Text window with a file named 'test_pyspark.py'. The code reads a CSV file 'Advertising.csv' and prints the top 5 rows of the DataFrame. To the right of the Sublime Text window is a terminal window showing the execution of the script and its output. The terminal output includes several warning messages from SparkUI about port binding, followed by the DataFrame schema and the first five rows of data.

```

1 ## set up SparkSession
2 from pyspark.sql import SparkSession
3
4 spark = SparkSession \
5     .builder \
6     .appName("Python Spark SQL basic example") \
7     .config("spark.some.config.option", "some-value") \
8     .getOrCreate()
9
10 df = spark.read.format('com.databricks.spark.csv').\
11     options(header='true', \
12             inferSchema='true').\
13     load("/home/feng/Spark/Code/data/Advertising.csv")
14
15 df.show(5)
16 df.printSchema()

```

```

feng@feng-ThinkPad:~/Spark/Code$ python test_pyspark.py
to bind to another address
17/05/21 19:12:47 WARN Utils: Service 'SparkUI' could not bind on port 4040. Attempting port 4041.
17/05/21 19:12:47 WARN Utils: Service 'SparkUI' could not bind on port 4041. Attempting port 4042.
+---+---+---+---+
|_c0| TV|Radio|Newspaper|Sales|
+---+---+---+---+
| 1|230.1| 37.8| 69.2| 22.1|
| 2| 44.5| 39.3| 45.1| 10.4|
| 3| 17.2| 45.9| 69.3| 9.3|
| 4|151.5| 41.3| 58.5| 18.5|
| 5|180.8| 10.8| 58.4| 12.9|
+---+---+---+---+
only showing top 5 rows

root
 |-- _c0: integer (nullable = true)
 |-- TV: double (nullable = true)
 |-- Radio: double (nullable = true)
 |-- Newspaper: double (nullable = true)
 |-- Sales: double (nullable = true)

feng@feng-ThinkPad:~/Spark/Code$
```

3.4.4 PySpark With Eclipse

If you want to run PySpark code on Eclipse, you need to add the paths for the **External Libraries** for your **Current Project** as follows:

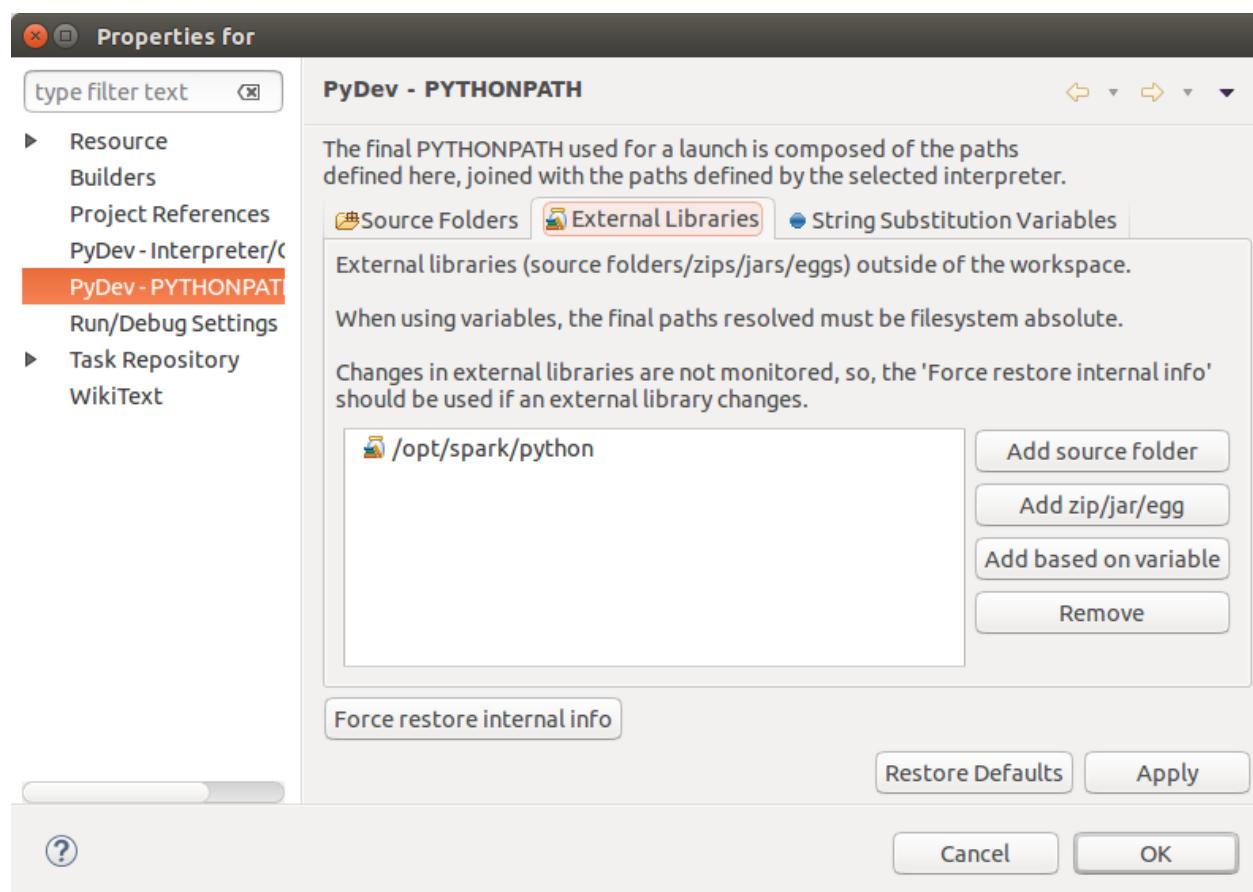
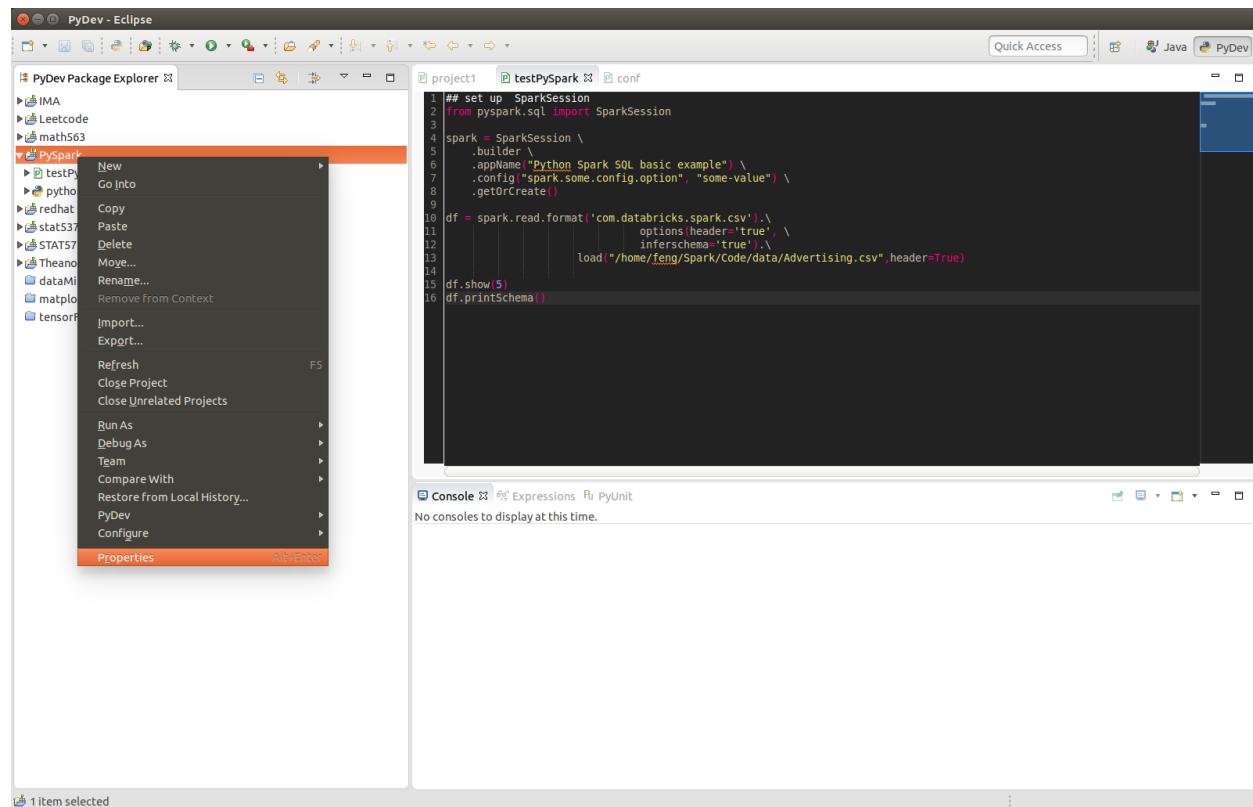
1. Open the properties of your project
2. Add the paths for the **External Libraries**

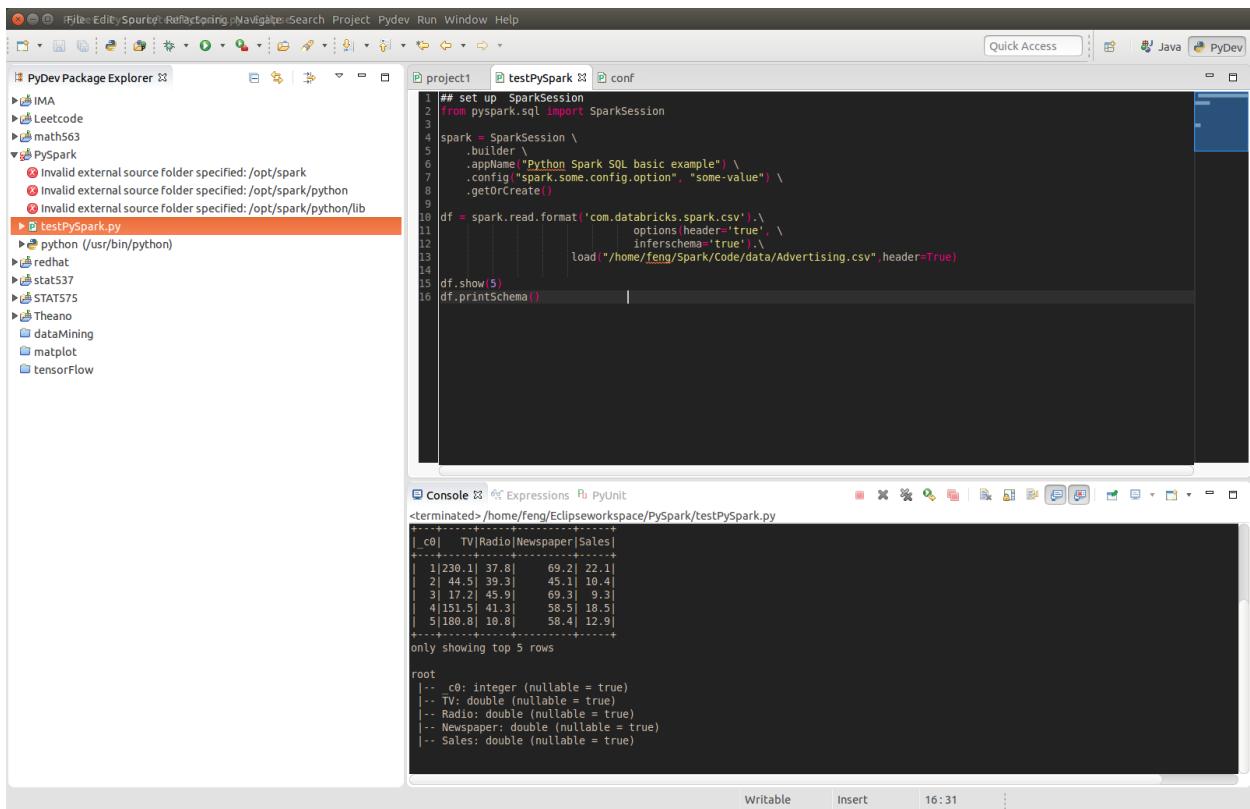
And then you should be good to run your code on Eclipse with PyDev.

3.5 Set up Spark on Cloud

Folloing the setup steps in [Configure Spark on Mac and Ubuntu](#), you can set up your own cluster on the cloud, for example AWS, Google Cloud. Actually, for those clouds, they have their own Big Data tool. You can run them directly whitout any setting just like Databricks Community Cloud. If you want more details, please feel free to contact with me.

Learning Apache Spark with Python, Release v1.0





3.6 Demo Code in this Section

The code for this section is available for download `test_pyspark`, and the Jupyter notebook can be download from `test_pyspark_ipynb`.

- Python Source code

```

## set up SparkSession
from pyspark.sql import SparkSession

spark = SparkSession \
    .builder \
    .appName("Python Spark SQL basic example") \
    .config("spark.some.config.option", "some-value") \
    .getOrCreate()

df = spark.read.format('com.databricks.spark.csv') \
    .options(header='true', \
    inferSchema='true') \
    .load("/home/feng/Spark/Code/data/Advertising.csv",header=True)

df.show(5)
df.printSchema()

```


AN INTRODUCTION TO APACHE SPARK

Note: **Know yourself and know your enemy, and you will never be defeated** – idiom, from Sunzi's Art of War

4.1 Core Concepts

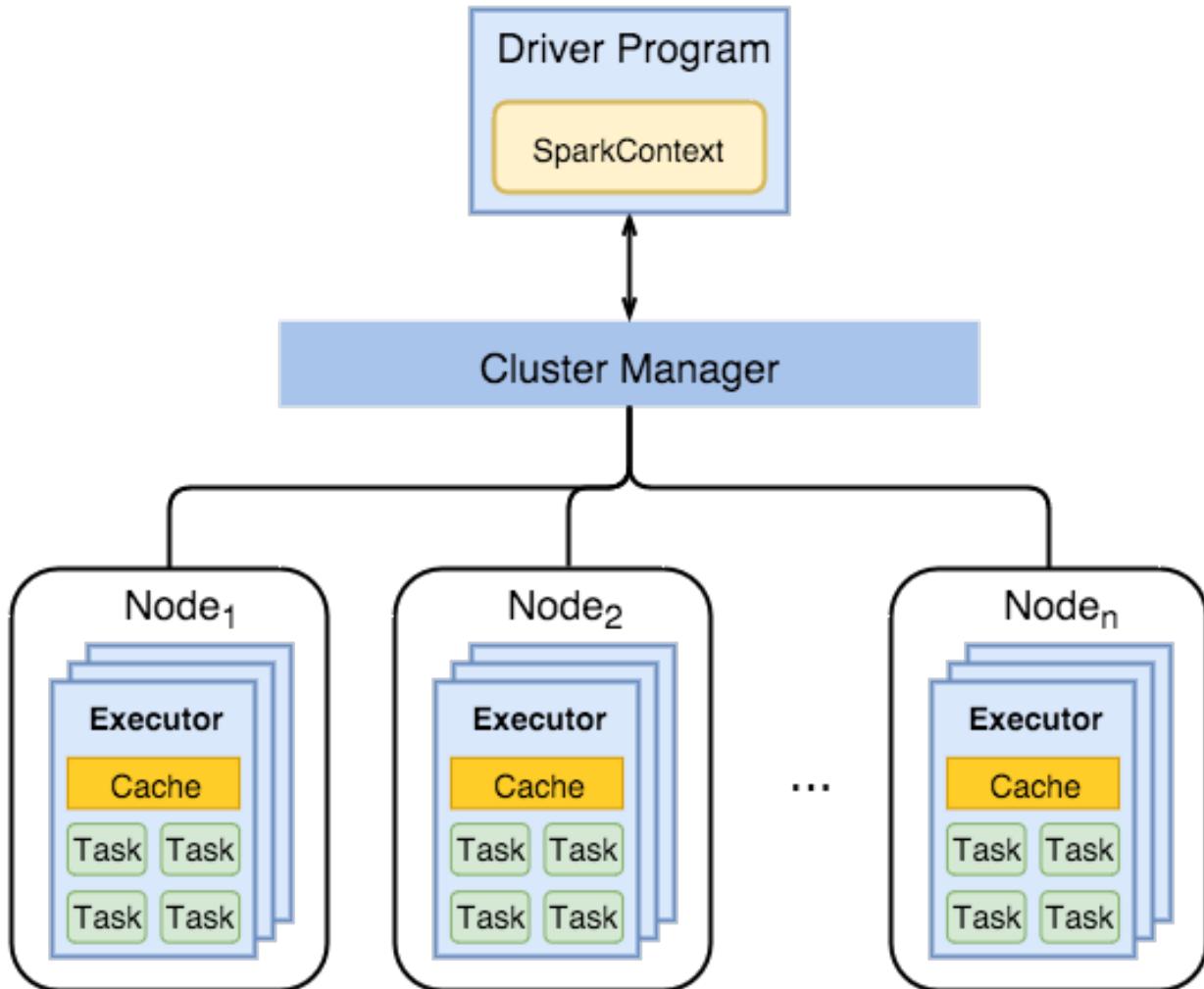
Most of the following content comes from [\[Kirillov2016\]](#). So the copyright belongs to **Anton Kirillov**. I will refer you to get more details from [Apache Spark core concepts, architecture and internals](#).

Before diving deep into how Apache Spark works, lets understand the jargon of Apache Spark

- Job: A piece of code which reads some input from HDFS or local, performs some computation on the data and writes some output data.
- Stages: Jobs are divided into stages. Stages are classified as a Map or reduce stages (Its easier to understand if you have worked on Hadoop and want to correlate). Stages are divided based on computational boundaries, all computations (operators) cannot be Updated in a single Stage. It happens over many stages.
- Tasks: Each stage has some tasks, one task per partition. One task is executed on one partition of data on one executor (machine).
- DAG: DAG stands for Directed Acyclic Graph, in the present context its a DAG of operators.
- Executor: The process responsible for executing a task.
- Master: The machine on which the Driver program runs
- Slave: The machine on which the Executor program runs

4.2 Spark Components

1. Spark Driver
 - separate process to execute user applications



- creates SparkContext to schedule jobs execution and negotiate with cluster manager

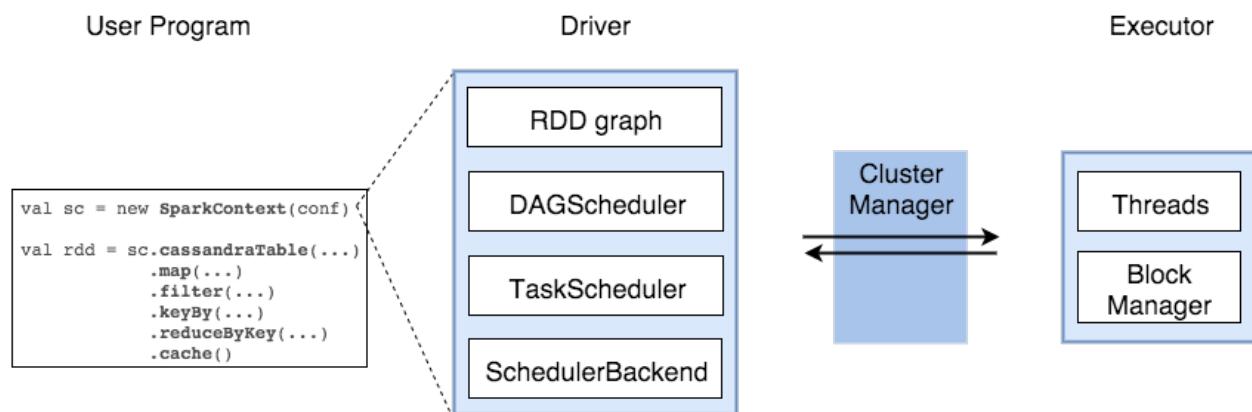
2. Executors

- run tasks scheduled by driver
- store computation results in memory, on disk or off-heap
- interact with storage systems

3. Cluster Manager

- Mesos
- YARN
- Spark Standalone

Spark Driver contains more components responsible for translation of user code into actual jobs executed on cluster:



- **SparkContext**
 - represents the connection to a Spark cluster, and can be used to create RDDs, accumulators and broadcast variables on that cluster
- **DAGScheduler**
 - computes a DAG of stages for each job and submits them to TaskScheduler determines preferred locations for tasks (based on cache status or shuffle files locations) and finds minimum schedule to run the jobs
- **TaskScheduler**
 - responsible for sending tasks to the cluster, running them, retrying if there are failures, and mitigating stragglers
- **SchedulerBackend**
 - backend interface for scheduling systems that allows plugging in different implementations(Mesos, YARN, Standalone, local)

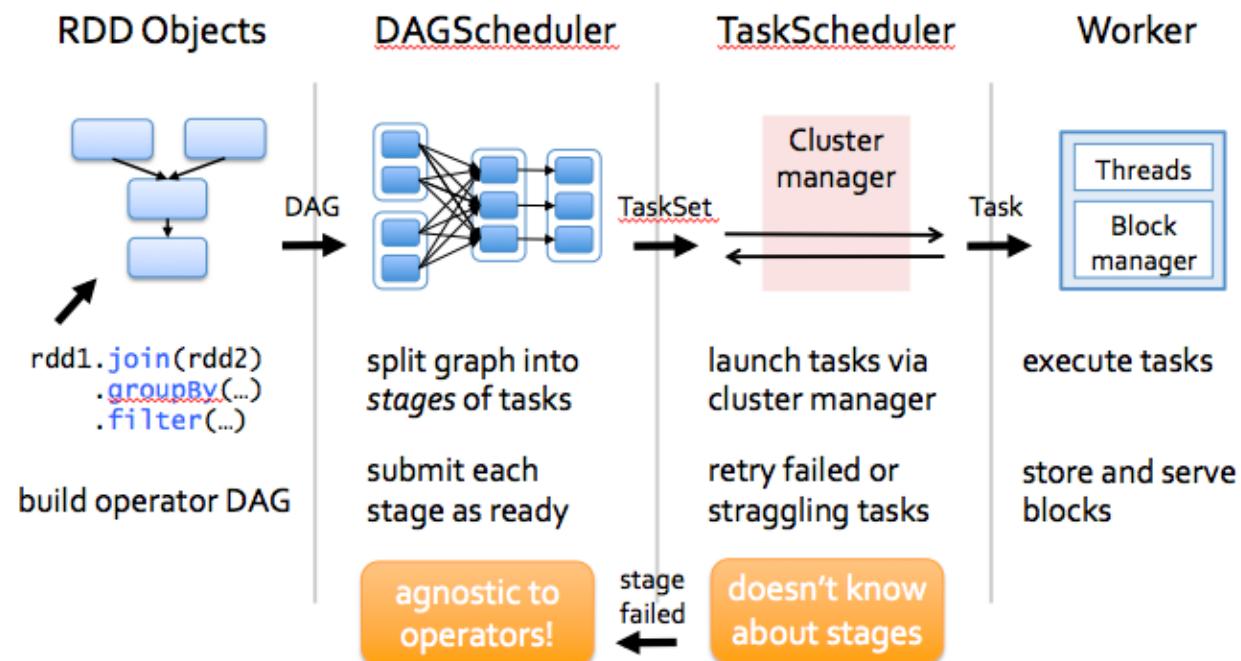
- BlockManager
 - provides interfaces for putting and retrieving blocks both locally and remotely into various stores (memory, disk, and off-heap)

4.3 Architecture

4.4 How Spark Works?

Spark has a small code base and the system is divided in various layers. Each layer has some responsibilities. The layers are independent of each other.

The first layer is the interpreter, Spark uses a Scala interpreter, with some modifications. As you enter your code in spark console (creating RDD's and applying operators), Spark creates a operator graph. When the user runs an action (like collect), the Graph is submitted to a DAG Scheduler. The DAG scheduler divides operator graph into (map and reduce) stages. A stage is comprised of tasks based on partitions of the input data. The DAG scheduler pipelines operators together to optimize the graph. For e.g. Many map operators can be scheduled in a single stage. This optimization is key to Spaks performance. The final result of a DAG scheduler is a set of stages. The stages are passed on to the Task Scheduler. The task scheduler launches tasks via cluster manager. (Spark Standalone/Yarn/Mesos). The task scheduler doesn't know about dependencies among stages.



PROGRAMMING WITH RDDS

Note: If you only know yourself, but not your opponent, you may win or may lose. If you know neither yourself nor your enemy, you will always endanger yourself – idiom, from Sunzi's Art of War

RDD represents **Resilient Distributed Dataset**. An RDD in Spark is simply an immutable distributed collection of objects sets. Each RDD is split into multiple partitions (similar pattern with smaller sets), which may be computed on different nodes of the cluster.

5.1 Create RDD

Usually, there are two popular way to create the RDDs: loading an external dataset, or distributing a set of collection of objects. The following examples show some simplest ways to create RDDs by using `parallelize()` fucntion which takes an already existing collection in your program and pass the same to the Spark Context.

1. By using `parallelize()` fucntion

```
from pyspark.sql import SparkSession

spark = SparkSession \
    .builder \
    .appName("Python Spark create RDD example") \
    .config("spark.some.config.option", "some-value") \
    .getOrCreate()

df = spark.sparkContext.parallelize([(1, 2, 3, 'a b c'),
                                    (4, 5, 6, 'd e f'),
                                    (7, 8, 9, 'g h i')]).toDF(['col1', 'col2', 'col3', 'col4'])
```

Then you will get the RDD data:

```
df.show()

+---+---+---+---+
|col1|col2|col3| col4|
+---+---+---+---+
|    1|    2|    3|a b c|
|    4|    5|    6|d e f|
```

```
|    7|    8|    9|g h i|
+----+----+----+----+
```

```
from pyspark.sql import SparkSession

spark = SparkSession \
    .builder \
    .appName("Python Spark create RDD example") \
    .config("spark.some.config.option", "some-value") \
    .getOrCreate()

myData = spark.sparkContext.parallelize([(1,2), (3,4), (5,6), (7,8), (9,10)])
```

Then you will get the RDD data:

```
myData.collect()

[(1, 2), (3, 4), (5, 6), (7, 8), (9, 10)]
```

2. By using `createDataFrame()` function

```
from pyspark.sql import SparkSession

spark = SparkSession \
    .builder \
    .appName("Python Spark create RDD example") \
    .config("spark.some.config.option", "some-value") \
    .getOrCreate()

Employee = spark.createDataFrame([
    ('1', 'Joe', '70000', '1'),
    ('2', 'Henry', '80000', '2'),
    ('3', 'Sam', '60000', '2'),
    ('4', 'Max', '90000', '1'),
    ['Id', 'Name', 'Salary', 'DepartmentId']
])
```

Then you will get the RDD data:

```
+---+---+---+---+
| Id| Name|Salary|DepartmentId|
+---+---+---+---+
| 1| Joe| 70000| 1|
| 2| Henry| 80000| 2|
| 3| Sam| 60000| 2|
| 4| Max| 90000| 1|
+---+---+---+---+
```

3. By using `read` and `load` functions

1. Read dataset from .csv file

```
## set up SparkSession
from pyspark.sql import SparkSession
```

```

spark = SparkSession \
    .builder \
    .appName("Python Spark create RDD example") \
    .config("spark.some.config.option", "some-value") \
    .getOrCreate()

df = spark.read.format('com.databricks.spark.csv').\
    options(header='true', \
    inferSchema='true').\
    load("/home/feng/Spark/Code/data/Advertising.csv", header=True)

df.show(5)
df.printSchema()

```

Then you will get the RDD data:

```

+---+---+---+---+
| _c0 | TV | Radio | Newspaper | Sales |
+---+---+---+---+
| 1 | 230.1 | 37.8 | 69.2 | 22.1 |
| 2 | 44.5 | 39.3 | 45.1 | 10.4 |
| 3 | 17.2 | 45.9 | 69.3 | 9.3 |
| 4 | 151.5 | 41.3 | 58.5 | 18.5 |
| 5 | 180.8 | 10.8 | 58.4 | 12.9 |
+---+---+---+---+
only showing top 5 rows

```

```

root
|-- _c0: integer (nullable = true)
|-- TV: double (nullable = true)
|-- Radio: double (nullable = true)
|-- Newspaper: double (nullable = true)
|-- Sales: double (nullable = true)

```

Once created, RDDs offer two types of operations: transformations and actions.

2. Read dataset from DataBase

```

## set up SparkSession
from pyspark.sql import SparkSession

spark = SparkSession \
    .builder \
    .appName("Python Spark create RDD example") \
    .config("spark.some.config.option", "some-value") \
    .getOrCreate()

## User information
user = 'your_username'
pw   = 'your_password'

## Database information
table_name = 'table_name'
url = 'jdbc:postgresql://###.###.###.##:5432/dataset?user=' + user + '&password=' + pw

```

```
properties ={'driver': 'org.postgresql.Driver', 'password': pw, 'user': user}

df = spark.read.jdbc(url=url, table=table_name, properties=properties)

df.show(5)
df.printSchema()
```

Then you will get the RDD data:

```
+----+----+----+----+----+
| _c0 | TV | Radio | Newspaper | Sales |
+----+----+----+----+----+
| 1 | 230.1 | 37.8 | 69.2 | 22.1 |
| 2 | 44.5 | 39.3 | 45.1 | 10.4 |
| 3 | 17.2 | 45.9 | 69.3 | 9.3 |
| 4 | 151.5 | 41.3 | 58.5 | 18.5 |
| 5 | 180.8 | 10.8 | 58.4 | 12.9 |
+----+----+----+----+
only showing top 5 rows
```

```
root
|-- _c0: integer (nullable = true)
|-- TV: double (nullable = true)
|-- Radio: double (nullable = true)
|-- Newspaper: double (nullable = true)
|-- Sales: double (nullable = true)
```

Note: Reading tables from Database needs the proper drive for the corresponding Database. For example, the above demo needs `org.postgresql.Driver` and **you need to download it and put it in “jars” folder of your spark installation path.** I download `postgresql-42.1.1.jar` from the official website and put it in jars folder.

5.2 Spark Transformations

Transformations construct a new RDD from a previous one. For example, one common transformation is filtering data that matches a predicate.

5.3 Spark Actions

Actions, on the other hand, compute a result based on an RDD, and either return it to the driver program or save it to an external storage system (e.g., HDFS).

CHAPTER
SIX

STATISTICS PRELIMINARY

Note: If you only know yourself, but not your opponent, you may win or may lose. If you know neither yourself nor your enemy, you will always endanger yourself – idiom, from Sunzi's Art of War

6.1 Notations

- m : the number of the samples
- n : the number of the features
- y_i : i-th label
- \bar{y} : the mean of y .

6.2 Measurement Formula

- Mean squared error

In statistics, the **MSE** (Mean Squared Error) of an estimator (of a procedure for estimating an unobserved quantity) measures the average of the squares of the errors or deviations—that is, the difference between the estimator and what is estimated.

$$\text{MSE} = \frac{1}{m} \sum_{i=1}^m (\hat{y}_i - y_i)^2$$

- Root Mean squared error

$$\text{RMSE} = \sqrt{\text{MSE}} = \sqrt{\frac{1}{m} \sum_{i=1}^m (\hat{y}_i - y_i)^2}$$

- Total sum of squares

In statistical data analysis the **TSS** (Total Sum of Squares) is a quantity that appears as part of a standard way of presenting results of such analyses. It is defined as being the sum, over all observations, of the squared differences of each observation from the overall mean.

$$\text{TSS} = \sum_{i=1}^m (y_i - \bar{y})^2$$

CHAPTER SEVEN

REGRESSION

Note: A journey of a thousand miles begins with a single step – old Chinese proverb

In statistical modeling, regression analysis focuses on investigating the relationship between a dependent variable and one or more independent variables. [Wikipedia Regression analysis](#)

In data mining, Regression is a model to represent the relationship between the value of lable (or target, it is numerical variable) and on one or more features (or predictors they can be numerical and categorical variables).

7.1 Linear Regression

7.1.1 Introduction

Given that a data set $\{x_{i1}, \dots, x_{in}, y_i\}_{i=1}^m$ which contains n features (variables) and m samples (data points), in simple linear regression model for modeling m data points with one independent variable: x_{i1} , the formula is given by:

$$y_i = \beta_0 + \beta_1 x_{i1}, \text{ where, } i = 1, \dots, m.$$

In matrix notation, the data set is written as $\mathbf{X} = [\mathbf{X}_1, \dots, \mathbf{X}_n]$ with $\mathbf{X}_i = \{x_{i.}\}_{i=1}^n$, $\mathbf{y} = \{y_i\}_{i=1}^m$ and $\boldsymbol{\beta}^\top = \{\beta_i\}_{i=1}^m$. Then the normal equations are written as

$$\mathbf{y} = \mathbf{X}\boldsymbol{\beta}.$$

7.1.2 How to solve it?

1. Direct Methods
2. Iterative Methods

7.1.3 Demo

- The Jupyter notebook can be download from Linear Regression which was implemented without using Pipeline.
- The Jupyter notebook can be download from Linear Regression with Pipeline which was implemented with using Pipeline.
- I will only present the code with pipeline style in the following.
- For more details about the parameters, please visit [Linear Regression API](#).

1. Set up spark context and SparkSession

```
from pyspark.sql import SparkSession

spark = SparkSession \
    .builder \
    .appName("Python Spark regression example") \
    .config("spark.some.config.option", "some-value") \
    .getOrCreate()
```

2. Load dataset

```
df = spark.read.format('com.databricks.spark.csv') \
    .options(header='true', \
             inferschema='true') \
    .load("../data/Advertising.csv", header=True);
```

check the data set

```
df.show(5, True)
df.printSchema()
```

Then you will get

```
+---+---+---+---+
| TV|Radio|Newspaper|Sales|
+---+---+---+---+
| 230.1| 37.8|     69.2| 22.1|
| 44.5| 39.3|     45.1| 10.4|
| 17.2| 45.9|     69.3|  9.3|
|151.5| 41.3|     58.5| 18.5|
|180.8| 10.8|     58.4| 12.9|
+---+---+---+---+
only showing top 5 rows
```

```
root
 |-- TV: double (nullable = true)
 |-- Radio: double (nullable = true)
 |-- Newspaper: double (nullable = true)
 |-- Sales: double (nullable = true)
```

You can also get the Statistical results from the data frame (Unfortunately, it only works for numerical).

```
df.describe().show()
```

Then you will get

| summary | TV | Radio | Newspaper | Sales |
|---------|-------------------|--------------------|--------------------|--------------------|
| count | 200 | 200 | 200 | 200 |
| mean | 147.0425 | 23.264000000000024 | 30.553999999999995 | 14.022500000000003 |
| stddev | 85.85423631490805 | 14.846809176168728 | 21.77862083852283 | 5.217456565710477 |
| min | 0.7 | 0.0 | 0.3 | 1.6 |
| max | 296.4 | 49.6 | 114.0 | 27.0 |

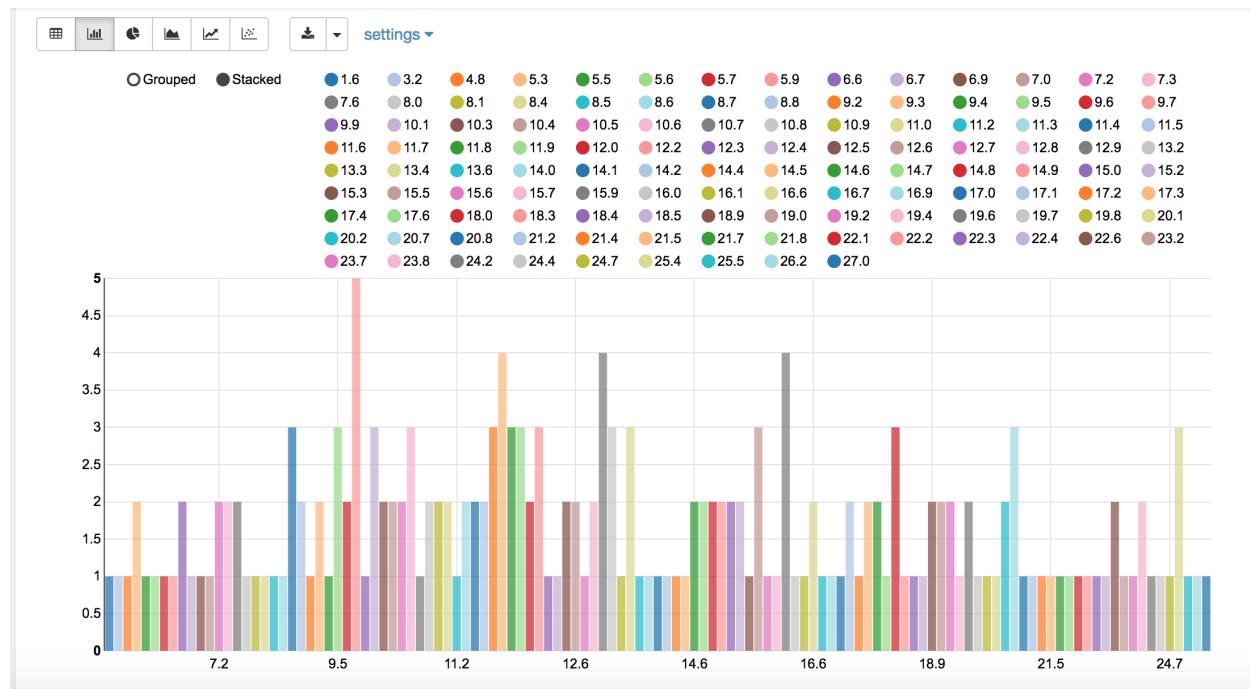


Figure 7.1: Sales distribution

3. Convert the data to dense vector (**features** and **label**)

```
from pyspark.sql import Row
from pyspark.ml.linalg import Vectors

# I provide two ways to build the features and labels

# method 1 (good for small feature):
def transData(row):
    return Row(label=row["Sales"],
               features=Vectors.dense([row["TV"],
                                      row["Radio"],
                                      row["Newspaper"]]))

# Method 2 (good for large features):
```

```
def transData(data):
    return data.rdd.map(lambda r: [Vectors.dense(r[:-1]), r[-1]]).toDF(['features','label'])
```

4. Transform the dataset to DataFrame

```
transformed= transData(df)
transformed.show(5)
```

```
+-----+-----+
|      features|label |
+-----+-----+
| [230.1,37.8,69.2]| 22.1|
| [44.5,39.3,45.1]| 10.4|
| [17.2,45.9,69.3]|  9.3|
| [151.5,41.3,58.5]| 18.5|
| [180.8,10.8,58.4]| 12.9|
+-----+-----+
only showing top 5 rows
```

Note: You will find out that all of the machine learning algorithms in Spark are based on the **features** and **label**. That is to say, you can play with all of the machine learning algorithms in Spark when you get ready the **features** and **label**.

5. Deal With Categorical Variables

```
from pyspark.ml import Pipeline
from pyspark.ml.regression import LinearRegression
from pyspark.ml.feature import VectorIndexer
from pyspark.ml.evaluation import RegressionEvaluator

# Automatically identify categorical features, and index them.
# We specify maxCategories so features with > 4 distinct values are treated as continuous.

featureIndexer = VectorIndexer(inputCol="features", \
                                outputCol="indexedFeatures", \
                                maxCategories=4).fit(transformed)

data = featureIndexer.transform(transformed)
```

Now you check your dataset with

```
data.show(5, True)
```

you will get

```
+-----+-----+-----+
|      features|label | indexedFeatures|
+-----+-----+-----+
| [230.1,37.8,69.2]| 22.1|[230.1,37.8,69.2]|
| [44.5,39.3,45.1]| 10.4|[44.5,39.3,45.1]|
| [17.2,45.9,69.3]|  9.3|[17.2,45.9,69.3]|
| [151.5,41.3,58.5]| 18.5|[151.5,41.3,58.5]|
| [180.8,10.8,58.4]| 12.9|[180.8,10.8,58.4]|

```

```
+-----+-----+
only showing top 5 rows
```

6. Split the data into training and test sets (40% held out for testing)

```
# Split the data into training and test sets (40% held out for testing)
(trainingData, testData) = transformed.randomSplit([0.6, 0.4])
```

You can check your train and test data as follows (In my opinion, it is always good to keep tracking your data during prototype phase):

```
trainingData.show(5)
testData.show(5)
```

Then you will get

```
+-----+-----+
|      features|label|indexedFeatures|
+-----+-----+
| [4.1,11.6,5.7]|  3.2| [4.1,11.6,5.7]|
| [5.4,29.9,9.4]|  5.3| [5.4,29.9,9.4]|
| [7.3,28.1,41.4]|  5.5|[7.3,28.1,41.4]|
| [7.8,38.9,50.6]|  6.6|[7.8,38.9,50.6]|
| [8.6,2.1,1.0]|  4.8| [8.6,2.1,1.0]|
+-----+-----+
only showing top 5 rows

+-----+-----+
|      features|label| indexedFeatures|
+-----+-----+
| [0.7,39.6,8.7]|  1.6| [0.7,39.6,8.7]|
| [8.4,27.2,2.1]|  5.7| [8.4,27.2,2.1]|
| [11.7,36.9,45.2]|  7.3|[11.7,36.9,45.2]|
| [13.2,15.9,49.6]|  5.6|[13.2,15.9,49.6]|
| [16.9,43.7,89.4]|  8.7|[16.9,43.7,89.4]|
+-----+-----+
only showing top 5 rows
```

7. Fit Ordinary Least Square Regression Model

For more details about the parameters, please visit [Linear Regression API](#).

```
# Import LinearRegression class
from pyspark.ml.regression import LinearRegression

# Define LinearRegression algorithm
lr = LinearRegression()
```

8. Pipeline Architecture

```
# Chain indexer and tree in a Pipeline
pipeline = Pipeline(stages=[featureIndexer, lr])

model = pipeline.fit(trainingData)
```

9. Summary of the Model

Spark has a poor summary function for data and model. I wrote a summary function which has similar format as **R** output for the linear regression in PySpark.

```
def modelsummary(model):
    import numpy as np
    print ("Note: the last rows are the information for Intercept")
    print ("##", "-----")
    print ("##", " Estimate | Std.Error | t Values | P-value")
    coef = np.append(list(model.coefficients),model.intercept)
    Summary=model.summary

    for i in range(len(Summary.pValues)):
        print ('##', '{:10.6f}'.format(coef[i]), \
               '{:10.6f}'.format(Summary.coefficientStandardErrors[i]), \
               '{:8.3f}'.format(Summary.tValues[i]), \
               '{:10.6f}'.format(Summary.pValues[i]))

    print ("##", '--')
    print ("##", "Mean squared error: % .6f" \
           % Summary.meanSquaredError, ", RMSE: % .6f" \
           % Summary.rootMeanSquaredError )
    print ("##", "Multiple R-squared: %f" % Summary.r2, ", \
           Total iterations: %i"% Summary.totalIterations)

modelsummary(model.stages[-1])
```

You will get the following summary results:

```
Note: the last rows are the information for Intercept
('##', '-----')
('##', ' Estimate | Std.Error | t Values | P-value')
('##', ' 0.044186', ' 0.001663', ' 26.573', ' 0.000000')
('##', ' 0.206311', ' 0.010846', ' 19.022', ' 0.000000')
('##', ' 0.001963', ' 0.007467', ' 0.263', ' 0.793113')
('##', ' 2.596154', ' 0.379550', ' 6.840', ' 0.000000')
('##', '--')
('##', 'Mean squared error: 2.588230', ', RMSE: 1.608798')
('##', 'Multiple R-squared: 0.911869', ', Total iterations: 1')
```

10. Make predictions

```
# Make predictions.
predictions = model.transform(testData)

# Select example rows to display.
predictions.select("features","label","predictedLabel").show(5)

+-----+----+-----+
|      features|label|      prediction|
+-----+----+-----+
| [0.7,39.6,8.7]| 1.6| 10.81405928637388|
| [8.4,27.2,2.1]| 5.7| 8.583086404079918|
```

```
| [11.7,36.9,45.2] | 7.3|10.814712818232422 |
| [13.2,15.9,49.6] | 5.6| 6.557106943899219|
| [16.9,43.7,89.4] | 8.7|12.534151375058645|
+-----+-----+
only showing top 5 rows
```

9. Evaluation

```
from pyspark.ml.evaluation import RegressionEvaluator
# Select (prediction, true label) and compute test error
evaluator = RegressionEvaluator(labelCol="label",
                                 predictionCol="prediction",
                                 metricName="rmse")

rmse = evaluator.evaluate(predictions)
print("Root Mean Squared Error (RMSE) on test data = %g" % rmse)
```

The final Root Mean Squared Error (RMSE) is as follows:

```
Root Mean Squared Error (RMSE) on test data = 1.63114
```

You can also check the R^2 value for the test data:

```
y_true = predictions.select("label").toPandas()
y_pred = predictions.select("prediction").toPandas()

import sklearn.metrics
r2_score = sklearn.metrics.r2_score(y_true, y_pred)
print('r2_score: {0}'.format(r2_score))
```

Then you will get

```
r2_score: 0.854486655585
```

Warning: You should know most softwares are using different formula to calculate the R^2 value when no intercept is included in the model. You can get more information from the discussion at [StackExchange](#).

7.2 Generalized linear regression

7.2.1 Introduction

7.2.2 How to solve it?

7.2.3 Demo

- The Jupyter notebook can be download from [Generalized Linear Regression](#).
- For more details about the parameters, please visit [Generalized Linear Regression API](#).

1. Set up spark context and SparkSession

```
from pyspark.sql import SparkSession

spark = SparkSession \
    .builder \
    .appName("Python Spark regression example") \
    .config("spark.some.config.option", "some-value") \
    .getOrCreate()
```

2. Load dataset

```
df = spark.read.format('com.databricks.spark.csv') \
    .options(header='true', \
    inferschema='true') \
    .load("../data/Advertising.csv", header=True);
```

check the data set

```
df.show(5, True)
df.printSchema()
```

Then you will get

```
+-----+-----+-----+
|   TV|Radio|Newspaper|Sales|
+-----+-----+-----+
| 230.1| 37.8|     69.2| 22.1|
|  44.5| 39.3|     45.1| 10.4|
| 17.2| 45.9|     69.3|  9.3|
|151.5| 41.3|     58.5| 18.5|
|180.8| 10.8|     58.4| 12.9|
+-----+-----+-----+
only showing top 5 rows
```

```
root
 |-- TV: double (nullable = true)
 |-- Radio: double (nullable = true)
 |-- Newspaper: double (nullable = true)
 |-- Sales: double (nullable = true)
```

You can also get the Statistical results from the data frame (Unfortunately, it only works for numerical).

```
df.describe().show()
```

Then you will get

```
+-----+-----+-----+-----+-----+
|summary|          TV|        Radio|      Newspaper|       Sales|
+-----+-----+-----+-----+-----+
|  count|      200|      200|      200|      200|
|  mean| 147.0425|23.26400000000024|30.553999999999995|14.022500000000003|
| stddev|85.85423631490805|14.846809176168728| 21.77862083852283| 5.217456565710477|
|   min|       0.7|        0.0|       0.3|      1.6|
+-----+-----+-----+-----+-----+
```

| | | | | | |
|---|--------------------------------|-------|------|-------|------|
| | max | 296.4 | 49.6 | 114.0 | 27.0 |
| + | -----+-----+-----+-----+-----+ | | | | |

3. Convert the data to dense vector (**features** and **label**)

```
from pyspark.sql import Row
from pyspark.ml.linalg import Vectors

# I provide two ways to build the features and labels

# method 1 (good for small feature):
def transData(row):
    return Row(label=row["Sales"],
               features=Vectors.dense([row["TV"],
                                      row["Radio"],
                                      row["Newspaper"]]))

# Method 2 (good for large features):
def transData(data):
    return data.rdd.map(lambda r: [Vectors.dense(r[:-1]), r[-1]]).toDF(['features', 'label'])

transformed= transData(df)
transformed.show(5)

+-----+-----+
|      features|label|
+-----+-----+
| [230.1,37.8,69.2]| 22.1 |
| [44.5,39.3,45.1]| 10.4 |
| [17.2,45.9,69.3]|  9.3 |
| [151.5,41.3,58.5]| 18.5 |
| [180.8,10.8,58.4]| 12.9 |
+-----+-----+
only showing top 5 rows
```

Note: You will find out that all of the machine learning algorithms in Spark are based on the **features** and **label**. That is to say, you can play with all of the machine learning algorithms in Spark when you get ready the **features** and **label**.

4. Convert the data to dense vector

```
# convert the data to dense vector
def transData(data):
    return data.rdd.map(lambda r: [r[-1], Vectors.dense(r[:-1])]).\
        toDF(['label','features'])

from pyspark.sql import Row
from pyspark.ml.linalg import Vectors

data= transData(df)
data.show()
```

5. Deal with the Categorical variables

```
from pyspark.ml import Pipeline
from pyspark.ml.regression import LinearRegression
from pyspark.ml.feature import VectorIndexer
from pyspark.ml.evaluation import RegressionEvaluator

# Automatically identify categorical features, and index them.
# We specify maxCategories so features with > 4
# distinct values are treated as continuous.

featureIndexer = VectorIndexer(inputCol="features", \
                                outputCol="indexedFeatures", \
                                maxCategories=4).fit(transformed)

data = featureIndexer.transform(transformed)
```

When you check your data at this point, you will get

```
+-----+-----+
|      features|label| indexedFeatures|
+-----+-----+
| [230.1,37.8,69.2]| 22.1|[230.1,37.8,69.2]|
| [44.5,39.3,45.1]| 10.4|[44.5,39.3,45.1]|
| [17.2,45.9,69.3]|  9.3|[17.2,45.9,69.3]|
| [151.5,41.3,58.5]| 18.5|[151.5,41.3,58.5]|
| [180.8,10.8,58.4]| 12.9|[180.8,10.8,58.4]|
+-----+-----+
only showing top 5 rows
```

6. Split the data into training and test sets (40% held out for testing)

```
# Split the data into training and test sets (40% held out for testing)
(trainingData, testData) = transformed.randomSplit([0.6, 0.4])
```

You can check your train and test data as follows (In my opinion, it is always good to keep tracking your data during prototype phase):

```
trainingData.show(5)
testData.show(5)
```

Then you will get

```
+-----+-----+
|      features|label| indexedFeatures|
+-----+-----+
| [5.4,29.9,9.4]|  5.3|[5.4,29.9,9.4]|
| [7.8,38.9,50.6]| 6.6|[7.8,38.9,50.6]|
| [8.4,27.2,2.1]|  5.7|[8.4,27.2,2.1]|
| [8.7,48.9,75.0]| 7.2|[8.7,48.9,75.0]|
| [11.7,36.9,45.2]| 7.3|[11.7,36.9,45.2]|
+-----+-----+
only showing top 5 rows

+-----+-----+
|      features|label| indexedFeatures|
```

```
+-----+-----+
| [0.7,39.6,8.7] | 1.6 | [0.7,39.6,8.7] |
| [4.1,11.6,5.7] | 3.2 | [4.1,11.6,5.7] |
| [7.3,28.1,41.4] | 5.5 | [7.3,28.1,41.4] |
| [8.6,2.1,1.0] | 4.8 | [8.6,2.1,1.0] |
| [17.2,4.1,31.6] | 5.9 | [17.2,4.1,31.6] |
+-----+-----+
only showing top 5 rows
```

7. Fit Generalized Linear Regression Model

```
# Import LinearRegression class
from pyspark.ml.regression import GeneralizedLinearRegression

# Define LinearRegression algorithm
glr = GeneralizedLinearRegression(family="gaussian", link="identity", \
maxIter=10, regParam=0.3)
```

8. Pipeline Architecture

```
# Chain indexer and tree in a Pipeline
pipeline = Pipeline(stages=[featureIndexer, glr])

model = pipeline.fit(trainingData)
```

9. Summary of the Model

Spark has a poor summary function for data and model. I wrote a summary function which has similar format as R output for the linear regression in PySpark.

```
def modelsummary(model):
    import numpy as np
    print ("Note: the last rows are the information for Intercept")
    print ("##", "-----")
    print ("##", " Estimate | Std.Error | t Values | P-value")
    coef = np.append(list(model.coefficients),model.intercept)
    Summary=model.summary

    for i in range(len(Summary.pValues)):
        print ("##",'{:10.6f}'.format(coef[i]),\
        '{:10.6f}'.format(Summary.coefficientStandardErrors[i]),\
        '{:8.3f}'.format(Summary.tValues[i]),\
        '{:10.6f}'.format(Summary.pValues[i]))

    print ("##",'---')
    #     print ("##", "Mean squared error: % .6f" \
    #             "% Summary.meanSquaredError, ", RMSE: % .6f" \
    #             "% Summary.rootMeanSquaredError )
    #     print ("##", "Multiple R-squared: %f" % Summary.r2, ", \
    #             Total iterations: %i" % Summary.totalIterations)

modelsummary(model.stages[-1])
```

You will get the following summary results:

```
Note: the last rows are the information for Intercept
('##', '-----')
('##', ' Estimate | Std.Error | t Values | P-value')
('##', ' 0.042857', ' 0.001668', ' 25.692', ' 0.000000')
('##', ' 0.199922', ' 0.009881', ' 20.232', ' 0.000000')
('##', ' -0.001957', ' 0.006917', ' -0.283', ' 0.777757')
('##', ' 3.007515', ' 0.406389', ' 7.401', ' 0.000000')
('##', '---')
```

10. Make predictions

```
# Make predictions.
predictions = model.transform(testData)

# Select example rows to display.
predictions.select("features", "label", "predictedLabel").show(5)

+-----+-----+-----+
| features|label| prediction|
+-----+-----+-----+
| [0.7,39.6,8.7]| 1.6|10.937383732327625|
| [4.1,11.6,5.7]| 3.2| 5.491166258750164|
| [7.3,28.1,41.4]| 5.5| 8.8571603947873|
| [8.6,2.1,1.0]| 4.8| 3.793966281660073|
| [17.2,4.1,31.6]| 5.9| 4.502507124763654|
+-----+-----+-----+
only showing top 5 rows
```

11. Evaluation

```
from pyspark.ml.evaluation import RegressionEvaluator
from pyspark.ml.evaluation import RegressionEvaluator
# Select (prediction, true label) and compute test error
evaluator = RegressionEvaluator(labelCol="label",
                                 predictionCol="prediction",
                                 metricName="rmse")

rmse = evaluator.evaluate(predictions)
print("Root Mean Squared Error (RMSE) on test data = %g" % rmse)
```

The final Root Mean Squared Error (RMSE) is as follows:

```
Root Mean Squared Error (RMSE) on test data = 1.89857
```

```
y_true = predictions.select("label").toPandas()
y_pred = predictions.select("prediction").toPandas()

import sklearn.metrics
r2_score = sklearn.metrics.r2_score(y_true, y_pred)
print('r2_score: {0}'.format(r2_score))
```

Then you will get the R^2 value:

```
r2_score: 0.87707391843
```

7.3 Decision tree Regression

7.3.1 Introduction

7.3.2 How to solve it?

7.3.3 Demo

- The Jupyter notebook can be download from [Decision Tree Regression](#).
 - For more details about the parameters, please visit [Decision Tree Regressor API](#).
1. Set up spark context and SparkSession

```
from pyspark.sql import SparkSession

spark = SparkSession \
    .builder \
    .appName("Python Spark regression example") \
    .config("spark.some.config.option", "some-value") \
    .getOrCreate()
```

2. Load dataset

```
df = spark.read.format('com.databricks.spark.csv') \
    .options(header='true', \
    inferschema='true') \
    .load("../data/Advertising.csv", header=True);
```

check the data set

```
df.show(5, True)
df.printSchema()
```

Then you will get

```
+----+----+----+----+
|    TV|Radio|Newspaper|Sales|
+----+----+----+----+
| 230.1| 37.8|     69.2|  22.1|
|  44.5| 39.3|     45.1| 10.4|
|  17.2| 45.9|     69.3|   9.3|
| 151.5| 41.3|     58.5| 18.5|
| 180.8| 10.8|     58.4| 12.9|
+----+----+----+----+
only showing top 5 rows
```

```
root
 |-- TV: double (nullable = true)
```

```
| -- Radio: double (nullable = true)
| -- Newspaper: double (nullable = true)
| -- Sales: double (nullable = true)
```

You can also get the Statistical results from the data frame (Unfortunately, it only works for numerical).

```
df.describe().show()
```

Then you will get

| summary | TV | Radio | Newspaper | Sales |
|---------|-------------------|--------------------|-------------------|-------------------|
| count | 200 | 200 | 200 | 200 |
| mean | 147.0425 | 23.26400000000024 | 30.55399999999995 | 14.02250000000003 |
| stddev | 85.85423631490805 | 14.846809176168728 | 21.77862083852283 | 5.217456565710477 |
| min | 0.7 | 0.0 | 0.3 | 1.6 |
| max | 296.4 | 49.6 | 114.0 | 27.0 |

3. Convert the data to dense vector (**features** and **label**)

```
from pyspark.sql import Row
from pyspark.ml.linalg import Vectors

# I provide two ways to build the features and labels

# method 1 (good for small feature):
def transData(row):
    return Row(label=row["Sales"],
               features=Vectors.dense([row["TV"],
                                      row["Radio"],
                                      row["Newspaper"]]))

# Method 2 (good for large features):
def transData(data):
    return data.rdd.map(lambda r: [Vectors.dense(r[:-1]), r[-1]]).toDF(['features', 'label'])

transformed= transData(df)
transformed.show(5)

+-----+-----+
|      features|label|
+-----+-----+
| [230.1,37.8,69.2]| 22.1|
| [44.5,39.3,45.1]| 10.4|
| [17.2,45.9,69.3]|  9.3|
| [151.5,41.3,58.5]| 18.5|
| [180.8,10.8,58.4]| 12.9|
+-----+-----+
only showing top 5 rows
```

Note: You will find out that all of the machine learning algorithms in Spark are based on the **features** and

label. That is to say, you can play with all of the machine learning algorithms in Spark when you get ready the **features** and **label**.

4. Convert the data to dense vector

```
# convert the data to dense vector
def transData(data):
    return data.rdd.map(lambda r: [r[-1], Vectors.dense(r[:-1])]).\
        toDF(['label', 'features'])

transformed = transData(df)
transformed.show(5)
```

5. Deal with the Categorical variables

```
from pyspark.ml import Pipeline
from pyspark.ml.regression import LinearRegression
from pyspark.ml.feature import VectorIndexer
from pyspark.ml.evaluation import RegressionEvaluator

# Automatically identify categorical features, and index them.
# We specify maxCategories so features with > 4
# distinct values are treated as continuous.

featureIndexer = VectorIndexer(inputCol="features", \
                                outputCol="indexedFeatures", \
                                maxCategories=4).fit(transformed)

data = featureIndexer.transform(transformed)
```

When you check your data at this point, you will get

```
+-----+-----+-----+
|      features|label| indexedFeatures|
+-----+-----+-----+
| [230.1,37.8,69.2]| 22.1|[230.1,37.8,69.2]|
| [44.5,39.3,45.1]| 10.4|[44.5,39.3,45.1]|
| [17.2,45.9,69.3]|  9.3|[17.2,45.9,69.3]|
| [151.5,41.3,58.5]| 18.5|[151.5,41.3,58.5]|
| [180.8,10.8,58.4]| 12.9|[180.8,10.8,58.4]|
+-----+-----+-----+
only showing top 5 rows
```

6. Split the data into training and test sets (40% held out for testing)

```
# Split the data into training and test sets (40% held out for testing)
(trainingData, testData) = transformed.randomSplit([0.6, 0.4])
```

You can check your train and test data as follows (In my opinion, it is always good to keep tracking your data during prototype phase):

```
trainingData.show(5)
testData.show(5)
```

Then you will get

```
+-----+-----+-----+
|      features|label|indexedFeatures|
+-----+-----+-----+
| [4.1,11.6,5.7]| 3.2| [4.1,11.6,5.7]|
| [7.3,28.1,41.4]| 5.5|[7.3,28.1,41.4]|
| [8.4,27.2,2.1]| 5.7| [8.4,27.2,2.1]|
| [8.6,2.1,1.0]| 4.8| [8.6,2.1,1.0]|
| [8.7,48.9,75.0]| 7.2|[8.7,48.9,75.0]|
+-----+-----+-----+
only showing top 5 rows

+-----+-----+-----+
|      features|label| indexedFeatures|
+-----+-----+-----+
| [0.7,39.6,8.7]| 1.6| [0.7,39.6,8.7]|
| [5.4,29.9,9.4]| 5.3| [5.4,29.9,9.4]|
| [7.8,38.9,50.6]| 6.6| [7.8,38.9,50.6]|
| [17.2,45.9,69.3]| 9.3|[17.2,45.9,69.3]|
| [18.7,12.1,23.4]| 6.7|[18.7,12.1,23.4]|
+-----+-----+-----+
only showing top 5 rows
```

7. Fit Decision Tree Regression Model

```
from pyspark.ml.regression import DecisionTreeRegressor

# Train a DecisionTree model.
dt = DecisionTreeRegressor(featuresCol="indexedFeatures")
```

8. Pipeline Architecture

```
# Chain indexer and tree in a Pipeline
pipeline = Pipeline(stages=[featureIndexer, dt])

model = pipeline.fit(trainingData)
```

9. Make predictions

```
# Make predictions.
predictions = model.transform(testData)

# Select example rows to display.
predictions.select("features", "label", "predictedLabel").show(5)
```

```
+-----+-----+-----+
|prediction|label|      features|
+-----+-----+-----+
|       7.2| 1.6| [0.7,39.6,8.7]|
|       7.3| 5.3| [5.4,29.9,9.4]|
|       7.2| 6.6| [7.8,38.9,50.6]|
|      8.64| 9.3|[17.2,45.9,69.3]|
|      6.45| 6.7|[18.7,12.1,23.4]|
+-----+-----+-----+
```

```
+-----+-----+-----+
only showing top 5 rows
```

10. Evaluation

```
from pyspark.ml.evaluation import RegressionEvaluator
from pyspark.ml.evaluation import RegressionEvaluator
# Select (prediction, true label) and compute test error
evaluator = RegressionEvaluator(labelCol="label",
                                 predictionCol="prediction",
                                 metricName="rmse")

rmse = evaluator.evaluate(predictions)
print("Root Mean Squared Error (RMSE) on test data = %g" % rmse)
```

The final Root Mean Squared Error (RMSE) is as follows:

```
Root Mean Squared Error (RMSE) on test data = 1.50999
```

```
y_true = predictions.select("label").toPandas()
y_pred = predictions.select("prediction").toPandas()

import sklearn.metrics
r2_score = sklearn.metrics.r2_score(y_true, y_pred)
print('r2_score: {0}'.format(r2_score))
```

Then you will get the R^2 value:

```
r2_score: 0.911024318967
```

You may also check the importance of the features:

```
model.stages[1].featureImportances
```

The you will get the weight for each features

```
SparseVector(3, {0: 0.6811, 1: 0.3187, 2: 0.0002})
```

7.4 Random Forest Regression

7.4.1 Introduction

7.4.2 How to solve it?

7.4.3 Demo

- The Jupyter notebook can be download from Random Forest Regression.
- For more details about the parameters, please visit [Random Forest Regressor API](#).

7.5 Gradient-boosted tree regression

7.5.1 Introduction

7.5.2 How to solve it?

7.5.3 Demo

- The Jupyter notebook can be download from Gradient-boosted tree regression.
- For more details about the parameters, please visit [Gradient boosted tree API](#).

**CHAPTER
EIGHT**

CLASSIFICATION

Note: Birds of a feather folock together. – old Chinese proverb

8.1 Logistic regression

TO DO...

8.2 Decision tree Classification

8.2.1 Introduction

8.2.2 Demo

- The Jupyter notebook can be download from Decision Tree Classification.
 - For more details, please visit [DecisionTreeClassifier API](#) .
1. Set up spark context and SparkSession

```
from pyspark.sql import SparkSession

spark = SparkSession \
    .builder \
    .appName("Python Spark Decision Tree classification") \
    .config("spark.some.config.option", "some-value") \
    .getOrCreate()
```

2. Load dataset

```
df = spark.read.format('com.databricks.spark.csv') \
    .options(header='true', \
    inferschema='true') \
    .load("../data/WineData2.csv", header=True);
df.show(5, True)
```

```
+-----+-----+-----+-----+-----+-----+-----+-----+-----+
|fixed|volatile|citric|sugar|chlorides|free|total|density| pH|sulphates|alcohol|quality|
+-----+-----+-----+-----+-----+-----+-----+-----+-----+
| 7.4|    0.7|   0.0|   1.9|   0.076|11.0| 34.0| 0.9978|3.51|   0.56|   9.4|   5|
| 7.8|    0.88|   0.0|   2.6|   0.098|25.0| 67.0| 0.9968|3.2|   0.68|   9.8|   5|
| 7.8|    0.76|   0.04|   2.3|   0.092|15.0| 54.0| 0.997|3.26|   0.65|   9.8|   5|
| 11.2|   0.28|   0.56|   1.9|   0.075|17.0| 60.0| 0.998|3.16|   0.58|   9.8|   6|
| 7.4|    0.7|   0.0|   1.9|   0.076|11.0| 34.0| 0.9978|3.51|   0.56|   9.4|   5|
+-----+-----+-----+-----+-----+-----+-----+-----+-----+
only showing top 5 rows

# Convert to float format
def string_to_float(x):
    return float(x)

#
def condition(r):
    if (0 <= r <= 4):
        label = "low"
    elif(4 < r <= 6):
        label = "medium"
    else:
        label = "high"
    return label

from pyspark.sql.functions import udf
from pyspark.sql.types import StringType, DoubleType
string_to_float_udf = udf(string_to_float, DoubleType())
quality_udf = udf(lambda x: condition(x), StringType())

df = df.withColumn("quality", quality_udf("quality"))
df.show(5, True)
df.printSchema()

+-----+-----+-----+-----+-----+-----+-----+-----+-----+
|fixed|volatile|citric|sugar|chlorides|free|total|density| pH|sulphates|alcohol|quality|
+-----+-----+-----+-----+-----+-----+-----+-----+-----+
| 7.4|    0.7|   0.0|   1.9|   0.076|11.0| 34.0| 0.9978|3.51|   0.56|   9.4| medium|
| 7.8|    0.88|   0.0|   2.6|   0.098|25.0| 67.0| 0.9968|3.2|   0.68|   9.8| medium|
| 7.8|    0.76|   0.04|   2.3|   0.092|15.0| 54.0| 0.997|3.26|   0.65|   9.8| medium|
| 11.2|   0.28|   0.56|   1.9|   0.075|17.0| 60.0| 0.998|3.16|   0.58|   9.8| medium|
| 7.4|    0.7|   0.0|   1.9|   0.076|11.0| 34.0| 0.9978|3.51|   0.56|   9.4| medium|
+-----+-----+-----+-----+-----+-----+-----+-----+-----+
only showing top 5 rows

root
|-- fixed: double (nullable = true)
|-- volatile: double (nullable = true)
|-- citric: double (nullable = true)
|-- sugar: double (nullable = true)
|-- chlorides: double (nullable = true)
|-- free: double (nullable = true)
|-- total: double (nullable = true)
```

```
| -- density: double (nullable = true)
| -- pH: double (nullable = true)
| -- sulphates: double (nullable = true)
| -- alcohol: double (nullable = true)
| -- quality: string (nullable = true)
```

3. Convert the data to dense vector

```
# !!!!caution: not from pyspark.mllib.linalg import Vectors
from pyspark.ml.linalg import Vectors
from pyspark.ml import Pipeline
from pyspark.ml.feature import IndexToString, StringIndexer, VectorIndexer
from pyspark.ml.tuning import CrossValidator, ParamGridBuilder
from pyspark.ml.evaluation import MulticlassClassificationEvaluator

def transData(data):
    return data.rdd.map(lambda r: [Vectors.dense(r[:-1]), r[-1]]).toDF(['features', 'label'])
```

4. Transform the dataset to DataFrame

```
transformed = transData(df)
transformed.show(5)
```

```
+-----+-----+
|      features| label|
+-----+-----+
|[7.4,0.7,0.0,1.9,...|medium|
|[7.8,0.88,0.0,2.6...|medium|
|[7.8,0.76,0.04,2....|medium|
|[11.2,0.28,0.56,1...|medium|
|[7.4,0.7,0.0,1.9,...|medium|
+-----+-----+
only showing top 5 rows
```

5. Deal with Categorical Label and Variables

```
# Index labels, adding metadata to the label column
labelIndexer = StringIndexer(inputCol='label',
                             outputCol='indexedLabel').fit(transformed)
labelIndexer.transform(transformed).show(5, True)

+-----+-----+-----+
|      features| label|indexedLabel|
+-----+-----+-----+
|[7.4,0.7,0.0,1.9,...|medium|          0.0|
|[7.8,0.88,0.0,2.6...|medium|          0.0|
|[7.8,0.76,0.04,2....|medium|          0.0|
|[11.2,0.28,0.56,1...|medium|          0.0|
|[7.4,0.7,0.0,1.9,...|medium|          0.0|
+-----+-----+-----+
only showing top 5 rows
```

```
# Automatically identify categorical features, and index them.
# Set maxCategories so features with > 4 distinct values are treated as continuous.
featureIndexer = VectorIndexer(inputCol="features", \
                                outputCol="indexedFeatures", \
                                maxCategories=4).fit(transformed)
featureIndexer.transform(transformed).show(5, True)

+-----+-----+-----+
|     features| label| indexedFeatures|
+-----+-----+-----+
|[7.4,0.7,0.0,1.9,...|medium|[7.4,0.7,0.0,1.9,...|
|[7.8,0.88,0.0,2.6....|medium|[7.8,0.88,0.0,2.6....|
|[7.8,0.76,0.04,2....|medium|[7.8,0.76,0.04,2....|
|[11.2,0.28,0.56,1....|medium|[11.2,0.28,0.56,1....|
|[7.4,0.7,0.0,1.9,...|medium|[7.4,0.7,0.0,1.9,...|
+-----+-----+-----+
only showing top 5 rows
```

6. Split the data to training and test data sets

```
# Split the data into training and test sets (40% held out for testing)
(trainingData, testData) = transformed.randomSplit([0.6, 0.4])

trainingData.show(5)
testData.show(5)

+-----+-----+
|     features| label|
+-----+-----+
|[4.6,0.52,0.15,2....| low|
|[4.7,0.6,0.17,2.3....|medium|
|[5.0,1.02,0.04,1....| low|
|[5.0,1.04,0.24,1....|medium|
|[5.1,0.585,0.0,1....| high|
+-----+-----+
only showing top 5 rows

+-----+-----+
|     features| label|
+-----+-----+
|[4.9,0.42,0.0,2.1....| high|
|[5.0,0.38,0.01,1....|medium|
|[5.0,0.4,0.5,4.3,...|medium|
|[5.0,0.42,0.24,2....| high|
|[5.0,0.74,0.0,1.2....|medium|
+-----+-----+
only showing top 5 rows
```

7. Fit Decision Tree Classification Model

```
from pyspark.ml.classification import DecisionTreeClassifier

# Train a DecisionTree model
dTree = DecisionTreeClassifier(labelCol='indexedLabel', featuresCol='indexedFeatures')
```

8. Pipeline Architecture

```
# Convert indexed labels back to original labels.
labelConverter = IndexToString(inputCol="prediction", outputCol="predictedLabel",
                                labels=labelIndexer.labels)

# Chain indexers and tree in a Pipeline
pipeline = Pipeline(stages=[labelIndexer, featureIndexer, dTree, labelConverter])

# Train model. This also runs the indexers.
model = pipeline.fit(trainingData)
```

9. Make predictions

```
# Make predictions.
predictions = model.transform(testData)
# Select example rows to display.
predictions.select("features", "label", "predictedLabel").show(5)

+-----+-----+-----+
| features| label|predictedLabel|
+-----+-----+-----+
| [4.9,0.42,0.0,2.1...| high|      high|
| [5.0,0.38,0.01,1....|medium|    medium|
| [5.0,0.4,0.5,4.3,...|medium|    medium|
| [5.0,0.42,0.24,2....| high|    medium|
| [5.0,0.74,0.0,1.2...|medium|    medium|
+-----+-----+-----+
only showing top 5 rows
```

10. Evaluation

```
from pyspark.ml.evaluation import MulticlassClassificationEvaluator

# Select (prediction, true label) and compute test error
evaluator = MulticlassClassificationEvaluator(
    labelCol="indexedLabel", predictionCol="prediction", metricName="accuracy")
accuracy = evaluator.evaluate(predictions)
print("Test Error = %g" % (1.0 - accuracy))

rfModel = model.stages[-2]
print(rfModel) # summary only

Test Error = 0.45509
DecisionTreeClassificationModel (uid=DecisionTreeClassifier_4545ac8dca9c8438ef2a)
of depth 5 with 59 nodes
```

11. visualization

```
import matplotlib.pyplot as plt
import numpy as np
import itertools

def plot_confusion_matrix(cm, classes,
```

```
normalize=False,
title='Confusion matrix',
cmap=plt.cm.Blues):
"""
This function prints and plots the confusion matrix.
Normalization can be applied by setting 'normalize=True'.
"""
if normalize:
    cm = cm.astype('float') / cm.sum(axis=1)[:, np.newaxis]
    print("Normalized confusion matrix")
else:
    print('Confusion matrix, without normalization')

print(cm)

plt.imshow(cm, interpolation='nearest', cmap=cmap)
plt.title(title)
plt.colorbar()
tick_marks = np.arange(len(classes))
plt.xticks(tick_marks, classes, rotation=45)
plt.yticks(tick_marks, classes)

fmt = '.2f' if normalize else 'd'
thresh = cm.max() / 2.
for i, j in itertools.product(range(cm.shape[0]), range(cm.shape[1])):
    plt.text(j, i, format(cm[i, j], fmt),
             horizontalalignment="center",
             color="white" if cm[i, j] > thresh else "black")

plt.tight_layout()
plt.ylabel('True label')
plt.xlabel('Predicted label')

class_temp = predictions.select("label").groupBy("label") \
    .count().sort('count', ascending=False).toPandas()
class_temp = class_temp["label"].values.tolist()
class_names = map(str, class_temp)
# # print(class_name)
class_names

['medium', 'high', 'low']

from sklearn.metrics import confusion_matrix
y_true = predictions.select("label")
y_true = y_true.toPandas()

y_pred = predictions.select("predictedLabel")
y_pred = y_pred.toPandas()

cnf_matrix = confusion_matrix(y_true, y_pred, labels=class_names)
cnf_matrix
```

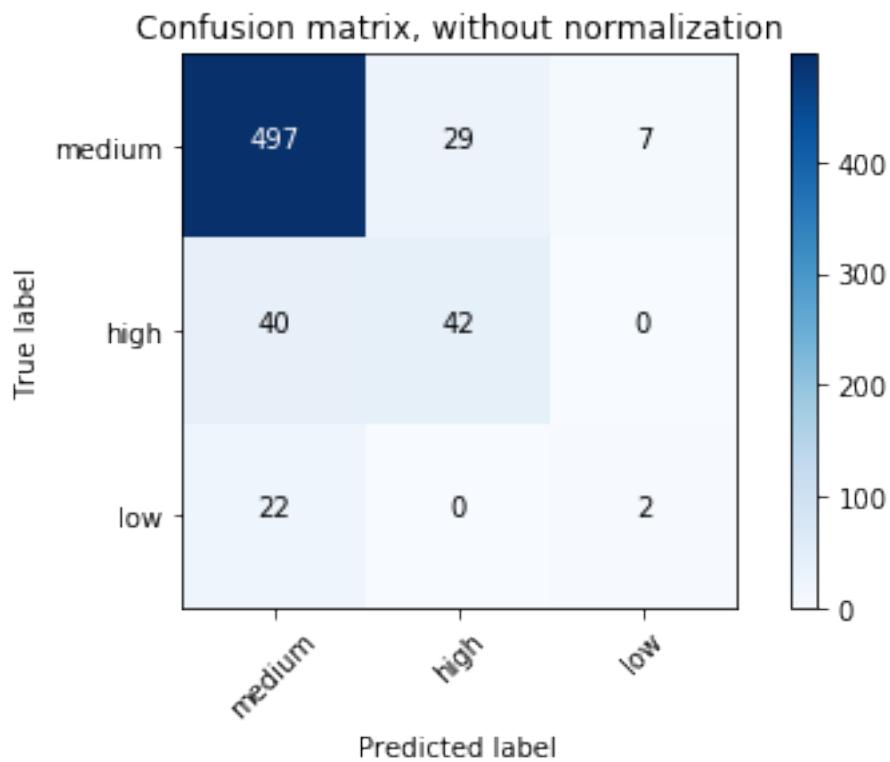
```

array([[497,  29,   7],
       [ 40,  42,   0],
       [ 22,   0,   2]])

# Plot non-normalized confusion matrix
plt.figure()
plot_confusion_matrix(cnf_matrix, classes=class_names,
                      title='Confusion matrix, without normalization')
plt.show()

Confusion matrix, without normalization
[[497  29   7]
 [ 40  42   0]
 [ 22   0   2]]

```



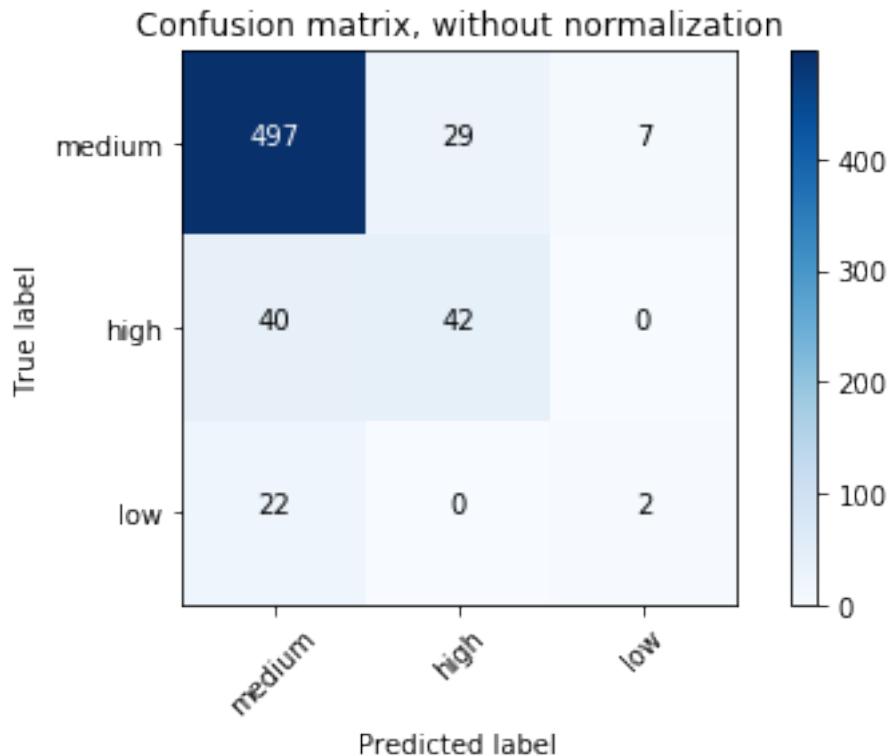
```

# Plot normalized confusion matrix
plt.figure()
plot_confusion_matrix(cnf_matrix, classes=class_names, normalize=True,
                      title='Normalized confusion matrix')

plt.show()

Normalized confusion matrix
[[ 0.93245779  0.05440901  0.01313321]
 [ 0.48780488  0.51219512  0.          ]
 [ 0.91666667  0.          0.08333333]]

```



8.3 Random forest Classification

8.3.1 Introduction

8.3.2 Demo

- The Jupyter notebook can be download from Random forest Classification.
 - For more details, please visit [RandomForestClassifier API](#).
1. Set up spark context and SparkSession

```
from pyspark.sql import SparkSession

spark = SparkSession \
    .builder \
    .appName("Python Spark Decision Tree classification") \
    .config("spark.some.config.option", "some-value") \
    .getOrCreate()
```

2. Load dataset

```
df = spark.read.format('com.databricks.spark.csv') \
    .options(header='true', \
    inferschema='true') \
    .load("../data/WineData2.csv", header=True);
df.show(5, True)
```

```
+---+---+---+---+---+---+---+---+---+---+---+---+---+---+---+---+
|fixed|volatile|citric|sugar|chlorides|free|total|density| pH|sulphates|alcohol|quality|
+---+---+---+---+---+---+---+---+---+---+---+---+---+---+---+---+
| 7.4|    0.7|   0.0|  1.9|  0.076|11.0| 34.0|  0.9978|3.51|  0.56|  9.4|  5|
| 7.8|    0.88|   0.0|  2.6|  0.098|25.0| 67.0|  0.9968| 3.2|  0.68|  9.8|  5|
| 7.8|    0.76|   0.04|  2.3|  0.092|15.0| 54.0|  0.997|3.26|  0.65|  9.8|  5|
| 11.2|   0.28|   0.56|  1.9|  0.075|17.0| 60.0|  0.998|3.16|  0.58|  9.8|  6|
| 7.4|    0.7|   0.0|  1.9|  0.076|11.0| 34.0|  0.9978|3.51|  0.56|  9.4|  5|
+---+---+---+---+---+---+---+---+---+---+---+---+---+---+---+---+
only showing top 5 rows
```

```
# Convert to float format
def string_to_float(x):
    return float(x)
```

```
#  
def condition(r):
    if (0<= r <= 4):
        label = "low"
    elif(4< r <= 6):
        label = "medium"
    else:
        label = "high"
    return label
```

```
from pyspark.sql.functions import udf
from pyspark.sql.types import StringType, DoubleType
string_to_float_udf = udf(string_to_float, DoubleType())
quality_udf = udf(lambda x: condition(x), StringType())

df = df.withColumn("quality", quality_udf("quality"))
df.show(5, True)
df.printSchema()
```

```
+---+---+---+---+---+---+---+---+---+---+---+---+---+---+---+---+
|fixed|volatile|citric|sugar|chlorides|free|total|density| pH|sulphates|alcohol|quality|
+---+---+---+---+---+---+---+---+---+---+---+---+---+---+---+---+
| 7.4|    0.7|   0.0|  1.9|  0.076|11.0| 34.0|  0.9978|3.51|  0.56|  9.4| medium|
| 7.8|    0.88|   0.0|  2.6|  0.098|25.0| 67.0|  0.9968| 3.2|  0.68|  9.8| medium|
| 7.8|    0.76|   0.04|  2.3|  0.092|15.0| 54.0|  0.997|3.26|  0.65|  9.8| medium|
| 11.2|   0.28|   0.56|  1.9|  0.075|17.0| 60.0|  0.998|3.16|  0.58|  9.8| medium|
| 7.4|    0.7|   0.0|  1.9|  0.076|11.0| 34.0|  0.9978|3.51|  0.56|  9.4| medium|
+---+---+---+---+---+---+---+---+---+---+---+---+---+---+---+---+
only showing top 5 rows
```

```
root
 |-- fixed: double (nullable = true)
 |-- volatile: double (nullable = true)
 |-- citric: double (nullable = true)
 |-- sugar: double (nullable = true)
 |-- chlorides: double (nullable = true)
 |-- free: double (nullable = true)
 |-- total: double (nullable = true)
```

```
| -- density: double (nullable = true)
| -- pH: double (nullable = true)
| -- sulphates: double (nullable = true)
| -- alcohol: double (nullable = true)
| -- quality: string (nullable = true)
```

3. Convert the data to dense vector

```
# !!!!caution: not from pyspark.mllib.linalg import Vectors
from pyspark.ml.linalg import Vectors
from pyspark.ml import Pipeline
from pyspark.ml.feature import IndexToString, StringIndexer, VectorIndexer
from pyspark.ml.tuning import CrossValidator, ParamGridBuilder
from pyspark.ml.evaluation import MulticlassClassificationEvaluator

def transData(data):
    return data.rdd.map(lambda r: [Vectors.dense(r[:-1]), r[-1]]).toDF(['features', 'label'])
```

4. Transform the dataset to DataFrame

```
transformed = transData(df)
transformed.show(5)
```

```
+-----+-----+
|      features| label|
+-----+-----+
|[7.4,0.7,0.0,1.9,...|medium|
|[7.8,0.88,0.0,2.6...|medium|
|[7.8,0.76,0.04,2....|medium|
|[11.2,0.28,0.56,1...|medium|
|[7.4,0.7,0.0,1.9,...|medium|
+-----+-----+
only showing top 5 rows
```

5. Deal with Categorical Label and Variables

```
# Index labels, adding metadata to the label column
labelIndexer = StringIndexer(inputCol='label',
                             outputCol='indexedLabel').fit(transformed)
labelIndexer.transform(transformed).show(5, True)

+-----+-----+-----+
|      features| label|indexedLabel|
+-----+-----+-----+
|[7.4,0.7,0.0,1.9,...|medium|          0.0|
|[7.8,0.88,0.0,2.6...|medium|          0.0|
|[7.8,0.76,0.04,2....|medium|          0.0|
|[11.2,0.28,0.56,1...|medium|          0.0|
|[7.4,0.7,0.0,1.9,...|medium|          0.0|
+-----+-----+-----+
only showing top 5 rows
```

```
# Automatically identify categorical features, and index them.
# Set maxCategories so features with > 4 distinct values are treated as continuous.
featureIndexer = VectorIndexer(inputCol="features", \
                                outputCol="indexedFeatures", \
                                maxCategories=4).fit(transformed)
featureIndexer.transform(transformed).show(5, True)

+-----+-----+
|      features| label|      indexedFeatures|
+-----+-----+
|[7.4,0.7,0.0,1.9,...|medium|[7.4,0.7,0.0,1.9,...|
|[7.8,0.88,0.0,2.6....|medium|[7.8,0.88,0.0,2.6....|
|[7.8,0.76,0.04,2....|medium|[7.8,0.76,0.04,2....|
|[11.2,0.28,0.56,1....|medium|[11.2,0.28,0.56,1....|
|[7.4,0.7,0.0,1.9,...|medium|[7.4,0.7,0.0,1.9,...|
+-----+
only showing top 5 rows
```

6. Split the data to training and test data sets

```
# Split the data into training and test sets (40% held out for testing)
(trainingData, testData) = transformed.randomSplit([0.6, 0.4])

trainingData.show(5)
testData.show(5)

+-----+-----+
|      features| label|
+-----+-----+
|[4.6,0.52,0.15,2....| low|
|[4.7,0.6,0.17,2.3....|medium|
|[5.0,1.02,0.04,1....| low|
|[5.0,1.04,0.24,1....|medium|
|[5.1,0.585,0.0,1....| high|
+-----+
only showing top 5 rows

+-----+-----+
|      features| label|
+-----+-----+
|[4.9,0.42,0.0,2.1....| high|
|[5.0,0.38,0.01,1....|medium|
|[5.0,0.4,0.5,4.3,...|medium|
|[5.0,0.42,0.24,2....| high|
|[5.0,0.74,0.0,1.2....|medium|
+-----+
only showing top 5 rows
```

7. Fit Random Forest Classification Model

```
from pyspark.ml.classification import RandomForestClassifier

# Train a RandomForest model.
rf = RandomForestClassifier(labelCol="indexedLabel", featuresCol="indexedFeatures", numTrees=2)
```

8. Pipeline Architecture

```
# Convert indexed labels back to original labels.
labelConverter = IndexToString(inputCol="prediction", outputCol="predictedLabel",
                                labels=labelIndexer.labels)

# Chain indexers and tree in a Pipeline
pipeline = Pipeline(stages=[labelIndexer, featureIndexer, rf,labelConverter])

# Train model. This also runs the indexers.
model = pipeline.fit(trainingData)
```

9. Make predictions

```
# Make predictions.
predictions = model.transform(testData)
# Select example rows to display.
predictions.select("features", "label", "predictedLabel").show(5)

+-----+-----+-----+
| features| label|predictedLabel|
+-----+-----+-----+
| [4.9,0.42,0.0,2.1...| high|      high|
| [5.0,0.38,0.01,1....|medium|    medium|
| [5.0,0.4,0.5,4.3,...|medium|    medium|
| [5.0,0.42,0.24,2....| high|    medium|
| [5.0,0.74,0.0,1.2...|medium|    medium|
+-----+-----+-----+
only showing top 5 rows
```

10. Evaluation

```
from pyspark.ml.evaluation import MulticlassClassificationEvaluator

# Select (prediction, true label) and compute test error
evaluator = MulticlassClassificationEvaluator(
    labelCol="indexedLabel", predictionCol="prediction", metricName="accuracy")
accuracy = evaluator.evaluate(predictions)
print("Test Error = %g" % (1.0 - accuracy))

rfModel = model.stages[-2]
print(rfModel) # summary only

Test Error = 0.173502
RandomForestClassificationModel (uid=rfc_a3395531f1d2) with 10 trees
```

11. visualization

```
import matplotlib.pyplot as plt
import numpy as np
import itertools

def plot_confusion_matrix(cm, classes,
                        normalize=False,
```

```

        title='Confusion matrix',
        cmap=plt.cm.Blues):
"""

This function prints and plots the confusion matrix.
Normalization can be applied by setting 'normalize=True'.
"""

if normalize:
    cm = cm.astype('float') / cm.sum(axis=1)[:, np.newaxis]
    print("Normalized confusion matrix")
else:
    print('Confusion matrix, without normalization')

print(cm)

plt.imshow(cm, interpolation='nearest', cmap=cmap)
plt.title(title)
plt.colorbar()
tick_marks = np.arange(len(classes))
plt.xticks(tick_marks, classes, rotation=45)
plt.yticks(tick_marks, classes)

fmt = '.2f' if normalize else 'd'
thresh = cm.max() / 2.
for i, j in itertools.product(range(cm.shape[0]), range(cm.shape[1])):
    plt.text(j, i, format(cm[i, j], fmt),
             horizontalalignment="center",
             color="white" if cm[i, j] > thresh else "black")

plt.tight_layout()
plt.ylabel('True label')
plt.xlabel('Predicted label')

class_temp = predictions.select("label").groupBy("label") \
    .count().sort('count', ascending=False).toPandas()
class_temp = class_temp["label"].values.tolist()
class_names = map(str, class_temp)
## print(class_name)
class_names

['medium', 'high', 'low']

from sklearn.metrics import confusion_matrix
y_true = predictions.select("label")
y_true = y_true.toPandas()

y_pred = predictions.select("predictedLabel")
y_pred = y_pred.toPandas()

cnf_matrix = confusion_matrix(y_true, y_pred, labels=class_names)
cnf_matrix

array([[502,    9,    0],
       [ 73,   22,    0],
       [ 14,    0, 463]])

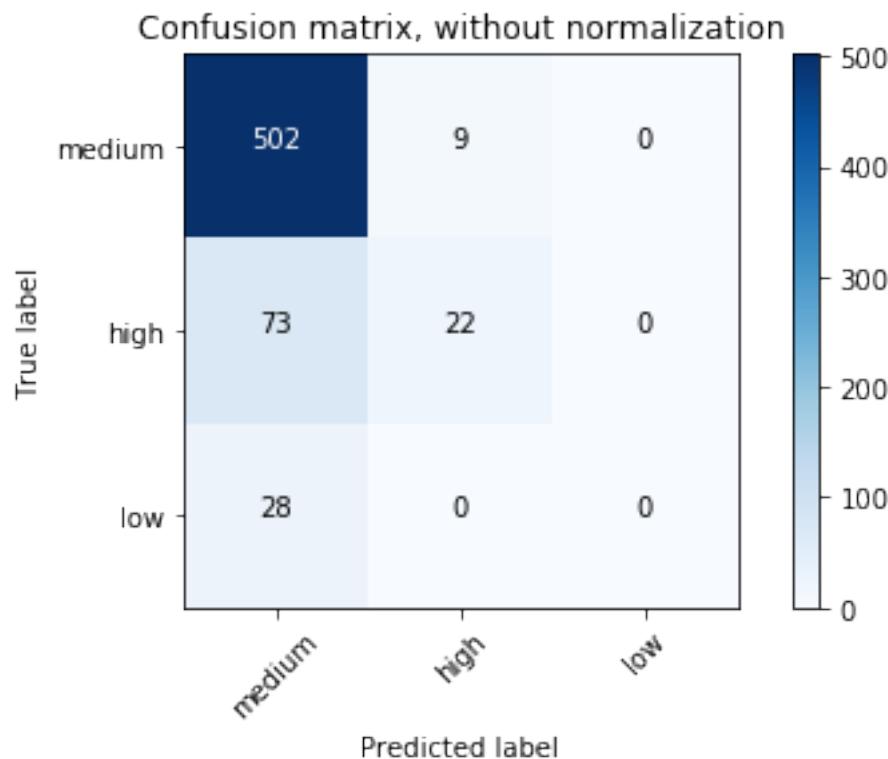
```

```
[ 28,    0,    0]])
```

```
# Plot non-normalized confusion matrix
plt.figure()
plot_confusion_matrix(cnf_matrix, classes=class_names,
                      title='Confusion matrix, without normalization')
plt.show()
```

Confusion matrix, without normalization

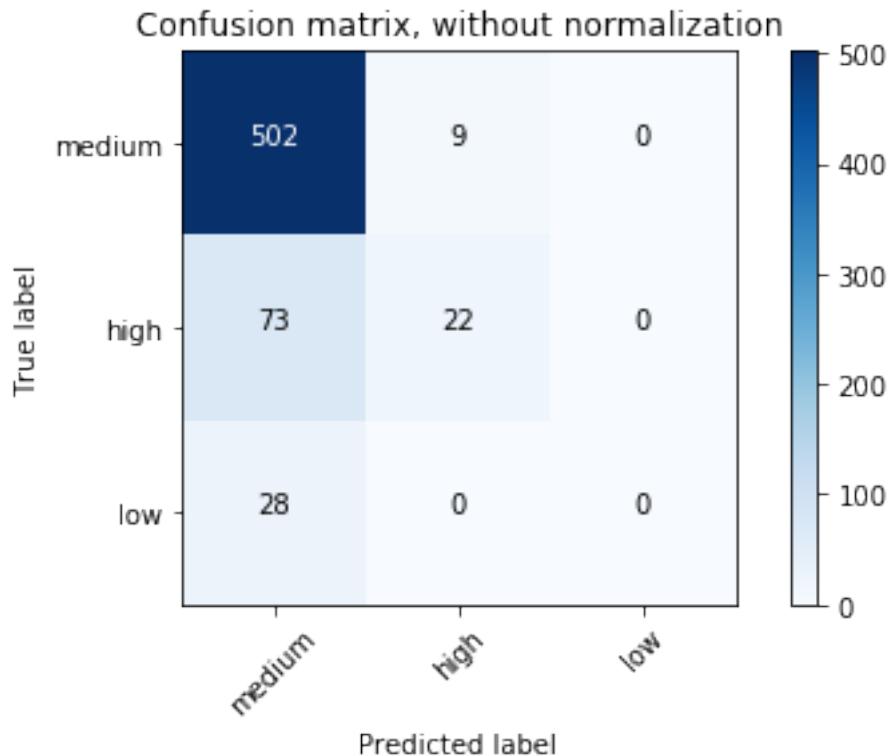
```
[[502   9   0]
 [ 73  22   0]
 [ 28    0   0]]
```



```
# Plot normalized confusion matrix
plt.figure()
plot_confusion_matrix(cnf_matrix, classes=class_names, normalize=True,
                      title='Normalized confusion matrix')

plt.show()
```

```
Normalized confusion matrix
[[ 0.98238748  0.01761252  0.        ]
 [ 0.76842105  0.23157895  0.        ]
 [ 1.          0.          0.        ]]
```



8.4 Gradient-boosted tree Classification

8.4.1 Introduction

8.4.2 Demo

- The Jupyter notebook can be download from Gradient boosted tree Classification.
- For more details, please visit [GBTClassifier API](#).

Warning: Unfortunately, the GBTClassifier currently only supports binary labels.

8.5 Naive Bayes Classification

8.5.1 Introduction

8.5.2 Demo

- The Jupyter notebook can be download from Naive Bayes Classification.
- For more details, please visit [NaiveBayes API](#).

**CHAPTER
NINE**

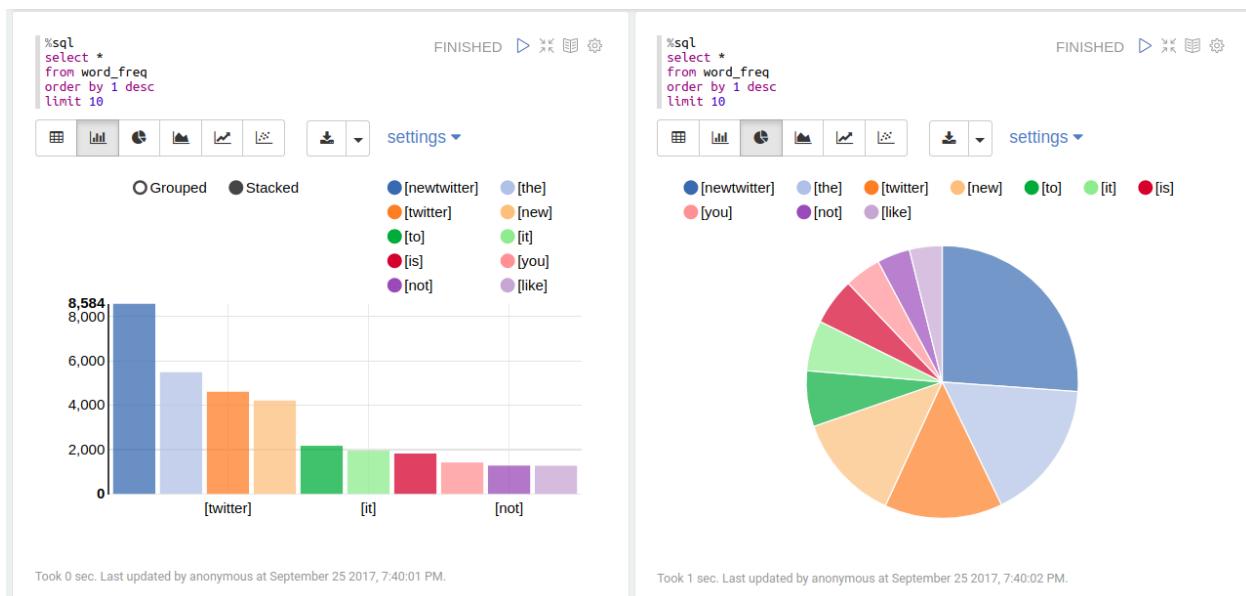
CLUSTERING

Note: Sharpening the knife longer can make it easier to hack the firewood – old Chinese proverb

9.1 K-Means Model

TEXT MINING

Note: Sharpening the knife longer can make it easier to hack the firewood – old Chinese proverb



10.1 Text Collection

10.1.1 Image to text

- My img2txt function

```
def img2txt(img_dir):
    """
    convert images to text
    """
    import os, PythonMagick
    from datetime import datetime
    import PyPDF2

    from PIL import Image
```

```
import pytesseract

f = open('doc4img.txt','wa')
for img in [img_file for img_file in os.listdir(img_dir)
            if (img_file.endswith(".png") or
                img_file.endswith(".jpg") or
                img_file.endswith(".jpeg"))]:
    start_time = datetime.now()

    input_img = img_dir + "/" + img

    print('-----')
    print(img)
    print('Converting ' + img + '.....')
    print('-----')

    # extract the text information from images
    text = pytesseract.image_to_string(Image.open(input_img))
    print(text)

    # output text file
    f.write(img + "\n")
    f.write(text.encode('utf-8'))

    print "CPU Time for converting" + img + ":" + str(datetime.now() - start_time) + "\n"
f.write("\n-----\n")

f.close()
```

- Demo

I applied my img2txt function to the image in Image folder.

```
image_dir = r"Image"

img2txt(image_dir)
```

Then I got the following results:

```
-----
feng.pdf_0.png
Converting feng.pdf_0.png.....
-----
l I l w

Wenqiang Feng
Data Scientist
DST APPLIED ANALYTICS GROUP
```

Wenqiang Feng is Data Scientist **for** DST's Applied Analytics Group. Dr. Feng's responsibilities

include providing DST clients with access to cutting--edge skills and technologies, including Data analytic solutions, advanced analytic and data enhancement techniques and modeling.

Dr. Feng has deep analytic expertise in data mining, analytic systems, machine learning algorithms, business intelligence, and applying Big Data tools to strategically solve industrial problems in a cross--functional business. Before joining the DST Applied Analytics Group, Dr. Feng holds a MA Data Science Fellow at The Institute **for** Mathematics and Its Applications (IMA) at the University of Minnesota. While there, he helped startup companies make marketing decisions based on deep predictive analytics.

Dr. Feng graduated from University of Tennessee, Knoxville with PhD in Computational mathematics and Master's degree in Statistics. He also holds Master's degree in Computational Mathematics at Missouri University of Science and Technology (MST) and Master's degree in Applied Mathematics at University of science and technology of China (USTC).
CPU Time **for** convertingfeng.pdf_0.png:0:00:02.061208

10.1.2 Image Enhanced to text

- My img2txt_enhance function

```
def img2txt_enhance(img_dir,scaler):  
    """  
    convert images files to text  
    """  
  
    import numpy as np  
    import os, PythonMagick  
    from datetime import datetime  
    import PyPDF2  
  
    from PIL import Image, ImageEnhance, ImageFilter  
    import pytesseract  
  
    f = open('doc4img.txt','wa')  
    for img in [img_file for img_file in os.listdir(img_dir)  
                if (img_file.endswith(".png") or  
                    img_file.endswith(".jpg") or  
                    img_file.endswith(".jpeg"))]:  
  
        start_time = datetime.now()  
  
        input_img = img_dir + "/" + img  
        enhanced_img = img_dir + "/" +"Enhanced" + "/" + img  
  
        im = Image.open(input_img) # the second one  
        im = im.filter(ImageFilter.MedianFilter())  
        enhancer = ImageEnhance.Contrast(im)  
        im = enhancer.enhance(1)  
        im = im.convert('1')  
        im.save(enhanced_img)  
  
        for scale in np.ones(scaler):
```

```
im = Image.open(enhanced_img) # the second one
im = im.filter(ImageFilter.MedianFilter())
enhancer = ImageEnhance.Contrast(im)
im = enhancer.enhance(scale)
im = im.convert('1')
im.save(enhanced_img)

print('-----')
print(img)
print('Converting ' + img + '.....')
print('-----')

# extract the text information from images
text = pytesseract.image_to_string(Image.open(enhanced_img))
print(text)

# output text file
f.write(img + "\n")
f.write(text.encode('utf-8'))

print "CPU Time for converting" + img + ":" + str(datetime.now() - start_time) + "\n"
f.write("\n-----\n")

f.close()
```

- Demo

I applied my `img2txt_enhance` function to the following noised image in Enhance folder.



```
image_dir = r"Enhance"

pdf2txt_enhance(image_dir)
```

Then I got the following results:

```
-----
noised.jpg
Converting noised.jpg.....  

-----
zHHH
CPU Time for convertingnoised.jpg:0:00:00.135465
```

while the result from `img2txt` function is

```
-----
noised.jpg
Converting noised.jpg.....
-----
,2 WW
CPU Time for convertingnoised.jpg:0:00:00.133508
```

which is not correct.

10.1.3 PDF to text

- My pdf2txt function

```
def pdf2txt (pdf_dir,image_dir):
    """
    convert PDF to text
    """

    import os, PythonMagick
    from datetime import datetime
    import PyPDF2

    from PIL import Image
    import pytesseract

    f = open('doc.txt','wa')
    for pdf in [pdf_file for pdf_file in os.listdir(pdf_dir) if pdf_file.endswith(".pdf")]

        start_time = datetime.now()

        input_pdf = pdf_dir + "/" + pdf

        pdf_im = PyPDF2.PdfFileReader(file(input_pdf, "rb"))
        npage = pdf_im.getNumPages()

        print('-----')
        print(pdf)
        print('Converting %d pages.' % npage)
        print('-----')

        f.write( "\n-----\n"

        for p in range(npage):

            pdf_file = input_pdf + '[' + str(p) + ']'
            image_file = image_dir + "/" + pdf+ '_' + str(p)+ '.png'

            # convert PDF files to Images
            im = PythonMagick.Image()
            im.density('300')
            im.read(pdf_file)
            im.write(image_file)
```

```
# extract the text information from images
text = pytesseract.image_to_string(Image.open(image_file))

#print(text)

# ouput text file
f.write( pdf + "\n")
f.write(text.encode('utf-8'))

print "CPU Time for converting" + pdf + ":" + str(datetime.now() - start_time) + "\n"

f.close()
```

- Demo

I applied my pdf2txt function to my scanned bio pdf file in pdf folder.

```
pdf_dir = r"pdf"
image_dir = r"Image"

pdf2txt(pdf_dir,image_dir)
```

Then I got the following results:

```
-----
feng.pdf
Converting 1 pages.

-----
l l l w

Wenqiang Feng
Data Scientist
DST APPLIED ANALYTICS GROUP
```

Wenqiang Feng is Data Scientist **for** DST's Applied Analytics Group. Dr. Feng's responsibilities include providing DST clients with access to cutting--edge skills and technologies, including Data analytic solutions, advanced analytic and data enhancement techniques and modeling.

Dr. Feng has deep analytic expertise in data mining, analytic systems, machine learning algorithms, business intelligence, and applying Big Data tools to strategically solve industrial problems in a cross--functional business. Before joining the DST Applied Analytics Group, Dr. Feng holds a MA Data Science Fellow at The Institute **for** Mathematics and Its Applications (IMA) at the University of Minnesota. While there, he helped startup companies make marketing decisions based on deep predictive analytics.

Dr. Feng graduated from University of Tennessee, Knoxville with PhD in Computational mathematics and Master's degree in Statistics. He also holds Master's degree in Computational Mathematics at Missouri University of Science and Technology (MST) and Master's degree in Applied Mathematics at University of science and technology of China (USTC).
CPU Time **for** convertingfeng.pdf:0:00:03.143800

10.1.4 Audio to text

- My audio2txt function

```
def audio2txt(audio_dir):
    ''' convert audio to text'''

    import speech_recognition as sr
    r = sr.Recognizer()

    f = open('doc.txt','wa')
    for audio_n in [audio_file for audio_file in os.listdir(audio_dir) \
                    if audio_file.endswith(".wav")]:
        filename = audio_dir + "/" + audio_n

        # Read audio data
        with sr.AudioFile(filename) as source:
            audio = r.record(source) # read the entire audio file

        # Google Speech Recognition
        text = r.recognize_google(audio)

        # output text file
        f.write( audio_n + ": ")
        f.write(text.encode('utf-8'))
        f.write("\n")

    print('You said: ' + text)

f.close()
```

- Demo

I applied my audio2txt function to my audio records in audio folder.

```
audio_dir = r"audio"

audio2txt(audio_dir)
```

Then I got the following results:

```
You said: hello this is George welcome to my tutorial
You said: mathematics is important in daily life
You said: call me tomorrow
You said: do you want something to eat
You said: I want to speak with him
You said: nice to see you
You said: can you speak slowly
You said: have a good day
```

By the way, you can use my following python code to record your own audio and play with audio2txt function in Command-line python record.py "demo2.wav":

```
import sys, getopt

import speech_recognition as sr

audio_filename = sys.argv[1]

r = sr.Recognizer()
with sr.Microphone() as source:
    r.adjust_for_ambient_noise(source)
    print("Hey there, say something, I am recording!")
    audio = r.listen(source)
    print("Done listening!")

with open(audio_filename, "wb") as f:
    f.write(audio.get_wav_data())
```

10.2 Text Preprocessing

- check to see if a row only contains whitespace

```
def check_blanks(data_str):
    is_blank = str(data_str.isspace())
    return is_blank
```

- Determine whether the language of the text content is english or not: Use langid module to classify the language to make sure we are applying the correct cleanup actions for English langid

```
def check_lang(data_str):
    predict_lang = langid.classify(data_str)
    if predict_lang[1] >= .9:
        language = predict_lang[0]
    else:
        language = 'NA'
    return language
```

- Remove features

```
def remove_features(data_str):
    # compile regex
    url_re = re.compile('https?://(www.)?\w+\.\w+(/(\w+)*)/?')
    punc_re = re.compile('[%s]' % re.escape(string.punctuation))
    num_re = re.compile('(\d+)')
    mention_re = re.compile('@(\w+)')
    alpha_num_re = re.compile("^[a-z0-9_.]+$")
    # convert to lowercase
    data_str = data_str.lower()
    # remove hyperlinks
    data_str = url_re.sub(' ', data_str)
    # remove @mentions
    data_str = mention_re.sub(' ', data_str)
    # remove punctuation
```

```

data_str = punc_re.sub(' ', data_str)
# remove numeric 'words'
data_str = num_re.sub(' ', data_str)
# remove non a-z 0-9 characters and words shorter than 3 characters
list_pos = 0
cleaned_str = ''
for word in data_str.split():
    if list_pos == 0:
        if alpha_num_re.match(word) and len(word) > 2:
            cleaned_str = word
    else:
        cleaned_str = ''
else:
    if alpha_num_re.match(word) and len(word) > 2:
        cleaned_str = cleaned_str + ' ' + word
    else:
        cleaned_str += ' '
list_pos += 1
return cleaned_str

```

- removes stop words

```

def remove_stops(data_str):
    # expects a string
    stops = set(stopwords.words("english"))
    list_pos = 0
    cleaned_str = ''
    text = data_str.split()
    for word in text:
        if word not in stops:
            # rebuild cleaned_str
            if list_pos == 0:
                cleaned_str = word
            else:
                cleaned_str = cleaned_str + ' ' + word
            list_pos += 1
    return cleaned_str

```

- tagging text

```

def tag_and_remove(data_str):
    cleaned_str = ''
    # noun tags
    nn_tags = ['NN', 'NNP', 'NNP', 'NNPS', 'NNS']
    # adjectives
    jj_tags = ['JJ', 'JJR', 'JJS']
    # verbs
    vb_tags = ['VB', 'VBD', 'VBG', 'VBN', 'VBP', 'VBZ']
    nltk_tags = nn_tags + jj_tags + vb_tags

    # break string into 'words'
    text = data_str.split()

    # tag the text and keep only those with the right tags

```

```

tagged_text = pos_tag(text)
for tagged_word in tagged_text:
    if tagged_word[1] in nltk_tags:
        cleaned_str += tagged_word[0] + ' '

return cleaned_str

```

- lemmatization

```

def lemmatize(data_str):
    # expects a string
    list_pos = 0
    cleaned_str = ''
    lmtzr = WordNetLemmatizer()
    text = data_str.split()
    tagged_words = pos_tag(text)
    for word in tagged_words:
        if 'v' in word[1].lower():
            lemma = lmtzr.lemmatize(word[0], pos='v')
        else:
            lemma = lmtzr.lemmatize(word[0], pos='n')
        if list_pos == 0:
            cleaned_str = lemma
        else:
            cleaned_str = cleaned_str + ' ' + lemma
        list_pos += 1
    return cleaned_str

```

define the preprocessing function in PySpark

```

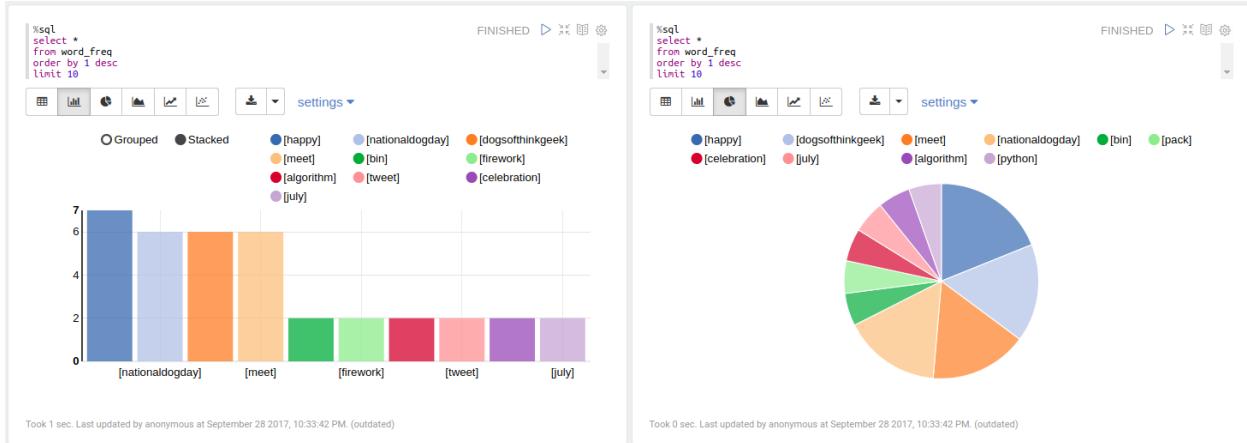
from pyspark.sql.functions import udf
from pyspark.sql.types import StringType
import preproc as pp

check_lang_udf = udf(pp.check_lang, StringType())
remove_stops_udf = udf(pp.remove_stops, StringType())
remove_features_udf = udf(pp.remove_features, StringType())
tag_and_remove_udf = udf(pp.tag_and_remove, StringType())
lemmatize_udf = udf(pp.lemmatize, StringType())
check_blanks_udf = udf(pp.check_blanks, StringType())

```

10.3 Text Classification

Theoretically speaking, you may apply any classification algorithms to do classification. I will only present Naive Bayes method is the following.



10.3.1 Introduction

10.3.2 Demo

1. create spark contexts

```
import pyspark
from pyspark.sql import SQLContext

# create spark contexts
sc = pyspark.SparkContext()
sqlContext = SQLContext(sc)
```

2. load dataset

```
# Load a text file and convert each line to a Row.
data_rdd = sc.textFile("../data/raw_data.txt")
parts_rdd = data_rdd.map(lambda l: l.split("\t"))

# Filter bad rows out
garantee_col_rdd = parts_rdd.filter(lambda l: len(l) == 3)
typed_rdd = guarantee_col_rdd.map(lambda p: (p[0], p[1], float(p[2])))

#Create DataFrame
data_df = sqlContext.createDataFrame(typed_rdd, ["text", "id", "label"])

# get the raw columns
raw_cols = data_df.columns

#data_df.show()
data_df.printSchema()

root
 |-- text: string (nullable = true)
 |-- id: string (nullable = true)
 |-- label: double (nullable = true)
```

```
+-----+-----+-----+
|      text|          id|label|
+-----+-----+-----+
|Fresh install of ...|    1018769417|  1.0|
|Well. Now I know ...|    10284216536|  1.0|
| "Literally six we...|    10298589026|  1.0|
|Mitsubishi i MiEV...|109017669432377344|  1.0|
+-----+-----+-----+
only showing top 4 rows
```

3. setup pyspark udf function

```
from pyspark.sql.functions import udf
from pyspark.sql.types import StringType
import preproc as pp

# Register all the functions in Preproc with Spark Context
check_lang_udf = udf(pp.check_lang, StringType())
remove_stops_udf = udf(pp.remove_stops, StringType())
remove_features_udf = udf(pp.remove_features, StringType())
tag_and_remove_udf = udf(pp.tag_and_remove, StringType())
lemmatize_udf = udf(pp.lemmatize, StringType())
check_blanks_udf = udf(pp.check_blanks, StringType())
```

4. language identification

```
lang_df = data_df.withColumn("lang", check_lang_udf(data_df["text"]))
en_df = lang_df.filter(lang_df["lang"] == "en")
en_df.show(4)
```

```
+-----+-----+-----+
|      text|          id|label|lang|
+-----+-----+-----+
|RT @goeentertain:...|665305154954989568|  1.0| en|
|Teforia Uses Mach...|660668007975268352|  1.0| en|
| Apple TV or Roku?|    25842461136|  1.0| en|
|Finished http://t...|    9412369614|  1.0| en|
+-----+-----+-----+
only showing top 4 rows
```

5. remove stop words

```
rm_stops_df = en_df.select(raw_cols) \
    .withColumn("stop_text", remove_stops_udf(en_df["text"]))
rm_stops_df.show(4)
```

```
+-----+-----+-----+-----+
|      text|          id|label|      stop_text|
+-----+-----+-----+-----+
|RT @goeentertain:...|665305154954989568|  1.0|RT @goeentertain:...|
|Teforia Uses Mach...|660668007975268352|  1.0|Teforia Uses Mach...|
| Apple TV or Roku?|    25842461136|  1.0|     Apple TV Roku?|
|Finished http://t...|    9412369614|  1.0|Finished http://t...|
+-----+-----+-----+-----+
```

only showing top 4 rows

6. remove irrelevant features

```
rm_features_df = rm_stops_df.select(raw_cols+["stop_text"]) \
    .withColumn("feat_text", \
    remove_features_udf(rm_stops_df["stop_text"]))
rm_features_df.show(4)

+-----+-----+-----+-----+
|      text|      id|label|      stop_text|      feat_text|
+-----+-----+-----+-----+
|RT @goeentertain:...|665305154954989568| 1.0|RT @goeentertain:...| future blase ...|
|Teforia Uses Mach...|660668007975268352| 1.0|Teforia Uses Mach...|teforia uses mach...|
| Apple TV or Roku?| 25842461136| 1.0| Apple TV Roku?|      apple roku|
|Finished http://t...| 9412369614| 1.0|Finished http://t...|      finished|
+-----+-----+-----+-----+
only showing top 4 rows
```

7. tag the words

```
tagged_df = rm_features_df.select(raw_cols+["feat_text"]) \
    .withColumn("tagged_text", \
    tag_and_remove_udf(rm_features_df.feat_text))
tagged_df.show(4)

+-----+-----+-----+-----+
|      text|      id|label|      feat_text|      tagged_text|
+-----+-----+-----+-----+
|RT @goeentertain:...|665305154954989568| 1.0| future blase ...| future blase vic...|
|Teforia Uses Mach...|660668007975268352| 1.0|teforia uses mach...| teforia uses mac...|
| Apple TV or Roku?| 25842461136| 1.0|      apple roku|      apple roku |
|Finished http://t...| 9412369614| 1.0|      finished|      finished |
+-----+-----+-----+-----+
only showing top 4 rows
```

8. lemmatization of words

```
lemm_df = tagged_df.select(raw_cols+["tagged_text"]) \
    .withColumn("lemm_text", lemmatize_udf(tagged_df["tagged_text"]))
lemm_df.show(4)

+-----+-----+-----+-----+
|      text|      id|label|      tagged_text|      lemm_text|
+-----+-----+-----+-----+
|RT @goeentertain:...|665305154954989568| 1.0| future blase vic...|future blase vice...|
|Teforia Uses Mach...|660668007975268352| 1.0|teforia uses mac...|teforia use machi...|
| Apple TV or Roku?| 25842461136| 1.0|      apple roku|      apple roku |
|Finished http://t...| 9412369614| 1.0|      finished|      finish |
+-----+-----+-----+-----+
only showing top 4 rows
```

9. remove blank rows and drop duplicates

```
check_blanks_df = lemm_df.select(raw_cols+["lemm_text"]) \
    .withColumn("is_blank", check_blanks_udf(lemm_df["lemm_text"]))

# remove blanks
no_blanks_df = check_blanks_df.filter(check_blanks_df["is_blank"] == "False")

# drop duplicates
dedup_df = no_blanks_df.dropDuplicates(['text', 'label'])

dedup_df.show(4)

+-----+-----+-----+-----+
|      text|      id|label|      lemm_text|is_blank|
+-----+-----+-----+-----+
|RT @goentertain:...|665305154954989568| 1.0|future blase vice...| False|
|Teforia Uses Mach...|660668007975268352| 1.0|teforia use machi...| False|
| Apple TV or Roku?| 25842461136| 1.0|          apple roku| False|
|Finished http://t...| 9412369614| 1.0|             finish| False|
+-----+-----+-----+-----+
only showing top 4 rows
```

10. add unique ID

```
from pyspark.sql.functions import monotonically_increasing_id
# Create Unique ID
dedup_df = dedup_df.withColumn("uid", monotonically_increasing_id())
dedup_df.show(4)

+-----+-----+-----+-----+-----+
|      text|      id|label|      lemm_text|is_blank|      uid|
+-----+-----+-----+-----+-----+
|      dragon| 1546813742| 1.0|        dragon| False| 85899345920|
| hurt much| 1558492525| 1.0| hurt much| False| 111669149696|
|seth blog word se...|383221484023709697| 1.0|seth blog word se...| False| 128849018880|
|teforia use machi...|660668007975268352| 1.0|teforia use machi...| False| 137438953472|
+-----+-----+-----+-----+
only showing top 4 rows
```

11. create final dataset

```
data = dedup_df.select('uid','id', 'text','label')
```

```
data.show(4)
```

```
+-----+-----+-----+
|      uid|      id|      text|label|
+-----+-----+-----+
| 85899345920| 1546813742| dragon| 1.0|
|111669149696| 1558492525| hurt much| 1.0|
|128849018880|383221484023709697|seth blog word se...| 1.0|
|137438953472|660668007975268352|teforia use machi...| 1.0|
+-----+-----+-----+
only showing top 4 rows
```

12. Create training and test sets

```
# Split the data into training and test sets (40% held out for testing)
(trainingData, testData) = data.randomSplit([0.6, 0.4])
```

13. NaiveBayes Pipeline

```
from pyspark.ml.feature import HashingTF, IDF, Tokenizer
from pyspark.ml import Pipeline
from pyspark.ml.classification import NaiveBayes, RandomForestClassifier
from pyspark.ml.classification import DecisionTreeClassifier
from pyspark.ml.evaluation import MulticlassClassificationEvaluator
from pyspark.ml.tuning import ParamGridBuilder
from pyspark.ml.tuning import CrossValidator
from pyspark.ml.feature import IndexToString, StringIndexer, VectorIndexer
from pyspark.ml.feature import CountVectorizer

# Configure an ML pipeline, which consists of tree stages: tokenizer, hashingTF, and nb.
tokenizer = Tokenizer(inputCol="text", outputCol="words")
hashingTF = HashingTF(inputCol=tokenizer.getOutputCol(), outputCol="rawFeatures")
# vectorizer = CountVectorizer(inputCol= "words", outputCol="rawFeatures")
idf = IDF(minDocFreq=3, inputCol="rawFeatures", outputCol="features")

# Naive Bayes model
nb = NaiveBayes()

# Pipeline Architecture
pipeline = Pipeline(stages=[tokenizer, hashingTF, idf, nb])

# Train model. This also runs the indexers.
model = pipeline.fit(trainingData)
```

14. Make predictions

```
predictions = model.transform(testData)

# Select example rows to display.
predictions.select("text", "label", "prediction").show(5, False)

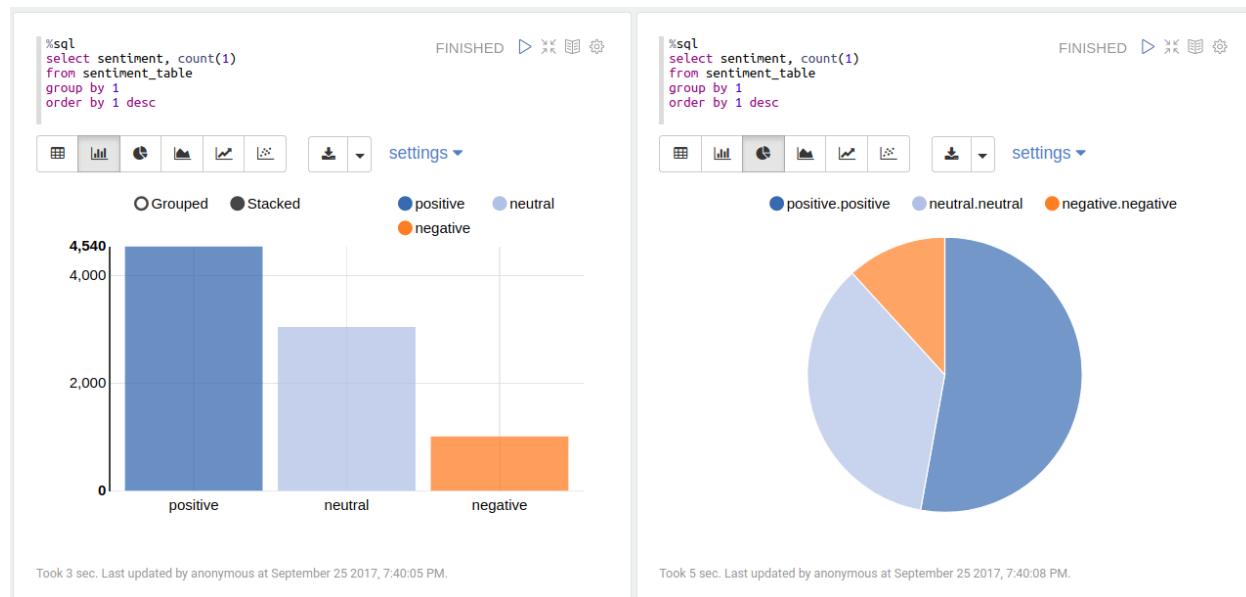
+-----+-----+
|text |label|prediction|
+-----+-----+
|finish |1.0 |1.0 |
|meet rolo dogsofthinkgeek happy nationaldogday |1.0 |1.0 |
|pumpkin family |1.0 |1.0 |
|meet jet dogsofthinkgeek happy nationaldogday |1.0 |1.0 |
|meet vixie dogsofthinkgeek happy nationaldogday|1.0 |1.0 |
+-----+-----+
only showing top 5 rows
```

15. evaluation

```
from pyspark.ml.evaluation import MulticlassClassificationEvaluator
evaluator = MulticlassClassificationEvaluator(predictionCol="prediction")
evaluator.evaluate(predictions)
```

0.912655971479501

10.4 Sentiment analysis



10.4.1 Introduction

Sentiment analysis (sometimes known as opinion mining or emotion AI) refers to the use of natural language processing, text analysis, computational linguistics, and biometrics to systematically identify, extract, quantify, and study affective states and subjective information. Sentiment analysis is widely applied to voice of the customer materials such as reviews and survey responses, online and social media, and healthcare materials for applications that range from marketing to customer service to clinical medicine.

Generally speaking, sentiment analysis aims to **determine the attitude** of a speaker, writer, or other subject with respect to some topic or the overall contextual polarity or emotional reaction to a document, interaction, or event. The attitude may be a judgment or evaluation (see appraisal theory), affective state (that is to say, the emotional state of the author or speaker), or the intended emotional communication (that is to say, the emotional effect intended by the author or interlocutor).

Sentiment analysis in business, also known as opinion mining is a process of identifying and cataloging a piece of text according to the tone conveyed by it. It has broad application:

- Sentiment Analysis in Business Intelligence Build up
- Sentiment Analysis in Business for Competitive Advantage
- Enhancing the Customer Experience through Sentiment Analysis in Business



Figure 10.1: Sentiment Analysis Pipeline

10.4.2 Pipeline

10.4.3 Demo

1. Set up spark context and SparkSession

```
from pyspark.sql import SparkSession

spark = SparkSession \
    .builder \
    .appName("Python Spark Sentiment Analysis example") \
    .config("spark.some.config.option", "some-value") \
    .getOrCreate()
```

2. Load dataset

```
df = spark.read.format('com.databricks.spark.csv') \
    .options(header='true', \
    inferschema='true') \
    .load("../data/newtwitter.csv", header=True);

+-----+-----+-----+
|      text|      id|pubdate|
+-----+-----+-----+
| 10 Things Missing...|2602860537| 18536|
| RT @_NATURALBWINN...|2602850443| 18536|
| RT @HBO24 yo the ...|2602761852| 18535|
| Aaaaaaaaand I have...|2602738438| 18535|
| can I please have...|2602684185| 18535|
+-----+-----+-----+
only showing top 5 rows
```

3. Text Preprocessing

- remove non ASCII characters

```
from pyspark.sql.functions import udf
from pyspark.sql.types import StringType

from nltk.stem.wordnet import WordNetLemmatizer
from nltk.corpus import stopwords
from nltk import pos_tag
import string
import re
```

```
# remove non ASCII characters
def strip_non_ascii(data_str):
    """ Returns the string without non ASCII characters"""
    stripped = (c for c in data_str if 0 < ord(c) < 127)
    return ''.join(stripped)
# setup pyspark udf function
strip_non_ascii_udf = udf(strip_non_ascii, StringType())
```

check:

```
df = df.withColumn('text_non_ascii', strip_non_ascii_udf(df['text']))
df.show(5, True)
```

output:

| text | id | pubdate | text_non_ascii |
|-----------------------|------------|---------|-----------------------|
| 10 Things Missing... | 2602860537 | 18536 | 10 Things Missing... |
| RT @_NATURALBWINN... | 2602850443 | 18536 | RT @_NATURALBWINN... |
| RT @_HBO24 yo the ... | 2602761852 | 18535 | RT @_HBO24 yo the ... |
| Aaaaaaaaand I have... | 2602738438 | 18535 | Aaaaaaaaand I have... |
| can I please have... | 2602684185 | 18535 | can I please have... |

only showing top 5 rows

- fixed abbreviation

```
# fixed abbreviation
def fix_abbreviation(data_str):
    data_str = data_str.lower()
    data_str = re.sub(r'\bthat\b', 'that is', data_str)
    data_str = re.sub(r'\bive\b', 'i have', data_str)
    data_str = re.sub(r'\bim\b', 'i am', data_str)
    data_str = re.sub(r'\bya\b', 'yeah', data_str)
    data_str = re.sub(r'\bcant\b', 'can not', data_str)
    data_str = re.sub(r'\bdont\b', 'do not', data_str)
    data_str = re.sub(r'\bwont\b', 'will not', data_str)
    data_str = re.sub(r'\bid\b', 'i would', data_str)
    data_str = re.sub(r'\wtf', 'what the fuck', data_str)
    data_str = re.sub(r'\bwth\b', 'what the hell', data_str)
    data_str = re.sub(r'\br\b', 'are', data_str)
    data_str = re.sub(r'\bu\b', 'you', data_str)
    data_str = re.sub(r'\bk\b', 'OK', data_str)
    data_str = re.sub(r'\bsux\b', 'sucks', data_str)
    data_str = re.sub(r'\bno+\b', 'no', data_str)
    data_str = re.sub(r'\bcoo+\b', 'cool', data_str)
    data_str = re.sub(r'\rt\b', '', data_str)
    data_str = data_str.strip()
    return data_str
```

```
fix_abbreviation_udf = udf(fix_abbreviation, StringType())
```

check:

```
df = df.withColumn('fixed_abbrev', fix_abbreviation_udf(df['text_non_ascii']))
df.show(5, True)
```

output:

```
+-----+-----+-----+-----+
|       text|      id|pubdate|text_non_ascii|fixed_abbrev|
+-----+-----+-----+-----+
| 10 Things Missing...|2602860537| 18536|10 Things Missing...|10 things missing...
|RT @_NATURALBWINN...|2602850443| 18536|RT @_NATURALBWINN...|@_naturalbwinner ...
|RT @HBO24 yo the ...|2602761852| 18535|RT @HBO24 yo the ...|@hbo24 yo the #ne...
|Aaaaaaaaand I have...|2602738438| 18535|Aaaaaaaaand I have...|aaaaaaaand i have...
|can I please have...|2602684185| 18535|can I please have...|can i please have...
+-----+-----+-----+-----+
only showing top 5 rows
```

- remove irrelevant features

```
def remove_features(data_str):
    # compile regex
    url_re = re.compile('https?://(www.)?\w+\.\w+(/(\w+)*)/?')
    punc_re = re.compile('[%s]' % re.escape(string.punctuation))
    num_re = re.compile('(\d+)')
    mention_re = re.compile('@(\w+)')
    alpha_num_re = re.compile("^[a-z0-9_.]+$")
    # convert to lowercase
    data_str = data_str.lower()
    # remove hyperlinks
    data_str = url_re.sub(' ', data_str)
    # remove @mentions
    data_str = mention_re.sub(' ', data_str)
    # remove punctuation
    data_str = punc_re.sub(' ', data_str)
    # remove numeric 'words'
    data_str = num_re.sub(' ', data_str)
    # remove non a-z 0-9 characters and words shorter than 1 characters
    list_pos = 0
    cleaned_str = ''
    for word in data_str.split():
        if list_pos == 0:
            if alpha_num_re.match(word) and len(word) > 1:
                cleaned_str = word
            else:
                cleaned_str = ''
        else:
            if alpha_num_re.match(word) and len(word) > 1:
                cleaned_str = cleaned_str + ' ' + word
            else:
                cleaned_str += ' '
        list_pos += 1
    # remove unwanted space, *.split() will automatically split on
    # whitespace and discard duplicates, the ".join() joins the
    # resulting list into one string.
    return " ".join(cleaned_str.split())
```

```
# setup pyspark udf function
remove_features_udf = udf(remove_features, StringType())
```

check:

```
df = df.withColumn('removed', remove_features_udf(df['fixed_abbrev']))
df.show(5, True)
```

output:

```
+-----+-----+-----+-----+
|      text |      id |pubdate|      text_non_ascii |      fixed_abbrev |
+-----+-----+-----+-----+
| 10 Things Missing...|2602860537| 18536|10 Things Missing...|10 things missing...|things m
|RT @_NATURALBWINN...|2602850443| 18536|RT @_NATURALBWINN...|@naturalbwinner ...|oh and
|RT @_HBO24 yo the ...|2602761852| 18535|RT @_HBO24 yo the ...|@hbo24 yo the #ne.../yo the
|Aaaaaaaaaand I have...|2602738438| 18535|Aaaaaaaaaand I have...|aaaaaaaaand i have...|aaaaaaaaa
|can I please have...|2602684185| 18535|can I please have...|can i please have...|can ple
+-----+-----+-----+-----+
only showing top 5 rows
```

4. Sentiment Analysis main function

```
from pyspark.sql.types import FloatType

from textblob import TextBlob

def sentiment_analysis(text):
    return TextBlob(text).sentiment.polarity

sentiment_analysis_udf = udf(sentiment_analysis, FloatType())

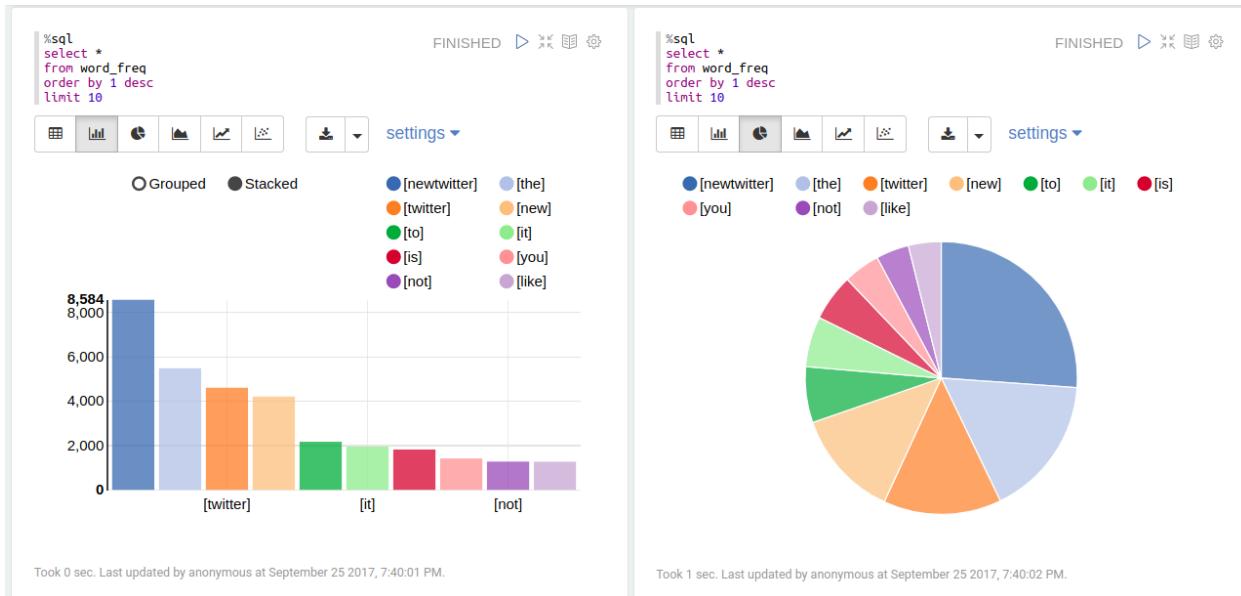
df = df.withColumn("sentiment_score", sentiment_analysis_udf(df['removed']))
df.show(5, True)
```

- Sentiment score

```
+-----+
|      removed | sentiment_score |
+-----+
|things missing in...| -0.03181818 |
|oh and do not lik...| -0.03181818 |
|yo the newtwitter...| 0.3181818 |
|aaaaaaaaand have t...| 0.11818182 |
|can please have t...| 0.13636364 |
+-----+
only showing top 5 rows
```

- Words frequency
- Sentiment Classification

```
def condition(r):
    if (r >= 0.1):
        label = "positive"
```



```

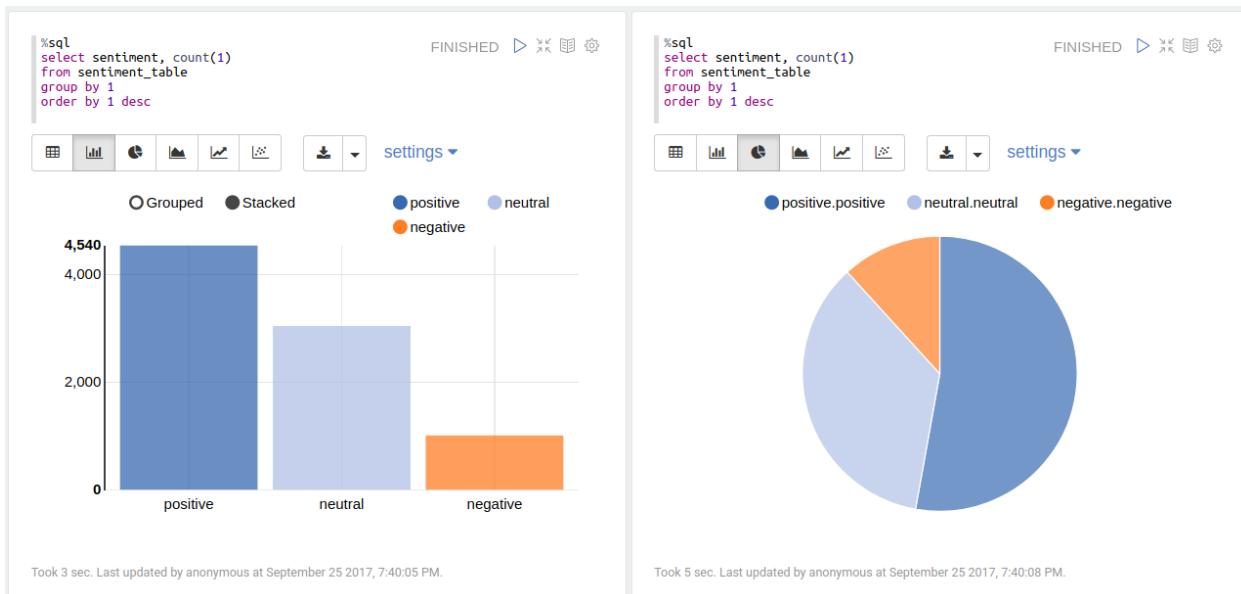
    elif(r <= -0.1):
        label = "negative"
    else:
        label = "neutral"
    return label

```

```
sentiment_udf = udf(lambda x: condition(x), StringType())
```

5. Output

- Sentiment Class



- Top tweets from each sentiment class

```
+-----+-----+-----+
|          text|sentiment_score|sentiment|
+-----+-----+-----+
| and this #newtwit... |      1.0| positive|
| "RT @SarahsJokes:... |      1.0| positive|
| #newtwitter using... |      1.0| positive|
| The #NewTwitter h... |      1.0| positive|
| You can now undo ...|      1.0| positive|
+-----+-----+-----+
only showing top 5 rows

+-----+-----+-----+
|          text|sentiment_score|sentiment|
+-----+-----+-----+
| Lists on #NewTwit... |     -0.1| neutral|
| Too bad most of m... |     -0.1| neutral|
| the #newtwitter i... |     -0.1| neutral|
| Looks like our re... |     -0.1| neutral|
| i switched to the...|     -0.1| neutral|
+-----+-----+-----+
only showing top 5 rows

+-----+-----+-----+
|          text|sentiment_score|sentiment|
+-----+-----+-----+
| oh. #newtwitter i... |     -1.0| negative|
| RT @chqwn: #NewTw... |     -1.0| negative|
| Copy that - its W... |     -1.0| negative|
| RT @chqwn: #NewTw... |     -1.0| negative|
| #NewTwitter has t... |     -1.0| negative|
+-----+-----+-----+
only showing top 5 rows
```

10.5 N-grams and Correlations

10.6 Topic Model: Latent Dirichlet Allocation

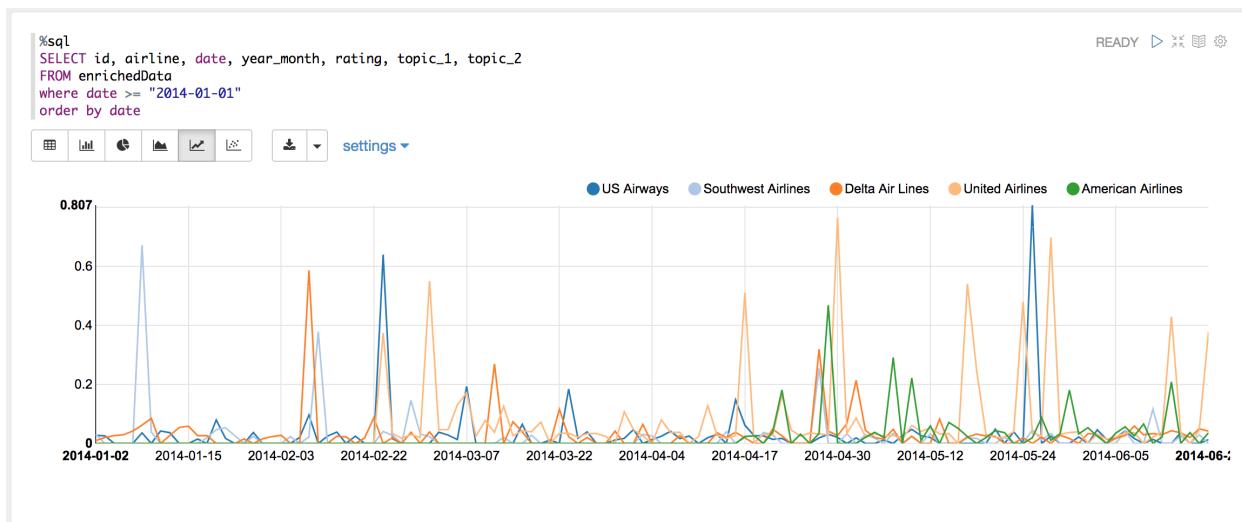
10.6.1 Introduction

In text mining, a topic model is a unsupervised model for discovering the abstract “topics” that occur in a collection of documents.

Latent Dirichlet Allocation (LDA) is a mathematical method for estimating both of these at the same time: finding the mixture of words that is associated with each topic, while also determining the mixture of topics that describes each document.

10.6.2 Demo

1. Load data



```
rawdata = spark.read.load("../data/airlines.csv", format="csv", header=True)
rawdata.show(5)
```

```
+-----+-----+-----+-----+-----+-----+
| id |      airline |      date | location | rating | cabin | value | recommended |
+-----+-----+-----+-----+-----+-----+
| 10001 | Delta Air Lines | 21-Jun-14 | Thailand | 7 | Economy | 4 | YES|Flew Mar 3 |
| 10002 | Delta Air Lines | 19-Jun-14 | USA | 0 | Economy | 2 | NO|Flight 246 |
| 10003 | Delta Air Lines | 18-Jun-14 | USA | 0 | Economy | 1 | NO|Delta Webs |
| 10004 | Delta Air Lines | 17-Jun-14 | USA | 9 | Business | 4 | YES|"I just re |
| 10005 | Delta Air Lines | 17-Jun-14 | Ecuador | 7 | Economy | 3 | YES|"Round-tri |
+-----+-----+-----+-----+-----+-----+
```

only showing top 5 rows

1. Text preprocessing

I will use the following raw column names to keep my table concise:

```
raw_cols = rawdata.columns
raw_cols

['id', 'airline', 'date', 'location', 'rating', 'cabin', 'value', 'recommended', 'review']

rawdata = rawdata.dropDuplicates(['review'])

from pyspark.sql.functions import udf, col
from pyspark.sql.types import StringType, DoubleType, DateType

from nltk.stem.wordnet import WordNetLemmatizer
from nltk.corpus import stopwords
from nltk import pos_tag
import langid
import string
import re
```

- remove non ASCII characters

```
# remove non ASCII characters
def strip_non_ascii(data_str):
    ''' Returns the string without non ASCII characters'''
    stripped = (c for c in data_str if 0 < ord(c) < 127)
    return ''.join(stripped)
```

- check it blank line or not

```
# check to see if a row only contains whitespace
def check_blanks(data_str):
    is_blank = str(data_str.isspace())
    return is_blank
```

- check the language (a little bit slow, I skited this step)

```
# check the language (only apply to english)
def check_lang(data_str):
    from langid.langid import LanguageIdentifier, model
    identifier = LanguageIdentifier.from_modelstring(model, norm_probs=True)
    predict_lang = identifier.classify(data_str)

    if predict_lang[1] >= .9:
        language = predict_lang[0]
    else:
        language = predict_lang[0]
    return language
```

- fixed abbreviation

```
# fixed abbreviation
def fix_abbreviation(data_str):
    data_str = data_str.lower()
    data_str = re.sub(r'\bthats\b', 'that is', data_str)
    data_str = re.sub(r'\bive\b', 'i have', data_str)
    data_str = re.sub(r'\bim\b', 'i am', data_str)
    data_str = re.sub(r'\bya\b', 'yeah', data_str)
    data_str = re.sub(r'\bcant\b', 'can not', data_str)
    data_str = re.sub(r'\bdont\b', 'do not', data_str)
    data_str = re.sub(r'\bwont\b', 'will not', data_str)
    data_str = re.sub(r'\bid\b', 'i would', data_str)
    data_str = re.sub(r'\wtf', 'what the fuck', data_str)
    data_str = re.sub(r'\bwth\b', 'what the hell', data_str)
    data_str = re.sub(r'\br\b', 'are', data_str)
    data_str = re.sub(r'\bu\b', 'you', data_str)
    data_str = re.sub(r'\bk\b', 'OK', data_str)
    data_str = re.sub(r'\bsux\b', 'sucks', data_str)
    data_str = re.sub(r'\bno+\b', 'no', data_str)
    data_str = re.sub(r'\bcoo+\b', 'cool', data_str)
    data_str = re.sub(r'\rt\b', '', data_str)
    data_str = data_str.strip()
    return data_str
```

- remove irrelevant features

```

# remove irrelevant features
def remove_features(data_str):
    # compile regex
    url_re = re.compile('https?://(www.)?\w+\.\w+(/(\w+)*)/?')
    punc_re = re.compile('[%s]' % re.escape(string.punctuation))
    num_re = re.compile('(\d+)')
    mention_re = re.compile('@(\w+)')
    alpha_num_re = re.compile("^[a-z0-9_.]+$")
    # convert to lowercase
    data_str = data_str.lower()
    # remove hyperlinks
    data_str = url_re.sub(' ', data_str)
    # remove @mentions
    data_str = mention_re.sub(' ', data_str)
    # remove punctuation
    data_str = punc_re.sub(' ', data_str)
    # remove numeric 'words'
    data_str = num_re.sub(' ', data_str)
    # remove non a-z 0-9 characters and words shorter than 1 characters
    list_pos = 0
    cleaned_str = ''
    for word in data_str.split():
        if list_pos == 0:
            if alpha_num_re.match(word) and len(word) > 1:
                cleaned_str = word
            else:
                cleaned_str = ' '
        else:
            if alpha_num_re.match(word) and len(word) > 1:
                cleaned_str = cleaned_str + ' ' + word
            else:
                cleaned_str += ' '
        list_pos += 1
    # remove unwanted space, *.split() will automatically split on
    # whitespace and discard duplicates, the ".join() joins the
    # resulting list into one string.
    return " ".join(cleaned_str.split())

```

- removes stop words

```

# removes stop words
def remove_stops(data_str):
    # expects a string
    stops = set(stopwords.words("english"))
    list_pos = 0
    cleaned_str = ''
    text = data_str.split()
    for word in text:
        if word not in stops:
            # rebuild cleaned_str
            if list_pos == 0:
                cleaned_str = word
            else:

```

```

        cleaned_str = cleaned_str + ' ' + word
    list_pos += 1
    return cleaned_str

```

- Part-of-Speech Tagging

```

# Part-of-Speech Tagging
def tag_and_remove(data_str):
    cleaned_str = ''
    # noun tags
    nn_tags = ['NN', 'NNP', 'NNP', 'NNPS', 'NNS']
    # adjectives
    jj_tags = ['JJ', 'JJR', 'JJS']
    # verbs
    vb_tags = ['VB', 'VBD', 'VBG', 'VBN', 'VBP', 'VBZ']
    nltk_tags = nn_tags + jj_tags + vb_tags

    # break string into 'words'
    text = data_str.split()

    # tag the text and keep only those with the right tags
    tagged_text = pos_tag(text)
    for tagged_word in tagged_text:
        if tagged_word[1] in nltk_tags:
            cleaned_str += tagged_word[0] + ' '

    return cleaned_str

```

- lemmatization

```

# lemmatization
def lemmatize(data_str):
    # expects a string
    list_pos = 0
    cleaned_str = ''
    lmtzr = WordNetLemmatizer()
    text = data_str.split()
    tagged_words = pos_tag(text)
    for word in tagged_words:
        if 'v' in word[1].lower():
            lemma = lmtzr.lemmatize(word[0], pos='v')
        else:
            lemma = lmtzr.lemmatize(word[0], pos='n')
        if list_pos == 0:
            cleaned_str = lemma
        else:
            cleaned_str = cleaned_str + ' ' + lemma
        list_pos += 1
    return cleaned_str

```

- setup pyspark udf function

```

# setup pyspark udf function
strip_non_ascii_udf = udf(strip_non_ascii, StringType())

```

```
check_blanks_udf = udf(check_blanks, StringType())
check_lang_udf = udf(check_lang, StringType())
fix_abbreviation_udf = udf(fix_abbreviation, StringType())
remove_stops_udf = udf(remove_stops, StringType())
remove_features_udf = udf(remove_features, StringType())
tag_and_remove_udf = udf(tag_and_remove, StringType())
lemmatize_udf = udf(lemmatize, StringType())
```

1. Text processing

- correct the data schema

```
rawdata = rawdata.withColumn('rating', rawdata.rating.cast('float'))

rawdata.printSchema()

root
|-- id: string (nullable = true)
|-- airline: string (nullable = true)
|-- date: string (nullable = true)
|-- location: string (nullable = true)
|-- rating: float (nullable = true)
|-- cabin: string (nullable = true)
|-- value: string (nullable = true)
|-- recommended: string (nullable = true)
|-- review: string (nullable = true)

from datetime import datetime
from pyspark.sql.functions import col

# https://docs.python.org/2/library/datetime.html#strftime-and-strptime-behavior
# 21-Jun-14 <----> %d-%b-%y
to_date = udf (lambda x: datetime.strptime(x, '%d-%b-%y'), DateType())

rawdata = rawdata.withColumn('date', to_date(col('date')))

rawdata.printSchema()

root
|-- id: string (nullable = true)
|-- airline: string (nullable = true)
|-- date: date (nullable = true)
|-- location: string (nullable = true)
|-- rating: float (nullable = true)
|-- cabin: string (nullable = true)
|-- value: string (nullable = true)
|-- recommended: string (nullable = true)
|-- review: string (nullable = true)

rawdata.show(5)

+---+---+---+---+---+
| id | airline | date | location | rating | cabin | value | recommended |
+---+---+---+---+---+
```

```
+-----+-----+-----+-----+-----+-----+
| 10551 | Southwest Airlines | 2013-11-06 | USA | 1.0 | Business | 2 | NO|Flight
| 10298 | US Airways | 2014-03-31 | UK | 1.0 | Business | 0 | NO|Flight
| 10564 | Southwest Airlines | 2013-09-06 | USA | 10.0 | Economy | 5 | YES|I'm Ex
| 10134 | Delta Air Lines | 2013-12-10 | USA | 8.0 | Economy | 4 | YES|MSP-JF
| 10912 | United Airlines | 2014-04-07 | USA | 3.0 | Economy | 1 | NO|Worst
+-----+-----+-----+-----+-----+-----+
only showing top 5 rows

rawdata = rawdata.withColumn('non_ascii', strip_non_ascii_udf(rawdata['review']))


+-----+-----+-----+-----+-----+-----+
| id | airline | date | location | rating | cabin | value | recommended |
+-----+-----+-----+-----+-----+-----+
| 10551 | Southwest Airlines | 2013-11-06 | USA | 1.0 | Business | 2 | NO|Flight
| 10298 | US Airways | 2014-03-31 | UK | 1.0 | Business | 0 | NO|Flight
| 10564 | Southwest Airlines | 2013-09-06 | USA | 10.0 | Economy | 5 | YES|I'm Ex
| 10134 | Delta Air Lines | 2013-12-10 | USA | 8.0 | Economy | 4 | YES|MSP-JF
| 10912 | United Airlines | 2014-04-07 | USA | 3.0 | Economy | 1 | NO|Worst
+-----+-----+-----+-----+-----+-----+
only showing top 5 rows

rawdata = rawdata.select(raw_cols+['non_ascii']) \
    .withColumn('fixed_abbrev', fix_abbreviation_udf(rawdata['non_ascii']))


+-----+-----+-----+-----+-----+-----+
| id | airline | date | location | rating | cabin | value | recommended |
+-----+-----+-----+-----+-----+-----+
| 10551 | Southwest Airlines | 2013-11-06 | USA | 1.0 | Business | 2 | NO|Flight
| 10298 | US Airways | 2014-03-31 | UK | 1.0 | Business | 0 | NO|Flight
| 10564 | Southwest Airlines | 2013-09-06 | USA | 10.0 | Economy | 5 | YES|I'm Ex
| 10134 | Delta Air Lines | 2013-12-10 | USA | 8.0 | Economy | 4 | YES|MSP-JF
| 10912 | United Airlines | 2014-04-07 | USA | 3.0 | Economy | 1 | NO|Worst
+-----+-----+-----+-----+-----+-----+
only showing top 5 rows

rawdata = rawdata.select(raw_cols+['fixed_abbrev']) \
    .withColumn('stop_text', remove_stops_udf(rawdata['fixed_abbrev']))


+-----+-----+-----+-----+-----+-----+
| id | airline | date | location | rating | cabin | value | recommended |
+-----+-----+-----+-----+-----+-----+
| 10551 | Southwest Airlines | 2013-11-06 | USA | 1.0 | Business | 2 | NO|Flight
| 10298 | US Airways | 2014-03-31 | UK | 1.0 | Business | 0 | NO|Flight
| 10564 | Southwest Airlines | 2013-09-06 | USA | 10.0 | Economy | 5 | YES|I'm Ex
| 10134 | Delta Air Lines | 2013-12-10 | USA | 8.0 | Economy | 4 | YES|MSP-JF
| 10912 | United Airlines | 2014-04-07 | USA | 3.0 | Economy | 1 | NO|Worst
+-----+-----+-----+-----+-----+-----+
only showing top 5 rows

rawdata = rawdata.select(raw_cols+['stop_text']) \
    .withColumn('feat_text', remove_features_udf(rawdata['stop_text']))
```

```
+-----+-----+-----+-----+-----+-----+
|   id|      airline|      date|location|rating|    cabin|value|recommended|
+-----+-----+-----+-----+-----+-----+
| 10551|Southwest Airlines|2013-11-06|     USA|    1.0|Business|    2|      NO|Flight
| 10298|        US Airways|2014-03-31|     UK|    1.0|Business|    0|      NO|Flight
| 10564|Southwest Airlines|2013-09-06|     USA|   10.0| Economy|    5|      YES|I'm Ex
| 10134|    Delta Air Lines|2013-12-10|     USA|    8.0| Economy|    4|      YES|MSP-JF
| 10912|    United Airlines|2014-04-07|     USA|    3.0| Economy|    1|      NO|Worst
+-----+-----+-----+-----+-----+-----+
only showing top 5 rows

rawdata = rawdata.select(raw_cols+['feat_text']) \
    .withColumn('tagged_text',tag_and_remove_udf(rawdata['feat_text']))

+-----+-----+-----+-----+-----+-----+
|   id|      airline|      date|location|rating|    cabin|value|recommended|
+-----+-----+-----+-----+-----+-----+
| 10551|Southwest Airlines|2013-11-06|     USA|    1.0|Business|    2|      NO|Flight
| 10298|        US Airways|2014-03-31|     UK|    1.0|Business|    0|      NO|Flight
| 10564|Southwest Airlines|2013-09-06|     USA|   10.0| Economy|    5|      YES|I'm Ex
| 10134|    Delta Air Lines|2013-12-10|     USA|    8.0| Economy|    4|      YES|MSP-JF
| 10912|    United Airlines|2014-04-07|     USA|    3.0| Economy|    1|      NO|Worst
+-----+-----+-----+-----+-----+-----+
only showing top 5 rows

rawdata = rawdata.select(raw_cols+['tagged_text']) \
    .withColumn('lemm_text',lemmatize_udf(rawdata['tagged_text']))

+-----+-----+-----+-----+-----+-----+
|   id|      airline|      date|location|rating|    cabin|value|recommended|
+-----+-----+-----+-----+-----+-----+
| 10551|Southwest Airlines|2013-11-06|     USA|    1.0|Business|    2|      NO|Flight
| 10298|        US Airways|2014-03-31|     UK|    1.0|Business|    0|      NO|Flight
| 10564|Southwest Airlines|2013-09-06|     USA|   10.0| Economy|    5|      YES|I'm Ex
| 10134|    Delta Air Lines|2013-12-10|     USA|    8.0| Economy|    4|      YES|MSP-JF
| 10912|    United Airlines|2014-04-07|     USA|    3.0| Economy|    1|      NO|Worst
+-----+-----+-----+-----+-----+-----+
only showing top 5 rows

rawdata = rawdata.select(raw_cols+['lemm_text']) \
    .withColumn("is_blank", check_blanks_udf(rawdata["lemm_text"]))

+-----+-----+-----+-----+-----+-----+
|   id|      airline|      date|location|rating|    cabin|value|recommended|
+-----+-----+-----+-----+-----+-----+
| 10551|Southwest Airlines|2013-11-06|     USA|    1.0|Business|    2|      NO|Flight
| 10298|        US Airways|2014-03-31|     UK|    1.0|Business|    0|      NO|Flight
| 10564|Southwest Airlines|2013-09-06|     USA|   10.0| Economy|    5|      YES|I'm Ex
| 10134|    Delta Air Lines|2013-12-10|     USA|    8.0| Economy|    4|      YES|MSP-JF
| 10912|    United Airlines|2014-04-07|     USA|    3.0| Economy|    1|      NO|Worst
+-----+-----+-----+-----+-----+-----+
```

only showing top 5 rows

```
from pyspark.sql.functions import monotonically_increasing_id
# Create Unique ID
rawdata = rawdata.withColumn("uid", monotonically_increasing_id())
data = rawdata.filter(rawdata["is_blank"] == "False")

+-----+-----+-----+-----+-----+-----+
| id | airline | date | location | rating | cabin | value | recommended |
+-----+-----+-----+-----+-----+-----+
| 10551 | Southwest Airlines | 2013-11-06 | USA | 1.0 | Business | 2 | NO | Flight
| 10298 | US Airways | 2014-03-31 | UK | 1.0 | Business | 0 | NO | Flight
| 10564 | Southwest Airlines | 2013-09-06 | USA | 10.0 | Economy | 5 | YES | I'm Ex
| 10134 | Delta Air Lines | 2013-12-10 | USA | 8.0 | Economy | 4 | YES | MSP-JF
| 10912 | United Airlines | 2014-04-07 | USA | 3.0 | Economy | 1 | NO | Worst
+-----+-----+-----+-----+-----+-----+
only showing top 5 rows
```

Pipeline for LDA model

```
from pyspark.ml.feature import HashingTF, IDF, Tokenizer
from pyspark.ml import Pipeline
from pyspark.ml.classification import NaiveBayes, RandomForestClassifier
from pyspark.ml.clustering import LDA
from pyspark.ml.classification import DecisionTreeClassifier
from pyspark.ml.evaluation import MulticlassClassificationEvaluator
from pyspark.ml.tuning import ParamGridBuilder
from pyspark.ml.tuning import CrossValidator
from pyspark.ml.feature import IndexToString, StringIndexer, VectorIndexer
from pyspark.ml.feature import CountVectorizer

# Configure an ML pipeline, which consists of tree stages: tokenizer, hashingTF, and n
tokenizer = Tokenizer(inputCol="lemm_text", outputCol="words")
#data = tokenizer.transform(data)
vectorizer = CountVectorizer(inputCol= "words", outputCol="rawFeatures")
idf = IDF(inputCol="rawFeatures", outputCol="features")
#idfModel = idf.fit(data)

lda = LDA(k=20, seed=1, optimizer="em")

pipeline = Pipeline(stages=[tokenizer, vectorizer,idf, lda])

model = pipeline.fit(data)
```

1. Results presentation

- Topics

```
+-----+-----+-----+
|topic| termIndices | termWeights |
+-----+-----+-----+
| 0|[60, 7, 12, 483, ...|[0.01349507958269...
| 1|[363, 29, 187, 55...|[0.01247250144447...
```

```

| 2|[46, 107, 672, 27...|[0.01188684264641...
| 3|[76, 43, 285, 152...|[0.01132638300115...
| 4|[201, 13, 372, 69...|[0.01337529863256...
| 5|[122, 103, 181, 4...|[0.00930415977117...
| 6|[14, 270, 18, 74,...|[0.01253817708163...
| 7|[111, 36, 341, 10...|[0.01269584954257...
| 8|[477, 266, 297, 1...|[0.01017486869509...
| 9|[10, 73, 46, 1, 2...|[0.01050875237546...
| 10|[57, 29, 411, 10,...|[0.01777350667863...
| 11|[293, 119, 385, 4...|[0.01280305149305...
| 12|[116, 218, 256, 1...|[0.01570714218509...
| 13|[433, 171, 176, 3...|[0.00819684813575...
| 14|[74, 84, 45, 108,...|[0.01700630002172...
| 15|[669, 215, 14, 58...|[0.00779310974971...
| 16|[198, 21, 98, 164...|[0.01030577084202...
| 17|[96, 29, 569, 444...|[0.01297142577633...
| 18|[18, 60, 140, 64...|[0.01306356985169...
| 19|[33, 178, 95, 2, ...|[0.00907425683229...
+-----+

```

- Topic terms

```

from pyspark.sql.types import ArrayType, StringType

def termsIdx2Term(vocabulary):
    def termsIdx2Term(termIndices):
        return [vocabulary[int(index)] for index in termIndices]
    return udf(termsIdx2Term, ArrayType(StringType()))

```

vectorizerModel = model.stages[1]
vocabList = vectorizerModel.vocabulary
final = ldatopics.withColumn("Terms", termsIdx2Term(vocabList) ("termIndices"))

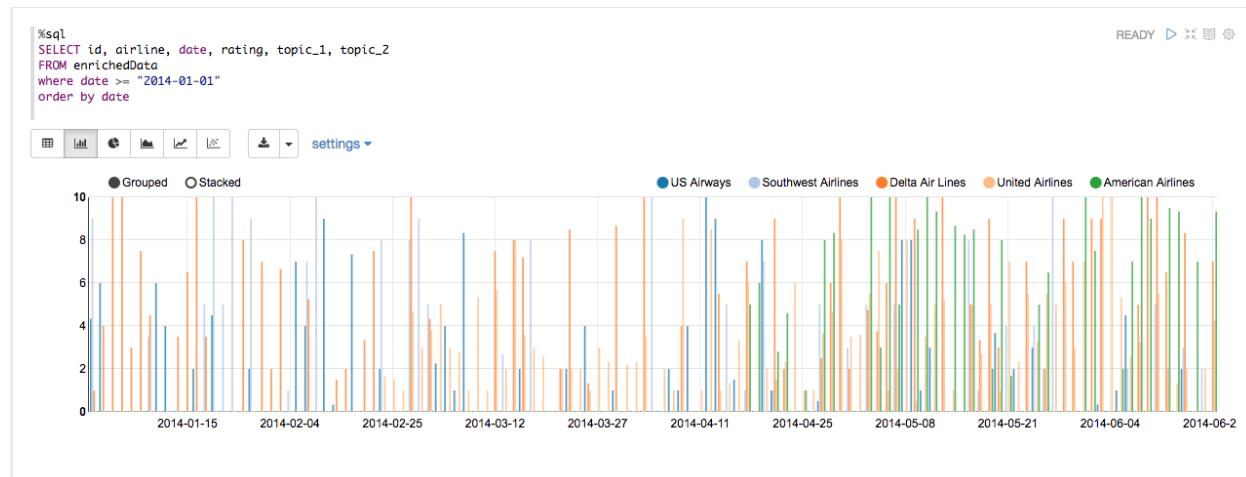
| topic | termIndices | Terms |
|-------|--------------------------------------------------|--------------------------------|
| 0 | [60, 7, 12, 483, 292, 326, 88, 4, 808, 32] | pm, plane, board, kid, online |
| 1 | [363, 29, 187, 55, 48, 647, 30, 9, 204, 457] | dublin, class, th, sit, enter |
| 2 | [46, 107, 672, 274, 92, 539, 23, 27, 279, 8] | economy, sfo, milwaukee, dece |
| 3 | [76, 43, 285, 152, 102, 34, 300, 113, 24, 31] | [didn, pay, lose, different, e |
| 4 | [201, 13, 372, 692, 248, 62, 211, 187, 105, 110] | [houston, crew, heathrow, loui |
| 5 | [122, 103, 181, 48, 434, 10, 121, 147, 934, 169] | [lhr, serve, screen, entertain |
| 6 | [14, 270, 18, 74, 70, 37, 16, 450, 3, 20] | [check, employee, gate, line, |
| 7 | [111, 36, 341, 10, 320, 528, 844, 19, 195, 524] | [atlanta, first, toilet, delta |
| 8 | [477, 266, 297, 185, 1, 33, 22, 783, 17, 908] | [fuel, group, pas, boarding, s |
| 9 | [10, 73, 46, 1, 248, 302, 213, 659, 48, 228] | [delta, lax, economy, seat, lo |
| 10 | [57, 29, 411, 10, 221, 121, 661, 19, 805, 733] | [business, class, fra, delta, |
| 11 | [293, 119, 385, 481, 503, 69, 13, 87, 176, 545] | [march, ua, manchester, phx, e |
| 12 | [116, 218, 256, 156, 639, 20, 365, 18, 22, 136] | [san, clt, francisco, second, |
| 13 | [433, 171, 176, 339, 429, 575, 10, 26, 474, 796] | [daughter, small, aa, ba, segm |
| 14 | [74, 84, 45, 108, 342, 111, 315, 87, 52, 4] | [line, agent, next, hotel, sta |
| 15 | [669, 215, 14, 58, 561, 59, 125, 179, 93, 5] | [fit, carry, check, people, ba |
| 16 | [198, 21, 98, 164, 57, 141, 345, 62, 121, 174] | [ife, good, nice, much, busine |
| 17 | [96, 29, 569, 444, 15, 568, 21, 103, 657, 505] | [phl, class, diego, lady, food |

```
| 18 | [18, 60, 140, 64, 47, 40, 31, 35, 2, 123] | [gate, pm, phoenix, connection
| 19 | [33, 178, 95, 2, 9, 284, 42, 4, 89, 31] | [trip, counter, philadelphia,
+----+-----+-----+-----+-----+-----+
```

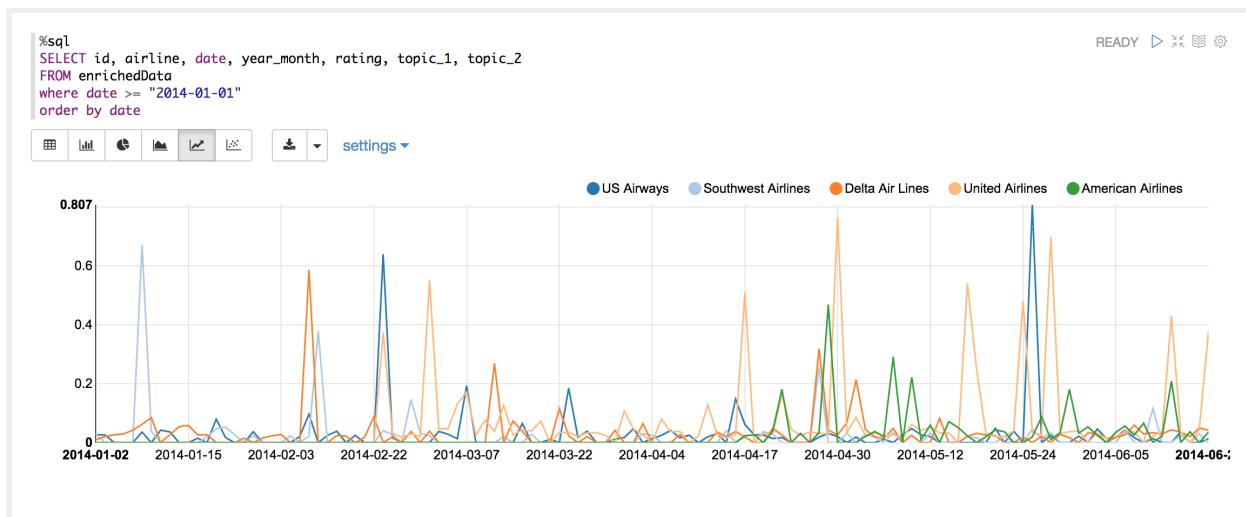
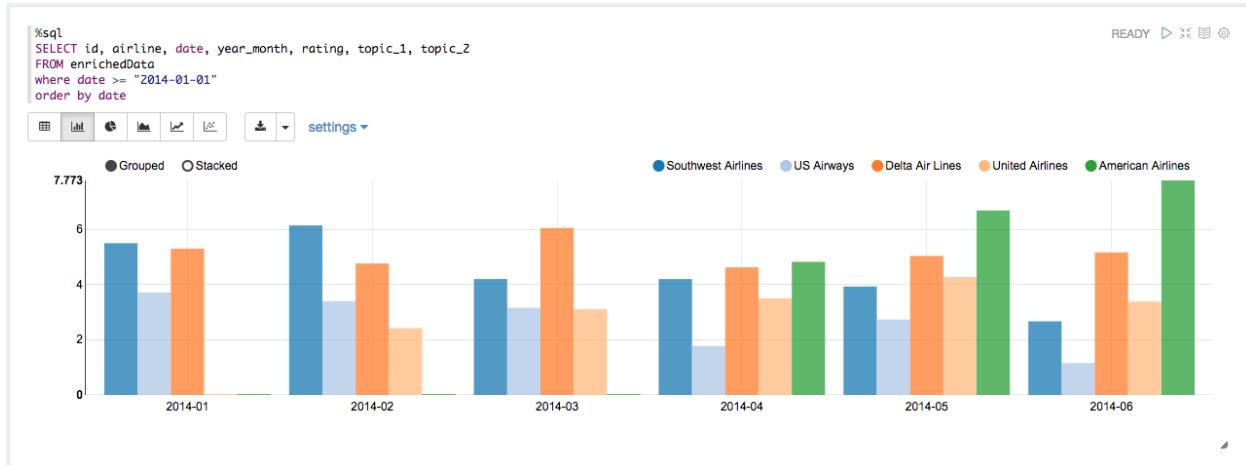
- LDA results

| id | airline | date | cabin | rating | words |
|--------------------------|--------------------|------------|-------------|--------|------------------------------------|
| 10551 | Southwest Airlines | 2013-11-06 | Business | 1.0 | [flight, chicago,...] (4695, [0, |
| 10298 | US Airways | 2014-03-31 | Business | 1.0 | [flight, manchest...] (4695, [0, |
| 10564 | Southwest Airlines | 2013-09-06 | Economy | 10.0 | [executive, plati...] (4695, [0, |
| 10134 | Delta Air Lines | 2013-12-10 | Economy | 8.0 | [msp, jfk, mxp, r...] (4695, [0, |
| 10912 | United Airlines | 2014-04-07 | Economy | 3.0 | [worst, airline, ...] (4695, [0, |
| 10089 | Delta Air Lines | 2014-02-18 | Economy | 2.0 | [dl, mia, lax, im...] (4695, [2, |
| 10385 | US Airways | 2013-10-21 | Economy | 10.0 | [flew, gla, phl, ...] (4695, [0, |
| 10249 | US Airways | 2014-06-17 | Economy | 1.0 | [friend, book, fl...] (4695, [0, |
| 10289 | US Airways | 2014-04-12 | Economy | 10.0 | [flew, air, rome,...] (4695, [0, |
| 10654 | Southwest Airlines | 2012-07-10 | Economy | 8.0 | [lhr, jfk, think,...] (4695, [0, |
| 10754 | American Airlines | 2014-05-04 | Economy | 10.0 | [san, diego, moli...] (4695, [0, |
| 10646 | Southwest Airlines | 2012-08-17 | Economy | 7.0 | [toledo, co, stop...] (4695, [0, |
| 10097 | Delta Air Lines | 2014-02-03 | First Class | 10.0 | [honolulu, la, fi...] (4695, [0, |
| 10132 | Delta Air Lines | 2013-12-16 | Economy | 7.0 | [manchester, uk, ...] (4695, [0, |
| 10560 | Southwest Airlines | 2013-09-20 | Economy | 9.0 | [first, time, sou...] (4695, [0, |
| 10579 | Southwest Airlines | 2013-07-25 | Economy | 0.0 | [plane, land, pm,...] (4695, [2, |
| 10425 | US Airways | 2013-08-06 | Economy | 3.0 | [airway, bad, pro...] (4695, [2, |
| 10650 | Southwest Airlines | 2012-07-27 | Economy | 9.0 | [flew, jfk, lhr, ...] (4695, [0, |
| 10260 | US Airways | 2014-06-03 | Economy | 1.0 | [february, air, u...] (4695, [0, |
| 10202 | Delta Air Lines | 2013-09-14 | Economy | 10.0 | [aug, lhr, jfk, b...] (4695, [1, |
| only showing top 20 rows | | | | | |

- Average rating and airlines for each day



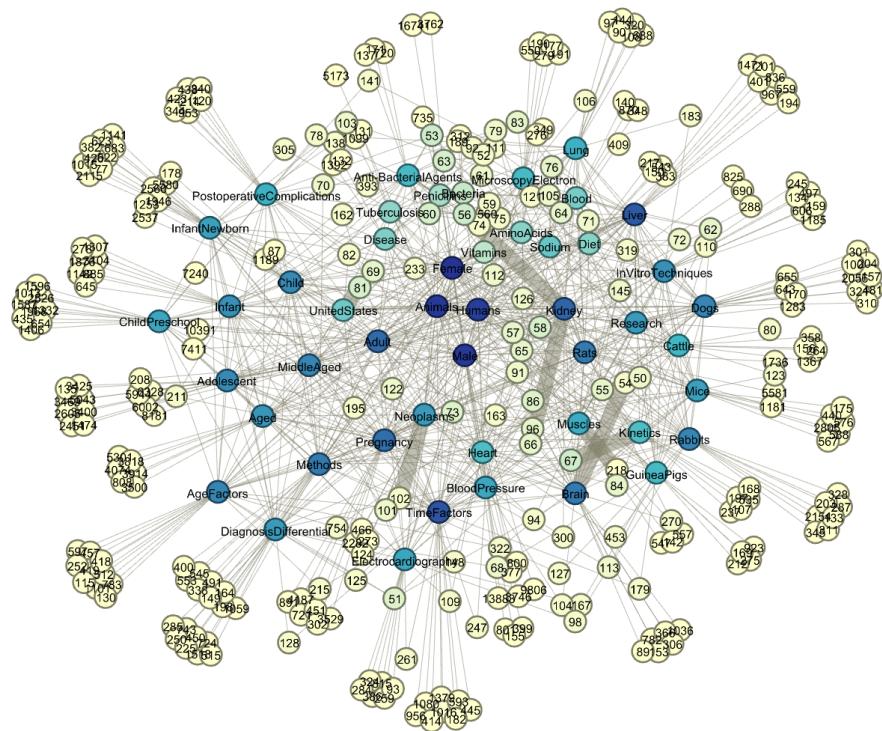
- Average rating and airlines for each month
- Topic 1 corresponding to time line
- reviews (documents) relate to topic 1



| id | airline | date | review |
|--------------------|-------------------------|----------------------|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| 10263 | US Airways | 2014-05-25 | "Delays on all booked flights. Outward bound - Dublin to Philadelphia Philadelphia to Vegas. Vegas to LA. Baggage did not arrive some hours later. Cabin staff were unfriendly and quite rude. From Dublin We were sitting at the back of the plane and and we were told ""thats what you get when you travel at the back"" . I opened my little tub of butter which had been heated in hot liquid and went all over my hand. I said to the stewardess who was passing by who could have brought me a napkin to sped by saying ""oh I know that happens"". Only that I had a tray of food on my lap she would have had more to deal with! What baggage was to be stored in the overhead lockers or underneath the seat in front. This obviously does not apply to cabin staff back centre aisle seats of the plane it was not secured in any way. Their baggage was a danger to all the passengers in that what they preach and put staff baggage in the hold. Cabin crew were ungroomed in appearance. Homeward bound to Dublin delayed resulting in us overnighting in Orlando very grateful for the overnight accommodation provided at the Hyatt. Flew to Charlotte Boarding for Dublin at Charlotte was very confused and inefficiently exercised by Gate staff - resulting in delay in take-off. Enjoyed quality on those flights that had the facility. General impression overall. Very Disappointing." |

SOCIAL NETWORK ANALYSIS

Note: A Touch of Cloth, linked in countless ways. – old Chinese proverb



11.1 Co-occurrence Network

Co-occurrence networks are generally used to provide a graphic visualization of potential relationships between people, organizations, concepts or other entities represented within written material. The generation and visualization of co-occurrence networks has become practical with the advent of electronically stored text amenable to text mining.

11.1.1 Methodology

- Build Corpus C
- Build Document-Term matrix D based on Corpus C
- Compute Term-Document matrix D^T
- Adjacency Matrix $A = D^T \cdot D$

There are four main components in this algorithm in the algorithm: Corpus C, Document-Term matrix D, Term-Document matrix D^T and Adjacency Matrix A. In this demo part, I will show how to build those four main components.

Given that we have three groups of friends, they are

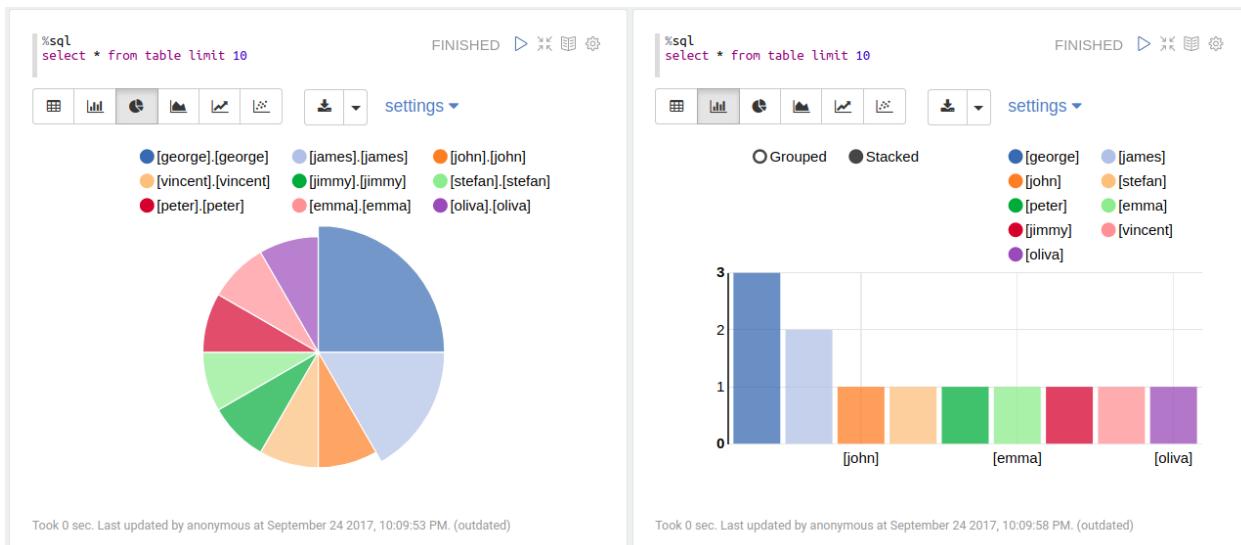
```
+-----+
| words
+-----+
|[ [george] [jimmy] [john] [peter]] |
|[ [vincent] [george] [stefan] [james]] |
|[ [emma] [james] [olivia] [george]] |
+-----+
```

1. Corpus C

Then we can build the following corpus based on the unique elements in the given group data:

```
[u'george', u'james', u'jimmy', u'peter', u'stefan', u'vencent', u'olivia', u'john', u'emma']
```

The corresponding elements frequency:



2. Document-Term matrix D based on Corpus C (CountVectorizer)

```
from pyspark.ml.feature import CountVectorizer
count_vectorizer_wo = CountVectorizer(inputCol='term', outputCol='features')
```

```

# with total unique vocabulary
countVectorizer_mod_wo = count_vectorizer_wo.fit(df)
countVectorizer_twitter_wo = countVectorizer_mod_wo.transform(df)
# with truncated unique vocabulary (99%)
count_vectorizer = CountVectorizer(vocabSize=48, inputCol='term', outputCol='features')
countVectorizer_mod = count_vectorizer.fit(df)
countVectorizer_twitter = countVectorizer_mod.transform(df)

+-----+
| features |
+-----+
| (9,[0,2,3,7],[1.0,1.0,1.0,1.0]) |
| (9,[0,1,4,5],[1.0,1.0,1.0,1.0]) |
| (9,[0,1,6,8],[1.0,1.0,1.0,1.0]) |
+-----+

```

- Term-Document matrix D^T

RDD:

```
[array([ 1.,  1.,  1.]), array([ 0.,  1.,  1.]), array([ 1.,  0.,  0.]),
 array([ 1.,  0.,  0.]), array([ 0.,  1.,  0.]), array([ 0.,  1.,  0.]),
 array([ 0.,  0.,  1.]), array([ 1.,  0.,  0.]), array([ 0.,  0.,  1.])]
```

Matrix:

```
array([[ 1.,  1.,  1.],
       [ 0.,  1.,  1.],
       [ 1.,  0.,  0.],
       [ 1.,  0.,  0.],
       [ 0.,  1.,  0.],
       [ 0.,  1.,  0.],
       [ 0.,  0.,  1.],
       [ 1.,  0.,  0.],
       [ 0.,  0.,  1.]])
```

3. Adjacency Matrix $A = D^T \cdot D$

RDD:

```
[array([ 1.,  1.,  1.]), array([ 0.,  1.,  1.]), array([ 1.,  0.,  0.]),
 array([ 1.,  0.,  0.]), array([ 0.,  1.,  0.]), array([ 0.,  1.,  0.]),
 array([ 0.,  0.,  1.]), array([ 1.,  0.,  0.]), array([ 0.,  0.,  1.])]
```

Matrix:

```
array([[ 3.,  2.,  1.,  1.,  1.,  1.,  1.,  1.,  1.],
       [ 2.,  2.,  0.,  0.,  1.,  1.,  1.,  0.,  1.],
       [ 1.,  0.,  1.,  1.,  0.,  0.,  0.,  1.,  0.],
       [ 1.,  0.,  1.,  1.,  0.,  0.,  0.,  1.,  0.],
       [ 1.,  1.,  0.,  0.,  1.,  1.,  0.,  0.,  0.],
       [ 1.,  1.,  0.,  0.,  1.,  1.,  0.,  0.,  0.],
       [ 1.,  1.,  0.,  0.,  0.,  0.,  1.,  0.,  1.],
       [ 1.,  0.,  1.,  1.,  0.,  0.,  0.,  1.,  0.],
       [ 1.,  1.,  0.,  0.,  0.,  0.,  1.,  0.,  1.]])
```

11.1.2 Coding Puzzle from my interview

- Problem

The attached utf-8 encoded text file contains the tags associated with an online biomedical scientific article formatted as follows (size: 100000). Each Scientific article is represented by a line in the file delimited by carriage return.

```
+-----+
|          words |
+-----+
| [ACTH Syndrome, E...|
| [Antibody Formati...|
| [Adaptation, Phys...|
| [Aerosol Propella...|
+-----+
only showing top 4 rows
```

Write a program that, using this file as input, produces a list of pairs of tags which appear TOGETHER in any order and position in at least fifty different Scientific articles. For example, in the above sample, [Female] and [Humans] appear together twice, but every other pair appears only once. Your program should output the pair list to stdout in the same form as the input (eg tag 1, tag 2n).

- My solution

The corresponding words frequency:

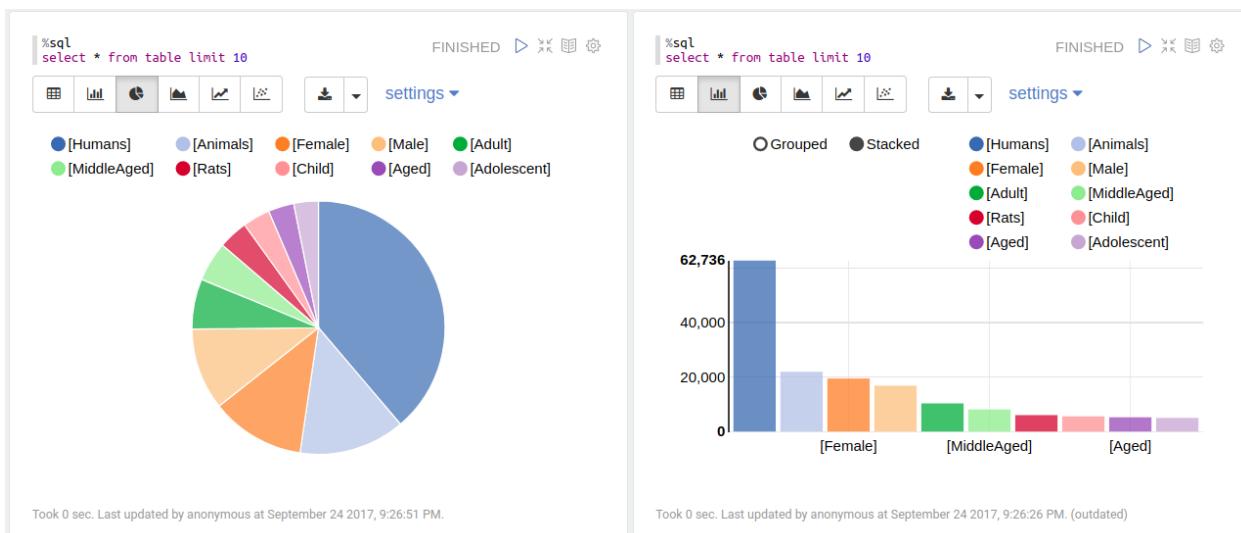


Figure 11.1: Word frequency

Output:

```
+-----+-----+-----+
|      term.x|term.y|    freq|
+-----+-----+-----+
|      Female|Humans|16741.0|
```

```
|   Male|Humans| 13883.0 |
| Adult|Humans| 10391.0 |
|   Male|Female|  9806.0 |
|MiddleAged|Humans|  8181.0 |
|       Adult|Female|  7411.0 |
|       Adult|   Male|  7240.0 |
|MiddleAged|   Male|  6328.0 |
|MiddleAged|Female|  6002.0 |
|MiddleAged| Adult|  5944.0 |
+-----+-----+-----+
only showing top 10 rows
```

The corresponding Co-occurrence network:

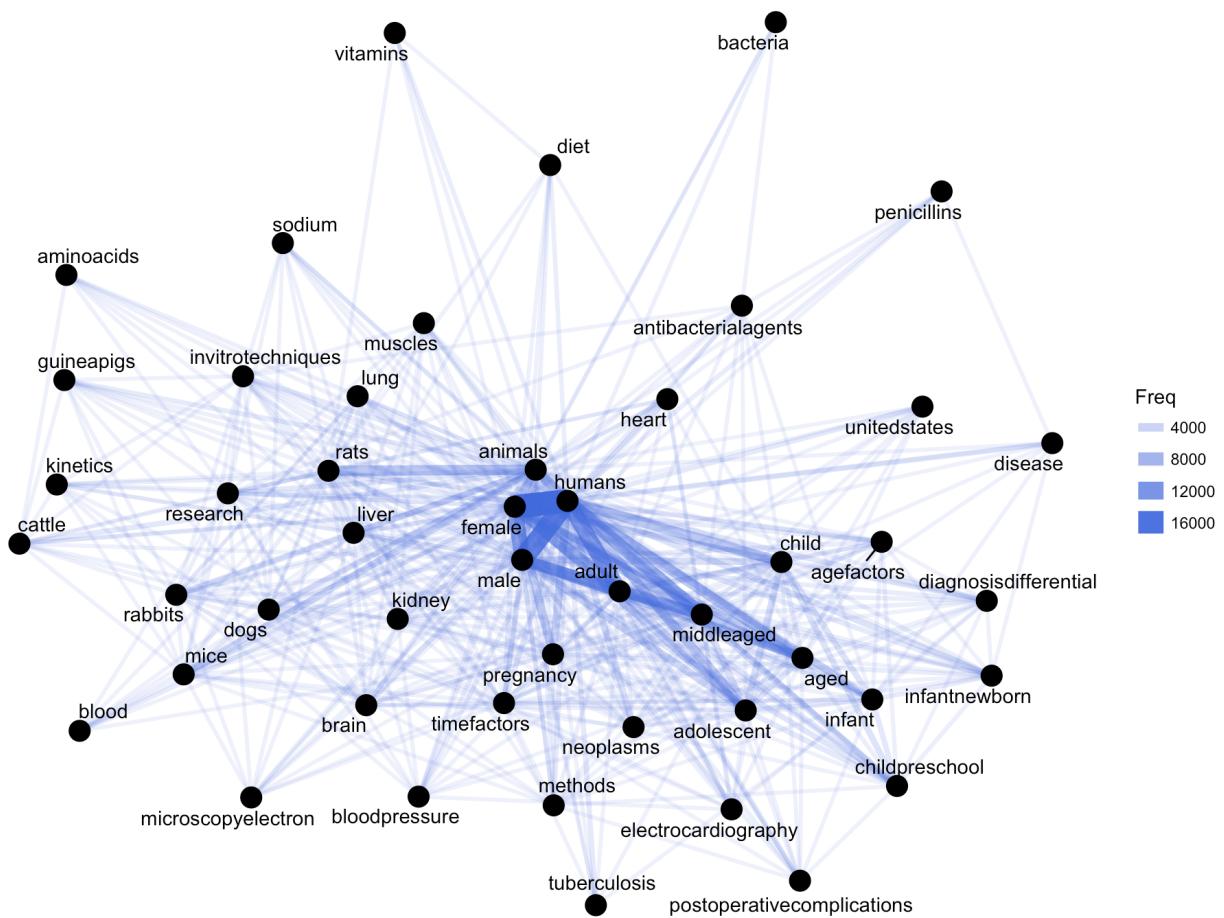


Figure 11.2: Co-occurrence network

Then you will get Figure *Co-occurrence network*

11.2 Correlation Network

NEURAL NETWORK

Note: Sharpening the knife longer can make it easier to hack the firewood – old Chinese proverb

12.1 Feedforward Neural Network

12.1.1 Introduction

A feedforward neural network is an artificial neural network wherein connections between the units do not form a cycle. As such, it is different from recurrent neural networks.

The feedforward neural network was the first and simplest type of artificial neural network devised. In this network, the information moves in only one direction, forward (see Fig. *MultiLayer Neural Network*), from the input nodes, through the hidden nodes (if any) and to the output nodes. There are no cycles or loops in the network.

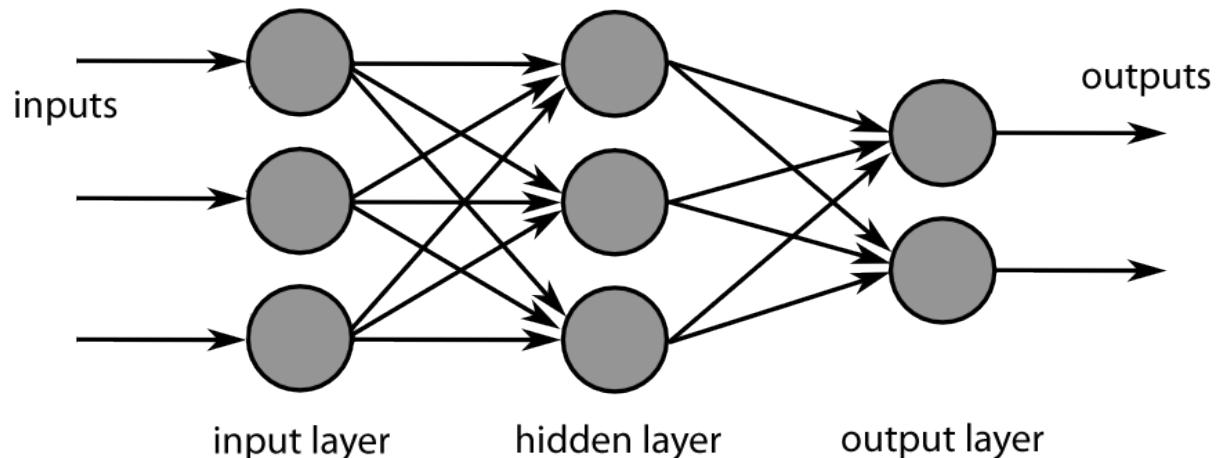


Figure 12.1: MultiLayer Neural Network

12.1.2 Demo

1. Set up spark context and SparkSession

```
from pyspark.sql import SparkSession

spark = SparkSession \
    .builder \
    .appName("Python Spark Feedforward neural network example") \
    .config("spark.some.config.option", "some-value") \
    .getOrCreate()
```

2. Load dataset

```
+-----+-----+-----+-----+-----+-----+-----+-----+-----+
|fixed|volatile|citric|sugar|chlorides|free|total|density| pH|sulphates|alcohol|quality|
+-----+-----+-----+-----+-----+-----+-----+-----+-----+
|  7.4|     0.7|    0.0|   1.9|  0.076|11.0| 34.0| 0.9978|3.51|  0.56|    9.4|    5|
|  7.8|     0.88|   0.0|   2.6|  0.098|25.0| 67.0| 0.9968| 3.2|  0.68|    9.8|    5|
|  7.8|     0.76|   0.04|   2.3|  0.092|15.0| 54.0| 0.997|3.26|  0.65|    9.8|    5|
| 11.2|     0.28|   0.56|   1.9|  0.075|17.0| 60.0| 0.998|3.16|  0.58|    9.8|    6|
|  7.4|     0.7|    0.0|   1.9|  0.076|11.0| 34.0| 0.9978|3.51|  0.56|    9.4|    5|
+-----+-----+-----+-----+-----+-----+-----+-----+-----+
only showing top 5 rows
```

3. change categorical variable size

```
# Convert to float format
def string_to_float(x):
    return float(x)

#
def condition(r):
    if (0 <= r <= 4):
        label = "low"
    elif(4 < r <= 6):
        label = "medium"
    else:
        label = "high"
    return label

from pyspark.sql.functions import udf
from pyspark.sql.types import StringType, DoubleType
string_to_float_udf = udf(string_to_float, DoubleType())
quality_udf = udf(lambda x: condition(x), StringType())
df= df.withColumn("quality", quality_udf("quality"))
```

4. Convert the data to dense vector

```
# convert the data to dense vector
def transData(data):
    return data.rdd.map(lambda r: [r[-1], Vectors.dense(r[:-1])]).\
        toDF(['label','features'])
```

```

from pyspark.sql import Row
from pyspark.ml.linalg import Vectors

data= transData(df)
data.show()

```

5. Split the data into training and test sets (40% held out for testing)

```

# Split the data into train and test
(trainingData, testData) = data.randomSplit([0.6, 0.4])

```

6. Train neural network

```

# specify layers for the neural network:
# input layer of size 11 (features), two intermediate of size 5 and 4
# and output of size 7 (classes)
layers = [11, 5, 4, 4, 3, 7]

# create the trainer and set its parameters
FNN = MultilayerPerceptronClassifier(labelCol="indexedLabel", \
                                      featuresCol="indexedFeatures", \
                                      maxIter=100, layers=layers, \
                                      blockSize=128, seed=1234)
# Convert indexed labels back to original labels.
labelConverter = IndexToString(inputCol="prediction", outputCol="predictedLabel", \
                                 labels=labelIndexer.labels)
# Chain indexers and forest in a Pipeline
from pyspark.ml import Pipeline
pipeline = Pipeline(stages=[labelIndexer, featureIndexer, FNN, labelConverter])
# train the model
# Train model. This also runs the indexers.
model = pipeline.fit(trainingData)

```

7. Make predictions

```

# Make predictions.
predictions = model.transform(testData)
# Select example rows to display.
predictions.select("features", "label", "predictedLabel").show(5)

```

8. Evaluation

```

# Select (prediction, true label) and compute test error
evaluator = MulticlassClassificationEvaluator(
    labelCol="indexedLabel", predictionCol="prediction", metricName="accuracy")
accuracy = evaluator.evaluate(predictions)
print("Predictions accuracy = %g, Test Error = %g" % (accuracy, (1.0 - accuracy)))

```

**CHAPTER
THIRTEEN**

MAIN REFERENCE

BIBLIOGRAPHY

- [Bird2009] 19. Bird, E. Klein, and E. Loper. Natural language processing with Python: analyzing text with the natural language toolkit. O'Reilly Media, Inc., 2009.
- [Feng2017] 23. Feng and M. Chen. [Learning Apache Spark](#), Github 2017.
- [Karau2015] 8. Karau, A. Konwinski, P. Wendell and M. Zaharia. Learning Spark: Lightning-Fast Big Data Analysis. O'Reilly Media, Inc., 2015
- [Kirillov2016] Anton Kirillov. Apache Spark: core concepts, architecture and internals.
<http://datastrophic.io/core-concepts-architecture-and-internals-of-apache-spark/>

INDEX

C

Configure Spark on Mac and Ubuntu, [14](#)

R

Run on Databricks Community Cloud, [9](#)

S

Set up Spark on Cloud, [19](#)