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DEPARTMENT OF COMPUTER SCIENCE AND
ENGINEERING



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SUBJECT: Big Data
Analytics[18CS72]

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INTRODUCTION



What is Apache Spark?

Apache Spark is a multi-language engine for executing data engineering, data science, and machine learning on single-node machines or clusters.

Features:

- Lightning fast real-time processing framework, Written in Scala (JVM).
- For python interface, Py4J library is used
- in-memory computations, Lazy execution and Parallel Processing
- Apache Hadoop MapReduce was performing batch processing only and lacked a real-time processing feature. Spark does Batch and Real time processing
- It leverages Apache Hadoop for both storage and processing. It uses HDFS (Hadoop Distributed File system) for storage and it can run Spark applications on YARN as well.
- Spark can load data directly from disk, memory and other data storage technologies such as Amazon S3, Hadoop Distributed File System (HDFS), HBase, Cassandra

Difference Between Spark and Map Reduce:

MAP REDUCE	SPARK
Computing Framework Engine, open source managed by Apache	Computing Framework Engine, open source managed by Apache
Yes , Map Reduce is Faster than traditional system but it does not leverage the memory of hadoop cluster to the maximum	spark has been proved to execute the batch processing jobs 10 to 100 times faster
Map Reduce is disk Oriented completely. Higher latency. No caching support.	Spark ensures lower latency computations by caching the partials results across its memory of distributed hardware. Stores data in memory
MapReduce is a cheaper option available while comparing it in terms of cost.	As spark requires a lot of RAM to run in-memory. Thus, increases the cluster, and also its cost.
Writing Map reduce pipelines is complex and lengthy as it is purely Java	Writing Spark code is always easy and we can write in 4 languages
Batch Processing	Batch/Iterative/ Real Time /Interactive Processing
Fault Tolerance and Highly Scalable and Cross platform	Fault Tolerance and Highly Scalable and Cross platform
Map Reduce has been tested on 15000 nodes	Spark has been tested on 8000 nodes
it has not inbuilt support to various things like SQL,ML,RT	it has in built support to various things like SQL,ML,RT
It is basic data processing engine.	It is data analytics engine. Hence, it is a choice for Data Scientist.
MapReduce runs very well on commodity hardware.	Spark needs mid to high-level hardware.



PySpark:

PySpark is an interface for Apache Spark in Python. It not only allows you to write Spark applications using Python APIs, but also provides the PySpark shell for interactively analyzing your data in a distributed environment. PySpark supports most of Spark's features such as Spark SQL, DataFrame, Streaming, MLlib (Machine Learning) and Spark Core.



- Apache Spark community released a tool, PySpark.
- It lets us use the power of Apache Spark in order to tame Big Data.
- It is because of a library called Py4j that they are able to achieve this.
- To use PySpark you will have to install python and Apache spark on your machine.
- Using PySpark, we can work with RDDs in Python programming language also.

Installing Spark in Local Environment

1. Install Java 8

Run the executable, and JAVA by default will be installed in:

C:\Program Files\Java\jdk1.8.0_201

Add the following environment variable:

```
JAVA_HOME = C:\Program Files\Java\jdk1.8.0_201
```

Add to PATH variable the following directory:

```
C:\Program Files\Java\jdk1.8.0_201\bin
```

2. Download and Install Spark

Extract the file to your chosen directory (7z can open tgz). In my case, it was C:\spark. There is another compressed directory in the tar, extract it (into here) as well.

Setup the environment variables

```
SPARK_HOME = C:\spark\spark-2.3.2-bin-hadoop2.7  
HADOOP_HOME = C:\spark\spark-2.3.2-bin-hadoop2.7
```

Add the following path to PATH environment variable:

```
C:\spark\spark-2.3.2-bin-hadoop2.7\bin
```

3. Download and setup winutils.exe

In hadoop binaries repository, <https://github.com/steveloughran/winutils> choose your hadoop version, then goto bin, and download the [winutils.exe](#) file. In my case: <https://github.com/steveloughran/winutils/blob/master/hadoop-2.7.1/bin/winutils.exe>

Save [winutils.exe](#) in to bin directory of your spark installation

4. Check PySpark installation

In your anaconda prompt, or any python supporting cmd, type pyspark, to enter pyspark shell. To be prepared, best to check it in the python environment from which you run jupyter notebook. You supposed to see the following:

```
(py36) C:\Users\naomi>pyspark
Python 3.6.5 [Anaconda custom (64-bit)] (default, Mar 29 2018, 13:32:41) [MSC v.1900 64 bit (AMD64)] on win32
Type "help", "copyright", "credits" or "license" for more information.
2019-01-20 23:23:03 WARN NativeCodeLoader:62 - Unable to load native-hadoop library for your platform... using builtin-
java classes where applicable
Setting default log level to "WARN".
To adjust logging level use sc.setLogLevel(newLevel). For SparkR, use setLogLevel(newLevel).
Welcome to

  ____      __
  /  _ \    / /
 /  /_\ \  / /
/_____\ \_/ /
         \_/_/ version 2.4.0

Using Python version 3.6.5 (default, Mar 29 2018 13:32:41)
SparkSession available as 'spark'.
>>>
```

5. PySpark with Jupyter notebook

Install conda findspark, to access spark instance from jupyter notebook. Check current installation in [Anaconda cloud](#). In time of writing:
conda install -c conda-forge findspark

Open your python jupyter notebook, and write inside:

```
import findspark
findspark.init()
import pyspark
findspark.find()
```

Last line will output SPARK_HOME path. It's just for test, you can delete it.

```
from pyspark import SparkContext, SparkConf
from pyspark.sql import SparkSessionConf =
pyspark.SparkConf().setAppName('appName').setMaster('local')
sc = pyspark.SparkContext(conf=conf)
spark = SparkSession(sc)
```

`pyspark.sql.Session` : Main entry point for `DataFrame` and SQL functionality.

DATA SETS

Data Set Link: <https://www.kaggle.com/mathchi/diabetes-data-set?select=diabetes.csv>

Context

This dataset is originally from the National Institute of Diabetes and Digestive and Kidney Diseases. The objective is to predict based on diagnostic measurements whether a patient has diabetes.

Content

Several constraints were placed on the selection of these instances from a larger database. In particular, all patients here are females at least 21 years old of Pima Indian heritage.

- Pregnancies: Number of times pregnant
- Glucose: Plasma glucose concentration a 2 hours in an oral glucose tolerance test
- BloodPressure: Diastolic blood pressure (mm Hg)
- SkinThickness: Triceps skin fold thickness (mm)
- Insulin: 2-Hour serum insulin (mu U/ml)
- BMI: Body mass index (weight in kg/(height in m)²)
- DiabetesPedigreeFunction: Diabetes pedigree function
- Age: Age (years)
- Outcome: Class variable (0 or 1)

Number of Instances: 768

Number of Attributes: 8 plus class

For Each Attribute: (all numeric-valued)

1. Number of times pregnant
2. Plasma glucose concentration a 2 hours in an oral glucose tolerance test
3. Diastolic blood pressure (mm Hg)
4. Triceps skin fold thickness (mm)
5. 2-Hour serum insulin (mu U/ml)

6. Body mass index (weight in kg/(height in m)^2)
7. Diabetes pedigree function
8. Age (years)
9. Class variable (0 or 1)

Missing Attribute Values: Yes

Class Distribution: (class value 1 is interpreted as "tested positive for diabetes")

Problem Statement:

Diabetes:

According to WHO, Diabetes is a chronic disease that occurs either when the pancreas does not produce enough insulin or when the body cannot effectively use the insulin it produces. Insulin is a hormone that regulates blood sugar. Hyperglycaemia, or raised blood sugar, is a common effect of uncontrolled diabetes and over time leads to serious damage to many of the body's systems, especially the nerves and blood vessels.

Using various ML Algorithms, we are classifying the datasets and checking which gives better accuracy.

ScreenShots:

```
In [10]: import findspark
findspark.init()
findspark.find()
from pyspark.sql import SparkSession

from pyspark.ml.feature import VectorAssembler
from pyspark.ml.feature import StandardScaler

from pyspark.ml.classification import LogisticRegression
from pyspark.ml.classification import NaiveBayes
from pyspark.ml.classification import GBTClassifier
from pyspark.ml.classification import RandomForestClassifier

from pyspark.mllib.evaluation import BinaryClassificationMetrics
from pyspark.ml.evaluation import MulticlassClassificationEvaluator
```

```
In [11]: spark = SparkSession.builder.appName("Classification with Spark").getOrCreate()
```

```
In [12]: dataset = spark.read.csv("diabetes.csv",header=True)
```

```
In [13]: dataset.show()
```

Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age	Outcome
6	148	72	35	0	33.6	0.627	50	1
1	85	66	29	0	26.6	0.351	31	0
8	183	64	0	0	23.3	0.672	32	1
1	89	66	23	94	28.1	0.167	21	0
0	137	40	35	168	43.1	2.288	33	1
5	116	74	0	0	25.6	0.201	30	0
3	78	50	32	88	31	0.248	26	1
10	115	0	0	0	35.3	0.134	29	0
2	197	70	45	543	30.5	0.158	53	1
8	125	96	0	0	0	0.232	54	1
4	110	92	0	0	37.6	0.191	30	0
10	168	74	0	0	38	0.537	34	1
10	139	80	0	0	27.1	1.441	57	0
1	189	60	23	846	30.1	0.398	59	1
5	166	72	19	175	25.8	0.587	51	1
7	100	0	0	0	30	0.484	32	1
0	118	84	47	230	45.8	0.551	31	1
7	107	74	0	0	29.6	0.254	31	1
1	103	30	38	83	43.3	0.183	33	0
1	115	70	30	96	34.6	0.529	32	1

only showing top 20 rows

```
In [14]: dataset.printSchema()
```

```
root
|-- Pregnancies: string (nullable = true)
|-- Glucose: string (nullable = true)
|-- BloodPressure: string (nullable = true)
|-- SkinThickness: string (nullable = true)
|-- Insulin: string (nullable = true)
|-- BMI: string (nullable = true)
|-- DiabetesPedigreeFunction: string (nullable = true)
|-- Age: string (nullable = true)
|-- Outcome: string (nullable = true)
```

```
In [15]: from pyspark.sql.functions import col
new_data = dataset.select(*(col(c).cast("float").alias(c) for c in dataset.columns))
```

```
In [16]: new_data.printSchema()
```

```
root
|-- Pregnancies: float (nullable = true)
|-- Glucose: float (nullable = true)
|-- BloodPressure: float (nullable = true)
|-- SkinThickness: float (nullable = true)
|-- Insulin: float (nullable = true)
|-- BMI: float (nullable = true)
|-- DiabetesPedigreeFunction: float (nullable = true)
|-- Age: float (nullable = true)
|-- Outcome: float (nullable = true)
```



```
In [17]: from pyspark.sql.functions import col, count, isnan, when
#checking for null in nan type values in our columns
new_data.select([count(when(col(c).isNull(), c)).alias(c) for c in new_data.columns]).show()
```

Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age	Outcome
0	0	0	0	0	0	0	0	0

```
In [18]: cols=new_data.columns
cols.remove("Outcome")
assembler = VectorAssembler(inputCols=cols,outputCol="features")

# Now let us use the transform method to transform our dataset
data=assembler.transform(new_data)

data.select("features", 'Outcome').show(truncate=False)
```

features	Outcome
[6.0,148.0,72.0,35.0,0.0,33.599998474121094,0.6269999742507935,50.0]	1.0
[1.0,85.0,66.0,29.0,0.0,26.600000381469727,0.35100001096725464,31.0]	0.0
[8.0,183.0,64.0,0.0,0.0,23.299999237060547,0.671999990940094,32.0]	1.0
[1.0,89.0,66.0,23.0,94.0,28.100000381469727,0.16699999570846558,21.0]	0.0
[0.0,137.0,40.0,35.0,168.0,43.099998474121094,2.2880001068115234,33.0]	1.0
[5.0,116.0,74.0,0.0,0.0,25.600000381469727,0.20100000500679016,30.0]	0.0
[3.0,78.0,50.0,32.0,88.0,31.0,0.24799999594688416,26.0]	1.0
[10.0,115.0,0.0,0.0,0.0,35.29999923706055,0.1340000033378601,29.0]	0.0
[2.0,197.0,70.0,45.0,543.0,30.5,0.15800000727176666,53.0]	1.0
[8.0,125.0,96.0,0.0,0.0,0.0,0.23199999332427979,54.0]	1.0
[4.0,110.0,92.0,0.0,0.0,37.599998474121094,0.19099999964237213,30.0]	0.0
[10.0,168.0,74.0,0.0,0.0,38.0,0.5370000004768372,34.0]	1.0
[10.0,139.0,80.0,0.0,0.0,27.100000381469727,1.440999984741211,57.0]	0.0
[1.0,189.0,60.0,23.0,846.0,30.100000381469727,0.39800000190734863,59.0]	1.0
[5.0,166.0,72.0,19.0,175.0,25.799999237060547,0.5870000123977661,51.0]	1.0
[7.0,100.0,0.0,0.0,0.0,30.0,0.48399999737739563,32.0]	1.0
[0.0,118.0,84.0,47.0,230.0,45.79999923706055,0.5509999990463257,31.0]	1.0
[7.0,107.0,74.0,0.0,0.0,29.600000381469727,0.2540000081062317,31.0]	1.0
[1.0,103.0,30.0,38.0,83.0,43.29999923706055,0.18299999833106995,33.0]	0.0
[1.0,115.0,70.0,30.0,96.0,34.599998474121094,0.5289999842643738,32.0]	1.0

only showing top 20 rows

```
In [19]: standardscaler=StandardScaler().setInputCol("features").setOutputCol("Scaled_features")
data=standardscaler.fit(data).transform(data)
```

```
In [20]: data.select("features", "Outcome", "Scaled_features").show(truncate=False)
```

```
+-----+-----+-----+
|features|Outcome|Scaled_features|
+-----+-----+-----+
|[6.0,148.0,72.0,35.0,0.0,0.0,33.599998474121094,0.6269999742507935,50.0]|1.0|[1.7806383732194306,4.628960915766174,3.7198138711154307,2.1940523222807116,0.0,4.261709202425419,1.8923810993699686,4.251616970894646]|
|[1.0,85.0,66.0,29.0,0.0,26.600000381469727,0.35100001096725464,31.0]|0.0|[0.29677306220323846,2.658524850271114,3.4098293818558116,1.8179290670325896,0.0,3.373853320188119,1.0593713140527197,2.6360025219546803]|
|[8.0,183.0,64.0,0.0,0.0,23.299999237060547,0.671999990940094,32.0]|1.0|[2.3741844976259077,5.723647618818986,3.306501218769272,0.0,0.0,2.955292430788826,2.028197980632078,2.721034861372573]|
|[1.0,89.0,66.0,23.0,94.0,28.100000381469727,0.16699999570846558,21.0]|0.0|[0.29677306220323846,2.783631902048578,3.4098293818558116,1.4418058117844677,0.8156606685129459,3.564108203936454,0.5040313372439763,1.785679127775751]|
|[0.0,137.0,40.0,35.0,168.0,43.099998474121094,2.2880001068115234,33.0]|1.0|[0.0,4.284916523378148,2.0665632617307947,2.1940523222807116,1.4577765139380312,5.466656799498205,6.905531635244907,2.806067200790466]|
|[5.0,116.0,74.0,0.0,0.0,25.600000381469727,0.20100000500679016,30.0]|0.0|[1.4838653110161923,3.628104501546461,3.823142034201971,0.0,0.0,3.247016731022563,0.6066485264255773,2.5509701825367874]|
|[3.0,78.0,50.0,32.0,88.0,31.0,0.24799999594688416,26.0]|1.0|[0.8903191866097153,2.4395875096605515,2.5832040771634937,2.0059906946566506,0.7635972215865877,3.9319342641322486,0.7485016335678398,2.210840824865216]|
|[10.0,115.0,0.0,0.0,0.0,35.29999923706055,0.1340000033378601,29.0]|0.0|[2.9677306220323847,3.596827738602095,0.0,0.0,0.0,4.477331500775503,0.4044323509503849,2.4659378431188945]|
|[2.0,197.0,70.0,45.0,543.0,30.5,0.15800000727176666,53.0]|1.0|[0.5935461244064769,6.161522300040111,3.616485708028891,2.8209244143609147,4.711741946835422,3.8685159695494704,0.4768680059655209,4.5067139891483246]|
|[8.0,125.0,96.0,0.0,0.0,0.0,23199999332427979,54.0]|1.0|[2.3741844976259077,3.9095953680457556,4.959751828153908,0.0,0.0,0.0,7002111968910825,4.5917463285662174]|
|[4.0,110.0,92.0,0.0,0.0,0.0,37.599998474121094,0.19099999964237213,30.0]|0.0|[1.1870922488129538,3.440443923880265,4.7530955019808285,0.0,0.0,4.7690555590876444,0.5764669922591124,2.5509701825367874]|
|[10.0,168.0,74.0,0.0,0.0,0.0,38.0,0.5370000004768372,34.0]|1.0|[2.9677306220323847,5.254496174653495,3.823142034201971,0.0,0.0,4.8197903882911435,1.6207475167416163,2.891099540208359]|
|[10.0,139.0,80.0,0.0,0.0,27.100000381469727,1.440999984741211,57.0]|0.0|[2.9677306220323847,4.34747004926688,4.1331265234615895,0.0,0.0,3.4372716147708973,4.349156694264776,4.846843346819896]|
|[1.0,189.0,60.0,23.0,846.0,30.100000381469727,0.39800000190734863,59.0]|1.0|[0.29677306220323846,5.911308196485182,3.0998448925961926,1.4418058117844677,7.340946016616514,3.8177813822675666,1.201224421194982,5.016908025655682]|
|[5.0,166.0,72.0,19.0,175.0,25.799999237060547,0.5870000123977661,51.0]|1.0|[1.4838653110161923,5.191942648764763,3.7198138711154307,1.1910569749523863,1.5185172020187825,3.272383903702717,1.7716551425999747,4.336649310312539]|
|[7.0,100.0,0.0,0.0,0.0,30.0,0.48399999737739563,32.0]|1.0|[2.077411435422669,3.127676294436604,0.0,0.0,0.0,3.8050976749666923,1.4607854621150949,2.721034861372573]|
|[0.0,118.0,84.0,47.0,230.0,45.79999923706055,0.5509999990463257,31.0]|1.0|[0.0,3.6906580274351932,4.33978284963467,2.9462988327769555,1.9957654655103998,5.809115687013845,1.6630016375902872,2.6360025219546803]|
|[7.0,107.0,74.0,0.0,0.0,29.600000381469727,0.2540000081062317,31.0]|1.0|[2.077411435422669,3.3466136350471665,3.823142034201971,0.0,0.0,3.7543630876847884,0.7666105810520987,2.6360025219546803]|
|[1.0,103.0,30.0,38.0,83.0,43.29999923706055,0.1829999833106995,33.0]|0.0|[0.29677306220323846,3.2215065832697025,1.5499224462980963,2.3821139499047725,0.7202110158146225,5.4920242140999544,0.5523217739207337,2.806067200790466]|
|[1.0,115.0,70.0,30.0,96.0,34.599998474121094,0.5289999842643738,32.0]|1.0|[0.29677306220323846,3.596827738602095,3.616485708028891,1.88061627624061,0.833015150821732,4.388545791590976,1.596602253429271,2.721034861372573]|
+-----+-----+-----+
```

only showing top 20 rows

```
In [21]: assembled_data = data.select("Scaled_features", "Outcome")
assembled_data.show()
```

```
+-----+-----+
|Scaled_features|Outcome|
+-----+-----+
|[1.78063837321943...]|1.0|
|[0.29677306220323...]|0.0|
|[2.37418449762590...]|1.0|
|[0.29677306220323...]|0.0|
|[0.0,4.2849165233...]|1.0|
|[1.48386531101619...]|0.0|
|[0.89031918660971...]|1.0|
|[2.96773062203238...]|0.0|
|[0.59354612440647...]|1.0|
|[2.37418449762590...]|1.0|
|[1.18709224881295...]|0.0|
|[2.96773062203238...]|1.0|
|[2.96773062203238...]|0.0|
|[0.29677306220323...]|1.0|
|[1.48386531101619...]|1.0|
|[2.07741143542266...]|1.0|
|[0.0,3.6906580274...]|1.0|
|[2.07741143542266...]|1.0|
|[0.29677306220323...]|0.0|
|[0.29677306220323...]|1.0|
+-----+-----+
```

only showing top 20 rows

```
In [22]: train, test = assembled_data.randomSplit([0.7, 0.3])
```

```
In [23]: train.show()
```

```
+-----+-----+
| Scaled_features|Outcome|
+-----+-----+
|(8,[0,1,6,7],[0.5...| 0.0|
|(8,[0,1,6,7],[0.5...| 0.0|
|(8,[0,1,6,7],[0.8...| 0.0|
|(8,[0,1,6,7],[1.7...| 0.0|
|(8,[0,1,6,7],[2.9...| 1.0|
|(8,[1,5,6,7],[3.0...| 0.0|
|(8,[1,5,6,7],[3.6...| 0.0|
|(8,[1,5,6,7],[4.3...| 1.0|
|(8,[1,5,6,7],[4.4...| 1.0|
|(8,[1,5,6,7],[4.5...| 1.0|
|(8,[1,5,6,7],[5.2...| 1.0|
|(8,[1,6,7],[2.940...| 0.0|
|[0.0,1.7827754878...| 0.0|
|[0.0,2.3144804578...| 0.0|
|[0.0,2.4395875096...| 0.0|
|[0.0,2.6272480873...| 0.0|
|[0.0,2.6898016132...| 0.0|
|[0.0,2.8461854279...| 0.0|
|[0.0,2.8461854279...| 0.0|
|[0.0,2.9087389538...| 0.0|
+-----+-----+
only showing top 20 rows
```

```
In [24]: test.show()
```

```
+-----+-----+
| Scaled_features|Outcome|
+-----+-----+
|(8,[0,1,6,7],[2.0...| 0.0|
|(8,[1,5,6,7],[2.2...| 0.0|
|(8,[1,5,6,7],[3.7...| 1.0|
|(8,[1,5,6,7],[4.0...| 1.0|
|[0.0,2.0955431172...| 0.0|
|[0.0,2.6272480873...| 0.0|
|[0.0,2.9087389538...| 0.0|
|[0.0,2.9400157167...| 0.0|
|[0.0,3.1276762944...| 0.0|
|[0.0,3.1589530573...| 0.0|
|[0.0,3.1902298203...| 0.0|
|[0.0,3.1902298203...| 0.0|
|[0.0,3.1902298203...| 0.0|
|[0.0,3.2840601091...| 1.0|
|[0.0,3.2840601091...| 0.0|
|[0.0,3.3153368721...| 0.0|
|[0.0,3.3466136350...| 0.0|
|[0.0,3.5342742127...| 0.0|
|[0.0,3.5655509756...| 0.0|
|[0.0,3.7219347903...| 0.0|
+-----+-----+
only showing top 20 rows
```

Logistic Regression

```
In [25]: log_reg = LogisticRegression(labelCol="Outcome", featuresCol="Scaled_features",maxIter=40)
         model=log_reg.fit(train)
```

```
In [26]: prediction_test=model.transform(test)
```

```
In [27]: prediction_test.show()
```

```
+-----+-----+-----+-----+-----+
| Scaled_features|Outcome| rawPrediction| probability|prediction|
+-----+-----+-----+-----+-----+
|(8,[0,1,6,7],[2.0...| 0.0|[3.00934626047817...|[0.95299457813441...| 0.0|
|(8,[1,5,6,7],[2.2...| 0.0|[2.86249672911400...|[0.94596107132278...| 0.0|
|(8,[1,5,6,7],[3.7...| 1.0|[0.43302150915964...|[0.60659494563541...| 0.0|
|(8,[1,5,6,7],[4.0...| 1.0|[0.0873447563720...|[0.25211860776150...| 1.0|
|[0.0,2.0955431172...| 0.0|[2.02100635901620...|[0.88298502870374...| 0.0|
|[0.0,2.6272480873...| 0.0|[2.21764386312331...|[0.90182278440525...| 0.0|
|[0.0,2.9087389538...| 0.0|[1.23263301888761...|[0.77427908187886...| 0.0|
|[0.0,2.9400157167...| 0.0|[1.47187569539789...|[0.81334231509700...| 0.0|
|[0.0,3.1276762944...| 0.0|[0.65635090074451...|[0.65844019316943...| 0.0|
|[0.0,3.1589530573...| 0.0|[2.85982177280004...|[0.94582416773803...| 0.0|
|[0.0,3.1902298203...| 0.0|[1.26717365409503...|[0.78025854021615...| 0.0|
|[0.0,3.1902298203...| 0.0|[2.19723997633928...|[0.90000138590173...| 0.0|
|[0.0,3.1902298203...| 0.0|[2.26711075930569...|[0.90611628955997...| 0.0|
|[0.0,3.2840601091...| 1.0|[1.57367137141972...|[0.82830636161183...| 0.0|
|[0.0,3.2840601091...| 0.0|[2.28199514129786...|[0.90737486630932...| 0.0|
|[0.0,3.3153368721...| 0.0|[1.18340640009529...|[0.76555973069936...| 0.0|
|[0.0,3.3466136350...| 0.0|[0.54445468871403...|[0.63284808202811...| 0.0|
|[0.0,3.5342742127...| 0.0|[1.58300582535699...|[0.82962979500114...| 0.0|
|[0.0,3.5655509756...| 0.0|[0.92099615367912...|[0.71524503539201...| 0.0|
|[0.0,3.7219347903...| 0.0|[1.00434322689320...|[0.73191165143244...| 0.0|
+-----+-----+-----+-----+-----+
only showing top 20 rows
```

```
In [19]: prediction_test.select("Outcome", "prediction").show(10)
```

```
+-----+-----+
|Outcome|prediction|
+-----+-----+
|    0.0|      0.0|
|    0.0|      0.0|
|    0.0|      1.0|
|    0.0|      0.0|
|    0.0|      0.0|
|    0.0|      0.0|
|    0.0|      0.0|
|    0.0|      0.0|
|    0.0|      0.0|
|    1.0|      0.0|
+-----+-----+
only showing top 10 rows
```

```
In [20]: # Compute raw scores on the test set
predictionAndLabels = prediction_test.select("Outcome", "prediction").rdd
```

```
In [21]: predictionAndLabels.collect()
```

```
Out[21]: [Row(Outcome=0.0, prediction=0.0),
Row(Outcome=0.0, prediction=0.0),
Row(Outcome=0.0, prediction=1.0),
Row(Outcome=0.0, prediction=0.0),
Row(Outcome=0.0, prediction=0.0),
Row(Outcome=0.0, prediction=0.0),
Row(Outcome=0.0, prediction=0.0),
Row(Outcome=0.0, prediction=0.0),
Row(Outcome=0.0, prediction=0.0),
Row(Outcome=0.0, prediction=0.0),
Row(Outcome=1.0, prediction=0.0),
Row(Outcome=0.0, prediction=0.0),
Row(Outcome=1.0, prediction=0.0),
Row(Outcome=0.0, prediction=0.0),
Row(Outcome=1.0, prediction=0.0),
Row(Outcome=0.0, prediction=0.0),
Row(Outcome=0.0, prediction=0.0),
Row(Outcome=0.0, prediction=0.0),
Row(Outcome=1.0, prediction=0.0),
Row(Outcome=0.0, prediction=0.0),
Row(Outcome=0.0, prediction=0.0)]
```

```
In [22]: metrics = BinaryClassificationMetrics(predictionAndLabels)
```

```
# Area under ROC curve
print("Area under ROC = %s" % metrics.areaUnderROC)
```

```
C:\Users\anjali\anaconda3\lib\site-packages\pyspark\sql\context.py:125: FutureWarning: Deprecated in 3.0.0. Use SparkSession.builder.getOrCreate() instead.
  warnings.warn(
```

```
Area under ROC = 0.7630208333333334
```

```
In [ ]:
```

```
In [28]: evaluator = MulticlassClassificationEvaluator(labelCol="Outcome", predictionCol="prediction", metricName="accuracy")
accuracy_LR = evaluator.evaluate(prediction_test)
print("Accuracy = ", accuracy_LR)
```

```
Accuracy = 0.7860082304526749
```

NaiveBayes

```
In [29]: naive_bayes = NaiveBayes(featuresCol='Scaled_features', labelCol='Outcome', smoothing=1.0)
```

```
In [30]: model = naive_bayes.fit(train)
```

```
In [31]: # select example rows to display.
prediction_test = model.transform(test)
```

```
In [32]: prediction_test.show()
```

Scaled_features	Outcome	rawPrediction	probability	prediction
(8,[0,1,6,7],[2.0...	0.0	[-17.913465045042...	[0.51471712239396...	0.0
(8,[1,5,6,7],[2.2...	0.0	[-14.945093079062...	[0.61304772443910...	0.0
(8,[1,5,6,7],[3.7...	1.0	[-17.727518454082...	[0.60898156364314...	0.0
(8,[1,5,6,7],[4.0...	1.0	[-21.774920893756...	[0.60370782413439...	0.0
(0.0,2.0955431172...	0.0	[-27.815736937756...	[0.77140623381313...	0.0
(0.0,2.6272480873...	0.0	[-30.276441952212...	[0.69731740037420...	0.0
(0.0,2.9087389538...	0.0	[-44.210915011055...	[0.74817864098683...	0.0
(0.0,2.9400157167...	0.0	[-33.517912998034...	[0.69230045040051...	0.0
(0.0,3.1276762944...	0.0	[-47.780870074750...	[0.72812810729529...	0.0
(0.0,3.1589530573...	0.0	[-21.601004666834...	[0.70885996825772...	0.0
(0.0,3.1902298203...	0.0	[-36.109334899503...	[0.71123489140353...	0.0
(0.0,3.1902298203...	0.0	[-33.878582573975...	[0.73064702441743...	0.0
(0.0,3.1902298203...	0.0	[-34.225051895099...	[0.68586842051537...	0.0
(0.0,3.2840601091...	1.0	[-33.906667660597...	[0.73762889361350...	0.0
(0.0,3.2840601091...	0.0	[-27.874920063310...	[0.76761285064617...	0.0
(0.0,3.3153368721...	0.0	[-38.191889234909...	[0.65903992353788...	0.0
(0.0,3.3466136350...	0.0	[-30.217174573846...	[0.72486341052346...	0.0
(0.0,3.5342742127...	0.0	[-31.755486086323...	[0.72470730298884...	0.0
(0.0,3.5655509756...	0.0	[-41.303986218189...	[0.60598558671805...	0.0
(0.0,3.7219347903...	0.0	[-29.556753428990...	[0.74591685075410...	0.0

only showing top 20 rows

```
In [28]: prediction_test.select("Outcome","prediction").show(10)
```

Outcome	prediction
0.0	0.0
0.0	0.0
0.0	0.0
0.0	0.0
0.0	0.0
0.0	0.0
0.0	0.0
0.0	0.0
0.0	0.0
1.0	0.0

only showing top 10 rows

```
In [29]: predictionAndLabels = prediction_test.select("Outcome","prediction").rdd
```

```
In [30]: # Select (prediction, true label) and compute test error
evaluator = MulticlassClassificationEvaluator(labelCol="Outcome", predictionCol="prediction", metricName="accuracy")
accuracy_NB = evaluator.evaluate(prediction_test)
```

```
In [31]: print ("Accuracy",accuracy_NB)
```

Accuracy 0.6637931034482759

```
In [32]: metrics = BinaryClassificationMetrics(predictionAndLabels)

# Area under ROC curve
print("Area under ROC = %s" % metrics.areaUnderROC)

Area under ROC = 0.665151515151515
```

GBTCClassifier

```
In [33]: gradient_boost_class = GBTCClassifier(labelCol="Outcome", featuresCol="Scaled_features")
```

```
In [34]: model = gradient_boost_class.fit(train)
```

```
In [35]: prediction_test = model.transform(test)
```

In [36]: prediction_test.show()

Scaled_features	Outcome	rawPrediction	probability	prediction
[8,[0,1,6,7],[0.5...]	0.0	[1.44568213655613...	[0.94741788737785...	0.0
[8,[0,1,6,7],[0.8...]	0.0	[1.44568213655613...	[0.94741788737785...	0.0
[8,[1,5,6,7],[3.6...]	0.0	[-0.2717930506072...	[0.36735375875999...	1.0
[8,[1,6,7],[2.940...]	0.0	[1.50198599908887...	[0.95275324620783...	0.0
[0.0,2.3144804578...]	0.0	[1.50522683353396...	[0.95304416054471...	0.0
[0.0,2.6898016132...]	0.0	[1.09956867281198...	[0.90017201748161...	0.0
[0.0,2.9087389538...]	0.0	[1.57134073008306...	[0.95861938047406...	0.0
[0.0,2.9087389538...]	0.0	[1.35099731931943...	[0.93714424045724...	0.0
[0.0,2.9712924797...]	0.0	[1.31419458311707...	[0.93266645995597...	0.0
[0.0,2.9712924797...]	1.0	[1.04792819086640...	[0.89049978823396...	0.0
[0.0,3.0651227685...]	0.0	[1.60420294495114...	[0.96114938322129...	0.0
[0.0,3.2527833462...]	1.0	[1.15156570570070...	[0.90913604928283...	0.0
[0.0,3.2840601091...]	0.0	[1.27112161713480...	[0.92705067680045...	0.0
[0.0,3.2840601091...]	1.0	[0.46267033234851...	[0.71612905203861...	0.0
[0.0,3.3153368721...]	0.0	[1.01285658080524...	[0.88347047119139...	0.0
[0.0,3.3466136350...]	0.0	[1.60420294495114...	[0.96114938322129...	0.0
[0.0,3.4717206868...]	0.0	[1.57771527148241...	[0.95912216785821...	0.0
[0.0,3.5342742127...]	1.0	[1.36992895918271...	[0.93933800107683...	0.0
[0.0,3.8470418421...]	0.0	[0.96996381183291...	[0.87434419197093...	0.0
[0.0,4.0347024198...]	0.0	[-0.0345097970698...	[0.48275194797327...	1.0

only showing top 20 rows

In [37]: prediction_test.select("Outcome","prediction").show(10)

Outcome	prediction
0.0	0.0
0.0	0.0
0.0	1.0
0.0	0.0
0.0	0.0
0.0	0.0
0.0	0.0
0.0	0.0
0.0	0.0
1.0	0.0

only showing top 10 rows

In [38]: predictionAndLabels = prediction_test.select("Outcome","prediction").rdd

In [39]: metrics = BinaryClassificationMetrics(predictionAndLabels)

```
# Area under ROC curve
print("Area under ROC = %s" % metrics.areaUnderROC)
```

Area under ROC = 0.7170138888888888

In [40]: # Select (prediction, true label) and compute test error
evaluator = MulticlassClassificationEvaluator(labelCol="Outcome", predictionCol="prediction", metricName="accuracy")
accuracy_GBT = evaluator.evaluate(prediction_test)

In [41]: print ("Accuracy",accuracy_GBT)

Accuracy 0.7413793103448276

RandomForestClassifier

In [42]: random_forest_classifier = RandomForestClassifier(labelCol="Outcome", featuresCol="Scaled_features", numTrees=40)

In [43]: model = random_forest_classifier.fit(train)

In [44]: prediction_test = model.transform(test)

In [45]: prediction_test.show()

Scaled_features	Outcome	rawPrediction	probability	prediction
(8,[0,1,6,7],[0.5...]	0.0	[38.4902255771088...	[0.96225563942772...	0.0
(8,[0,1,6,7],[0.8...]	0.0	[38.2809672738907...	[0.95702418184726...	0.0
(8,[1,5,6,7],[3.6...]	0.0	[19.6691676645421...	[0.49172919161355...	1.0
(8,[1,6,7],[2.940...]	0.0	[38.1018706800663...	[0.95254676700165...	0.0
[0.0,2.3144804578...	0.0	[37.7177580420233...	[0.94294395105058...	0.0
[0.0,2.6898016132...	0.0	[34.5139232462476...	[0.86284808115619...	0.0
[0.0,2.9087389538...	0.0	[37.7177580420233...	[0.94294395105058...	0.0
[0.0,2.9087389538...	0.0	[25.2310398131261...	[0.63077599532815...	0.0
[0.0,2.9712924797...	0.0	[33.0527424559379...	[0.82631856139844...	0.0
[0.0,2.9712924797...	1.0	[35.9363678820332...	[0.89840919705083...	0.0
[0.0,3.0651227685...	0.0	[38.3197183345369...	[0.95799295836342...	0.0
[0.0,3.2527833462...	1.0	[35.3244895789060...	[0.88311223947265...	0.0
[0.0,3.2840601091...	0.0	[33.8725146472889...	[0.84681286618222...	0.0
[0.0,3.2840601091...	1.0	[32.8643056727631...	[0.82160764181907...	0.0
[0.0,3.3153368721...	0.0	[33.0552269501800...	[0.82638067375450...	0.0
[0.0,3.3466136350...	0.0	[38.2721347172117...	[0.95680336793029...	0.0
[0.0,3.4717206868...	0.0	[34.0701464003202...	[0.85175366000800...	0.0
[0.0,3.5342742127...	1.0	[34.3960493803103...	[0.85990123450776...	0.0
[0.0,3.8470418421...	0.0	[26.3864734907176...	[0.65966183726794...	0.0
[0.0,4.0347024198...	0.0	[17.2623736099806...	[0.43155934024951...	1.0

only showing top 20 rows

In [46]: prediction_test.select("Outcome","prediction").show(10)

Outcome	prediction
0.0	0.0
0.0	0.0
0.0	1.0
0.0	0.0
0.0	0.0
0.0	0.0
0.0	0.0
0.0	0.0
0.0	0.0
1.0	0.0

only showing top 10 rows

In [47]: predictionAndLabels = prediction_test.select("Outcome","prediction").rdd

In [48]: metrics = BinaryClassificationMetrics(predictionAndLabels)

```
# Area under ROC curve
print("Area under ROC = %s" % metrics.areaUnderROC)
```

Area under ROC = 0.735632183908046

In [49]: # Select (prediction, true label) and compute test error
evaluator = MulticlassClassificationEvaluator(labelCol="Outcome", predictionCol="prediction", metricName="accuracy")
accuracy_RF= evaluator.evaluate(prediction_test)

In [50]: print ("Accuracy",accuracy_RF)

Accuracy 0.75

In [51]: print("Accuracy of GBT : ",accuracy_GBT)
print("Accuracy of LR : ",accuracy_LR)
print("Accuracy of NB : ",accuracy_NB)
print("Accuracy of RF : ",accuracy_RF)

Accuracy of GBT : 0.7413793103448276
Accuracy of LR : 0.7758620689655172
Accuracy of NB : 0.6637931034482759
Accuracy of RF : 0.75