Overview

This notebook will show you how to create and query a table or DataFrame that you uploaded to DBFS. [DBFS (https://docs.databricks.com/user-guide/dbfs-databricks-file-system.html)](https://docs.databricks.com/user-guide/dbfs-databricks-file-system.html) is a Databricks File System that allows you to store data for querying inside of Databricks. This notebook assumes that you have a file already inside of DBFS that you would like to read from.

This notebook is written in **Python** so the default cell type is Python. However, you can use different languages by using the `%LANGUAGE` syntax. Python, Scala, SQL, and R are all supported.

In [2]:

```
# Importação Bibliotecas
from pyspark.sql import SparkSession
from pyspark import HiveContext
from pyspark.sql.functions import monotonically_increasing_id
from pyspark.ml.linalg import Vectors
from pyspark.ml.feature import VectorAssembler
from pyspark.ml.evaluation import RegressionEvaluator
from pyspark.ml.classification import LogisticRegression, LogisticRegressionModel
from pyspark.mllib.evaluation import BinaryClassificationMetrics as metric
from pyspark.ml.feature import OneHotEncoder, StringIndexer, VectorAssembler,OneHotEnco
from pyspark.ml.classification import RandomForestClassifier, RandomForestClassificatio
from pyspark.mllib.evaluation import BinaryClassificationMetrics as metric
from pyspark.ml import Pipeline
```

In [3]:

```
spark.sparkContext._conf.getAll()
```

Out[3]:

```
[('spark.sql.catalogImplementation', 'hive'),
 ('spark.rdd.compress', 'True'),
 ('spark.driver.host', '10.30.30.21'),
 ('spark.app.id', 'local-1559699171437'),
 ('spark.serializer.objectStreamReset', '100'),
 ('spark.master', 'local[*]'),
 ('spark.executor.id', 'driver'),
 ('spark.submit.deployMode', 'client'),
 ('spark.app.name', 'PySparkShell'),
 ('spark.driver.port', '35371')]
```

In [4]:

```
conf = spark.sparkContext._conf.setAll([
("hive.metastore.uris", "thrift://localhost:9083")])
```

In [5]:

```
spark.stop()
```

In [6]:

```
sc = SparkContext()
```

In [7]:

```
spark.sparkContext._conf.getAll()
```

Out[7]:

```
[('spark.sql.catalogImplementation', 'hive'),
 ('spark.rdd.compress', 'True'),
 ('spark.driver.host', '10.30.30.21'),
 ('spark.app.id', 'local-1559699171437'),
 ('hive.metastore.uris', 'thrift://localhost:9083'),
 ('spark.serializer.objectStreamReset', '100'),
 ('spark.master', 'local[*]'),
 ('spark.executor.id', 'driver'),
 ('spark.submit.deployMode', 'client'),
 ('spark.app.name', 'PySparkShell'),
 ('spark.driver.port', '35371')]
```

In [8]:

```
df = spark.sql("SHOW TABLES")
df.show()
```

```
+--------+--------------+-----------+
|database|     tableName|isTemporary|
+--------+--------------+-----------+
| default|boosting_output|      false|
+--------+--------------+-----------+
```

In [9]:

```
spark = SparkSession.builder.config(conf=conf).getOrCreate()
```

In [10]:

```
# Carga do Arquivo via HDFS
#file_location = "/FileStore/tables/bank_additional_full_no_header-a99ad.csv"
file_location = 'hdfs:///user/labdata/marketing/bank-additional-full.csv'
file_type = "csv"

# CSV options
infer_schema = "true"
first_row_is_header = "false"
delimiter = ";"

# The applied options are for CSV files. For other file types, these will be ignored.
df_marketing_data = spark.read.format(file_type) \
  .option("inferSchema", infer_schema) \
  .option("header", first_row_is_header) \
  .option("sep", delimiter) \
  .load(file_location)
```

In [11]:

```
# Definição dos Nomes de Variaveis
DefColumnNames=df_marketing_data.schema.names
HeaderNames=['age','job','marital','education','default','housing','loan','contact','mo

for Idx in range(0,21):
    df_marketing_data=df_marketing_data.withColumnRenamed(DefColumnNames[Idx],HeaderNam
df_marketing_data = df_marketing_data.drop ('duration')
df_marketing_data.printSchema()
```

```
root
 |-- age: integer (nullable = true)
 |-- job: string (nullable = true)
 |-- marital: string (nullable = true)
 |-- education: string (nullable = true)
 |-- default: string (nullable = true)
 |-- housing: string (nullable = true)
 |-- loan: string (nullable = true)
 |-- contact: string (nullable = true)
 |-- month: string (nullable = true)
 |-- day_of_week: string (nullable = true)
 |-- campaign: integer (nullable = true)
 |-- pdays: integer (nullable = true)
 |-- previous: integer (nullable = true)
 |-- poutcome: string (nullable = true)
 |-- emp_var_rate: double (nullable = true)
 |-- cons_price_idx: double (nullable = true)
 |-- cons_conf_idx: double (nullable = true)
 |-- euribor3m: double (nullable = true)
 |-- nr_employed: double (nullable = true)
 |-- deposit: string (nullable = true)
```

In [12]:

```
# Segregação Variaveis Categoricas e Numericas em Listas Específicas
categoricalColumns = []
numericCols = []
for i in df_marketing_data.dtypes:
    if i[1]=='string':
        categoricalColumns  += [i[0]]
    elif i[1]=='int' or i[1]=='double':
        numericCols  += [i[0]]

print(categoricalColumns)
print(numericCols)
```

```
['job', 'marital', 'education', 'default', 'housing', 'loan', 'contact',
'month', 'day_of_week', 'poutcome', 'deposit']
['age', 'campaign', 'pdays', 'previous', 'emp_var_rate', 'cons_price_id
x', 'cons_conf_idx', 'euribor3m', 'nr_employed']
```

In [13]:

```
# Tratamento de Variáveis Categoricas
stages = []
for categoricalCol in categoricalColumns:
  stringIndexer = StringIndexer(inputCol=categoricalCol, outputCol=categoricalCol+"Inde
  encoder = OneHotEncoder(inputCol=categoricalCol+"Index", outputCol=categoricalCol+"cl
  stages += [stringIndexer, encoder]

#numericCols = ['age', 'balance', 'duration', 'campaign', 'pdays', 'previous']
label_stringIdx = StringIndexer(inputCol = "deposit", outputCol = "label")
stages += [label_stringIdx]
```

In [14]:

```
## Assembler Inputs
assemblerInputs = ['jobclassVec', 'maritalclassVec', 'educationclassVec', 'defaultclass
assembler = VectorAssembler(inputCols=assemblerInputs, outputCol="features")
stages += [assembler]
```

In [15]:

```
## PipeLine
pipeline = Pipeline(stages=stages)
pipelineModel = pipeline.fit(df_marketing_data)
df_marketing_data_prep = pipelineModel.transform(df_marketing_data)
df_marketing_data_prep.printSchema()
```

```
root
 |-- age: integer (nullable = true)
 |-- job: string (nullable = true)
 |-- marital: string (nullable = true)
 |-- education: string (nullable = true)
 |-- default: string (nullable = true)
 |-- housing: string (nullable = true)
 |-- loan: string (nullable = true)
 |-- contact: string (nullable = true)
 |-- month: string (nullable = true)
 |-- day_of_week: string (nullable = true)
 |-- campaign: integer (nullable = true)
 |-- pdays: integer (nullable = true)
 |-- previous: integer (nullable = true)
 |-- poutcome: string (nullable = true)
 |-- emp_var_rate: double (nullable = true)
 |-- cons_price_idx: double (nullable = true)
 |-- cons_conf_idx: double (nullable = true)
 |-- euribor3m: double (nullable = true)
 |-- nr_employed: double (nullable = true)
 |-- deposit: string (nullable = true)
 |-- jobIndex: double (nullable = true)
 |-- jobclassVec: vector (nullable = true)
 |-- maritalIndex: double (nullable = true)
 |-- maritalclassVec: vector (nullable = true)
 |-- educationIndex: double (nullable = true)
 |-- educationclassVec: vector (nullable = true)
 |-- defaultIndex: double (nullable = true)
 |-- defaultclassVec: vector (nullable = true)
 |-- housingIndex: double (nullable = true)
 |-- housingclassVec: vector (nullable = true)
 |-- loanIndex: double (nullable = true)
 |-- loanclassVec: vector (nullable = true)
 |-- contactIndex: double (nullable = true)
 |-- contactclassVec: vector (nullable = true)
 |-- monthIndex: double (nullable = true)
 |-- monthclassVec: vector (nullable = true)
 |-- day_of_weekIndex: double (nullable = true)
 |-- day_of_weekclassVec: vector (nullable = true)
 |-- poutcomeIndex: double (nullable = true)
 |-- poutcomeclassVec: vector (nullable = true)
 |-- depositIndex: double (nullable = true)
 |-- depositclassVec: vector (nullable = true)
 |-- label: double (nullable = true)
 |-- features: vector (nullable = true)
```

In [16]:

```
df_marketing_data_prep.take(5)
```

Out[16]:

```
[Row(age=56, job='housemaid', marital='married', education='basic.4y', de
fault='no', housing='no', loan='no', contact='telephone', month='may', da
y_of_week='mon', campaign=1, pdays=999, previous=0, poutcome='nonexisten
t', emp_var_rate=1.1, cons_price_idx=93.994, cons_conf_idx=-36.4, euribor
3m=4.857, nr_employed=5191.0, deposit='no', jobIndex=8.0, jobclassVec=Spa
rseVector(11, {8: 1.0}), maritalIndex=0.0, maritalclassVec=SparseVector
(3, {0: 1.0}), educationIndex=4.0, educationclassVec=SparseVector(7, {4:
1.0}), defaultIndex=0.0, defaultclassVec=SparseVector(2, {0: 1.0}), housi
ngIndex=1.0, housingclassVec=SparseVector(2, {1: 1.0}), loanIndex=0.0, lo
anclassVec=SparseVector(2, {0: 1.0}), contactIndex=1.0, contactclassVec=S
parseVector(1, {}), monthIndex=0.0, monthclassVec=SparseVector(9, {0: 1.
0}), day_of_weekIndex=1.0, day_of_weekclassVec=SparseVector(4, {1: 1.0}),
poutcomeIndex=0.0, poutcomeclassVec=SparseVector(2, {0: 1.0}), depositInd
ex=0.0, depositclassVec=SparseVector(1, {0: 1.0}), label=0.0, features=Sp
arseVector(52, {8: 1.0, 11: 1.0, 18: 1.0, 21: 1.0, 24: 1.0, 25: 1.0, 28:
1.0, 38: 1.0, 41: 1.0, 43: 56.0, 44: 1.0, 45: 999.0, 47: 1.1, 48: 93.994,
49: -36.4, 50: 4.857, 51: 5191.0})),
 Row(age=57, job='services', marital='married', education='high.school',
default='unknown', housing='no', loan='no', contact='telephone', month='m
ay', day_of_week='mon', campaign=1, pdays=999, previous=0, poutcome='none
xistent', emp_var_rate=1.1, cons_price_idx=93.994, cons_conf_idx=-36.4, e
uribor3m=4.857, nr_employed=5191.0, deposit='no', jobIndex=3.0, jobclassV
ec=SparseVector(11, {3: 1.0}), maritalIndex=0.0, maritalclassVec=SparseVe
ctor(3, {0: 1.0}), educationIndex=1.0, educationclassVec=SparseVector(7,
{1: 1.0}), defaultIndex=1.0, defaultclassVec=SparseVector(2, {1: 1.0}), h
ousingIndex=1.0, housingclassVec=SparseVector(2, {1: 1.0}), loanIndex=0.
0, loanclassVec=SparseVector(2, {0: 1.0}), contactIndex=1.0, contactclass
Vec=SparseVector(1, {}), monthIndex=0.0, monthclassVec=SparseVector(9,
{0: 1.0}), day_of_weekIndex=1.0, day_of_weekclassVec=SparseVector(4, {1:
1.0}), poutcomeIndex=0.0, poutcomeclassVec=SparseVector(2, {0: 1.0}), dep
ositIndex=0.0, depositclassVec=SparseVector(1, {0: 1.0}), label=0.0, feat
ures=SparseVector(52, {3: 1.0, 11: 1.0, 15: 1.0, 22: 1.0, 24: 1.0, 25: 1.
0, 28: 1.0, 38: 1.0, 41: 1.0, 43: 57.0, 44: 1.0, 45: 999.0, 47: 1.1, 48:
93.994, 49: -36.4, 50: 4.857, 51: 5191.0})),
 Row(age=37, job='services', marital='married', education='high.school',
default='no', housing='yes', loan='no', contact='telephone', month='may',
day_of_week='mon', campaign=1, pdays=999, previous=0, poutcome='nonexiste
nt', emp_var_rate=1.1, cons_price_idx=93.994, cons_conf_idx=-36.4, euribo
r3m=4.857, nr_employed=5191.0, deposit='no', jobIndex=3.0, jobclassVec=Sp
arseVector(11, {3: 1.0}), maritalIndex=0.0, maritalclassVec=SparseVector
(3, {0: 1.0}), educationIndex=1.0, educationclassVec=SparseVector(7, {1:
1.0}), defaultIndex=0.0, defaultclassVec=SparseVector(2, {0: 1.0}), housi
ngIndex=0.0, housingclassVec=SparseVector(2, {0: 1.0}), loanIndex=0.0, lo
anclassVec=SparseVector(2, {0: 1.0}), contactIndex=1.0, contactclassVec=S
parseVector(1, {}), monthIndex=0.0, monthclassVec=SparseVector(9, {0: 1.
0}), day_of_weekIndex=1.0, day_of_weekclassVec=SparseVector(4, {1: 1.0}),
poutcomeIndex=0.0, poutcomeclassVec=SparseVector(2, {0: 1.0}), depositInd
ex=0.0, depositclassVec=SparseVector(1, {0: 1.0}), label=0.0, features=Sp
arseVector(52, {3: 1.0, 11: 1.0, 15: 1.0, 21: 1.0, 23: 1.0, 25: 1.0, 28:
1.0, 38: 1.0, 41: 1.0, 43: 37.0, 44: 1.0, 45: 999.0, 47: 1.1, 48: 93.994,
49: -36.4, 50: 4.857, 51: 5191.0})),
 Row(age=40, job='admin.', marital='married', education='basic.6y', defau
lt='no', housing='no', loan='no', contact='telephone', month='may', day_o
f_week='mon', campaign=1, pdays=999, previous=0, poutcome='nonexistent',
```

```
emp_var_rate=1.1, cons_price_idx=93.994, cons_conf_idx=-36.4, euribor3m=
4.857, nr_employed=5191.0, deposit='no', jobIndex=0.0, jobclassVec=Sparse
Vector(11, {0: 1.0}), maritalIndex=0.0, maritalclassVec=SparseVector(3,
{0: 1.0}), educationIndex=5.0, educationclassVec=SparseVector(7, {5: 1.
0}), defaultIndex=0.0, defaultclassVec=SparseVector(2, {0: 1.0}), housing
Index=1.0, housingclassVec=SparseVector(2, {1: 1.0}), loanIndex=0.0, loan
classVec=SparseVector(2, {0: 1.0}), contactIndex=1.0, contactclassVec=Spa
rseVector(1, {}), monthIndex=0.0, monthclassVec=SparseVector(9, {0: 1.
0}), day_of_weekIndex=1.0, day_of_weekclassVec=SparseVector(4, {1: 1.0}),
poutcomeIndex=0.0, poutcomeclassVec=SparseVector(2, {0: 1.0}), depositInd
ex=0.0, depositclassVec=SparseVector(1, {0: 1.0}), label=0.0, features=Sp
arseVector(52, {0: 1.0, 11: 1.0, 19: 1.0, 21: 1.0, 24: 1.0, 25: 1.0, 28:
1.0, 38: 1.0, 41: 1.0, 43: 40.0, 44: 1.0, 45: 999.0, 47: 1.1, 48: 93.994,
49: -36.4, 50: 4.857, 51: 5191.0})),
 Row(age=56, job='services', marital='married', education='high.school',
default='no', housing='no', loan='yes', contact='telephone', month='may',
day_of_week='mon', campaign=1, pdays=999, previous=0, poutcome='nonexiste
nt', emp_var_rate=1.1, cons_price_idx=93.994, cons_conf_idx=-36.4, euribo
r3m=4.857, nr_employed=5191.0, deposit='no', jobIndex=3.0, jobclassVec=Sp
arseVector(11, {3: 1.0}), maritalIndex=0.0, maritalclassVec=SparseVector
(3, {0: 1.0}), educationIndex=1.0, educationclassVec=SparseVector(7, {1:
1.0}), defaultIndex=0.0, defaultclassVec=SparseVector(2, {0: 1.0}), housi
ngIndex=1.0, housingclassVec=SparseVector(2, {1: 1.0}), loanIndex=1.0, lo
anclassVec=SparseVector(2, {1: 1.0}), contactIndex=1.0, contactclassVec=S
parseVector(1, {}), monthIndex=0.0, monthclassVec=SparseVector(9, {0: 1.
0}), day_of_weekIndex=1.0, day_of_weekclassVec=SparseVector(4, {1: 1.0}),
poutcomeIndex=0.0, poutcomeclassVec=SparseVector(2, {0: 1.0}), depositInd
ex=0.0, depositclassVec=SparseVector(1, {0: 1.0}), label=0.0, features=Sp
arseVector(52, {3: 1.0, 11: 1.0, 15: 1.0, 21: 1.0, 24: 1.0, 26: 1.0, 28:
1.0, 38: 1.0, 41: 1.0, 43: 56.0, 44: 1.0, 45: 999.0, 47: 1.1, 48: 93.994,
49: -36.4, 50: 4.857, 51: 5191.0}))]
```

In [17]:

```
#Configurando o modelo para 100 iterações
modelo =  LogisticRegression(labelCol='label',featuresCol="features",maxIter=100)
```

In [18]:

```
# Divisão Teste/Treino
(marketing_model_treino, marketing_model_teste) = df_marketing_data_prep.randomSplit([0
```

In [19]:

```
# Ajuste Modelo
modelo_treino = modelo.fit(marketing_model_treino)
```

In [20]:

```
print("Coefficients: " + str(modelo_treino.coefficients))
print("Intercept: " + str(modelo_treino.intercept))
```

```
Coefficients: [0.07228744920214636,-0.1823426344642905,0.0430586707794122
16,-0.01883575734932906,0.020471150492064376,0.309900243321121,0.15349816
856792098,-0.06432047069863493,-0.1400150462940802,-0.002065678868611054
7,0.24121218200088926,-0.016954238633392234,0.02325671326311776,-0.042225
64404035784,0.054928930286601604,-0.08017466339569781,-0.0359619276043454
05,0.005322309614727278,-0.01938181814730077,0.07707091629458984,0.073784
4541872536,0.12767177016763268,-0.12429696421317507,-0.00685663740998846
8,0.02712818241933672,0.014291818446949078,0.022766872495474766,0.4456242
753007335,-0.5384796111547651,0.34323584560280646,0.07928836381942911,0.2
193636673715537,-0.1788984376052925,0.10988741726505098,0.109305924514261
66,-0.09864335736514403,1.2179087053600615,0.039407318052363,-0.234098438
02890684,0.13166500396570288,0.022384823939739673,-0.037130229052209335,-
0.5670373053301918,0.0005058246587037442,-0.04375394361054687 3,-0.0014133
142529665966,-0.018416573586666075,-0.17781047722186252,0.319901639609342
6,0.024852701484729234,-0.14656094785240206,-0.005336499935256 27]
Intercept: -2.0689878211161257
```

In [21]:

```
## Sumario
print(modelo_treino.summary.predictions.stat)
```

```
<pyspark.sql.dataframe.DataFrameStatFunctions object at 0x7f12dc7a0f28>
```

In [22]:

```
# Salva o Modelo no HDFS
hdfs_path = "/user/labdata/modelo_LR"
modelo_treino.write().overwrite().save(hdfs_path)
```

In [23]:

```
# Regressão Logística
modelo_treino2 = LogisticRegressionModel.load(hdfs_path)
```

In [24]:

```
## Executa a Predição
predict = modelo_treino2.transform(marketing_model_treino)
```

In [25]:

```
## Exibe Predição
predict.show()
```

```
+---+-----------+-------+-----------+-------+-------+----+---------+---
--+-----------+--------+-----+-------+-----------+-----------+-------
-------+------------+--------+-----------+-------+--------+----------
-----+-----------+--------------+-------------+-----------------+---
---------+--------------+-----------+--------------+---------+------
-------+-----------+--------------+---------+------------+---------
-------+------------------+------------+--------------+------------
+--------------+-----+------------------+------------------+------
--------------+----------+
|age|        job|marital|  education|default|housing|loan|  contact|mon
th|day_of_week|campaign|pdays|previous|   poutcome|emp_var_rate|cons_pr
ice_idx|cons_conf_idx|euribor3m|nr_employed|deposit|jobIndex|    jobcla
ssVec|maritalIndex|maritalclassVec|educationIndex|educationclassVec|def
aultIndex|defaultclassVec|housingIndex|housingclassVec|loanIndex| loanc
lassVec|contactIndex|contactclassVec|monthIndex|monthclassVec|day_of_we
ekIndex|day_of_weekclassVec|poutcomeIndex|poutcomeclassVec|depositIndex
|depositclassVec|label|            features|       rawPrediction|
   probability|prediction|
+---+-----------+-------+-----------+-------+-------+----+---------+---
```

In [26]:

```
results = predict.select(['probability', 'label'])
```

In [27]:

```
results_collect = results.collect()
results_list = [(float(i[0][0]), 1.0-float(i[1])) for i in results_collect]
scoreAndLabels = sc.parallelize(results_list)
```

In [28]:

```
# Exibe ROC
metrics = metric(scoreAndLabels)
print("The ROC score is (@iterações =100): ", metrics.areaUnderROC)
```

```
The ROC score is (@iterações =100):  0.7935651781484536
```

In [29]:

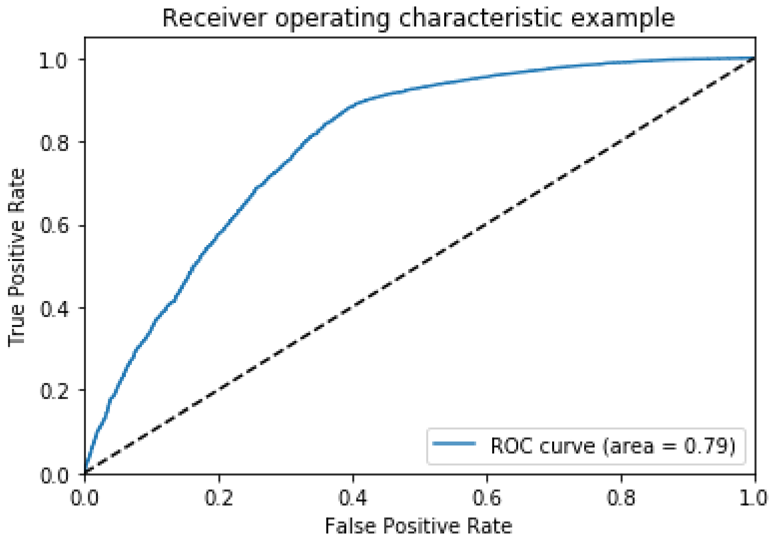
```
from sklearn.metrics import roc_curve, auc
from matplotlib import pyplot as plt

fpr = dict()
tpr = dict()
roc_auc = dict()

y_test = [i[1] for i in results_list]
y_score = [i[0] for i in results_list]

fpr, tpr, _ = roc_curve(y_test, y_score)
roc_auc = auc(fpr, tpr)

get_ipython().run_line_magic('matplotlib', 'inline')
plt.figure()
plt.plot(fpr, tpr, label='ROC curve (area = %0.2f)' % roc_auc)
plt.plot([0, 1], [0, 1], 'k--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver operating characteristic example')
plt.legend(loc="lower right")
plt.show()
display()
```



In [ ]: