Bank_pyspark

June 1, 2021

[ ]:
```
# mount
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

[ ]:
```
!pip install pyspark
```

```
Collecting pyspark
  Downloading https://files.pythonhosted.org/packages/89/db/e18cfd78e408de
957821ec5ca56de1250645b05f8523d169803d8df35a64/pyspark-3.1.2.tar.gz (212.4MB)
     || 212.4MB 66kB/s
Collecting py4j==0.10.9
  Downloading https://files.pythonhosted.org/packages/9e/b6/6a4fb90cd235dc
8e265a6a2067f2a2c99f0d91787f06aca4bcf7c23f3f80/py4j-0.10.9-py2.py3-none-any.whl
(198kB)
     || 204kB 20.4MB/s
Building wheels for collected packages: pyspark
  Building wheel for pyspark (setup.py) ... done
  Created wheel for pyspark: filename=pyspark-3.1.2-py2.py3-none-any.whl
size=212880768
sha256=a9e7803006fd7770ea459f18acbb5247780943faf5ad09fd758870bcd3c5db89
  Stored in directory: /root/.cache/pip/wheels/40/1b/2c/30f43be2627857ab80062bef
1527c0128f7b4070b6b2d02139
Successfully built pyspark
Installing collected packages: py4j, pyspark
Successfully installed py4j-0.10.9 pyspark-3.1.2
```

[ ]:
```
import pyspark
from pyspark.sql import SparkSession
spark = SparkSession.builder.appName("Bank-ml-pyspark").getOrCreate()
```

[ ]:
```
df = spark.read.format('csv').option('header', True).load("/content/drive/
 ↪MyDrive/Bank_PySpark /bank.csv",inferSchema = True)
```

[ ]:
```
df.show(5)
```

```
+---+----------+-------+---------+-------+-------+-------+----+-------+---+-----
+--------+--------+-----+--------+-------+-------+
|age|       job|marital|education|default|balance|housing|loan|contact|day|month
|duration|campaign|pdays|previous|poutcome|deposit|
+---+----------+-------+---------+-------+-------+-------+----+-------+---+-----
+--------+--------+-----+--------+-------+-------+
| 59|    admin.|married|secondary|     no|   2343|    yes|  no|unknown|  5|
may|    1042|       1|   -1|       0| unknown|    yes|
| 56|    admin.|married|secondary|     no|     45|     no|  no|unknown|  5|
may|    1467|       1|   -1|       0| unknown|    yes|
| 41|technician|married|secondary|     no|   1270|    yes|  no|unknown|  5|
may|    1389|       1|   -1|       0| unknown|    yes|
| 55|  services|married|secondary|     no|   2476|    yes|  no|unknown|  5|
may|     579|       1|   -1|       0| unknown|    yes|
| 54|    admin.|married| tertiary|     no|    184|     no|  no|unknown|  5|
may|     673|       2|   -1|       0| unknown|    yes|
+---+----------+-------+---------+-------+-------+-------+----+-------+---+-----
+--------+--------+-----+--------+-------+-------+
only showing top 5 rows
```

[ ]:
```
df.printSchema()
```

```
root
 |-- age: integer (nullable = true)
 |-- job: string (nullable = true)
 |-- marital: string (nullable = true)
 |-- education: string (nullable = true)
 |-- default: string (nullable = true)
 |-- balance: integer (nullable = true)
 |-- housing: string (nullable = true)
 |-- loan: string (nullable = true)
 |-- contact: string (nullable = true)
 |-- day: integer (nullable = true)
 |-- month: string (nullable = true)
 |-- duration: integer (nullable = true)
 |-- campaign: integer (nullable = true)
 |-- pdays: integer (nullable = true)
 |-- previous: integer (nullable = true)
 |-- poutcome: string (nullable = true)
 |-- deposit: string (nullable = true)
```

[ ]:
```
df.groupby('deposit').count().show()
```

```
+-------+-----+
|deposit|count|
```

```
+-------+-----+
|     no| 5873|
|    yes| 5289|
+-------+-----+
```

[ ]:
```
df.describe().show()
```

```
+-------+------------------+-------+--------+---------+-------+-----------------
-+-------+-----+--------+------------------+-----+------------------+-----------
-------+------------------+------------------+--------+-------+
|summary|               age|    job| marital|education|default|
balance|housing| loan| contact|               day|month|          duration|
campaign|             pdays|          previous|poutcome|deposit|
+-------+------------------+-------+--------+---------+-------+-----------------
-+-------+-----+--------+------------------+-----+------------------+-----------
-------+------------------+------------------+--------+-------+
|  count|             11162|  11162|   11162|    11162|  11162|
11162|  11162|11162|   11162|             11162|11162|             11162|
11162|             11162|             11162|   11162|  11162|
|   mean|41.231947679627304|   null|    null|     null|
null|1528.5385235620856|   null| null|    null|15.658036194230425|
null|371.99381831213043| 2.508421429851281|
51.33040673714388|0.8325568894463358|    null|   null|
| stddev|11.913369192215518|   null|    null|     null|   null|
3225.413325946149|   null| null|    null| 8.420739541006462|
null|347.12838571630687|2.7220771816614824|108.75828197197717|
2.292007218670508|    null|   null|
|    min|                18| admin.|divorced|  primary|     no|
-6847|     no|   no|cellular|                 1|  apr|                 2|
1|                -1|                 0| failure|     no|
|    max|                95|unknown|  single|  unknown|    yes|
81204|    yes|  yes| unknown|                31|  sep|              3881|
63|               854|                58| unknown|    yes|
+-------+------------------+-------+--------+---------+-------+-----------------
-+-------+-----+--------+------------------+-----+------------------+-----------
-------+------------------+------------------+--------+-------+
```

[ ]:
```
df.dtypes
```

[ ]:
```
[('age', 'int'),
 ('job', 'string'),
 ('marital', 'string'),
 ('education', 'string'),
 ('default', 'string'),
 ('balance', 'int'),
 ('housing', 'string'),
```

```
 ('loan', 'string'),
 ('contact', 'string'),
 ('day', 'int'),
 ('month', 'string'),
 ('duration', 'int'),
 ('campaign', 'int'),
 ('pdays', 'int'),
 ('previous', 'int'),
 ('poutcome', 'string'),
 ('deposit', 'string')]
```

[ ]:
```
## Extract all numeric columns

numeric_variables = []

for i in df.dtypes:
    if i[1] == 'int':
        numeric_variables.append(i[0])

numeric_variables
```

[ ]:
```
['age', 'balance', 'day', 'duration', 'campaign', 'pdays', 'previous']
```

[ ]:
```
df.select(numeric_variables).describe().show()
```

```
+-------+------------------+------------------+------------------+--------------
----+------------------+------------------+------------------+
|summary|               age|           balance|               day|
duration|          campaign|             pdays|          previous|
+-------+------------------+------------------+------------------+--------------
----+------------------+------------------+------------------+
|  count|             11162|             11162|             11162|
11162|             11162|             11162|             11162|
|   mean|41.231947679627304|1528.5385235620856|15.658036194230425|371.9938183121
3043| 2.508421429851281| 51.33040673714388|0.8325568894463358|
| stddev|11.913369192215518| 3225.413325946149|
8.420739541006462|347.12838571630687|2.7220771816614824|108.75828197197717|
2.292007218670508|
|    min|                18|             -6847|                 1|
2|                 1|                -1|                 0|
|    max|                95|             81204|                31|
3881|                63|               854|                58|
+-------+------------------+------------------+------------------+--------------
----+------------------+------------------+------------------+
```

[ ]:
```
numeric_data = df.select(numeric_variables)
numeric_data.show()
```

```
+---+-------+---+--------+--------+-----+--------+
|age|balance|day|duration|campaign|pdays|previous|
+---+-------+---+--------+--------+-----+--------+
| 59|   2343|  5|    1042|       1|   -1|       0|
| 56|     45|  5|    1467|       1|   -1|       0|
| 41|   1270|  5|    1389|       1|   -1|       0|
| 55|   2476|  5|     579|       1|   -1|       0|
| 54|    184|  5|     673|       2|   -1|       0|
| 42|      0|  5|     562|       2|   -1|       0|
| 56|    830|  6|    1201|       1|   -1|       0|
| 60|    545|  6|    1030|       1|   -1|       0|
| 37|      1|  6|     608|       1|   -1|       0|
| 28|   5090|  6|    1297|       3|   -1|       0|
| 38|    100|  7|     786|       1|   -1|       0|
| 30|    309|  7|    1574|       2|   -1|       0|
| 29|    199|  7|    1689|       4|   -1|       0|
| 46|    460|  7|    1102|       2|   -1|       0|
| 31|    703|  8|     943|       2|   -1|       0|
| 35|   3837|  8|    1084|       1|   -1|       0|
| 32|    611|  8|     541|       3|   -1|       0|
| 49|     -8|  8|    1119|       1|   -1|       0|
| 41|     55|  8|    1120|       2|   -1|       0|
| 49|    168|  8|     513|       1|   -1|       0|
+---+-------+---+--------+--------+-----+--------+
only showing top 20 rows
```

[ ]:
```python
#Correlation Matrix
from pyspark.ml.feature import VectorAssembler
from pyspark.ml.stat import Correlation

assembler = VectorAssembler(
  inputCols = ['age', 'balance', 'day', 'duration', 'campaign', 'pdays',␣
 ↪'previous']
  , outputCol = "features"
)
assembled = assembler.transform(numeric_data)

pearson_corr = Correlation.corr(assembled, "features")

corr_list = pearson_corr.head()[0].toArray().tolist()
pearson_corr_df = spark.createDataFrame(corr_list)
pearson_corr_df.show(truncate=False)
```

```
+---------------------+---------------------+---------------------+-------------
--------+---------------------+---------------------+---------------------+
|_1                   |_2                   |_3                   |_4
```

```
|_5                   |_6                   |_7                   |
+---------------------+---------------------+---------------------+------------
--------+---------------------+--------------------+---------------------+
|1.0                  |0.11229988859873077
|-7.624209205460373E-4|1.892280737142355E-4
|-0.005277936156040414|0.002773834311769889|0.020168561218448653 |
|0.11229988859873077  |1.0                  |0.010467439549070189
|0.022436131268962788 |-0.013893822542985367|0.0174111486326 7663
|0.03080524687156654  |
|-7.624209205460373E-4|0.010467439549070189 |1.0
|-0.018511399167089358|0.13700683429735389
|-0.07723161298141434|-0.05898068354621966 |
|1.892280737142355E-4 |0.022436131268962788 |-0.018511399167089358|1.0
|-0.04155745875962242 |-0.02739155324504362|-0.026716171271672622|
|-0.005277936156040414|-0.013893822542985367|0.13700683429735389
|-0.04155745875962242 |1.0
|-0.10272604750935362|-0.0496994979745621  |
|0.002773834311769889 |0.0174111486326 7663  |-0.07723161298141434
|-0.02739155324504362 |-0.10272604750935362 |1.0
|0.507271588372842    |
|0.020168561218448653 |0.03080524687156654  |-0.05898068354621966
|-0.026716171271672622|-0.0496994979745621  |0.507271588372842   |1.0
|
+---------------------+---------------------+---------------------+------------
--------+---------------------+--------------------+---------------------+
```

[ ]:
```
df.show()
```

```
+---+-----------+--------+---------+-------+-------+-------+----+-------+---+---
--+--------+--------+-----+--------+--------+-------+
|age|        job| marital|education|default|balance|housing|loan|contact|day|mon
th|duration|campaign|pdays|previous|poutcome|deposit|
+---+-----------+--------+---------+-------+-------+-------+----+-------+---+---
--+--------+--------+-----+--------+--------+-------+
| 59|     admin.| married|secondary|     no|   2343|    yes|  no|unknown|  5|
may|    1042|       1|   -1|       0| unknown|    yes|
| 56|     admin.| married|secondary|     no|     45|     no|  no|unknown|  5|
may|    1467|       1|   -1|       0| unknown|    yes|
| 41| technician| married|secondary|     no|   1270|    yes|  no|unknown|  5|
may|    1389|       1|   -1|       0| unknown|    yes|
| 55|   services| married|secondary|     no|   2476|    yes|  no|unknown|  5|
may|     579|       1|   -1|       0| unknown|    yes|
| 54|     admin.| married| tertiary|     no|    184|     no|  no|unknown|  5|
may|     673|       2|   -1|       0| unknown|    yes|
| 42| management|  single| tertiary|     no|      0|    yes| yes|unknown|  5|
may|     562|       2|   -1|       0| unknown|    yes|
```

```
| 56| management| married| tertiary|     no|    830|    yes| yes|unknown|  6|
may|    1201|       1|   -1|       0| unknown|    yes|
| 60|    retired|divorced|secondary|     no|    545|    yes|  no|unknown|  6|
may|    1030|       1|   -1|       0| unknown|    yes|
| 37| technician| married|secondary|     no|      1|    yes|  no|unknown|  6|
may|     608|       1|   -1|       0| unknown|    yes|
| 28|   services|  single|secondary|     no|   5090|    yes|  no|unknown|  6|
may|    1297|       3|   -1|       0| unknown|    yes|
| 38|     admin.|  single|secondary|     no|    100|    yes|  no|unknown|  7|
may|     786|       1|   -1|       0| unknown|    yes|
| 30|blue-collar| married|secondary|     no|    309|    yes|  no|unknown|  7|
may|    1574|       2|   -1|       0| unknown|    yes|
| 29| management| married| tertiary|     no|    199|    yes| yes|unknown|  7|
may|    1689|       4|   -1|       0| unknown|    yes|
| 46|blue-collar|  single| tertiary|     no|    460|    yes|  no|unknown|  7|
may|    1102|       2|   -1|       0| unknown|    yes|
| 31| technician|  single| tertiary|     no|    703|    yes|  no|unknown|  8|
may|     943|       2|   -1|       0| unknown|    yes|
| 35| management|divorced| tertiary|     no|   3837|    yes|  no|unknown|  8|
may|    1084|       1|   -1|       0| unknown|    yes|
| 32|blue-collar|  single|  primary|     no|    611|    yes|  no|unknown|  8|
may|     541|       3|   -1|       0| unknown|    yes|
| 49|   services| married|secondary|     no|     -8|    yes|  no|unknown|  8|
may|    1119|       1|   -1|       0| unknown|    yes|
| 41|     admin.| married|secondary|     no|     55|    yes|  no|unknown|  8|
may|    1120|       2|   -1|       0| unknown|    yes|
| 49|     admin.|divorced|secondary|     no|    168|    yes| yes|unknown|  8|
may|     513|       1|   -1|       0| unknown|    yes|
+---+-----------+--------+---------+-------+-------+-------+----+-------+---+---
--+--------+--------+-----+--------+-------+-------+
only showing top 20 rows
```

[ ]:
```
# Dropping day and month columns from original dataframe
df_final = df.drop("day","month")
```

[ ]:
```
df_final.show()
```

```
+---+-----------+--------+---------+-------+-------+-------+----+-------+-------
-+--------+-----+--------+--------+-------+
|age|        job| marital|education|default|balance|housing|loan|contact|duratio
n|campaign|pdays|previous|poutcome|deposit|
+---+-----------+--------+---------+-------+-------+-------+----+-------+-------
-+--------+-----+--------+--------+-------+
| 59|     admin.| married|secondary|     no|   2343|    yes|  no|unknown|
1042|       1|   -1|       0| unknown|    yes|
| 56|     admin.| married|secondary|     no|     45|     no|  no|unknown|
1467|       1|   -1|       0| unknown|    yes|
```

```
| 41| technician| married|secondary|     no|   1270|    yes|   no|unknown|
1389|        1|   -1|       0| unknown|    yes|
| 55|   services| married|secondary|     no|   2476|    yes|   no|unknown|
579|        1|   -1|       0| unknown|    yes|
| 54|     admin.| married| tertiary|     no|    184|     no|   no|unknown|
673|        2|   -1|       0| unknown|    yes|
| 42| management|  single| tertiary|     no|      0|    yes|  yes|unknown|
562|        2|   -1|       0| unknown|    yes|
| 56| management| married| tertiary|     no|    830|    yes|  yes|unknown|
1201|        1|   -1|       0| unknown|    yes|
| 60|    retired|divorced|secondary|     no|    545|    yes|   no|unknown|
1030|        1|   -1|       0| unknown|    yes|
| 37| technician| married|secondary|     no|      1|    yes|   no|unknown|
608|        1|   -1|       0| unknown|    yes|
| 28|   services|  single|secondary|     no|   5090|    yes|   no|unknown|
1297|        3|   -1|       0| unknown|    yes|
| 38|     admin.|  single|secondary|     no|    100|    yes|   no|unknown|
786|        1|   -1|       0| unknown|    yes|
| 30|blue-collar| married|secondary|     no|    309|    yes|   no|unknown|
1574|        2|   -1|       0| unknown|    yes|
| 29| management| married| tertiary|     no|    199|    yes|  yes|unknown|
1689|        4|   -1|       0| unknown|    yes|
| 46|blue-collar|  single| tertiary|     no|    460|    yes|   no|unknown|
1102|        2|   -1|       0| unknown|    yes|
| 31| technician|  single| tertiary|     no|    703|    yes|   no|unknown|
943|        2|   -1|       0| unknown|    yes|
| 35| management|divorced| tertiary|     no|   3837|    yes|   no|unknown|
1084|        1|   -1|       0| unknown|    yes|
| 32|blue-collar|  single|  primary|     no|    611|    yes|   no|unknown|
541|        3|   -1|       0| unknown|    yes|
| 49|   services| married|secondary|     no|     -8|    yes|   no|unknown|
1119|        1|   -1|       0| unknown|    yes|
| 41|     admin.| married|secondary|     no|     55|    yes|   no|unknown|
1120|        2|   -1|       0| unknown|    yes|
| 49|     admin.|divorced|secondary|     no|    168|    yes|  yes|unknown|
513|        1|   -1|       0| unknown|    yes|
+---+-----------+--------+---------+-------+-------+-------+----+-------+-------
-+--------+-----+--------+--------+-------+
only showing top 20 rows
```

[ ]:
```
print((df.count(), len(df.columns)))
print((df_final.count(), len(df_final.columns)))
print((numeric_data.count(), len(numeric_data.columns)))
df_final.dtypes
```

```
(11162, 17)
```

```
(11162, 15)
(11162, 7)
```

[ ]:
```
[('age', 'int'),
 ('job', 'string'),
 ('marital', 'string'),
 ('education', 'string'),
 ('default', 'string'),
 ('balance', 'int'),
 ('housing', 'string'),
 ('loan', 'string'),
 ('contact', 'string'),
 ('duration', 'int'),
 ('campaign', 'int'),
 ('pdays', 'int'),
 ('previous', 'int'),
 ('poutcome', 'string'),
 ('deposit', 'string')]
```

[ ]:
```
from pyspark.ml.feature import OneHotEncoder, StringIndexer, VectorAssembler
categorical_variables = []

for i in df.dtypes:
    if i[1] == 'string':
        categorical_variables.append(i[0])
print(categorical_variables)
categorical_variables.remove('deposit')
categorical_variables.remove('month')
print(categorical_variables)
stages = []
print(stages)

#Stringindexer and OneHotEncoderEstimator for all categorical variables
for categorical_col in categorical_variables:
  stringIndexer = StringIndexer(inputCol= categorical_col, outputCol=␣
 ↪categorical_col + "Index")
  encoder = OneHotEncoder(inputCols=[stringIndexer.getOutputCol()],␣
 ↪outputCols=[categorical_col + "classVec"])
  stages += [stringIndexer, encoder]
print(stages)

#StringIndexer for target variable
string_indexer_label = StringIndexer(inputCol='deposit', outputCol= 'label')
stages +=[string_indexer_label]
print(stages)

#########Vector Assembler#######
```

```
###NOTE: When running the first time, please uncomment the next two commented␣
↪code for removing the 2nd item in list (since we don't need it)
del(numeric_variables[2])
numeric_variables

assembler_inputs = [x + "classVec" for x in categorical_variables] +␣
↪numeric_variables
assembler_inputs
assembler = VectorAssembler(inputCols=assembler_inputs, outputCol="features")
stages +=[assembler]
print(stages)
```

```
['job', 'marital', 'education', 'default', 'housing', 'loan', 'contact',
'month', 'poutcome', 'deposit']
['job', 'marital', 'education', 'default', 'housing', 'loan', 'contact',
'poutcome']
[]
[StringIndexer_f9ec692fd80c, OneHotEncoder_6be121e2da2a,
StringIndexer_3aa7b56d57e1, OneHotEncoder_347aafc19a80,
StringIndexer_af6cf4689557, OneHotEncoder_ec6f0699a16f,
StringIndexer_651f1b4ea40f, OneHotEncoder_a8cd6d2c1a4f,
StringIndexer_621212989207, OneHotEncoder_57b800a9104c,
StringIndexer_7c75f1f74325, OneHotEncoder_e986f7099853,
StringIndexer_d95c52f9d115, OneHotEncoder_f3045f1ab21d,
StringIndexer_0d16e0841eb9, OneHotEncoder_58a373fc5b67]
[StringIndexer_f9ec692fd80c, OneHotEncoder_6be121e2da2a,
StringIndexer_3aa7b56d57e1, OneHotEncoder_347aafc19a80,
StringIndexer_af6cf4689557, OneHotEncoder_ec6f0699a16f,
StringIndexer_651f1b4ea40f, OneHotEncoder_a8cd6d2c1a4f,
StringIndexer_621212989207, OneHotEncoder_57b800a9104c,
StringIndexer_7c75f1f74325, OneHotEncoder_e986f7099853,
StringIndexer_d95c52f9d115, OneHotEncoder_f3045f1ab21d,
StringIndexer_0d16e0841eb9, OneHotEncoder_58a373fc5b67,
StringIndexer_414bf78dde83]
[StringIndexer_f9ec692fd80c, OneHotEncoder_6be121e2da2a,
StringIndexer_3aa7b56d57e1, OneHotEncoder_347aafc19a80,
StringIndexer_af6cf4689557, OneHotEncoder_ec6f0699a16f,
StringIndexer_651f1b4ea40f, OneHotEncoder_a8cd6d2c1a4f,
StringIndexer_621212989207, OneHotEncoder_57b800a9104c,
StringIndexer_7c75f1f74325, OneHotEncoder_e986f7099853,
StringIndexer_d95c52f9d115, OneHotEncoder_f3045f1ab21d,
StringIndexer_0d16e0841eb9, OneHotEncoder_58a373fc5b67,
StringIndexer_414bf78dde83, VectorAssembler_93d558470c57]
```

[ ]:
```
#Building our Machine Learning Pipeline
cols = df_final.columns
from pyspark.ml import Pipeline
```

```python
pipeline = Pipeline(stages = stages)
pipeline_model = pipeline.fit(df_final)
df_final = pipeline_model.transform(df_final)
all_columns = ['label', 'features'] + cols
df_final = df_final.select(all_columns)
df_final.dtypes
```

[ ]:
```
[('label', 'double'),
 ('features', 'vector'),
 ('age', 'int'),
 ('job', 'string'),
 ('marital', 'string'),
 ('education', 'string'),
 ('default', 'string'),
 ('balance', 'int'),
 ('housing', 'string'),
 ('loan', 'string'),
 ('contact', 'string'),
 ('duration', 'int'),
 ('campaign', 'int'),
 ('pdays', 'int'),
 ('previous', 'int'),
 ('poutcome', 'string'),
 ('deposit', 'string')]
```

[ ]:
```python
df_pandas = df_final.toPandas()
#df_pandas.head(3)
df_pandas.iloc[3,1]
```

[ ]:
```
SparseVector(30, {4: 1.0, 11: 1.0, 13: 1.0, 16: 1.0, 18: 1.0, 20: 1.0, 21: 1.0,
24: 55.0, 25: 2476.0, 26: 579.0, 27: 1.0, 28: -1.0})
```

[ ]:
```python
#df_pandas
```

[ ]:
```python
categorical_variables
for i in df_pandas[categorical_variables]:
  print(i, df_pandas[i].unique(), len(df_pandas[i].unique()))
# We need to perform n - 1 for each category because of DropLast = True.
# Currently, there are n categories for each feature in this loop.
# Post n-1, we get a total of 24 categories in dataset and combining them with␣
 ↪6 numeric features, gives us a total of 30 features, which can be
# seen from the feature variable, which has been created via assembling all␣
 ↪data points per row to form a feature vector (per row).
```

```
job ['admin.' 'technician' 'services' 'management' 'retired' 'blue-collar'
 'unemployed' 'entrepreneur' 'housemaid' 'unknown' 'self-employed'
 'student'] 12
marital ['married' 'single' 'divorced'] 3
education ['secondary' 'tertiary' 'primary' 'unknown'] 4
default ['no' 'yes'] 2
```

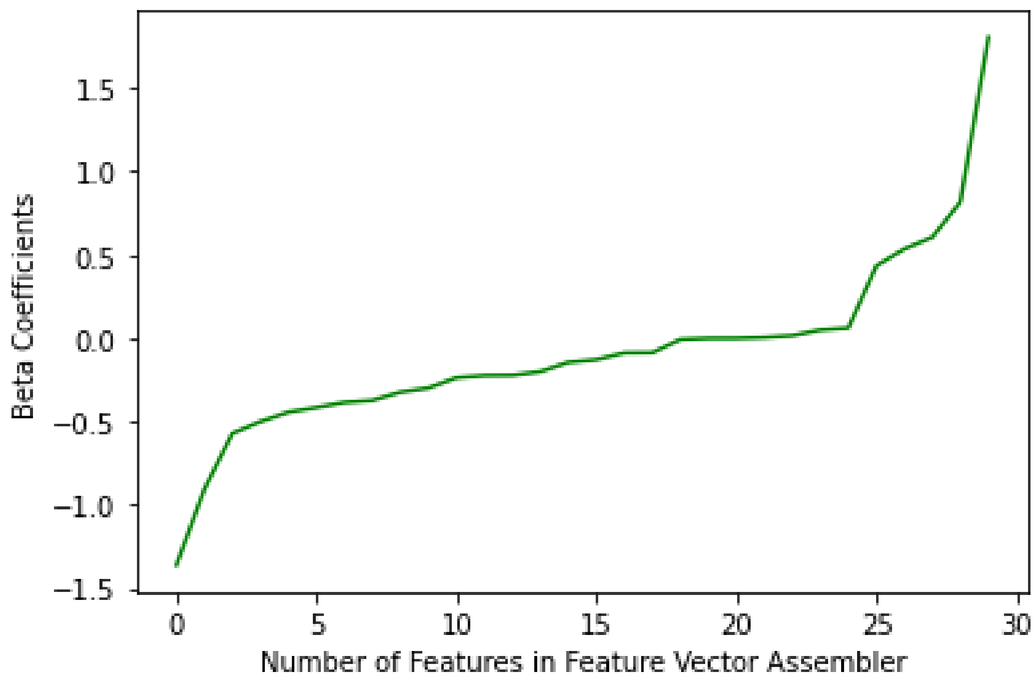
```
housing ['yes' 'no'] 2
loan ['no' 'yes'] 2
contact ['unknown' 'cellular' 'telephone'] 3
poutcome ['unknown' 'other' 'failure' 'success'] 4
```

[ ]:
```
#Train - Test Split
train, test = df_final.randomSplit([0.7, 0.3], seed = 111)
print("Training Dataset Count: " + str(train.count()))
print("Test Dataset Count: " + str(test.count()))
```

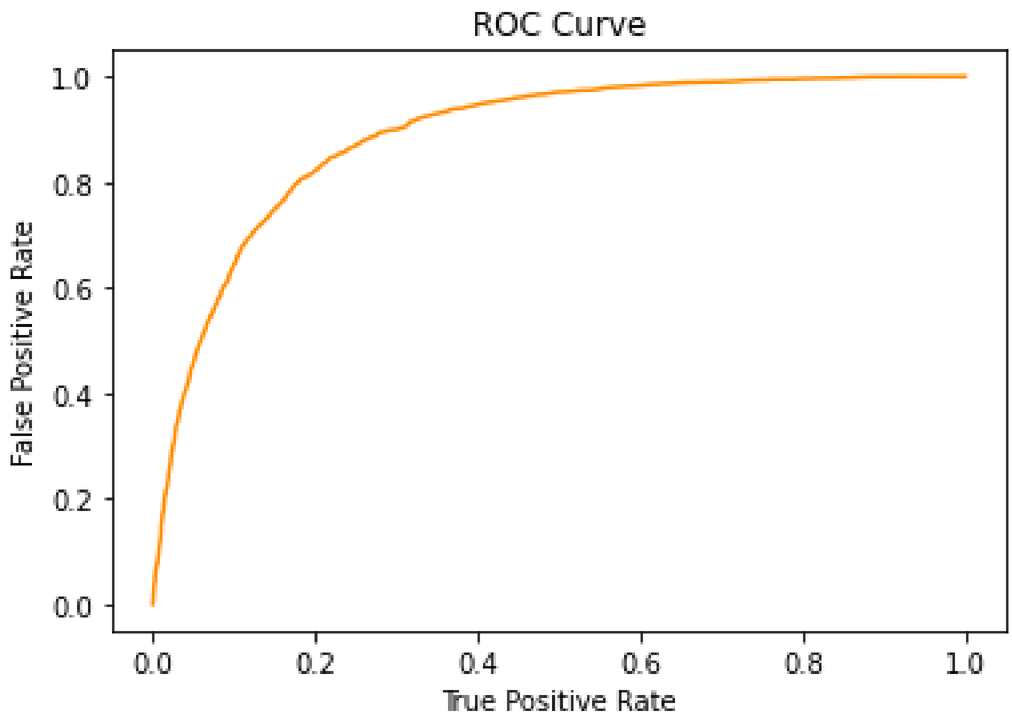
```
Training Dataset Count: 7843
Test Dataset Count: 3319
```

[ ]:
```
#Logistic Regression
from pyspark.ml.classification import LogisticRegression
lr = LogisticRegression(featuresCol = 'features', labelCol = 'label',␣
 ↪maxIter=20)
lrModel = lr.fit(train)
```

[ ]:
```
import matplotlib.pyplot as plt
import numpy as np
beta = np.sort(lrModel.coefficients)
plt.plot(beta, color = 'green')
plt.ylabel('Beta Coefficients')
plt.xlabel('Number of Features in Feature Vector Assembler')
plt.show()
```

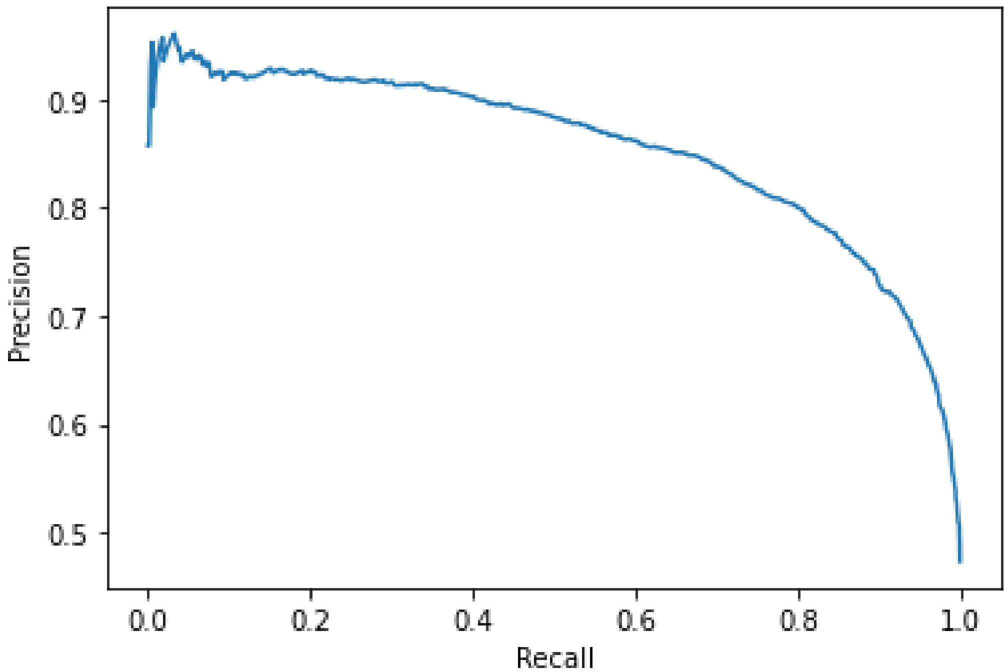


[ ]:
```
trainingSummary = lrModel.summary
roc = trainingSummary.roc.toPandas()
plt.plot(roc['FPR'],roc['TPR'], color = "darkorange")
plt.ylabel('False Positive Rate')
plt.xlabel('True Positive Rate')
plt.title('ROC Curve')
plt.show()
print('Training set areaUnderROC: ' + str(trainingSummary.areaUnderROC))
```




```
Training set areaUnderROC: 0.8873176438519467
```

[ ]:
```
pr = trainingSummary.pr.toPandas()
plt.plot(pr['recall'],pr['precision'])
plt.ylabel('Precision')
plt.xlabel('Recall')
plt.show()
```



[ ]:
```python
predictions = lrModel.transform(test)
predictions.select('age', 'job', 'label', 'rawPrediction', 'prediction',
 'probability').show(10)
```

```
+---+----------+-----+--------------------+----------+--------------------+
|age|       job|label|       rawPrediction|prediction|         probability|
+---+----------+-----+--------------------+----------+--------------------+
| 34|management|  0.0|[0.23227426403389...|       0.0|[0.55780889383587...|
| 37|management|  0.0|[1.07827232318531...|       0.0|[0.74616689732780...|
| 42|management|  0.0|[1.42350053763192...|       0.0|[0.80588660378317...|
| 32|management|  0.0|[1.13670611552191...|       0.0|[0.75707436465925...|
| 44|management|  0.0|[0.94144140626849...|       0.0|[0.71939072279361...|
| 57|management|  0.0|[1.08710009769855...|       0.0|[0.74783525786982...|
| 36|management|  0.0|[1.13336142708195...|       0.0|[0.75645870494901...|
| 40|management|  0.0|[1.53363719113977...|       0.0|[0.82253785555589...|
| 46|management|  0.0|[2.10550235325418...|       0.0|[0.89143682923626...|
| 47|management|  0.0|[0.60209164847146...|       0.0|[0.64613469651098...|
+---+----------+-----+--------------------+----------+--------------------+
only showing top 10 rows
```

[ ]:
```python
from pyspark.ml.evaluation import BinaryClassificationEvaluator
evaluator = BinaryClassificationEvaluator()
print('Test Area Under ROC', evaluator.evaluate(predictions))
```

```
Test Area Under ROC 0.882180280221685
```

[ ]:
```python
# Decision Trees
from pyspark.ml.classification import DecisionTreeClassifier
dt = DecisionTreeClassifier(featuresCol = 'features', labelCol = 'label',␣
 ↪maxDepth = 3)
dtModel = dt.fit(train)
predictions = dtModel.transform(test)
predictions.select('age', 'job', 'label', 'rawPrediction', 'prediction',␣
 ↪'probability').show(10)
```

```
+---+----------+-----+--------------+----------+--------------------+
|age|       job|label| rawPrediction|prediction|         probability|
+---+----------+-----+--------------+----------+--------------------+
| 34|management|  0.0|[845.0,1392.0]|       1.0|[0.37773804202056...|
| 37|management|  0.0|[2489.0,487.0]|       0.0|[0.83635752688172...|
| 42|management|  0.0|[2489.0,487.0]|       0.0|[0.83635752688172...|
| 32|management|  0.0|[2489.0,487.0]|       0.0|[0.83635752688172...|
| 44|management|  0.0|[2489.0,487.0]|       0.0|[0.83635752688172...|
| 57|management|  0.0|[2489.0,487.0]|       0.0|[0.83635752688172...|
| 36|management|  0.0|  [416.0,38.0]|       0.0|[0.91629955947136...|
| 40|management|  0.0|  [416.0,38.0]|       0.0|[0.91629955947136...|
| 46|management|  0.0|[2489.0,487.0]|       0.0|[0.83635752688172...|
| 47|management|  0.0|[845.0,1392.0]|       1.0|[0.37773804202056...|
+---+----------+-----+--------------+----------+--------------------+
only showing top 10 rows
```

[ ]:
```python
evaluator = BinaryClassificationEvaluator()
print("Test Area Under ROC: " + str(evaluator.evaluate(predictions, {evaluator.
 ↪metricName: "areaUnderROC"})))
```

```
Test Area Under ROC: 0.7688262112991489
```

[ ]:
```python
from pyspark.ml.classification import RandomForestClassifier
rf = RandomForestClassifier(featuresCol = 'features', labelCol = 'label')
rfModel = rf.fit(train)
predictions = rfModel.transform(test)
predictions.select('age', 'job', 'label', 'rawPrediction', 'prediction',␣
 ↪'probability').show(10)
```

```
+---+----------+-----+--------------------+----------+--------------------+
|age|       job|label|       rawPrediction|prediction|         probability|
+---+----------+-----+--------------------+----------+--------------------+
| 34|management|  0.0|[9.60493129370130...|       1.0|[0.48024656468506...|
| 37|management|  0.0|[14.7931681953967...|       0.0|[0.73965840976983...|
```

```
| 42|management|  0.0|[14.2619205875643...|       0.0|[0.71309602937821...|
| 32|management|  0.0|[15.1212713916369...|       0.0|[0.75606356958184...|
| 44|management|  0.0|[14.7931681953967...|       0.0|[0.73965840976983...|
| 57|management|  0.0|[14.5923319837989...|       0.0|[0.72961659918994...|
| 36|management|  0.0|[14.0456675757228...|       0.0|[0.70228337878614...|
| 40|management|  0.0|[14.0456675757228...|       0.0|[0.70228337878614...|
| 46|management|  0.0|[16.5317096662812...|       0.0|[0.82658548331406...|
| 47|management|  0.0|[8.74282839146477...|       1.0|[0.43714141957323...|
+---+----------+-----+--------------------+----------+--------------------+
only showing top 10 rows
```

[ ]:
```python
evaluator = BinaryClassificationEvaluator()
print("Test Area Under ROC: " + str(evaluator.evaluate(predictions, {evaluator.
 ↪metricName: "areaUnderROC"})))
```

```
Test Area Under ROC: 0.8740465851804623
```

[ ]:
```python
#Gradient Boosting Tree Classifier
from pyspark.ml.classification import GBTClassifier
gbt = GBTClassifier(maxIter=10)
gbtModel = gbt.fit(train)
predictions = gbtModel.transform(test)
predictions.select('age', 'job', 'label', 'rawPrediction', 'prediction',␣
 ↪'probability').show(10)
```

```
+---+----------+-----+--------------------+----------+--------------------+
|age|       job|label|       rawPrediction|prediction|         probability|
+---+----------+-----+--------------------+----------+--------------------+
| 34|management|  0.0|[-0.1379334480210...|       1.0|[0.43146735146133...|
| 37|management|  0.0|[0.62197489330243...|       0.0|[0.77625078341155...|
| 42|management|  0.0|[1.20862248237840...|       0.0|[0.91813290106157...|
| 32|management|  0.0|[0.70697416510970...|       0.0|[0.80438795213405...|
| 44|management|  0.0|[0.66751006881570...|       0.0|[0.79166981202314...|
| 57|management|  0.0|[0.56219096811074...|       0.0|[0.75480061571150...|
| 36|management|  0.0|[1.12218258958006...|       0.0|[0.90416337754277...|
| 40|management|  0.0|[1.22491088090701...|       0.0|[0.92054841562509...|
| 46|management|  0.0|[0.58568503698017...|       0.0|[0.76339257374513...|
| 47|management|  0.0|[-0.2573502089919...|       1.0|[0.37409228589155...|
+---+----------+-----+--------------------+----------+--------------------+
only showing top 10 rows
```

[ ]:
```python
evaluator = BinaryClassificationEvaluator()
print("Test Area Under ROC: " + str(evaluator.evaluate(predictions, {evaluator.
 ↪metricName: "areaUnderROC"})))
```

```
Test Area Under ROC: 0.8836635519598336
```

[ ]:
```python
# K-Fold Cross Validation with hyperparameter tuning (for GBT Classifier since␣
↪it provided highest accuracy prior to cross validation)
from pyspark.ml.tuning import ParamGridBuilder, CrossValidator
paramGrid = (ParamGridBuilder()
             .addGrid(gbt.maxDepth, [2, 4, 6])
             .addGrid(gbt.maxBins, [20, 60])
             .addGrid(gbt.maxIter, [10, 20])
             .build())
cv = CrossValidator(estimator=gbt, estimatorParamMaps=paramGrid,␣
↪evaluator=evaluator, numFolds=5)

cvModel = cv.fit(train)
predictions = cvModel.transform(test)
evaluator.evaluate(predictions)
```

[ ]: 0.8910054649344297

[ ]:
```python
!wget -nc https://raw.githubusercontent.com/brpy/colab-pdf/master/colab_pdf.py
from colab_pdf import colab_pdf
colab_pdf('Bank_pyspark.ipynb')
```

```
File colab_pdf.py already there; not retrieving.


WARNING: apt does not have a stable CLI interface. Use with caution in scripts.


WARNING: apt does not have a stable CLI interface. Use with caution in scripts.

Extracting templates from packages: 100%
```

[ ]:
```python
```