experimentation

November 17, 2022

1 MiniProject2 - Project Summary

https://github.com/0Architectus0/BAN5753_MiniProject2 ## Data Description The data consists of 41188 observations of 20 features and the subscribe response: 'y'.

1.0.1 Client demographics:

1. **age** (numeric)
2. **job**: type of job (categorical)
3. **marital**: marital status (categorical)
4. **education** (categorical)
5. **default**: has credit in default? (categorical)
6. **housing**: has housing loan? (categorical)
7. **loan**: has personal loan? (categorical) ### Attributes regarding the latest contact in the ongoing campaign:
8. **contact**: contact communication type (categorical)
9. **month**: last contact month of year (categorical)
10. **day_of_week**: last contact day of the week (categorical)
11. **duration**: last contact duration, in seconds (numeric) ### Other attributes:
12. **campaign**: number of contacts performed during this campaign and for this client (numeric, includes last contact)
13. **pdays**: number of days that passed by after the client was last contacted from a previous campaign (numeric; 999 means client was not previously contacted)
14. **previous**: number of contacts performed before this campaign and for this client (numeric)
15. **poutcome**: outcome of the previous marketing campaign (categorical) ### Social and economic context attributes:
16. **emp.var.rate**: employment variation rate - quarterly indicator (numeric)
17. **cons.price.idx**: consumer price index - monthly indicator (numeric)
18. **cons.conf.idx**: consumer confidence index - monthly indicator (numeric)
19. **euribor3m**: euribor 3 month rate - daily indicator (numeric)
20. **nr.employed**: number of employees - quarterly indicator (numeric)

1.1 Data Loading and Cleaning

The majority of the data processing was handled with PySpark, a Python interface of Apache Spark. Please reference the latest documentation with questions regarding the syntax or API methods.

PySpark Documentation

1.1.1 Load and inspect

The PySpark API loaded the data easily after discovering the delimiter was altered from the standard comma to a semi-colon. Additional parameters were included to indicate the presence of a header and to attempt to infer the data's schema.

[1]:
```
import findspark
findspark.init()
```

[52]:
```
from pyspark.sql import SparkSession
from pyspark.conf import SparkConf
from pyspark.sql.types import *
import pyspark.sql.functions as F
from pyspark.sql.functions import col, asc, desc
import matplotlib.pyplot as plt
import numpy as np
import seaborn as sns
from pyspark.sql import SQLContext
from pyspark.mllib.stat import Statistics
import pandas as pd
from pyspark.sql.functions import udf
from pyspark.ml.feature import OneHotEncoder, StringIndexer,␣
↪VectorAssembler,StandardScaler
from pyspark.ml import Pipeline
from sklearn.metrics import confusion_matrix

pd.options.display.max_columns=None
pd.options.display.max_rows=None

%matplotlib inline

spark=SparkSession.builder \
.master ("local[*]")\
.appName("MiniProject2")\
.getOrCreate()
```

[3]:
```
sc=spark.sparkContext
sqlContext=SQLContext(sc)
```

```
/usr/local/spark/python/pyspark/sql/context.py:112: FutureWarning: Deprecated in
3.0.0. Use SparkSession.builder.getOrCreate() instead.
  warnings.warn(
```

[4]:
```
df=spark.read \
 .option("header","True")\
 .option("inferSchema","True")\
 .option("sep",";")\
 .csv("../data/XYZ_Bank_Deposit_Data_Classification.csv")
```

```python
print("There are",df.count(),"rows",len(df.columns),
      "columns" ,"in the data.")
```

```
There are 41188 rows 21 columns in the data.
```

[53]:
```python
df.show(4)
```

```
+---+---------+-------+-----------+-------+-------+----+---------+-----+--------
---+--------+--------+-----+--------+-----------+------------+-------------+---
----------+---------+----------+---+
|age|      job|marital|  education|default|housing|loan|
contact|month|day_of_week|duration|campaign|pdays|previous|
poutcome|emp.var.rate|cons.price.idx|cons.conf.idx|euribor3m|nr.employed|  y|
+---+---------+-------+-----------+-------+-------+----+---------+-----+--------
---+--------+--------+-----+--------+-----------+------------+-------------+---
----------+---------+----------+---+
| 56|housemaid|married|   basic.4y|     no|     no|  no|telephone|  may|
mon|     261|       1|  999|       0|nonexistent|         1.1|        93.994|
-36.4|    4.857|     5191.0| no|
| 57| services|married|high.school|unknown|     no|  no|telephone|  may|
mon|     149|       1|  999|       0|nonexistent|         1.1|        93.994|
-36.4|    4.857|     5191.0| no|
| 37| services|married|high.school|     no|    yes|  no|telephone|  may|
mon|     226|       1|  999|       0|nonexistent|         1.1|        93.994|
-36.4|    4.857|     5191.0| no|
| 40|   admin.|married|   basic.6y|     no|     no|  no|telephone|  may|
mon|     151|       1|  999|       0|nonexistent|         1.1|        93.994|
-36.4|    4.857|     5191.0| no|
+---+---------+-------+-----------+-------+-------+----+---------+-----+--------
---+--------+--------+-----+--------+-----------+------------+-------------+---
----------+---------+----------+---+
only showing top 4 rows
```

[6]:
```python
df.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)
 |-- duration: integer (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)
 |-- y: string (nullable = true)
```

Column names are not setup for analysis. The period within each name causes issues when selecting. Altering columns names to avoid errors.

[7]:
```
# renamed columns
df2 = df.withColumnRenamed("cons.price.idx","cons_price_idx")\
.withColumnRenamed("emp.var.rate", "emp_var_rate")\
.withColumnRenamed("cons.conf.idx","cons_conf_idx")\
.withColumnRenamed("nr.employed", "nr_employed")
```

1.2 Numeric Features

1.2.1 Summary Statistics

[8]:
```
numeric_features = [t[0] for t in df2.dtypes if t[1] != 'string' ]
df2.select(numeric_features).summary().toPandas().set_index('summary').
 ↪transpose()
```

[8]:
```
summary         count                 mean               stddev     min  \
age             41188    40.02406040594348    10.421249980934043      17
duration        41188    258.2850101971448    259.27924883646455       0
campaign        41188    2.567592502670681    2.770013542902331       1
pdays           41188    962.4754540157328     186.910907344741       0
previous        41188  0.17296299893172767  0.49490107983928927      0
emp_var_rate    41188  0.08188550063178966     1.57095974051703    -3.4
cons_price_idx  41188     93.5756643682899   0.5788400489540823  92.201
cons_conf_idx   41188  -40.502600271918276    4.628197856174573   -50.8
euribor3m       41188    3.621290812858533   1.7344474048512595   0.634
nr_employed     41188    5167.035910943957    72.25152766826338  4963.6

summary          25%     50%     75%     max
age               32      38      47      98
duration         102     180     319    4918
campaign           1       2       3      56
pdays            999     999     999     999
previous           0       0       0       7
emp_var_rate    -1.8     1.1     1.4     1.4
```

```
cons_price_idx  93.075  93.749  93.994  94.767
cons_conf_idx    -42.7   -41.8   -36.4   -26.9
euribor3m        1.344   4.857   4.961   5.045
nr_employed     5099.1  5191.0  5228.1  5228.1
```

Looking over these stats reveals some abnormalities in the data. 'pdays' stands out first as the 999 value is the value for all quartile groups and the max. Meaning it comprises the majority of the observations. Since 999 is a placeholder for NULL/NA it can be assumed the majority of the observations are actually empty and the column might be of little use unless transformed.

1.2.2 Initial Null Count Inspection

[9]:
```
from pyspark.sql.functions import col,isnan, when, count
df2.select([count(when(isnan(c) | col(c).isNull(), c)).alias(c) for c in␣
↪numeric_features]).toPandas().head()

#df2.select([count(when(isnan(c) | col(c).isNull(), c)).alias(c) for c in df2.
↪columns]).show() # for README
```

[9]:
```
   age  duration  campaign  pdays  previous  emp_var_rate  cons_price_idx  \
0    0         0         0      0         0             0               0

   cons_conf_idx  euribor3m  nr_employed
0              0          0            0
```

Since the count doesn't bear this out, I'll transform the data by adding back the null instances wihtin the the column and creating a null indicator column for the feature. Doing this allows me to try to capture any value of the missing data while getting a better idea of the distribution of the actual values of pdays.

[10]:
```
df3 = df2.withColumn("pdays_na_ind",when(df2.pdays==999,1).otherwise(0))\
.withColumn("pdays",when(df2.pdays==999,np.nan).otherwise(df2.pdays))
```

[11]:
```
df3.select([count(when(isnan(c) | col(c).isNull(), c)).alias(c) for c in␣
↪numeric_features]).toPandas().head()
```

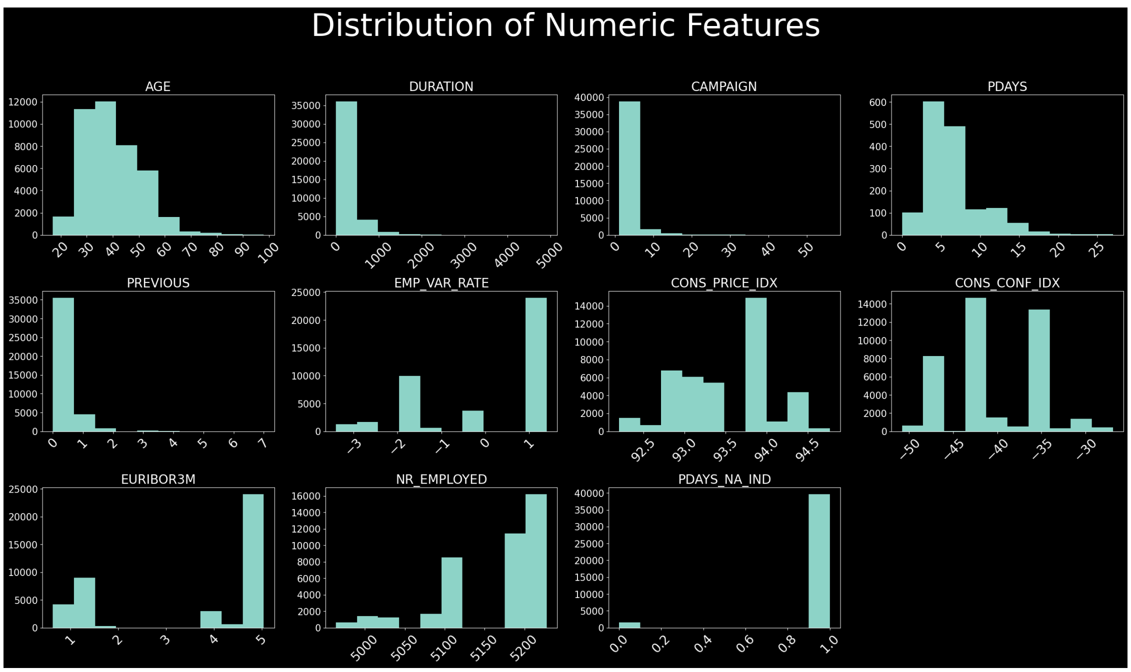
[11]:
```
   age  duration  campaign  pdays  previous  emp_var_rate  cons_price_idx  \
0    0         0         0  39673         0             0               0

   cons_conf_idx  euribor3m  nr_employed
0              0          0            0
```

There's the nulls! Quite a few of them actually for 'pdays'. Since no other feature has documentation describing a null surrogate, it's assumed none are made.

1.3 EDA/descriptive statistics

1.3.1 Numeric Feature Distributions

[13]:
```python
from matplotlib import cm
fig = plt.figure(figsize=(25,15)) ## Plot Size
st = fig.suptitle("Distribution of Numeric Features", fontsize=50,
                  verticalalignment='center') # Plot Main Title

for col,num in zip(df3.toPandas().describe().columns, range(1,22)):
    ax = fig.add_subplot(3,4,num)
    ax.hist(df3.toPandas()[col])
    plt.style.use('dark_background')
    plt.grid(False)
    plt.xticks(rotation=45,fontsize=20)
    plt.yticks(fontsize=15)
    plt.title(col.upper(),fontsize=20)
plt.tight_layout()
st.set_y(0.95)
fig.subplots_adjust(top=0.85,hspace = 0.4)
plt.show()
```



Now we can see a clearer representation of the acutal values for 'pdays' as well as an estimatation of the proportion of null values for the column in our na indicator column. It's clear the vast majority of data is missing. Imputation at this level of missingness is not advisable.

- 'age' slight right-skew with a mean of ~40
- 'duration' is heavily right-skewed with the majority of values being below 500.
- 'campaign' another heavily right-skewed variable; most values being below 50
- 'pdays' after cleaning the distribution of the remaining data is fairly normal with a right-skew
- 'previous' another heavily right-skewed variable; most values being below 50
- 'emp_var_rate' this variable is the first with negative values, but most of the values are 1
- 'cons_price_idx' the varialbe appears bimodal with the mean appearing to be close to 93.75
- 'cons_conf_idx' this value has no clear pattern but all values are negative
- 'euribor3m' anther bimodal set with one lower group group being approx 1.25 and the other ~ 4.75
- 'nr_employed' this distribution appears to be left skewed
- 'pdays_na_ind' this is the null indicator column created earlier clearly outlining the large amount of missing values for pdays.

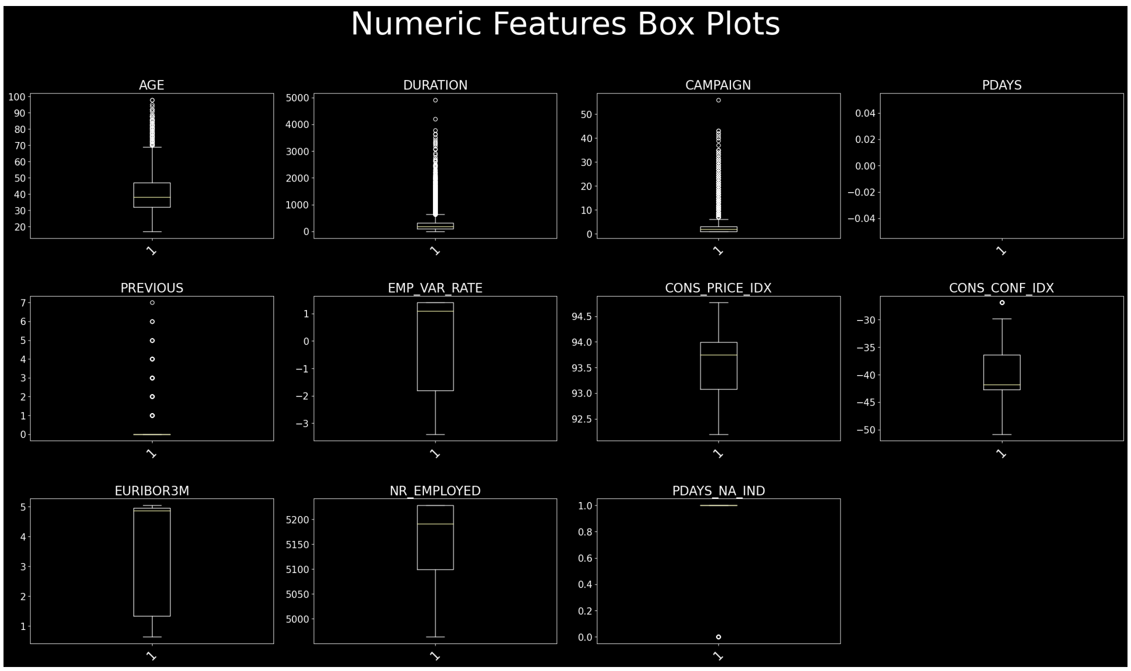
Now let's get a better idea of the numeric statistics using a box an whisker plot.

[14]:
```
numeric_features = [t[0] for t in df3.dtypes if t[1] != 'string' ]
df3.select(numeric_features).summary().toPandas().set_index('summary').
 ↪transpose()
```

[14]:
```
summary         count                mean              stddev     min  \
age             41188   40.02406040594348   10.421249980934043      17
duration        41188   258.2850101971448   259.27924883646455       0
campaign        41188   2.567592502670681    2.770013542902331       1
pdays           41188                 NaN                  NaN     0.0
previous        41188 0.17296299893172767  0.49490107983928927       0
emp_var_rate    41188 0.08188550063178966     1.57095974051703    -3.4
cons_price_idx  41188    93.5756643682899   0.5788400489540823  92.201
cons_conf_idx   41188 -40.502600271918276    4.628197856174573   -50.8
euribor3m       41188   3.621290812858533   1.7344474048512595   0.634
nr_employed     41188   5167.035910943957    72.25152766826338  4963.6
pdays_na_ind    41188  0.9632174419733903  0.18822981077618453       0

summary            25%     50%     75%     max
age                 32      38      47      98
duration           102     180     319    4918
campaign             1       2       3      56
pdays              NaN     NaN     NaN     NaN
previous             0       0       0       7
emp_var_rate      -1.8     1.1     1.4     1.4
cons_price_idx  93.075  93.749  93.994  94.767
cons_conf_idx    -42.7   -41.8   -36.4   -26.9
euribor3m        1.344   4.857   4.961   5.045
nr_employed     5099.1  5191.0  5228.1  5228.1
pdays_na_ind         1       1       1       1
```

[15]:
```
from matplotlib import cm
fig = plt.figure(figsize=(25,15)) ## Plot Size
```

```python
st = fig.suptitle("Numeric Features Box Plots", fontsize=50,
                  verticalalignment='center') # Plot Main Title

for col,num in zip(df3.toPandas().describe().columns, range(1,22)):
    ax = fig.add_subplot(3,4,num)
    ax.boxplot(df3.toPandas()[col])
    plt.style.use('dark_background')
    plt.grid(False)
    plt.xticks(rotation=45,fontsize=20)
    plt.yticks(fontsize=15)
    plt.title(col.upper(),fontsize=20)
plt.tight_layout()
st.set_y(0.95)
fig.subplots_adjust(top=0.85,hspace = 0.4)
plt.show()
```



1.4 Categorical Features

First the response variable.

[16]:
```python
df3.groupby("y").count().show()
```

```
+---+-----+
|  y|count|
+---+-----+
| no|36548|
|yes| 4640|
```

```
+---+-----+
```

The classes are not evenly distbuted and the class of interest is the minority class. Let's look at the rest.

[17]:
```python
categorical_features = [t[0] for t in df2.dtypes if t[1] == 'string' and t[0] !
 ↪= 'y']
```

[49]:
```python
df3.groupby("job").count().show()
df3.groupby("marital").count().show()
df3.groupby("education").count().show()
df3.groupby("default").count().show()
df3.groupby("housing").count().show()
df3.groupby("loan").count().show()
df3.groupby("contact").count().show()
df3.groupby("month").count().show()
df3.groupby("day_of_week").count().show()
df3.groupby("poutcome").count().show()
```

```
+-------------+-----+
|          job|count|
+-------------+-----+
|   management| 2924|
|      retired| 1720|
|      unknown|  330|
|self-employed| 1421|
|      student|  875|
|  blue-collar| 9254|
| entrepreneur| 1456|
|       admin.|10422|
|   technician| 6743|
|     services| 3969|
|    housemaid| 1060|
|   unemployed| 1014|
+-------------+-----+

+--------+-----+
| marital|count|
+--------+-----+
| unknown|   80|
|divorced| 4612|
| married|24928|
|  single|11568|
+--------+-----+

+-------------------+-----+
|          education|count|
```

```
+-------------------+-----+
|        high.school| 9515|
|            unknown| 1731|
|           basic.6y| 2292|
|professional.course| 5243|
|  university.degree|12168|
|         illiterate|   18|
|           basic.4y| 4176|
|           basic.9y| 6045|
+-------------------+-----+

+-------+-----+
|default|count|
+-------+-----+
|unknown| 8597|
|     no|32588|
|    yes|    3|
+-------+-----+

+-------+-----+
|housing|count|
+-------+-----+
|unknown|  990|
|     no|18622|
|    yes|21576|
+-------+-----+

+-------+-----+
|   loan|count|
+-------+-----+
|unknown|  990|
|     no|33950|
|    yes| 6248|
+-------+-----+

+---------+-----+
|  contact|count|
+---------+-----+
| cellular|26144|
|telephone|15044|
+---------+-----+

+-----+-----+
|month|count|
+-----+-----+
|  jun| 5318|
|  aug| 6178|
|  may|13769|
```

```
|  mar|  546|
|  oct|  718|
|  jul| 7174|
|  nov| 4101|
|  apr| 2632|
|  dec|  182|
|  sep|  570|
+-----+-----+

+-----------+-----+
|day_of_week|count|
+-----------+-----+
|        fri| 7827|
|        thu| 8623|
|        tue| 8090|
|        wed| 8134|
|        mon| 8514|
+-----------+-----+

+-----------+-----+
|   poutcome|count|
+-----------+-----+
|    success| 1373|
|    failure| 4252|
|nonexistent|35563|
+-----------+-----+
```

Now we'll remove the null filler and bring back the actual nulls to get a better idea of the missing values within the set

[ ]:
```
df4=df3.withColumn("marital",when(df3.marital=="unknown",np.nan).otherwise(df3.
 ↪marital))\
.withColumn("education",when(df3.education=="unknown",np.nan).otherwise(df3.
 ↪education))\
.withColumn("default",when(df3.default=="unknown",np.nan).otherwise(df3.
 ↪default))\
.withColumn("housing",when(df3.housing=="unknown",np.nan).otherwise(df3.
 ↪housing))\
.withColumn("loan",when(df3.loan=="unknown",np.nan).otherwise(df3.loan))\
.withColumn("y_int",when(df3.pdays=="no",0).otherwise(1))
```

[29]:
```
df4 = df3.withColumn("marital_na_ind",when(df3.marital=="unknown",1).
 ↪otherwise(0))\
         .withColumn("marital",when(df3.marital=="unknown",np.nan).
 ↪otherwise(df3.marital))\
```

```
        .withColumn("education_na_ind",when(df3.education=="unknown",1).
↪otherwise(0))\
        .withColumn("education",when(df3.education=="unknown",np.nan).
↪otherwise(df3.education))\
        .withColumn("default_na_ind",when(df3.default=="unknown",1).
↪otherwise(0))\
        .withColumn("default",when(df3.default=="unknown",np.nan).
↪otherwise(df3.default))\
        .withColumn("housing_na_ind",when(df3.housing=="unknown",1).
↪otherwise(0))\
        .withColumn("housing",when(df3.housing=="unknown",np.nan).
↪otherwise(df3.housing))\
        .withColumn("load_na_ind",when(df3.loan=="unknown",1).otherwise(0))\
        .withColumn("loan",when(df3.loan=="unknown",np.nan).otherwise(df3.
↪loan))\
        .withColumn("y_ind",when(df3.pdays=="no",0).otherwise(1))
```

[51]:
```
from pyspark.sql.functions import col, when, count

df4.select([count(when(isnan(c) | col(c).isNull(), c)).alias(c) for c in df4.
↪columns]).toPandas().head()
```

[51]:
```
   age  job  marital  education  default  housing  loan  contact  month  \
0    0    0       80       1731     8597      990   990        0      0

   day_of_week  …  euribor3m  nr_employed  y  pdays_na_ind  marital_na_ind  \
0            0  …          0            0  0             0               0

   education_na_ind  default_na_ind  housing_na_ind  load_na_ind  y_ind
0                 0               0               0            0      0

[1 rows x 28 columns]
```

[31]:
```
from pyspark.ml.feature import QuantileDiscretizer
#education_udf = udf(udf_multiple)
#df3.withColumn("age_group",pd.qcut(df3.age, q=5)).show(5)

qds1 = QuantileDiscretizer(inputCol="age", outputCol="age_buckets")
qds1.setNumBuckets(5)
qds1.setRelativeError(0.01)
qds1.setHandleInvalid("error")
bucketizer = qds1.fit(df2)
qds1.setHandleInvalid("keep").fit(df2).transform(df2).count()
```

[31]: 41188

[32]:
```
qds1.setHandleInvalid("skip").fit(df4).transform(df4).count()
```

[32]: 41188

[33]:
```
splits = bucketizer.getSplits()
splits
```

[33]: [-inf, 31.0, 35.0, 41.0, 49.0, inf]

[34]:
```
df5 = qds1.setHandleInvalid("keep").fit(df4).transform(df4)
```

[35]:
```
df5.show(5)
```

```
+---+---------+-------+-----------+-------+-------+----+---------+-----+--------
---+--------+--------+-----+--------+-----------+------------+-------------+---
----------+---------+-----------+---+------------+--------------+---------------
-+--------------+--------------+------------+-----+-----------+
|age|      job|marital|  education|default|housing|loan|
contact|month|day_of_week|duration|campaign|pdays|previous|
poutcome|emp_var_rate|cons_price_idx|cons_conf_idx|euribor3m|nr_employed|  y|pda
ys_na_ind|marital_na_ind|education_na_ind|default_na_ind|housing_na_ind|load_na_
ind|y_ind|age_buckets|
+---+---------+-------+-----------+-------+-------+----+---------+-----+--------
---+--------+--------+-----+--------+-----------+------------+-------------+---
----------+---------+-----------+---+------------+--------------+---------------
-+--------------+--------------+------------+-----+-----------+
| 56|housemaid|married|   basic.4y|     no|     no|  no|telephone|  may|
mon|     261|       1|  NaN|       0|nonexistent|         1.1|        93.994|
-36.4|     4.857|      5191.0| no|           1|            0|              0|
0|             0|           0|    1|        4.0|
| 57| services|married|high.school|    NaN|     no|  no|telephone|  may|
mon|     149|       1|  NaN|       0|nonexistent|         1.1|        93.994|
-36.4|     4.857|      5191.0| no|           1|            0|              0|
1|             0|           0|    1|        4.0|
| 37| services|married|high.school|     no|    yes|  no|telephone|  may|
mon|     226|       1|  NaN|       0|nonexistent|         1.1|        93.994|
-36.4|     4.857|      5191.0| no|           1|            0|              0|
0|             0|           0|    1|        2.0|
| 40|   admin.|married|   basic.6y|     no|     no|  no|telephone|  may|
mon|     151|       1|  NaN|       0|nonexistent|         1.1|        93.994|
-36.4|     4.857|      5191.0| no|           1|            0|              0|
0|             0|           0|    1|        2.0|
| 56| services|married|high.school|     no|     no| yes|telephone|  may|
mon|     307|       1|  NaN|       0|nonexistent|         1.1|        93.994|
-36.4|     4.857|      5191.0| no|           1|            0|              0|
0|             0|           0|    1|        4.0|
+---+---------+-------+-----------+-------+-------+----+---------+-----+--------
```

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

2 Feature Groups

[36]:
```
categorical_features = [t[0] for t in df3.dtypes if t[1] == 'string' and t[0]!
 ↪='y' ]
categorical_features
```

[36]:
```
['job',
 'marital',
 'education',
 'default',
 'housing',
 'loan',
 'contact',
 'month',
 'day_of_week',
 'poutcome']
```

[56]:
```
numeric_features = [t[0] for t in df2.dtypes if t[1] != 'string' and t[0] !=␣
 ↪'wasPreviouslyContacted' and t[0]!='y_ind']
numeric_features
```

[56]:
```
['age',
 'duration',
 'campaign',
 'pdays',
 'previous',
 'emp_var_rate',
 'cons_price_idx',
 'cons_conf_idx',
 'euribor3m',
 'nr_employed']
```

3 Correlation

3.1 Pearson

[38]:
```
numeric_features_df=df5.select(numeric_features)

col_names =numeric_features_df.columns
features = numeric_features_df.rdd.map(lambda row: row[0:])
```

```
corr_mat=Statistics.corr(features, method="pearson")
corr_df = pd.DataFrame(corr_mat)
corr_df.index, corr_df.columns = col_names, col_names

corr_df
```

[38]:

```
                    age  duration  campaign  pdays  previous  emp_var_rate  \
age            1.000000 -0.000866  0.004594    NaN  0.024365     -0.000371
duration      -0.000866  1.000000 -0.071699    NaN  0.020640     -0.027968
campaign       0.004594 -0.071699  1.000000    NaN -0.079141      0.150754
pdays               NaN       NaN       NaN    1.0       NaN           NaN
previous       0.024365  0.020640 -0.079141    NaN  1.000000     -0.420489
emp_var_rate  -0.000371 -0.027968  0.150754    NaN -0.420489      1.000000
cons_price_idx  0.000857  0.005312  0.127836    NaN -0.203130      0.775334
cons_conf_idx  0.129372 -0.008173 -0.013733    NaN -0.050936      0.196041
euribor3m      0.010767 -0.032897  0.135133    NaN -0.454494      0.972245
nr_employed   -0.017725 -0.044703  0.144095    NaN -0.501333      0.906970

                cons_price_idx  cons_conf_idx  euribor3m  nr_employed
age                   0.000857       0.129372   0.010767    -0.017725
duration              0.005312      -0.008173  -0.032897    -0.044703
campaign              0.127836      -0.013733   0.135133     0.144095
pdays                      NaN            NaN        NaN          NaN
previous             -0.203130      -0.050936  -0.454494    -0.501333
emp_var_rate          0.775334       0.196041   0.972245     0.906970
cons_price_idx        1.000000       0.058986   0.688230     0.522034
cons_conf_idx         0.058986       1.000000   0.277686     0.100513
euribor3m             0.688230       0.277686   1.000000     0.945154
nr_employed           0.522034       0.100513   0.945154     1.000000
```

[39]:

```
# pick one, drop others, correlated features:
# 'housing_na_ind', 'load_na_ind' - 1.000
# 'euribor3m', 'emp_var_rate' - 0.972245
# 'euribor3m', 'nr_employed' - 0.945
# 'emp_var_rate', 'nr_employed' - 0.906970
# 'cons_price_idx', 'emp_var_rate' - 0.775334

multicollinearity_features = ('euribor3m', 'emp_var_rate','cons_price_idx',␣
 ↪'nr_employed', 'housing_na_ind', 'load_na_ind', "pdays")
df6 = df5.drop(*multicollinearity_features)

numeric_features = [t[0] for t in df6.dtypes if t[1] != 'string' and t[0] !=␣
 ↪'wasPreviouslyContacted' and t[0]!='y_ind']
```

[40]:

```
df6.select(categorical_features).show(5)
```

```
+---------+-------+-----------+-------+-------+----+---------+-----+-----------
```

```
+-----------+
|      job|marital|  education|default|housing|loan|  contact|month|day_of_week|
poutcome|
+---------+-------+-----------+-------+-------+----+---------+-----+-----------
+-----------+
|housemaid|married|   basic.4y|     no|     no|  no|telephone|  may|
mon|nonexistent|
| services|married|high.school|    NaN|     no|  no|telephone|  may|
mon|nonexistent|
| services|married|high.school|     no|    yes|  no|telephone|  may|
mon|nonexistent|
|   admin.|married|   basic.6y|     no|     no|  no|telephone|  may|
mon|nonexistent|
| services|married|high.school|     no|     no| yes|telephone|  may|
mon|nonexistent|
+---------+-------+-----------+-------+-------+----+---------+-----+-----------
+-----------+
only showing top 5 rows
```

[46]:

```
#from pyspark.sql.DataFrame.dropn

df7 = df6.filter()
```

[47]:

```
df7.show(5)
```

```
+---+---------+-------+-----------+-------+-------+----+---------+-----+--------
---+--------+--------+--------+-----------+-------------+---+-----------+------
--------+----------------+--------------+-----+-----------+
|age|      job|marital|  education|default|housing|loan|
contact|month|day_of_week|duration|campaign|previous|   poutcome|cons_conf_idx|
y|pdays_na_ind|marital_na_ind|education_na_ind|default_na_ind|y_ind|age_buckets|
+---+---------+-------+-----------+-------+-------+----+---------+-----+--------
---+--------+--------+--------+-----------+-------------+---+-----------+------
--------+----------------+--------------+-----+-----------+
| 56|housemaid|married|   basic.4y|     no|     no|  no|telephone|  may|
mon|     261|       1|       0|nonexistent|        -36.4| no|          1|
0|              0|             0|    1|        4.0|
| 57| services|married|high.school|    NaN|     no|  no|telephone|  may|
mon|     149|       1|       0|nonexistent|        -36.4| no|          1|
0|              0|             1|    1|        4.0|
| 37| services|married|high.school|     no|    yes|  no|telephone|  may|
mon|     226|       1|       0|nonexistent|        -36.4| no|          1|
0|              0|             0|    1|        2.0|
| 40|   admin.|married|   basic.6y|     no|     no|  no|telephone|  may|
mon|     151|       1|       0|nonexistent|        -36.4| no|          1|
0|              0|             0|    1|        2.0|
| 56| services|married|high.school|     no|     no| yes|telephone|  may|
```

```
mon|      307|        1|        0|nonexistent|        -36.4| no|            1|
0|                 0|              0|     1|        4.0|
+---+---------+-------+-----------+-------+-------+----+---------+-----+--------
---+--------+--------+--------+-----------+-------------+---+-----------+------
--------+----------------+--------------+-----+-----------+
only showing top 5 rows
```

[ ]:
```
#null_features =  ["marital", "education", "default", "housing","loan"]
#idx_outputs =   ["marital_indexed", "education_indexed", "default_indexed",␣
↪"housing_indexed","loan_indexed"]
#impute_outputs =   ["marital_imputed", "education_imputed", "default_imputed",␣
↪"housing_imputed","loan_imputed"]

#stringIndexer = StringIndexer(inputCols=null_features, outputCols=idx_outputs)
#model = stringIndexer.fit(df6)
#result = model.transform(df6)
```

[70]:
```
df2 = df2.drop('pdays')
categorical_features = [t[0] for t in df2.dtypes if t[1] == 'string' and t[0]!
↪='y' ]
categorical_features
numeric_features = [t[0] for t in df2.dtypes if t[1] != 'string' and t[0] !=␣
↪'wasPreviouslyContacted' and t[0]!='y_ind']
numeric_features
```

[70]:
```
['age',
 'duration',
 'campaign',
 'previous',
 'emp_var_rate',
 'cons_price_idx',
 'cons_conf_idx',
 'euribor3m',
 'nr_employed']
```

[ ]:
```
# nope
imputer = Imputer(inputCols = idx_outputs,
                  outputCols = impute_outputs)
model = stringIndexer.fit(result)
imputer = model.transform(result)
```

[71]:
```
from pyspark.ml.feature import OneHotEncoder
from pyspark.ml.feature import Imputer

indexers = [
    StringIndexer(inputCol= col, outputCol="{0}_indexed".format(col))
```

```
    for col in categorical_features
]

y_indexer = [StringIndexer(inputCol= "y",
                          outputCol="label")]

encoder = OneHotEncoder(
    inputCols=[indexer.getOutputCol() for indexer in indexers],
    outputCols=[
        "{0}_encoded".format(indexer.getOutputCol()) for indexer in indexers]
)

assembler = VectorAssembler(
    inputCols=encoder.getOutputCols()+numeric_features,
    outputCol="vectorized_features"
)

scaler = StandardScaler()\
         .setInputCol ("vectorized_features")\
         .setOutputCol ("scaled_features")\
         #.setHandleInvalid("skip")

pipeline = Pipeline(stages=indexers + y_indexer + [encoder, assembler, scaler])
df8 = pipeline.fit(df2).transform(df2)
```

[58]:
```
pipeline.getStages()
```

[58]:
```
[StringIndexer_102c3aa30fd4,
 StringIndexer_2bfb0a7ba0dd,
 StringIndexer_0b3a8dfbcefa,
 StringIndexer_01120e5f5b7c,
 StringIndexer_3c5d928a42fd,
 StringIndexer_8066ad444706,
 StringIndexer_9b1df1475a3e,
 StringIndexer_fb8d765e4868,
 StringIndexer_375fd42abb66,
 StringIndexer_a15ab2846679,
 StringIndexer_bacc2cf33fb6,
 OneHotEncoder_5e9a800e63f7,
 VectorAssembler_bfc9226cd68e,
 StandardScaler_f7dbf57a702c]
```

[72]:
```
import pandas as pd
pd.set_option('display.max_colwidth', 80)
pd.set_option("display.max_columns", 12)
```

[74]:
```
df9 = df8.select(['label','scaled_features'])
df2.write.option("header",True) \
 .csv("../data/simple_featureset")
```

[75]:
```
train, test = df9.randomSplit([0.8, 0.2], seed = 2018)
print("Training Dataset Count: " + str(train.count()))
print("Test Dataset Count: " + str(test.count()))
```

```
Training Dataset Count: 32894
Test Dataset Count: 8294
```

[79]:
```
test.groupBy('label').count().show()
```

```
+-----+-----+
|label|count|
+-----+-----+
|  0.0| 7363|
|  1.0|  931|
+-----+-----+
```

[77]:
```
from pyspark.ml.classification import LogisticRegression
lr = LogisticRegression(featuresCol = 'scaled_features', labelCol = 'label',␣
 ↪maxIter=5)
lrModel = lr.fit(train)
predictions = lrModel.transform(test)
#predictions_train = lrModel.transform(train)
predictions.select('label', 'scaled_features', 'rawPrediction', 'prediction',␣
 ↪'probability').toPandas().head(5)
```

[77]:
```
   label  \
0    0.0
1    0.0
2    0.0
3    0.0
4    0.0

scaled_features  \
0  (2.300140577866327, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0,
2.0457…
1  (2.300140577866327, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0,
2.0457…
2  (2.300140577866327, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0,
2.0457…
3  (2.300140577866327, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0,
2.0457…
4  (2.300140577866327, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0,
```

```
2.0457…

                              rawPrediction  prediction  \
0    [4.063225084942794, -4.063225084942794]         0.0
1  [3.9307808945352507, -3.9307808945352507]         0.0
2    [3.573495236885482, -3.573495236885482]         0.0
3    [4.975440777593673, -4.975440777593673]         0.0
4        [3.1867865038586, -3.1867865038586]         0.0

                                 probability
0   [0.983097139802578, 0.016902860197422043]
1  [0.9807495161174413, 0.019250483882558678]
2    [0.9727081306506139, 0.0272918693493861]
3  [0.9931418840545987, 0.006858115945401311]
4   [0.9603339908889523, 0.03966600911104767]
```

[80]:
```python
predictions.groupBy('label','prediction').count().show()
```

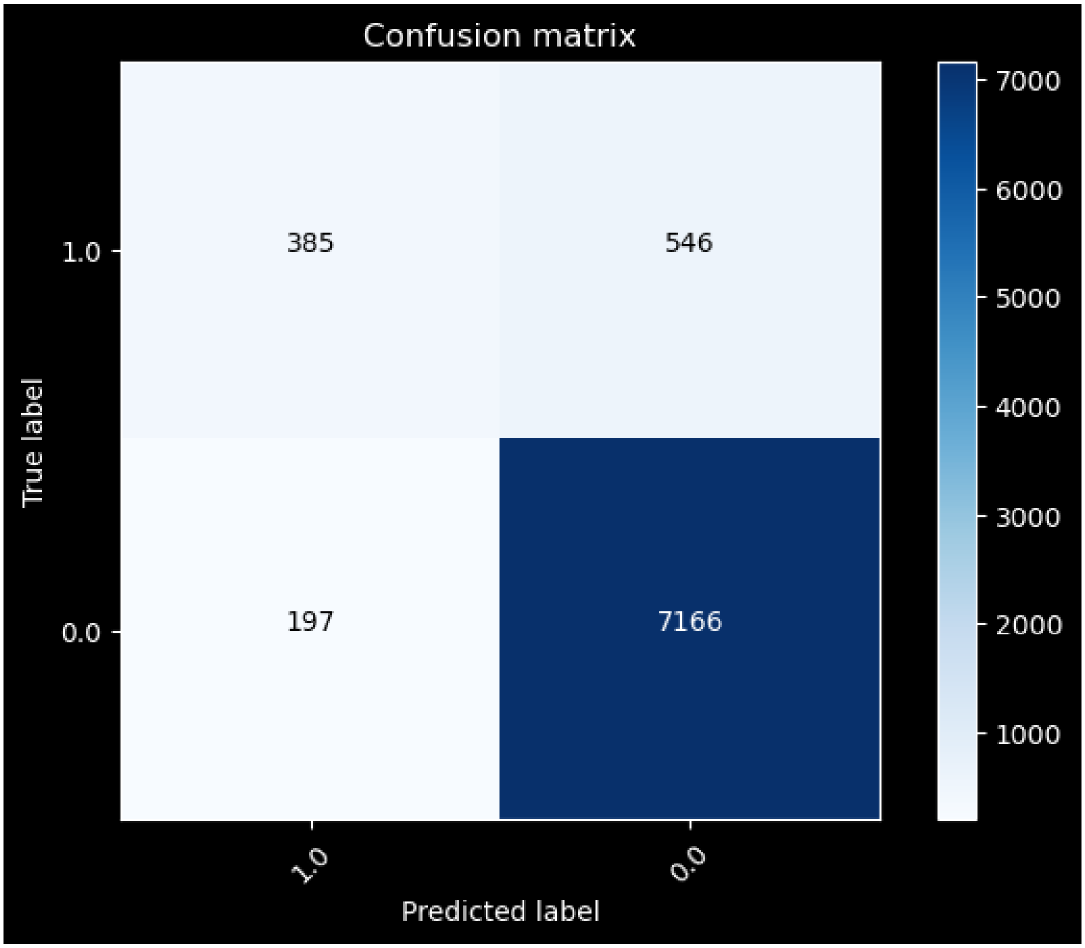
```
+-----+----------+-----+
|label|prediction|count|
+-----+----------+-----+
|  1.0|       1.0|  385|
|  0.0|       1.0|  197|
|  1.0|       0.0|  546|
|  0.0|       0.0| 7166|
+-----+----------+-----+
```

[81]:
```python
class_names=[1.0,0.0]
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)
```

```python
    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')
```

[82]:
```python
y_true = predictions.select("label")
y_true = y_true.toPandas()

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

cnf_matrix = confusion_matrix(y_true, y_pred,labels=class_names)
#cnf_matrix
plt.figure()
plot_confusion_matrix(cnf_matrix, classes=class_names,
                      title='Confusion matrix')
plt.show()
```

```
Confusion matrix, without normalization
[[ 385  546]
 [ 197 7166]]
```



[83]:
```
accuracy = predictions.filter(predictions.label == predictions.prediction).
  ↪count() / float(predictions.count())
print("Accuracy : ",accuracy)
```

```
Accuracy :  0.9104171690378587
```

[84]:
```
# in the earlier example
trainingSummary = lrModel.summary

# Obtain the objective per iteration
objectiveHistory = trainingSummary.objectiveHistory
print("objectiveHistory:")
for objective in objectiveHistory:
    print(objective)
```

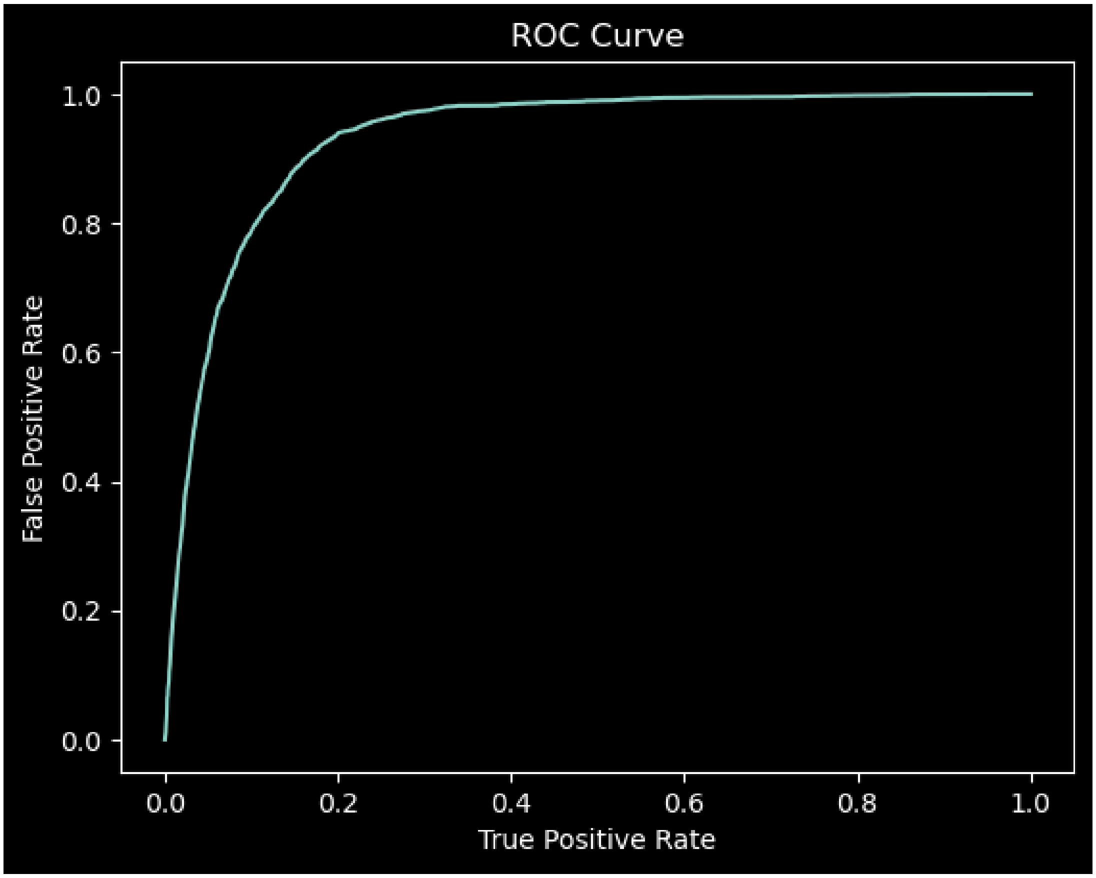
```
objectiveHistory:
0.35223916681289025
0.2776820677451751
```

```
0.2535629567569434
0.22324054909886942
0.21562116908050205
0.21218382217733378
```

[88]:
```
print("Labels: " + str(trainingSummary.labels))
print("Accuracy: " + str(trainingSummary.accuracy))
print("False Positives By Label: " + str(trainingSummary.
 ↪falsePositiveRateByLabel))
print("Precision By Label: " + str(trainingSummary.precisionByLabel))
print("Recall By Label: " + str(trainingSummary.recallByLabel))
print("Weighted False Positive Rate: " + str(trainingSummary.
 ↪weightedFalsePositiveRate))
```

```
Labels: [0.0, 1.0]
Accuracy: 0.9092843679698426
False Positives By Label: [0.6117551900781882, 0.0244988864142538 96]
Precision By Label: [0.9261849767396467, 0.6682134570765661]
Recall By Label: [0.9755011135857461, 0.3882448099218118]
Weighted False Positive Rate: 0.5455384444622845
```

[89]:
```
roc = trainingSummary.roc.toPandas()
plt.plot(roc['FPR'],roc['TPR'])
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: 0.9320642023280693
```

[93]:
```
from pyspark.ml.evaluation import BinaryClassificationEvaluator
evaluator = BinaryClassificationEvaluator()

from pyspark.ml.tuning import ParamGridBuilder, CrossValidator

# Create ParamGrid for Cross Validation
paramGrid = (ParamGridBuilder()
             .addGrid(lr.regParam, [0.01, 0.5, 2.0])# regularization parameter
             .addGrid(lr.elasticNetParam, [0.0, 0.5, 1.0])# Elastic Net␣
 ↪Parameter (Ridge = 0)
             .addGrid(lr.maxIter, [1, 5, 10])#Number of iterations
             .build())

cv = CrossValidator(estimator=lr, estimatorParamMaps=paramGrid,
                    evaluator=evaluator, numFolds=5)

cvModel = cv.fit(train)
```

[94]:
```python
## Evaluate Best Model
cv_predictions = cvModel.transform(test)
print('Best Model Test Area Under ROC', evaluator.evaluate(cv_predictions))
```

```
Best Model Test Area Under ROC 0.9353638894387751
```

[95]:
```python
cvModel.bestModel
```

[95]:
```
LogisticRegressionModel: uid=LogisticRegression_b25e681710ee, numClasses=2,
numFeatures=52
```

[96]:
```python
weights = cvModel.bestModel.coefficients
weights = [(float(w),) for w in weights]
weightsDF = sqlContext.createDataFrame(weights, ["Feature Weight"])
weightsDF.toPandas().head(10)
```

[96]:

	Feature Weight
0	0.003079
1	-0.049596
2	0.000000
3	0.000000
4	0.000000
5	0.050256
6	0.000000
7	0.000000
8	0.000000
9	0.000000

[98]:
```python
best_model=cvModel.bestModel
best_model.explainParams().split("\n")
```

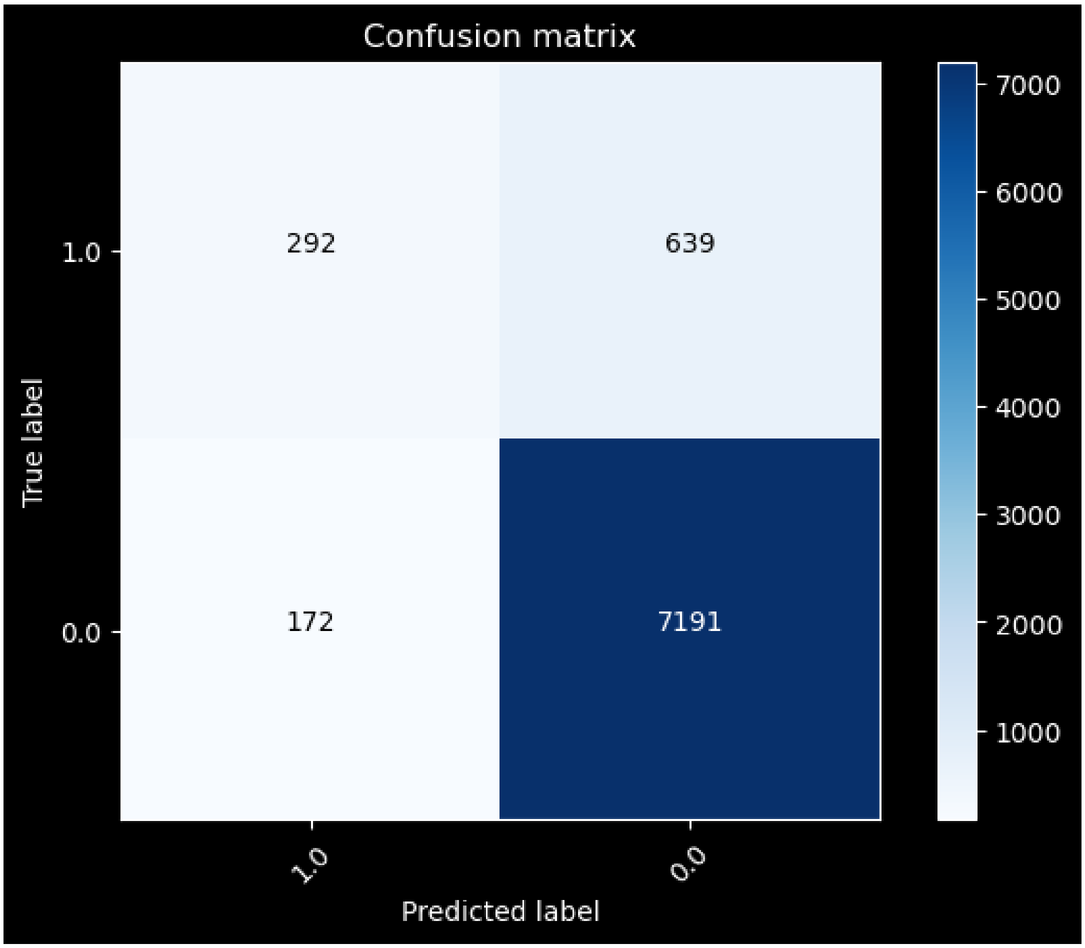
[98]:
```
['aggregationDepth: suggested depth for treeAggregate (>= 2). (default: 2)',
 'elasticNetParam: the ElasticNet mixing parameter, in range [0, 1]. For alpha =
0, the penalty is an L2 penalty. For alpha = 1, it is an L1 penalty. (default:
0.0, current: 0.5)',
 'family: The name of family which is a description of the label distribution to
be used in the model. Supported options: auto, binomial, multinomial (default:
auto)',
 'featuresCol: features column name. (default: features, current:
scaled_features)',
 'fitIntercept: whether to fit an intercept term. (default: True)',
 'labelCol: label column name. (default: label, current: label)',
 'lowerBoundsOnCoefficients: The lower bounds on coefficients if fitting under
bound constrained optimization. The bound matrix must be compatible with the
shape (1, number of features) for binomial regression, or (number of classes,
number of features) for multinomial regression. (undefined)',
 'lowerBoundsOnIntercepts: The lower bounds on intercepts if fitting under bound
```

```
constrained optimization. The bounds vector size must beequal with 1 for
binomial regression, or the number oflasses for multinomial regression.
(undefined)',
 'maxBlockSizeInMB: maximum memory in MB for stacking input data into blocks.
Data is stacked within partitions. If more than remaining data size in a
partition then it is adjusted to the data size. Default 0.0 represents choosing
optimal value, depends on specific algorithm. Must be >= 0. (default: 0.0)',
 'maxIter: max number of iterations (>= 0). (default: 100, current: 5)',
 'predictionCol: prediction column name. (default: prediction)',
 'probabilityCol: Column name for predicted class conditional probabilities.
Note: Not all models output well-calibrated probability estimates! These
probabilities should be treated as confidences, not precise probabilities.
(default: probability)',
 'rawPredictionCol: raw prediction (a.k.a. confidence) column name. (default:
rawPrediction)',
 'regParam: regularization parameter (>= 0). (default: 0.0, current: 0.01)',
 'standardization: whether to standardize the training features before fitting
the model. (default: True)',
 'threshold: Threshold in binary classification prediction, in range [0, 1]. If
threshold and thresholds are both set, they must match.e.g. if threshold is p,
then thresholds must be equal to [1-p, p]. (default: 0.5)',
 "thresholds: Thresholds in multi-class classification to adjust the probability
of predicting each class. Array must have length equal to the number of classes,
with values > 0, excepting that at most one value may be 0. The class with
largest value p/t is predicted, where p is the original probability of that
class and t is the class's threshold. (undefined)",
 'tol: the convergence tolerance for iterative algorithms (>= 0). (default:
1e-06)',
 'upperBoundsOnCoefficients: The upper bounds on coefficients if fitting under
bound constrained optimization. The bound matrix must be compatible with the
shape (1, number of features) for binomial regression, or (number of classes,
number of features) for multinomial regression. (undefined)',
 'upperBoundsOnIntercepts: The upper bounds on intercepts if fitting under bound
constrained optimization. The bound vector size must be equal with 1 for
binomial regression, or the number of classes for multinomial regression.
(undefined)',
 'weightCol: weight column name. If this is not set or empty, we treat all
instance weights as 1.0. (undefined)']
```

[100]:
```
y_true = cv_predictions.select("label")
y_true = y_true.toPandas()

y_pred = cv_predictions.select("prediction")
y_pred = y_pred.toPandas()

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

```python
plt.figure()
plot_confusion_matrix(cnf_matrix, classes=class_names,
                      title='Confusion matrix')
plt.show()
```

```
Confusion matrix, without normalization
[[ 292  639]
 [ 172 7191]]
```



[101]:

```python
trainingSummary_cv = best_model.summary
print("Labels: " + str(trainingSummary_cv.labels))
print("Accuracy: " + str(trainingSummary_cv.accuracy))
print("False Positives By Label: " + str(trainingSummary_cv.
 ↪falsePositiveRateByLabel))
print("Precision By Label: " + str(trainingSummary_cv.precisionByLabel))
print("Recall By Label: " + str(trainingSummary_cv.recallByLabel))
print("Weighted False Positive Rate: " + str(trainingSummary_cv.
 ↪weightedFalsePositiveRate))
```

```
Labels: [0.0, 1.0]
Accuracy: 0.9042682556089257
False Positives By Label: [0.6934483688325694, 0.01977043001541888]
Precision By Label: [0.9175112251443233, 0.6633605600933489]
Recall By Label: [0.9802295699845811, 0.30655163116743056]
Weighted False Positive Rate: 0.617487054456914
```

3.2 Oversampling minority class

[102]:
```python
from pyspark.sql.functions import col, asc, desc

major_df = df9.filter(col('label') == 0.0)
minor_df = df9.filter(col("label") == 1.0)
ratio = int(major_df.count()/minor_df.count())
print("ratio: {}".format(ratio))
```

```
ratio: 7
```

[103]:
```python
a = range(ratio)
```

[104]:
```python
from pyspark.sql.functions import col, explode, array, lit
# duplicate the minority rows
oversampled_df = minor_df.withColumn("dummy", explode(array([lit(x) for x in␣
↪a]))).drop('dummy')
```

[105]:
```python
# combine both oversampled minority rows and previous majority rows
combined_df = major_df.unionAll(oversampled_df)
```

[106]:
```python
train_over, test_over = combined_df.randomSplit([0.8, 0.2], seed = 2018)
print("Training Dataset Count: " + str(train.count()))
print("Test Dataset Count: " + str(test.count()))
```

```
Training Dataset Count: 32894
Test Dataset Count: 8294
```

[107]:
```python
train.groupBy('label').count().show()
```

```
+-----+-----+
|label|count|
+-----+-----+
|  0.0|29185|
|  1.0| 3709|
+-----+-----+
```

[108]:
```python
train_over.groupBy('label').count().show()
```

```
+-----+-----+
|label|count|
+-----+-----+
|  0.0|29185|
|  1.0|26037|
+-----+-----+
```

3.3 Fit Oversampled set

[109]:
```
lr2 = LogisticRegression(featuresCol = 'scaled_features', labelCol = 'label',␣
 ↪maxIter=5)

lrModel2 = lr2.fit(train_over)

predictions2 = lrModel2.transform(test)

#predictions_train = lrModel.transform(train)
predictions2.select('label', 'scaled_features', 'rawPrediction', 'prediction',␣
 ↪'probability').toPandas().head(5)
```

[109]:
```
   label  \
0    0.0
1    0.0
2    0.0
3    0.0
4    0.0

scaled_features  \
0  (2.300140577866327, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0,
2.0457…
1  (2.300140577866327, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0,
2.0457…
2  (2.300140577866327, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0,
2.0457…
3  (2.300140577866327, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0,
2.0457…
4  (2.300140577866327, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0,
2.0457…

                              rawPrediction  prediction  \
0  [2.9895076196553703, -2.9895076196553703]         0.0
1  [2.7506154727322603, -2.7506154727322603]         0.0
2    [2.232045016122651, -2.232045016122651]         0.0
3    [4.183136486740899, -4.183136486740899]         0.0
4  [1.6813324563954986, -1.6813324563954986]         0.0
```

```
                                     probability
0    [0.9520978588989161, 0.04790214110108393]
1    [0.9399481000047215, 0.06005189999527849]
2    [0.9030904824570439, 0.09690951754295607]
3   [0.9849784878882868, 0.015021512111713209]
4     [0.843080889698308, 0.15691911030169203]
```

[110]:

```
predictions2.groupBy('label','prediction').count().show()
```

```
+-----+----------+-----+
|label|prediction|count|
+-----+----------+-----+
|  1.0|       1.0|  818|
|  0.0|       1.0|  997|
|  1.0|       0.0|  113|
|  0.0|       0.0| 6366|
+-----+----------+-----+
```

[111]:

```
# in the earlier example
training2Summary = lrModel2.summary
```

[113]:

```
print("Labels: " + str(training2Summary.labels))
print("Accuracy: " + str(training2Summary.accuracy))
print("False Positives By Label: " + str(training2Summary.
 ↪falsePositiveRateByLabel))
print("Precision By Label: " + str(training2Summary.precisionByLabel))
print("Recall By Label: " + str(training2Summary.recallByLabel))
print("Weighted False Positive Rate: " + str(training2Summary.
 ↪weightedFalsePositiveRate))
```

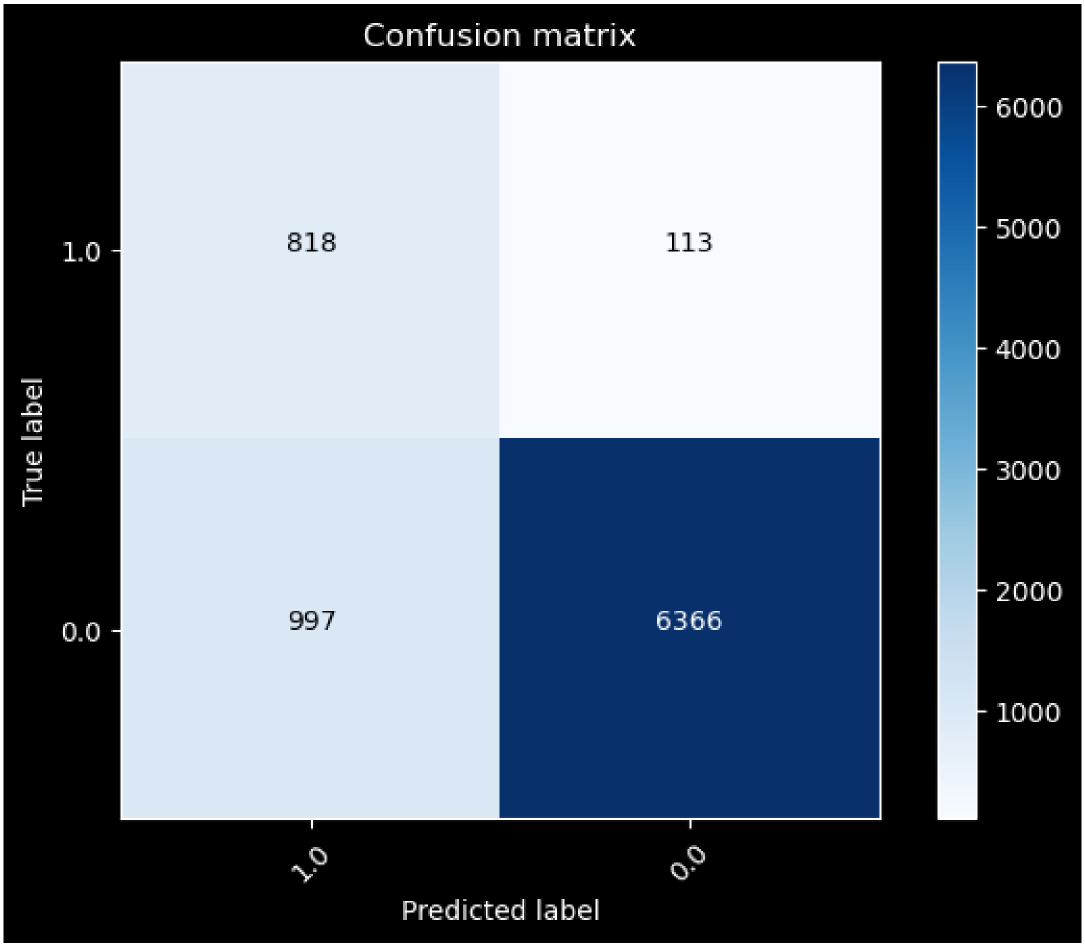
```
Labels: [0.0, 1.0]
Accuracy: 0.8657600231791677
False Positives By Label: [0.13688212927756654, 0.1318828165153332]
Precision By Label: [0.8766782006920415, 0.8537725096877137]
Recall By Label: [0.8681171834846668, 0.8631178707224335]
Weighted False Positive Rate: 0.13452496897206748
```

[114]:

```
y_true = predictions2.select("label")
y_true = y_true.toPandas()

y_pred = predictions2.select("prediction")
y_pred = y_pred.toPandas()

cnf_matrix = confusion_matrix(y_true, y_pred,labels=class_names)
#cnf_matrix
plt.figure()
```

```
plot_confusion_matrix(cnf_matrix, classes=class_names,
                      title='Confusion matrix')
plt.show()
```

```
Confusion matrix, without normalization
[[ 818  113]
 [ 997 6366]]
```



[115]:
```
from pyspark.ml.evaluation import BinaryClassificationEvaluator
evaluator = BinaryClassificationEvaluator()

from pyspark.ml.tuning import ParamGridBuilder, CrossValidator

# Create ParamGrid for Cross Validation
paramGrid = (ParamGridBuilder()
             .addGrid(lr2.regParam, [0.01, 0.5, 2.0])# regularization parameter
             .addGrid(lr2.elasticNetParam, [0.0, 0.5, 1.0])# Elastic Net␣
 ↪Parameter (Ridge = 0)
```

```
            .addGrid(lr2.maxIter, [1, 5, 10])#Number of iterations
            .build())

cv = CrossValidator(estimator=lr2, estimatorParamMaps=paramGrid,
                    evaluator=evaluator, numFolds=5)

cvModel = cv.fit(train)
```

[116]:
```
## Evaluate Best Model
cv_predictions2 = cvModel.transform(test)
print('Best Model Test Area Under ROC', evaluator.evaluate(cv_predictions2))
```

```
Best Model Test Area Under ROC 0.9353643270785372
```

[117]:
```
cvModel.bestModel
```

[117]:
```
LogisticRegressionModel: uid=LogisticRegression_3dfab395808e, numClasses=2,
numFeatures=52
```

[118]:
```
weights = cvModel.bestModel.coefficients
weights = [(float(w),) for w in weights]
weightsDF = sqlContext.createDataFrame(weights, ["Feature Weight"])
weightsDF.toPandas().head(10)
```

[118]:

	Feature Weight
0	0.003079
1	-0.049596
2	0.000000
3	0.000000
4	0.000000
5	0.050256
6	0.000000
7	0.000000
8	0.000000
9	0.000000

[119]:
```
best_model=cvModel.bestModel
best_model.explainParams().split("\n")
```

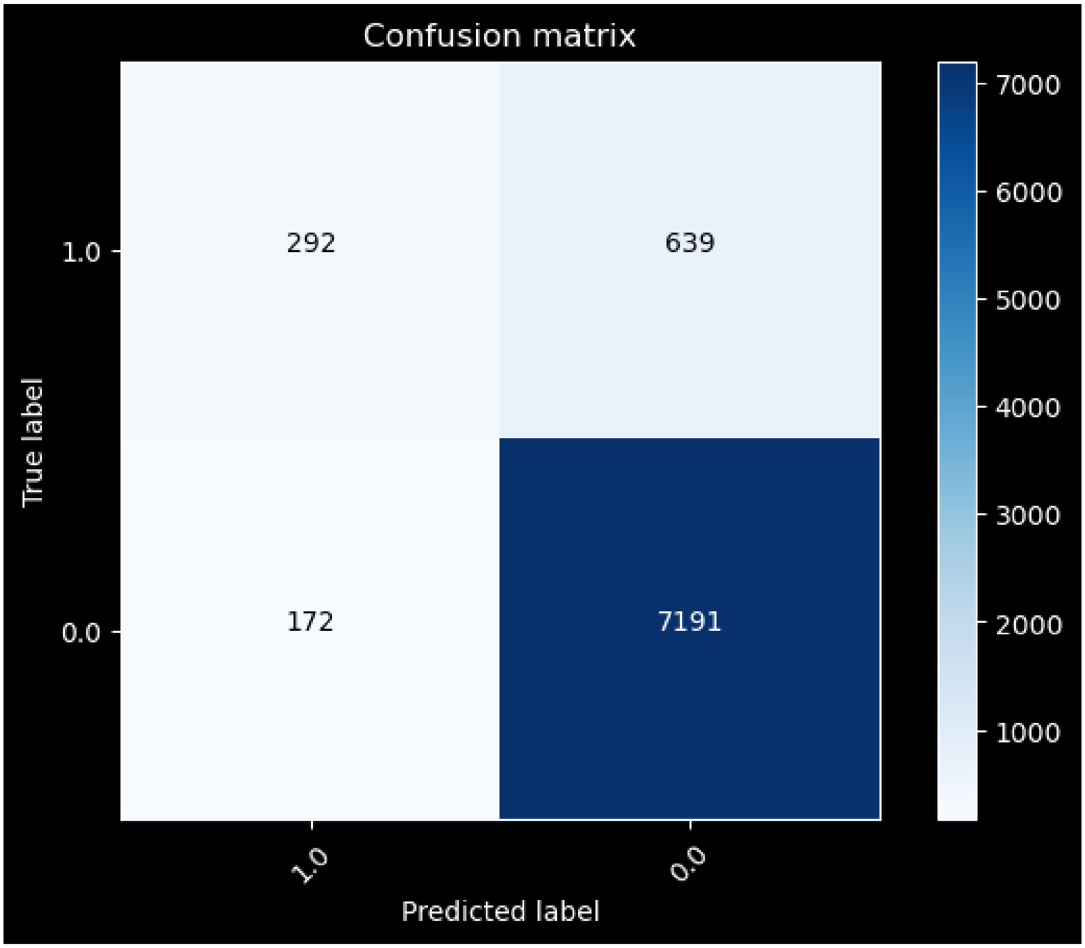
[119]:
```
['aggregationDepth: suggested depth for treeAggregate (>= 2). (default: 2)',
 'elasticNetParam: the ElasticNet mixing parameter, in range [0, 1]. For alpha =
0, the penalty is an L2 penalty. For alpha = 1, it is an L1 penalty. (default:
0.0, current: 0.5)',
 'family: The name of family which is a description of the label distribution to
be used in the model. Supported options: auto, binomial, multinomial (default:
auto)',
 'featuresCol: features column name. (default: features, current:
```

```
scaled_features)',
 'fitIntercept: whether to fit an intercept term. (default: True)',
 'labelCol: label column name. (default: label, current: label)',
 'lowerBoundsOnCoefficients: The lower bounds on coefficients if fitting under
bound constrained optimization. The bound matrix must be compatible with the
shape (1, number of features) for binomial regression, or (number of classes,
number of features) for multinomial regression. (undefined)',
 'lowerBoundsOnIntercepts: The lower bounds on intercepts if fitting under bound
constrained optimization. The bounds vector size must beequal with 1 for
binomial regression, or the number oflasses for multinomial regression.
(undefined)',
 'maxBlockSizeInMB: maximum memory in MB for stacking input data into blocks.
Data is stacked within partitions. If more than remaining data size in a
partition then it is adjusted to the data size. Default 0.0 represents choosing
optimal value, depends on specific algorithm. Must be >= 0. (default: 0.0)',
 'maxIter: max number of iterations (>= 0). (default: 100, current: 5)',
 'predictionCol: prediction column name. (default: prediction)',
 'probabilityCol: Column name for predicted class conditional probabilities.
Note: Not all models output well-calibrated probability estimates! These
probabilities should be treated as confidences, not precise probabilities.
(default: probability)',
 'rawPredictionCol: raw prediction (a.k.a. confidence) column name. (default:
rawPrediction)',
 'regParam: regularization parameter (>= 0). (default: 0.0, current: 0.01)',
 'standardization: whether to standardize the training features before fitting
the model. (default: True)',
 'threshold: Threshold in binary classification prediction, in range [0, 1]. If
threshold and thresholds are both set, they must match.e.g. if threshold is p,
then thresholds must be equal to [1-p, p]. (default: 0.5)',
 "thresholds: Thresholds in multi-class classification to adjust the probability
of predicting each class. Array must have length equal to the number of classes,
with values > 0, excepting that at most one value may be 0. The class with
largest value p/t is predicted, where p is the original probability of that
class and t is the class's threshold. (undefined)",
 'tol: the convergence tolerance for iterative algorithms (>= 0). (default:
1e-06)',
 'upperBoundsOnCoefficients: The upper bounds on coefficients if fitting under
bound constrained optimization. The bound matrix must be compatible with the
shape (1, number of features) for binomial regression, or (number of classes,
number of features) for multinomial regression. (undefined)',
 'upperBoundsOnIntercepts: The upper bounds on intercepts if fitting under bound
constrained optimization. The bound vector size must be equal with 1 for
binomial regression, or the number of classes for multinomial regression.
(undefined)',
 'weightCol: weight column name. If this is not set or empty, we treat all
instance weights as 1.0. (undefined)']
```

[120]:

```
y_true = cv_predictions2.select("label")
y_true = y_true.toPandas()

y_pred = cv_predictions2.select("prediction")
y_pred = y_pred.toPandas()

cnf_matrix = confusion_matrix(y_true, y_pred,labels=class_names)
#cnf_matrix
plt.figure()
plot_confusion_matrix(cnf_matrix, classes=class_names,
                      title='Confusion matrix')
plt.show()
```

```
Confusion matrix, without normalization
[[ 292  639]
 [ 172 7191]]
```



[121]:
```python
trainingSummary_cv = best_model.summary
print("Labels: " + str(trainingSummary_cv.labels))
print("Accuracy: " + str(trainingSummary_cv.accuracy))
print("False Positives By Label: " + str(trainingSummary_cv.
 ↪falsePositiveRateByLabel))
print("Precision By Label: " + str(trainingSummary_cv.precisionByLabel))
print("Recall By Label: " + str(trainingSummary_cv.recallByLabel))
print("Weighted False Positive Rate: " + str(trainingSummary_cv.
 ↪weightedFalsePositiveRate))
```

```
Labels: [0.0, 1.0]
Accuracy: 0.9042682556089257
False Positives By Label: [0.6934483688325694, 0.01977043001541888]
Precision By Label: [0.9175112251443233, 0.6633605600933489]
Recall By Label: [0.9802295699845811, 0.30655163116743056]
Weighted False Positive Rate: 0.617487054456914
```

[ ]:
```python
y_true = predictions3.select("label")
y_true = y_true.toPandas()

y_pred = predictions3.select("prediction")
y_pred = y_pred.toPandas()

cnf_matrix = confusion_matrix(y_true, y_pred,labels=class_names)
#cnf_matrix
plt.figure()
plot_confusion_matrix(cnf_matrix, classes=class_names,
                      title='Confusion matrix')
plt.show()
```

[36]:
```python
class Struct(object):
    def __init__(self, *args):
        self.__header__ = str(args[0]) if args else None

    def __repr__(self):
        if self.__header__ is None:
             return super(Struct, self).__repr__()
        return self.__header__

    def next(self):
        """ Fake iteration functionality.
        """
        raise StopIteration

    def __iter__(self):
        """ Fake iteration functionality.
        We skip magic attribues and Structs, and return the rest.
```

```
        """
        ks = self.__dict__.keys()
        for k in ks:
            if not k.startswith('__') and not isinstance(k, Struct):
                yield getattr(self, k)

    def __len__(self):
        """ Don't count magic attributes or Structs.
        """
        ks = self.__dict__.keys()
        return len([k for k in ks if not k.startswith('__')\
                    and not isinstance(k, Struct)])

conf = Struct("smote_config")
conf.seed = 48
conf.bucketLength = 100
conf.k = 4
conf.multiplier = 3
```

[37]:
```
from pyspark.ml.feature import␣
↪VectorAssembler,BucketedRandomProjectionLSH,VectorSlicer

def smote(vectorized_sdf,smote_config):
    '''
    contains logic to perform smote oversampling, given a spark df with 2␣
↪classes
    inputs:
    * vectorized_sdf: cat cols are already stringindexed, num cols are␣
↪assembled into 'features' vector
      df target col should be 'label'
    * smote_config: config obj containing smote parameters
    output:
    * oversampled_df: spark df after smote oversampling
    '''
    dataInput_min = vectorized_sdf[vectorized_sdf['label'] == 1]
    dataInput_maj = vectorized_sdf[vectorized_sdf['label'] == 0]

    # LSH, bucketed random projection
    brp = BucketedRandomProjectionLSH(inputCol="features",␣
↪outputCol="hashes",seed=smote_config.seed, bucketLength=smote_config.
↪bucketLength)
    # smote only applies on existing minority instances
    model = brp.fit(dataInput_min)
    model.transform(dataInput_min)

    # here distance is calculated from brp's param inputCol
```

```
    self_join_w_distance = model.approxSimilarityJoin(dataInput_min,␣
↪dataInput_min, float("inf"), distCol="EuclideanDistance")

    # remove self-comparison (distance 0)
    self_join_w_distance = self_join_w_distance.filter(self_join_w_distance.
↪EuclideanDistance > 0)

    over_original_rows = Window.partitionBy("datasetA").
↪orderBy("EuclideanDistance")

    self_similarity_df = self_join_w_distance.withColumn("r_num", F.
↪row_number().over(over_original_rows))

    self_similarity_df_selected = self_similarity_df.filter(self_similarity_df.
↪r_num <= smote_config.k)

    over_original_rows_no_order = Window.partitionBy('datasetA')

    # list to store batches of synthetic data
    res = []

    # two udf for vector add and subtract, subtraction include a random factor␣
↪[0,1]
    subtract_vector_udf = F.udf(lambda arr: random.uniform(0,␣
↪1)*(arr[0]-arr[1]), VectorUDT())
    add_vector_udf = F.udf(lambda arr: arr[0]+arr[1], VectorUDT())

    # retain original columns
    original_cols = dataInput_min.columns

    for i in range(smote_config.multiplier):
        print("generating batch %s of synthetic instances"%i)
        # logic to randomly select neighbour: pick the largest random number␣
↪generated row as the neighbour
        df_random_sel = self_similarity_df_selected.withColumn("rand", F.
↪rand()).withColumn('max_rand', F.max('rand').
↪over(over_original_rows_no_order))\
                            .where(F.col('rand') == F.col('max_rand')).
↪drop(*['max_rand','rand','r_num'])
        # create synthetic feature numerical part
        df_vec_diff = df_random_sel.select('*', subtract_vector_udf(F.
↪array('datasetA.features', 'datasetB.features')).alias('vec_diff'))
        df_vec_modified = df_vec_diff.select('*', add_vector_udf(F.
↪array('datasetA.features', 'vec_diff')).alias('features'))
```

```
        # for categorical cols, either pick original or the neighbour's cat␣
↪values
        for c in original_cols:
            # randomly select neighbour or original data
            col_sub = random.choice(['datasetA','datasetB'])
            val = "{0}.{1}".format(col_sub,c)
            if c != 'features':
                # do not unpack original numerical features
                df_vec_modified = df_vec_modified.withColumn(c,F.col(val))

        # this df_vec_modified is the synthetic minority instances,
        df_vec_modified = df_vec_modified.
↪drop(*['datasetA','datasetB','vec_diff','EuclideanDistance'])

        res.append(df_vec_modified)

    dfunion = reduce(DataFrame.unionAll, res)
    # union synthetic instances with original full (both minority and majority)␣
↪df
    oversampled_df = dfunion.union(vectorized_sdf.select(dfunion.columns))

    return oversampled_df
```

[41]:

```
import random
from functools import reduce
from pyspark.sql.window import Window
from pyspark.sql import Row, DataFrame
from pyspark.ml.linalg import Vectors,VectorUDT
from pyspark.sql.types import ArrayType, DoubleType
from pyspark.ml.feature import StandardScaler, ChiSqSelector, StringIndexer,␣
↪VectorAssembler, BucketedRandomProjectionLSH, VectorSlicer

smoted_train_df = smote(df9,conf)
```

```
generating batch 0 of synthetic instances
generating batch 1 of synthetic instances
generating batch 2 of synthetic instances
```

[44]:

```
def to_array(col):
    def to_array_(v):
        return v.toArray().tolist()
    return udf(to_array_, ArrayType(DoubleType())).asNondeterministic()(col)

def restore_smoted_df(num_cols,smoted_df,vectorized_col):
    '''
    restore smoted df to original type
    with original num_cols names
```

```
    and stringIndexed cat cols, suffix _index
    depending on to_array udf to unpack vectorized col
    * vectorized_col: str, col that is vectorized
    '''
    # based on the assumption that vectorization is by the list sequence of␣
↪num_cols
    # to array first
    smoted_df = smoted_df.withColumn("array_num_cols",␣
↪to_array(col(vectorized_col)))
    # restore all num_cols
    for i in range(len(num_cols)):
        smoted_df = smoted_df.withColumn(num_cols[i], col("array_num_cols")[i])

    drop_cols = [vectorized_col,'array_num_cols']
    return smoted_df.drop(*drop_cols)
```

[ ]:
```
lrModel.save("../models/lrModel1")
```

[ ]:
```

```