HW4_LogReg

June 27, 2021

1 HW4

Gamze Atmaca , Bulut Fıçıcı

[1]:
```
import sys
from pyspark import SparkConf, SparkContext, SQLContext
import numpy as np
import matplotlib.pyplot as plt
from sklearn.metrics import confusion_matrix
```

[2]:
```
from pyspark.sql.types import StructType,StructField, StringType, IntegerType
from pyspark.sql.types import ArrayType, DoubleType, BooleanType
from pyspark.sql.functions import corr
from pyspark.ml.classification import LogisticRegression
from pyspark.ml.regression import LinearRegression
from pyspark.ml.linalg import Vector
from pyspark.ml.feature import VectorAssembler
from pyspark.ml.evaluation import BinaryClassificationEvaluator
from pyspark.ml.evaluation import MulticlassClassificationEvaluator
from pyspark.ml import Pipeline
from pyspark.sql.functions import *
```

[3]:
```
from pyspark.sql import SparkSession
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 sklearn.metrics import confusion_matrix
```

[4]:
```
sc = SparkContext.getOrCreate()
sqlcont = SQLContext(sc)
```

2 Logistic Regression

[5]:
```
# Creating a new dataframe to use logistic regression.

schema = StructType() \
      .add("Open Time",DoubleType(),True) \
      .add("Open",DoubleType(),True) \
      .add("High",DoubleType(),True) \
      .add("Low",DoubleType(),True) \
      .add("Close",DoubleType(),True) \
      .add("Volume",DoubleType(),True) \
      .add("Close Time",DoubleType(),True) \
      .add("Quote asset volume",DoubleType(),True) \
      .add("Number of trades",IntegerType(),True) \
      .add("Taker buy base asset volume",DoubleType(),True) \
      .add("Taker buy quote asset volume",DoubleType(),True) \
      .add("Ignore",StringType(),True) \

df = sqlcont.read.format("csv") \
      .option("header", True) \
      .schema(schema) \
      .load('csv/btc_2021_hourly.csv')
```

[6]:
```
df=df.drop("Open Time").drop("Close Time").drop("Ignore")
print("There are",df.count(),"rows",len(df.columns),
      "columns" ,"in the data.")
```

```
There are 3632 rows 9 columns in the data.
```

[7]:
```
df.show(1,vertical=True)
```

```
-RECORD 0-----------------------------------------
 Open                          | 28995.13
 High                          | 29470.0
 Low                           | 28960.35
 Close                         | 29409.99
 Volume                        | 5403.068471
 Quote asset volume            | 1.583578168180572E8
 Number of trades              | 103896
 Taker buy base asset volume   | 3160.041701
 Taker buy quote asset volume | 9.261399193555292E7
only showing top 1 row
```

[8]:
```
df.printSchema()
```

```
root
 |-- Open: double (nullable = true)
 |-- High: double (nullable = true)
 |-- Low: double (nullable = true)
 |-- Close: double (nullable = true)
 |-- Volume: double (nullable = true)
 |-- Quote asset volume: double (nullable = true)
 |-- Number of trades: integer (nullable = true)
 |-- Taker buy base asset volume: double (nullable = true)
 |-- Taker buy quote asset volume: double (nullable = true)
```

[9]:
```
#let's see the statistics
numeric_features = [t[0] for t in df.dtypes if (t[1] == 'int' or t[1] ==␣
 ↪'double')]
df.select(numeric_features).describe().toPandas().transpose()
```

[9]:

	0	1	2	3	4
summary	count	mean	stddev	min	max
Open	3632	47763.097794603425	9758.78706201656	28995.13	64577.25
High	3632	48127.30659691632	9730.966051054123	29125.32	64854.0
Low	3632	47363.61166024227	9795.233758474216	28130.0	
Close	3632	47765.06958700446	9755.696878505894	29000.01	
Volume	3632	3756.4256987472536	2804.2740859967826	0.0	
Quote asset volume	3632	1.7048093031037322E8	1.116667597067393E8	0.0	
Number of trades	3632	96093.00633259912	49861.75701668211	0	
Taker buy base asset volume	3632	1845.195042224671	1369.1507788728309	0.0	
Taker buy quote asset volume	3632	8.377469610648279E7	5.4824905157718435E7	0.0	

```
Low                                    64280.0
Close                                  64577.26
Volume                                44239.811778
Quote asset volume            1.5144648252185037E9
Number of trades                         799206
Taker buy base asset volume           19904.321262
Taker buy quote asset volume   6.839264854908676E8
```

[10]:
```
#adding the target variable
# Target variable is Up_Down which takes the value of "Yes" if BTC rises, "No"␣
 ↪if it falls between the opening and closing time.
df=df.withColumn("Up_Down", \
   when(((df.Close-df.Open) >= 0), lit('Yes')) \
     .when(((df.Close-df.Open) < 0), lit('No')) \
  )
```

[11]:
```
df.groupby("Up_Down").count().show()
```

```
+-------+-----+
|Up_Down|count|
+-------+-----+
|     No| 1779|
|    Yes| 1853|
+-------+-----+
```

[12]:
```
#null check
from pyspark.sql.functions import isnan, when, count, col
df.select([count(when(isnan(c), c)).alias(c) for c in df.columns]).toPandas().
 ↪head()
```

[12]:

	Open	High	Low	Close	Volume	Quote asset volume	Number of trades	Taker buy base asset volume	Taker buy quote asset volume	Up_Down
0	0	0	0	0	0	0	0	0	0	0

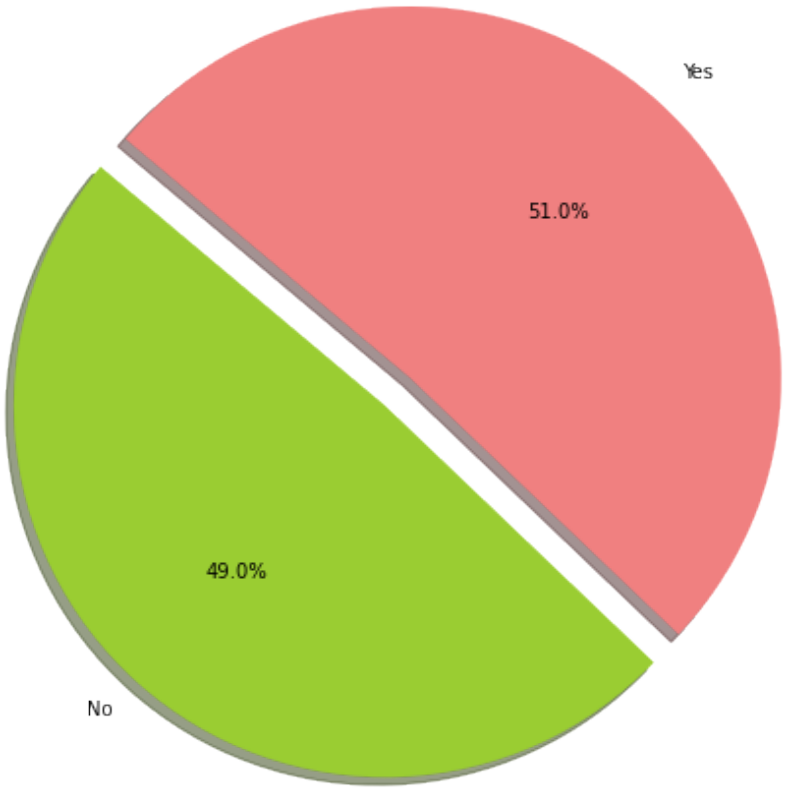
Our dataset does not contain any categorical data except the target. So there is no need to encode

[13]:
```
#grouping our target variable with the column 'Number of trades'
from pyspark.sql import functions as F
from pyspark.sql.functions import rank,sum,col
from pyspark.sql import Window

window = Window.rowsBetween(Window.unboundedPreceding,Window.unboundedFollowing)
tab = df.select(['Up_Down','Number of trades']).\
   groupBy('Up_Down').\
```

```
        agg(F.count('Number of trades').alias('UserCount'),
            F.mean('Number of trades').alias('NoT_AVG'),
            F.min('Number of trades').alias('NoT'),
            F.max('Number of trades').alias('NoT_MAX')).\
        withColumn('total',sum(col('UserCount')).over(window)).\
        withColumn('Percent',col('UserCount')*100/col('total')).\
        drop(col('total')).sort(desc("Percent"))
tab.show()
```

```
+-------+---------+-----------------+-----+-------+------------------+
|Up_Down|UserCount|          NoT_AVG|  NoT|NoT_MAX|           Percent|
+-------+---------+-----------------+-----+-------+------------------+
|    Yes|     1853|94364.88127361036|    0| 799206|51.018722466960355|
|     No|     1779|97893.01517706577|32918| 571162|48.981277533039645|
+-------+---------+-----------------+-----+-------+------------------+
```

[14]:
```
# Data to plot
labels = list(tab.select('Up_Down').distinct().toPandas()['Up_Down'])
sizes =  list(tab.select('Percent').distinct().toPandas()['Percent'])
colors = ['yellowgreen', 'lightcoral']
explode = (0.1, 0.0)  # explode 1st slice

# Plot
plt.figure(figsize=(10,8))
plt.pie(sizes, explode=explode, labels=labels, colors=colors,
        autopct='%1.1f%%', shadow=True, startangle=140)

plt.axis('equal')
plt.show()
```



[15]:
```
#Correlation Matrix
```

[16]:
```
numeric_features = [t[0] for t in df.dtypes if t[1] != 'string']
numeric_features_df=df.select(numeric_features)
numeric_features_df.toPandas().head()
```

[16]:

	Open	High	Low	Close	Volume	Quote asset volume	\
0	28995.13	29470.00	28960.35	29409.99	5403.068471	1.583578e+08	
1	29410.00	29465.26	29120.03	29194.65	2384.231560	6.984265e+07	
2	29195.25	29367.00	29150.02	29278.40	1461.345077	4.276078e+07	
3	29278.41	29395.00	29029.40	29220.31	2038.046803	5.961464e+07	
4	29220.31	29235.28	29084.11	29187.01	1469.956262	4.286454e+07	

	Number of trades	Taker buy base asset volume	Taker buy quote asset volume
0	103896	3160.041701	9.261399e+07
1	57646	1203.433506	3.525275e+07
2	42510	775.915666	2.270555e+07
3	55414	1003.342834	2.934638e+07
4	41800	679.846742	1.982719e+07

[17]:
```
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
```

[17]:

	Open	High	Low	Close	Volume	Quote asset volume	Number of trades	Taker buy base asset volume	Taker buy quote asset volume
Open	1.000000	0.999428	0.998985	0.998744	-0.319449	-0.042727	-0.121478	-0.322548	-0.043383
High	0.999428	1.000000	0.998687	0.999359	-0.305863	-0.027954	-0.107775	-0.307128	-0.026637
Low	0.998985	0.998687	1.000000	0.999225	-0.346126	-0.071284	-0.149084	-0.346527	-0.068885
Close	0.998744	0.999359	0.999225	1.000000	-0.323427	-0.047111	-0.125812	-0.323105	-0.043981
Volume	-0.319449	-0.305863	-0.346126	-0.323427	1.000000	0.939635	0.925198	0.990117	0.926133
Quote asset volume	-0.042727	-0.027954	-0.071284	-0.047111	0.939635	1.000000	0.946821	0.931000	0.988221
Number of trades	-0.121478	-0.107775	-0.149084	-0.125812	0.925198	0.946821	1.000000	0.916904	0.935690
Taker buy base asset volume	-0.322548	-0.307128	-0.346527	-0.323105	0.990117	0.931000	0.916904	1.000000	0.938579
Taker buy quote asset volume	-0.043383	-0.026637	-0.068885	-0.043981	0.926133	0.988221	0.935690	0.938579	1.000000

```
Number of trades                                0.935690
Taker buy base asset volume                     0.938579
Taker buy quote asset volume                    1.000000
```

[18]:
```
#Dropping the highly correlated features
df=df.drop("High").drop("Low")
```

[19]:
```
df2=df
df3=df
```

[20]:
```
df.columns
```

[20]:
```
['Open',
 'Close',
 'Volume',
 'Quote asset volume',
 'Number of trades',
 'Taker buy base asset volume',
 'Taker buy quote asset volume',
 'Up_Down']
```

[21]:
```
# Vectorize
assembler = VectorAssembler()\
         .setInputCols (['Open','Close',"Volume","Quote asset volume","Number␣
 ↪of trades","Taker buy base asset volume","Taker buy quote asset volume"])\
         .setOutputCol ("vectorized_features")

assembler_df=assembler.transform(df)
assembler_df.toPandas().head()
```

[21]:

	Open	Close	Volume	Quote asset volume	Number of trades	\
0	28995.13	29409.99	5403.068471	1.583578e+08	103896	
1	29410.00	29194.65	2384.231560	6.984265e+07	57646	
2	29195.25	29278.40	1461.345077	4.276078e+07	42510	
3	29278.41	29220.31	2038.046803	5.961464e+07	55414	
4	29220.31	29187.01	1469.956262	4.286454e+07	41800	

	Taker buy base asset volume	Taker buy quote asset volume	Up_Down	\
0	3160.041701	9.261399e+07	Yes	
1	1203.433506	3.525275e+07	No	
2	775.915666	2.270555e+07	Yes	
3	1003.342834	2.934638e+07	No	
4	679.846742	1.982719e+07	No	

	vectorized_features
0	[28995.13, 29409.99, 5403.068471, 158357816.81…
1	[29410.0, 29194.65, 2384.23156, 69842653.67342…

```
2  [29195.25, 29278.4, 1461.345077, 42760776.7255…
3  [29278.41, 29220.31, 2038.046803, 59614637.303…
4  [29220.31, 29187.01, 1469.956262, 42864538.704…
```

[22]:
```
label_indexer = StringIndexer()\
                 .setInputCol ("Up_Down")\
                 .setOutputCol ("label")

label_indexer_model=label_indexer.fit(assembler_df)
label_indexer_df=label_indexer_model.transform(assembler_df)
label_indexer_df.select("Up_Down", "label").toPandas().head()
```

[22]:

	Up_Down	label
0	Yes	0.0
1	No	1.0
2	Yes	0.0
3	No	1.0
4	No	1.0

[23]:
```
#Scale
scaler = StandardScaler()\
                 .setInputCol ("vectorized_features")\
                 .setOutputCol ("features")

scaler_model=scaler.fit(label_indexer_df)
scaler_df=scaler_model.transform(label_indexer_df)
pd.set_option('display.max_colwidth', 40)
scaler_df.select("vectorized_features", "features").toPandas().head()
```

[23]:

	vectorized_features	features
0	[28995.13, 29409.99, 5403.068471, 15…	[2.9711817478686164, 3.0146477864433…
1	[29410.0, 29194.65, 2384.23156, 6984…	[3.0136942032960707, 2.9925745298957…
2	[29195.25, 29278.4, 1461.345077, 427…	[2.9916883947221904, 3.0011592574700…
3	[29278.41, 29220.31, 2038.046803, 59…	[3.0002099455534075, 2.9952047879203…
4	[29220.31, 29187.01, 1469.956262, 42…	[2.994256336807692, 2.99179139773252…

[24]:
```
#trying second methodology
pipeline_stages=Pipeline()\
                .setStages([assembler,label_indexer,scaler])
pipeline_model=pipeline_stages.fit(df3)
```

```
pipeline_df=pipeline_model.transform(df3)
pipeline_df.toPandas().head()
```

[24]:

	Open	Close	Volume	Quote asset volume	Number of trades	Taker buy base asset volume	Taker buy quote asset volume	Up_Down	vectorized_features	label	features
0	28995.13	29409.99	5403.068471	1.583578e+08	103896	3160.041701	9.261399e+07	Yes	[28995.13, 29409.99, 5403.068471, 15…	0.0	[2.9711817478686164, 3.0146477864433…
1	29410.00	29194.65	2384.231560	6.984265e+07	57646	1203.433506	3.525275e+07	No	[29410.0, 29194.65, 2384.23156, 6984…	1.0	[3.0136942032960707, 2.9925745298957…
2	29195.25	29278.40	1461.345077	4.276078e+07	42510	775.915666	2.270555e+07	Yes	[29195.25, 29278.4, 1461.345077, 427…	0.0	[2.9916883947221904, 3.0011592574700…
3	29278.41	29220.31	2038.046803	5.961464e+07	55414	1003.342834	2.934638e+07	No	[29278.41, 29220.31, 2038.046803, 59…	1.0	[3.0002099455534075, 2.9952047879203…
4	29220.31	29187.01	1469.956262	4.286454e+07	41800	679.846742	1.982719e+07	No	[29220.31, 29187.01, 1469.956262, 42…	1.0	[2.994256336807692, 2.99179139773252…

3 Model Training & Prediction

[25]:
```
train, test = pipeline_df.randomSplit([0.8, 0.2], seed = 2021)
print("Training count: " + str(train.count()))
print("Test count: " + str(test.count()))
```

```
Training count: 2919
Test count: 713
```

[26]:
```
train.groupBy("Up_Down").count().show()
```

```
+-------+-----+
|Up_Down|count|
+-------+-----+
|     No| 1432|
```

```
|    Yes| 1487|
+-------+-----+
```

[27]:
```
from pyspark.ml.classification import LogisticRegression
lr = LogisticRegression(featuresCol = "features", labelCol = 'label', maxIter=5)
lrModel = lr.fit(train)
predictions = lrModel.transform(test)
predictions.
 ↪select('label','features','rawPrediction','prediction','probability').
 ↪toPandas().head(5)
```

[27]:

	label	features	rawPrediction	prediction	probability
0	1.0	[2.9791304816105297, 2.9755988077036…	[0.11832307148680171, -0.11832307148…	0.0	[0.5295463043642462, 0.4704536956357…
1	0.0	[2.988401100943144, 2.99951098977581…	[0.17787638962819796, -0.17787638962…	0.0	[0.5443522169790758, 0.4556477830209…
2	0.0	[2.991014130599181, 3.00343177580230…	[0.17479676627872293, -0.17479676627…	0.0	[0.5435882653848426, 0.4564117346151…
3	0.0	[3.034483672183004, 3.04242642731081…	[0.1374656930095023, -0.137465693009…	0.0	[0.5343124073227662, 0.4656875926772…
4	0.0	[3.1112667800875187, 3.1439947737180…	[-0.008068806539898138, 0.0080688065…	1.0	[0.49798280930922095, 0.502017190690…

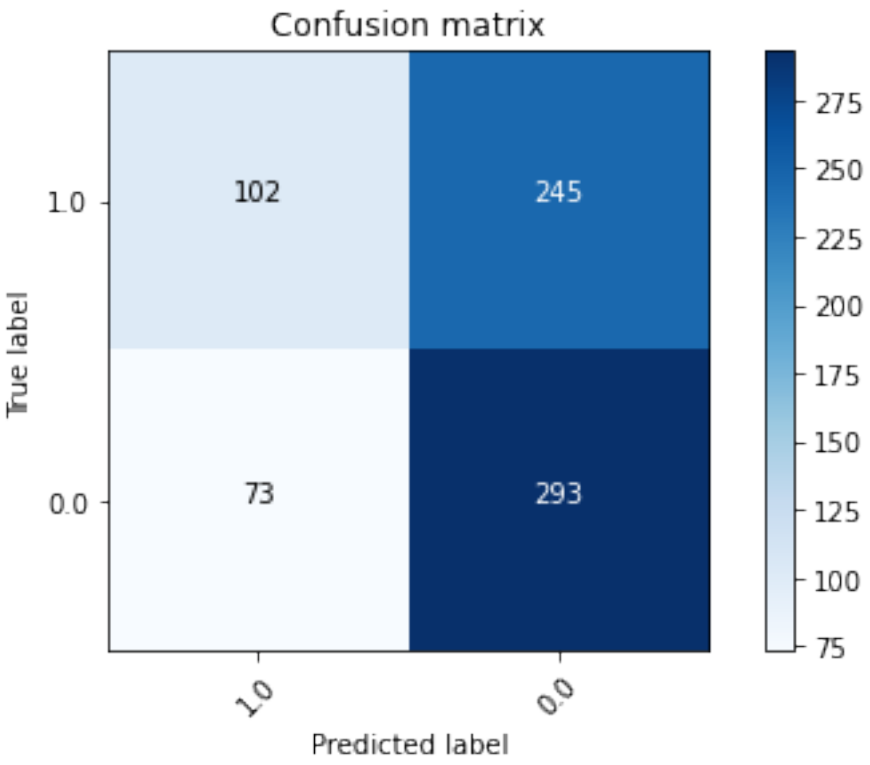
4 Performance Metrics

[28]:
```
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)
    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')
```

[29]:
```
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()
```

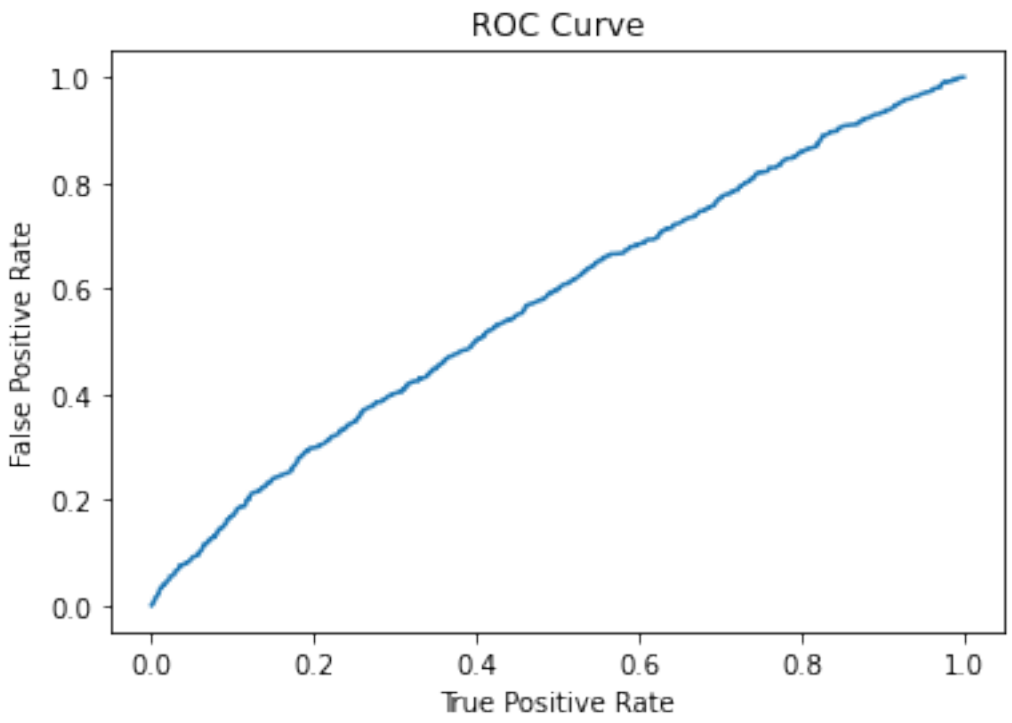
```
Confusion matrix, without normalization
[[102 245]
 [ 73 293]]
```



[30]:
```
accuracy = predictions.filter(predictions.label == predictions.prediction).
 ↪count() / float(predictions.count())
print("Accuracy: ", accuracy)
```

```
Accuracy:  0.5539971949509116
```

[31]:
```
trainingSummary = lrModel.summary
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: 0.5735724509999144
```

[32]:
```
from pyspark.ml.evaluation import BinaryClassificationEvaluator
evaluator = BinaryClassificationEvaluator()
print('Test Area Under ROC', evaluator.evaluate(predictions))
```

```
Test Area Under ROC 0.5344167808380974
```

5 Cross Validation and Best Model

[33]:
```
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)
```

[34]:
```
predictions = cvModel.transform(test)
print('Best Model Test Area Under ROC', evaluator.evaluate(predictions))
```

```
Best Model Test Area Under ROC 0.6773672855545594
```

[35]:
```
cvModel.bestModel
```

[35]:
```
LogisticRegressionModel: uid=LogisticRegression_30611361a999, numClasses=2,
numFeatures=7
```

[36]:
```
best_model=cvModel.bestModel
best_model.explainParams().split("\n")
```

[36]:
```
['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: 0.0)',
 '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: 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: 10)',
 '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)']
```