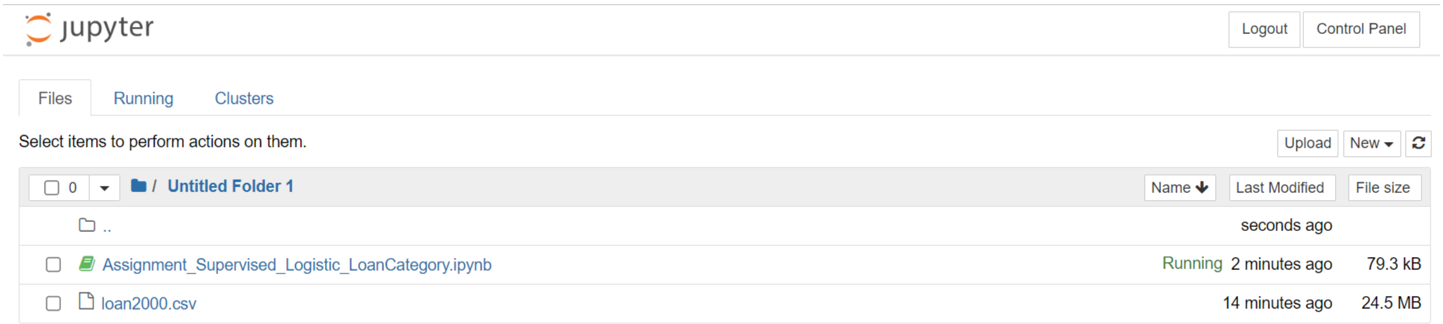
Supervised Learning Output:

- The data is on loan category prediction and logistic regression is used to classify the loan condition category as “Good Loan” or “Bad Loan”.
- The size of the input file is 24.5 MB as shown in the figure below.



1 Initializing Pyspark and Importing the necessary libraries

In [1]:
```
import findspark
findspark.init('/usr/spark2.4.3')
```

In [2]:
```
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 OneHotEncoderEstimator, StringIndexer, VectorAssembler,StandardScaler
from pyspark.ml import Pipeline
from sklearn.metrics import confusion_matrix
```

2 Reading the input Data and checking the datatypes with info functions

In [3]:

```
# Read data from the vehicle_stolen_datHaset.csv
loan_data = pd.read_csv("loan2000.csv",low_memory=False)
#Sets the Spark master URL to run locally.
spark = SparkSession.builder.master("local[*]").getOrCreate()

#print("There are",loan_data.count(),"rows",len(loan_data.columns),
#       "columns" ,"in the data.")

loan_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 359985 entries, 0 to 359984
Data columns (total 17 columns):
emp_length_int          359985 non-null float64
home_ownership_cat      359985 non-null int64
annual_inc              359985 non-null int64
income_cat              359985 non-null int64
loan_amount             359985 non-null int64
term_cat                359985 non-null int64
application_type_cat    359985 non-null int64
purpose_cat             359985 non-null int64
interest_payment_cat    359985 non-null int64
loan_condition_cat      359985 non-null int64
interest_rate           359985 non-null float64
grade_cat               359985 non-null int64
dti                     359985 non-null float64
total_pymnt             359985 non-null float64
total_rec_prncp         359985 non-null float64
recoveries              359985 non-null float64
installment             359985 non-null float64
dtypes: float64(7), int64(10)
memory usage: 46.7 MB
```

3 Creating spark data frame from pandas data frame

In [4]:

```
#Create DataFrame
df = spark.createDataFrame(loan_data)
df.show(5)
```

```
+--------------+------------------+----------+----------+-----------+--------+--------------------+-----------+-------------
-------+------------------+-------------+---------+-----+-----------+---------------+----------+-----------+
|emp_length_int|home_ownership_cat|annual_inc|income_cat|loan_amount|term_cat|application_type_cat|purpose_cat|interest_paym
ent_cat|loan_condition_cat|interest_rate|grade_cat|  dti|total_pymnt|total_rec_prncp|recoveries|installment|
+--------------+------------------+----------+----------+-----------+--------+--------------------+-----------+-------------
-------+------------------+-------------+---------+-----+-----------+---------------+----------+-----------+
|          10.0|                 1|     24000|         1|       5000|       1|                   1|          1|
1|                 0|        10.65|        2|27.65|5861.071414|         5000.0|       0.0|     162.87|
|           0.5|                 1|     30000|         1|       2500|       2|                   1|          2|
2|                 1|        15.27|        3|  1.0|    1008.71|         456.46|    117.08|      59.83|
|          10.0|                 1|     12252|         1|       2400|       1|                   1|          3|
2|                 0|        15.96|        3| 8.72|3003.653644|         2400.0|       0.0|      84.33|
|          10.0|                 1|     49200|         1|      10000|       1|                   2|          4|
2|                 0|        13.49|        3| 20.0|12226.30221|        10000.0|       0.0|     339.31|
|           1.0|                 1|     80000|         1|       3000|       2|                   1|          4|
1|                 0|        12.69|        2|17.94|    3242.17|         2233.1|       0.0|      67.79|
+--------------+------------------+----------+----------+-----------+--------+--------------------+-----------+-------------
-------+------------------+-------------+---------+-----+-----------+---------------+----------+-----------+
only showing top 5 rows
```

4 Checking the Schema of spark dataframe

In [5]:
```
df.printSchema()
```

```
root
 |-- emp_length_int: double (nullable = true)
 |-- home_ownership_cat: long (nullable = true)
 |-- annual_inc: long (nullable = true)
 |-- income_cat: long (nullable = true)
 |-- loan_amount: long (nullable = true)
 |-- term_cat: long (nullable = true)
 |-- application_type_cat: long (nullable = true)
 |-- purpose_cat: long (nullable = true)
 |-- interest_payment_cat: long (nullable = true)
 |-- loan_condition_cat: long (nullable = true)
 |-- interest_rate: double (nullable = true)
 |-- grade_cat: long (nullable = true)
 |-- dti: double (nullable = true)
 |-- total_pymnt: double (nullable = true)
 |-- total_rec_prncp: double (nullable = true)
 |-- recoveries: double (nullable = true)
 |-- installment: double (nullable = true)
```

5 Counting the number of observations in each category of dependent variable and also checking if there is any null value in any of the column

In [6]:
```
numeric_features = [t[0] for t in df.dtypes if t[1] == 'int']
df.select(numeric_features).describe().toPandas().transpose()
```

Out[6]:

0	1	2	3	4
summary	count	mean	stddev	min	max

In [7]:
```
df.groupby("loan_condition_cat").count().show()
```

```
+------------------+------+
|loan_condition_cat| count|
+------------------+------+
|                 0|316145|
|                 1| 43840|
+------------------+------+
```

In [8]:
```
#check for null values if any

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()
```

Out[8]:

	emp_length_int	home_ownership_cat	annual_inc	income_cat	loan_amount	term_cat	application_type_cat	purpose_cat	interest_payment_cat	loan_cor
0	0	0	0	0	0	0	0	0	0	

6 Checking for the correlation between different variables

In [9]:

```
numeric_features = [t[0] for t in df.dtypes if t[1] != 'string']
numeric_features_df=df.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
```

term_cat	0.081425	0.118353	0.070792	0.043934	0.418287	1.000000	-0.000294	0.035645
application_type_cat	0.001316	-0.001124	-0.002434	-0.002274	-0.001080	-0.000294	1.000000	-0.000131
purpose_cat	0.006490	0.018268	0.013164	0.009658	-0.025099	0.035645	-0.000131	1.000000
interest_payment_cat	0.018633	-0.064503	-0.045976	-0.045203	0.124952	0.343407	-0.002490	0.087573
loan_condition_cat	-0.013167	-0.043655	-0.047611	-0.044598	0.018842	0.070249	0.000643	0.027956
interest_rate	0.024720	-0.075746	-0.042833	-0.045981	0.177772	0.427937	-0.002615	0.100506
grade_cat	0.011910	-0.072963	-0.033398	-0.035140	0.172993	0.438498	-0.002196	0.106752
dti	0.056417	0.004300	-0.184494	-0.184894	0.062111	0.093518	-0.001306	-0.024874
total_pymnt	0.080666	0.151020	0.289601	0.269511	0.738089	0.183849	0.000461	-0.007256
total_rec_prncp	0.060731	0.138081	0.270290	0.254097	0.617067	0.022456	0.001236	-0.016070
recoveries	0.008370	0.005813	0.018405	0.014113	0.115019	0.092360	-0.000912	0.014107
installment	0.106607	0.167778	0.358701	0.335350	0.948679	0.164697	-0.002021	-0.028109

7 Encoding the categorial columns and pre-processing the data to build the model

In [11]:

```
categoricalColumns = [
 'home_ownership_cat',
 'income_cat',
 'term_cat',
 'application_type_cat',
 'purpose_cat',
 'interest_payment_cat',
 'grade_cat'
]
stages = []
for categoricalCol in categoricalColumns:
    stringIndexer = StringIndexer(inputCol = categoricalCol, outputCol = categoricalCol + 'Index')
    encoder = OneHotEncoderEstimator(inputCols=[stringIndexer.getOutputCol()], outputCols=[categoricalCol + "classVec"])
    stages += [stringIndexer, encoder]
label_stringIdx = StringIndexer(inputCol = 'loan_condition_cat', outputCol = 'label')
stages += [label_stringIdx]
numericCols = ["emp_length_int", 'annual_inc', 'loan_amount', 'interest_rate','dti','total_pymnt','total_rec_prncp',
               'recoveries','installment']
assemblerInputs = [c + "classVec" for c in categoricalColumns] + numericCols
assembler = VectorAssembler(inputCols=assemblerInputs, outputCol="vectorized_features")
stages += [assembler]
scaler = StandardScaler(inputCol="vectorized_features", outputCol="features")
stages += [scaler]
```

In [12]:
```
cols = df.columns
cols
```
Out[12]:
```
['emp_length_int',
 'home_ownership_cat',
 'annual_inc',
 'income_cat',
 'loan_amount',
 'term_cat',
 'application_type_cat',
 'purpose_cat',
 'interest_payment_cat',
 'loan_condition_cat',
 'interest_rate',
 'grade_cat',
 'dti',
 'total_pymnt',
 'total_rec_prncp',
 'recoveries',
 'installment']
```

In [13]:
```
stages
```
Out[13]:
```
[StringIndexer_66a152483742,
 OneHotEncoderEstimator_6bfe7adef479,
 StringIndexer_cf36987f8fec,
 OneHotEncoderEstimator_f50115a19da3,
 StringIndexer_84ea899fb5b3,
 OneHotEncoderEstimator_0f552a55218f,
 StringIndexer_7ad8cd07b03b,
 OneHotEncoderEstimator_af4bd8d0811d,
 StringIndexer_97af0858132d,
 OneHotEncoderEstimator_c8f24080d74f,
 StringIndexer_82a344d7a468,
 OneHotEncoderEstimator_c7c262349660,
 StringIndexer_f609bbaac27d,
 OneHotEncoderEstimator_19a9f1d8e605,
 StringIndexer_5671671c4443,
 VectorAssembler_31a10b893c37,
 StandardScaler_85e693fc34fc]
```

In [14]:
```
cols = df.columns
pipeline = Pipeline(stages = stages)
pipelineModel = pipeline.fit(df)
df = pipelineModel.transform(df)
selectedCols = ['label', 'features'] + cols
df = df.select(selectedCols)
df.printSchema()
```

```
root
 |-- label: double (nullable = false)
 |-- features: vector (nullable = true)
 |-- emp_length_int: double (nullable = true)
 |-- home_ownership_cat: long (nullable = true)
 |-- annual_inc: long (nullable = true)
 |-- income_cat: long (nullable = true)
 |-- loan_amount: long (nullable = true)
 |-- term_cat: long (nullable = true)
 |-- application_type_cat: long (nullable = true)
 |-- purpose_cat: long (nullable = true)
 |-- interest_payment_cat: long (nullable = true)
 |-- loan_condition_cat: long (nullable = true)
 |-- interest_rate: double (nullable = true)
 |-- grade_cat: long (nullable = true)
 |-- dti: double (nullable = true)
 |-- total_pymnt: double (nullable = true)
 |-- total_rec_prncp: double (nullable = true)
 |-- recoveries: double (nullable = true)
 |-- installment: double (nullable = true)
```

8 Creating train and test data. Applying the logistic regression model

In [15]:
```
train, test = df.randomSplit([0.8, 0.2], seed = 2023)
print("Training Dataset Count: " + str(train.count()))
print("Test Dataset Count: " + str(test.count()))
```

```
Training Dataset Count: 288288
Test Dataset Count: 71697
```

In [16]:
```
from pyspark.ml.classification import LogisticRegression
lr = LogisticRegression(featuresCol = 'features', labelCol = 'label', maxIter=5)
lrModel = lr.fit(train)
predictions = lrModel.transform(test)
predictions_train = lrModel.transform(train)
#predictions.select('label', 'features',  'rawPrediction', 'prediction', 'probability').toPandas().head(5)
```

In [22]:
```
predictions.select('label', 'features',  'rawPrediction', 'prediction', 'probability').toPandas().head(5)
```

Out[22]:

	label	features	rawPrediction	prediction	probability
0	0.0	(2.0000106881665136, 0.0, 0.0, 0.0, 0.0, 2.706...	[2.4877569255368264, -2.4877569255368264]	0.0	[0.9232790656229303, 0.07672093437706975]
1	0.0	(2.0000106881665136, 0.0, 0.0, 0.0, 0.0, 2.706...	[3.1751160916322534, -3.1751160916322534]	0.0	[0.9598870382626068, 0.04011296173739326]
2	0.0	(2.0000106881665136, 0.0, 0.0, 0.0, 0.0, 2.706...	[2.4405881040437043, -2.4405881040437043]	0.0	[0.9198704469804013, 0.08012955301959854]
3	0.0	(2.0000106881665136, 0.0, 0.0, 0.0, 0.0, 2.706...	[2.9146884027765934, -2.9146884027765934]	0.0	[0.9485677790280281, 0.05143222097197184 4]
4	0.0	(2.0000106881665136, 0.0, 0.0, 0.0, 0.0, 2.706...	[3.579747554356233, -3.579747554356233]	0.0	[0.9728736214170769, 0.027126378582923195]

9 Creating the graph of model output

In [17]:

```
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')
```

10 Printing the confusion matrix for the output of logistic regression model

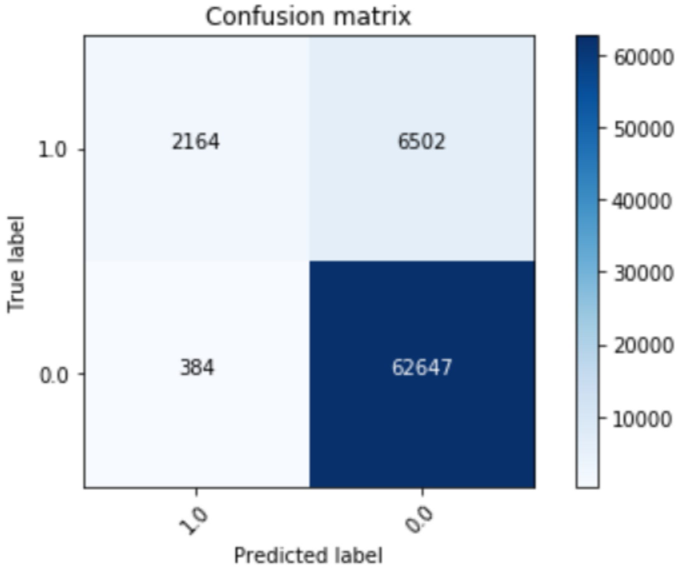
In [18]:

```
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
[[ 2164  6502]
 [  384 62647]]
```

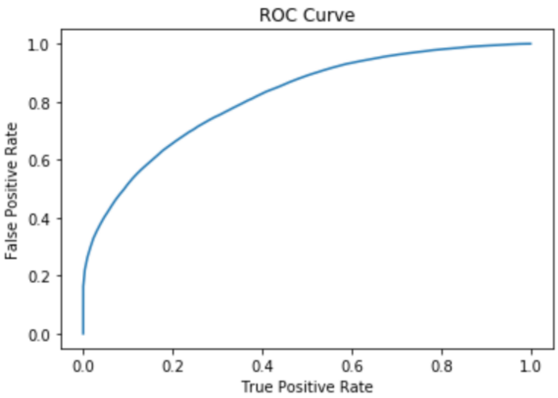


11 Checking for model accuracy along with ROC curve plot and area under the curve.

In [19]:
```
accuracy = predictions.filter(predictions.label == predictions.prediction).count() / float(predictions.count())
print("Accuracy : ",accuracy)
```

```
Accuracy :  0.9039569298575951
```

In [20]:
```
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: 0.8161702615863812
```

In [21]:
```
from pyspark.ml.evaluation import BinaryClassificationEvaluator
evaluator = BinaryClassificationEvaluator()
print('Test Area Under ROC', evaluator.evaluate(predictions))
```

```
Test Area Under ROC 0.8235242665184784
```