Project-4-spark

December 1, 2020

[449]:
```
import os

# # Install java
! apt-get install -y openjdk-8-jdk-headless -qq > /dev/null
os.environ["JAVA_HOME"] = "/usr/lib/jvm/java-8-openjdk-amd64"
os.environ["PATH"] = os.environ["JAVA_HOME"] + "/bin:" + os.environ["PATH"]
! java -version

# Install pyspark
! pip install --ignore-installed pyspark==2.4.4
```

```
openjdk version "1.8.0_275"
OpenJDK Runtime Environment (build 1.8.0_275-8u275-b01-0ubuntu1~18.04-b01)
OpenJDK 64-Bit Server VM (build 25.275-b01, mixed mode)
Processing /root/.cache/pip/wheels/ab/09/4d/0d184230058e654eb1b04467dbc1292f00ea
a186544604b471/pyspark-2.4.4-py2.py3-none-any.whl
Collecting py4j==0.10.7
  Using cached https://files.pythonhosted.org/packages/e3/53/c737818eb9a7dc32a7c
d4f1396e787bd94200c3997c72c1dbe028587bd76/py4j-0.10.7-py2.py3-none-any.whl
Installing collected packages: py4j, pyspark
Successfully installed py4j-0.10.7 pyspark-2.4.4
```

[450]:
```
! java -version
```

```
openjdk version "1.8.0_275"
OpenJDK Runtime Environment (build 1.8.0_275-8u275-b01-0ubuntu1~18.04-b01)
OpenJDK 64-Bit Server VM (build 25.275-b01, mixed mode)
```

[451]:
```
import sys
import time

#Spark ML and SQL
from pyspark.ml import Pipeline, PipelineModel
from pyspark.sql.functions import array_contains
from pyspark.sql import SparkSession
from pyspark.sql.types import StructType, StructField, IntegerType, StringType
import numpy as np
```

```python
from pyspark.sql.functions import isnan, when, count, col
```

[452]:
```python
from pyspark.sql import SparkSession
import pyspark.sql as sparksql
spark = SparkSession.builder.appName('stroke').getOrCreate()
# train = spark.read.csv('https://raw.githubusercontent.com/aman1002/
↪McKinseyOnlineHackathon-Healthcare-/master/train.csv',␣
↪inferSchema=True,header=True)
```

[453]:
```python
import pandas as pd
train = pd.read_csv("https://raw.githubusercontent.com/aman1002/
↪McKinseyOnlineHackathon-Healthcare-/master/train.csv")
train['smoking_status'] = train['smoking_status'].fillna('No Info')
train.head()
```

[453]:
```
      id  gender   age  ...   bmi   smoking_status stroke
0  30669    Male   3.0  ...  18.0          No Info      0
1  30468    Male  58.0  ...  39.2     never smoked      0
2  16523  Female   8.0  ...  17.6          No Info      0
3  56543  Female  70.0  ...  35.9  formerly smoked      0
4  46136    Male  14.0  ...  19.1          No Info      0

[5 rows x 12 columns]
```

[454]:
```python
train.dtypes
```

[454]:
```
id                     int64
gender                object
age                  float64
hypertension           int64
heart_disease          int64
ever_married          object
work_type             object
Residence_type        object
avg_glucose_level    float64
bmi                  float64
smoking_status        object
stroke                 int64
dtype: object
```

[455]:
```python
train['bmi'] = train['bmi'].fillna((train['bmi'].mean()))
```

[456]:
```python
train = spark.createDataFrame(train)
train.show()
```

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

```
|   id|gender| age|hypertension|heart_disease|ever_married|
work_type|Residence_type|avg_glucose_level| bmi| smoking_status|stroke|
+-----+------+----+------------+-------------+------------+------------+-------
-------+-----------------+----+---------------+------+
|30669|  Male| 3.0|           0|            0|          No|     children|
Rural|            95.12|18.0|        No Info|     0|
|30468|  Male|58.0|           1|            0|         Yes|      Private|
Urban|            87.96|39.2|   never smoked|     0|
|16523|Female| 8.0|           0|            0|          No|      Private|
Urban|           110.89|17.6|        No Info|     0|
|56543|Female|70.0|           0|            0|         Yes|      Private|
Rural|            69.04|35.9|formerly smoked|     0|
|46136|  Male|14.0|           0|            0|          No| Never_worked|
Rural|           161.28|19.1|        No Info|     0|
|32257|Female|47.0|           0|            0|         Yes|      Private|
Urban|           210.95|50.1|        No Info|     0|
|52800|Female|52.0|           0|            0|         Yes|      Private|
Urban|            77.59|17.7|formerly smoked|     0|
|41413|Female|75.0|           0|            1|         Yes|Self-employed|
Rural|           243.53|27.0|   never smoked|     0|
|15266|Female|32.0|           0|            0|         Yes|      Private|
Rural|            77.67|32.3|         smokes|     0|
|28674|Female|74.0|           1|            0|         Yes|Self-employed|
Urban|           205.84|54.6|   never smoked|     0|
|10460|Female|79.0|           0|            0|         Yes|     Govt_job|
Urban|            77.08|35.0|        No Info|     0|
|64908|  Male|79.0|           0|            1|         Yes|      Private|
Urban|            57.08|22.0|formerly smoked|     0|
|63884|Female|37.0|           0|            0|         Yes|      Private|
Rural|           162.96|39.4|   never smoked|     0|
|37893|Female|37.0|           0|            0|         Yes|      Private|
Rural|             73.5|26.1|formerly smoked|     0|
|67855|Female|40.0|           0|            0|         Yes|      Private|
Rural|            95.04|42.4|   never smoked|     0|
|25774|  Male|35.0|           0|            0|          No|      Private|
Rural|            85.37|33.0|   never smoked|     0|
|19584|Female|20.0|           0|            0|          No|      Private|
Urban|            84.62|19.7|         smokes|     0|
|24447|Female|42.0|           0|            0|         Yes|      Private|
Rural|            82.67|22.5|   never smoked|     0|
|49589|Female|44.0|           0|            0|         Yes|     Govt_job|
Urban|            57.33|24.6|         smokes|     0|
|17986|Female|79.0|           0|            1|         Yes|Self-employed|
Urban|            67.84|25.2|         smokes|     0|
+-----+------+----+------------+-------------+------------+------------+-------
-------+-----------------+----+---------------+------+
only showing top 20 rows
```

[457]:
```
# fill in miss values for bmi
# as this is numecial data , we will simple fill the missing values with mean
from pyspark.sql.functions import mean
mean = train.select(mean(train['bmi'])).collect()
mean_bmi = mean[0][0]
print(mean_bmi)
train = train.fillna( { 'bmi':mean_bmi } )
#test = test.fillna( { 'bmi':mean_bmi } )
```

```
28.605038390004683
```

[458]:
```
#to print the categories of columns
print(train.select('gender').distinct().rdd.map(lambda r: r[0]).collect())
print(train.select('ever_married').distinct().rdd.map(lambda r: r[0]).collect())
print(train.select('work_type').distinct().rdd.map(lambda r: r[0]).collect())
print(train.select('Residence_type').distinct().rdd.map(lambda r: r[0]).
 ↪collect())
print(train.select('smoking_status').distinct().rdd.map(lambda r: r[0]).
 ↪collect())
print(train.select('stroke').distinct().rdd.map(lambda r: r[0]).collect())
```

```
['Female', 'Other', 'Male']
['No', 'Yes']
['Never_worked', 'Self-employed', 'Private', 'children', 'Govt_job']
['Urban', 'Rural']
['smokes', 'No Info', 'never smoked', 'formerly smoked']
[0, 1]
```

[459]:
```
train.dtypes
```

[459]:
```
[('id', 'bigint'),
 ('gender', 'string'),
 ('age', 'double'),
 ('hypertension', 'bigint'),
 ('heart_disease', 'bigint'),
 ('ever_married', 'string'),
 ('work_type', 'string'),
 ('Residence_type', 'string'),
 ('avg_glucose_level', 'double'),
 ('bmi', 'double'),
 ('smoking_status', 'string'),
 ('stroke', 'bigint')]
```

[460]:
```
train.select([count(when(isnan(c), c)).alias(c) for c in train.columns]).show()
```

```
+---+------+---+------------+-------------+------------+---------+--------------
+-----------------+---+--------------+------+
| id|gender|age|hypertension|heart_disease|ever_married|work_type|Residence_type
```

```
|avg_glucose_level|bmi|smoking_status|stroke|
+---+------+---+------------+-------------+------------+---------+--------------
+-----------------+---+-------------+------+
|  0|     0|  0|           0|            0|           0|        0|
0|                0|  0|            0|     0|
+---+------+---+------------+-------------+------------+---------+--------------
+-----------------+---+-------------+------+
```

[461]:
```python
test = pd.read_csv("https://raw.githubusercontent.com/aman1002/
 ↪McKinseyOnlineHackathon-Healthcare-/master/test.csv")
test['smoking_status'] = test['smoking_status'].fillna('No Info')
test = spark.createDataFrame(test)
#test.na.fill('No Info', subset=['smoking_status'])
test.show()
```

```
+-----+------+----+------------+-------------+------------+------------+-------
-------+-----------------+----+---------------+
|   id|gender| age|hypertension|heart_disease|ever_married|
work_type|Residence_type|avg_glucose_level| bmi| smoking_status|
+-----+------+----+------------+-------------+------------+------------+-------
-------+-----------------+----+---------------+
|36306|  Male|80.0|           0|            0|         Yes|      Private|
Urban|            83.84|21.1|formerly smoked|
|61829|Female|74.0|           0|            1|         Yes|Self-employed|
Rural|            179.5|26.0|formerly smoked|
|14152|Female|14.0|           0|            0|          No|     children|
Rural|            95.16|21.2|        No Info|
|12997|  Male|28.0|           0|            0|          No|      Private|
Urban|            94.76|23.4|        No Info|
|40801|Female|63.0|           0|            0|         Yes|     Govt_job|
Rural|            83.57|27.6|   never smoked|
| 9348|Female|66.0|           1|            0|         Yes|      Private|
Urban|           219.98|32.2|   never smoked|
|51550|Female|49.0|           0|            0|         Yes|Self-employed|
Rural|            74.03|25.1|        No Info|
|60512|  Male|46.0|           0|            0|         Yes|     Govt_job|
Urban|            120.8|32.5|   never smoked|
|31309|Female|75.0|           0|            0|         Yes|Self-employed|
Rural|            78.71|28.0|   never smoked|
|39199|  Male|75.0|           0|            0|         Yes|Self-employed|
Urban|             77.2|25.7|         smokes|
|15160|Female|17.0|           0|            0|          No|      Private|
Rural|            78.16|21.9|        No Info|
|21705|Female|10.0|           0|            0|          No|     children|
Urban|           107.23|19.4|        No Info|
|19042|Female|47.0|           0|            0|         Yes|      Private|
Rural|             91.6|26.7|   never smoked|
```

```
|12249|Female|42.0|           0|            0|          Yes|      Private|
Urban|             83.05|32.3|        No Info|
|33104|Female|67.0|           0|            0|          Yes|     Govt_job|
Urban|             236.6|24.2|   never smoked|
|55264|Female|52.0|           0|            0|           No|Self-employed|
Urban|            109.49|24.5|   never smoked|
|29445|  Male|73.0|           0|            0|          Yes|Self-employed|
Rural|            109.66|40.0|        No Info|
|49013|Female|19.0|           0|            0|           No|      Private|
Rural|             88.51|22.1|        No Info|
|  276|  Male|15.0|           0|            0|           No|     children|
Rural|            101.36|22.3|        No Info|
|47721|Female|37.0|           0|            0|          Yes|     Govt_job|
Urban|            165.44|36.1|formerly smoked|
+-----+------+----+------------+-------------+------------+-------------+-------
-------+-----------------+----+---------------+
only showing top 20 rows
```

[462]:

```
from pyspark.sql.functions import *
from pyspark.sql.types import *
a = [IntegerType(),StringType(),IntegerType(),IntegerType(),IntegerType(),
     StringType(),StringType(),StringType(),FloatType(),
     IntegerType(),StringType(),IntegerType()]
print(len(a))
print(len(train.columns))
train = train.withColumn("id", train["id"].cast(IntegerType()))
train = train.withColumn("gender", train["gender"].cast(StringType()))
train = train.withColumn("age", train["age"].cast(IntegerType()))
train = train.withColumn("hypertension", train["hypertension"].
 ↪cast(IntegerType()))
train = train.withColumn("heart_disease", train["heart_disease"].
 ↪cast(IntegerType()))
train = train.withColumn("ever_married", train["ever_married"].
 ↪cast(StringType()))
train = train.withColumn("work_type", train["work_type"].cast(StringType()))
train = train.withColumn("Residence_type", train["Residence_type"].
 ↪cast(StringType()))
train = train.withColumn("avg_glucose_level", train["avg_glucose_level"].
 ↪cast(FloatType()))
train = train.withColumn("bmi", train["bmi"].cast(FloatType()))
train = train.withColumn("smoking_status", train["smoking_status"].
 ↪cast(StringType()))
train = train.withColumn("stroke", train["stroke"].cast(IntegerType()))

  # train = train.withColumn(i, train[i].cast(i))
# train = train.withColumn("Plays", train["Plays"].cast(IntegerType()))
```

```
12
12
```

[463]:
```python
train.dtypes
```

[463]:
```
[('id', 'int'),
 ('gender', 'string'),
 ('age', 'int'),
 ('hypertension', 'int'),
 ('heart_disease', 'int'),
 ('ever_married', 'string'),
 ('work_type', 'string'),
 ('Residence_type', 'string'),
 ('avg_glucose_level', 'float'),
 ('bmi', 'float'),
 ('smoking_status', 'string'),
 ('stroke', 'int')]
```

[464]:
```python
test = test.withColumn("id", test["id"].cast(IntegerType()))
test = test.withColumn("gender", test["gender"].cast(StringType()))
test = test.withColumn("age", test["age"].cast(IntegerType()))
test = test.withColumn("hypertension", test["hypertension"].cast(IntegerType()))
test = test.withColumn("heart_disease", test["heart_disease"].
 ↪cast(IntegerType()))
test = test.withColumn("ever_married", test["ever_married"].cast(StringType()))
test = test.withColumn("work_type", test["work_type"].cast(StringType()))
test = test.withColumn("Residence_type", test["Residence_type"].
 ↪cast(StringType()))
test = test.withColumn("avg_glucose_level", test["avg_glucose_level"].
 ↪cast(FloatType()))
test = test.withColumn("bmi", test["bmi"].cast(FloatType()))
test = test.withColumn("smoking_status", test["smoking_status"].
 ↪cast(StringType()))
```

[465]:
```python
print("The number of row and columns: ")
print(str(train.count())+","+str(len(train.columns)))
```

```
The number of row and columns:
43400,12
```

[466]:
```python
train=train.dropDuplicates();
totalRow=train.count()
print("The number of row and columns after removing duplicate rows: ")
print(str(totalRow)+","+str(len(train.columns)))
```

```
The number of row and columns after removing duplicate rows:
43400,12
```

[467]:
```
print("nThe type of each column variable")
train.printSchema()
```

```
nThe type of each column variable
root
 |-- id: integer (nullable = true)
 |-- gender: string (nullable = true)
 |-- age: integer (nullable = true)
 |-- hypertension: integer (nullable = true)
 |-- heart_disease: integer (nullable = true)
 |-- ever_married: string (nullable = true)
 |-- work_type: string (nullable = true)
 |-- Residence_type: string (nullable = true)
 |-- avg_glucose_level: float (nullable = true)
 |-- bmi: float (nullable = false)
 |-- smoking_status: string (nullable = true)
 |-- stroke: integer (nullable = true)
```

[468]:
```
print("Data Classes :")
train.groupBy('stroke').count().show()
```

```
Data Classes :
+------+-----+
|stroke|count|
+------+-----+
|     1|  783|
|     0|42617|
+------+-----+
```

[469]:
```
train.stat.crosstab("gender", "stroke").show()
```

```
+-------------+-----+---+
|gender_stroke|    0|  1|
+-------------+-----+---+
|        Other|   11|  0|
|         Male|17372|352|
|       Female|25234|431|
+-------------+-----+---+
```

[470]:
```
train.stat.crosstab("smoking_status", "stroke").show()
```

```
+---------------------+-----+---+
|smoking_status_stroke|    0|  1|
+---------------------+-----+---+
|      formerly smoked| 7272|221|
```

```
|              No Info|13147|145|
|               smokes| 6429|133|
|         never smoked|15769|284|
+---------------------+-----+---+
```

[471]:
```
train.describe().show()
```

```
+-------+-----------------+------+------------------+-------------------+-------
------------+-----------+---------+-------------+------------------+----------
-------+-------------+------------------+
|summary|               id|gender|               age|       hypertension|
heart_disease|ever_married|work_type|Residence_type| avg_glucose_level|
bmi|smoking_status|            stroke|
+-------+-----------------+------+------------------+-------------------+-------
------------+-----------+---------+-------------+------------------+----------
-------+-------------+------------------+
|  count|            43400| 43400|             43400|              43400|
43400|       43400|    43400|          43400|             43400|
43400|         43400|             43400|
|   mean|36326.14235023042|  null|
42.20509216589862|0.09357142857142857|0.04751152073732719|        null|
null|          null|104.48274998273718|28.60503836335125|
null|0.01804147465437788|
| stddev|21072.13487918281|  null|22.543158642510683|
0.2912349063093972|0.21273274050209703|        null|     null|          null|
43.11175095897281|7.638023367240188|          null|0.13310292280179176|
|    min|                1|Female|                 0|                  0|
0|          No| Govt_job|        Rural|              55.0|               10.1|
No Info|                 0|
|    max|            72943| Other|                82|                  1|
1|         Yes| children|        Urban|            291.05|               97.6|
smokes|                 1|
+-------+-----------------+------+------------------+-------------------+-------
------------+-----------+---------+-------------+------------------+----------
-------+-------------+------------------+
```

[472]:
```
#correlation between age and bmi column
print('correlation among age and bmi', train.stat.corr("age","bmi"))
print('correlation among age and hypertension',  train.stat.
 ↪corr("age","hypertension"))
print('correlation among age and heart_disease',  train.stat.
 ↪corr("age","heart_disease"))
print('correlation among age and avg_glucose_level',  train.stat.
 ↪corr("age","avg_glucose_level"))
```

```
print('correlation among bmi and heart_disease',  train.stat.
 ↪corr("bmi","heart_disease"))
print('correlation among bmi and hypertension',  train.stat.
 ↪corr("bmi","hypertension"))
print('correlation among bmi and avg_glucose_level',  train.stat.
 ↪corr("bmi","avg_glucose_level"))
print('correlation among hypertension and avg_glucose_level',  train.stat.
 ↪corr("hypertension","avg_glucose_level"))
print('correlation among   heart_disease and avg_glucose_level',  train.stat.
 ↪corr("heart_disease","avg_glucose_level"))
print('correlation among   heart_disease and hypertension',  train.stat.
 ↪corr("heart_disease","hypertension"))
```

```
correlation among age and bmi 0.3526219495747763
correlation among age and hypertension 0.2720674109317827
correlation among age and heart_disease 0.2500543031637834
correlation among age and avg_glucose_level 0.23753865638184568
correlation among bmi and heart_disease 0.05413275950913033
correlation among bmi and hypertension 0.15377892038810498
correlation among bmi and avg_glucose_level 0.184198583300623
correlation among hypertension and avg_glucose_level 0.1602112855742868
correlation among   heart_disease and avg_glucose_level 0.14693806802039466
correlation among   heart_disease and hypertension 0.11977702589069274
```

[473]:
```
# create DataFrame as a temporary view for SQL queries
train.createOrReplaceTempView('table')
```

[474]:
```
# sql query to find the number of people in specific work_type who have had␣
 ↪stroke and not
spark.sql("SELECT work_type, COUNT(work_type) as work_type_count FROM table␣
 ↪WHERE stroke == 1 GROUP BY work_type ORDER BY COUNT(work_type) DESC").show()
spark.sql("SELECT work_type, COUNT(work_type) as work_type_count FROM table␣
 ↪WHERE stroke == 0 GROUP BY work_type ORDER BY COUNT(work_type) DESC").show()
spark.sql("SELECT gender, COUNT(gender) as gender_count, COUNT(gender)*100/
 ↪(SELECT COUNT(gender) FROM table WHERE gender == 'Male') as percentage FROM␣
 ↪table WHERE stroke== 1 AND gender = 'Male' GROUP BY gender").show()
spark.sql("SELECT gender, COUNT(gender) as gender_count, COUNT(gender)*100/
 ↪(SELECT COUNT(gender) FROM table WHERE gender == 'Female') as percentage FROM␣
 ↪table WHERE stroke== 1 AND gender = 'Female' GROUP BY gender").show()
```

```
+-------------+---------------+
|    work_type|work_type_count|
+-------------+---------------+
|      Private|            441|
|Self-employed|            251|
|     Govt_job|             89|
|     children|              2|
```

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

+-------------+---------------+
|    work_type|work_type_count|
+-------------+---------------+
|      Private|          24393|
|Self-employed|           6542|
|     children|           6154|
|     Govt_job|           5351|
| Never_worked|            177|
+-------------+---------------+

+------+------------+------------------+
|gender|gender_count|        percentage|
+------+------------+------------------+
|  Male|         352|1.9860076732114647|
+------+------------+------------------+

+------+------------+------------------+
|gender|gender_count|        percentage|
+------+------------+------------------+
|Female|         431|1.6793298266121177|
+------+------------+------------------+
```

1.68% female and almost 2% male had stroke.

Here we see that there are few missing values in smoking_status and bmi column Also there are few categorical data (gender, ever_married, work_type, Residence_type, smoking_status which we need to covert into one hot encoding

[475]:
```
# fill in missing values for smoking status
# As this is categorical data, we will add one data type "No Info" for the␣
↪missing one
train_f = train
test_f = test
```

[476]:
```
train_f.printSchema()
```

```
root
 |-- id: integer (nullable = true)
 |-- gender: string (nullable = true)
 |-- age: integer (nullable = true)
 |-- hypertension: integer (nullable = true)
 |-- heart_disease: integer (nullable = true)
 |-- ever_married: string (nullable = true)
 |-- work_type: string (nullable = true)
 |-- Residence_type: string (nullable = true)
 |-- avg_glucose_level: float (nullable = true)
```

```
 |-- bmi: float (nullable = false)
 |-- smoking_status: string (nullable = true)
 |-- stroke: integer (nullable = true)
```

[477]:
```
# from pyspark.sql.functions import mean
# mean = train_f.select(mean(train_f['bmi'])).collect()
# mean_bmi = mean[0][0]
# print(mean_bmi)
# print(mean)
```

[478]:
```
from pyspark.sql.functions import mean as _mean, stddev as _stddev, col

df_stats = train_f.select(
    _mean(col('bmi')).alias('mean'),
    _stddev(col('bmi')).alias('std')
).collect()

mean = df_stats[0]['mean']
std = df_stats[0]['std']
mean
```

[478]: 28.60503836335125

[479]:
```
train_f.describe().show()
```

```
+-------+-----------------+------+------------------+-------------------+-------
------------+-----------+---------+--------------+------------------+----------
-------+--------------+-------------------+
|summary|               id|gender|               age|       hypertension|
heart_disease|ever_married|work_type|Residence_type| avg_glucose_level|
bmi|smoking_status|             stroke|
+-------+-----------------+------+------------------+-------------------+-------
------------+-----------+---------+--------------+------------------+----------
-------+--------------+-------------------+
|  count|            43400| 43400|             43400|              43400|
43400|       43400|    43400|          43400|             43400|
43400|         43400|              43400|
|   mean|36326.14235023042|  null|
42.20509216589862|0.09357142857142857|0.04751152073732719|        null|
null|          null|104.48274998273718|28.60503836335125|
null|0.01804147465437788|
| stddev|21072.13487918281|  null|22.543158642510683|
0.2912349063093972|0.21273274050209703|        null|     null|          null|
43.11175095897281|7.638023367240188|          null|0.13310292280179176|
|    min|                1|Female|                 0|                  0|
0|          No| Govt_job|         Rural|              55.0|              10.1|
No Info|                  0|
```

```
|    max|            72943| Other|                82|                   1|
1|         Yes| children|         Urban|            291.05|              97.6|
smokes|                   1|
+-------+-----------------+------+-----------------+-------------------+-------
------------+------------+---------+--------------+------------------+----------
-------+--------------+-------------------+
```

[480]:
```python
test_f.describe().show()
```

```
+-------+------------------+------+-----------------+-------------------+------
--------------+------------+---------+--------------+------------------+-----+--
------------+
|summary|                id|gender|              age|       hypertension|
heart_disease|ever_married|work_type|Residence_type| avg_glucose_level|
bmi|smoking_status|
+-------+------------------+------+-----------------+-------------------+------
--------------+------------+---------+--------------+------------------+-----+--
------------+
|  count|             18601| 18601|            18601|              18601|
18601|       18601|    18601|         18601|             18601|18601|
18601|
|   mean| 36747.36804472878|
null|42.043868609214556|0.09316703403042847|0.048061932154185256|        null|
null|          null|104.38635932680779|  NaN|          null|
| stddev|21053.151123778687|  null| 22.55112733897937|0.29067418204733125|
0.21390288127048418|        null|     null|          null| 42.60671443150512|
NaN|          null|
|    min|                 2|Female|                0|                  0|
0|          No| Govt_job|         Rural|              55.0| 10.2|       No Info|
|    max|             72942| Other|               82|                  1|
1|         Yes| children|         Urban|            275.72|  NaN|        smokes|
+-------+------------------+------+-----------------+-------------------+------
--------------+------------+---------+--------------+------------------+-----+--
------------+
```

[480]:
```python

```

Now there is no missing values, Lets work on categorical columns now…

StringIndexer -> OneHotEncoder -> VectorAssembler

[480]:
```python

```

[481]:
```python
# indexing all categorical columns in the dataset
from pyspark.ml.feature import StringIndexer
indexer1 = StringIndexer(inputCol="gender", outputCol="genderIndex")
```

```
indexer2 = StringIndexer(inputCol="ever_married", outputCol="ever_marriedIndex")
indexer3 = StringIndexer(inputCol="work_type", outputCol="work_typeIndex")
indexer4 = StringIndexer(inputCol="Residence_type",␣
 ↪outputCol="Residence_typeIndex")
indexer5 = StringIndexer(inputCol="smoking_status",␣
 ↪outputCol="smoking_statusIndex")
```

[482]:
```
from pyspark.ml.feature import OneHotEncoderEstimator
encoder =␣
 ↪OneHotEncoderEstimator(inputCols=["genderIndex","ever_marriedIndex","work_typeIndex","Residen
                                              ␣
 ↪outputCols=["genderVec","ever_marriedVec","work_typeVec","Residence_typeVec","smoking_statusV
```

[483]:
```
from pyspark.ml.feature import VectorAssembler
assembler = VectorAssembler(inputCols=['genderVec',
 'age',
 'hypertension',
 'heart_disease',
 'ever_marriedVec',
 'work_typeVec',
 'Residence_typeVec',
 'avg_glucose_level',
 'bmi',
 'smoking_statusVec'],outputCol='features')
```

[484]:
```
from pyspark.ml import Pipeline
pipeline = Pipeline(stages=[indexer1, indexer2, indexer3, indexer4, indexer5,␣
 ↪encoder, assembler, dtc])
```

[485]:
```
# Doing one hot encoding of indexed data
from pyspark.ml.feature import OneHotEncoderEstimator
encoder =␣
 ↪OneHotEncoderEstimator(inputCols=["genderIndex","ever_marriedIndex","work_typeIndex","Residen
                                              ␣
 ↪outputCols=["genderVec","ever_marriedVec","work_typeVec","Residence_typeVec","smoking_statusV
```

[486]:
```
from pyspark.ml.feature import VectorAssembler
assembler = VectorAssembler(inputCols=['genderVec',
 'age',
 'hypertension',
 'heart_disease',
 'ever_marriedVec',
 'work_typeVec',
 'Residence_typeVec',
 'avg_glucose_level',
 'bmi',
 'smoking_statusVec'],outputCol='features')
```

[487]:
```
# splitting training and validation data
train_data,val_data = train_f.randomSplit([0.7,0.3])
```

[487]:
```

```

Random Forest

[488]:
```
from pyspark.ml.classification import RandomForestClassifier

from pyspark.ml import Pipeline
from pyspark.ml.classification import RandomForestClassifier
from sklearn.metrics import classification_report, confusion_matrix
import  matplotlib.pyplot as plt
import numpy as np
import itertools
from pyspark.ml import Pipeline
from pyspark.ml.evaluation import BinaryClassificationEvaluator
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.ylabel('True label')
    plt.xlabel('Predicted label')
    plt.tight_layout()
```

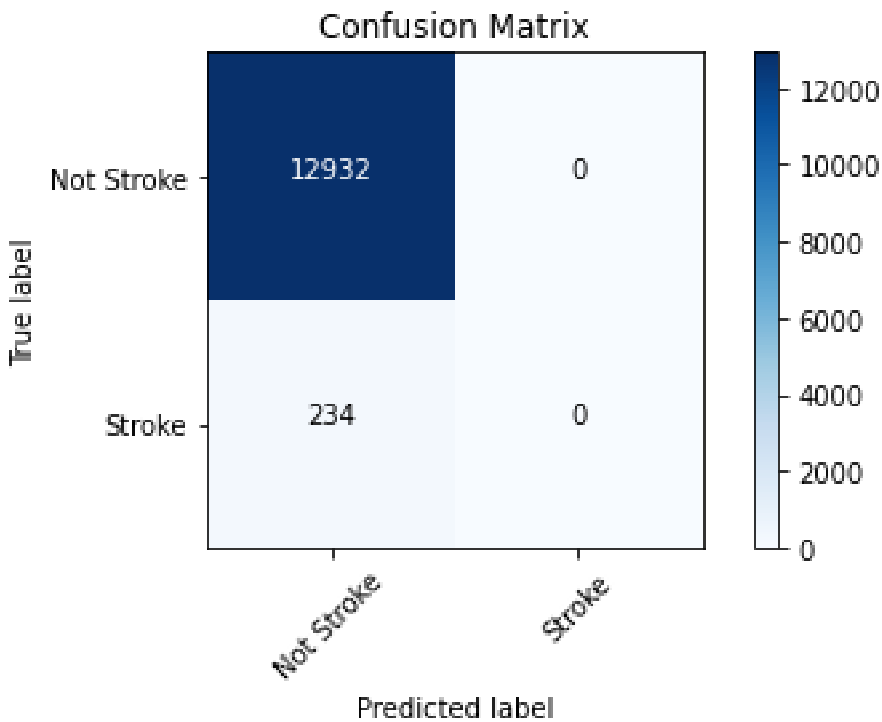
[489]:
```
rfc = RandomForestClassifier(labelCol='stroke',featuresCol='features')
pipeline = Pipeline(stages=[indexer1, indexer2, indexer3, indexer4, indexer5,␣
 ↪encoder, assembler, rfc])
# training model pipeline with data
model = pipeline.fit(train_data)
# making prediction on model with validation data
rfc_predictions = model.transform(val_data)
# Select (prediction, true label) and compute test error
acc_evaluator = MulticlassClassificationEvaluator(labelCol="stroke",␣
 ↪predictionCol="prediction", metricName="accuracy")
rfc_acc = acc_evaluator.evaluate(rfc_predictions)
print('A Random Forest algorithm had an accuracy of: {0:2.2f}%'.
 ↪format(rfc_acc*100))
# Select (prediction, true label) and compute test error
acc_evaluator = MulticlassClassificationEvaluator(labelCol="stroke",␣
 ↪predictionCol="prediction", metricName="f1")
#evaluator = BinaryClassificationEvaluator()
rfc_acc = acc_evaluator.evaluate(rfc_predictions)
print('A Random Forest algorithm had an F1-Score of: {0:2.2f}%'.
 ↪format(rfc_acc*100))
#AUC
evaluator = BinaryClassificationEvaluator(labelCol="stroke")
print('Test Area Under ROC', evaluator.evaluate(rfc_predictions))
```

```
A Random Forest algorithm had an accuracy of: 98.22%
A Random Forest algorithm had an F1-Score of: 97.34%
Test Area Under ROC 0.8358355738498021
```

[490]:
```
y_true = rfc_predictions.select(['stroke']).collect()
y_pred = rfc_predictions.select(['prediction']).collect()
print(classification_report(y_true, y_pred))

# argmax returns the index of the max value in a row
cm = confusion_matrix(y_true, y_pred)
cm_plot_labels = ['Not Stroke', 'Stroke']
plot_confusion_matrix(cm, cm_plot_labels, title='Confusion Matrix')
```

```
/usr/local/lib/python3.6/dist-packages/sklearn/metrics/_classification.py:1272:
UndefinedMetricWarning: Precision and F-score are ill-defined and being set to
0.0 in labels with no predicted samples. Use `zero_division` parameter to
control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))

              precision    recall  f1-score   support
```

```
              0       0.98      1.00      0.99     12932
              1       0.00      0.00      0.00       234

       accuracy                           0.98     13166
      macro avg       0.49      0.50      0.50     13166
   weighted avg       0.96      0.98      0.97     13166

Confusion matrix, without normalization
[[12932     0]
 [  234     0]]
```



[491]:

```
# Select example rows to display.
test_selected = rfc_predictions .select("id", "features",␣
↪"prediction","probability")
test_selected.limit(5).toPandas()
```

[491]:

```
     id  ...                                  probability
0   899  ...  [0.9879649107285038, 0.012035089271496142]
1  1521  ...  [0.9872669566246552, 0.012733043375344862]
2  2844  ...  [0.9869266267502438, 0.013073373249756281]
3  2883  ...   [0.9635631272345032, 0.03643687276549675]
4  3071  ...  [0.9774076183689575, 0.022592381631042595]
```

```
[5 rows x 4 columns]
```

[491]:

```

```

[492]:

```python
from pyspark.ml.classification import LogisticRegression
lg = LogisticRegression(labelCol='stroke',featuresCol='features')
pipeline = Pipeline(stages=[indexer1, indexer2, indexer3, indexer4, indexer5,␣
 ↪encoder, assembler, lg])
# training model pipeline with data
model = pipeline.fit(train_data)
# making prediction on model with validation data
lg_predictions = model.transform(val_data)
# Select (prediction, true label) and compute test error
acc_evaluator = MulticlassClassificationEvaluator(labelCol="stroke",␣
 ↪predictionCol="prediction", metricName="accuracy")
lg_acc = acc_evaluator.evaluate(lg_predictions)
print('A Logistic Regression algorithm had an accuracy of: {0:2.2f}%'.
 ↪format(lg_acc*100))
# Select (prediction, true label) and compute test error
acc_evaluator = MulticlassClassificationEvaluator(labelCol="stroke",␣
 ↪predictionCol="prediction", metricName="f1")
#evaluator = BinaryClassificationEvaluator()
lg_acc = acc_evaluator.evaluate(lg_predictions)
print('A logistic algorithm had an F1-Score of: {0:2.2f}%'.format(lg_acc*100))
#AUC
evaluator = BinaryClassificationEvaluator(labelCol="stroke")
print('Test Area Under ROC', evaluator.evaluate(lg_predictions))
```

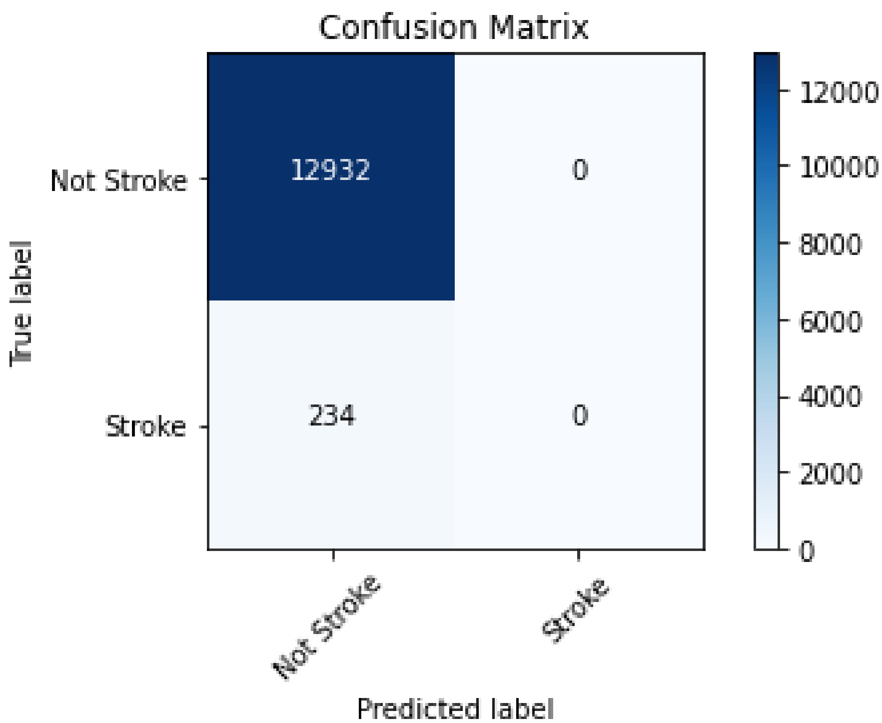
```
A Logistic Regression algorithm had an accuracy of: 98.22%
A logistic algorithm had an F1-Score of: 97.34%
Test Area Under ROC 0.8557712135271681
```

[493]:

```python
y_true = lg_predictions.select(['stroke']).collect()
y_pred = lg_predictions.select(['prediction']).collect()
print(classification_report(y_true, y_pred))

# argmax returns the index of the max value in a row
cm = confusion_matrix(y_true, y_pred)
cm_plot_labels = ['Not Stroke', 'Stroke']
plot_confusion_matrix(cm, cm_plot_labels, title='Confusion Matrix')
```

```
/usr/local/lib/python3.6/dist-packages/sklearn/metrics/_classification.py:1272:
UndefinedMetricWarning: Precision and F-score are ill-defined and being set to
0.0 in labels with no predicted samples. Use `zero_division` parameter to
control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```

```
              precision    recall  f1-score   support

           0       0.98      1.00      0.99     12932
           1       0.00      0.00      0.00       234

    accuracy                           0.98     13166
   macro avg       0.49      0.50      0.50     13166
weighted avg       0.96      0.98      0.97     13166

Confusion matrix, without normalization
[[12932     0]
 [  234     0]]
```



[494]:
```python
# balancing the dataset by duplicating the minority class samples
from pyspark.sql.functions import col, explode, array, lit,ceil
train_data
major_df = train_data.filter(col("stroke") == 0)
print(major_df.count())
minor_df = train_data.filter(col("stroke") == 1)
ratio = int(major_df.count()/minor_df.count())
print("ratio: {}".format(ratio))
```

```
29685
ratio: 54
```

[495]:

```
a = range(ratio+1)
# duplicate the minority rows
oversampled_df = minor_df.withColumn("dummy", explode(array([lit(x) for x in␣
 ↪a]))).drop('dummy')
# combine both oversampled minority rows and previous majority rows
combined_df = major_df.unionAll(oversampled_df)
combined_df.show()
print(combined_df.count())
```

```
+----+------+---+------------+-------------+------------+-------------+---------
-----+-----------------+---------+---------------+------+
|  id|gender|age|hypertension|heart_disease|ever_married|
work_type|Residence_type|avg_glucose_level|      bmi| smoking_status|stroke|
+----+------+---+------------+-------------+------------+-------------+---------
-----+-----------------+---------+---------------+------+
| 189|  Male| 65|           0|            0|         Yes|Self-employed|
Rural|            74.66|     30.6|formerly smoked|     0|
| 695|Female| 60|           0|            0|         Yes|      Private|
Rural|           103.25|     26.2|         smokes|     0|
|2143|Female| 74|           0|            0|         Yes|      Private|
Urban|            91.34|     22.0|formerly smoked|     0|
|2365|Female| 76|           0|            0|         Yes|      Private|
Urban|            95.94|     28.7|   never smoked|     0|
|3019|Female| 36|           0|            0|         Yes|      Private|
Urban|            87.94|     30.6|         smokes|     0|
|3946|Female| 22|           0|            0|         Yes|      Private|
Urban|            89.06|     27.7|   never smoked|     0|
|4635|Female| 68|           0|            0|         Yes|      Private|
Rural|            97.96|     31.3|   never smoked|     0|
|5650|Female| 26|           0|            0|          No|      Private|
Rural|            91.85|     34.1|   never smoked|     0|
|5820|Female| 63|           0|            0|         Yes|     Govt_job|
Rural|            67.21|     38.1|   never smoked|     0|
|5996|Female| 39|           0|            0|          No|      Private|
Rural|            94.67|     38.5|         smokes|     0|
|6779|  Male| 16|           0|            0|          No|      Private|
Urban|            71.75|     30.7|        No Info|     0|
|6821|Female| 47|           1|            0|         Yes|      Private|
Urban|            76.36|     30.1|   never smoked|     0|
|7122|Female| 41|           0|            0|          No|      Private|
Rural|             94.3|     41.6|        No Info|     0|
|7469|  Male| 16|           0|            0|          No|     children|
Rural|            81.02|     26.4|        No Info|     0|
|7703|Female| 63|           0|            0|         Yes|     Govt_job|
Rural|            83.52|     39.1|formerly smoked|     0|
|8557|Female| 51|           0|            0|         Yes|      Private|
Urban|           217.83|28.605038|formerly smoked|     0|
```

```
|8610|Female| 55|           0|            0|         Yes|      Private|
Urban|             82.22|     34.8|formerly smoked|     0|
|9426|  Male| 59|           0|            0|         Yes|      Private|
Urban|             72.81|     33.3|         smokes|     0|
|9730|  Male| 27|           0|            0|         Yes|      Private|
Urban|             76.19|     22.0|   never smoked|     0|
|9841|Female| 61|           1|            0|         Yes|Self-employed|
Rural|             97.83|     26.0|   never smoked|     0|
+----+------+---+------------+-------------+------------+-------------+---------
-----+-----------------+---------+---------------+------+
only showing top 20 rows

59880
```

[496]:

```python
train_data=combined_df
```

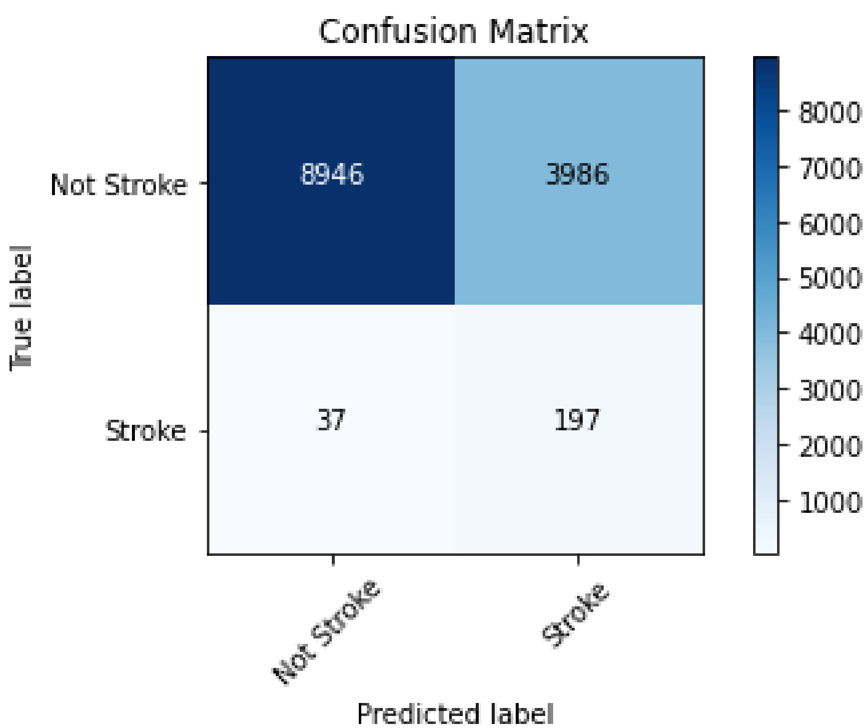
[497]:

```python
#random forest
rfc = RandomForestClassifier(labelCol='stroke',featuresCol='features')
pipeline = Pipeline(stages=[indexer1, indexer2, indexer3, indexer4, indexer5,␣
 ↪encoder, assembler, rfc])


# training model pipeline with data
model = pipeline.fit(train_data)
# making prediction on model with validation data
rfc_predictions = model.transform(val_data)
# Select (prediction, true label) and compute test error
acc_evaluator = MulticlassClassificationEvaluator(labelCol="stroke",␣
 ↪predictionCol="prediction", metricName="accuracy")
rfc_acc = acc_evaluator.evaluate(rfc_predictions)
print('A Random Forest algorithm had an accuracy of: {0:2.2f}%'.
 ↪format(rfc_acc*100))
# Select (prediction, true label) and compute test error
acc_evaluator = MulticlassClassificationEvaluator(labelCol="stroke",␣
 ↪predictionCol="prediction", metricName="f1")
#evaluator = BinaryClassificationEvaluator()
rfc_acc = acc_evaluator.evaluate(rfc_predictions)
print('A Random Forest algorithm had an F1-Score of: {0:2.2f}%'.
 ↪format(rfc_acc*100))
#AUC
evaluator = BinaryClassificationEvaluator(labelCol="stroke")
print('Test Area Under ROC', evaluator.evaluate(rfc_predictions))
```

```
A Random Forest algorithm had an accuracy of: 69.44%
A Random Forest algorithm had an F1-Score of: 80.35%
Test Area Under ROC 0.8411891855094761
```

[498]:
```
y_true = rfc_predictions.select(['stroke']).collect()
y_pred = rfc_predictions.select(['prediction']).collect()
print(classification_report(y_true, y_pred))

# argmax returns the index of the max value in a row
cm = confusion_matrix(y_true, y_pred)
cm_plot_labels = ['Not Stroke', 'Stroke']
plot_confusion_matrix(cm, cm_plot_labels, title='Confusion Matrix')
```

```
              precision    recall  f1-score   support

           0       1.00      0.69      0.82     12932
           1       0.05      0.84      0.09       234

    accuracy                           0.69     13166
   macro avg       0.52      0.77      0.45     13166
weighted avg       0.98      0.69      0.80     13166

Confusion matrix, without normalization
[[8946 3986]
 [  37  197]]
```



[499]:

```
#logistic Regression
lg = LogisticRegression(labelCol='stroke',featuresCol='features')
pipeline = Pipeline(stages=[indexer1, indexer2, indexer3, indexer4, indexer5,␣
 ↪encoder, assembler, lg])
# training model pipeline with data
model = pipeline.fit(train_data)
# making prediction on model with validation data
lg_predictions = model.transform(val_data)
# Select (prediction, true label) and compute test error
acc_evaluator = MulticlassClassificationEvaluator(labelCol="stroke",␣
 ↪predictionCol="prediction", metricName="accuracy")
lg_acc = acc_evaluator.evaluate(lg_predictions)
print('A Logistic Regression algorithm had an accuracy of: {0:2.2f}%'.
 ↪format(lg_acc*100))
# Select (prediction, true label) and compute test error
acc_evaluator = MulticlassClassificationEvaluator(labelCol="stroke",␣
 ↪predictionCol="prediction", metricName="f1")
#evaluator = BinaryClassificationEvaluator()
lg_acc = acc_evaluator.evaluate(lg_predictions)
print('A Random Forest algorithm had an F1-Score of: {0:2.2f}%'.
 ↪format(lg_acc*100))
#AUC
evaluator = BinaryClassificationEvaluator(labelCol="stroke")
print('Test Area Under ROC', evaluator.evaluate(lg_predictions))
```

```
A Logistic Regression algorithm had an accuracy of: 73.96%
A Random Forest algorithm had an F1-Score of: 83.45%
Test Area Under ROC 0.8554549636362195
```

[500]:

```
y_true = lg_predictions.select(['stroke']).collect()
y_pred = lg_predictions.select(['prediction']).collect()
print(classification_report(y_true, y_pred))

# argmax returns the index of the max value in a row
cm = confusion_matrix(y_true, y_pred)
cm_plot_labels = ['Not Stroke', 'Stroke']
plot_confusion_matrix(cm, cm_plot_labels, title='Confusion Matrix')
```

```
              precision    recall  f1-score   support

           0       1.00      0.74      0.85     12932
           1       0.05      0.81      0.10       234

    accuracy                           0.74     13166
   macro avg       0.52      0.77      0.47     13166
weighted avg       0.98      0.74      0.83     13166
```

```
Confusion matrix, without normalization
[[9549 3383]
 [  45  189]]
```