The goal of this analysis is to identify customers that are likely to open a term deposit account. Understanding the financial goals of customers will enable Bank XYZ to tailor products and services to meet the specific needs of the customer. It will also allow for effective resource allocation and narrow targeted marketing strategies. Term accounts involve long-term commitments leading to longer-lasting customer relationships that add to the stability of Bank XYZ's deposit base. This will lead to an enhanced overall risk management and financial planning strategy ensuring a more robust and sustainable business model.

The data set was generated from a telephone calling marking campaign that occurred between May 2008 and November 2010. It includes 41,188 rows with 20 columns relating to the customer, the contact, previous contacts during the campaign, and social/economic context attributes.

Libraries

In [1]:

```
import findspark
findspark.init()
```

In [2]:

```
# Import necessary libraries
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, when, explode, array, lit
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,StandardS
from pyspark.ml import Pipeline
from sklearn.metrics import confusion_matrix
#from imblearn.over_sampling import SMOTE


spark=SparkSession.builder \
.master ("local[*]")\
.appName("part3")\
.getOrCreate()

sc=spark.sparkContext
sqlContext=SQLContext(sc)
```

```
C:\Spark\spark-3.5.0-bin-hadoop3\spark-3.5.0-bin-hadoop3\python\pyspark\sql\context.p
y:113: FutureWarning: Deprecated in 3.0.0. Use SparkSession.builder.getOrCreate() ins
tead.
  warnings.warn(
```

In [3]:
```
# read in the dataframe for the assignment
df=spark.read \
 .option("header","True")\
 .option("inferSchema","True")\
 .option("sep",";")\
 .csv("/Users/Jacob/Downloads/XYZ_Bank_Deposit_Data_Classification.csv")
print("There are",df.count(),"rows",len(df.columns),
      "columns" ,"in the data.")
```

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

In [4]:
```
# Data Preprocessing
df = df.withColumnRenamed("emp.var.rate", "emp_var_rate")
df = df.withColumnRenamed("cons.price.idx", "cons_price_idx")
df = df.withColumnRenamed("cons.conf.idx", "cons_conf_idx")
df = df.withColumnRenamed("nr.employed", "nr_employed")
```

Data Exploration

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

```
+---+---------+-------+-----------+-------+-------+----+---------+-----+-----------+-
-------+--------+-----+--------+-----------+------------+-------------+-------------
+---------+-----------+---+
|age|      job|marital|  education|default|housing|loan|  contact|month|day_of_week|d
uration|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|
| 56| services|married|high.school|     no|     no| yes|telephone|  may|        mon|
307|       1|  999|       0|nonexistent|         1.1|        93.994|        -36.4|
4.857|     5191.0| no|
+---+---------+-------+-----------+-------+-------+----+---------+-----+-----------+-
-------+--------+-----+--------+-----------+------------+-------------+-------------
+---------+-----------+---+
only showing top 5 rows
```

In [6]:
```
df.summary().toPandas().transpose()
```

Out[6]:

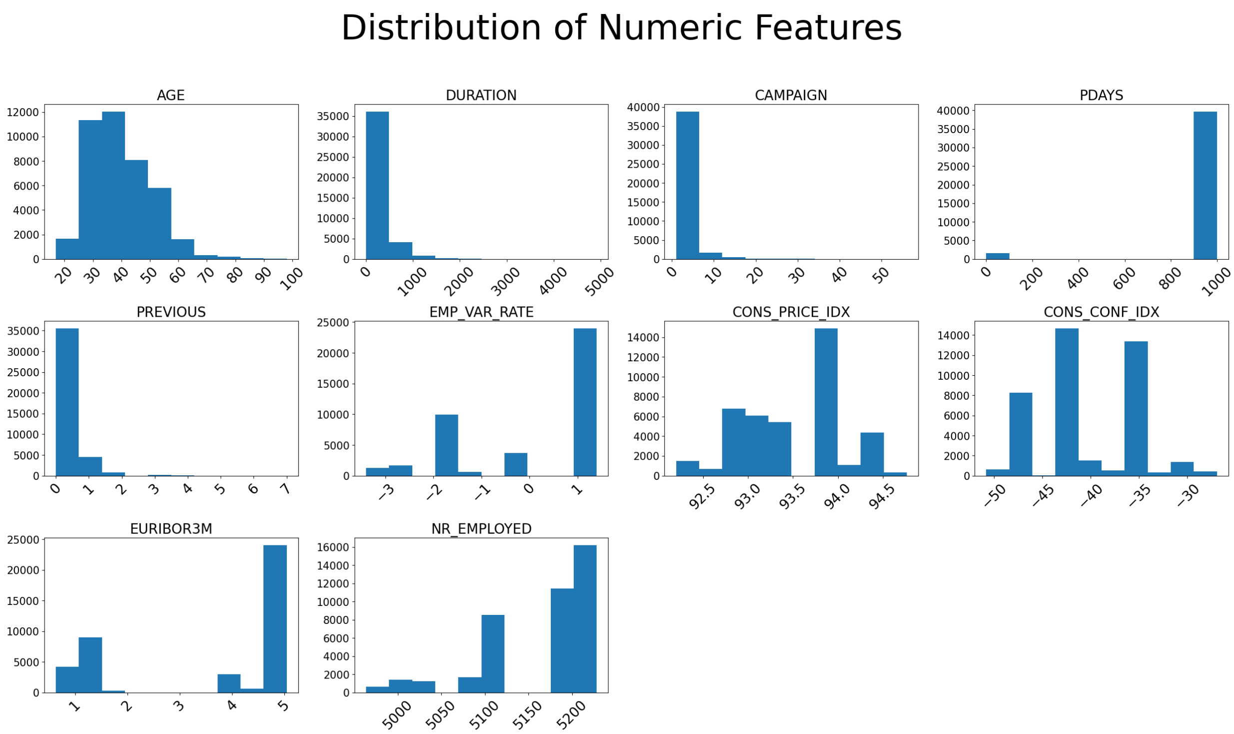
	0	1	2	3	4	5	6	
summary	count	mean	stddev	min	25%	50%	75%	
age	41188	40.02406040594348	10.421249980934043	17	32	38	47	
job	41188	None	None	admin.	None	None	None	ur
marital	41188	None	None	divorced	None	None	None	ur
education	41188	None	None	basic.4y	None	None	None	ur
default	41188	None	None	no	None	None	None	
housing	41188	None	None	no	None	None	None	
loan	41188	None	None	no	None	None	None	
contact	41188	None	None	cellular	None	None	None	tel
month	41188	None	None	apr	None	None	None	
day_of_week	41188	None	None	fri	None	None	None	
duration	41188	258.2850101971448	259.27924883646455	0	102	180	319	
campaign	41188	2.567592502670681	2.770013542902331	1	1	2	3	
pdays	41188	962.4754540157328	186.910907344741	0	999	999	999	
previous	41188	0.17296299893172767	0.49490107983928927	0	0	0	0	
poutcome	41188	None	None	failure	None	None	None	
emp_var_rate	41188	0.08188550063178966	1.57095974051703	-3.4	-1.8	1.1	1.4	
cons_price_idx	41188	93.5756643682899	0.5788400489540823	92.201	93.075	93.749	93.994	
cons_conf_idx	41188	-40.502600271918276	4.628197856174573	-50.8	-42.7	-41.8	-36.4	
euribor3m	41188	3.621290812858533	1.7344474048512595	0.634	1.344	4.857	4.961	
nr_employed	41188	5167.035910943957	72.25152766826338	4963.6	5099.1	5191.0	5228.1	
y	41188	None	None	no	None	None	None	

Exploratory Data Visualizations

In [7]:

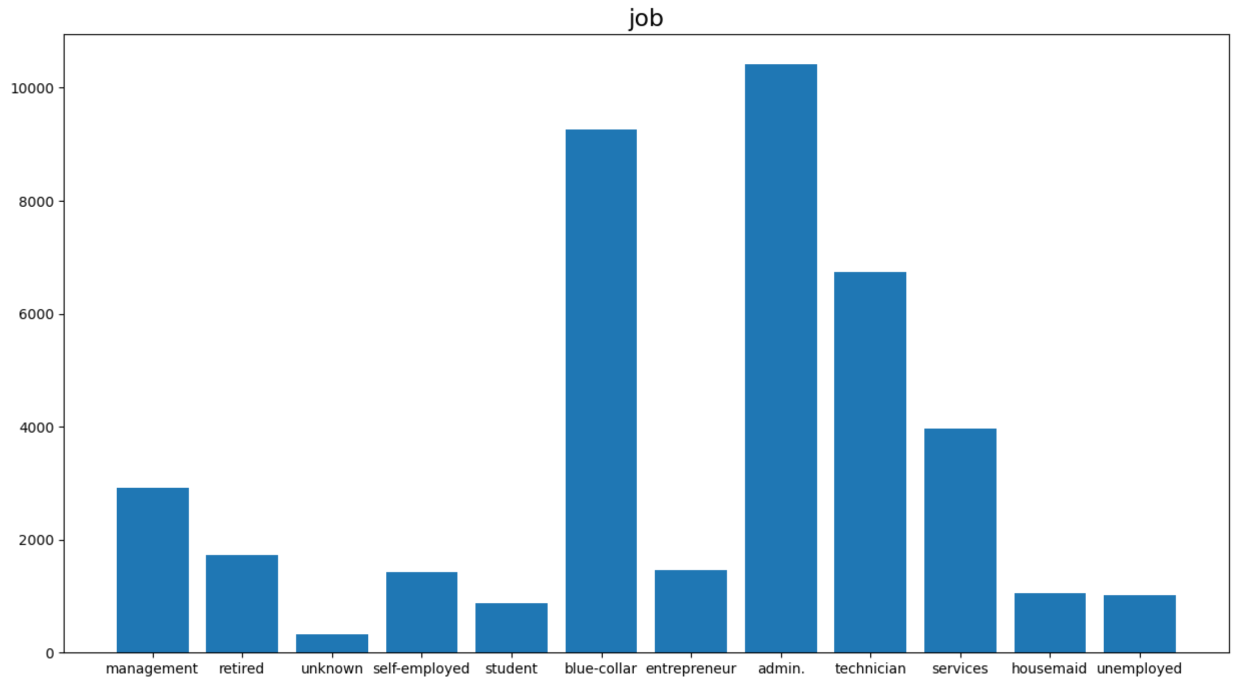
```python
from matplotlib import cm
fig = plt.figure(figsize=(25,15)) ## Plot Size
st = fig.suptitle("Distribution of Numeric Features", fontsize=50,
                  verticalalignment='center') # Plot Main Title

for col,num in zip(df.toPandas().describe().columns, range(1,11)):
    ax = fig.add_subplot(3,4,num)
    ax.hist(df.toPandas()[col])
    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()
```

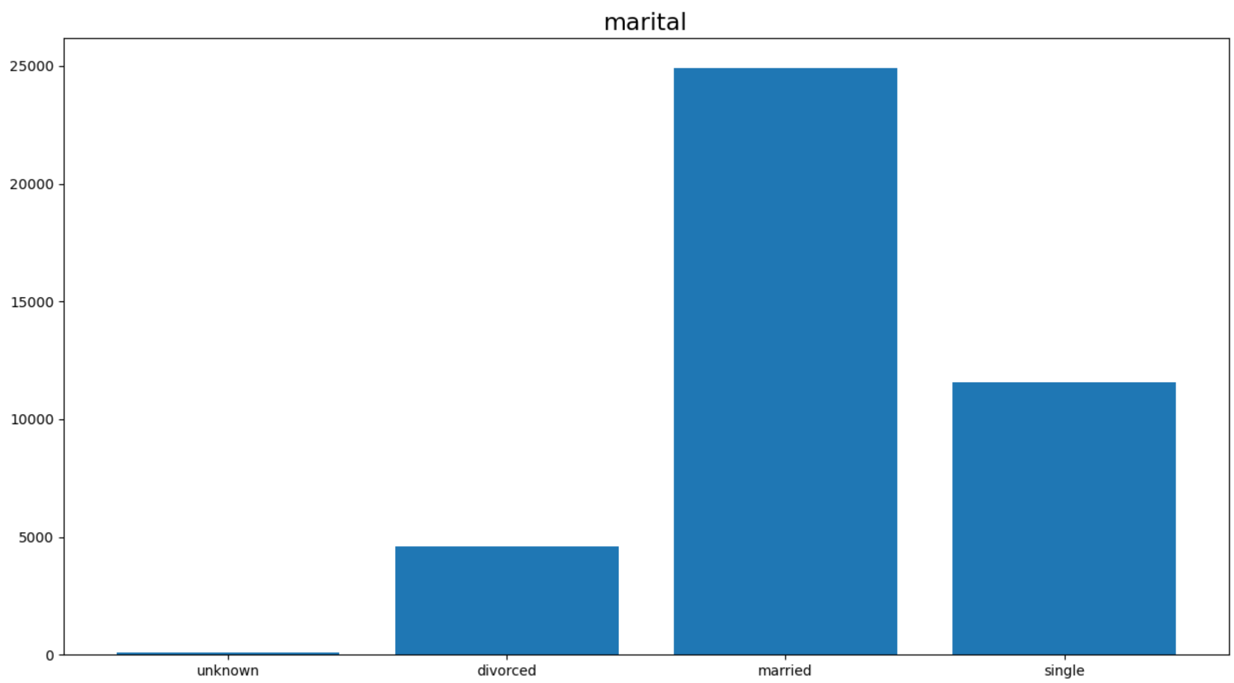


In [8]:
```
# Total string variables
string_features = [t[0] for t in df.dtypes if t[1] == 'string']
```

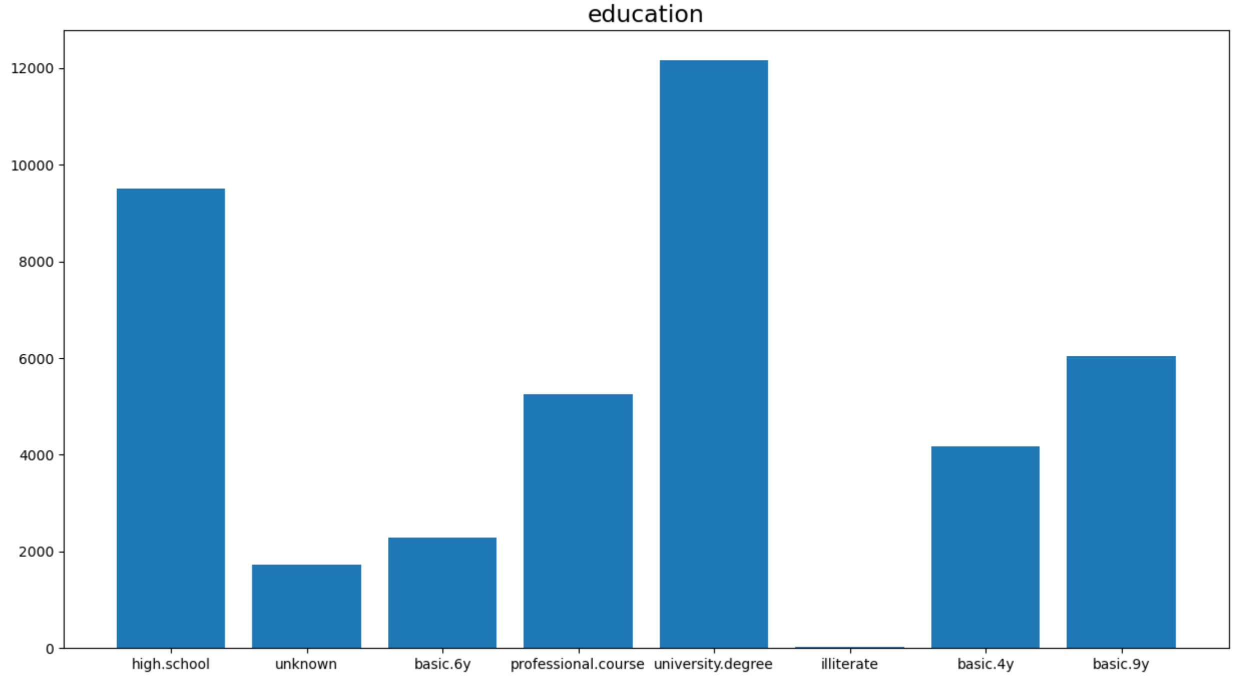
In [9]:
```
# A temporary view for the dataset
df.createOrReplaceTempView("DF")
for i in string_features:
    plt.figure(figsize=(15,8))
    new = spark.sql("select " + i + ", count(" + i + ") from DF group by " + i).toPanc
    plt.bar(new.iloc[:,0], new.iloc[:,1])
    plt.title(i, fontdict={'fontsize': 17})
    display(plt.show())
```


job
10000
8000
6000
4000
2000
0
management
retired
unknown
self-employed
student
blue-collar
entrepreneur
admin.
technician
services
housemaid
unemployed

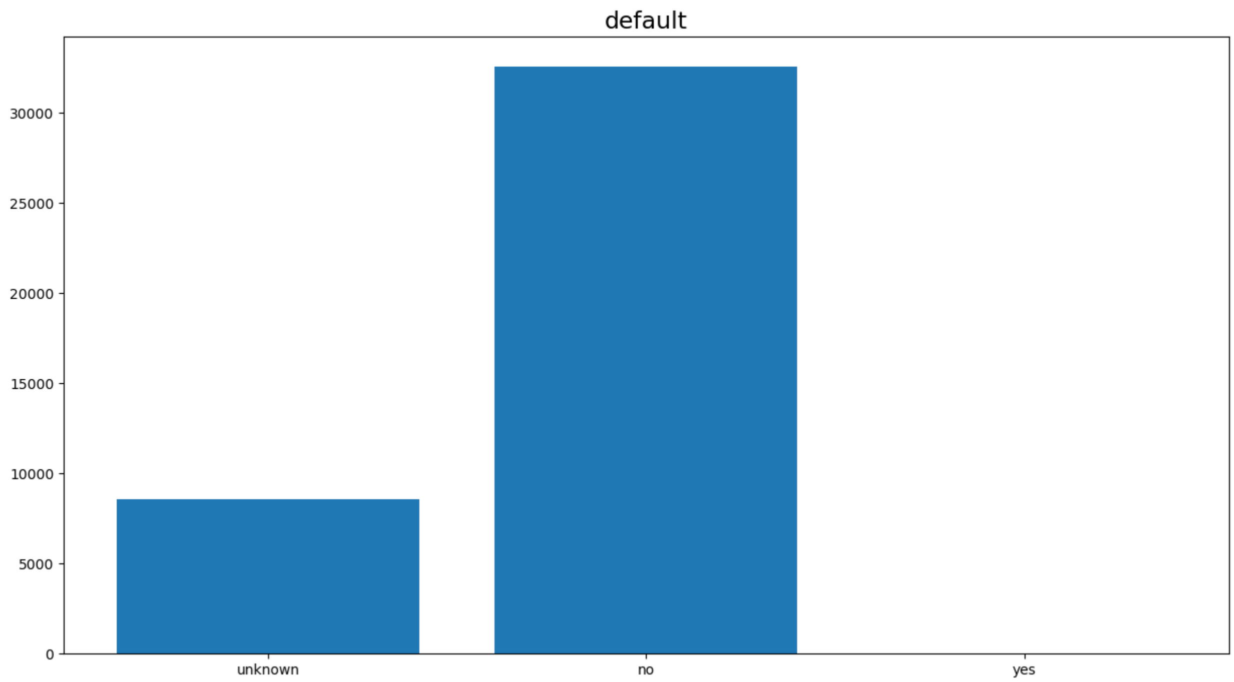
None


marital
25000
20000
15000
10000
5000
0
unknown
divorced
married
single

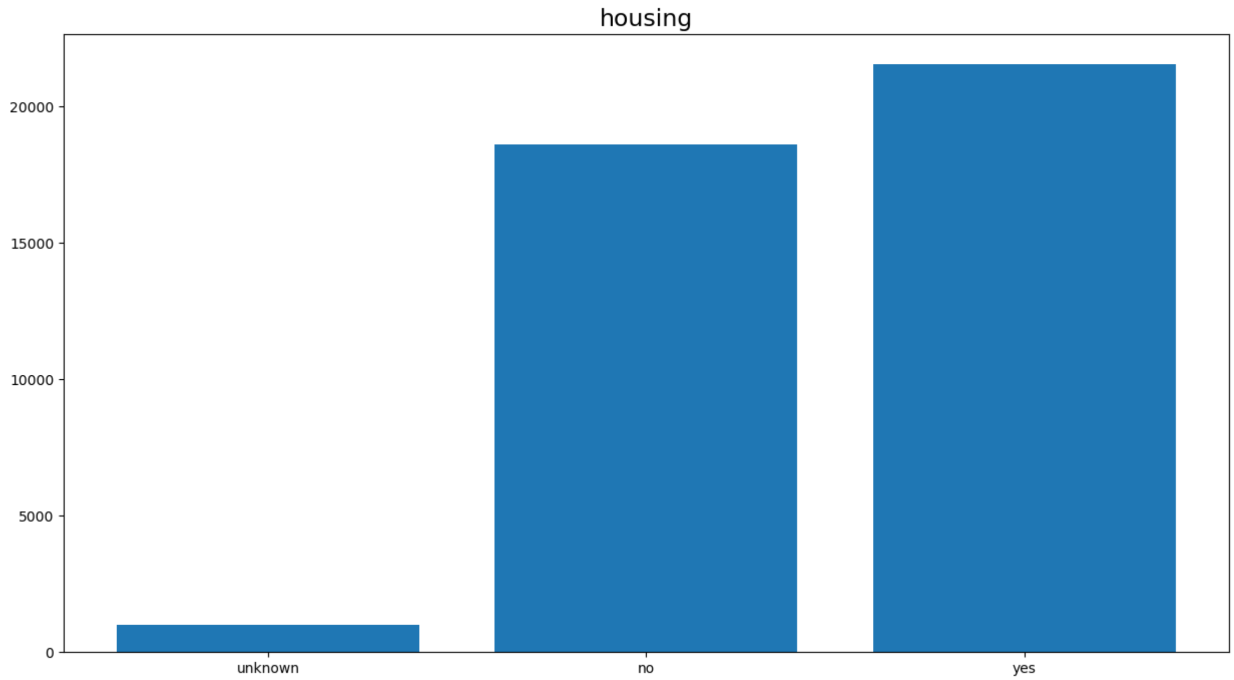
None


education
12000
10000
8000
6000
4000
2000
0
high.school
unknown
basic.6y
professional.course
university.degree
illiterate
basic.4y
basic.9y

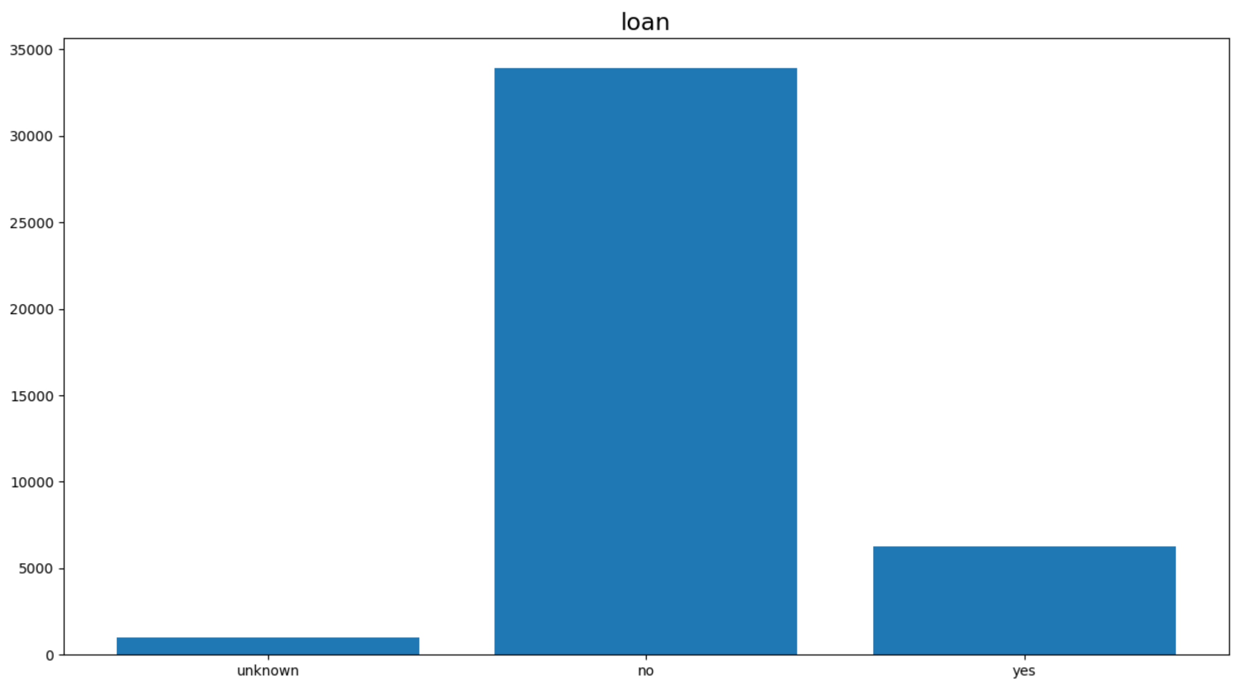
None


default
30000
25000
20000
15000
10000
5000
0
unknown
no
yes

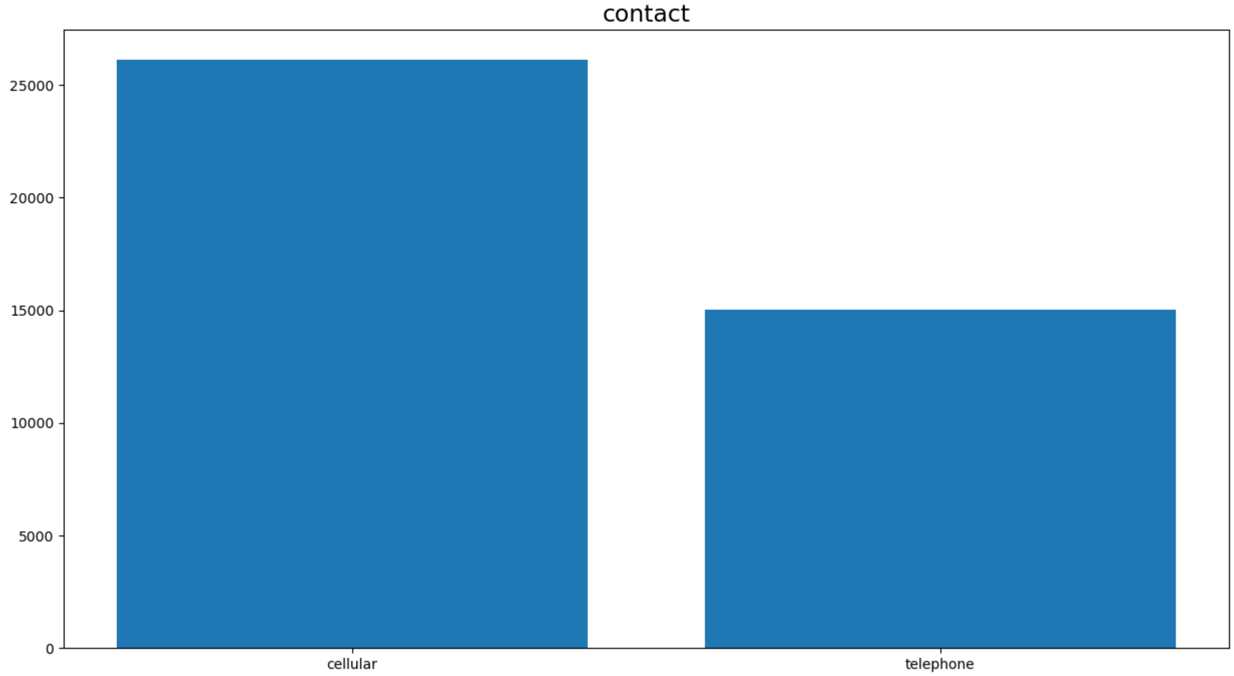
None


housing
0
5000
10000
15000
20000
unknown
no
yes

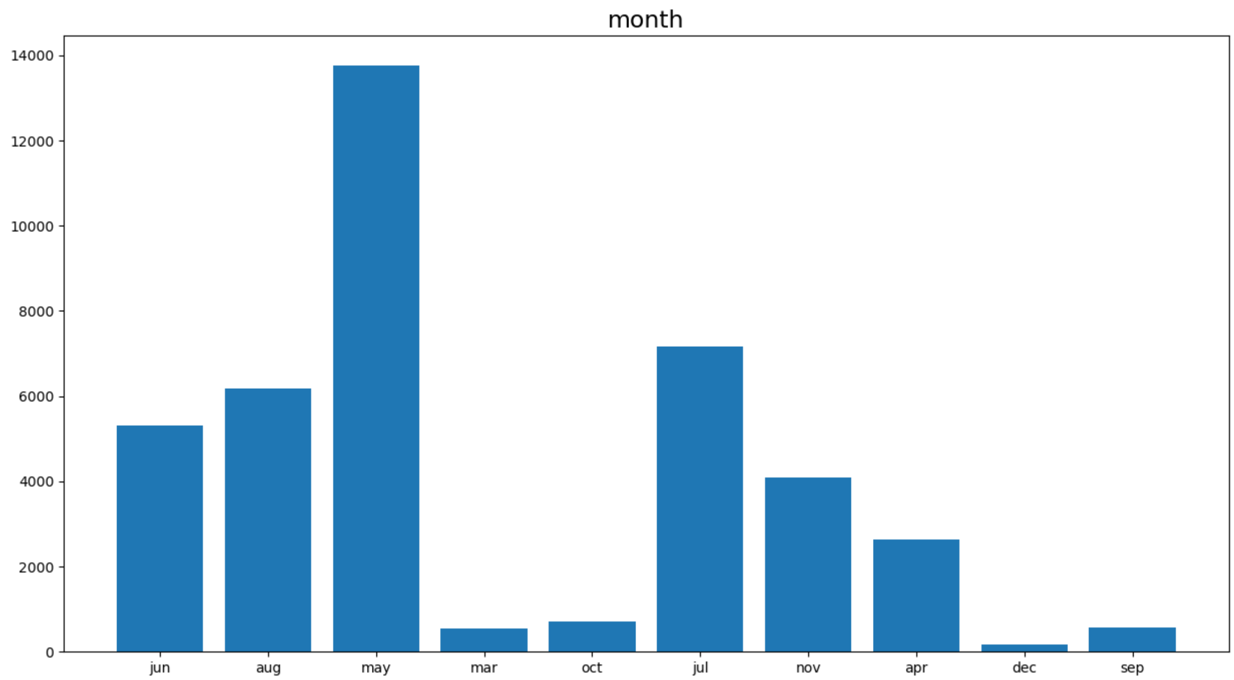
None


loan
0
5000
10000
15000
20000
25000
30000
35000
unknown
no
yes

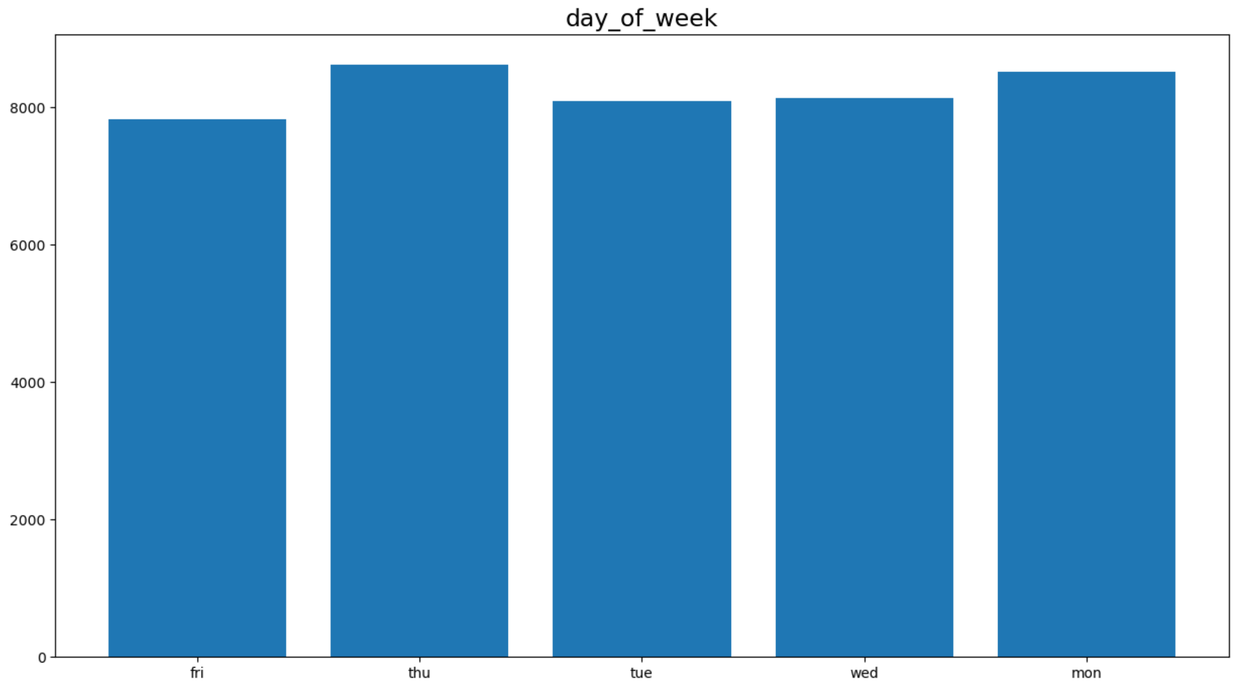
None


contact
25000
20000
15000
10000
5000
0
cellular
telephone

None

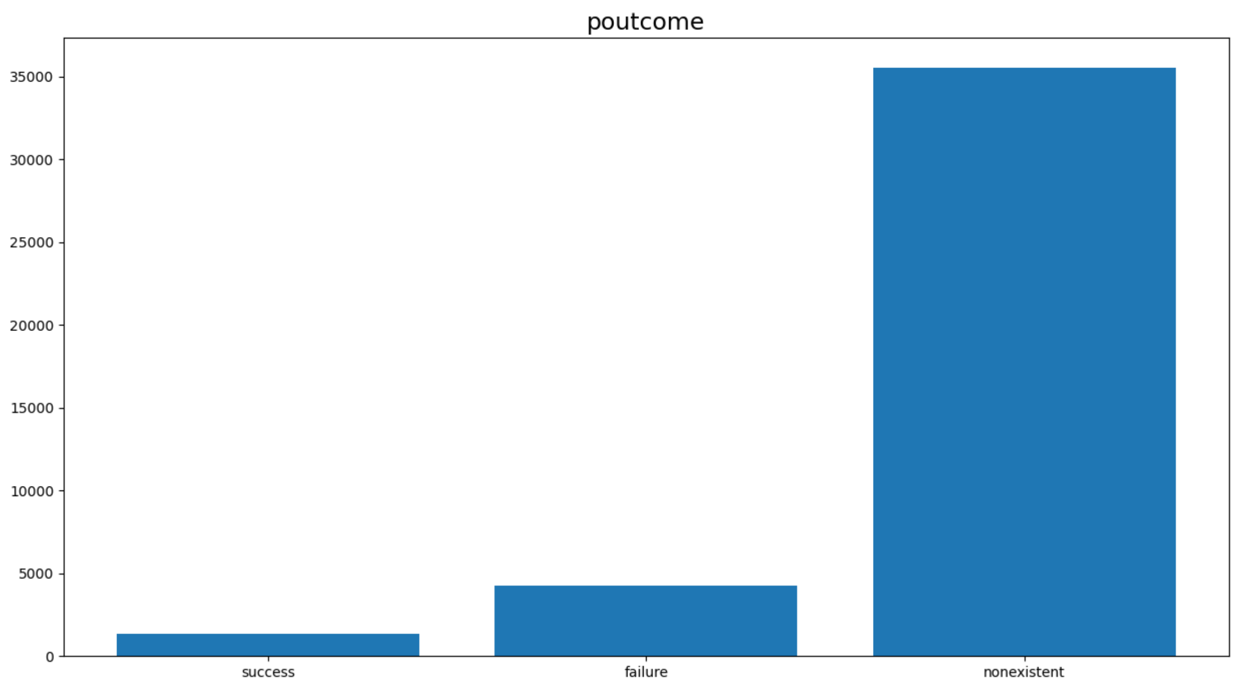

month
14000
12000
10000
8000
6000
4000
2000
0
jun
aug
may
mar
oct
jul
nov
apr
dec
sep

None



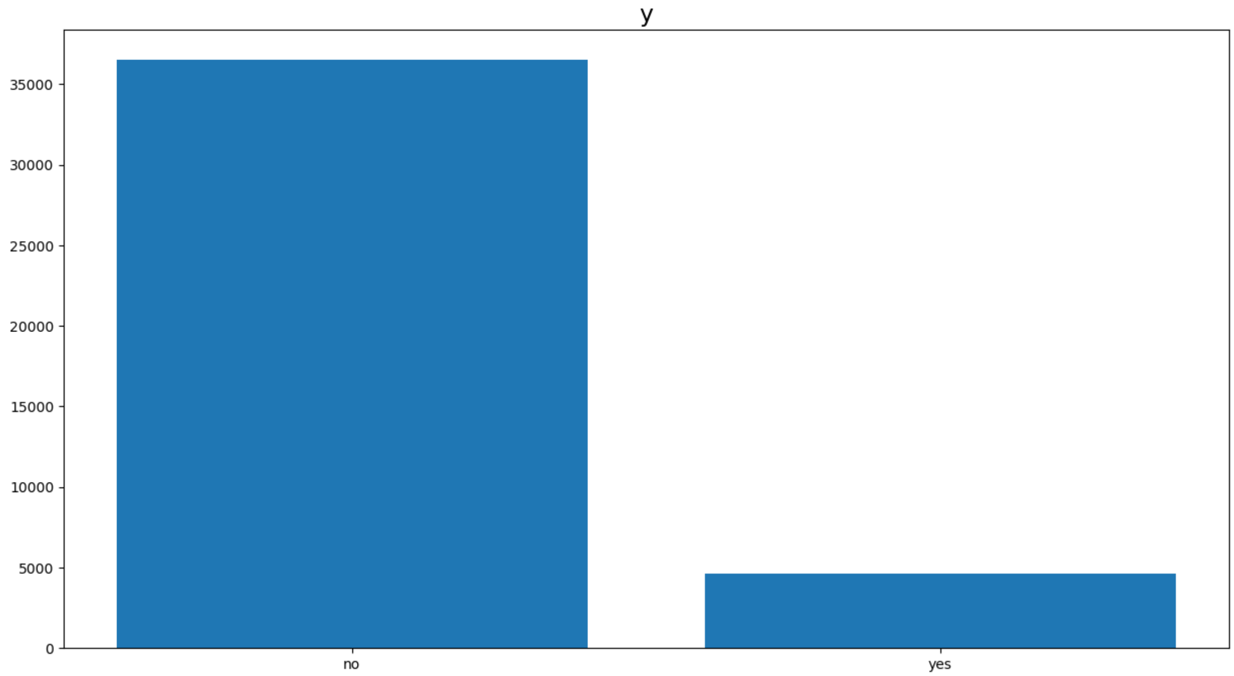
day_of_week
8000
6000
4000
2000
0
fri
thu
tue
wed
mon

None



poutcome
35000
30000
25000
20000
15000
10000
5000
0
success
failure
nonexistent

None



None

Correlation Matrix

In [7]:
```
# create df for correlation matrix
df1 = df[['age', 'duration', 'campaign', 'pdays', 'previous', 'emp_var_rate', 'cons_pr
```

In [8]:
```
import matplotlib.pyplot as plt
from pyspark.ml.feature import VectorAssembler
from pyspark.ml.stat import Correlation

columns = ['age', 'duration', 'campaign', 'pdays', 'previous', 'emp_var_rate', 'cons_p

vector_col = "corr_features"
assembler = VectorAssembler(inputCols=columns,
                            outputCol=vector_col)
my_vector = assembler.transform(df1).select(vector_col)
matrix = Correlation.corr(my_vector, vector_col)
```

In [9]:
```
# create list for correlation
matrix = Correlation.corr(my_vector, vector_col).collect()[0][0]
corrmatrix = matrix.toArray().tolist()
print(corrmatrix)
```

```
[[1.0, -0.0008657050101409137, 0.004593580493413432, -0.034368951166858994, 0.0243647
4093611654, -0.00037068546744101216, 0.0008567149710785426, 0.12937161424620508, 0.01
0767429541674797, -0.017725131911927514], [-0.0008657050101409137, 1.0, -0.0716992262
641536, -0.0475770154456121, 0.020640350701749122, -0.02796788448933175, 0.0053122677
62748574, -0.008172872813929487, -0.03289665570187576, -0.04470322316241789], [0.0045
93580493413432, -0.0716992262641536, 1.0, 0.052583573385026956, -0.07914147244884145,
0.15075380555786647, 0.12783591160945573, -0.013733098741901751, 0.13513251080435904,
0.14409489484472365], [-0.034368951166858994, -0.0475770154456121, 0.0525835733850269
56, 1.0, -0.587513856136789, 0.27100417426183293, 0.0788891087159522, -0.091342353978
35197, 0.29689911239700334, 0.37260474218583123], [0.02436474093611654, 0.02064035070
1749122, -0.07914147244884145, -0.587513856136789, 1.0, -0.42048910941333256, -0.2031
299674503254, -0.05093635090673017, -0.45449365360773475, -0.501332929036254 4], [-0.0
0037068546744101216, -0.02796788448933175, 0.15075380555786647, 0.27100417426183293,
-0.42048910941333256, 1.0, 0.7753341708352004, 0.19604126813197817, 0.972244671151690
8, 0.9069701012559852], [0.0008567149710785426, 0.005312267762748574, 0.1278359116094
5573, 0.0788891087159522, -0.2031299674503254, 0.7753341708352004, 1.0, 0.05898618174
887866, 0.6882301070378115, 0.5220339770133208], [0.12937161424620508, -0.00817287281
3929487, -0.013733098741901751, -0.09134235397835197, -0.05093635090673017, 0.1960412
6813197817, 0.05898618174887866, 1.0, 0.27768621966372714, 0.10051343183754938], [0.0
10767429541674797, -0.03289665570187576, 0.13513251080435904, 0.29689911239700334, -
0.45449365360773475, 0.9722446711516908, 0.6882301070378115, 0.27768621966372714, 1.
0, 0.9451544313981852], [-0.017725131911927514, -0.04470322316241789, 0.1440948948447
2365, 0.37260474218583123, -0.501332929036254 4, 0.9069701012559852, 0.522033977013320
8, 0.10051343183754938, 0.9451544313981852, 1.0]]
```

In [10]:

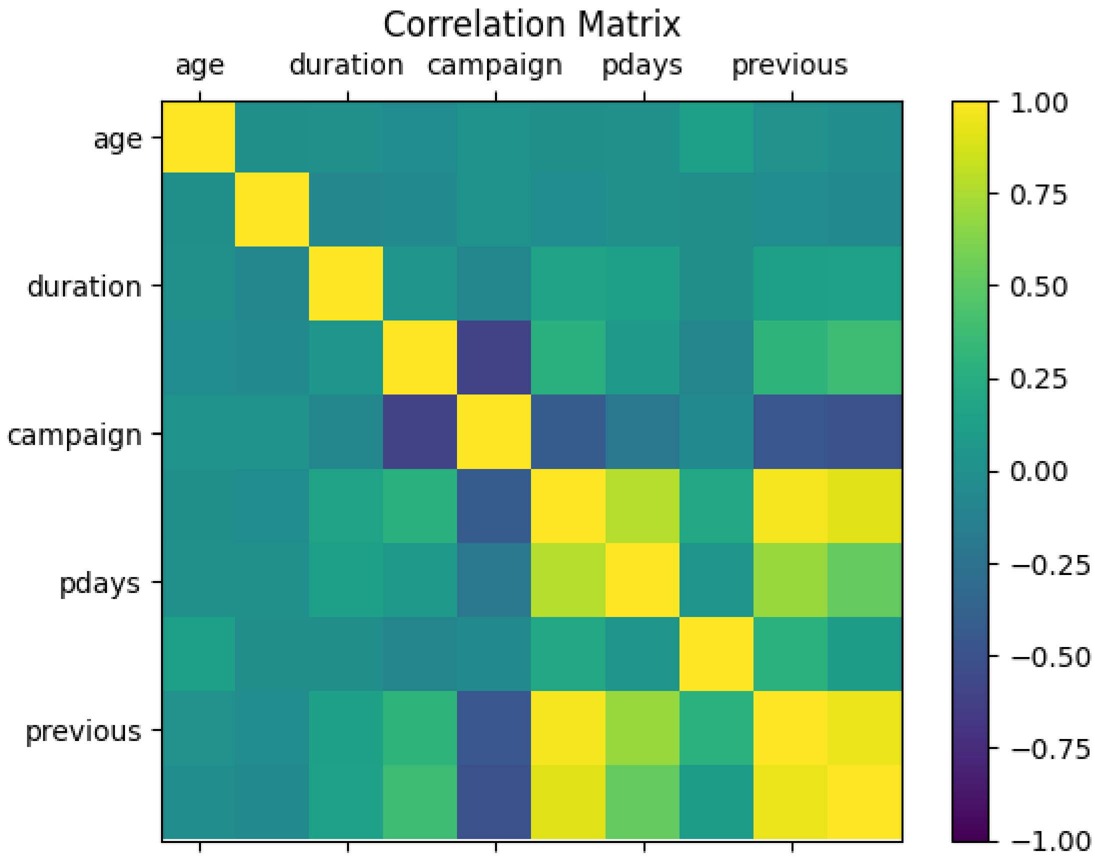
```python
# show correlation matrix
corr_df = spark.createDataFrame(corrmatrix,columns)
corr_df.show()
```

```
+--------------------+--------------------+--------------------+--------------------+
--------------------+--------------------+--------------------+--------------------+-
-------------------+--------------------+
|                 age|            duration|            campaign|               pdays|
previous|        emp_var_rate|      cons_price_idx|       cons_conf_idx|             eu
ribor3m|         nr_employed|
+--------------------+--------------------+--------------------+--------------------+
--------------------+--------------------+--------------------+--------------------+-
-------------------+--------------------+
|                 1.0|-8.65705010140913...|0.004593580493413432|-0.03436895116685...|
0.02436474093611654|-3.70685467441012...|8.567149710785426E-4| 0.12937161424620508|0.
010767429541674797|-0.01772513191192...|
|-8.65705010140913...|                 1.0| -0.0716992262641536| -0.0475770154456121|
0.020640350701749122|-0.02796788448933175|0.005312267762748574|-0.00817287281392...|-
0.03289665570187576|-0.04470322316241789|
|0.004593580493413432| -0.0716992262641536|                 1.0|0.052583573385026956|
-0.07914147244884145| 0.15075380555786647| 0.12783591160945573|-0.01373309874190...|
0.13513251080435904| 0.14409489484472365|
|-0.03436895116685...| -0.0475770154456121|0.052583573385026956|                 1.0|
-0.587513856136789| 0.27100417426183293|  0.0788891087159522|-0.09134235397835197| 0.
2968991123970034| 0.37260474218583123|
| 0.02436474093611654|0.020640350701749122|-0.07914147244884145|  -0.587513856136789|
1.0|-0.42048910941333256| -0.2031299674503254|-0.05093635090673017|-0.454493653607734
75| -0.5013329290362544|
|-3.70685467441012...|-0.02796788448933175| 0.15075380555786647| 0.27100417426183293|
-0.42048910941333256|                 1.0|  0.7753341708352004| 0.19604126813197817|
0.9722446711516908|  0.9069701012559852|
|8.567149710785426E-4|0.005312267762748574| 0.12783591160945573|  0.0788891087159522|
-0.2031299674503254|  0.7753341708352004|                 1.0| 0.05898618174887866|
0.6882301070378115|  0.5220339770133208|
| 0.12937161424620508|-0.00817287281392...|-0.01373309874190...|-0.09134235397835197|
-0.05093635090673017| 0.19604126813197817| 0.05898618174887866|                 1.0|
0.27768621966372714| 0.10051343183754938|
|0.010767429541674797|-0.03289665570187576| 0.13513251080435904| 0.2968991123970034|
-0.45449365360773475|  0.9722446711516908|  0.6882301070378115| 0.27768621966372714|
1.0|  0.9451544313981852|
|-0.01772513191192...|-0.04470322316241789| 0.14409489484472365| 0.37260474218583123|
-0.5013329290362544|  0.9069701012559852|  0.5220339770133208| 0.10051343183754938|
0.9451544313981852|                 1.0|
+--------------------+--------------------+--------------------+--------------------+
--------------------+--------------------+--------------------+--------------------+-
-------------------+--------------------+
```

In [11]:

```python
def plot_corr_matrix(correlations,attr,fig_no):
    fig=plt.figure(fig_no)
    ax=fig.add_subplot(111)
    ax.set_title("Correlation Matrix")
    ax.set_xticklabels(['']+attr)
    ax.set_yticklabels(['']+attr)
    cax=ax.matshow(correlations,vmax=1,vmin=-1)
    fig.colorbar(cax)
    plt.show()

plot_corr_matrix(corrmatrix, columns, 234)
```

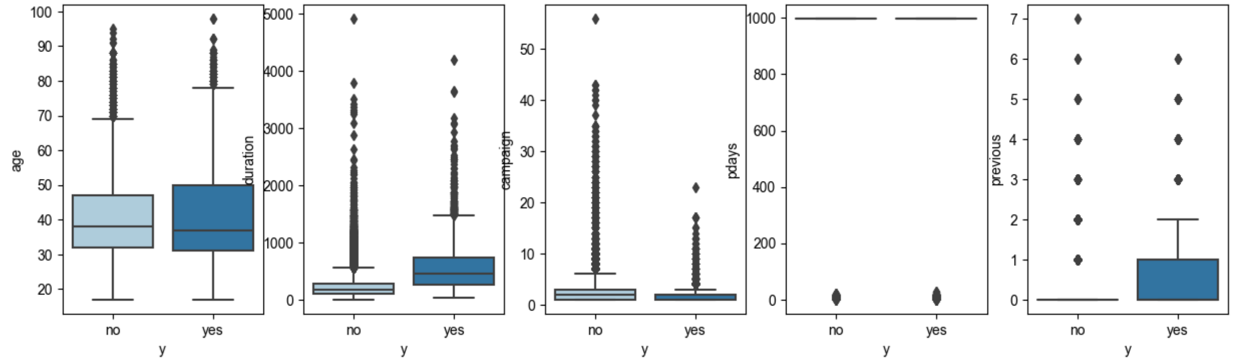
```
C:\Users\Jacob\AppData\Local\Temp\ipykernel_9236\2978521685.py:5: UserWarning: FixedF
ormatter should only be used together with FixedLocator
  ax.set_xticklabels(['']+attr)
C:\Users\Jacob\AppData\Local\Temp\ipykernel_9236\2978521685.py:6: UserWarning: FixedF
ormatter should only be used together with FixedLocator
  ax.set_yticklabels(['']+attr)
```



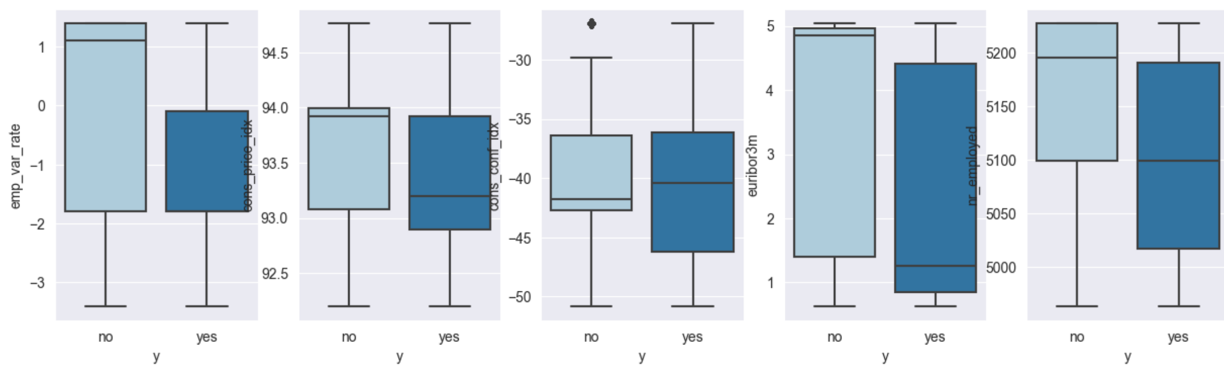
Boxplots

In [12]:
```python
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
#%matplotlib inline

# conversion
df2 = df.toPandas()
```

In [13]:
```python
sns.set_palette('Paired')
f, axes = plt.subplots(nrows=1, ncols=5, figsize = (15,4))
sns.set_style('darkgrid')

fig1 = sns.boxplot(x='y', y='age', data=df2, ax=axes[0])
fig2 = sns.boxplot(x='y', y='duration', data=df2, ax=axes[1])
fig3 = sns.boxplot(x='y', y='campaign', data=df2, ax=axes[2])
fig4 = sns.boxplot(x='y', y='pdays', data=df2, ax=axes[3])
fig5 = sns.boxplot(x='y', y='previous', data=df2, ax=axes[4])

plt.show()
```



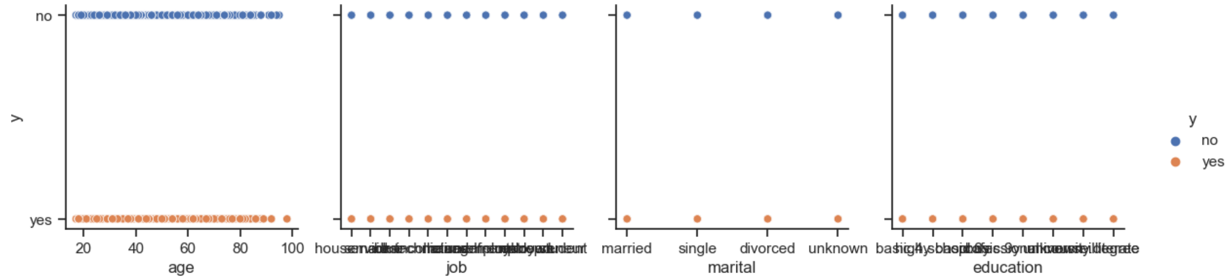
In [14]:
```python
sns.set_palette('Paired')
f, axes = plt.subplots(nrows=1, ncols=5, figsize = (15,4))
sns.set_style('darkgrid')

fig6 = sns.boxplot(x='y', y='emp_var_rate', data=df2, ax=axes[0])
fig7 = sns.boxplot(x='y', y='cons_price_idx', data=df2, ax=axes[1])
fig8 = sns.boxplot(x='y', y='cons_conf_idx', data=df2, ax=axes[2])
fig9 = sns.boxplot(x='y', y='euribor3m', data=df2, ax=axes[3])
fig10 = sns.boxplot(x='y', y='nr_employed', data=df2, ax=axes[4])

plt.show()
```



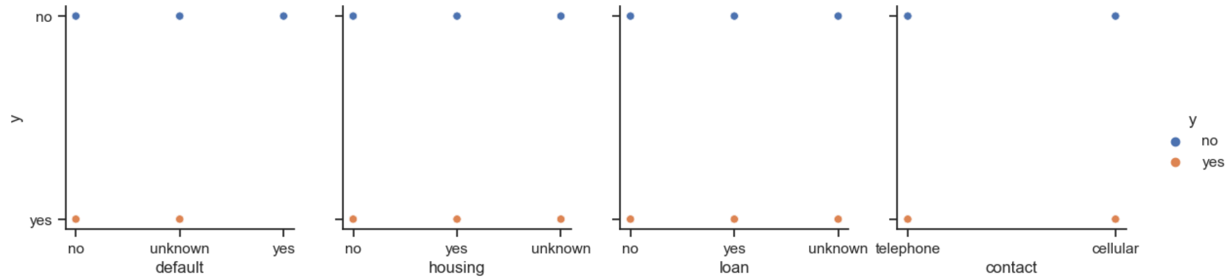
Bivariate Analysis

In [10]:
```python
import seaborn as sns
sns.set(style="ticks")

for x in range(0,len(df.columns[:-1]), 4):
    sns.pairplot(df.toPandas(), x_vars=df.columns[x:(x+4)], y_vars="y", hue="y", heigh
    plt.show()
```

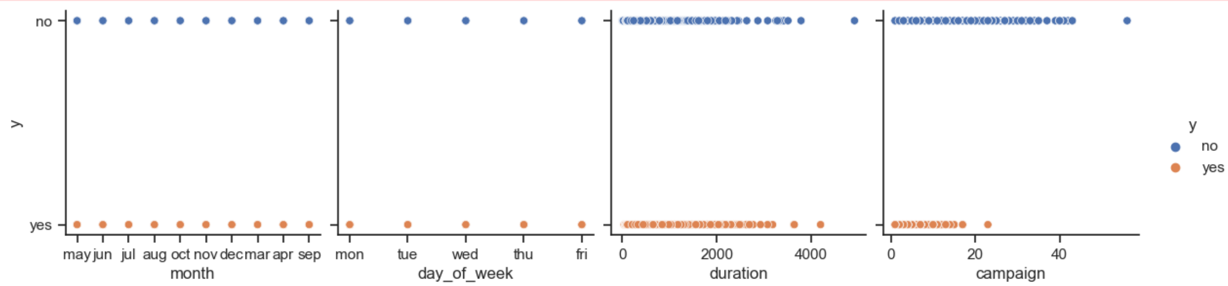
```
/Users/muralidhar/anaconda3/lib/python3.11/site-packages/seaborn/axisgrid.py:118: Use
rWarning: The figure layout has changed to tight
  self._figure.tight_layout(*args, **kwargs)
```



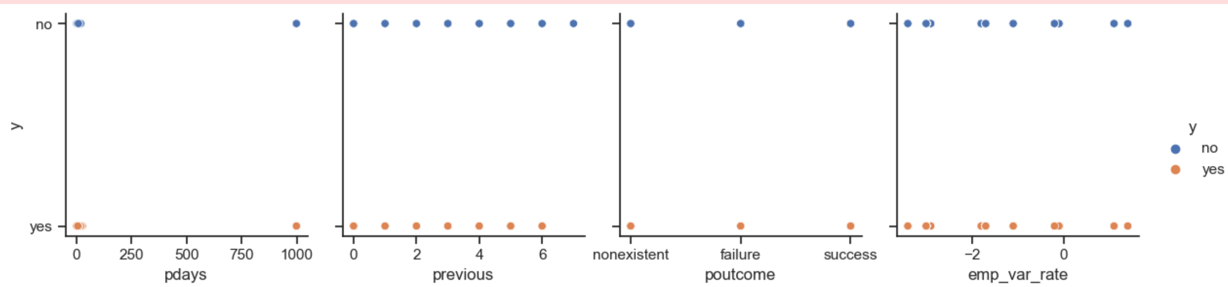

```
/Users/muralidhar/anaconda3/lib/python3.11/site-packages/seaborn/axisgrid.py:118: Use
rWarning: The figure layout has changed to tight
  self._figure.tight_layout(*args, **kwargs)
```



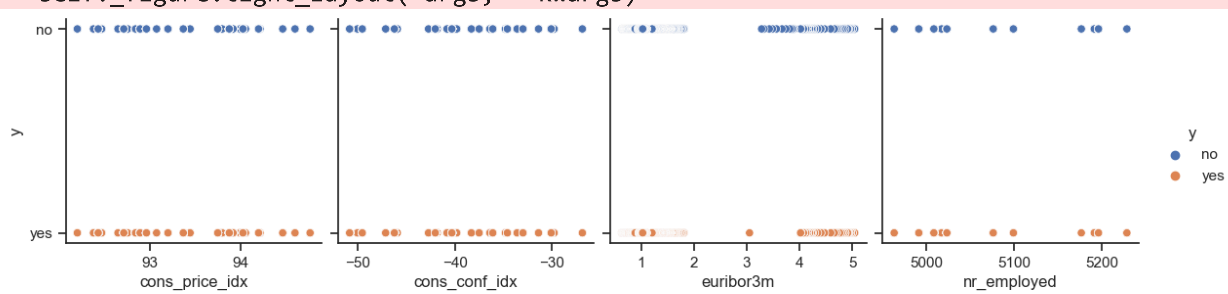

```
/Users/muralidhar/anaconda3/lib/python3.11/site-packages/seaborn/axisgrid.py:118: Use
rWarning: The figure layout has changed to tight
  self._figure.tight_layout(*args, **kwargs)
```




```
/Users/muralidhar/anaconda3/lib/python3.11/site-packages/seaborn/axisgrid.py:118: Use
rWarning: The figure layout has changed to tight
  self._figure.tight_layout(*args, **kwargs)
```




```
/Users/muralidhar/anaconda3/lib/python3.11/site-packages/seaborn/axisgrid.py:118: Use
rWarning: The figure layout has changed to tight
  self._figure.tight_layout(*args, **kwargs)
```



In [11]:
```python
# Checking for null values in the dataset
{col:df.filter(df[col].isNull()).count() for col in df.columns}
```

Out[11]:
```
{'age': 0,
 'job': 0,
 'marital': 0,
 'education': 0,
 'default': 0,
 'housing': 0,
 'loan': 0,
 'contact': 0,
 'month': 0,
 'day_of_week': 0,
 'duration': 0,
 'campaign': 0,
 'pdays': 0,
 'previous': 0,
 'poutcome': 0,
 'emp_var_rate': 0,
 'cons_price_idx': 0,
 'cons_conf_idx': 0,
 'euribor3m': 0,
 'nr_employed': 0,
 'y': 0}
```

In [12]:
```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)
```

In [13]:
```python
# Total numeric variables
numeric_features = [t[0] for t in df.dtypes if t[1] != 'string']
df.select(numeric_features).describe().toPandas().transpose()
```

Out[13]:

	0	1	2	3	4
summary	count	mean	stddev	min	max
age	41188	40.02406040594348	10.421249980934043	17	98
duration	41188	258.2850101971448	259.27924883646455	0	4918
campaign	41188	2.567592502670681	2.770013542902331	1	56
pdays	41188	962.4754540157328	186.910907344741	0	999
previous	41188	0.17296299893172767	0.49490107983928927	0	7
emp_var_rate	41188	0.08188550063178966	1.57095974051703	-3.4	1.4
cons_price_idx	41188	93.5756643682899	0.5788400489540823	92.201	94.767
cons_conf_idx	41188	-40.502600271918276	4.628197856174573	-50.8	-26.9
euribor3m	41188	3.621290812858533	1.7344474048512595	0.634	5.045
nr_employed	41188	5167.035910943957	72.25152766826338	4963.6	5228.1

In [14]:

```
# cardinality for the categorical variables
from pyspark.sql.functions import countDistinct
cardinality = [countDistinct(c).alias(c) for c in string_features]
df.select(cardinality).show()
```

```
+---+-------+---------+-------+-------+----+-------+-----+-----------+--------+---+
|job|marital|education|default|housing|loan|contact|month|day_of_week|poutcome|  y|
+---+-------+---------+-------+-------+----+-------+-----+-----------+--------+---+
| 12|      4|        8|      3|      3|   3|      2|   10|          5|       3|  2|
+---+-------+---------+-------+-------+----+-------+-----+-----------+--------+---+
```

In [15]:

```
for i in string_features:
    df.select(i).distinct().show()
```

```
+-------------+
|          job|
+-------------+
|   management|
|      retired|
|      unknown|
|self-employed|
|      student|
|  blue-collar|
| entrepreneur|
|       admin.|
|   technician|
|     services|
|    housemaid|
|   unemployed|
+-------------+

+--------+
| marital|
+--------+
| unknown|
|divorced|
| married|
|  single|
+--------+

+-------------------+
|          education|
+-------------------+
|        high.school|
|            unknown|
|           basic.6y|
|professional.course|
|  university.degree|
|         illiterate|
|           basic.4y|
|           basic.9y|
+-------------------+

+-------+
|default|
+-------+
|unknown|
|     no|
|    yes|
+-------+

+-------+
|housing|
+-------+
|unknown|
|     no|
|    yes|
+-------+

+-------+
|   loan|
+-------+
|unknown|
|     no|
```

```
|    yes|
+-------+

+---------+
|  contact|
+---------+
| cellular|
|telephone|
+---------+

+-----+
|month|
+-----+
|  jun|
|  aug|
|  may|
|  mar|
|  oct|
|  jul|
|  nov|
|  apr|
|  dec|
|  sep|
+-----+

+-----------+
|day_of_week|
+-----------+
|        fri|
|        thu|
|        tue|
|        wed|
|        mon|
+-----------+

+-----------+
|   poutcome|
+-----------+
|    success|
|    failure|
|nonexistent|
+-----------+

+---+
|  y|
+---+
| no|
|yes|
+---+
```

Splitting the dataset into training and test

In [16]:

```
df1 = df
train, test = df1.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
```

Oversample the minority class

In [17]:
```
# compute ratio needed to oversample

from pyspark.sql.functions import col
major_df = train.filter(col("y") == 'no')
minor_df = train.filter(col("y") == 'yes')
ratio = int(major_df.count()/minor_df.count())
print("ratio: {}".format(ratio))
```

```
ratio: 7
```

In [18]:
```
a = range(ratio)
# duplicate the minority rows
oversampled_df = minor_df.withColumn("dummy", explode(array([lit(x) for x in a]))).drc
# combine both oversampled minority rows and previous majority rows
train = major_df.unionAll(oversampled_df)
```

Feature Engineering/ Data Preprocessing

In [19]:
```
# For the string features
stages = []
for col in string_features[:-1]:
    stringIndexer = StringIndexer(inputCol=col, outputCol=col + 'coded')
    encoder = OneHotEncoder(inputCols=[stringIndexer.getOutputCol()], outputCols=[col
    stages += [stringIndexer, encoder]

# for the outcome label
label_string = StringIndexer(inputCol= 'y', outputCol='label')
stages += [label_string]

# for the numerical columns as well
assemblerInputs = [c + 'classVec' for c in string_features[:-1]] + numeric_features
assembler = VectorAssembler(inputCols=assemblerInputs, outputCol='vectorized_features'
stages += [assembler]

# scale down the features into something usable
scaler = StandardScaler(inputCol='vectorized_features', outputCol='features')
stages += [scaler]
```

In [20]:
```
cols = train.columns
pipeline = Pipeline(stages=stages)
pipelinemodel = pipeline.fit(train)
train = pipelinemodel.transform(train)
selectedCols = ['label', 'features'] + cols
train_set = train.select(selectedCols)
```

In [21]:
```
cols = test.columns
test = pipelinemodel.transform(test)
selectedCols = ['label', 'features'] + cols
test_set = test.select(selectedCols)
```

Logistic Regression

In [22]:
```
# training for the logistic regression
from pyspark.ml.classification import LogisticRegression
lr = LogisticRegression(featuresCol = 'features', labelCol = 'label', maxIter=5)
lrModel = lr.fit(train_set)
predictions = lrModel.transform(test_set)
predictions.select('label', 'features',  'rawPrediction', 'prediction', 'probability')
```

```
23/11/28 10:05:11 WARN InstanceBuilder: Failed to load implementation from:dev.ludovi
c.netlib.blas.JNIBLAS
23/11/28 10:05:11 WARN InstanceBuilder: Failed to load implementation from:dev.ludovi
c.netlib.blas.VectorBLAS
```

Out[22]:

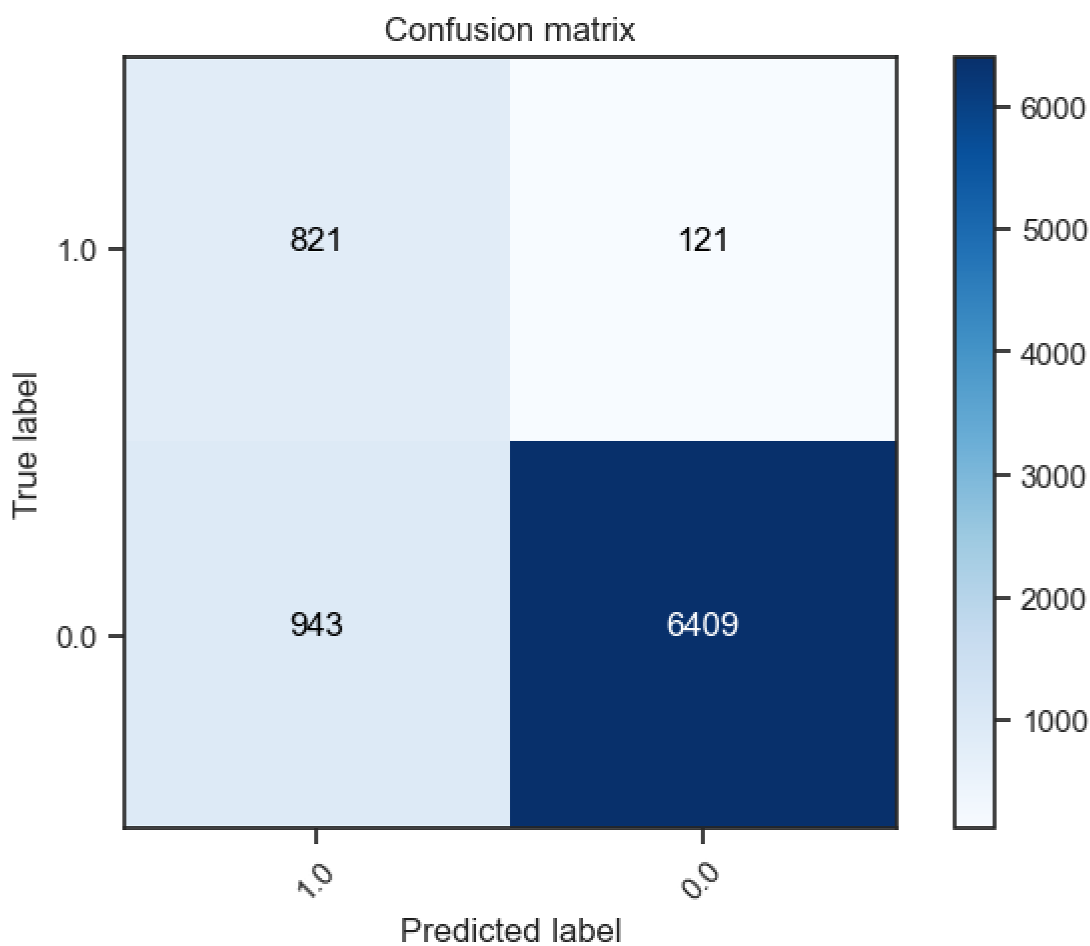
	label	features	rawPrediction	prediction	probability
0	0.0	(0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 5.4451539153755...	[2.58489651602412, -2.58489651602412]	0.0	[0.9298831968782764, 0.07011680312172364]
1	0.0	(0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 5.4451539153755...	[0.2997056847910464, -0.2997056847910464]	0.0	[0.5743705674367132, 0.4256294325632868]
2	1.0	(0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 5.4451539153755...	[-1.7709120160390945, 1.7709120160390945]	1.0	[0.14542894750254998, 0.85457105249745]
3	0.0	(0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 5.4451539153755...	[-0.08391178579701375, 0.08391178579701375]	1.0	[0.47903435402819833, 0.5209656459718017]
4	0.0	(0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 5.4451539153755...	[0.5272198990881947, -0.5272198990881947]	0.0	[0.6288344644875694, 0.3711655355124306]

In [23]:
```
# confusion matrix
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')
```

In [24]:
```
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()
```

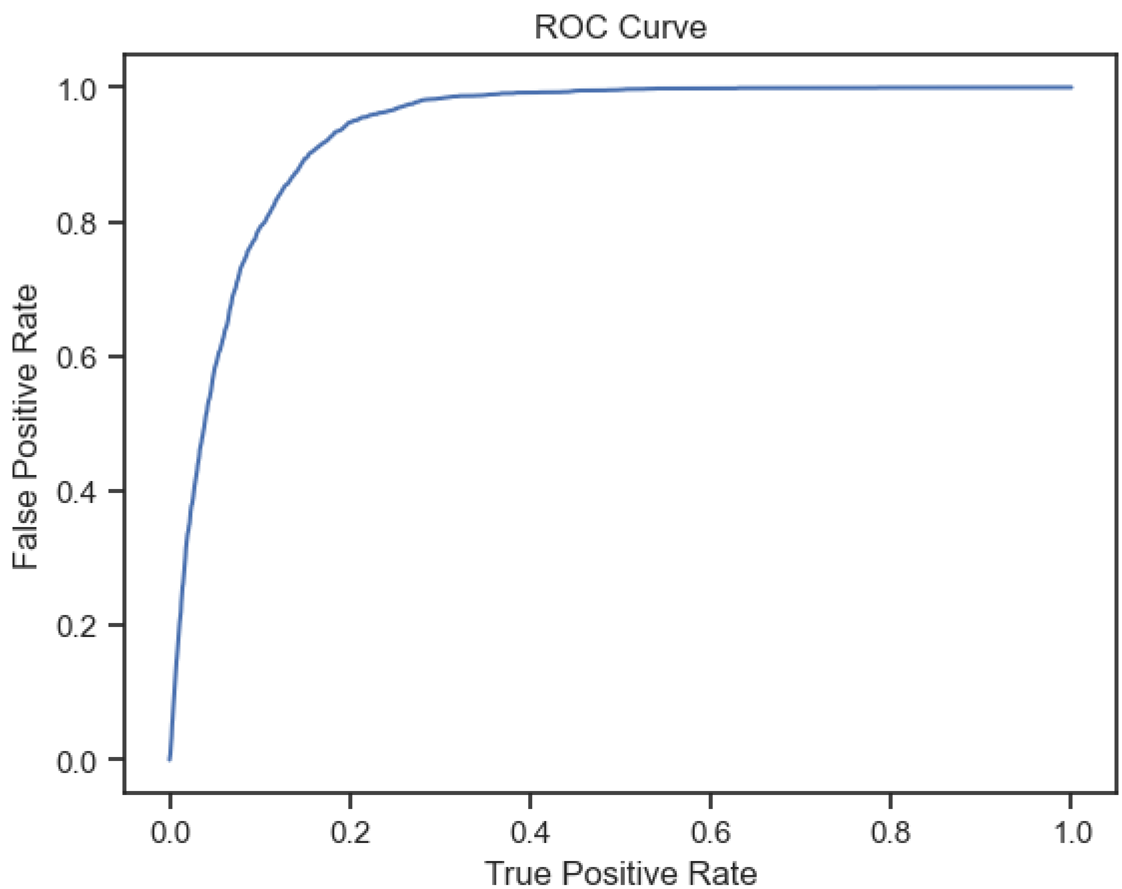
```
Confusion matrix, without normalization
[[ 821  121]
 [ 943 6409]]
```



In [25]:
```
# Model accuracy
accuracy = predictions.filter(predictions.label == predictions.prediction).count() / f
print("Accuracy : ",accuracy)
```

```
Accuracy :  0.8717144924041476
```

In [26]:
```
# Training ROC for the model
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 area under ROC: ' + str(trainingSummary.areaUnderROC))
```




```
Training set area under ROC: 0.9354450536316673
```

In [27]:
```
# Testing ROC for model
from pyspark.ml.evaluation import BinaryClassificationEvaluator
evaluator = BinaryClassificationEvaluator()
print('Test Area Under ROC', evaluator.evaluate(predictions))
```

```
Test Area Under ROC 0.9394022222530234
```

Decision Tree

In [28]:
```
from pyspark.ml.classification import DecisionTreeClassifier
dtc = DecisionTreeClassifier(featuresCol="features", labelCol="label")
dtcModel = dtc.fit(train_set)

predictions = dtcModel.transform(test_set)
predictions.select('label', 'features',  'rawPrediction', 'prediction', 'probability')
```

Out[28]:

	label	features	rawPrediction	prediction	probability
0	0.0	(0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 5.4451539153755...	[17348.0, 294.0]	0.0	[0.983335222763859, 0.016664777236141026]
1	0.0	(0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 5.4451539153755...	[492.0, 952.0]	1.0	[0.3407202216066482, 0.6592797783933518]
2	1.0	(0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 5.4451539153755...	[463.0, 1197.0]	1.0	[0.2789156626506024, 0.7210843373493976]
3	0.0	(0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 5.4451539153755...	[492.0, 952.0]	1.0	[0.3407202216066482, 0.6592797783933518]
4	0.0	(0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 5.4451539153755...	[459.0, 105.0]	0.0	[0.8138297872340425, 0.18617021276595744]

In [29]:

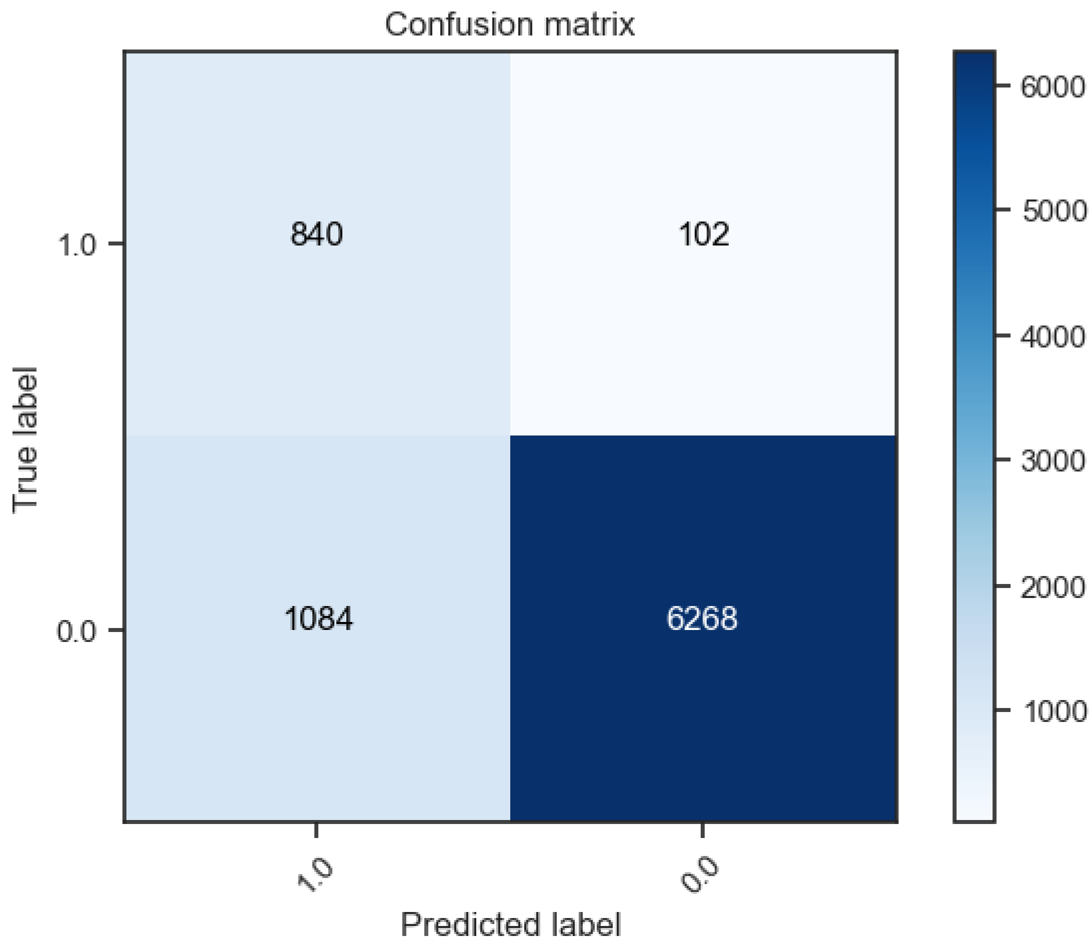
```
# Confusion matrix
class_names=[1.0,0.0]
import itertools
def plot_confusion_matrix(cm, classes,
                          normalize=False,
                          title='Confusion matrix',
                          cmap=plt.cm.Blues):
    """
    This function prints and plots the confusion matrix.
    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')
```

In [30]:

```
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
[[ 840  102]
 [1084 6268]]
```



In [31]:
```
# Model accuracy
accuracy = predictions.filter(predictions.label == predictions.prediction).count() / f
print("Accuracy : ",accuracy)
```

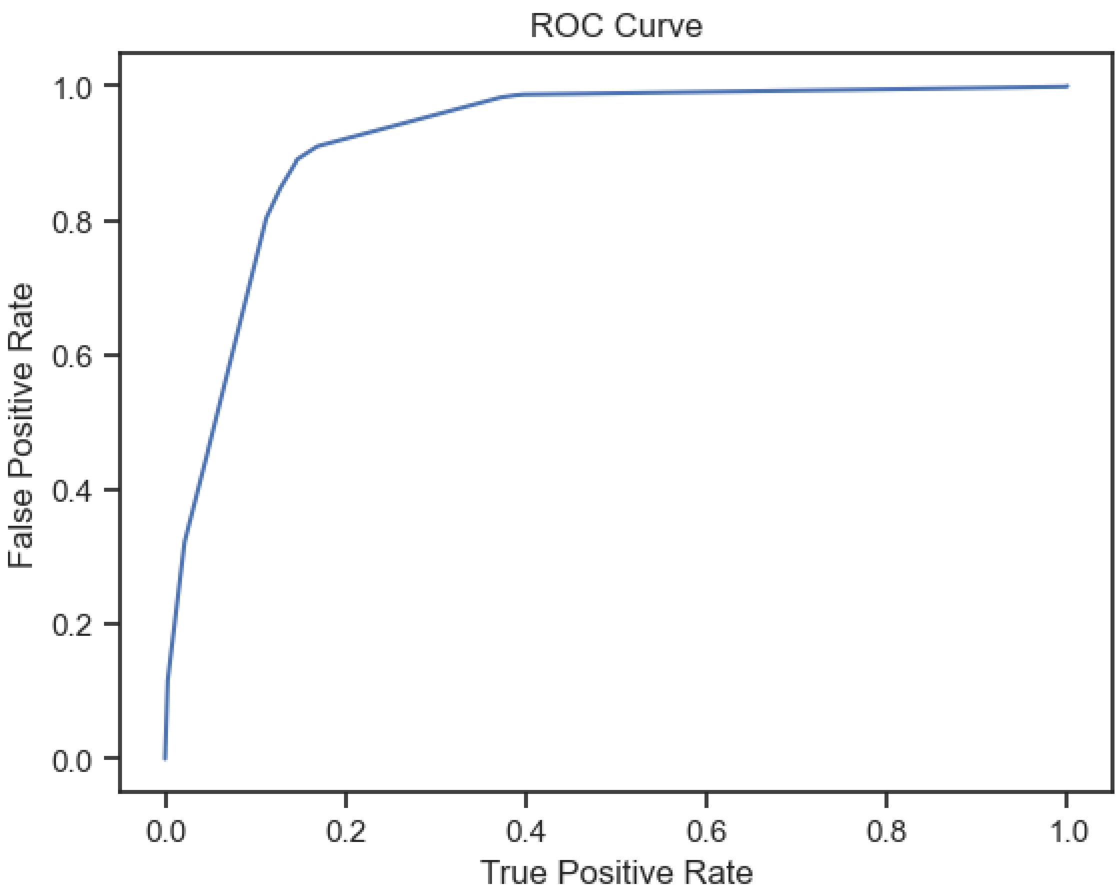
```
Accuracy :  0.8570050639016156
```

In [32]:
```
import matplotlib.pyplot as plt
from pyspark.mllib.evaluation import BinaryClassificationMetrics
class CurveMetrics(BinaryClassificationMetrics):
    def __init__(self, *args):
        super(CurveMetrics, self).__init__(*args)

    def _to_list(self, rdd):
        points = []
        for row in rdd.collect():
            points += [(float(row._1()), float(row._2()))]
        return points
```

```python
    def get_curve(self, method):
        rdd = getattr(self._java_model, method)().toJavaRDD()
        return self._to_list(rdd)

# Returns as a list (false positive rate, true positive rate)
preds = predictions.select('label','probability').rdd.map(lambda row: (float(row['prob
points = CurveMetrics(preds).get_curve('roc')

plt.figure()
x_val = [x[0] for x in points]
y_val = [x[1] for x in points]
plt.title('ROC Curve')
plt.xlabel('True Positive Rate')
plt.ylabel('False Positive Rate')
plt.plot(x_val, y_val)
print("Testing Area Under ROC: " + str(CurveMetrics(preds).areaUnderROC))
```

```
/opt/homebrew/opt/apache-spark/libexec/python/pyspark/sql/context.py:158: FutureWarni
ng: Deprecated in 3.0.0. Use SparkSession.builder.getOrCreate() instead.
  warnings.warn(
```

```
Testing Area Under ROC: 0.9201870918033772
```



In [33]:
```python
evaluator = BinaryClassificationEvaluator()
print("Test Area Under ROC: " + str(evaluator.evaluate(predictions, {evaluator.metricN
```

```
Test Area Under ROC: 0.8716839619590202
```

Random Forest

In [34]:

```
from pyspark.ml.classification import RandomForestClassifier
rf = RandomForestClassifier(featuresCol = 'features', labelCol = 'label')
rfModel = rf.fit(train_set)
predictions = rfModel.transform(test_set)
predictions.select('label', 'features',  'rawPrediction', 'prediction', 'probability')
```

Out[34]:

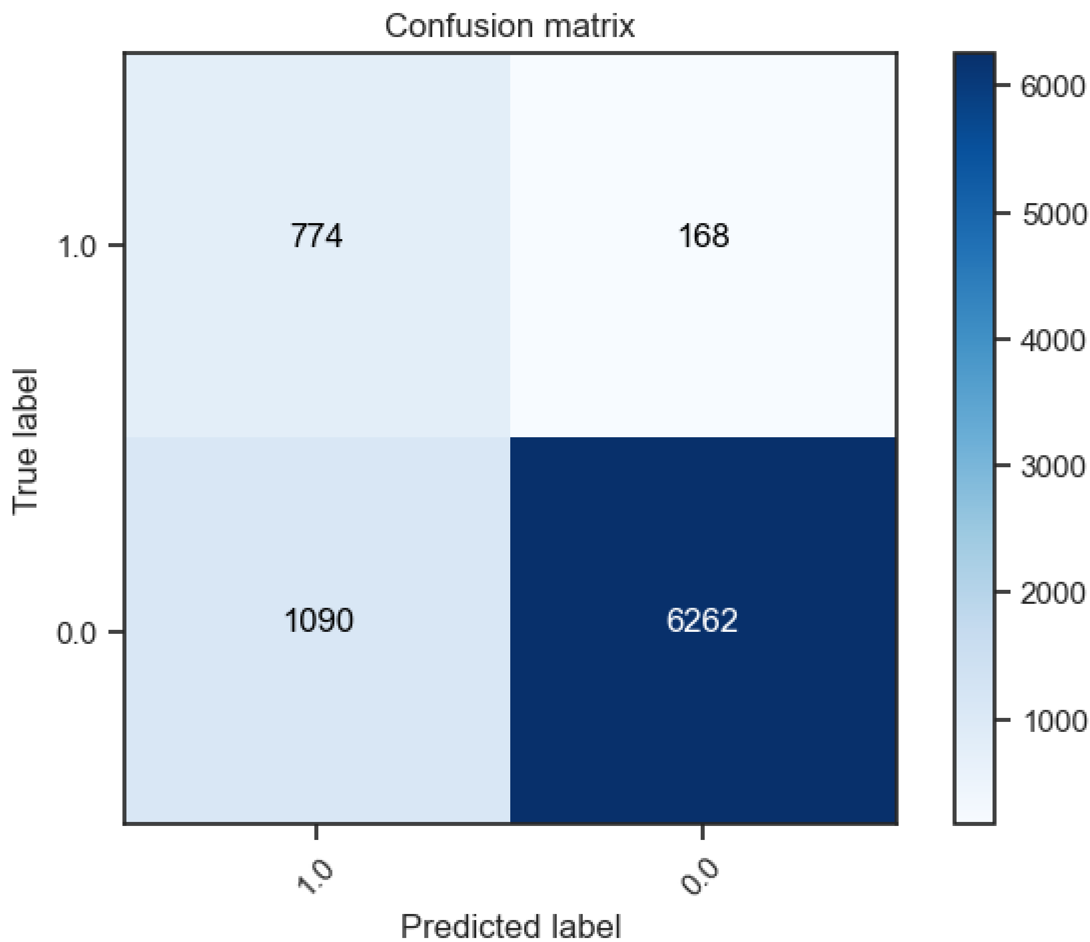
	label	features	rawPrediction	prediction	probability
0	0.0	(0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 5.4451539153755...	[16.54863628031938, 3.4513637196806197]	0.0	[0.8274318140159689, 0.17256818598403098]
1	0.0	(0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 5.4451539153755...	[9.71527235222658, 10.28472764777342]	1.0	[0.48576361761132897, 0.5142363823886711]
2	1.0	(0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 5.4451539153755...	[5.710601952314649, 14.289398047685347]	1.0	[0.2855300976157325, 0.7144699023842676]
3	0.0	(0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 5.4451539153755...	[9.652396941395486, 10.347603058604514]	1.0	[0.4826198470697743, 0.5173801529302258]
4	0.0	(0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 5.4451539153755...	[10.859207279506712, 9.140792720493288]	0.0	[0.5429603639753356, 0.45703963602466435]

In [35]:

```
# Confusion matrix
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')
```

In [36]:
```
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
[[ 774  168]
 [1090 6262]]
```



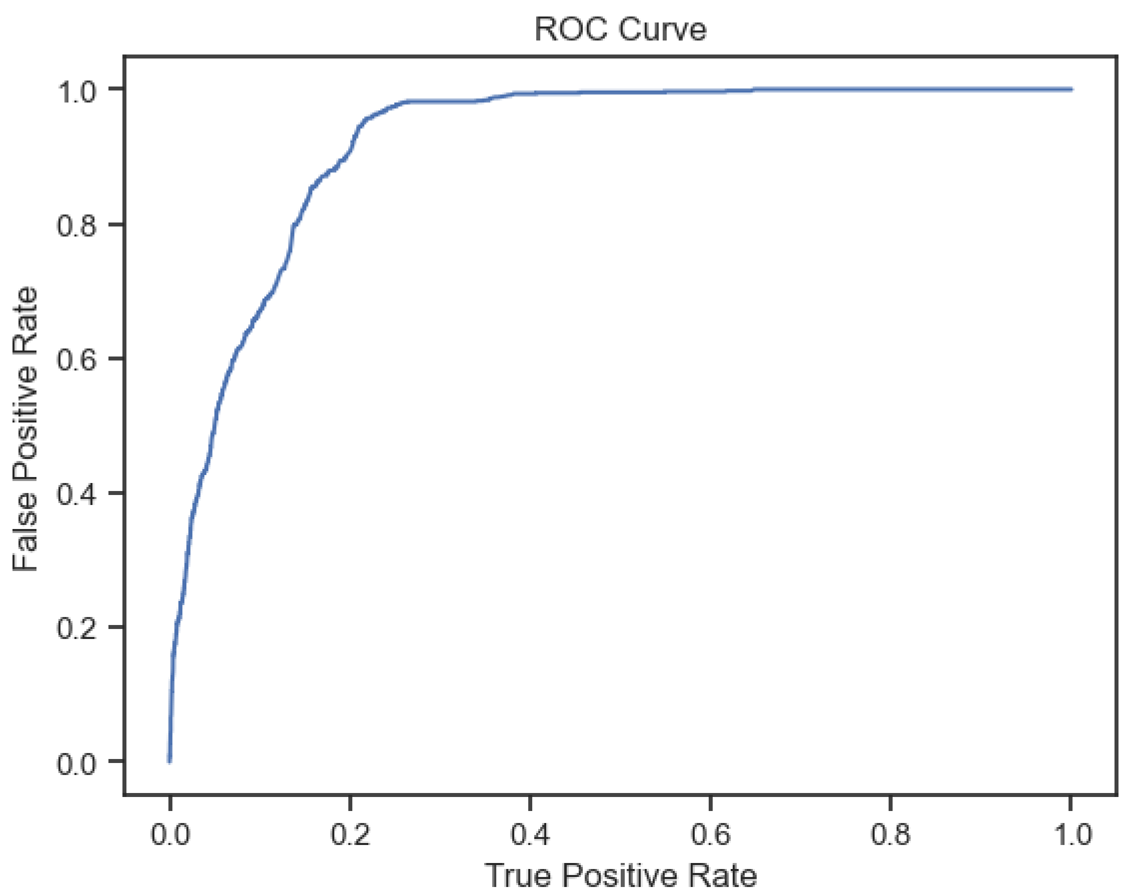
In [37]:
```
# Model accuracy
accuracy = predictions.filter(predictions.label == predictions.prediction).count() / f
print("Accuracy : ",accuracy)
```

```
Accuracy :  0.8483240897034
```

In [38]:
```
class CurveMetrics(BinaryClassificationMetrics):
    def __init__(self, *args):
        super(CurveMetrics, self).__init__(*args)

    def _to_list(self, rdd):
        points = []
        for row in rdd.collect():
```

```
            points += [(float(row._1()), float(row._2()))]
        return points

    def get_curve(self, method):
        rdd = getattr(self._java_model, method)().toJavaRDD()
        return self._to_list(rdd)

# Returns as a list (false positive rate, true positive rate)
preds = predictions.select('label','probability').rdd.map(lambda row: (float(row['prob
points = CurveMetrics(preds).get_curve('roc')

plt.figure()
x_val = [x[0] for x in points]
y_val = [x[1] for x in points]
plt.title('ROC Curve')
plt.xlabel('True Positive Rate')
plt.ylabel('False Positive Rate')
plt.plot(x_val, y_val)
print("Testing Area Under ROC: " + str(CurveMetrics(preds).areaUnderROC))
```

```
/opt/homebrew/opt/apache-spark/libexec/python/pyspark/sql/context.py:158: FutureWarni
ng: Deprecated in 3.0.0. Use SparkSession.builder.getOrCreate() instead.
  warnings.warn(
Testing Area Under ROC: 0.9215097961413783
```



In [39]:
```
evaluator = BinaryClassificationEvaluator()
print("Test Area Under ROC: " + str(evaluator.evaluate(predictions, {evaluator.metricN
```

```
Test Area Under ROC: 0.9215097961413782
```

Gradient Boosting Classifier

In [40]:

```
from pyspark.ml.classification import GBTClassifier
gbt = GBTClassifier(maxIter=10)
gbtModel = gbt.fit(train_set)
predictions = gbtModel.transform(test_set)
predictions.select('label', 'features',  'rawPrediction', 'prediction', 'probability')
```

Out[40]:

	label	features	rawPrediction	prediction	probability
0	0.0	(0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 5.4451539153755...	[1.2968082075767509, -1.2968082075767509]	0.0	[0.9304496112974169, 0.06955038870258312]
1	0.0	(0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 5.4451539153755...	[-0.06204448770853599, 0.06204448770853599]	1.0	[0.4690175018462084, 0.5309824981537916]
2	1.0	(0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 5.4451539153755...	[-0.36155497246207724, 0.36155497246207724]	1.0	[0.3267085198277025, 0.6732914801722976]
3	0.0	(0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 5.4451539153755...	[-0.11820483897879522, 0.11820483897879522]	1.0	[0.4411713179392003, 0.5588286820607997]
4	0.0	(0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 5.4451539153755...	[0.48204869444126525, -0.48204869444126525]	0.0	[0.7239414201889445, 0.2760585798110555]

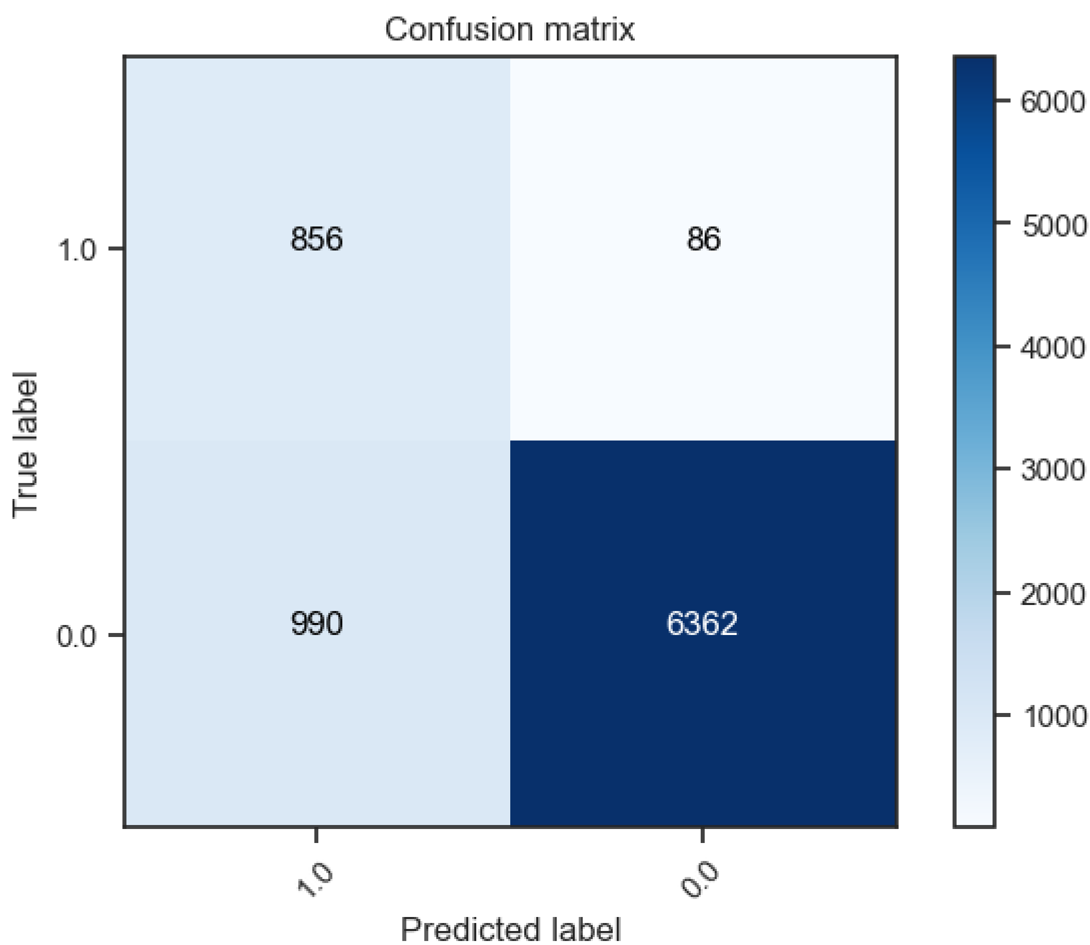
In [41]:

```
# Confusion matrix
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')
```

In [42]:
```
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
[[ 856   86]
 [ 990 6362]]
```



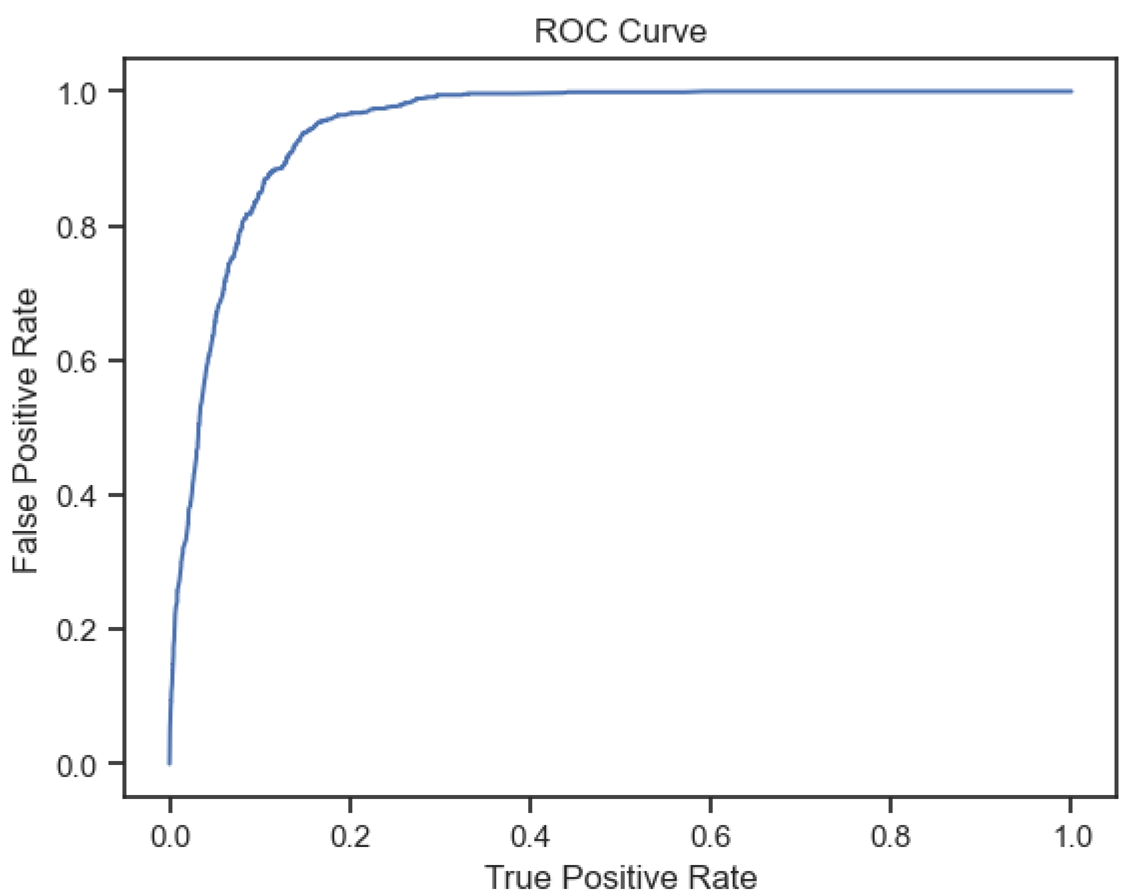
In [43]:
```
# Model accuracy
accuracy = predictions.filter(predictions.label == predictions.prediction).count() / f
print("Accuracy : ",accuracy)
```

```
Accuracy :  0.8702676633711116
```

In [44]:
```
class CurveMetrics(BinaryClassificationMetrics):
    def __init__(self, *args):
```

```
        super(CurveMetrics, self).__init__(*args)

    def _to_list(self, rdd):
        points = []
        for row in rdd.collect():
            points += [(float(row._1()), float(row._2()))]
        return points

    def get_curve(self, method):
        rdd = getattr(self._java_model, method)().toJavaRDD()
        return self._to_list(rdd)

# Returns as a list (false positive rate, true positive rate)
preds = predictions.select('label','probability').rdd.map(lambda row: (float(row['prob
points = CurveMetrics(preds).get_curve('roc')

plt.figure()
x_val = [x[0] for x in points]
y_val = [x[1] for x in points]
plt.title('ROC Curve')
plt.xlabel('True Positive Rate')
plt.ylabel('False Positive Rate')
plt.plot(x_val, y_val)
print("Testing Area Under ROC: " + str(CurveMetrics(preds).areaUnderROC))
```

```
/opt/homebrew/opt/apache-spark/libexec/python/pyspark/sql/context.py:158: FutureWarni
ng: Deprecated in 3.0.0. Use SparkSession.builder.getOrCreate() instead.
  warnings.warn(
Testing Area Under ROC: 0.9485901838747457
```



In [45]:
```
evaluator = BinaryClassificationEvaluator()
print("Test Area Under ROC: " + str(evaluator.evaluate(predictions, {evaluator.metricN
```

```
Test Area Under ROC: 0.9485901838747456
```

In [46]:
```python
gbtModel.featureImportances
```

Out[46]:
```
SparseVector(53, {1: 0.0055, 2: 0.0007, 5: 0.002, 6: 0.0008, 10: 0.0004, 12: 0.0011,
13: 0.0008, 14: 0.0034, 16: 0.0013, 17: 0.0025, 21: 0.0037, 23: 0.0, 25: 0.0004, 27:
0.0089, 28: 0.0095, 29: 0.0002, 30: 0.0001, 32: 0.0004, 33: 0.0029, 34: 0.0169, 36:
0.0042, 37: 0.0012, 38: 0.0156, 39: 0.0016, 40: 0.0011, 42: 0.0096, 43: 0.0312, 44:
0.4435, 45: 0.013, 46: 0.0106, 47: 0.0021, 48: 0.0678, 49: 0.0186, 50: 0.0363, 51: 0.
1649, 52: 0.1175})
```

K Means

In [47]:
```python
from pyspark.ml.clustering import KMeans
kmeans = KMeans(k=5, seed=1)
model = kmeans.fit(train_set.select('features'))
transformed = model.transform(train_set)
```

```
[Stage 519:===========================================>              (3 + 1) / 4]
```

In [48]:
```python
transformed.groupBy("prediction").count().show()
```

```
+----------+-----+
|prediction|count|
+----------+-----+
|         1|20405|
|         3|15429|
|         4| 7981|
|         2| 2981|
|         0| 8286|
+----------+-----+
```

In [49]:
```python
transformed.filter(transformed.prediction == 0).toPandas().head(20)
```

Out[49]:

	label	features	age	job	marital	education	default	housing	lo
0	0.0	(0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 5.4451539153755...	19	student	single	basic.9y	unknown	yes	
1	0.0	(0.0, 2.5553761110921385, 0.0, 0.0, 0.0, 0.0, ...	22	blue-collar	single	basic.6y	unknown	no	
2	0.0	(0.0, 2.5553761110921385, 0.0, 0.0, 0.0, 0.0, ...	22	blue-collar	single	basic.6y	unknown	unknown	unknc
3	0.0	(0.0, 2.5553761110921385, 0.0, 0.0, 0.0, 0.0, ...	22	blue-collar	single	basic.6y	unknown	yes	
4	0.0	(0.0, 2.5553761110921385, 0.0, 0.0, 0.0, 0.0, ...	22	blue-collar	single	unknown	unknown	no	
5	0.0	(0.0, 2.5553761110921385, 0.0, 0.0, 0.0, 0.0, ...	22	blue-collar	single	unknown	unknown	unknown	unknc
6	0.0	(0.0, 0.0, 0.0, 3.5498633758318805, 0.0, 0.0, ...	22	services	married	basic.9y	unknown	no	
7	0.0	(0.0, 0.0, 0.0, 3.5498633758318805, 0.0, 0.0, ...	22	services	married	high.school	unknown	yes	
8	0.0	(0.0, 0.0, 2.708579337991304, 0.0, 0.0, 0.0, 0...	22	technician	married	basic.9y	unknown	no	
9	0.0	(0.0, 2.5553761110921385, 0.0, 0.0, 0.0, 0.0, ...	23	blue-collar	married	basic.9y	unknown	yes	
10	0.0	(0.0, 2.5553761110921385, 0.0, 0.0, 0.0, 0.0, ...	23	blue-collar	married	professional.course	unknown	no	
11	0.0	(0.0, 2.5553761110921385, 0.0, 0.0, 0.0, 0.0, ...	23	blue-collar	single	high.school	unknown	yes	
12	0.0	(0.0, 0.0, 0.0, 3.5498633758318805, 0.0, 0.0, ...	23	services	single	professional.course	unknown	no	
13	0.0	(0.0, 0.0, 0.0, 3.5498633758318805, 0.0, 0.0, ...	23	services	single	professional.course	unknown	no	
14	0.0	(0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 5.4451539153755...	23	student	single	high.school	unknown	unknown	unknc
15	0.0	(2.2575892509892865, 0.0, 0.0, 0.0, 0.0, 0.0, ...	24	admin.	single	high.school	unknown	no	

	label	features	age	job	marital	education	default	housing	lo
16	0.0	(2.2575892509892865, 0.0, 0.0, 0.0, 0.0, 0.0, ...	24	admin.	single	high.school	unknown	unknown	unknc
17	0.0	(2.2575892509892865, 0.0, 0.0, 0.0, 0.0, 0.0, ...	24	admin.	single	high.school	unknown	yes	
18	0.0	(2.2575892509892865, 0.0, 0.0, 0.0, 0.0, 0.0, ...	24	admin.	single	high.school	unknown	yes	
19	0.0	(2.2575892509892865, 0.0, 0.0, 0.0, 0.0, 0.0, ...	24	admin.	single	high.school	unknown	yes	

20 rows × 24 columns

In [50]:

```
transformed.filter(transformed.prediction == 1).toPandas().head(20)
```

Out[50]:

	label	features	age	job	marital	education	default	housing	loan	
0	0.0	(2.2575892509892865, 0.0, 0.0, 0.0, 0.0, 0.0, ...	20	admin.	single	high.school	no	no	no	
1	0.0	(0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 5.665...	20	entrepreneur	single	high.school	no	no	no	t
2	0.0	(0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 5.665...	20	entrepreneur	single	high.school	no	no	no	t
3	0.0	(0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 5.665...	20	entrepreneur	single	high.school	no	no	no	t
4	0.0	(0.0, 0.0, 0.0, 3.5498633758318805, 0.0, 0.0, ...	20	services	single	high.school	no	no	no	t
5	0.0	(0.0, 0.0, 0.0, 3.5498633758318805, 0.0, 0.0, ...	20	services	single	high.school	no	yes	no	t
6	0.0	(0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 5.4451539153755...	20	student	single	high.school	no	yes	no	
7	0.0	(0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 5.4451539153755...	20	student	single	high.school	no	yes	yes	
8	0.0	(2.2575892509892865, 0.0, 0.0, 0.0, 0.0, 0.0, ...	21	admin.	married	unknown	no	yes	no	
9	0.0	(2.2575892509892865, 0.0, 0.0, 0.0, 0.0, 0.0, ...	21	admin.	single	high.school	no	yes	no	
10	0.0	(2.2575892509892865, 0.0, 0.0, 0.0, 0.0, 0.0, ...	21	admin.	single	high.school	no	yes	no	
11	0.0	(0.0, 2.5553761110921385, 0.0, 0.0, 0.0, 0.0, ...	21	blue-collar	married	basic.9y	no	no	no	
12	0.0	(0.0, 2.5553761110921385, 0.0, 0.0, 0.0, 0.0, ...	21	blue-collar	married	basic.9y	no	no	yes	
13	0.0	(0.0, 2.5553761110921385, 0.0, 0.0, 0.0, 0.0, ...	21	blue-collar	married	basic.9y	no	yes	no	
14	0.0	(0.0, 2.5553761110921385, 0.0, 0.0, 0.0, 0.0, ...	21	blue-collar	single	basic.9y	no	no	no	
15	0.0	(0.0, 2.5553761110921385, 0.0, 0.0, 0.0, 0.0, ...	21	blue-collar	single	basic.9y	no	no	no	
16	0.0	(0.0, 2.5553761110921385, 0.0, 0.0, 0.0, 0.0, ...	21	blue-collar	single	basic.9y	no	unknown	unknown	
17	0.0	(0.0, 2.5553761110921385,	21	blue-collar	single	basic.9y	no	unknown	unknown	

	label	features	age	job	marital	education	default	housing	loan
		0.0, 0.0, 0.0, 0.0, ...							
18	0.0	(0.0, 0.0, 0.0, 3.5498633758318805, 0.0, 0.0, ...	21	services	single	basic.9y	no	yes	no
19	0.0	(0.0, 0.0, 0.0, 3.5498633758318805, 0.0, 0.0, ...	21	services	single	high.school	no	yes	no

20 rows × 24 columns

In [51]:

```
transformed.filter(transformed.prediction == 2).toPandas().head(20)
```

Out[51]:

	label	features	age	job	marital	education	default	housing	loan
0	0.0	(0.0, 0.0, 0.0, 0.0, 0.0, 4.107637800298967, 0...	36	retired	married	high.school	no	yes	no
1	0.0	(0.0, 0.0, 0.0, 0.0, 0.0, 4.107637800298967, 0...	37	retired	divorced	basic.9y	unknown	yes	no
2	0.0	(0.0, 0.0, 0.0, 0.0, 0.0, 4.107637800298967, 0...	40	retired	divorced	basic.4y	no	no	no
3	0.0	(0.0, 0.0, 0.0, 0.0, 0.0, 4.107637800298967, 0...	40	retired	single	basic.4y	no	yes	yes
4	0.0	(0.0, 0.0, 0.0, 0.0, 0.0, 4.107637800298967, 0...	44	retired	divorced	professional.course	no	yes	no
5	0.0	(0.0, 0.0, 0.0, 0.0, 0.0, 4.107637800298967, 0...	44	retired	single	basic.9y	no	no	no
6	0.0	(0.0, 0.0, 0.0, 0.0, 0.0, 4.107637800298967, 0...	45	retired	married	basic.4y	no	no	no
7	0.0	(0.0, 0.0, 0.0, 0.0, 0.0, 4.107637800298967, 0...	46	retired	married	basic.6y	unknown	yes	no
8	0.0	(0.0, 0.0, 0.0, 0.0, 0.0, 4.107637800298967, 0...	47	retired	married	basic.4y	no	no	no
9	0.0	(0.0, 0.0, 0.0, 0.0, 0.0, 4.107637800298967, 0...	47	retired	married	basic.4y	no	unknown	unknown
10	0.0	(0.0, 0.0, 0.0, 0.0, 0.0, 4.107637800298967, 0...	47	retired	married	high.school	no	yes	no
11	0.0	(0.0, 0.0, 0.0, 0.0, 0.0, 4.107637800298967, 0...	48	retired	divorced	basic.4y	unknown	yes	no
12	0.0	(0.0, 0.0, 0.0, 0.0, 0.0, 4.107637800298967, 0...	48	retired	married	basic.4y	no	no	no
13	0.0	(0.0, 0.0, 0.0, 0.0, 0.0, 4.107637800298967, 0...	49	retired	married	basic.4y	no	no	no
14	0.0	(0.0, 0.0, 0.0, 0.0, 0.0, 4.107637800298967, 0...	49	retired	married	basic.4y	no	no	no
15	0.0	(0.0, 0.0, 0.0, 0.0, 0.0, 4.107637800298967,	50	retired	married	basic.4y	no	yes	no

	label	features	age	job	marital	education	default	housing	loan
		0...							
16	0.0	(0.0, 0.0, 0.0, 0.0, 0.0, 4.107637800298967, 0...	50	retired	married	basic.4y	no	yes	no
17	0.0	(0.0, 0.0, 0.0, 0.0, 0.0, 4.107637800298967, 0...	50	retired	single	university.degree	no	no	no
18	0.0	(0.0, 0.0, 0.0, 0.0, 0.0, 4.107637800298967, 0...	50	retired	single	university.degree	no	yes	no
19	0.0	(0.0, 0.0, 0.0, 0.0, 0.0, 4.107637800298967, 0...	51	retired	divorced	basic.4y	no	yes	yes

20 rows × 24 columns

In [52]:
```
transformed.filter(transformed.prediction == 3).toPandas().head(20)
```

Out[52]:

	label	features	age	job	marital	education	default	housing	loan
0	0.0	(0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 5.4451539153755...	18	student	single	high.school	no	yes	yes
1	0.0	(0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 5.4451539153755...	19	student	single	basic.9y	no	no	no
2	0.0	(0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 5.4451539153755...	19	student	single	basic.9y	no	no	no
3	0.0	(0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 5.4451539153755...	19	student	single	unknown	no	yes	no
4	0.0	(0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 5.4451539153755...	20	student	single	basic.9y	no	yes	no
5	0.0	(0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 5.4451539153755...	20	student	single	high.school	no	yes	no
6	0.0	(2.2575892509892865, 0.0, 0.0, 0.0, 0.0, 0.0, ...	21	admin.	single	high.school	no	yes	no
7	0.0	(0.0, 0.0, 0.0, 3.5498633758318805, 0.0, 0.0, ...	21	services	single	basic.9y	no	no	no
8	0.0	(0.0, 0.0, 0.0, 3.5498633758318805, 0.0, 0.0, ...	21	services	single	high.school	no	yes	no
9	0.0	(0.0, 0.0, 0.0, 3.5498633758318805, 0.0, 0.0, ...	21	services	single	high.school	no	yes	yes
10	0.0	(0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 5.4451539153755...	21	student	single	basic.4y	no	no	no
11	0.0	(2.2575892509892865, 0.0, 0.0, 0.0, 0.0, 0.0, ...	22	admin.	married	high.school	no	no	yes
12	0.0	(2.2575892509892865, 0.0, 0.0, 0.0, 0.0, 0.0, ...	22	admin.	married	high.school	no	yes	yes
13	0.0	(0.0, 0.0, 0.0, 0.0, 3.9005036471651136, 0.0, ...	22	management	single	university.degree	no	yes	no
14	0.0	(0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 5.4451539153755...	22	student	single	basic.9y	no	yes	no
15	0.0	(0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 5.4451539153755...	22	student	single	high.school	no	no	no
16	0.0	(0.0, 0.0, 0.0, 0.0, 0.0, 0.0,	22	student	single	high.school	no	yes	no

	label	features	age	job	marital	education	default	housing	loan
		5.4451539153755...							
17	0.0	(2.2575892509892865, 0.0, 0.0, 0.0, 0.0, 0.0, ...	23	admin.	single	university.degree	no	yes	no
18	0.0	(2.2575892509892865, 0.0, 0.0, 0.0, 0.0, 0.0, ...	23	admin.	single	university.degree	no	yes	no
19	0.0	(0.0, 2.5553761110921385, 0.0, 0.0, 0.0, 0.0, ...	23	blue-collar	single	basic.4y	no	yes	no

20 rows × 24 columns

In [53]:
```
transformed.filter(transformed.prediction == 4).toPandas().head(20)
```

Out[53]:

	label	features	age	job	marital	education	default	housing	loar
0	0.0	(0.0, 0.0, 0.0, 3.5498633758318805, 0.0, 0.0, ...	26	services	single	high.school	no	no	nc
1	0.0	(0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 5.61841138...	28	self-employed	married	university.degree	no	yes	nc
2	0.0	(0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 5.4451539153755...	28	student	single	university.degree	no	yes	nc
3	0.0	(0.0, 0.0, 2.708579337991304, 0.0, 0.0, 0.0, 0...	28	technician	single	professional.course	no	yes	nc
4	0.0	(2.2575892509892865, 0.0, 0.0, 0.0, 0.0, 0.0, ...	29	admin.	divorced	professional.course	no	no	yes
5	0.0	(2.2575892509892865, 0.0, 0.0, 0.0, 0.0, 0.0, ...	29	admin.	married	high.school	no	yes	yes
6	0.0	(2.2575892509892865, 0.0, 0.0, 0.0, 0.0, 0.0, ...	29	admin.	married	university.degree	no	no	nc
7	0.0	(2.2575892509892865, 0.0, 0.0, 0.0, 0.0, 0.0, ...	29	admin.	single	high.school	no	yes	nc
8	0.0	(2.2575892509892865, 0.0, 0.0, 0.0, 0.0, 0.0, ...	29	admin.	single	professional.course	no	no	nc
9	0.0	(2.2575892509892865, 0.0, 0.0, 0.0, 0.0, 0.0, ...	29	admin.	single	university.degree	no	yes	nc
10	0.0	(2.2575892509892865, 0.0, 0.0, 0.0, 0.0, 0.0, ...	29	admin.	single	university.degree	no	yes	nc
11	0.0	(2.2575892509892865, 0.0, 0.0, 0.0, 0.0, 0.0, ...	29	admin.	single	university.degree	no	yes	nc
12	0.0	(2.2575892509892865, 0.0, 0.0, 0.0, 0.0, 0.0, ...	29	admin.	single	university.degree	no	yes	nc
13	0.0	(2.2575892509892865, 0.0, 0.0, 0.0, 0.0, 0.0, ...	29	admin.	single	university.degree	no	yes	yes
14	0.0	(0.0, 2.5553761110921385, 0.0, 0.0, 0.0, 0.0, ...	29	blue-collar	married	basic.9y	no	yes	yes
15	0.0	(0.0, 0.0, 0.0, 0.0, 3.9005036471651136, 0.0, ...	29	management	single	university.degree	no	no	nc
16	0.0	(0.0, 0.0, 0.0, 0.0, 3.9005036471651136, 0.0, ...	29	management	single	university.degree	no	no	nc
17	0.0	(0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 5.61841138...	29	self-employed	married	university.degree	no	yes	nc
18	0.0	(0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 5.61841138...	29	self-employed	single	university.degree	no	yes	nc

	label	features	age	job	marital	education	default	housing	loan
19	0.0	(0.0, 0.0, 0.0, 3.5498633758318805, 0.0, 0.0, ...	29	services	married	basic.6y	no	no	no

20 rows × 24 columns

In [57]:

```
# Pipeline stages
stages = []
```

In [59]:

```
from pyspark.ml.feature import PCA
# Apply PCA for dimensionality reduction
pca = PCA(k=2, inputCol="features", outputCol="pcaFeatures")
stages += [pca]
```

In [60]:

```
# Define and add the K-means model to the pipeline
kmeans = KMeans().setK(3).setSeed(1).setFeaturesCol("pcaFeatures")
stages += [kmeans]
```

In [61]:

```
# Create a Pipeline
pipeline = Pipeline(stages=stages)
pipelineModel = pipeline.fit(train)

# Transform the test set
test_set = pipelineModel.transform(test)
```

```
23/11/28 10:35:48 WARN InstanceBuilder: Failed to load implementation from:dev.ludovi
c.netlib.lapack.JNILAPACK
```

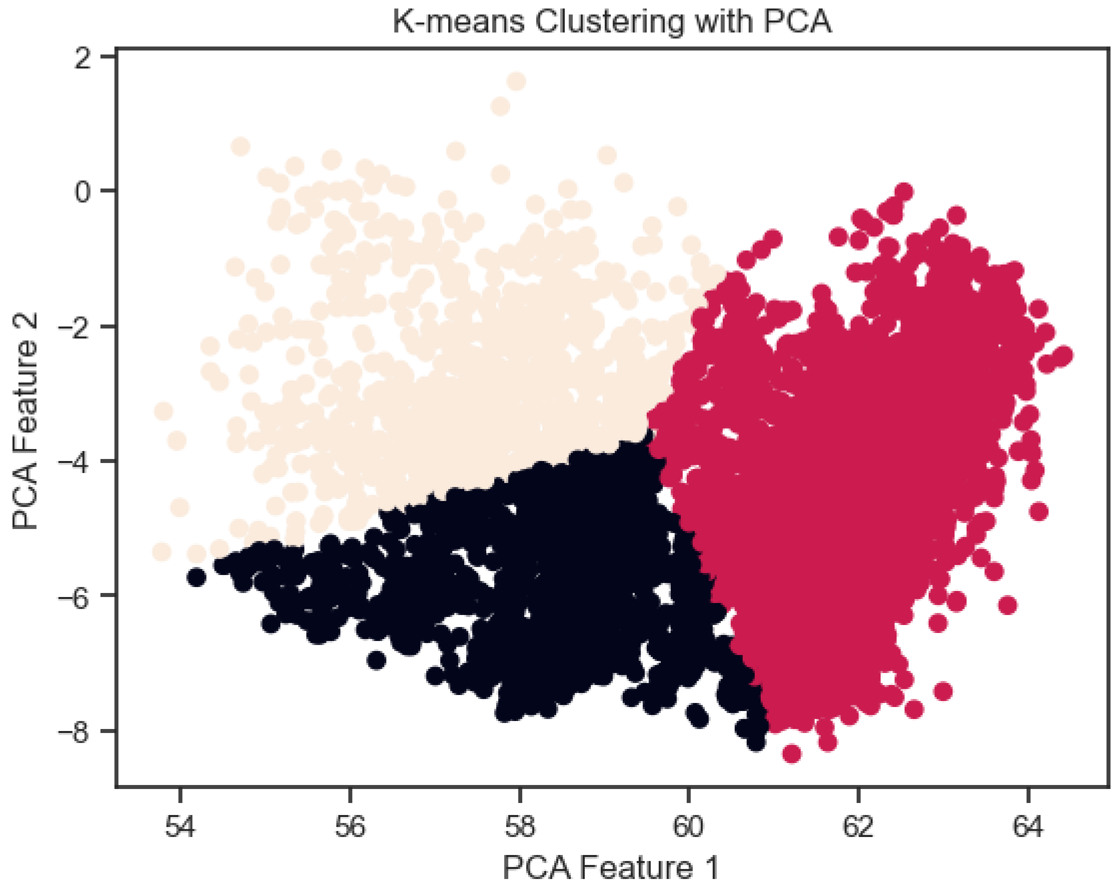
In [62]:

```
# Evaluate clustering by computing Silhouette score
evaluator = ClusteringEvaluator(featuresCol="pcaFeatures")
silhouette = evaluator.evaluate(test_set)
print("Silhouette with squared euclidean distance = " + str(silhouette))
```

```
Silhouette with squared euclidean distance = 0.5687624535573819
```

In [63]:

```
# Convert predictions to Pandas DataFrame for plotting
pandas_df = test_set.toPandas()

# Extract the PCA features for plotting
pandas_df['PCA1'] = pandas_df['pcaFeatures'].apply(lambda x: x[0])
pandas_df['PCA2'] = pandas_df['pcaFeatures'].apply(lambda x: x[1])

plt.scatter(pandas_df['PCA1'], pandas_df['PCA2'], c=pandas_df['prediction'])
plt.title("K-means Clustering with PCA")
plt.xlabel("PCA Feature 1")
plt.ylabel("PCA Feature 2")
plt.show()
```


K-means Clustering with PCA
PCA Feature 2
PCA Feature 1
2
0
−2
−4
−6
−8
54
56
58
60
62
64