In [ ]:
```
import pandas as pd
import pylab as pl
import numpy as np
import scipy.optimize as opt
from sklearn import preprocessing
#%matplotlib inline

import matplotlib as mpl
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn import preprocessing
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import confusion_matrix
from sklearn.metrics import jaccard_score
from sklearn.metrics import classification_report, confusion_matrix
import itertools
```

In [ ]:
```
bank_data= pd.read_csv('https://raw.githubusercontent.com/IndreBZ/bank/716b7cd2a11db98dc4175a8ccce927869caca041/bank2.csv')
print("The first 5 rows of the bank data")
bank_data.head()
```

```
The first 5 rows of the bank data
```

Out[ ]:

	age	job	marital	education	default	balance	housing	loan	contact	day	month	duration	campaign	pdays	previous
0	58	management	married	tertiary	no	2143	yes	no	unknown	5	may	261	1	-1	0
1	44	technician	single	secondary	no	29	yes	no	unknown	5	may	151	1	-1	0
2	33	entrepreneur	married	secondary	no	2	yes	yes	unknown	5	may	76	1	-1	0
3	47	blue-collar	married	unknown	no	1506	yes	no	unknown	5	may	92	1	-1	0
4	33	unknown	single	unknown	no	1	no	no	unknown	5	may	198	1	-1	0

In [ ]:
```
bank_data.shape
```

Out[ ]: (45211, 17)

In [ ]:
```
bank_data.dtypes
```

Out[ ]:
```
age           int64
job          object
marital      object
education    object
default      object
balance       int64
housing      object
loan         object
contact      object
day           int64
month        object
duration      int64
campaign      int64
pdays         int64
previous      int64
poutcome     object
y            object
dtype: object
```

In [ ]:
```
##find missing values
print('Find if there are missed values in data set')
missing_data = bank_data.isnull()
missing_data.head(5)
## no missing values
```

```
Find if there are missed values in data set
```

Out[ ]:

	age	job	marital	education	default	balance	housing	loan	contact	day	month	duration	campaign	pdays	previous	poutco
0	False	False	False	False	False	False	False	False	False	False	False	False	False	False	False	F
1	False	False	False	False	False	False	False	False	False	False	False	False	False	False	False	F
2	False	False	False	False	False	False	False	False	False	False	False	False	False	False	False	F
3	False	False	False	False	False	False	False	False	False	False	False	False	False	False	False	F
4	False	False	False	False	False	False	False	False	False	False	False	False	False	False	False	F

In [ ]:

```
##DATA MANIPULATION TASK
#1. select random subsample of data set
print('random subsample of data set')
sample = bank_data.sample(frac=0.5, replace=False, random_state=1)
print('50% sample of data set')
print(sample.shape)
```

```
random subsample of data set
50% sample of data set
(22606, 17)
```

In [ ]:

```
#2. filter desired rows using simple and more complex conditions;
df = bank_data
print("how many clients aged(30-50) subscribed a term deposit?")
age_df = df[(df["age"] > 30) & (df["age"] < 50) & (df["y"] == "yes")]
print(age_df.shape)
print("how many clients aged(30-50) didn't subscribe a term deposit?")
age_df1 = df[(df["age"] > 30) & (df["age"] < 50) & (df["y"] == "no")]
print(age_df1.shape)
print("group by job and term deposit and calculate sum of balance. Filter jobs where balance > average")
job_result_grouped = df.groupby(["y", "job"]).agg({"balance": "sum"})
balance =job_result_grouped ["balance"].mean()
print("Balance average",balance)
job_result = job_result_grouped[(job_result_grouped["balance"] > balance)]
print(job_result)
```

```
how many clients aged(30-50) subscribed a term deposit?
(2759, 17)
how many clients aged(30-50) didn't subscribe a term deposit?
(25228, 17)
group by job and term deposit and calculate sum of balance. Filter jobs where balance > average
Balance average 2566236.75
                  balance
y   job
no  admin.        4966497
    blue-collar   9596143
    management   13895227
    retired       3103899
    services      3731449
    technician    7972198
yes management    2785061
```

In [ ]:

```
#3. drop unnecessary variables, rename some variables
#unnecessary(guess) variables could be related with the last contact of the current campaign
df.drop(["contact", "day","month","duration"], axis=1, inplace=True)
print('rename some variables')
df.rename(columns={'campaign':'num_of_contact'}, inplace=True)
df.rename(columns={'pdays':'num_of_days'}, inplace=True)
df.head()
```

```
rename some variables
```

Out[ ]:

	age	job	marital	education	default	balance	housing	loan	num_of_contact	num_of_days	previous	poutcome	y
0	58	management	married	tertiary	no	2143	yes	no	1	-1	0	unknown	no
1	44	technician	single	secondary	no	29	yes	no	1	-1	0	unknown	no
2	33	entrepreneur	married	secondary	no	2	yes	yes	1	-1	0	unknown	no
3	47	blue-collar	married	unknown	no	1506	yes	no	1	-1	0	unknown	no
4	33	unknown	single	unknown	no	1	no	no	1	-1	0	unknown	no

In [ ]:

```
#4. calculate summarizing statistics (for full sample and by categorical variables as well)
#print(bank_data.dtypes)
```

```
print(bank_data.describe())##original dataset
print(bank_data.info())
```

```
                age        balance  num_of_contact   num_of_days      previous
count  45211.000000   45211.000000    45211.000000  45211.000000  45211.000000
mean      40.936210    1362.272058        2.763841     40.197828      0.580323
std       10.618762    3044.765829        3.098021    100.128746      2.303441
min       18.000000   -8019.000000        1.000000     -1.000000      0.000000
25%       33.000000      72.000000        1.000000     -1.000000      0.000000
50%       39.000000     448.000000        2.000000     -1.000000      0.000000
75%       48.000000    1428.000000        3.000000     -1.000000      0.000000
max       95.000000  102127.000000       63.000000    871.000000    275.000000
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 45211 entries, 0 to 45210
Data columns (total 13 columns):
 #   Column          Non-Null Count  Dtype 
---  ------          --------------  ----- 
 0   age             45211 non-null  int64 
 1   job             45211 non-null  object
 2   marital         45211 non-null  object
 3   education       45211 non-null  object
 4   default         45211 non-null  object
 5   balance         45211 non-null  int64 
 6   housing         45211 non-null  object
 7   loan            45211 non-null  object
 8   num_of_contact  45211 non-null  int64 
 9   num_of_days     45211 non-null  int64 
 10  previous        45211 non-null  int64 
 11  poutcome        45211 non-null  object
 12  y               45211 non-null  object
dtypes: int64(5), object(8)
memory usage: 4.5+ MB
None
```

In [ ]:

```
#summarizing statistics only for not categorical variables
df.describe()## updated datasetprint (classification_report(yyy_test, yyyhat))
## the best model evaluation: reason add variable duration which has bigger correlation coefficient
```

Out[ ]:

	age	balance	num_of_contact	num_of_days	previous
count	45211.000000	45211.000000	45211.000000	45211.000000	45211.000000
mean	40.936210	1362.272058	2.763841	40.197828	0.580323
std	10.618762	3044.765829	3.098021	100.128746	2.303441
min	18.000000	-8019.000000	1.000000	-1.000000	0.000000
25%	33.000000	72.000000	1.000000	-1.000000	0.000000
50%	39.000000	448.000000	2.000000	-1.000000	0.000000
75%	48.000000	1428.000000	3.000000	-1.000000	0.000000
max	95.000000	102127.000000	63.000000	871.000000	275.000000

In [ ]:

```
#5. create new variables using simple transformation and custom functions
print('change categorical columns to numeric')
df['y'].replace(['no', 'yes'],[0, 1], inplace=True)
df['job'].replace(["admin.","unknown","unemployed","management","housemaid","entrepreneur","student","blue-collar","self-emplo
df['marital'].replace(["married","divorced","single"],[0, 1,2], inplace=True)
df['education'].replace(["unknown","secondary","primary","tertiary"],[0,1,2,3], inplace=True)
df['default'].replace(['no', 'yes'],[0, 1], inplace=True)
df['housing'].replace(['no', 'yes'],[0, 1], inplace=True)
df['loan'].replace(['no', 'yes'],[0, 1], inplace=True)
df['poutcome'].replace(["unknown","other","failure","success"],[0,1,2,3], inplace=True)
```

```
change categorical columns to numeric
```

In [ ]:

```
print("Change column data type")
#look into updated data types and summarizing statistics for new dataset df
print(df.dtypes)
print(df.describe())
```

```
Change column data type
age               int64
job               int64
marital           int64
education         int64
default           int64
balance           int64
housing           int64
loan              int64
num_of_contact    int64
num_of_days       int64
previous          int64
poutcome          int64
y                 int64
dtype: object
                age           job       marital     education       default  \
count  45211.000000  45211.000000  45211.000000  45211.000000  45211.000000   
mean      40.936210      6.018159      0.680963      1.698856      0.018027   
std       10.618762      3.543218      0.884908      0.938627      0.133049   
min       18.000000      0.000000      0.000000      0.000000      0.000000   
25%       33.000000      3.000000      0.000000      1.000000      0.000000   
50%       39.000000      7.000000      0.000000      1.000000      0.000000   
75%       48.000000     10.000000      2.000000      3.000000      0.000000   
max       95.000000     11.000000      2.000000      3.000000      1.000000   

             balance       housing          loan  num_of_contact  \
count   45211.000000  45211.000000  45211.000000    45211.000000   
mean     1362.272058      0.555838      0.160226        2.763841   
std      3044.765829      0.496878      0.366820        3.098021   
min     -8019.000000      0.000000      0.000000        1.000000   
25%        72.000000      0.000000      0.000000        1.000000   
50%       448.000000      1.000000      0.000000        2.000000   
75%      1428.000000      1.000000      0.000000        3.000000   
max    102127.000000      1.000000      1.000000       63.000000   

        num_of_days      previous      poutcome             y  
count  45211.000000  45211.000000  45211.000000  45211.000000  
mean      40.197828      0.580323      0.357767      0.116985  
std      100.128746      2.303441      0.804435      0.321406  
min       -1.000000      0.000000      0.000000      0.000000  
25%       -1.000000      0.000000      0.000000      0.000000  
```

```
50%      -1.000000    0.000000    0.000000    0.000000
75%      -1.000000    0.000000    0.000000    0.000000
max     871.000000  275.000000    3.000000    1.000000
```

In [ ]:

```
#6. order data set by several variables.
#df['job'].value_counts()

sorted_balance = df.sort_values(by=['balance'], ascending=True)
print(sorted_balance.head(3))
sorted_age = df.sort_values(by=['age'], ascending=False)
print(sorted_age.head(3))
sorted_job_educational = df.sort_values(by=['job','education'], ascending=True)
print(sorted_job_educational.head(5))
```

```
       age  job  marital  education  default  balance  housing  loan  \
12909   26    7        2          1        1    -8019        0     1
15682   49    3        0          3        1    -6847        0     1
38736   60    3        1          3        0    -4057        1     0

       num_of_contact  num_of_days  previous  poutcome  y
12909               3           -1         0         0  0
15682               1           -1         0         0  0
38736               6           -1         0         0  0
       age  job  marital  education  default  balance  housing  loan  \
41663   95    9        0          1        0        0        0     0
33699   95    9        1          2        0     2282        0     0
31233   94    9        1          1        0     1234        0     0

       num_of_contact  num_of_days  previous  poutcome  y
41663               1           -1         0         0  0
33699              17           -1         0         0  1
31233               1           -1         0         0  0
     age  job  marital  education  default  balance  housing  loan  \
16    45    0        2          0        0       13        1     0
122   34    0        0          0        0        3        1     0
383   43    0        0          0        0      350        0     0
516   44    0        0          0        0       40        0     1
628   34    0        2          0        0     2434        1     0

     num_of_contact  num_of_days  previous  poutcome  y
16                1           -1         0         0  0
122               3           -1         0         0  0
383               1           -1         0         0  0
516               2           -1         0         0  0
628               4           -1         0         0  0
```

In [ ]:

```
##DATA VISUALISATION TASK
## try to find relations between variables
df.corr()
## correlations are very small
```

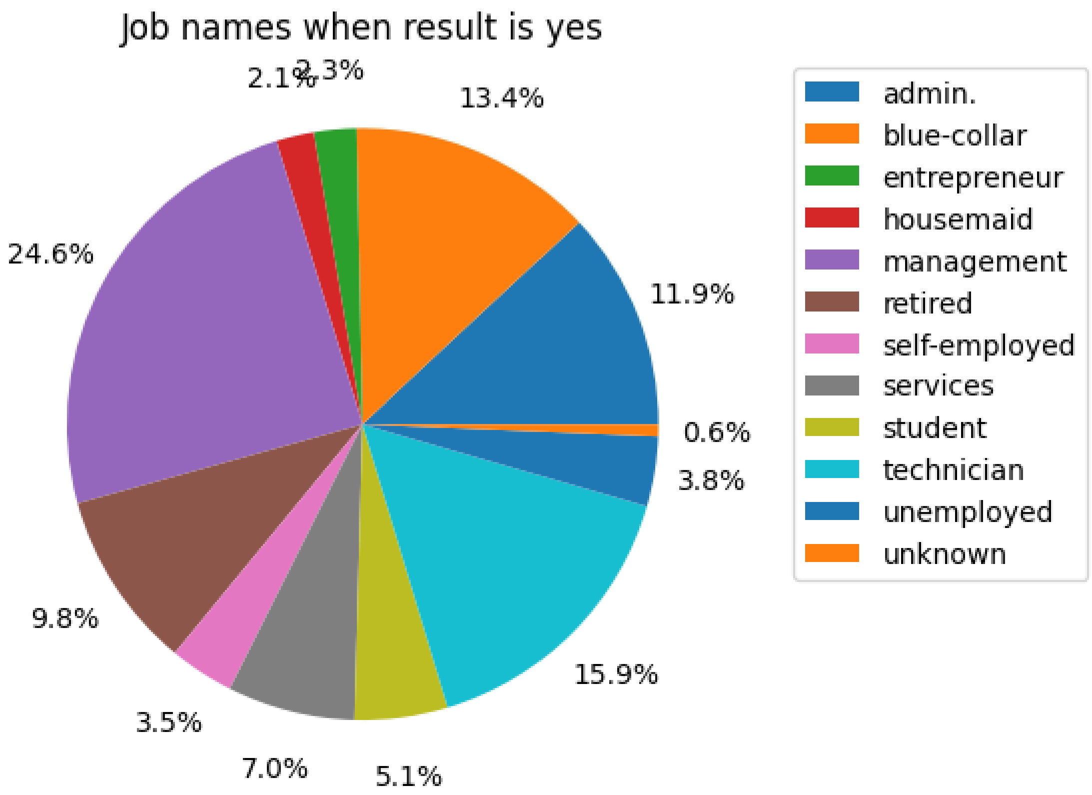
Out[ ]:

	age	job	marital	education	default	balance	housing	loan	num_of_contact	num_of_days	pre
age	1.000000	0.044237	-0.376104	-0.019044	-0.017879	0.097783	-0.185513	-0.015655	0.004760	-0.023758	0.0
job	0.044237	1.000000	-0.034681	-0.209193	0.002825	-0.030025	0.035074	0.026080	0.010301	-0.008086	-0.0
marital	-0.376104	-0.034681	1.000000	0.048662	0.009584	-0.020602	-0.020202	-0.046738	-0.029121	0.029490	0.0
education	-0.019044	-0.209193	0.048662	1.000000	-0.013916	0.073295	-0.082156	-0.038771	0.014960	-0.012525	0.0
default	-0.017879	0.002825	0.009584	-0.013916	1.000000	-0.066745	-0.006025	0.077234	0.016822	-0.029979	-0.0
balance	0.097783	-0.030025	-0.020602	0.073295	-0.066745	1.000000	-0.068768	-0.084350	-0.014578	0.003435	0.0
housing	-0.185513	0.035074	-0.020202	-0.082156	-0.006025	-0.068768	1.000000	0.041323	-0.023599	0.124178	0.0
loan	-0.015655	0.026080	-0.046738	-0.038771	0.077234	-0.084350	0.041323	1.000000	0.009980	-0.022754	-0.0
num_of_contact	0.004760	0.010301	-0.029121	0.014960	0.016822	-0.014578	-0.023599	0.009980	1.000000	-0.088628	-0.0
num_of_days	-0.023758	-0.008086	0.029490	-0.012525	-0.029979	0.003435	0.124178	-0.022754	-0.088628	1.000000	0.4
previous	0.001288	-0.016064	0.015676	0.017587	-0.018329	0.016674	0.037076	-0.011043	-0.032855	0.454820	1.0
poutcome	0.014363	-0.022410	0.027295	0.022000	-0.039593	0.034865	0.031062	-0.039928	-0.111592	0.790806	0.4
y	0.025155	-0.024649	0.065668	0.046539	-0.022419	0.052838	-0.139173	-0.068185	-0.073172	0.103621	0.0

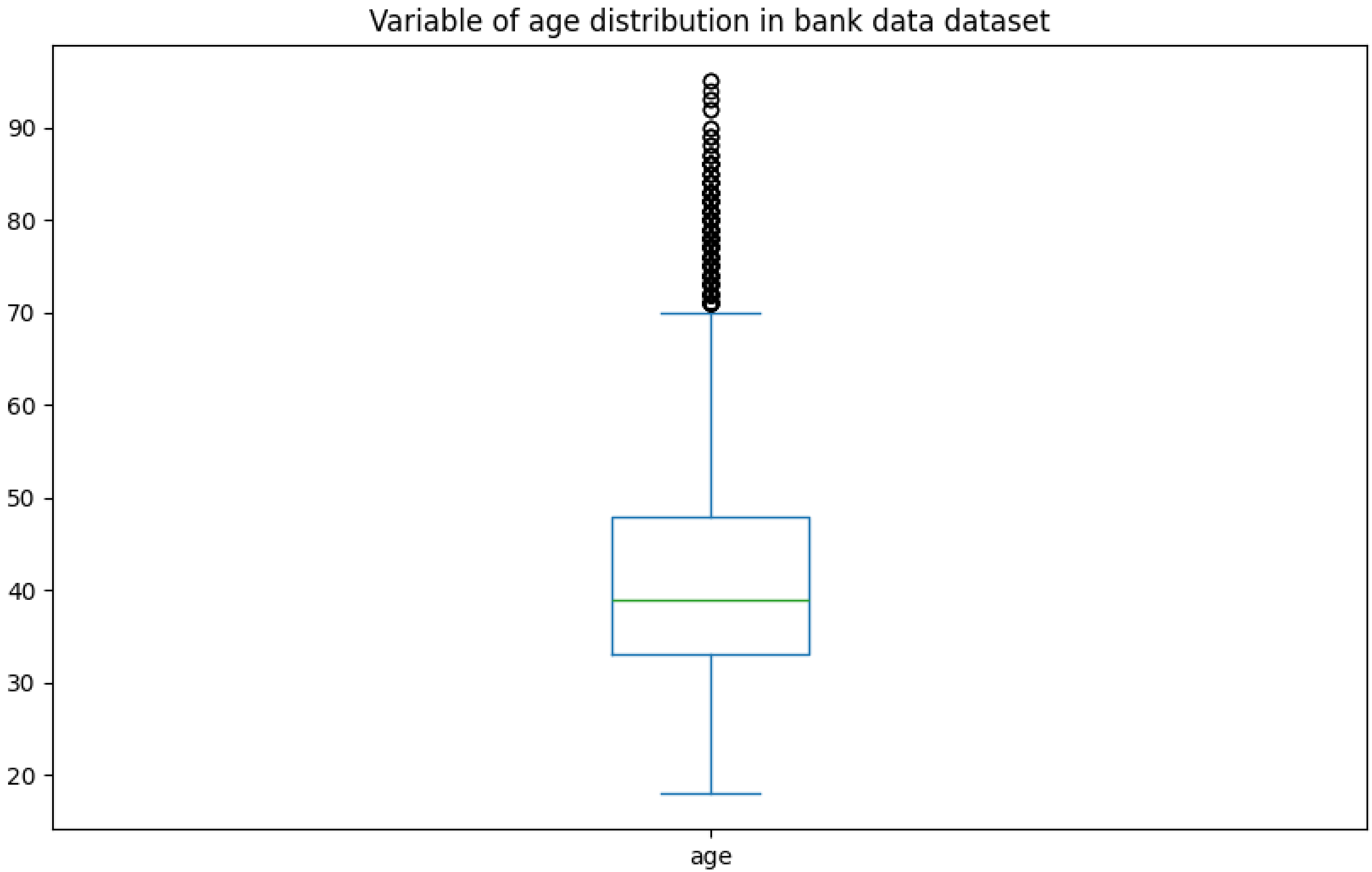
In [ ]:

```
##Pie
bank_data_yes =bank_data[(bank_data["y"] == "yes")]
#bank_data.head()
df_job = bank_data_yes.groupby(['job'])['y'].count().reset_index()
#df_job
label =list(df_job['job'])
label
#df_job['y']
#Pie on jobs
fig,ax=plt.subplots()
ax.pie(df_job['y'],autopct='%1.1f%%', pctdistance=1.2) #using explode to highlight the lowest
ax.set_aspect('equal')  # Ensure pie is drawn as a circle
plt.title('Job names when result is yes')
```

```
ax.legend(df_job['job'],bbox_to_anchor=(1, 0, 0.5, 1))#, include legend, if you donot want to pass the labels
plt.show()
```



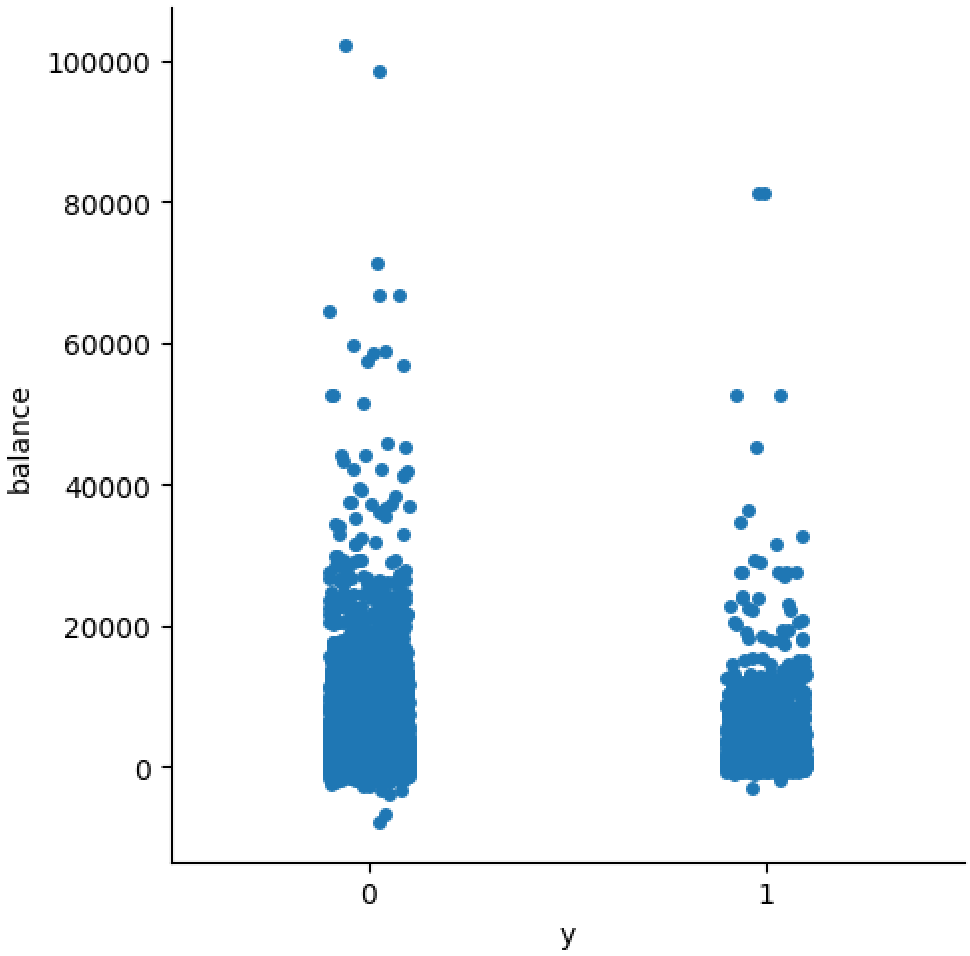
In [ ]:
```
df_age = df[['age']]
df_age.plot(kind='box', figsize=(10, 6))
plt.title('Variable of age distribution in bank data dataset')
plt.show()
```




```
In [ ]: sns.catplot(x = 'y', y = 'balance', data = df)
```

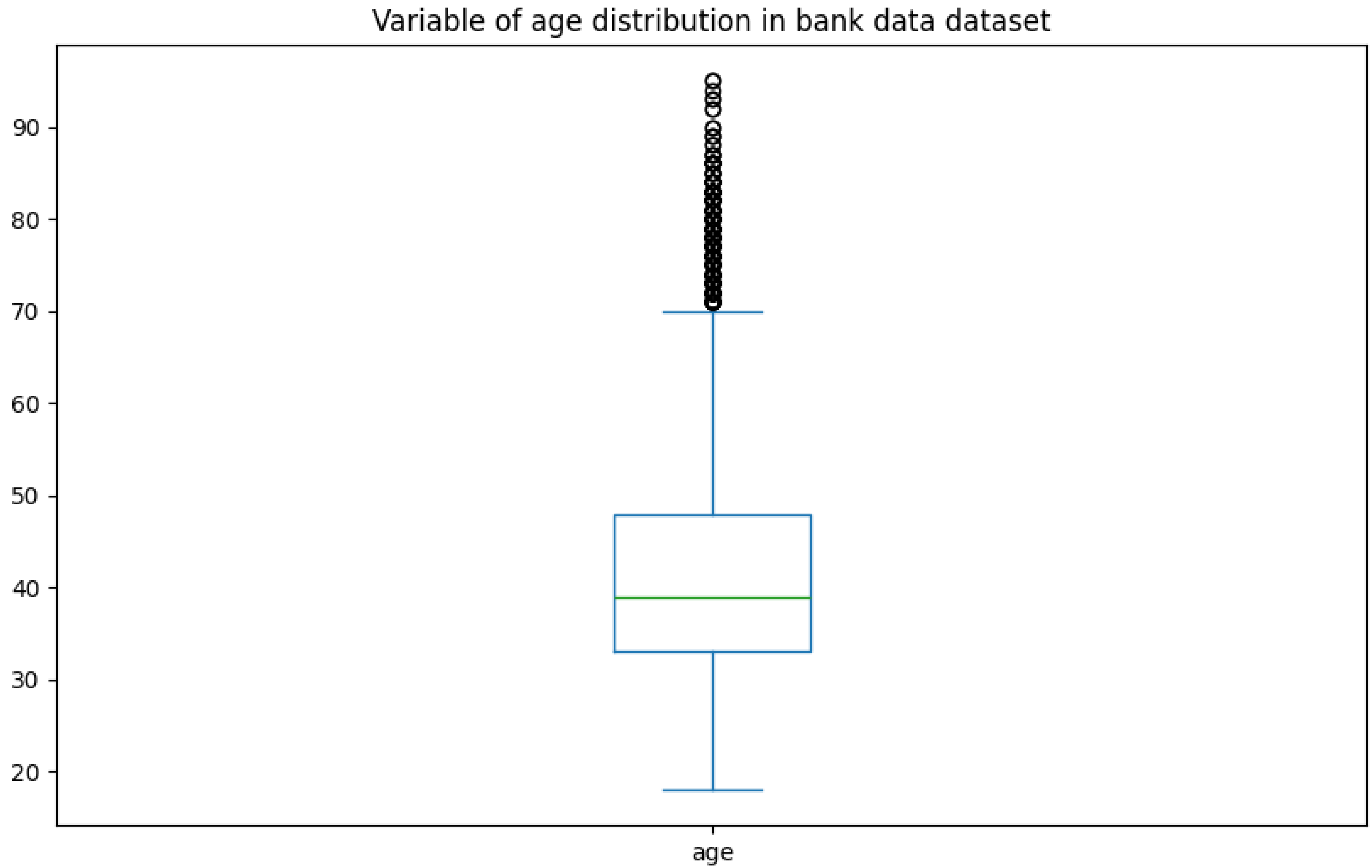
```
c:\Users\s7149b\AppData\Local\Programs\Python\Python312\Lib\site-packages\seaborn\_base.py:949: FutureWarning: When grouping wi
th a length-1 list-like, you will need to pass a length-1 tuple to get_group in a future version of pandas. Pass `(name,)` inst
ead of `name` to silence this warning.
  data_subset = grouped_data.get_group(pd_key)
```

```
Out[ ]: <seaborn.axisgrid.FacetGrid at 0x2325a419dc0>
```



In [ ]:
```
##BOX PLOT
new_df =df[['age']]
new_df.plot(kind='box', figsize=(10, 6))
plt.title('Variable of age distribution in bank data dataset')

plt.show()
```



In [ ]:
```
#MODELLING TASK
#logistic regression
df.head()
#the first model
#define x(dependent variable) and y(independent variable) of dataset
x = np.asarray(df[['age','job','marital','education','default','balance','housing','loan','num_of_contact','num_of_days','prev
print('x',x[0:5])
```

```
y = np.asarray(df['y'])
print('y',y[0:5])
```

```
x [[  58    3    0    3    0 2143    1    0    1   -1    0    0]
 [  44   10    2    1    0   29    1    0    1   -1    0    0]
 [  33    5    0    1    0    2    1    1    1   -1    0    0]
 [  47    7    0    0    0 1506    1    0    1   -1    0    0]
 [  33    1    2    0    0    1    0    0    1   -1    0    0]]
y [0 0 0 0 0]
```

In [ ]:
```
#normalize the dataset
x = preprocessing.StandardScaler().fit(x).transform(x)
x[0:5]
```

Out[ ]:
```
array([[ 1.60696496, -0.8518225 , -0.76953816,  1.38623556, -0.13548989,
         0.25641925,  0.89391541, -0.43680347, -0.56935064, -0.41145311,
        -0.25194037, -0.44474786],
       [ 0.28852927,  1.12380467,  1.49060994, -0.7445602 , -0.13548989,
        -0.43789469,  0.89391541, -0.43680347, -0.56935064, -0.41145311,
        -0.25194037, -0.44474786],
       [-0.74738448, -0.2873576 , -0.76953816, -0.7445602 , -0.13548989,
        -0.44676247,  0.89391541,  2.2893591 , -0.56935064, -0.41145311,
        -0.25194037, -0.44474786],
       [ 0.5710512 ,  0.27710731, -0.76953816, -1.80995809, -0.13548989,
         0.04720545,  0.89391541, -0.43680347, -0.56935064, -0.41145311,
        -0.25194037, -0.44474786],
       [-0.74738448, -1.41628741,  1.49060994, -1.80995809, -0.13548989,
        -0.44709091, -1.11867408, -0.43680347, -0.56935064, -0.41145311,
        -0.25194037, -0.44474786]])
```

In [ ]:
```
##Define train and test sets
#from sklearn.model_selection import train_test_split
x_train, x_test, y_train, y_test = train_test_split( x, y, test_size=0.3, random_state=5)## worse result with test_size=0.2
print ('Train set:', x_train.shape,  y_train.shape)
print ('Test set:', x_test.shape,  y_test.shape)
```

```
Train set: (31647, 12) (31647,)
Test set: (13564, 12) (13564,)
```

In [ ]:
```
#Define logistic regression model
LR = LogisticRegression(C=0.01, solver='liblinear').fit(x_train,y_train)
```

```
LR
```

Out[ ]:

```
LogisticRegression
LogisticRegression(C=0.01, solver='liblinear')
```

In [ ]:

```
#normalize the dataset
#from sklearn import preprocessing
x = preprocessing.StandardScaler().fit(x).transform(x)
x[0:5]
```

Out[ ]:

```
array([[ 1.60696496, -0.8518225 , -0.76953816,  1.38623556, -0.13548989,
         0.25641925,  0.89391541, -0.43680347, -0.56935064, -0.41145311,
        -0.25194037, -0.44474786],
       [ 0.28852927,  1.12380467,  1.49060994, -0.7445602 , -0.13548989,
        -0.43789469,  0.89391541, -0.43680347, -0.56935064, -0.41145311,
        -0.25194037, -0.44474786],
       [-0.74738448, -0.2873576 , -0.76953816, -0.7445602 , -0.13548989,
        -0.44676247,  0.89391541,  2.2893591 , -0.56935064, -0.41145311,
        -0.25194037, -0.44474786],
       [ 0.5710512 ,  0.27710731, -0.76953816, -1.80995809, -0.13548989,
         0.04720545,  0.89391541, -0.43680347, -0.56935064, -0.41145311,
        -0.25194037, -0.44474786],
       [-0.74738448, -1.41628741,  1.49060994, -1.80995809, -0.13548989,
        -0.44709091, -1.11867408, -0.43680347, -0.56935064, -0.41145311,
        -0.25194037, -0.44474786]])
```

In [ ]:

```
## MODELLING TASK
#logistic regression
df.head()
#the first model
#define X of datasert
x = np.asarray(df[['age','job','marital','education','default','balance','housing','loan','num_of_contact','num_of_days','prev
print('x',x[0:5])
y = np.asarray(df['y'])
print('y',y[0:5])
```

```
x [[  58    3    0    3    0 2143    1    0    1   -1    0    0]
 [  44   10    2    1    0   29    1    0    1   -1    0    0]
 [  33    5    0    1    0    2    1    1    1   -1    0    0]
 [  47    7    0    0    0 1506    1    0    1   -1    0    0]
 [  33    1    2    0    0    1    0    0    1   -1    0    0]]
y [0 0 0 0 0]
```

In [ ]:
```python
#jaccard index: for accuracy evaluation. we can define jaccard as the size of the intersection divided by the size of the unio
jaccard_score(y_test, yhat,pos_label=0)
```

Out[ ]:
```
0.8880256965713005
```

In [ ]:
```python
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')
print(confusion_matrix(y_test, yhat, labels=[1,0]))
```

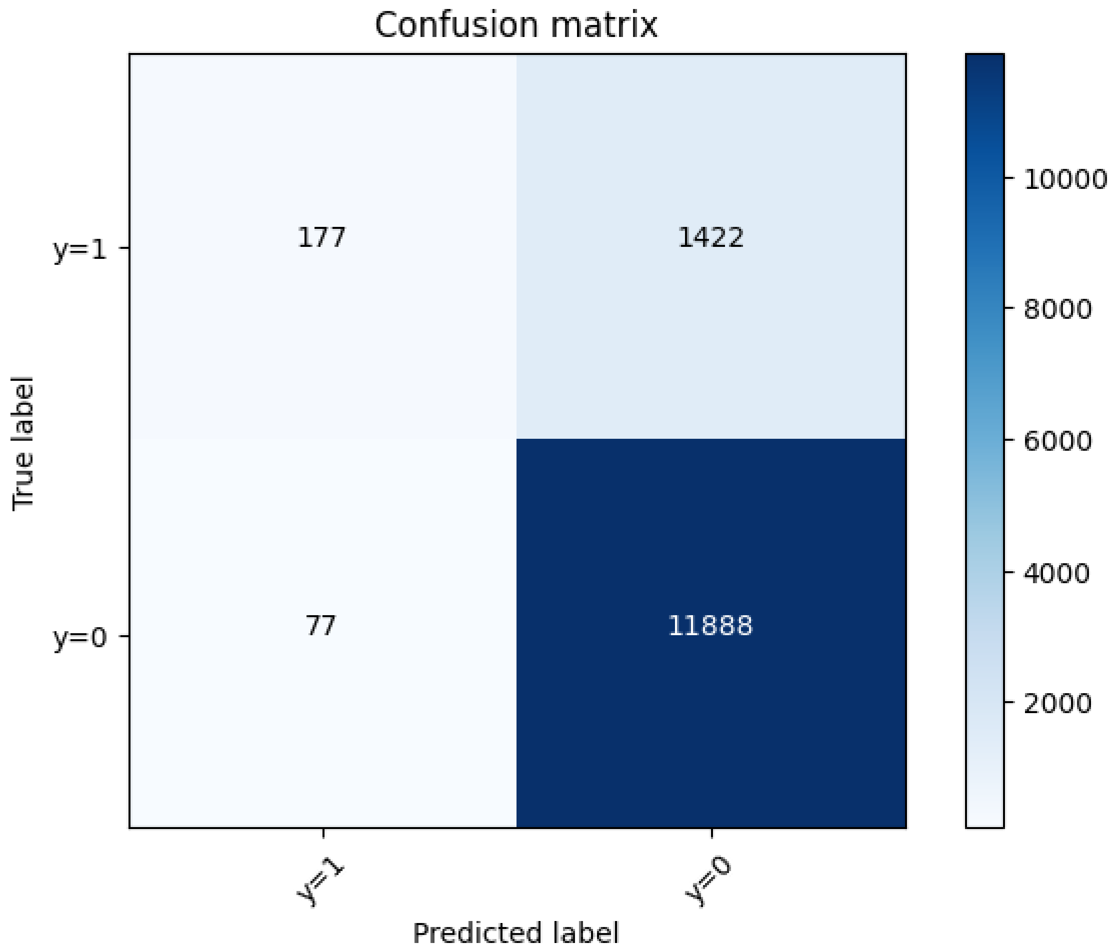
```
[[  177  1422]
 [   77 11888]]
```

In [ ]:

```
# Compute confusion matrix
cnf_matrix = confusion_matrix(y_test, yhat, labels=[1,0])
np.set_printoptions(precision=2)


# Plot non-normalized confusion matrix
plt.figure()
plot_confusion_matrix(cnf_matrix, classes=['y=1','y=0'],normalize= False,  title='Confusion matrix')
```

```
Confusion matrix, without normalization
[[  177  1422]
 [   77 11888]]
```



In [ ]:
```
print (classification_report(y_test, yhat))
##model predict y = 0 94% correct but only  19% for y=1
```

```
              precision    recall  f1-score   support

           0       0.89      0.99      0.94     11965
           1       0.70      0.11      0.19      1599

    accuracy                           0.89     13564
   macro avg       0.80      0.55      0.57     13564
weighted avg       0.87      0.89      0.85     13564
```

In [ ]:

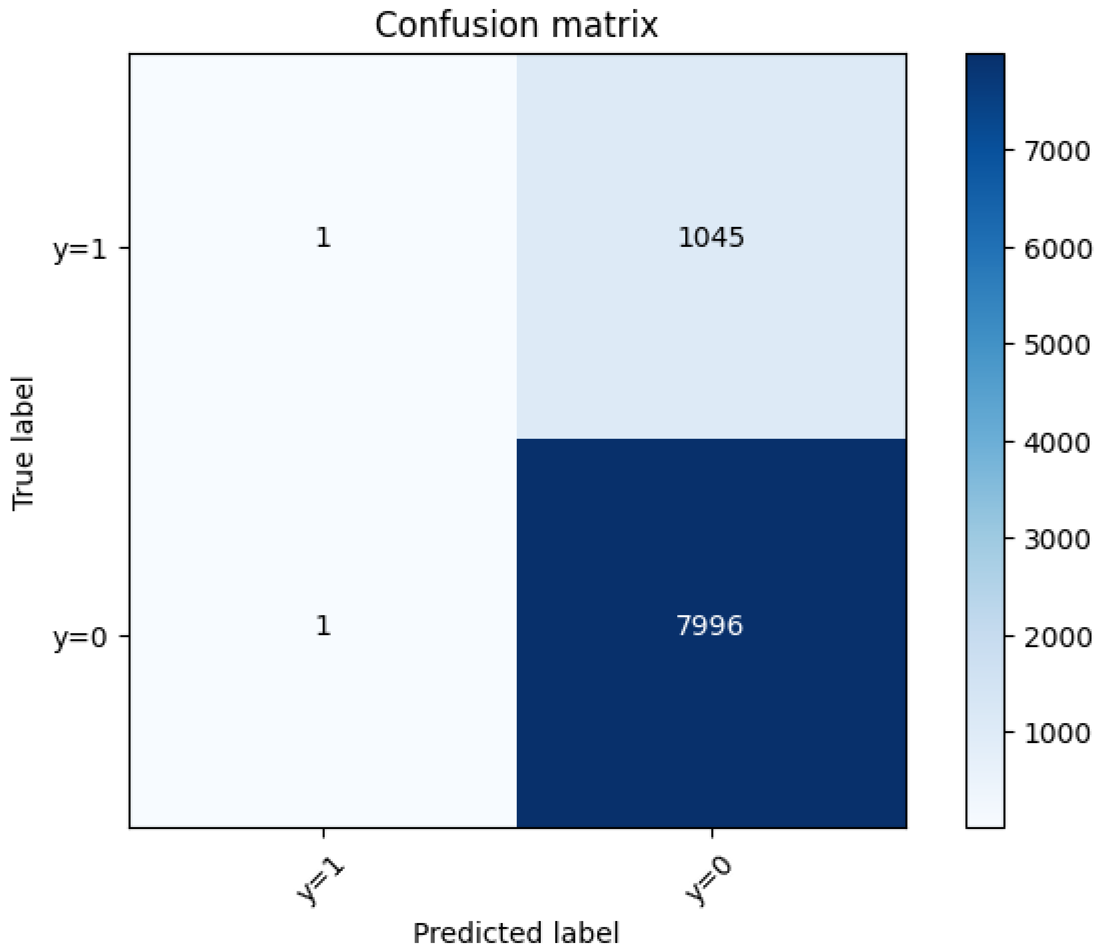
```
###the second model
xx = np.asarray(df[['age','job','education','marital','default','housing','balance','loan']])
yy = np.asarray(df['y'])
xx = preprocessing.StandardScaler().fit(xx).transform(xx)
xx_train, xx_test, yy_train, yy_test = train_test_split( xx, yy, test_size=0.2, random_state=5)
LR = LogisticRegression(C=0.01, solver='liblinear').fit(xx_train,yy_train)
yyhat = LR.predict(xx_test)
yyhat_prob = LR.predict_proba(xx_test)
jaccard_score(yy_test, yyhat,pos_label=0)
```

Out[ ]: 0.8843176288431763

In [ ]:

```
#jaccard index
jaccard_score(y_test, yhat,pos_label=0)
```

```
Confusion matrix, without normalization
[[   1 1045]
 [   1 7996]]
```



In [ ]:
```
print (classification_report(yy_test, yyhat))
## results are much worse than the first model
```

```
              precision    recall  f1-score   support

           0       0.88      1.00      0.94      7997
           1       0.50      0.00      0.00      1046

    accuracy                           0.88      9043
   macro avg       0.69      0.50      0.47      9043
weighted avg       0.84      0.88      0.83      9043
```

In [ ]:
```
cnf_matrix = confusion_matrix(yy_test, yyhat, labels=[1,0])
np.set_printoptions(precision=2)


# Plot non-normalized confusion matrix
plt.figure()
plot_confusion_matrix(cnf_matrix, classes=['y=1','y=0'],normalize= False,  title='Confusion matrix')
## in almost all cases model predict Y = 0, not good
```

In [ ]:
```
##The third model
df_LR_new = bank_data
print('change categorical columns to numeric')
df_LR_new['y'].replace(['no', 'yes'],[0, 1], inplace=True)
df_LR_new['job'].replace(["admin.","unknown","unemployed","management","housemaid","entrepreneur","student","blue-collar","sel
df_LR_new['marital'].replace(["married","divorced","single"],[0, 1,2], inplace=True)
df_LR_new['education'].replace(["unknown","secondary","primary","tertiary"],[0,1,2,3], inplace=True)
df_LR_new['default'].replace(['no', 'yes'],[0, 1], inplace=True)
df_LR_new['housing'].replace(['no', 'yes'],[0, 1], inplace=True)
df_LR_new['loan'].replace(['no', 'yes'],[0, 1], inplace=True)
df_LR_new['contact'].replace(['unknown','telephone','cellular'],[0, 1,2], inplace=True)
df_LR_new['month'].replace(['jan', 'feb','mar','apr','may','jun','jul','aug','sep','oct','nov','dec'],[0, 1,2,3,4,5,6,7,8,9,10
df_LR_new['poutcome'].replace(["unknown","other","failure","success"],[0,1,2,3], inplace=True)
print("Change column data type")
df_LR_new.dtypes
```

```
change categorical columns to numeric
Change column data type
```

Out[ ]:
```
age          int64
job          int64
marital      int64
education    int64
default      int64
balance      int64
housing      int64
loan         int64
contact      int64
day          int64
month        int64
duration     int64
campaign     int64
pdays        int64
previous     int64
poutcome     int64
y            int64
dtype: object
```

In [ ]:
```
df_LR_new.corr()
```

Out[ ]:

	age	job	marital	education	default	balance	housing	loan	contact	day	month	duratio
age	1.000000	0.044237	-0.376104	-0.019044	-0.017879	0.097783	-0.185513	-0.015655	-0.026221	-0.009120	0.092903	-0.00464
job	0.044237	1.000000	-0.034681	-0.209193	0.002825	-0.030025	0.035074	0.026080	-0.039296	0.008361	-0.010099	0.01242
marital	-0.376104	-0.034681	1.000000	0.048662	0.009584	-0.020602	-0.020202	-0.046738	0.040757	-0.007701	-0.069718	0.02289
education	-0.019044	-0.209193	0.048662	1.000000	-0.013916	0.073295	-0.082156	-0.038771	0.108624	0.013607	0.072804	-0.00038
default	-0.017879	0.002825	0.009584	-0.013916	1.000000	-0.066745	-0.006025	0.077234	-0.015404	0.009424	0.014989	-0.01002
balance	0.097783	-0.030025	-0.020602	0.073295	-0.066745	1.000000	-0.068768	-0.084350	0.027273	0.004503	0.094605	0.02156
housing	-0.185513	0.035074	-0.020202	-0.082156	-0.006025	-0.068768	1.000000	0.041323	-0.188123	-0.027982	-0.173887	0.00507
loan	-0.015655	0.026080	-0.046738	-0.038771	0.077234	-0.084350	0.041323	1.000000	0.010873	0.011370	0.021638	-0.01241
contact	-0.026221	-0.039296	0.040757	0.108624	-0.015404	0.027273	-0.188123	0.010873	1.000000	0.027936	0.173779	0.02083
day	-0.009120	0.008361	-0.007701	0.013607	0.009424	0.004503	-0.027982	0.011370	0.027936	1.000000	0.101989	-0.03020
month	0.092903	-0.010099	-0.069718	0.072804	0.014989	0.094605	-0.173887	0.021638	0.173779	0.101989	1.000000	-0.01186
duration	-0.004648	0.012426	0.022895	-0.000389	-0.010021	0.021560	0.005075	-0.012412	0.020839	-0.030206	-0.011866	1.00000
campaign	0.004760	0.010301	-0.029121	0.014960	0.016822	-0.014578	-0.023599	0.009980	-0.019614	0.162490	0.054868	-0.08457
pdays	-0.023758	-0.008086	0.029490	-0.012525	-0.029979	0.003435	0.124178	-0.022754	0.244816	-0.093044	-0.108940	-0.00156
previous	0.001288	-0.016064	0.015676	0.017587	-0.018329	0.016674	0.037076	-0.011043	0.147811	-0.051710	-0.035600	0.00120
poutcome	0.014363	-0.022410	0.027295	0.022000	-0.039593	0.034865	0.031062	-0.039928	0.272710	-0.081519	-0.036046	0.01330
y	0.025155	-0.024649	0.065668	0.046539	-0.022419	0.052838	-0.139173	-0.068185	0.148395	-0.028348	0.018717	0.39452

In [ ]:

```
xxx = np.asarray(df_LR_new[['age','job','education','marital','default','housing','balance','loan','contact','duration']])## a
yyy = np.asarray(df_LR_new['y'])
xxx = preprocessing.StandardScaler().fit(xxx).transform(xxx)
xxx_train, xxx_test, yyy_train, yyy_test = train_test_split( xxx, yyy, test_size=0.2, random_state=5)
LR = LogisticRegression(C=0.01, solver='liblinear').fit(xxx_train,yyy_train)
yyyhat = LR.predict(xxx_test)
```

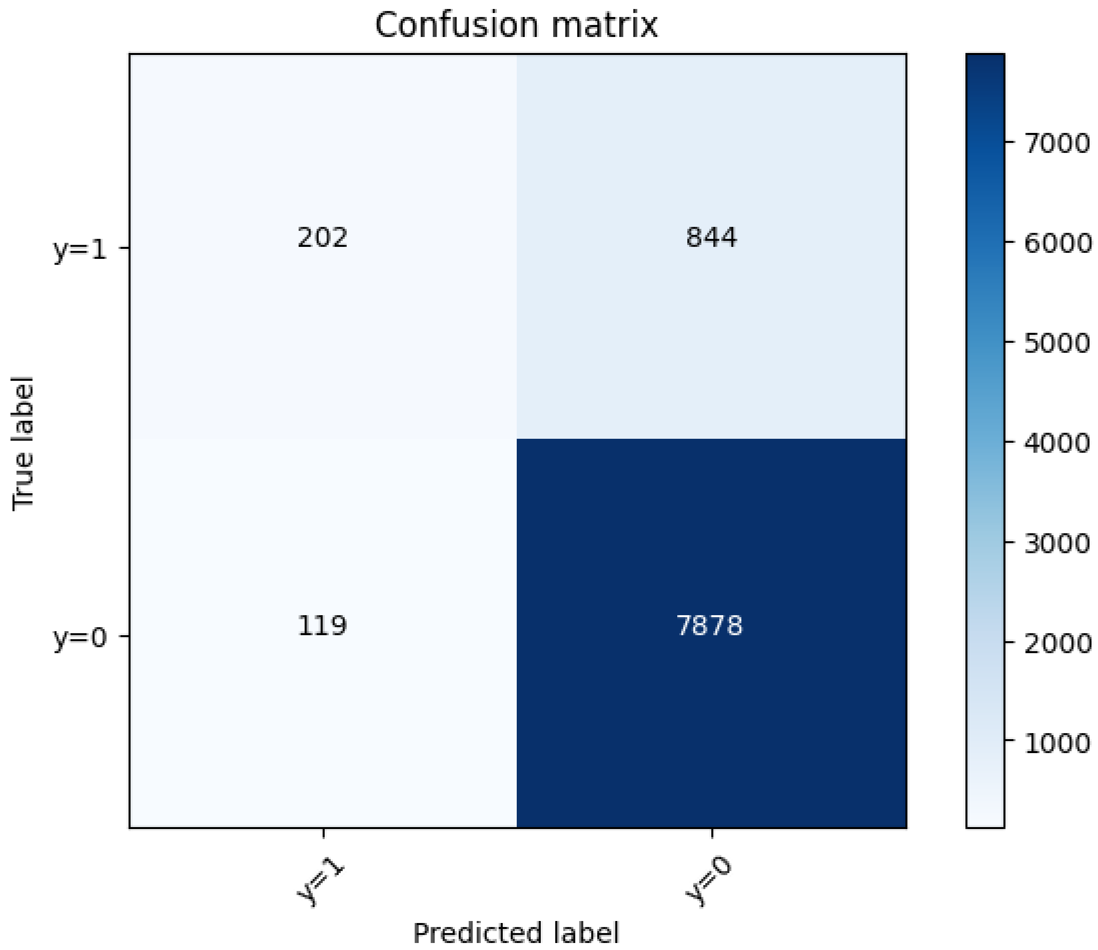
```
yyyhat_prob = LR.predict_proba(xxx_test)
jaccard_score(yyy_test, yyyhat,pos_label=0)
```

Out[ ]:
```
0.8910756701730573
```

In [ ]:
```
cnf_matrix = confusion_matrix(yyy_test, yyyhat, labels=[1,0])
np.set_printoptions(precision=2)


# Plot non-normalized confusion matrix
plt.figure()
plot_confusion_matrix(cnf_matrix, classes=['y=1','y=0'],normalize= False,  title='Confusion matrix')
```

```
Confusion matrix, without normalization
[[ 202  844]
 [ 119 7878]]
```



In [ ]:
```
df_LR_new.corr()
```

```
              precision    recall  f1-score   support

           0       0.90      0.99      0.94      7997
           1       0.63      0.19      0.30      1046

    accuracy                           0.89      9043
   macro avg       0.77      0.59      0.62      9043
weighted avg       0.87      0.89      0.87      9043
```