ation-of-termdeposit-bank-customer

September 12, 2023

0.1 MACHINE LEARNING SUPERVISED CLASSIFICATION

0.1.1 About the data set (Bank Client Data)

Bank client data: **age:** Age of the client **duration:** last contact duration, in seconds.

Other attributes: **campaign:** number of contacts performed during this campaign and for this client **pdays:** number of days that passed by after the client was last contacted from a previous campaign (999 means client was not previously contacted) **previous:** number of contacts performed before this campaign and for this client

Social and economic context **emp.var.rate:** employment variation rate - quarterly indicator **cons.price.idx:** consumer price index - monthly indicator **cons.conf.idx:** consumer confidence index - monthly indicator **euribor3m:** euribor 3 month rate - daily indicator **nr.employed:** number of employees - quarterly indicator

y - (Output variable) has the client subscribed a term deposit?

0.2 Task

To classify whether the client will subscribe for the term deposit or not based on the dependent variable like campaign, pdays, previous and the social & economic context by using 6 different models and find the optimal model

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4. Random Forest Model
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9. Intrepret your solution based on the results

1. Data Pre-Processing

Import the required libraries

[96]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn import preprocessing
from sklearn.preprocessing import StandardScaler
from warnings import filterwarnings
from sklearn.model_selection import train_test_split
import statsmodels
import statsmodels.api as sm
filterwarnings('ignore')



# import various functions from sklearn
from sklearn import metrics
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import classification_report
from sklearn.metrics import cohen_kappa_score
from sklearn.metrics import confusion_matrix
from sklearn.metrics import roc_curve
from sklearn.metrics import accuracy_score



from sklearn import linear_model, datasets, tree
import pydotplus
from IPython.display import Image


import pylab as pl
```

Load the csv file

[2]:
```
df_bank = pd.read_csv("bank.csv")
df_bank.head(2)
```

[2]:
```
   age  duration  campaign  pdays  previous  emp.var.rate  cons.price.idx  \
0   32       205         2    999         0           1.1          93.994
1   32       691        10    999         0           1.4          93.918

   cons.conf.idx  euribor3m  nr.employed    y
0          -36.4      4.858       5191.0   no
1          -42.7      4.960       5228.1  yes
```

[3]:
```
df_bank.shape
```

[3]: (9640, 11)

[4]:
```
df_bank.keys()
```

[4]:
```
Index(['age', 'duration', 'campaign', 'pdays', 'previous', 'emp.var.rate',
       'cons.price.idx', 'cons.conf.idx', 'euribor3m', 'nr.employed', 'y'],
      dtype='object')
```

[5]:
```
df_bank.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9640 entries, 0 to 9639
Data columns (total 11 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   age             9640 non-null   int64
 1   duration        9640 non-null   int64
 2   campaign        9640 non-null   int64
 3   pdays           9640 non-null   int64
 4   previous        9640 non-null   int64
 5   emp.var.rate    9640 non-null   float64
 6   cons.price.idx  9640 non-null   float64
 7   cons.conf.idx   9640 non-null   float64
 8   euribor3m       9640 non-null   float64
 9   nr.employed     9640 non-null   float64
 10  y               9640 non-null   object
dtypes: float64(5), int64(5), object(1)
memory usage: 828.6+ KB
```

[ ]:
```

```

[6]:
```
df_bank.describe()
```

[6]:
```
               age     duration     campaign        pdays     previous  \
count  9640.000000  9640.000000  9640.000000  9640.000000  9640.000000
mean     40.286618   379.564004     2.349170   893.100519     0.306120
std      11.901274   354.768370     2.384519   306.531615     0.684605
min      17.000000     0.000000     1.000000     0.000000     0.000000
25%      31.000000   141.000000     1.000000   999.000000     0.000000
50%      38.000000   260.000000     2.000000   999.000000     0.000000
75%      48.000000   512.000000     3.000000   999.000000     0.000000
max      98.000000  4199.000000    42.000000   999.000000     6.000000

       emp.var.rate  cons.price.idx  cons.conf.idx    euribor3m  nr.employed
count   9640.000000     9640.000000    9640.000000  9640.000000  9640.000000
mean      -0.460218       93.485750     -40.265373     3.003616  5137.407147
std        1.717852        0.631366       5.322795     1.886179    86.347481
```

```
min     -3.400000       92.201000      -50.800000      0.634000  4963.600000
25%     -1.800000       92.893000      -42.700000      1.250000  5076.200000
50%     -0.100000       93.444000      -41.800000      4.076000  5191.000000
75%      1.400000       93.994000      -36.400000      4.959000  5228.100000
max      1.400000       94.767000      -26.900000      5.045000  5228.100000
```

[7]:

```
df_bank.dtypes
```

[7]:

```
age                 int64
duration            int64
campaign            int64
pdays               int64
previous            int64
emp.var.rate      float64
cons.price.idx    float64
cons.conf.idx     float64
euribor3m         float64
nr.employed       float64
y                  object
dtype: object
```

We can see in the above output that each variable are given with the correct datatypes. so datatype parsing is not needed here

[8]:

```
# sort the variables on the basis of total null values in the variable
# 'isnull().sum()' returns the number of missing values in each variable
# 'ascending = False' sorts values in the descending order
# the variable with highest number of missing values will appear first


missing_total = df_bank.isnull().sum()
print(missing_total)
```

```
age               0
duration          0
campaign          0
pdays             0
previous          0
emp.var.rate      0
cons.price.idx    0
cons.conf.idx     0
euribor3m         0
nr.employed       0
y                 0
dtype: int64
```

As we see there is no missing values in or dataset

[9]:
```
# Here, There is no need calculating the missing percentage since there is no␣
↪missing values persent in dataset

# If needed we can use the below command to calculate the missing percentage

missing_percent = (df_bank.isnull().sum()*100/df_bank.isnull().count())
print(missing_percent)
```

```
age               0.0
duration          0.0
campaign          0.0
pdays             0.0
previous          0.0
emp.var.rate      0.0
cons.price.idx    0.0
cons.conf.idx     0.0
euribor3m         0.0
nr.employed       0.0
y                 0.0
dtype: float64
```

[10]:
```
# To show in the single table we can concat both and save in new varibale as␣
↪below

bank_missing_data = pd.concat([missing_total, missing_percent], axis=1, keys =␣
↪['Total', 'Percentage'])
print(bank_missing_data)
```

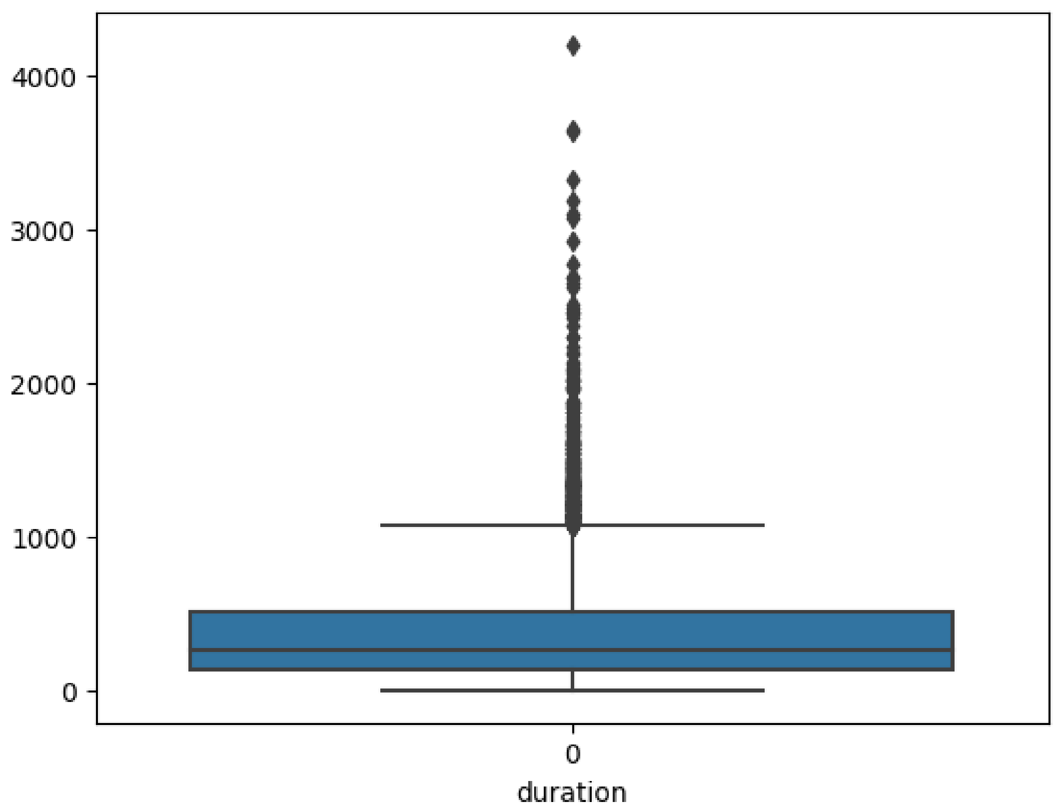
```
                Total  Percentage
age                 0         0.0
duration            0         0.0
campaign            0         0.0
pdays               0         0.0
previous            0         0.0
emp.var.rate        0         0.0
cons.price.idx      0         0.0
cons.conf.idx       0         0.0
euribor3m           0         0.0
nr.employed         0         0.0
y                   0         0.0
```

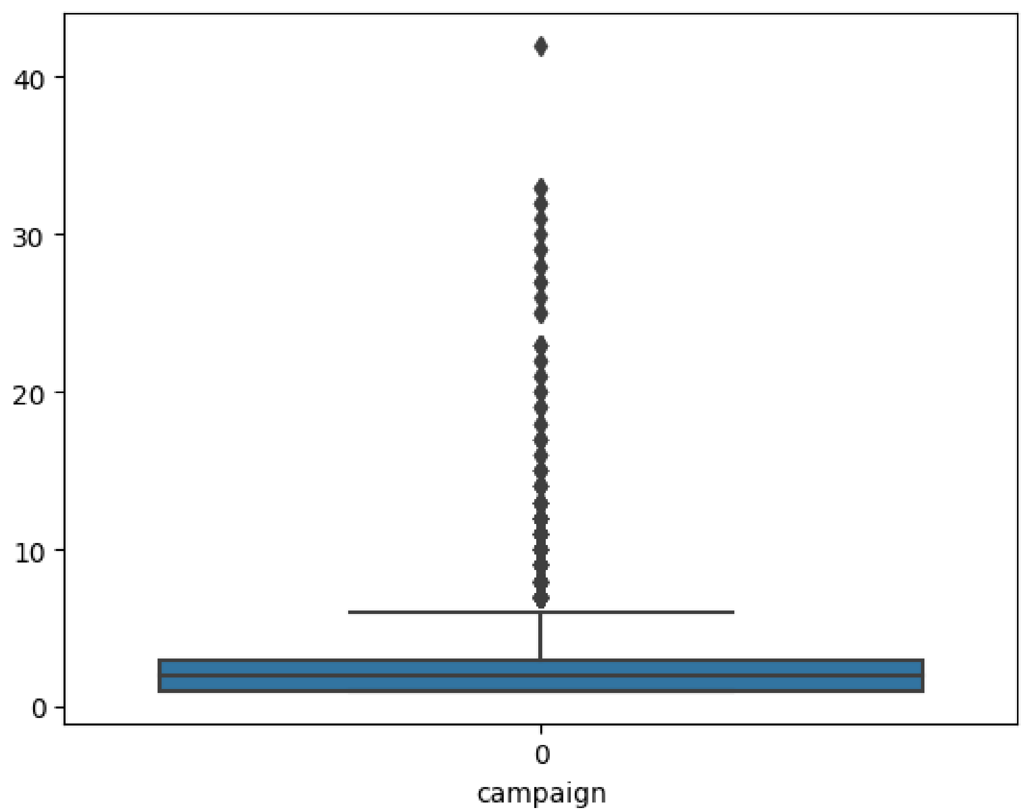
[11]:
```
df_bank.describe()
```

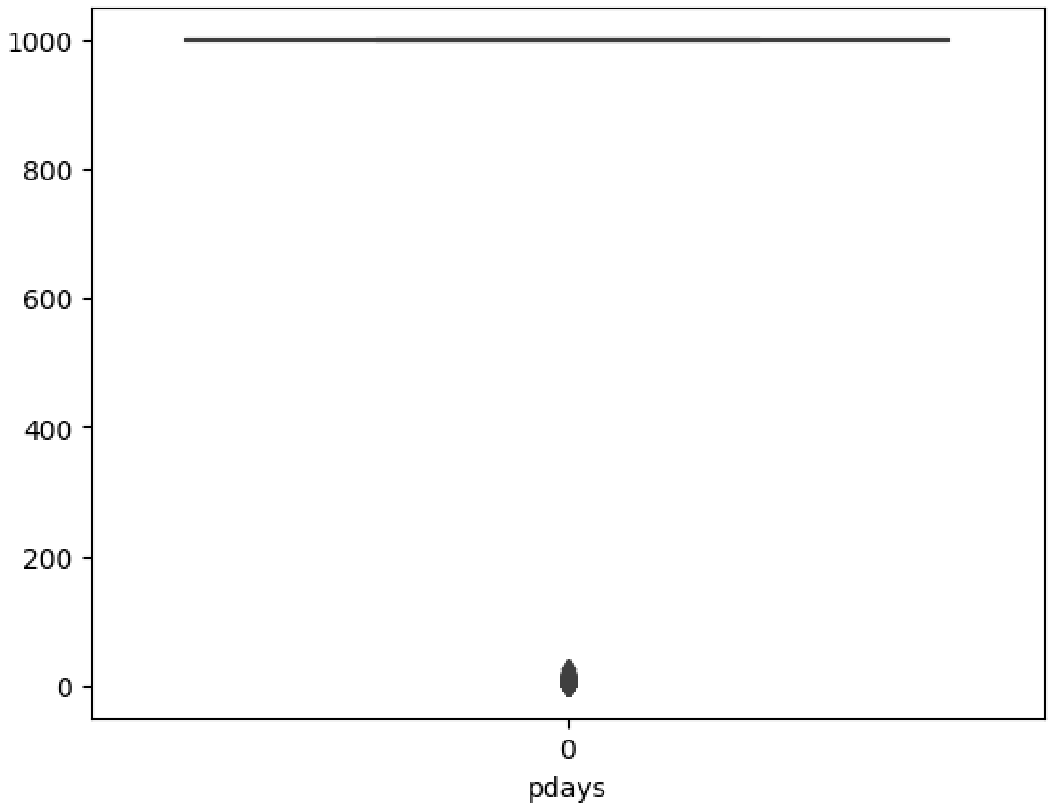
[11]:
```
               age     duration     campaign        pdays     previous  \
count  9640.000000  9640.000000  9640.000000  9640.000000  9640.000000
mean     40.286618   379.564004     2.349170   893.100519     0.306120
std      11.901274   354.768370     2.384519   306.531615     0.684605
```

```
min      17.000000     0.000000     1.000000     0.000000     0.000000
25%      31.000000   141.000000     1.000000   999.000000     0.000000
50%      38.000000   260.000000     2.000000   999.000000     0.000000
75%      48.000000   512.000000     3.000000   999.000000     0.000000
max      98.000000  4199.000000    42.000000   999.000000     6.000000

       emp.var.rate  cons.price.idx  cons.conf.idx    euribor3m  nr.employed
count   9640.000000     9640.000000    9640.000000  9640.000000  9640.000000
mean      -0.460218       93.485750     -40.265373     3.003616  5137.407147
std        1.717852        0.631366       5.322795     1.886179    86.347481
min       -3.400000       92.201000     -50.800000     0.634000  4963.600000
25%       -1.800000       92.893000     -42.700000     1.250000  5076.200000
50%       -0.100000       93.444000     -41.800000     4.076000  5191.000000
75%        1.400000       93.994000     -36.400000     4.959000  5228.100000
max        1.400000       94.767000     -26.900000     5.045000  5228.100000
```

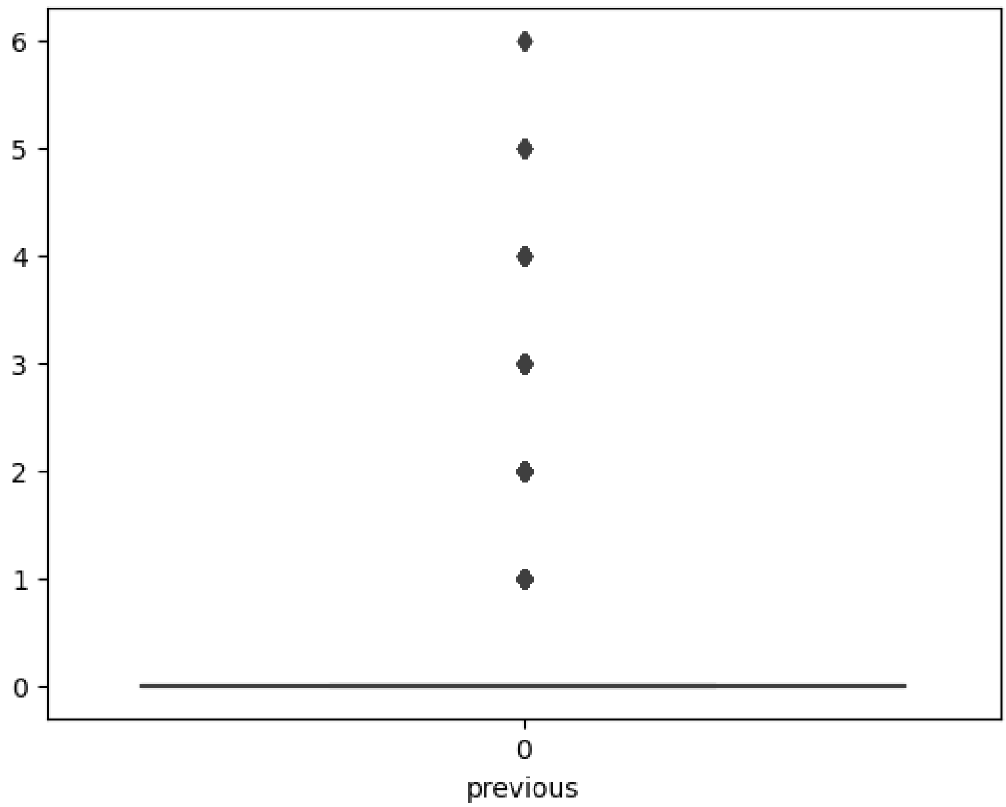
[12]:
```
for column in df_bank.columns:
    if column == "age" or column == "y":
        continue
    else:
        sns.boxplot(data=df_bank[column])
        plt.xlabel(column)
        plt.show()
```

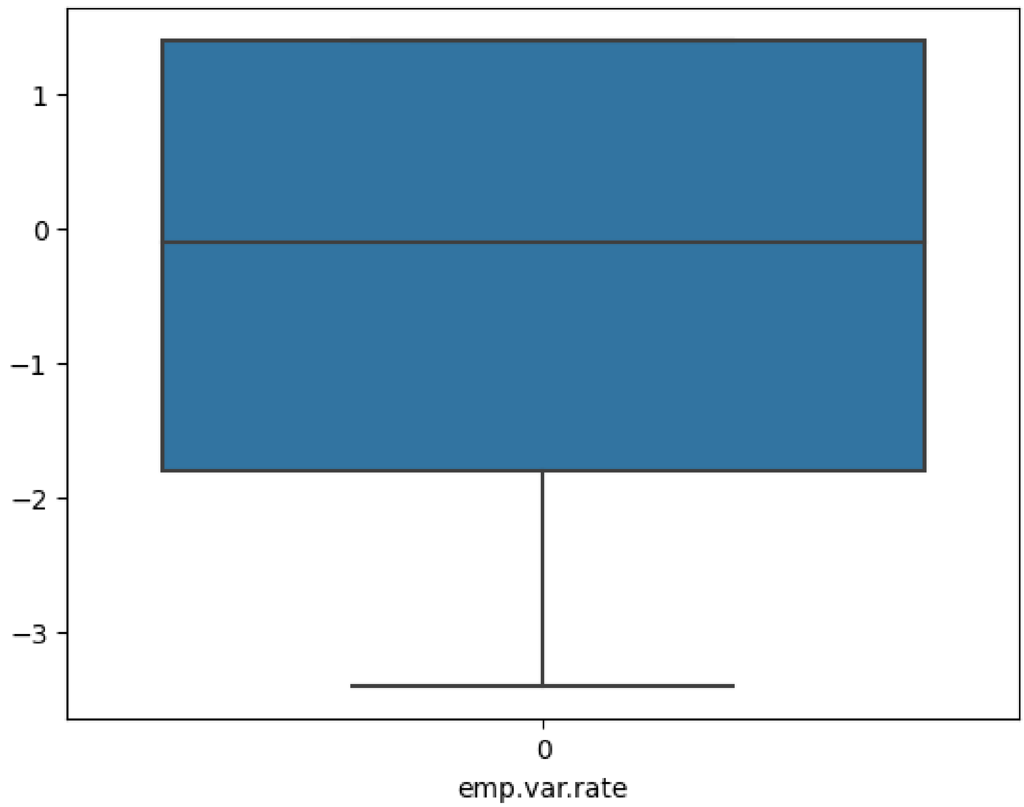


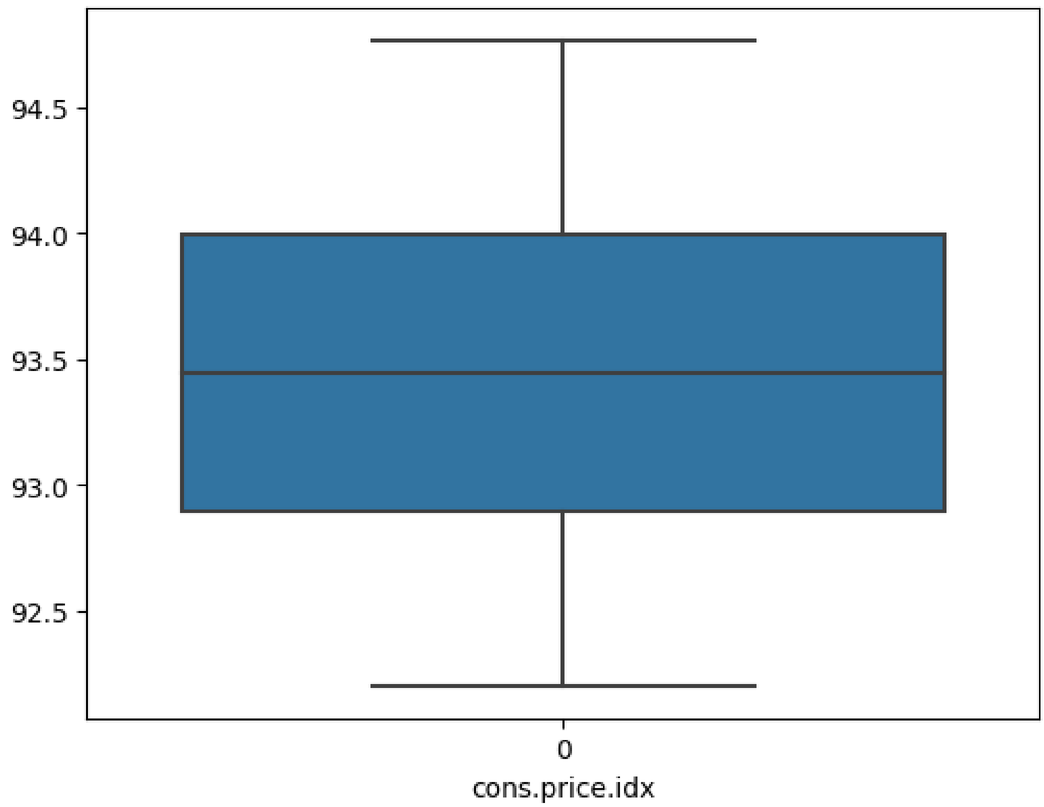

40
30
20
10
0
0
campaign

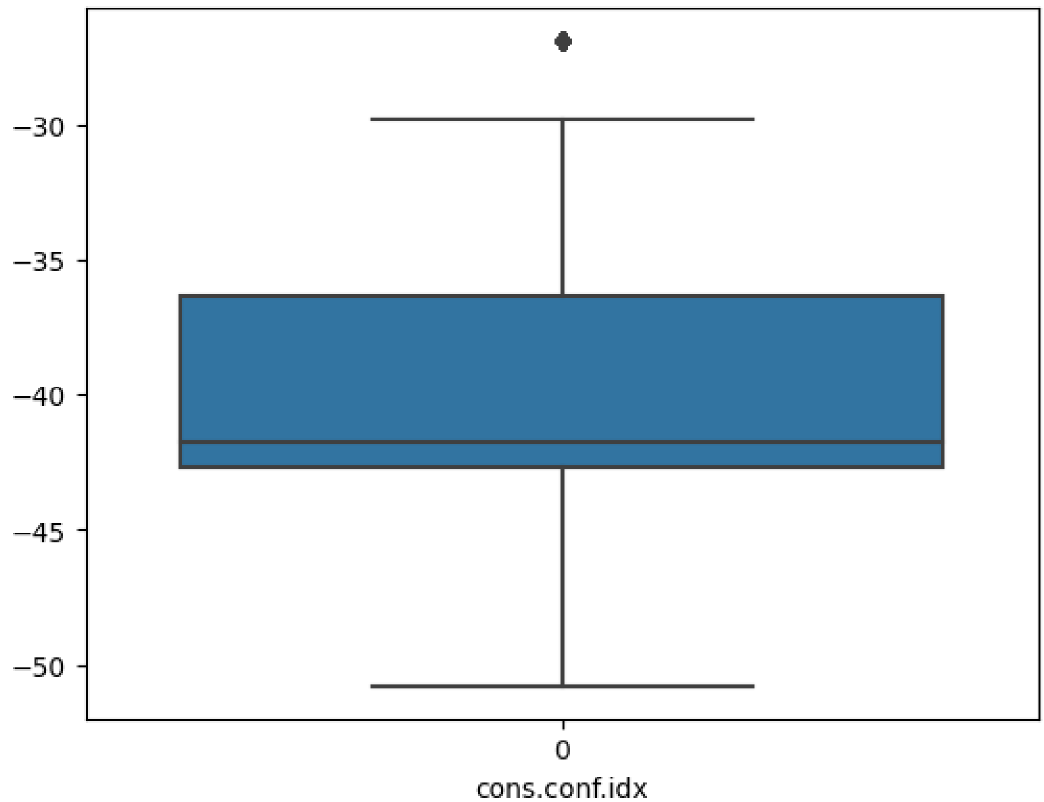


1000
800
600
400
200
0
0
pdays

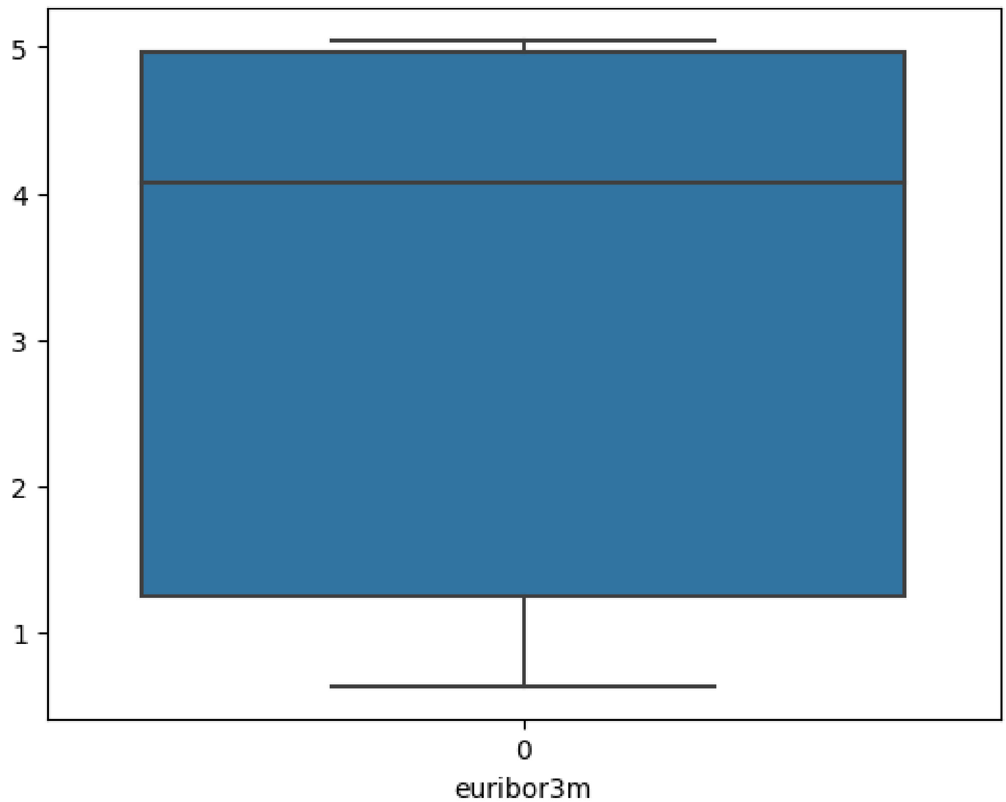

6
5
4
3
2
1
0
0
previous

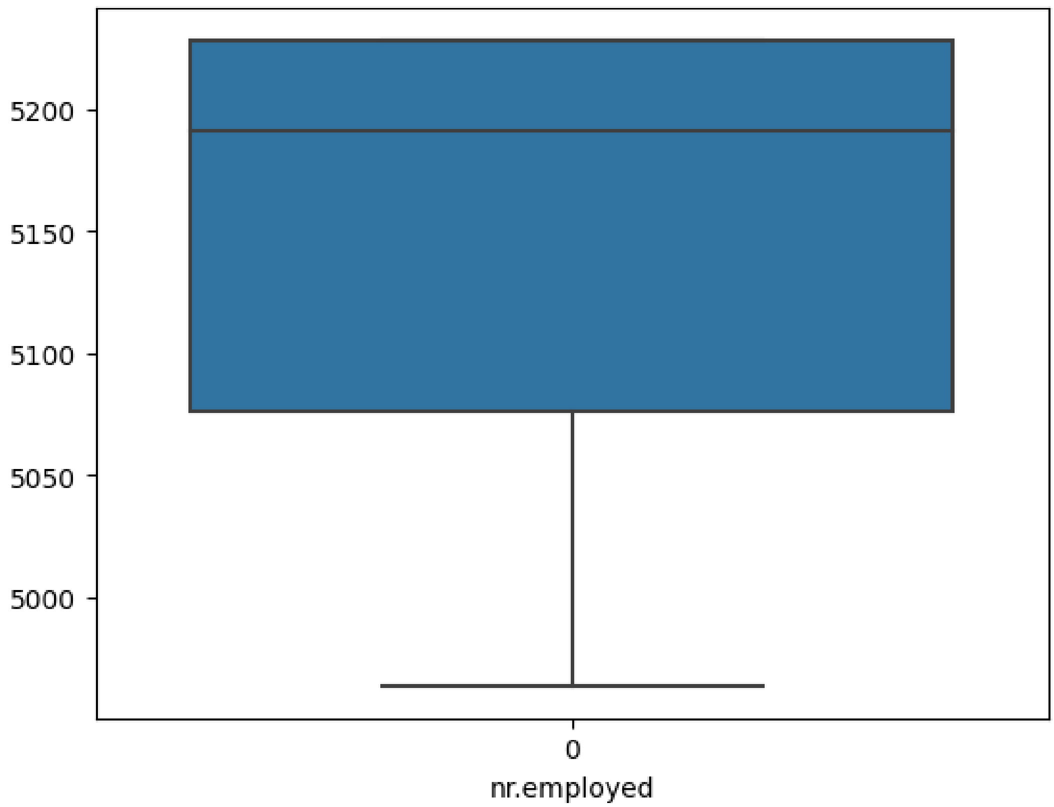

1
0
−1
−2
−3
0
emp.var.rate


94.5
94.0
93.5
93.0
92.5
0
cons.price.idx



−30
−35
−40
−45
−50
0
cons.conf.idx


5
4
3
2
1
0
euribor3m



From the above plot we can come to know that "duration", "campaign" have more outliers when compared to other dependent variables

[13]:
```
#Detecing outlier with IQR

for columns in df_bank.columns:
    if columns == "y" or columns == "age" :
        continue
        print("Yes")

    else:
        outliers = []
        q1 = np.percentile(df_bank[columns], 25)
        q3 = np.percentile(df_bank[columns], 75)
        IQR = q3 - q1
        lwr_bound = q1-(1.5*IQR)
        upr_bound = q3 + (1.5*IQR)

        for i in df_bank[columns]:
            if (i<lwr_bound or i> upr_bound):
                outliers.append(i)
```

```
        print("There are ", len(outliers), "outliers in the variable", columns )
```

```
There are  503 outliers in the variable duration
There are  426 outliers in the variable campaign
There are  1028 outliers in the variable pdays
There are  2088 outliers in the variable previous
There are  0 outliers in the variable emp.var.rate
There are  0 outliers in the variable cons.price.idx
There are  215 outliers in the variable cons.conf.idx
There are  0 outliers in the variable euribor3m
There are  0 outliers in the variable nr.employed
```

[14]:
```
#Replacing outlier with lower bound and upper bound values

for columns in df_bank.columns:
    if columns == "y" or columns == "age" :
        continue

    else:
        outliers = []
        median_df = df_bank[columns].median()
        q1 = np.percentile(df_bank[columns], 25)
        q3 = np.percentile(df_bank[columns], 75)
        IQR = q3 - q1
        lwr_bound = q1-(1.5*IQR)
        upr_bound = q3 + (1.5*IQR)

        for row_n, i in enumerate(df_bank[columns]):
            if (i<lwr_bound):
                df_bank.at[row_n, columns] = lwr_bound

            elif (i> upr_bound):
                df_bank.at[row_n, columns] = upr_bound
```

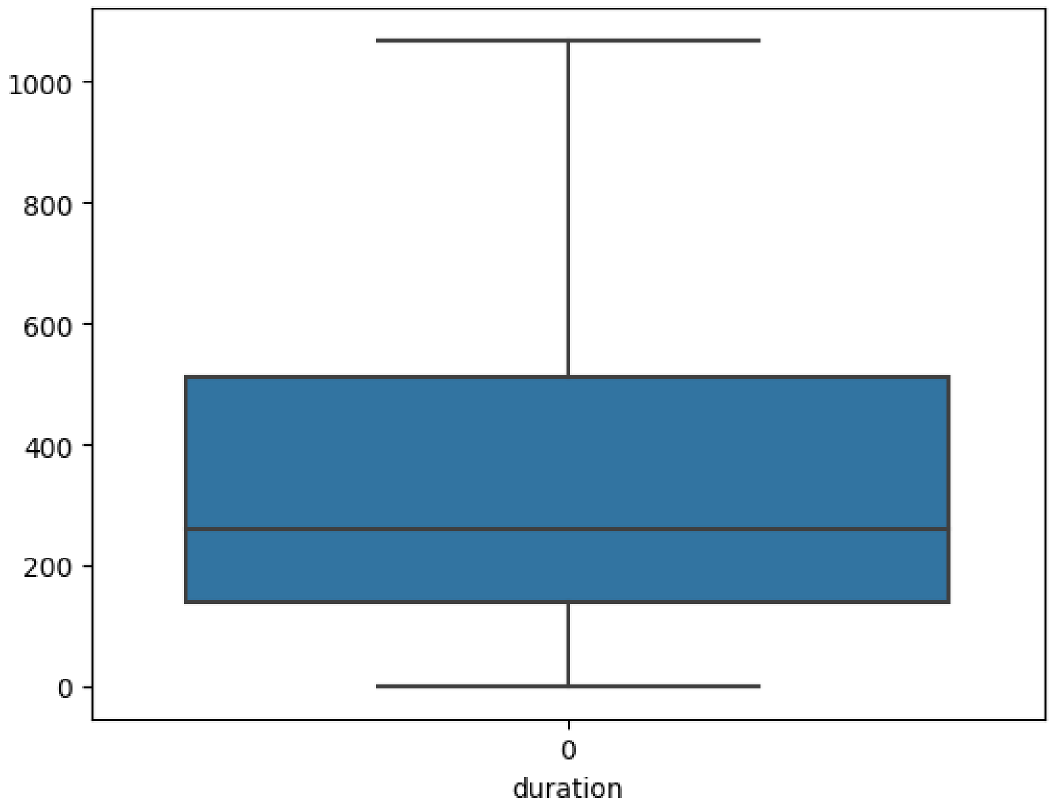
[15]:
```
#Again detecing outlier with IQR

for columns in df_bank.columns:
    if columns == "y" or columns == "age" :
        continue
        print("Yes")

    else:
        outliers = []
        q1 = np.percentile(df_bank[columns], 25)
        q3 = np.percentile(df_bank[columns], 75)
        IQR = q3 - q1
        lwr_bound = q1-(1.5*IQR)
```

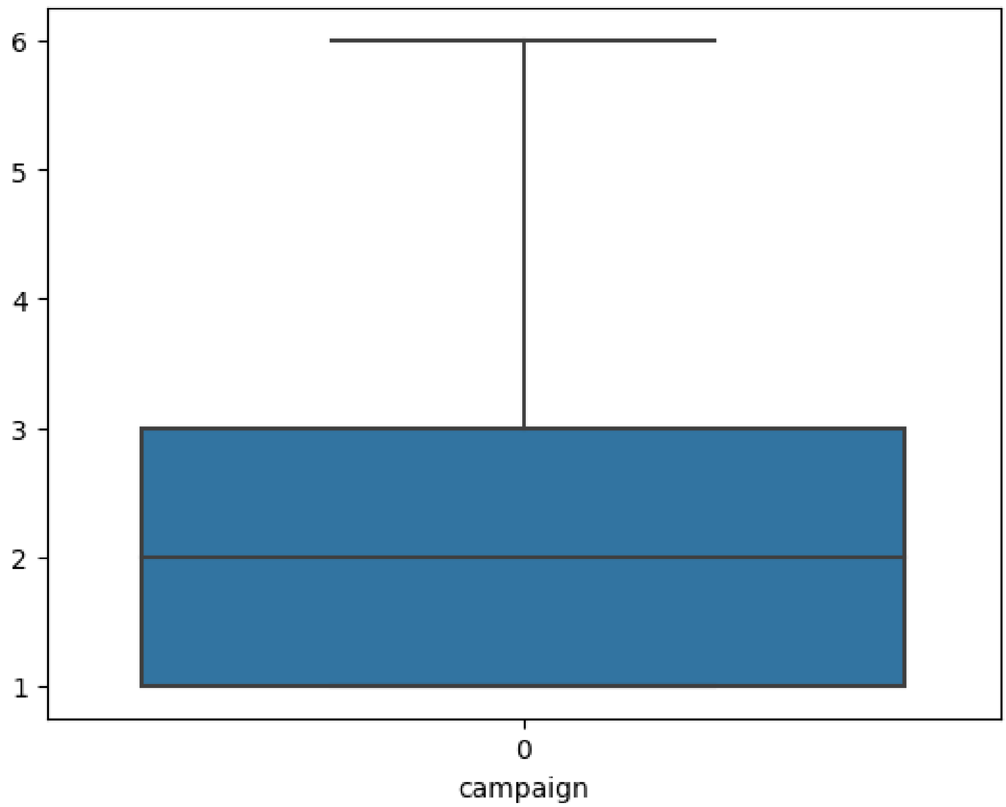
```
        upr_bound = q3 + (1.5*IQR)

        for i in df_bank[columns]:
            if (i<lwr_bound or i> upr_bound):
                outliers.append(i)
        print("There are ", len(outliers), "outliers in the variable", columns )
```

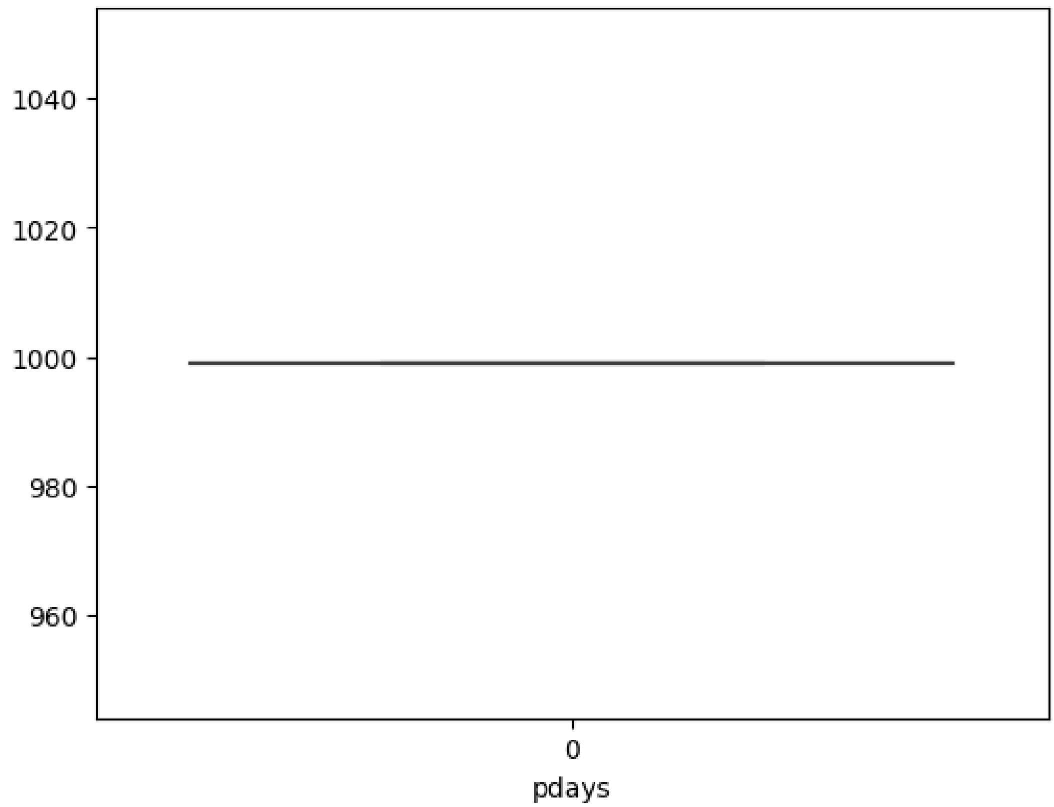
```
There are  0 outliers in the variable duration
There are  0 outliers in the variable campaign
There are  0 outliers in the variable pdays
There are  0 outliers in the variable previous
There are  0 outliers in the variable emp.var.rate
There are  0 outliers in the variable cons.price.idx
There are  0 outliers in the variable cons.conf.idx
There are  0 outliers in the variable euribor3m
There are  0 outliers in the variable nr.employed
```

[16]:

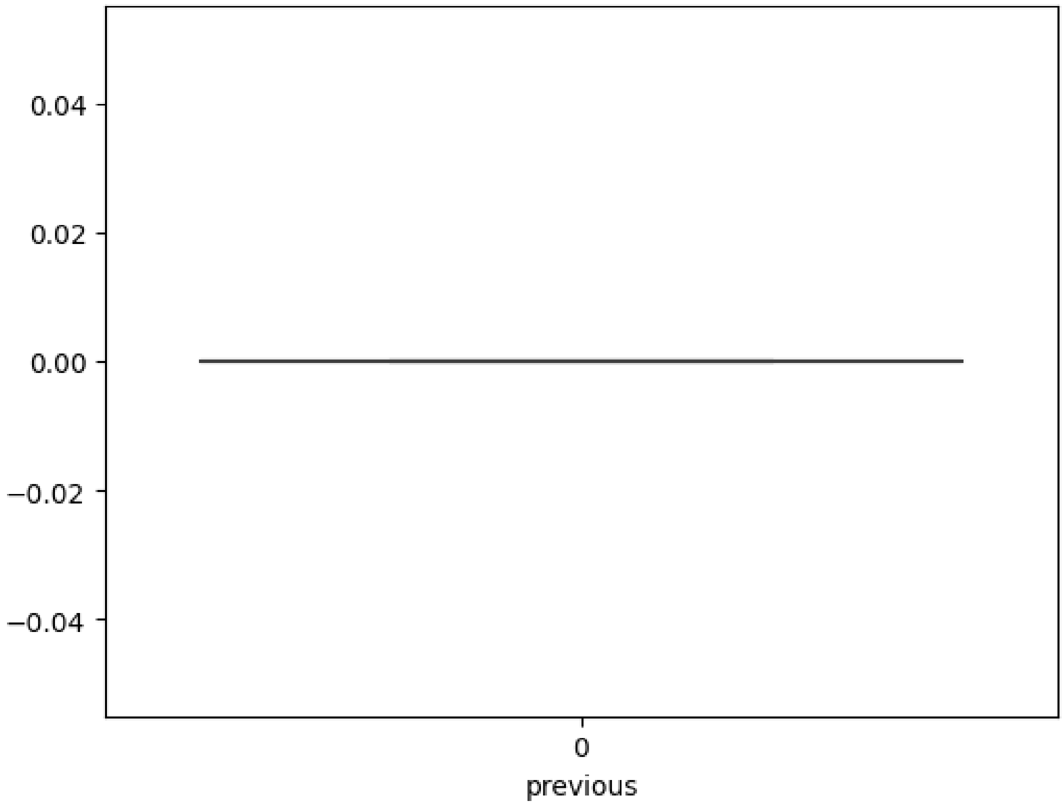
```
# plotting the box chart to check the outliers again

for column in df_bank.columns:
    if column == "age" or column == "y":
        continue
    else:
        sns.boxplot(data=df_bank[column])
        plt.xlabel(column)
        plt.show()

# df_bank[['duration','campaign','pdays','previous', 'emp.var.rate','cons.price.
↪idx', 'cons.conf.idx',  'euribor3m', 'nr.employed' ]].boxplot()
```

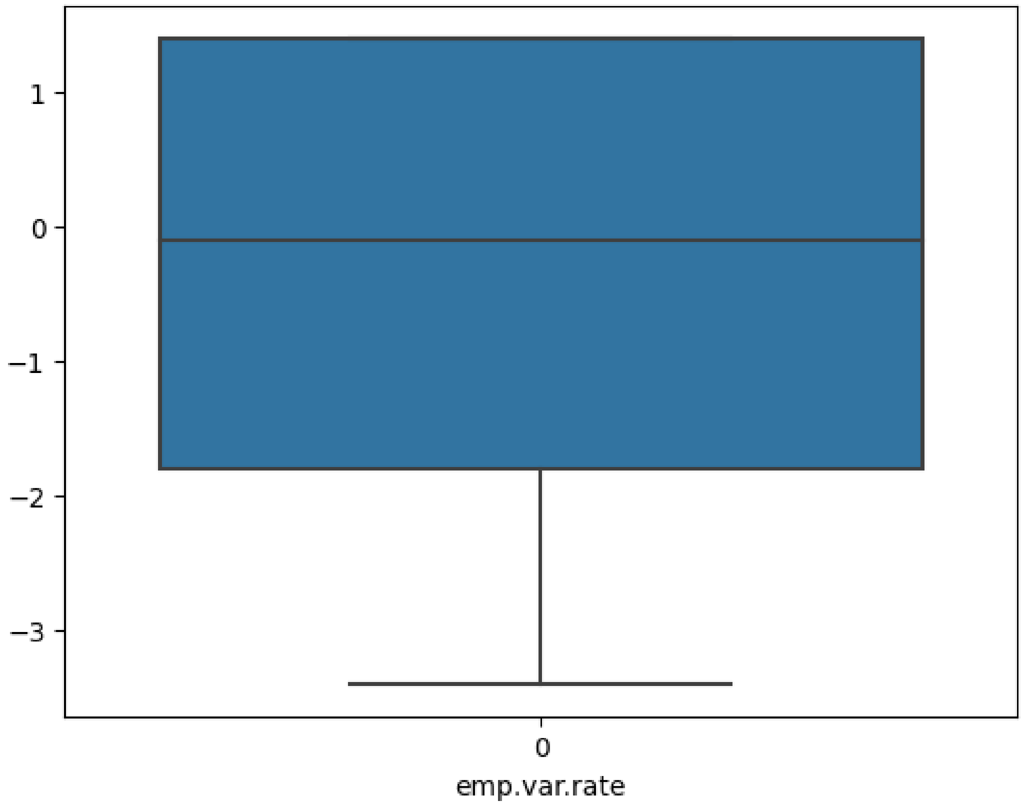

1000
800
600
400
200
0
0
duration

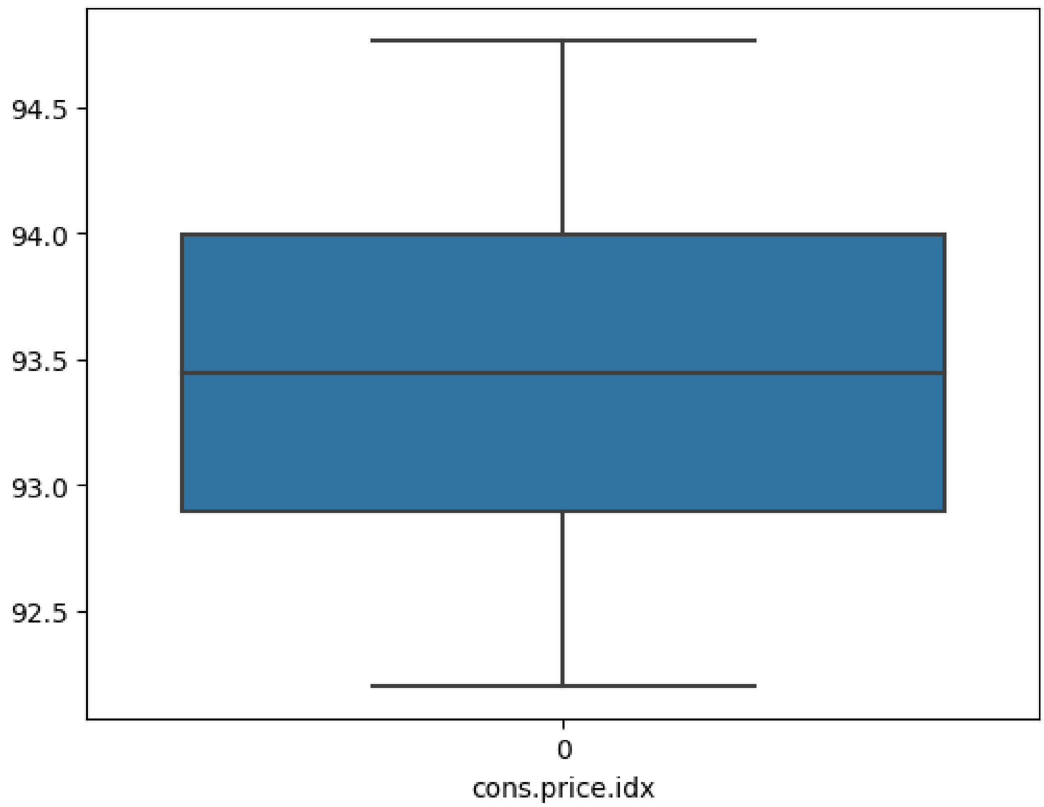

6
5
4
3
2
1
0
campaign

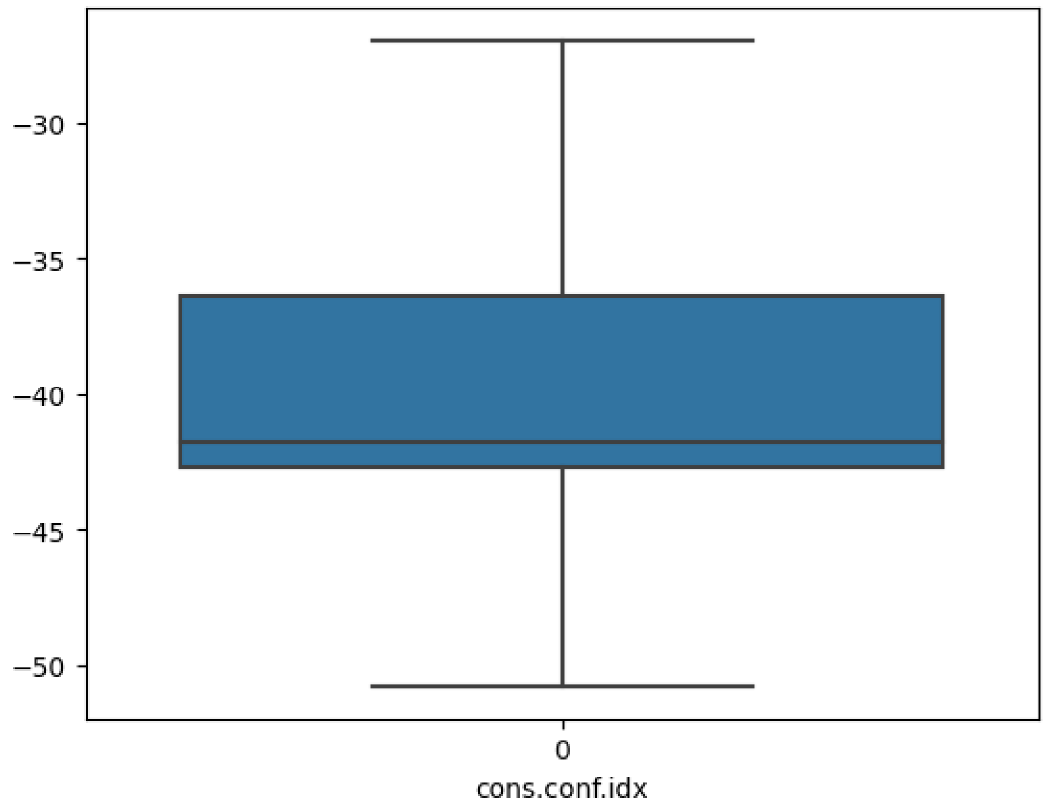


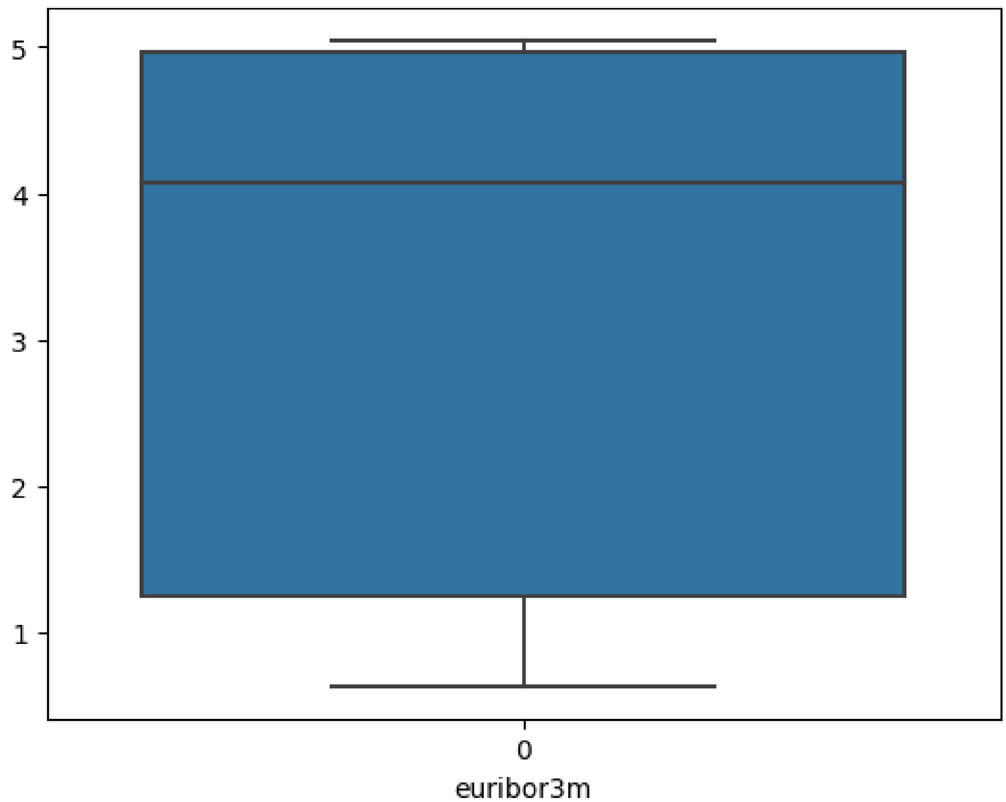
1040
1020
1000
980
960
0
pdays

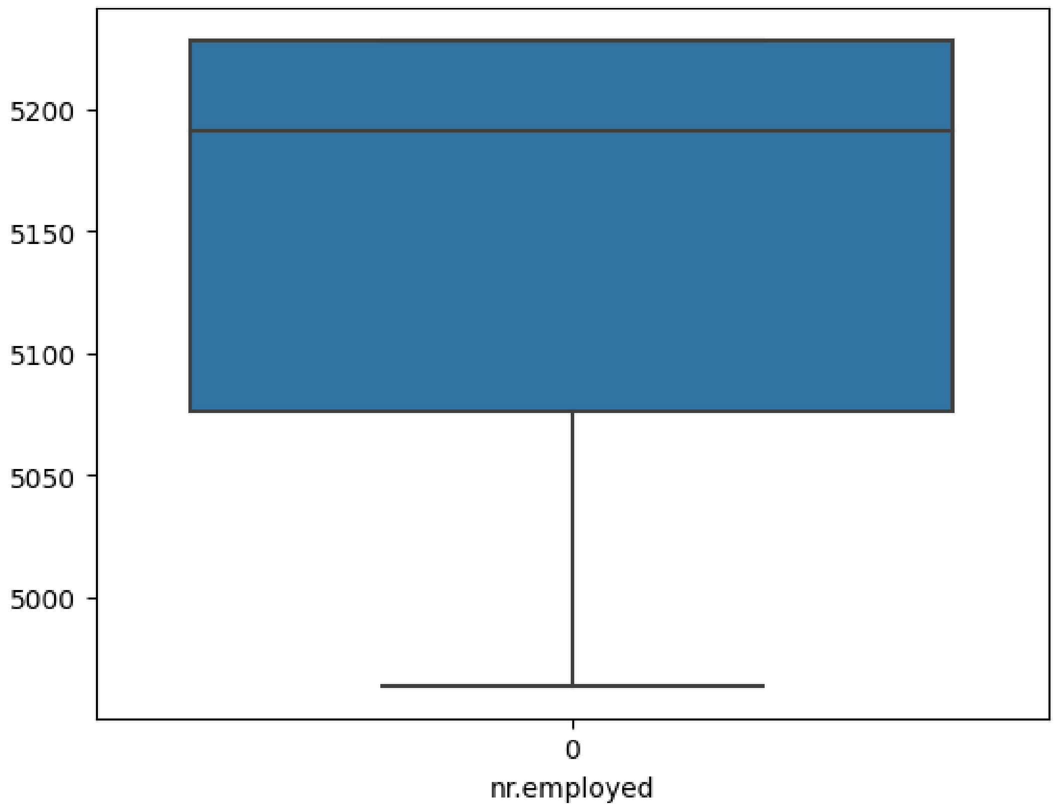

0.04
0.02
0.00
−0.02
−0.04
0
previous


1
0
−1
−2
−3
0
emp.var.rate


94.5
94.0
93.5
93.0
92.5
0
cons.price.idx


−30
−35
−40
−45
−50
0
cons.conf.idx


5
4
3
2
1
0
euribor3m



Here we ave replaced the outliers with lower and upper value, Here there is no outlier in the above box plot.

Separating the independent and dependent can be done before the train-test split, so we can encode the target variable for now

[17]:
```
df_bank.y.head(2)
```

[17]:
```
0     no
1    yes
Name: y, dtype: object
```

[18]:
```
df_bank['y']= df_bank.y.replace("yes", 0)
df_bank['y']= df_bank.y.replace("no", 1)
```

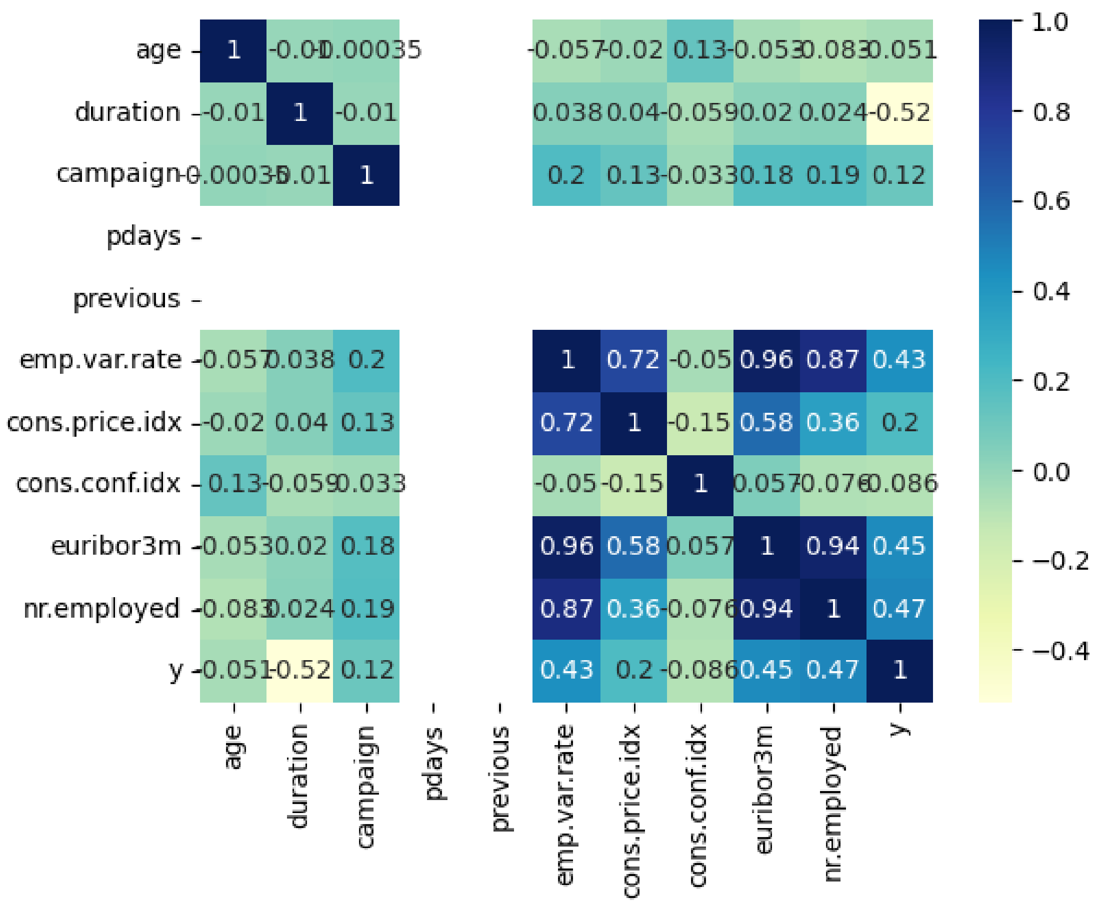
[19]:
```
df_bank.head(2)
```

[19]:
```
   age  duration  campaign  pdays  previous  emp.var.rate  cons.price.idx  \
0   32     205.0         2    999         0           1.1          93.994
1   32     691.0         6    999         0           1.4          93.918
```

```
   cons.conf.idx  euribor3m  nr.employed  y
0           -36.4      4.858       5191.0  1
1           -42.7      4.960       5228.1  0
```

We have replaced the yes and no as 'o' and '1' and separated the independent and dependent variable

[20]:
```python
# Heat map visualization

sns.heatmap(df_bank.corr(), cmap="YlGnBu", annot=True)
plt.show()
```



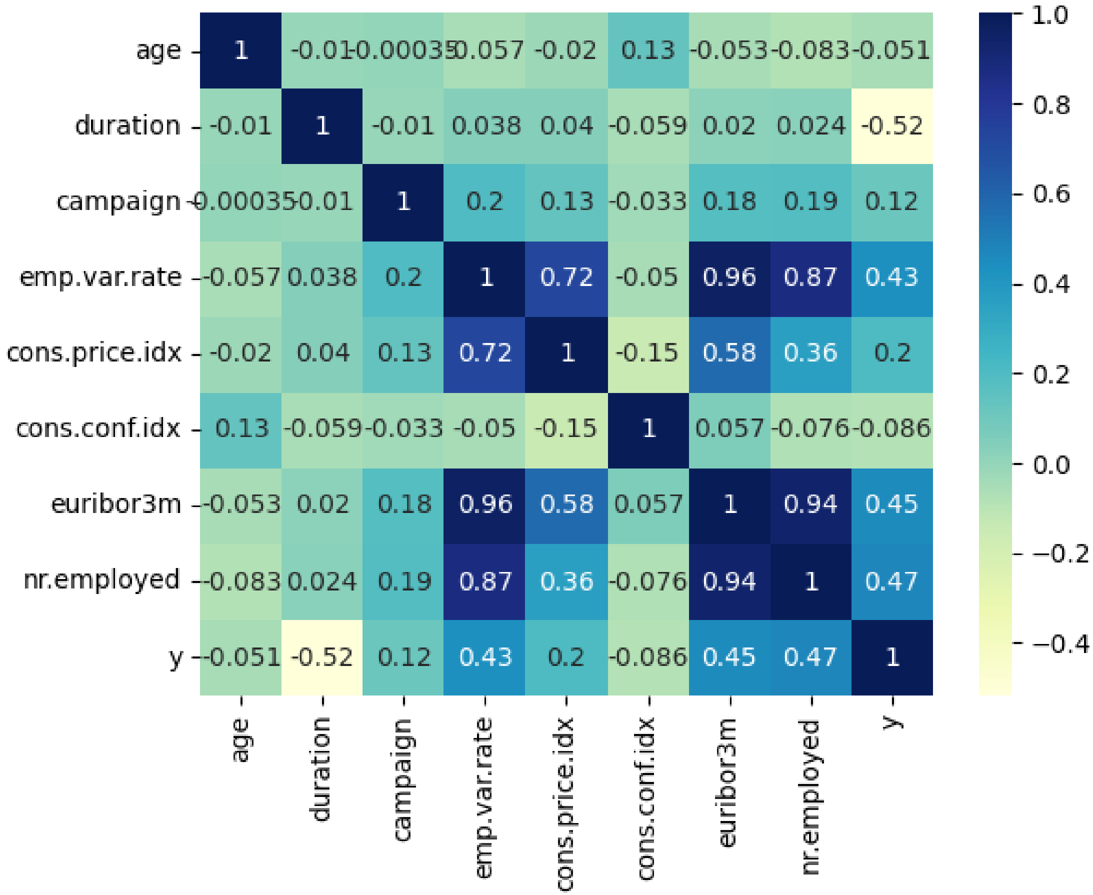
As per the above heat map pdays, previous have no correlation with the target variable which means there is no necessity between this two variable and the target variable

[21]:
```python
# Removing pdays and previous

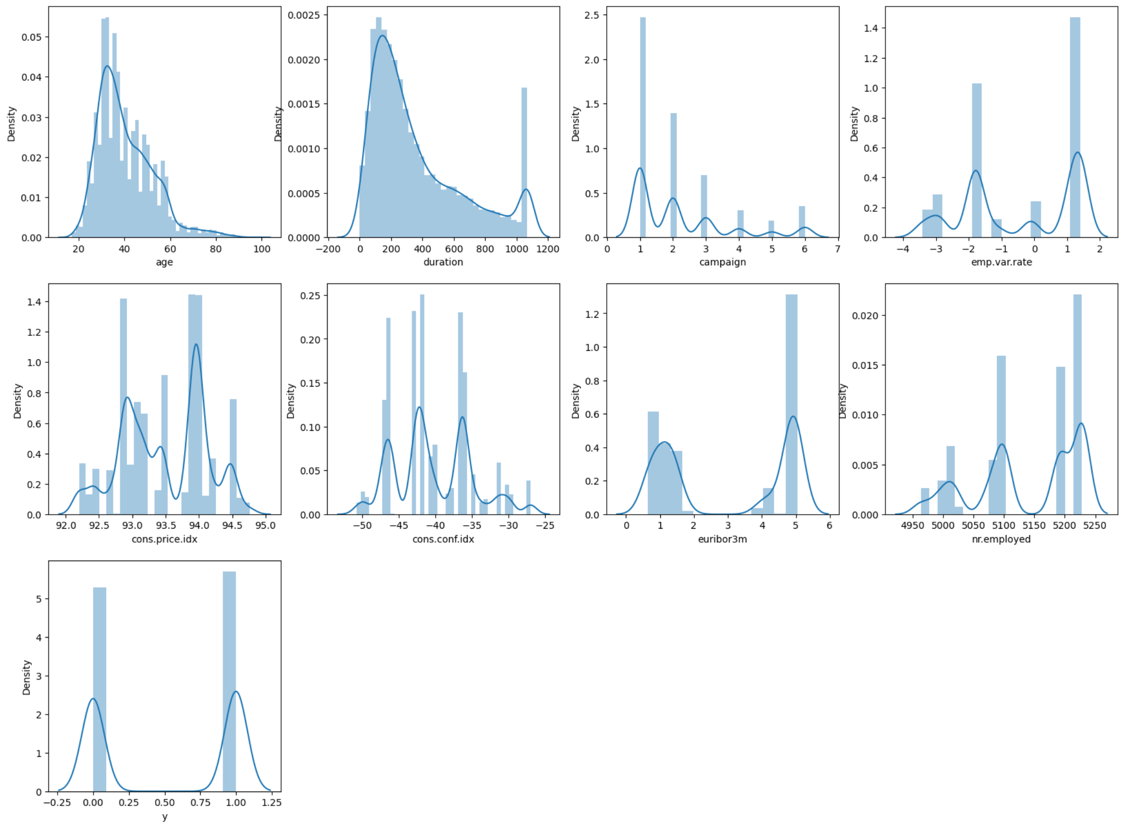
df_bank = df_bank.drop(['pdays', 'previous'], axis=1)
```

[22]:
```
# Heat map visualization

sns.heatmap(df_bank.corr(), cmap="YlGnBu", annot=True)
plt.show()
```



[23]:
```
plt.figure(figsize=(20,20))
i=1
for column in df_bank.columns:
    plt.subplot(4,4,i)
    sns.distplot(df_bank[column])
    i = i+1
```

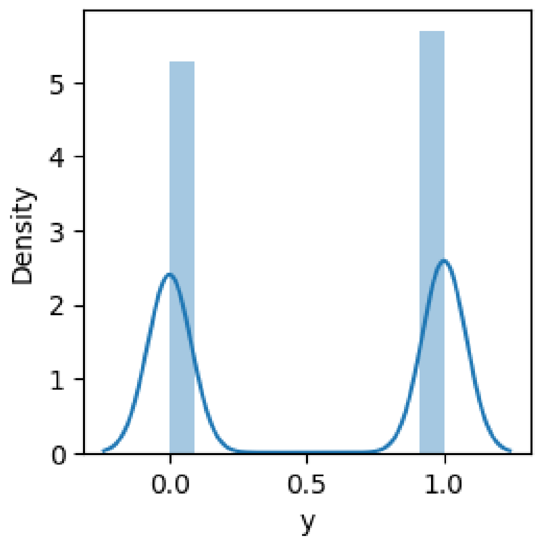


[24]:
```
df_bank.skew()
```

[24]:
```
age               0.990535
duration          1.089882
campaign          1.356104
emp.var.rate     -0.181234
cons.price.idx   -0.125216
cons.conf.idx     0.347668
euribor3m        -0.058332
nr.employed      -0.463581
y                -0.074753
dtype: float64
```

[25]:
```
plt.figure(figsize=(3,3))
sns.distplot(df_bank['y'])
```

[25]:
```
<AxesSubplot: xlabel='y', ylabel='Density'>
```



[ ]:

[ ]:

[ ]:

1.0.1 Data Separation

[26]:
```
independent_feature =['age','duration','campaign', 'emp.var.rate','cons.price.
↪idx', 'cons.conf.idx',  'euribor3m', 'nr.employed']
dependent_feature = ["y"]
df_feature = df_bank[independent_feature]
df_target = df_bank[dependent_feature]
X = df_feature
Y = df_target
```

[27]:
```
X.head(7)
```

[27]:
```
   age  duration  campaign  emp.var.rate  cons.price.idx  cons.conf.idx  \
0   32     205.0         2           1.1          93.994          -36.4
1   32     691.0         6           1.4          93.918          -42.7
2   45      45.0         6           1.4          93.444          -36.1
3   33     400.0         1          -1.1          94.601          -49.5
4   47     903.0         2          -1.8          93.075          -47.1
5   25     243.0         3          -1.8          92.843          -50.0
6   36     214.0         1          -0.1          93.200          -42.0

   euribor3m  nr.employed
```

```
0      4.858       5191.0
1      4.960       5228.1
2      4.963       5228.1
3      1.032       4963.6
4      1.415       5099.1
5      1.531       5099.1
6      4.120       5195.8
```

[28]:
```
Y.head(7)
```

[28]:
```
   y
0  1
1  0
2  1
3  0
4  0
5  0
6  1
```

[29]:
```
std_scalar = StandardScaler()
scaled_var = std_scalar.fit_transform(X)
df_bank_scaled = pd.DataFrame(scaled_var, columns = independent_feature)
```

[30]:
```
df_bank_scaled.head(6)
```

[30]:
```
        age  duration  campaign  emp.var.rate  cons.price.idx  cons.conf.idx  \
0 -0.696316 -0.535724 -0.103273      0.908285        0.805042       0.726821
1 -0.696316  1.132922  2.626141      1.082931        0.684662      -0.457451
2  0.396061 -1.085073  2.626141      1.082931       -0.066130       0.783215
3 -0.612287  0.133794 -0.785627     -0.372451        1.766500      -1.735713
4  0.564119  1.860809 -0.103273     -0.779958       -0.650607      -1.284561
5 -1.284519 -0.405254  0.579080     -0.779958       -1.018084      -1.829703

   euribor3m  nr.employed
0   0.983194     0.620697
1   1.037275     1.050379
2   1.038865     1.050379
3  -1.045350    -2.012985
4  -0.842284    -0.443662
5  -0.780781    -0.443662
```

[ ]:

1.0.2 Train-Test split

[31]:
```
from sklearn.model_selection import train_test_split

X_train, X_test, Y_train, Y_test = train_test_split(X, Y, random_state= 4,␣
 ↪test_size=0.3)


#Checking the dimension f train & test subset using 'shape'

print('X_train', X_train.shape)
print('Y_train', Y_train.shape)

print('X_test', X_test.shape)
print('Y_test', Y_test.shape)
```

```
X_train (6748, 8)
Y_train (6748, 1)
X_test (2892, 8)
Y_test (2892, 1)
```

[32]:
```
X
```

[32]:
```
      age  duration  campaign  emp.var.rate  cons.price.idx  cons.conf.idx  \
0      32     205.0         2           1.1          93.994          -36.4
1      32     691.0         6           1.4          93.918          -42.7
2      45      45.0         6           1.4          93.444          -36.1
3      33     400.0         1          -1.1          94.601          -49.5
4      47     903.0         2          -1.8          93.075          -47.1
…     …        …        …            …              …              …
9635   37     854.0         3           1.4          94.465          -41.8
9636   40     353.0         2           1.4          93.918          -42.7
9637   42      86.0         1          -0.1          93.200          -42.0
9638   39     233.0         1           1.4          94.465          -41.8
9639   35     417.0         1           1.4          94.465          -41.8

      euribor3m  nr.employed
0         4.858       5191.0
1         4.960       5228.1
2         4.963       5228.1
3         1.032       4963.6
4         1.415       5099.1
…          …           …
9635      4.961       5228.1
9636      4.960       5228.1
9637      4.191       5195.8
9638      4.864       5228.1
```

```
9639      4.962       5228.1

[9640 rows x 8 columns]
```

[ ]:

```

```

2. Logistic regression model

[33]:

```
import statsmodels
import statsmodels.api as sm

# build the model on train data (X_train and y_train)
# use fit() to fit the logistic regression model

logreg = sm.Logit(Y_train, X_train).fit()
```

```
Optimization terminated successfully.
         Current function value: 0.348894
         Iterations 7
```

[34]:

```
print(logreg.summary())
```

```
                           Logit Regression Results
==============================================================================
Dep. Variable:                      y   No. Observations:                 6748
Model:                          Logit   Df Residuals:                     6740
Method:                           MLE   Df Model:                            7
Date:                Fri, 30 Dec 2022   Pseudo R-squ.:                  0.4958
Time:                        19:35:27   Log-Likelihood:                -2354.3
converged:                       True   LL-Null:                       -4669.6
Covariance Type:            nonrobust   LLR p-value:                     0.000
================================================================================
==
                     coef    std err          z      P>|z|      [0.025
0.975]
--------------------------------------------------------------------------------
--
age               -0.0038      0.003     -1.246      0.213      -0.010
0.002
duration          -0.0073      0.000    -37.375      0.000      -0.008
-0.007
campaign           0.0768      0.028      2.774      0.006       0.023
0.131
emp.var.rate       0.9899      0.109      9.097      0.000       0.777
1.203
cons.price.idx    -0.6269      0.049    -12.733      0.000      -0.723
-0.530
cons.conf.idx     -0.0388      0.008     -4.868      0.000      -0.054
```

```
-0.023
euribor3m           -0.3707       0.119      -3.115       0.002       -0.604
-0.137
nr.employed          0.0119       0.001      12.137       0.000        0.010
0.014
================================================================================
==
```

[35]:

```
# 'aic' retuns the AIC value for the model
print('AIC:', logreg.aic)
```

```
AIC: 4724.676138086178
```

We can use the AIC value to compare different models created on the same dataset.

[36]:

```
# take the exponential of the coefficient of a variable to calculate the odds
# 'params' returns the coefficients of all the independent variables
# pass the required column name to the parameter, 'columns'
df_odds = pd.DataFrame(np.exp(logreg.params), columns= ['Odds'])

# print the dataframe
df_odds
```

[36]:

	Odds
age	0.996204
duration	0.992691
campaign	1.079844
emp.var.rate	2.691018
cons.price.idx	0.534261
cons.conf.idx	0.961953
euribor3m	0.690245
nr.employed	1.012010

odds_age = 0.99, It implies that the odds of client subcriber a terrm deposit increases by a factor of 0.9 due to 0.9 unit increases in the age, keeping other variabels constant

odds_duration = 0.99, It implies that the odds of client subcriber a terrm deposit increases by a factor of 0.9 due to 0.9 unit increases in the duration, keeping other variabels constant

odds_campaign = 1.07, It implies that the odds of client subcriber a terrm deposit increases by a factor of 1.07 due to 1.07 unit increases in the campaign, keeping other variabels constant

odds_emp_var_rate = 2.69, It implies that the odds of client subcriber a terrm deposit increases by a factor of 2.69 due to 2.69 unit increases in the emp.var.rate, keeping other variabels constant

odds_cons_price_idx = 0.5, It implies that the odds of client subcriber a terrm deposit increases by a factor of 0.5 due to 0.5 unit increases in the cons.price.idx, keeping other variabels constant

odds_cons_conf_idx = 0.96, It implies that the odds of client subcriber a terrm deposit increases by a factor of 0.96 due to 0.96 unit increases in the cons.conf.idx, keeping other variabels constant

odds_euribor3mx = 0.69, It implies that the odds of client subcriber a terrm deposit increases by a factor of 0.69 due to 0.69 unit increases in the euribor3m, keeping other variabels constant

odds_nr_employed = 1.01, It implies that the odds of client subcriber a terrm deposit increases by a factor of 1.01 due to 1.01 unit increases in the nr.employed, keeping other variabels constant

1.0.3 Do prediction on the test set

[38]:
```
# Let y_pred_prob be the predicted values of y

Y_pred_prob = logreg.predict(X_test)


Y_pred_prob.head(2)
```

[38]:
```
1684    0.930107
3991    0.405029
dtype: float64
```

Since the target variable can take only two values either 0 or 1. We decide the cut-off of 0.5. i.e. if 'y_pred_prob' is less than 0.5, then consider it to be 0 else consider it to be 1.

[39]:
```
# Convert probabilities to 0 & 1 using 'if_else'


Y_pred = [0 if val < 0.5 else 1 for val in Y_pred_prob]
```

[40]:
```
print(Y_pred)
```

```
[1, 0, 1, 1, 0, 0, 1, 1, 0, 1, 0, 0, 1, 1, 1, 0, 0, 1, 1, 1, 0, 1, 0, 0, 0, 1,
1, 0, 0, 1, 1, 0, 1, 1, 1, 0, 0, 1, 1, 1, 0, 1, 1, 1, 1, 0, 1, 1, 0, 0, 0, 1, 0,
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```

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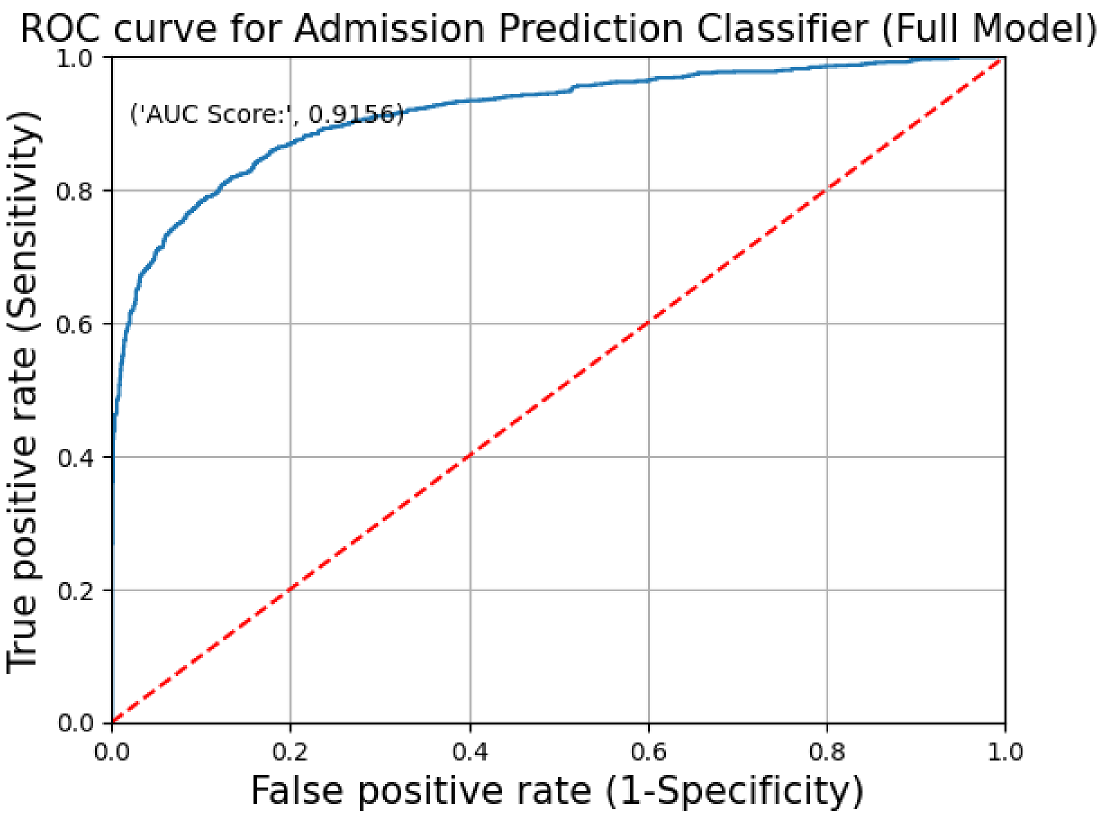
0, 1, 1, 0, 1, 1, 0, 0, 0, 0, 1, 1, 0, 1, 0, 0, 0, 1, 1, 0, 1, 1, 1, 1, 0, 1, 1,
0, 0, 0, 1]
```

[41]:
```python
# the roc_curve() returns the values for false positive rate, true positive
↪rate and threshold
# pass the actual target values and predicted probabilities to the function
fpr, tpr, thresholds = roc_curve(Y_test, Y_pred_prob)

# plot the ROC curve
plt.plot(fpr, tpr)

# set limits for x and y axes
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.0])

# plot the straight line showing worst prediction for the model
plt.plot([0, 1], [0, 1],'r--')

# add plot and axes labels
# set text size using 'fontsize'
plt.title('ROC curve for Admission Prediction Classifier (Full Model)',
↪fontsize = 15)
plt.xlabel('False positive rate (1-Specificity)', fontsize = 15)
plt.ylabel('True positive rate (Sensitivity)', fontsize = 15)

# add the AUC score to the plot
# 'x' and 'y' gives position of the text
# 's' is the text
# use round() to round-off the AUC score upto 4 digits
plt.text(x = 0.02, y = 0.9, s = ('AUC Score:', round(metrics.
↪roc_auc_score(Y_test, Y_pred_prob),4)))

# plot the grid
plt.grid(True)
```



[42]:

```
## To find the Optimum Threshold

# create a dataframe to store the values for false positive rate, true positive␣
↪rate and threshold
youdens_table = pd.DataFrame({'TPR': tpr,
                             'FPR': fpr,
                             'Threshold': thresholds})

# calculate the difference between TPR and FPR for each threshold and store the␣
↪values in a new column 'Difference'
youdens_table['Difference'] = youdens_table.TPR - youdens_table.FPR

# sort the dataframe based on the values of difference
# 'ascending = False' sorts the data in descending order
# 'reset_index' resets the index of the dataframe
# 'drop = True' drops the previous index
youdens_table = youdens_table.sort_values('Difference', ascending = False).
↪reset_index(drop = True)

# print the first five observations
youdens_table.head()
```

[42]:

	TPR	FPR	Threshold	Difference
0	0.808060	0.123249	0.557491	0.684811
1	0.818306	0.133754	0.535579	0.684553
2	0.811475	0.127451	0.551629	0.684024
3	0.816940	0.133053	0.535930	0.683887
4	0.781421	0.098039	0.611869	0.683382

** The Optimum threshold is 5.5 **

[ ]:

```

```

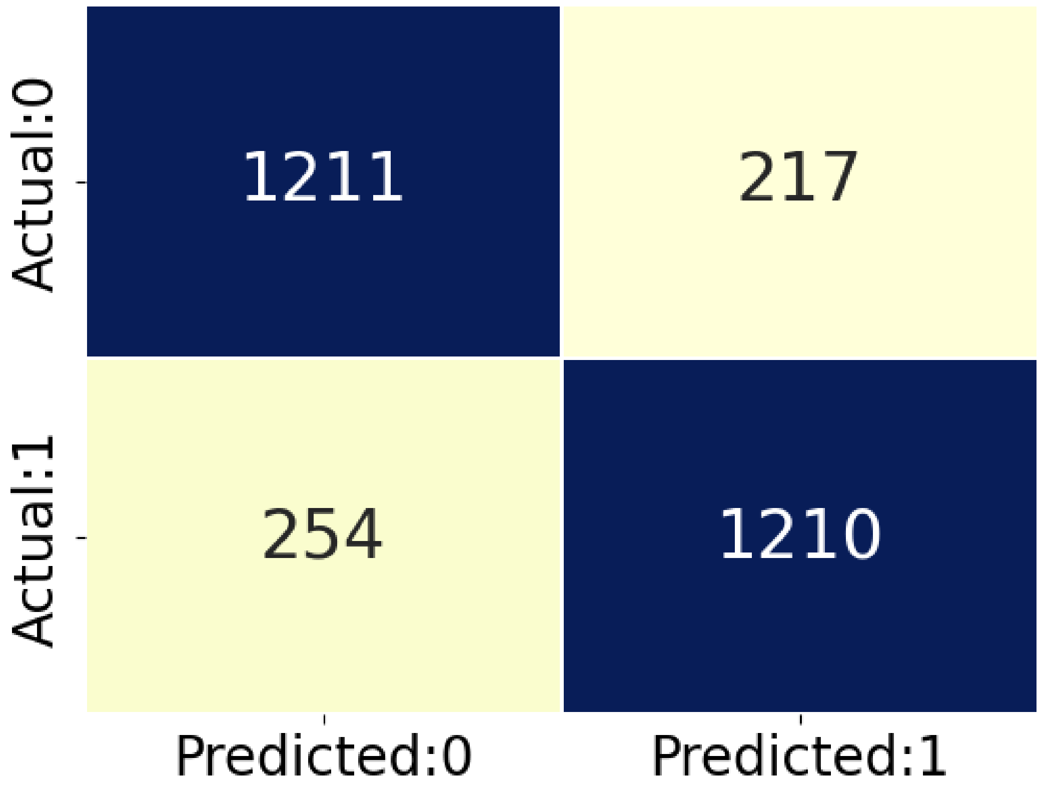
Plotting the confusion matrix

[43]:

```
from sklearn.metrics import confusion_matrix


cm = confusion_matrix(Y_test, Y_pred)

conf_matrix = pd.DataFrame(data=cm, columns=['Predicted:0', 'Predicted:1'],␣
↪index = ['Actual:0', 'Actual:1'])
```

[44]:

```
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap= "YlGnBu", cbar=False,␣
↪linewidths=0.1, annot_kws={'size':25})

# set the font size of x-axis ticks using 'fontsize'
plt.xticks(fontsize = 20)

# set the font size of y-axis ticks using 'fontsize'
plt.yticks(fontsize = 20)

# display the plot
plt.show()
```



[45]:
```
TN = cm[1,1]
TP = cm[0,0]
FP = cm[1,0]
FN = cm[0,1]
```

[46]:
```
print("True Negative", TN)
print("True Positive", TP)
print("False Positive", FP)
print("False Negative", FN)
```

```
True Negative 1210
True Positive 1211
False Positive 254
False Negative 217
```

Kappa score: It is a measure of inter-rater reliability. For logistic regression, the actual and predicted values of the target variable are the raters.

[47]:
```
# compute the kappa value
kappa = cohen_kappa_score(Y_test, Y_pred)

# print the kappa value
```

```
print('kappa value:',kappa)
```

```
kappa value: 0.674327127499333
```

[ ]:

```

```

Precision: It is defined as the ratio of true positives to the total positive predictions.

[48]:

```
# calculate the precision value
precision = TP / (TP+FP)

# print the value
precision
```

[48]:

```
0.8266211604095564
```

Recall: It is the ratio of true positives to the total actual positive observations. It is also known as, `Sensitivity` or `True Positive Rate`.

[49]:

```
# calculate the recall value
recall = TP / (TP+FN)

# print the value
recall
```

[49]:

```
0.8480392156862745
```

Specificity: It is the ratio of true negatives to the total actual negative observations.

[50]:

```
# calculate the specificity value
specificity = TN / (TN+FP)

# print the value
specificity
```

[50]:

```
0.8265027322404371
```

f1-score: It is defined as the harmonic mean of precision and recall.

[51]:

```
# calculate the f1_score
f1_score = 2*((precision*recall)/(precision+recall))

# print the f1_score
f1_score
```

[51]:

```
0.8371932250259247
```

Accuracy: It is the ratio of correct predictions (i.e. TN+TP) to the total observations. According to the confusion matrix, it is the ratio of the sum of diagonal elements to the sum of all the in the matrix. It is not a very good measure if the dataset is imbalanced.

[52]:
```
# calculate the accuracy
accuracy = (TN+TP) / (TN+FP+FN+TP)

# print the accuracy
accuracy
```

[52]:
```
0.8371369294605809
```

Classification Report

[53]:
```
# calculate various performance measures
acc_table = classification_report(Y_test, Y_pred)

# print the table
print(acc_table)
```

```
              precision    recall  f1-score   support

           0       0.83      0.85      0.84      1428
           1       0.85      0.83      0.84      1464

    accuracy                           0.84      2892
   macro avg       0.84      0.84      0.84      2892
weighted avg       0.84      0.84      0.84      2892
```

1.1 3.Build a Decision Tree model and generate a classification report.

[54]:
```
from sklearn.tree import DecisionTreeClassifier
decision_tree_classification = DecisionTreeClassifier(criterion='gini',␣
↪random_state= 10)
```

[55]:
```
decision_tree = decision_tree_classification.fit(X_train, Y_train)
```

[56]:
```
feat = pd.DataFrame({'feature':X_train.columns, 'feat_imp':decision_tree.
↪feature_importances_})
feat.sort_values('feat_imp', ascending = False)
```

[56]:

	feature	feat_imp
1	duration	0.397296
7	nr.employed	0.273070
6	euribor3m	0.124223
0	age	0.086714
5	cons.conf.idx	0.061922
2	campaign	0.034605
4	cons.price.idx	0.013082

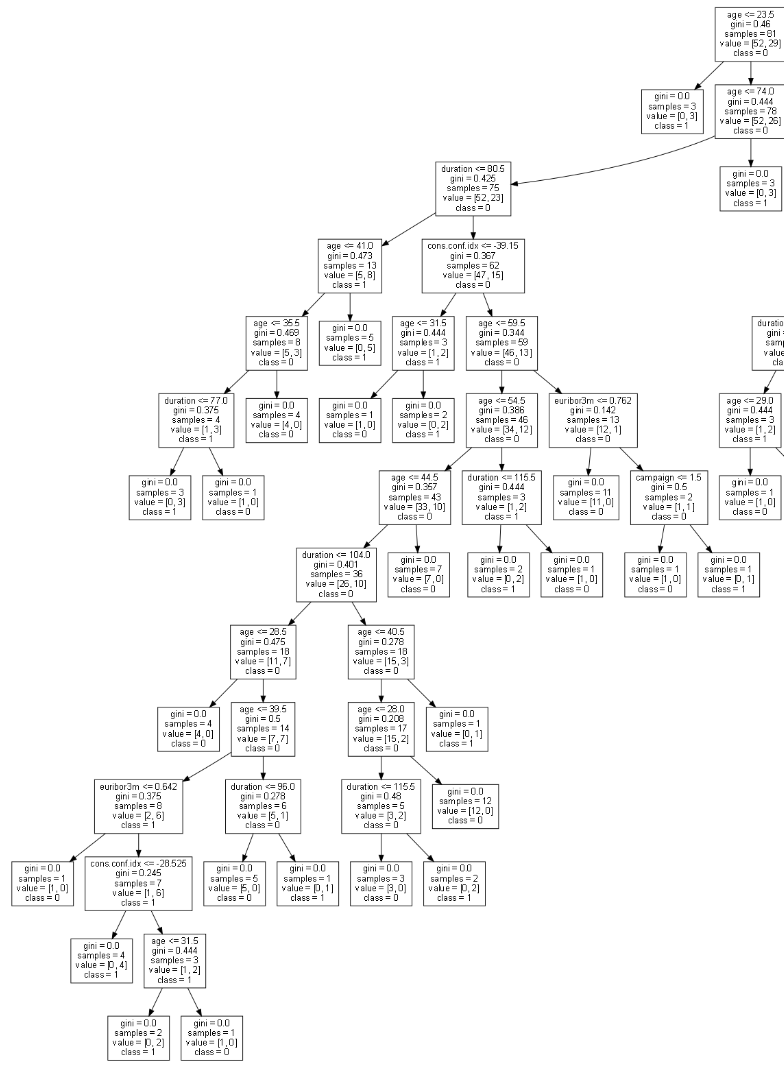
```
3    emp.var.rate  0.009088
```

[57]:

```python
from sklearn import linear_model, datasets, tree
import pydotplus
from IPython.display import Image

# save the column names in 'labels'
labels = X_train.columns

# export a decision tree in DOT format
# pass the 'decision_tree' to export it to Graphviz
# pass the column names to 'feature_names'
# pass the required class labels to 'class_names'
dot_data = tree.export_graphviz(decision_tree, feature_names = labels,␣
 ↪class_names = ["0","1"])

# plot the decision tree using DOT format in 'dot_data'
graph = pydotplus.graph_from_dot_data(dot_data)

# display the decision tree
Image(graph.create_png())
```

```
dot: graph is too large for cairo-renderer bitmaps. Scaling by 0.709611 to fit

(process:16700): GLib-GIO-WARNING **: 19:36:32.800: Unexpectedly, UWP app
`Clipchamp.Clipchamp_2.5.13.0_neutral__yxz26nhyzhsrt' (AUMId
`Clipchamp.Clipchamp_yxz26nhyzhsrt!App') supports 41 extensions but has no verbs
```

[57]:



[58]:

```python
# Let y_pred_prob be the predicted values of y

desicion_pred_prob = decision_tree.predict(X_test)
desicion_pred_prob
```

[58]: array([1, 0, 1, …, 0, 0, 1], dtype=int64)

[ ]:

```python

```

[59]:

```python
# Convert probabilities to 0 & 1 using 'if_else'


desicion_pred = [0 if val < 0.5 else 1 for val in desicion_pred_prob]
```

[60]:

```python
print(desicion_pred)
```

```
[1, 0, 1, 1, 0, 0, 1, 1, 1, 1, 0, 1, 1, 0, 1, 0, 0, 1, 1, 1, 0, 0, 0, 1, 0, 0,
1, 0, 0, 1, 1, 0, 0, 1, 0, 1, 0, 1, 1, 1, 0, 1, 1, 1, 1, 0, 1, 1, 0, 0, 0, 0, 0,
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```

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0, 0, 0, 1]
```

[ ]:

[61]:

```python
from sklearn.model_selection import GridSearchCV

parameters = [{'criterion':['gini','entropy'],'max_depth':
 ↪[4,5,6,7,8,9,10,11,12,15,20,30,40,50,70,90,120,150],
                'max_leaf_nodes': [2,4,6,10,15,30,40,50,100],␣
 ↪'min_samples_split': [2, 3, 4]}]
grid_search = GridSearchCV(estimator = decision_tree_classification,
                           param_grid = parameters,
                           scoring = 'accuracy',
                           cv = 10,
                           n_jobs = -1)

grid_search.fit(X_train, Y_train)
```

```
best_accuracy_dtc = grid_search.best_score_
best_parameters = grid_search.best_params_

print("Best Accurary", best_accuracy_dtc)
print("Best Paramerter",best_parameters)
```

```
Best Accurary 0.8891524343334432
Best Paramerter {'criterion': 'entropy', 'max_depth': 11, 'max_leaf_nodes': 40,
'min_samples_split': 2}
```

[ ]:

[62]:
```
# calculate various performance measures
acc_table = classification_report(Y_test, desicion_pred)

# print the table
print("Accuracy of the model without Grid serachCV",acc_table)
```

```
Accuracy of the model without Grid serachCV              precision    recall
f1-score   support

           0       0.83      0.81      0.82      1428
           1       0.82      0.84      0.83      1464

    accuracy                           0.82      2892
   macro avg       0.82      0.82      0.82      2892
weighted avg       0.82      0.82      0.82      2892
```

1.2 4.Build a Random Forest model with n_estimators=30 and generate a classification report.

[63]:
```
from sklearn.ensemble import RandomForestClassifier

rand_forest = RandomForestClassifier(n_estimators=100)
rand_forest.fit(X_train, Y_train)
```

[63]: RandomForestClassifier()

[64]:
```
# Let rand_pred_prob be the predicted values of y

rand_pred_prob = rand_forest.predict(X_test)
rand_pred_prob
```

[64]: array([1, 0, 1, …, 0, 0, 1], dtype=int64)

[65]:

```python
# Convert probabilities to 0 & 1 using 'if_else'

rand_pred = [0 if val < 0.5 else 1 for val in rand_pred_prob]
print(rand_pred)
```

```
[1, 0, 1, 1, 0, 0, 1, 1, 0, 1, 0, 0, 1, 0, 1, 0, 0, 1, 1, 1, 0, 0, 0, 0, 0, 1,
1, 0, 0, 1, 1, 0, 0, 1, 0, 1, 0, 1, 1, 1, 0, 1, 1, 1, 1, 0, 1, 1, 0, 0, 0, 1, 0,
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0, 1, 1, 1, 1, 1, 0, 0, 0, 0, 1, 1, 0, 1, 0, 0, 0, 1, 1, 0, 1, 1, 1, 1, 0, 1, 1,
0, 0, 0, 1]
```

[ ]:

[69]:
```
from sklearn.model_selection import GridSearchCV

parameters = [{'criterion':['gini','entropy'],'max_depth':[5,6,7,8,9],
               'max_leaf_nodes': [2,4,6,10], 'min_samples_split': [2, 3]}]
grid_search = GridSearchCV(estimator = rand_forest,
                           param_grid = parameters,
                           scoring = 'accuracy',
                           cv = 10,
                           n_jobs = -1)
grid_search.fit(X_train, Y_train)
best_accuracy_dtc = grid_search.best_score_
best_parameters = grid_search.best_params_
print("Best Accurary", best_accuracy_dtc)
print("Best Paramerter",best_parameters)
```

```
Best Accurary 0.8764057588746017
Best Paramerter {'criterion': 'gini', 'max_depth': 7, 'max_leaf_nodes': 10,
'min_samples_split': 2}
```

[74]:
```
# calculate various performance measures
acc_table = classification_report(Y_test, rand_pred)

# print the table
print("Accuracy of the model without Grid serachCV",acc_table)
```

```
Accuracy of the model without Grid serachCV              precision    recall
f1-score   support
```

```
              0       0.85      0.92      0.88      1428
              1       0.91      0.84      0.87      1464

       accuracy                           0.88      2892
      macro avg       0.88      0.88      0.88      2892
   weighted avg       0.88      0.88      0.88      2892
```

[ ]:

[ ]:

1.3 5.Build the XGBoost model with a learning rate of 0.4 and gamma equal to 3. Calculate the accuracy by plotting the confusion matrix

[111]:

```python
from xgboost import XGBClassifier
xgb_classifier = XGBClassifier(gamma=3,
                         learning_rate=0.4)
# Train Adaboost Classifer
xgb_classifier.fit(X_train, Y_train)

#Predict the response for test dataset
# Let rand_pred_prob be the predicted values of y

xg_s = xgb_pred_prob = xgb_classifier.predict(X_test)

# Convert probabilities to 0 & 1 using 'if_else'

xgb_pred = [0 if val < 0.5 else 1 for val in xgb_pred_prob]
print(xgb_pred)
```

```
[1, 0, 1, 1, 0, 0, 1, 1, 0, 0, 0, 0, 1, 0, 1, 0, 0, 1, 1, 1, 0, 0, 0, 1, 0, 1,
1, 0, 0, 1, 1, 0, 0, 1, 0, 1, 0, 1, 1, 1, 0, 1, 1, 1, 1, 0, 1, 1, 0, 0, 0, 1, 0,
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0, 0, 1, 0, 0, 1, 0, 0, 1, 0, 1, 0, 1, 1, 1, 1, 1, 0, 1, 0, 1, 0, 0, 0, 1, 1, 0,
0, 1, 1, 0, 1, 1, 1, 0, 0, 0, 0, 1, 0, 1, 0, 1, 1, 0, 0, 0, 1, 0, 1, 0, 0, 1, 1,
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1, 0, 1, 0, 0, 0, 0, 1, 1, 0, 1, 1, 1, 0, 0, 1, 0, 0, 1, 1, 1, 0, 1, 1, 0, 0, 0,
```

1, 0, 0, 0, 0, 1, 0, 1, 1, 0, 0, 1, 0, 1, 0, 1, 1, 1, 0, 0, 1, 1, 1, 1, 1, 0, 0,
1, 0, 1, 1, 1, 1, 0, 0, 0, 1, 0, 1, 0, 1, 1, 0, 0, 1, 1, 1, 0, 0, 1, 1, 0, 1, 0,
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0, 1, 1, 1, 1, 1, 0, 0, 0, 0, 1, 1, 0, 1, 0, 0, 0, 1, 1, 0, 1, 1, 1, 1, 0, 1, 1,
0, 0, 0, 1]
```

[ ]:

[72]:
```
from sklearn.model_selection import GridSearchCV

parameters = [{'criterion':['gini','entropy'],'max_depth':[5,6,7,8,9],
                'max_leaf_nodes': [2,4,6,10], 'min_samples_split': [2, 3]}]
grid_search = GridSearchCV(estimator = xgb_classifier,
                           param_grid = parameters,
                           scoring = 'accuracy',
                           cv = 10,
                           n_jobs = -1)
grid_search.fit(X_train, Y_train)
best_accuracy_dtc = grid_search.best_score_
best_parameters = grid_search.best_params_
print("Best Accurary", best_accuracy_dtc)
print("Best Paramerter",best_parameters)
```

```
[19:48:01] WARNING: C:/buildkite-agent/builds/buildkite-windows-cpu-autoscaling-
group-i-030221e36e1a46bfb-1/xgboost/xgboost-ci-windows/src/learner.cc:767:
Parameters: { "criterion", "max_leaf_nodes", "min_samples_split" } are not used.

Best Accurary 0.8938944939004287
Best Paramerter {'criterion': 'gini', 'max_depth': 7, 'max_leaf_nodes': 2,
'min_samples_split': 2}
```

[75]:
```
# calculate various performance measures
acc_table = classification_report(Y_test, xgb_pred)

# print the table
print("Accuracy of the model without Grid serachCV",acc_table)
```

```
Accuracy of the model without Grid serachCV               precision    recall
f1-score   support

           0       0.85      0.92      0.89      1428
           1       0.92      0.85      0.88      1464

    accuracy                           0.88      2892
   macro avg       0.89      0.88      0.88      2892
weighted avg       0.89      0.88      0.88      2892
```

1.4 6.Build the K - Nearest Neighbor Model

[76]:
```
from sklearn.neighbors import KNeighborsClassifier
knn_classifier = KNeighborsClassifier(n_neighbors=3, metric='euclidean')
knn_classifier.fit(X_train, Y_train)
```

[76]:
```
KNeighborsClassifier(metric='euclidean', n_neighbors=3)
```

[78]:

```
# Let knn_pred_prob be the predicted values of y

knn_pred_prob = knn_classifier.predict(X_test)
print(knn_pred_prob)



# Convert probabilities to 0 & 1 using 'if_else'

knn_pred = [0 if val < 0.5 else 1 for val in knn_pred_prob]
print(knn_pred)
```

```
[1 1 1 … 0 0 1]
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0, 0, 0, 1]
```

[ ]:

```

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[79]:

```
# calculate various performance measures
acc_table = classification_report(Y_test, knn_pred)

# print the table
print("Accuracy of the model without Grid serachCV",acc_table)
```

```
Accuracy of the model without Grid serachCV              precision    recall
f1-score   support

           0       0.82      0.85      0.83      1428
           1       0.85      0.81      0.83      1464

    accuracy                           0.83      2892
   macro avg       0.83      0.83      0.83      2892
weighted avg       0.83      0.83      0.83      2892
```

1.5 7. Build the Naive Bayes Model

[80]:
```python
from sklearn.naive_bayes import GaussianNB

naive_bayes = GaussianNB()
naive_bayes.fit(X_train, Y_train)
```

[80]:
```
GaussianNB()
```

[81]:
```python
# Let knn_pred_prob be the predicted values of y

naive_bayes_pred_prob = naive_bayes.predict(X_test)
print(naive_bayes_pred_prob)


# Convert probabilities to 0 & 1 using 'if_else'

naive_bayes_pred = [0 if val < 0.5 else 1 for val in naive_bayes_pred_prob]
print(naive_bayes_pred)
```

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0, 1, 1, 0, 1, 1, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 1, 1, 1, 0, 1, 0, 0, 0, 1, 0,
0, 0, 0, 1]
```

[83]:
```
# calculate various performance measures
acc_table = classification_report(Y_test, naive_bayes_pred)

# print the table
print(acc_table)
```

```
              precision    recall  f1-score   support

           0       0.74      0.87      0.80      1428
           1       0.84      0.70      0.77      1464

    accuracy                           0.78      2892
   macro avg       0.79      0.79      0.78      2892
weighted avg       0.79      0.78      0.78      2892
```

[84]:
```python
# importing classifier
from sklearn.naive_bayes import BernoulliNB

# initializaing the NB
classifer = BernoulliNB()

# training the model
classifer.fit(X_train, Y_train)

# testing the model
BNB_y_pred = classifer.predict(X_test)

# calculate various performance measures
acc_table = classification_report(Y_test, BNB_y_pred)

# print the table
print(acc_table)
```

```
              precision    recall  f1-score   support

           0       0.67      0.77      0.71      1428
           1       0.73      0.62      0.68      1464

    accuracy                           0.70      2892
   macro avg       0.70      0.70      0.69      2892
weighted avg       0.70      0.70      0.69      2892
```

1.6 8. Compare the results of all above mentioned algorithms

[92]:
```python
classification_all_model_accurary = pd.DataFrame()



classification_all_model_accurary['Logistic regression'] = ␣
 ↪[accuracy_score(Y_test, Y_pred)]
classification_all_model_accurary['Decision tree Classification'] = ␣
 ↪[accuracy_score(Y_test, desicion_pred)]
classification_all_model_accurary['Random forest Classification'] = ␣
 ↪[accuracy_score(Y_test, rand_pred)]
classification_all_model_accurary['XGBoost Classification'] = ␣
 ↪[accuracy_score(Y_test, xgb_pred)]
classification_all_model_accurary['KNN Classification'] = ␣
 ↪[accuracy_score(Y_test, knn_pred)]
classification_all_model_accurary['Naive Bayes Classification'] = ␣
 ↪[accuracy_score(Y_test, naive_bayes_pred)]
```

```
classification_all_model_accurary.index = ['Accuracy Score']
classification_all_model_accurary
```

[92]:

```
                Logistic regression  Decision tree Classification  \
Accuracy Score             0.837137                      0.823651

                Random forest Classification  XGBoost Classification  \
Accuracy Score                      0.877248                0.884509

                KNN Classification  Naive Bayes Classification
Accuracy Score            0.830221                    0.784232
```

[ ]:

From the 6 models we have used to train the models, I would say XGBoost give the high accuracy among the other models with the accuracy rate 88%

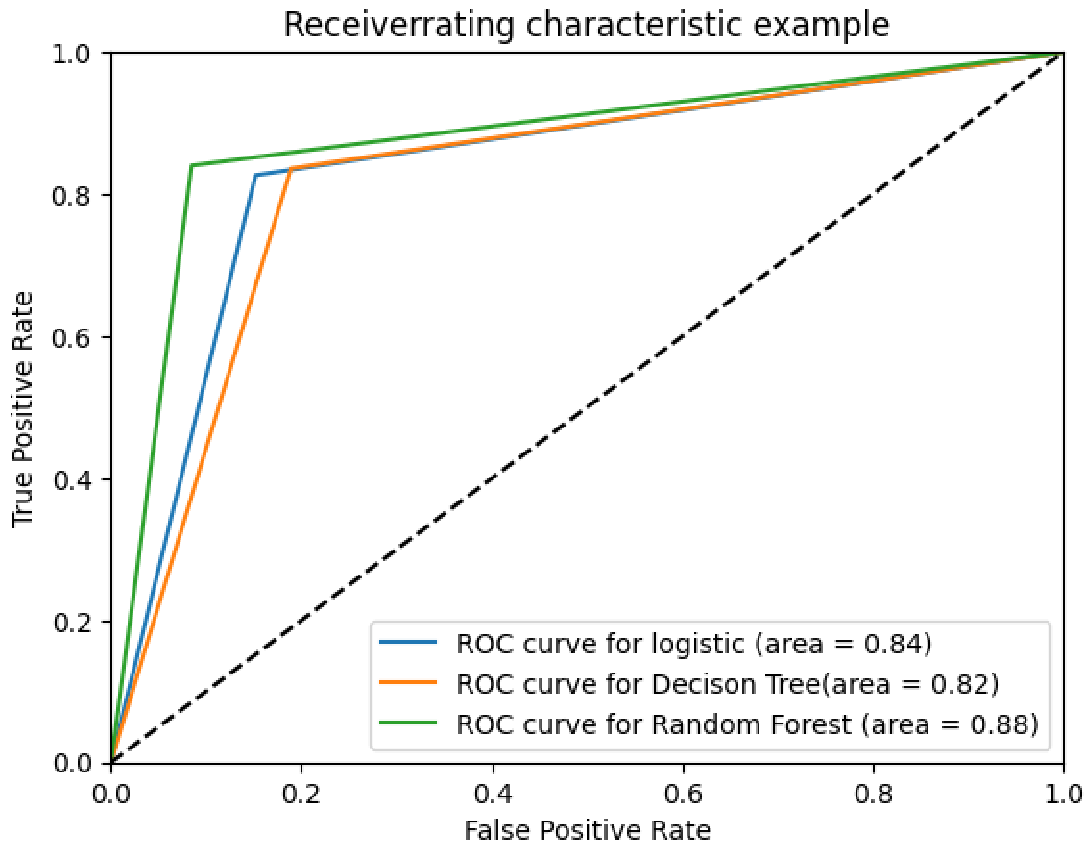
[106]:

```
from sklearn.metrics import roc_curve, auc


# Compute ROC curve and area the curve for logistic
fpr1, tpr1, thresholds1 = roc_curve(Y_test, Y_pred)
roc_auc1 = auc(fpr1, tpr1)
print("Logistic regression : Area under the ROC curve : %f" % roc_auc1)


# Compute ROC curve and area the curve for Descision
fpr2, tpr2, thresholds2 = roc_curve(Y_test, desicion_pred)
roc_auc2 = auc(fpr2, tpr2)
print("Decision Tree : Area under the ROC curve : %f" % roc_auc2)


# Compute ROC curve and area the curve for random foresy
fpr3, tpr3, thresholds3 = roc_curve(Y_test, rand_pred)
roc_auc3 = auc(fpr3, tpr3)
print("Random Forest : Area under the ROC curve : %f" % roc_auc3)


# Compute ROC curve and area the curve for XGboost
fpr4, tpr4, thresholds4 = roc_curve(Y_test, xgb_pred)
roc_auc4 = auc(fpr4, tpr4)
print("XGBoost : Area under the ROC curve : %f" % roc_auc4)


# Compute ROC curve and area the curve for KNN
fpr5, tpr5, thresholds5 = roc_curve(Y_test, knn_pred)
roc_auc5 = auc(fpr5, tpr5)
```

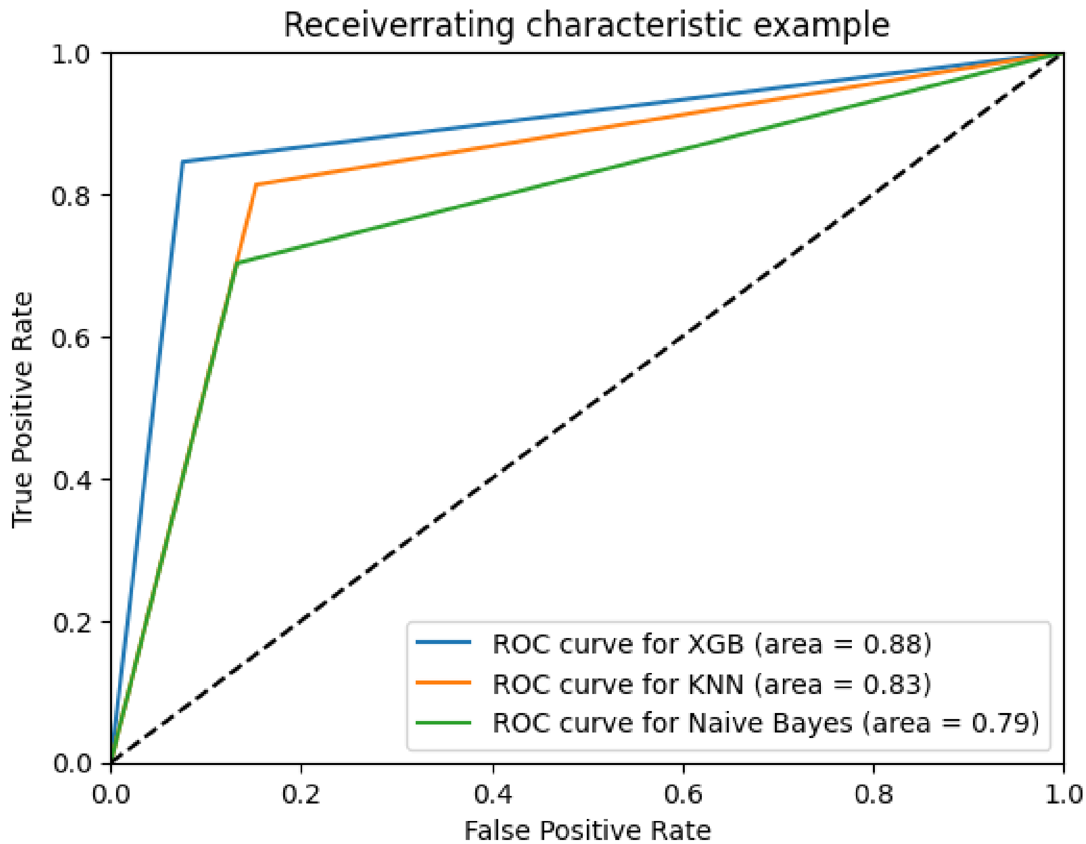
```
print("KNN : Area under the ROC curve : %f" % roc_auc5)


# Compute ROC curve and area the curve for Naive bayes
fpr6, tpr6, thresholds6= roc_curve(Y_test, naive_bayes_pred)
roc_auc6 = auc(fpr6, tpr6)
print("Naive Bayes : Area under the ROC curve : %f" % roc_auc6)
```

```
Logistic regression : Area under the ROC curve : 0.837271
Decision Tree : Area under the ROC curve : 0.823495
Random Forest : Area under the ROC curve : 0.877715
XGBoost : Area under the ROC curve : 0.884999
KNN : Area under the ROC curve : 0.830432
Naive Bayes : Area under the ROC curve : 0.785258
```

[107]:
```
import pylab as pl


# Plot ROC curve
plt.clf()
plt.plot(fpr1, tpr1, label='ROC curve for logistic (area = %0.2f)' % roc_auc1)
plt.plot(fpr2, tpr2, label='ROC curve for Decison Tree(area = %0.2f)' %␣
 ↪roc_auc2)
plt.plot(fpr3, tpr3, label='ROC curve for Random Forest (area = %0.2f)' %␣
 ↪roc_auc3)
plt.plot([0, 1], [0, 1], 'k--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.0])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiverrating characteristic example')
plt.legend(loc="lower right")
plt.show()
```



[108]:
```
pl.clf()
pl.plot(fpr4, tpr4, label='ROC curve for XGB (area = %0.2f)' % roc_auc4)
pl.plot(fpr5, tpr5, label='ROC curve for KNN (area = %0.2f)' % roc_auc5)
pl.plot(fpr6, tpr6, label='ROC curve for Naive Bayes (area = %0.2f)' % roc_auc6)
pl.plot([0, 1], [0, 1], 'k--')
pl.xlim([0.0, 1.0])
pl.ylim([0.0, 1.0])
pl.xlabel('False Positive Rate')
pl.ylabel('True Positive Rate')
pl.title('Receiverrating characteristic example')
pl.legend(loc="lower right")
pl.show()
```



1.7 9. Intrepret your solution based on the results

[ ]:

1.8 Based on our models performance I would say that XGBoost model will perform more efficiently than the other model where our accuracy factor and ROC curve both implies the same!

[109]:
```
print(logreg.summary())
```

```
                           Logit Regression Results
==============================================================================
Dep. Variable:                      y   No. Observations:                 6748
Model:                          Logit   Df Residuals:                     6740
Method:                           MLE   Df Model:                            7
Date:                Fri, 30 Dec 2022   Pseudo R-squ.:                  0.4958
Time:                        20:29:20   Log-Likelihood:                -2354.3
converged:                       True   LL-Null:                       -4669.6
Covariance Type:            nonrobust   LLR p-value:                     0.000
```

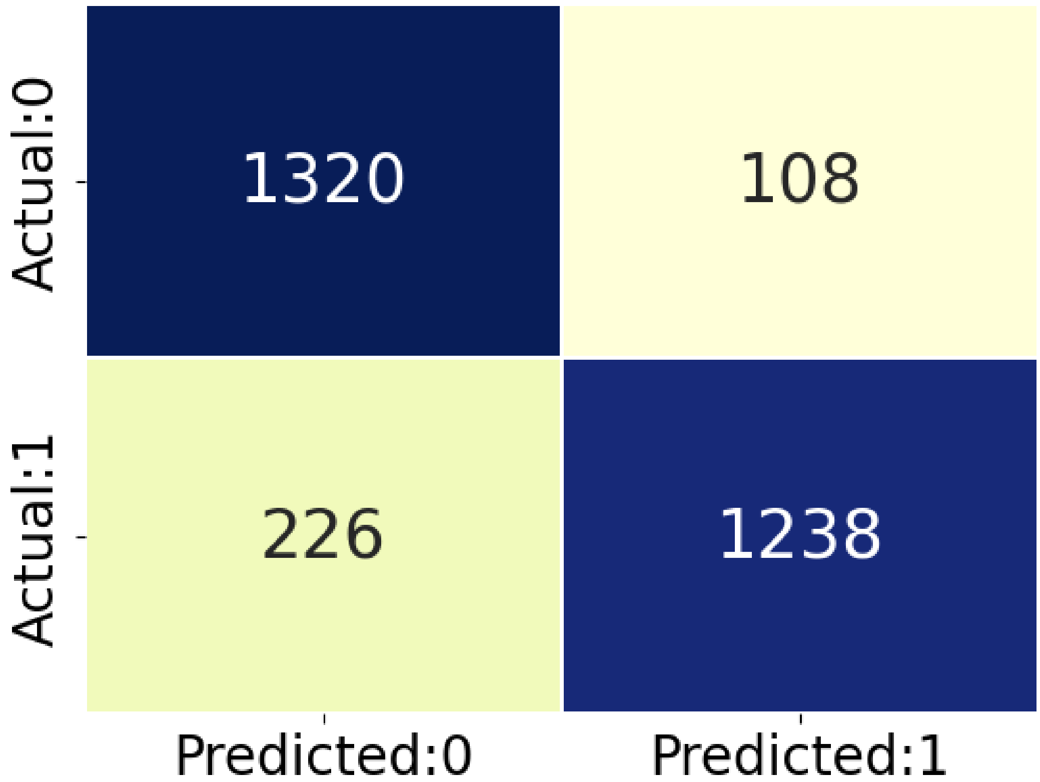
```
==================================================================================
==
                     coef    std err          z      P>|z|      [0.025
0.975]
----------------------------------------------------------------------------------
--
age               -0.0038      0.003     -1.246      0.213      -0.010
0.002
duration          -0.0073      0.000    -37.375      0.000      -0.008
-0.007
campaign           0.0768      0.028      2.774      0.006       0.023
0.131
emp.var.rate       0.9899      0.109      9.097      0.000       0.777
1.203
cons.price.idx    -0.6269      0.049    -12.733      0.000      -0.723
-0.530
cons.conf.idx     -0.0388      0.008     -4.868      0.000      -0.054
-0.023
euribor3m         -0.3707      0.119     -3.115      0.002      -0.604
-0.137
nr.employed        0.0119      0.001     12.137      0.000       0.010
0.014
==================================================================================
==
```

1.8.1 By checkingthe each and every summary of every model, we can come to know how many observation the model had made and R squared values. Also for the each and evry variable we can see the co-efficient and standard error

1.9 Where XGBoost stands out of the table when compared to other models and that is why the XGBoost model would perform much better that other

[117]:
```python
#Plotting the confusion matrix for the reference

from sklearn.metrics import confusion_matrix


cm = confusion_matrix(Y_test, xgb_pred)

conf_matrix = pd.DataFrame(data=cm, columns=['Predicted:0', 'Predicted:1'],␣
 ↪index = ['Actual:0', 'Actual:1'])

sns.heatmap(conf_matrix, annot=True, fmt='d', cmap= "YlGnBu", cbar=False,␣
 ↪linewidths=0.1, annot_kws={'size':25})

# set the font size of x-axis ticks using 'fontsize'
plt.xticks(fontsize = 20)
```

```
# set the font size of y-axis ticks using 'fontsize'
plt.yticks(fontsize = 20)

# display the plot
plt.show()
```



[118]:
```
TN = cm[1,1]
TP = cm[0,0]
FP = cm[1,0]
FN = cm[0,1]

print("True Negative", TN)
print("True Positive", TP)
print("False Positive", FP)
print("False Negative", FN)
```

```
True Negative 1238
True Positive 1320
False Positive 226
False Negative 108
```

I have plotted the confusion matrix to make an understanding on XGBoost success rate

1.9.1 From the above outtup we can see the True positive is 1320 which is highly appriciatable and the true negative which mean the result is no and predicted no is 1238. Miss calculations are 226 False positive and 108 False negative which is very minimal from 2000 record

[119]:
```
# calculate the accuracy
accuracy = (TN+TP) / (TN+FP+FN+TP)

# print the accuracy
accuracy
```

[119]:
```
0.8845089903181189
```

1.9.2 That again I conclude the XGBoost model as best performing model than others

[ ]:
```

```