```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline

import warnings
warnings.filterwarnings("ignore")
```

```
from keras.preprocessing import sequence
from keras.utils import np_utils
from keras.models import Sequential
from keras.layers import Dense, Dropout, Activation, Embedding
from keras.layers import LSTM, SimpleRNN, GRU
from keras.datasets import imdb
from keras.utils.np_utils import to_categorical
from sklearn.metrics import (precision_score, recall_score,f1_score,
accuracy_score,mean_squared_error,mean_absolute_error)
from sklearn import metrics
from sklearn.svm import SVC
from sklearn.preprocessing import Normalizer
from keras import callbacks
from keras.callbacks import ModelCheckpoint, EarlyStopping,
ReduceLROnPlateau, CSVLogger
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split
from imblearn.combine import SMOTETomek
from sklearn.linear_model import LogisticRegression
from sklearn import tree
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import GridSearchCV
from sklearn.model_selection import RandomizedSearchCV
from sklearn.model_selection import KFold
from sklearn.model_selection import StratifiedKFold
from sklearn.metrics import accuracy_score, confusion_matrix,
classification_report
```

```
pip install -U imbalanced-learn
```

```
Looking in indexes: https://pypi.org/simple, https://us-
python.pkg.dev/colab-wheels/public/simple/
Requirement already satisfied: imbalanced-learn in
/usr/local/lib/python3.7/dist-packages (0.9.0)
Collecting imbalanced-learn
  Using cached imbalanced_learn-0.9.1-py3-none-any.whl (199 kB)
Requirement already satisfied: joblib>=1.0.0 in
/usr/local/lib/python3.7/dist-packages (from imbalanced-learn) (1.1.0)
Requirement already satisfied: threadpoolctl>=2.0.0 in
/usr/local/lib/python3.7/dist-packages (from imbalanced-learn) (3.1.0)
Requirement already satisfied: numpy>=1.14.6 in
```

```
/usr/local/lib/python3.7/dist-packages (from imbalanced-learn)
(1.21.6)
Requirement already satisfied: scikit-learn>=1.0.1 in
/usr/local/lib/python3.7/dist-packages (from imbalanced-learn) (1.0.2)
Requirement already satisfied: scipy>=1.1.0 in
/usr/local/lib/python3.7/dist-packages (from imbalanced-learn) (1.7.3)
```

```
data= pd.read_csv("bank.csv")

# check shape of dataset
print("shape of the data:", data.shape)
data.head()
```

```
shape of the data: (32950, 16)

   age           job   marital          education  default housing
loan  \
0   49   blue-collar   married           basic.9y  unknown      no
no
1   37  entrepreneur   married  university.degree       no      no
no
2   78       retired   married           basic.4y       no      no
no
3   36        admin.   married  university.degree       no     yes
no
4   59       retired  divorced  university.degree       no      no
no

     contact month day_of_week  duration  campaign  pdays  previous  \
0   cellular   nov         wed       227         4    999         0
1  telephone   nov         wed       202         2    999         1
2   cellular   jul         mon      1148         1    999         0
3  telephone   may         mon       120         2    999         0
4   cellular   jun         tue       368         2    999         0

      poutcome    y
0  nonexistent   no
1      failure   no
2  nonexistent  yes
3  nonexistent   no
4  nonexistent   no
```

```
# check data types of all columns
data.dtypes
```

```
age             int64
job            object
marital        object
education      object
default        object
housing        object
```

```
loan            object
contact         object
month           object
day_of_week     object
duration         int64
campaign         int64
pdays            int64
previous         int64
poutcome        object
y               object
dtype: object
```

```
data.isnull().sum()
```

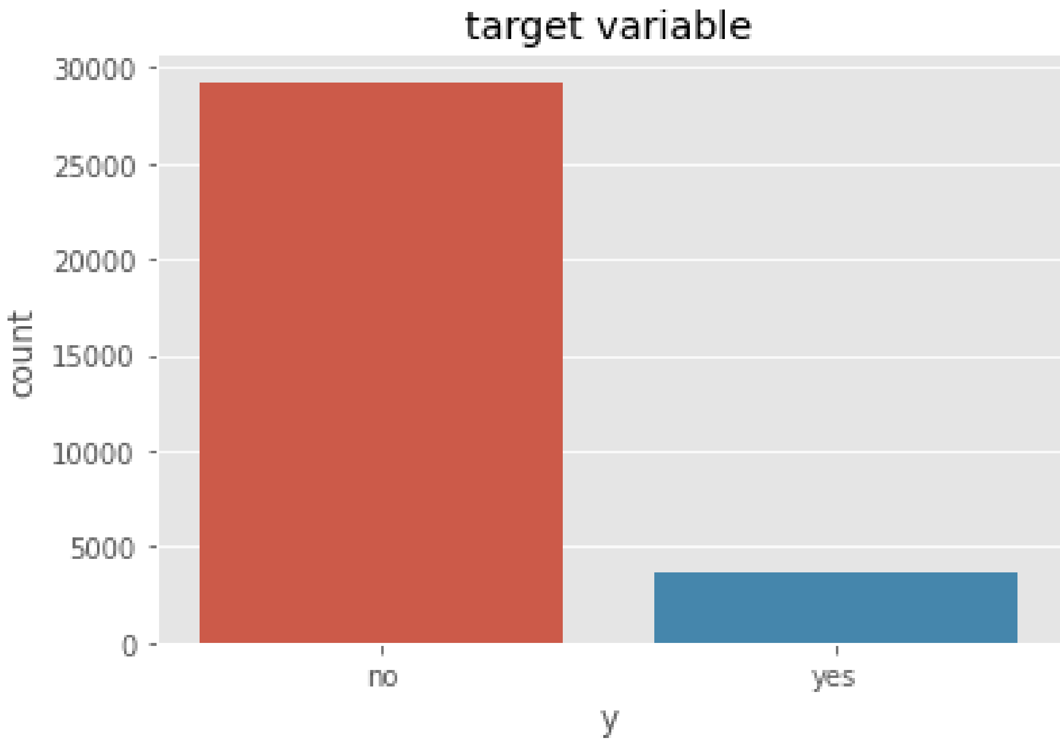
```
age             0
job             0
marital         0
education       0
default         0
housing         0
loan            0
contact         0
month           0
day_of_week     0
duration        0
campaign        0
pdays           0
previous        0
poutcome        0
y               0
dtype: int64
```

```
# target class count
data["y"].value_counts()
```

```
no     29238
yes     3712
Name: y, dtype: int64
```

```
sns.countplot(data["y"])
plt.title("target variable")
```

```
Text(0.5, 1.0, 'target variable')
```

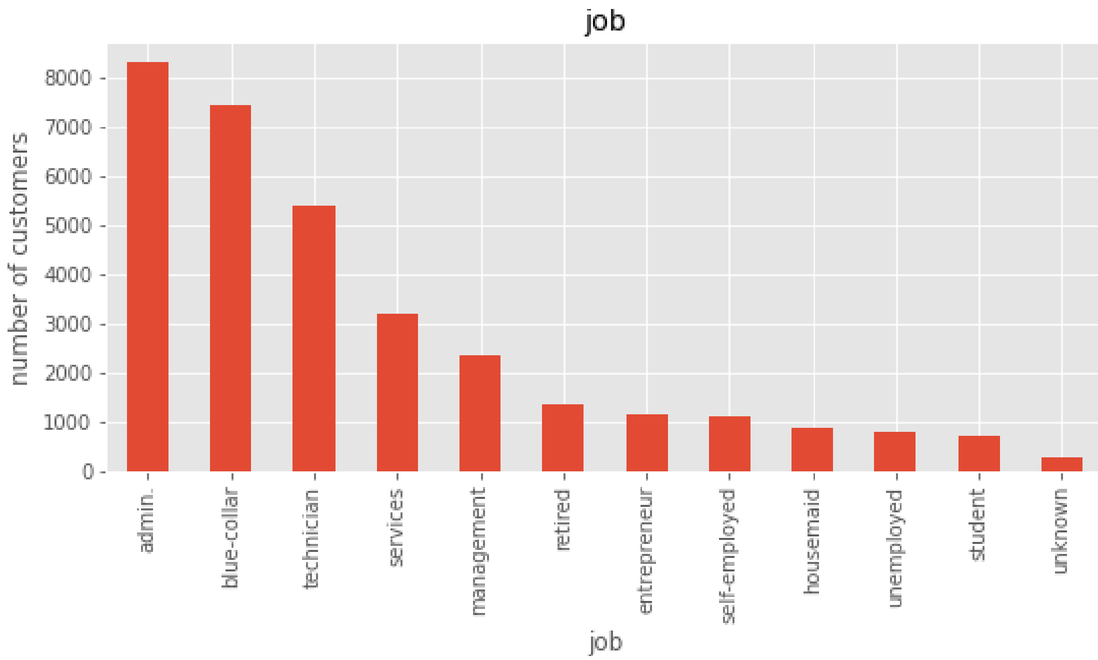


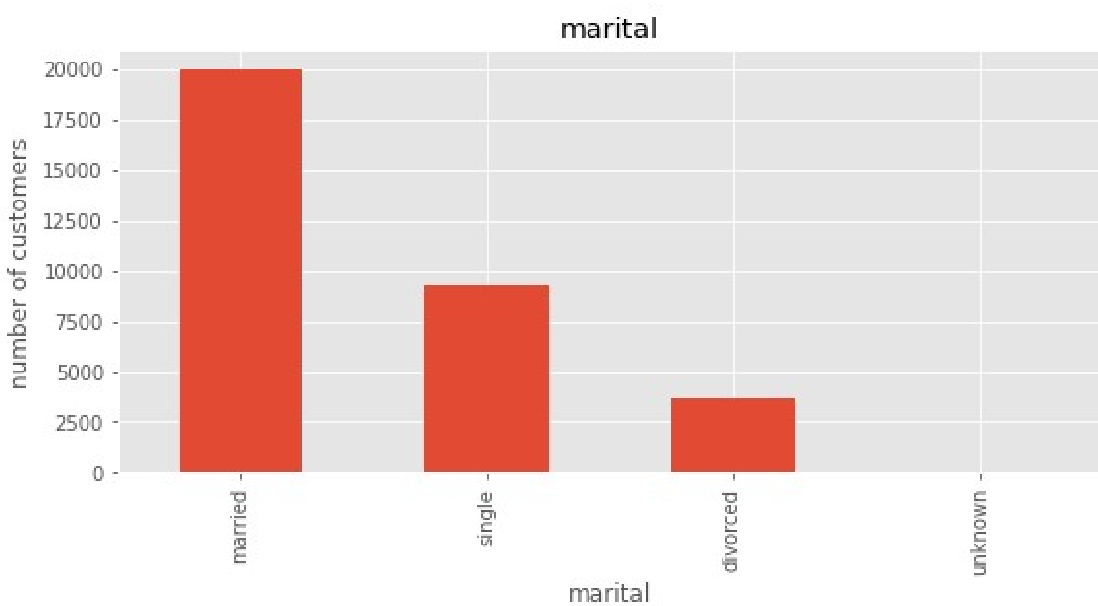

```
# percentage of class present in target variable(y)
print("percentage of NO and YES\
n",data["y"].value_counts()/len(data)*100)
```

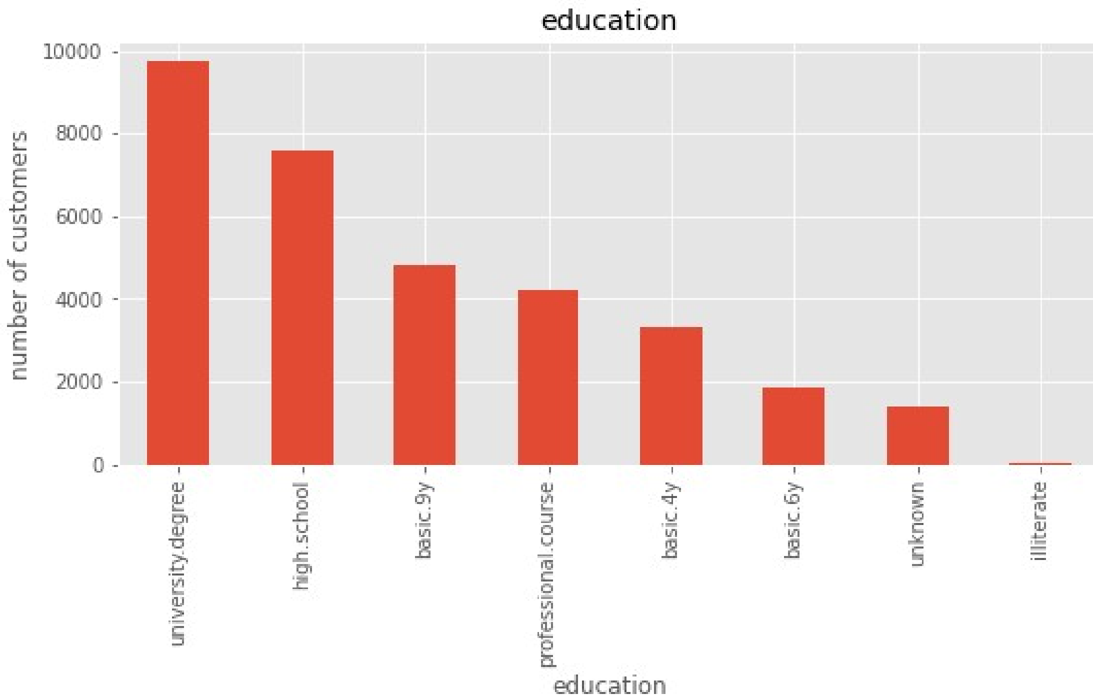
```
percentage of NO and YES
 no     88.734446
yes    11.265554
Name: y, dtype: float64
```

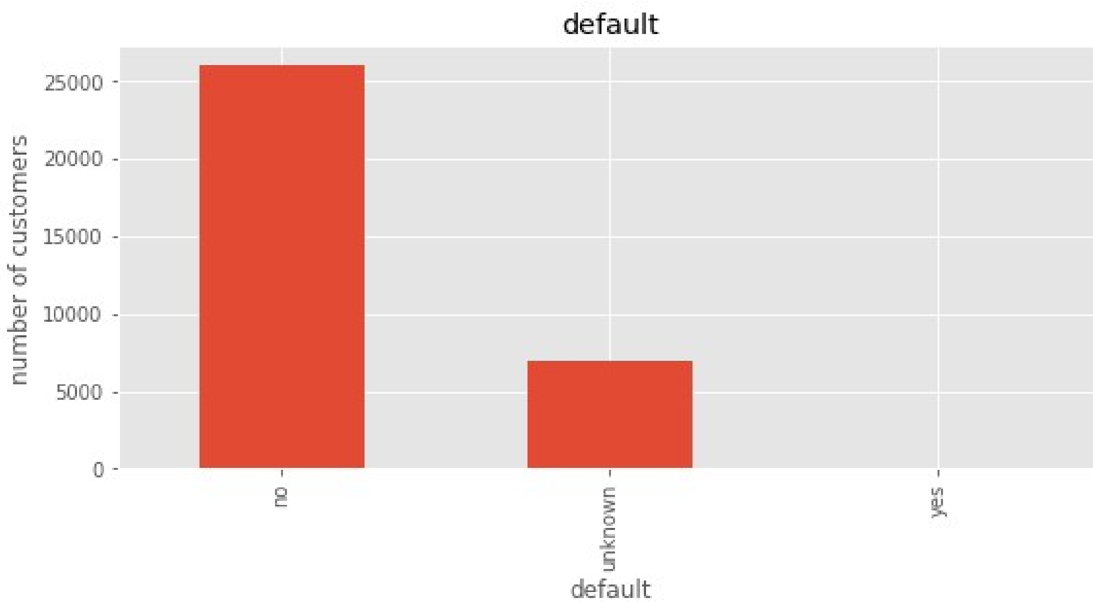
```
# indentifying the categorical variables
cat_var= data.select_dtypes(include= ["object"]).columns
print(cat_var)

# plotting bar chart for each categorical variable
plt.style.use("ggplot")

for column in cat_var:
    plt.figure(figsize=(20,4))
    plt.subplot(121)
    data[column].value_counts().plot(kind="bar")
    plt.xlabel(column)
    plt.ylabel("number of customers")
    plt.title(column)
```

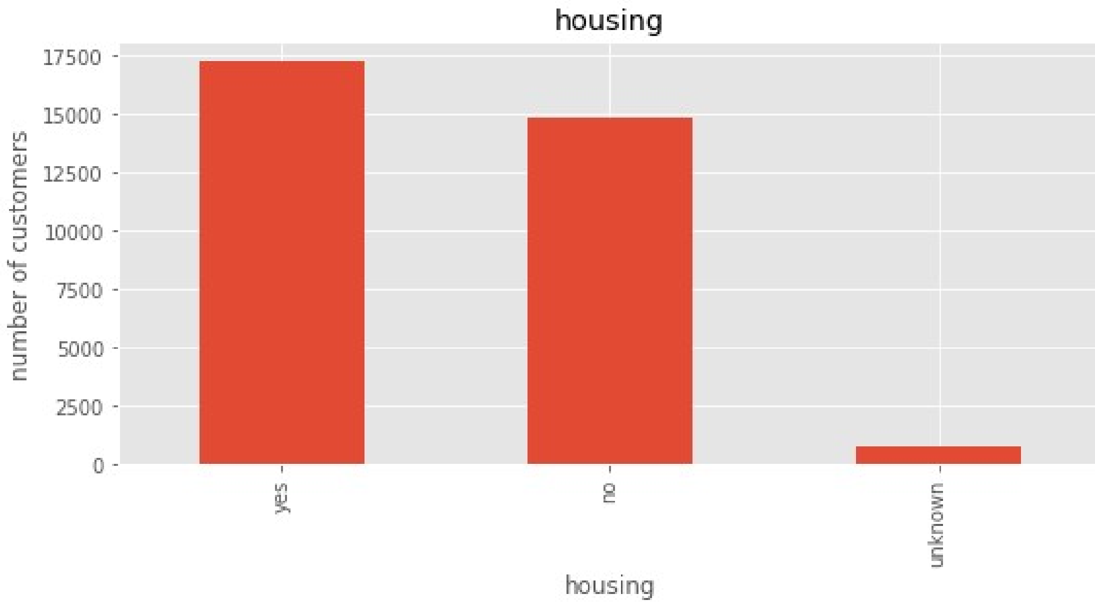
```
Index(['job', 'marital', 'education', 'default', 'housing', 'loan',
'contact',
       'month', 'day_of_week', 'poutcome', 'y'],
      dtype='object')
```

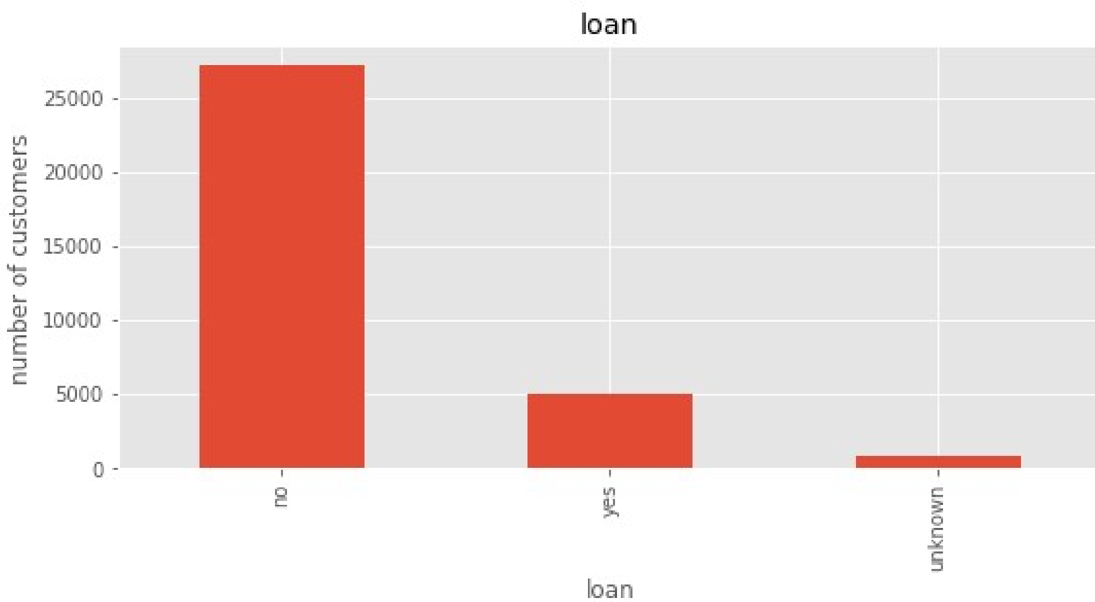

job
number of customers
8000
7000
6000
5000
4000
3000
2000
1000
0
admin.
blue-collar
technician
services
management
retired
entrepreneur
self-employed
housemaid
unemployed
student
unknown
job

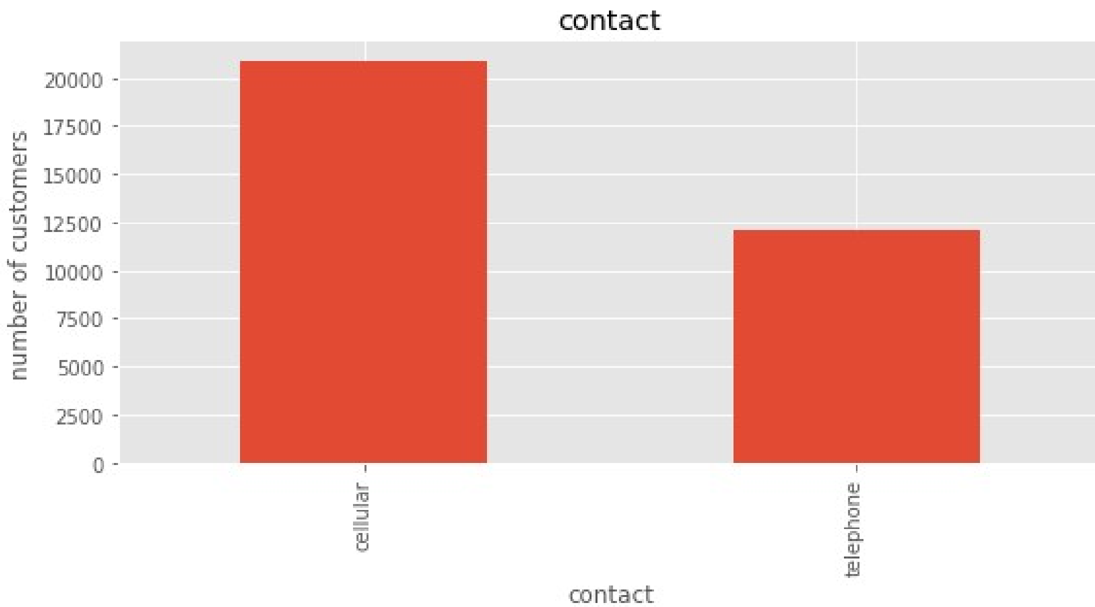

marital
number of customers
20000
17500
15000
12500
10000
7500
5000
2500
0
married
single
divorced
unknown
marital


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

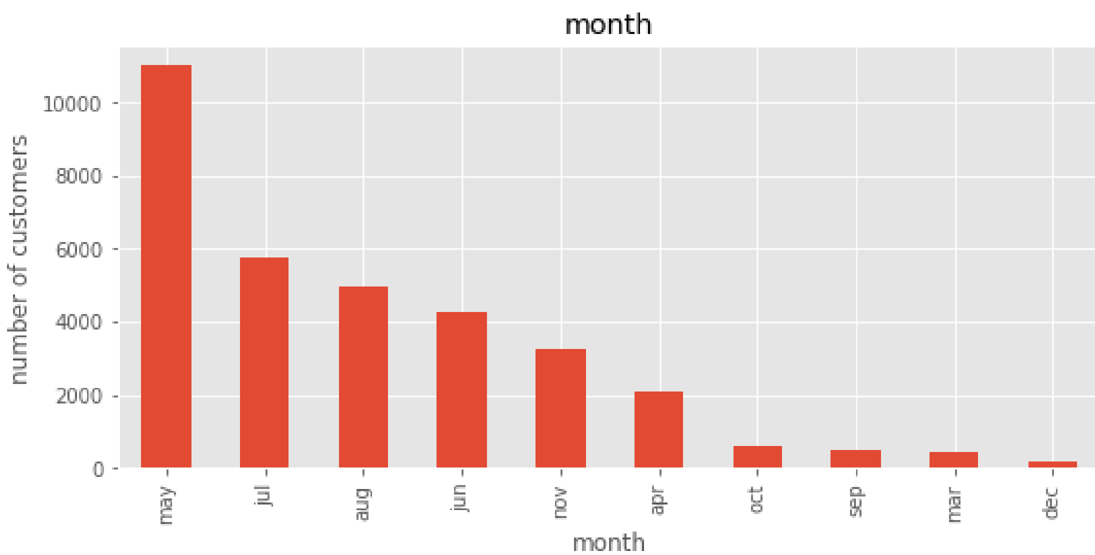

default
number of customers
25000
20000
15000
10000
5000
0
no
unknown
yes
default


housing
17500
15000
12500
10000
7500
5000
2500
0
number of customers
yes
no
unknown
housing

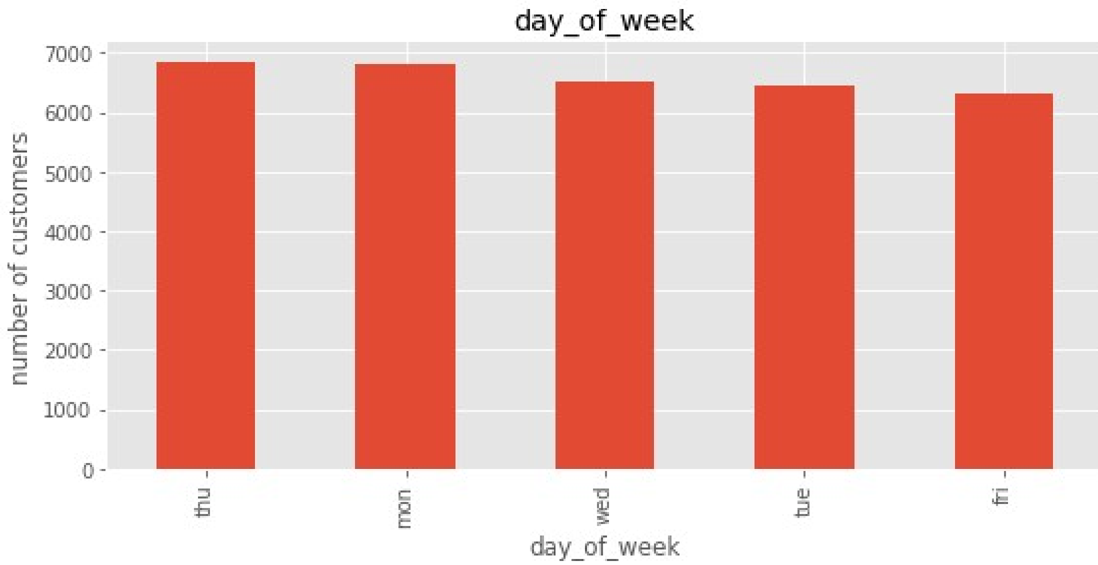

loan
25000
20000
15000
10000
5000
0
number of customers
no
yes
unknown
loan

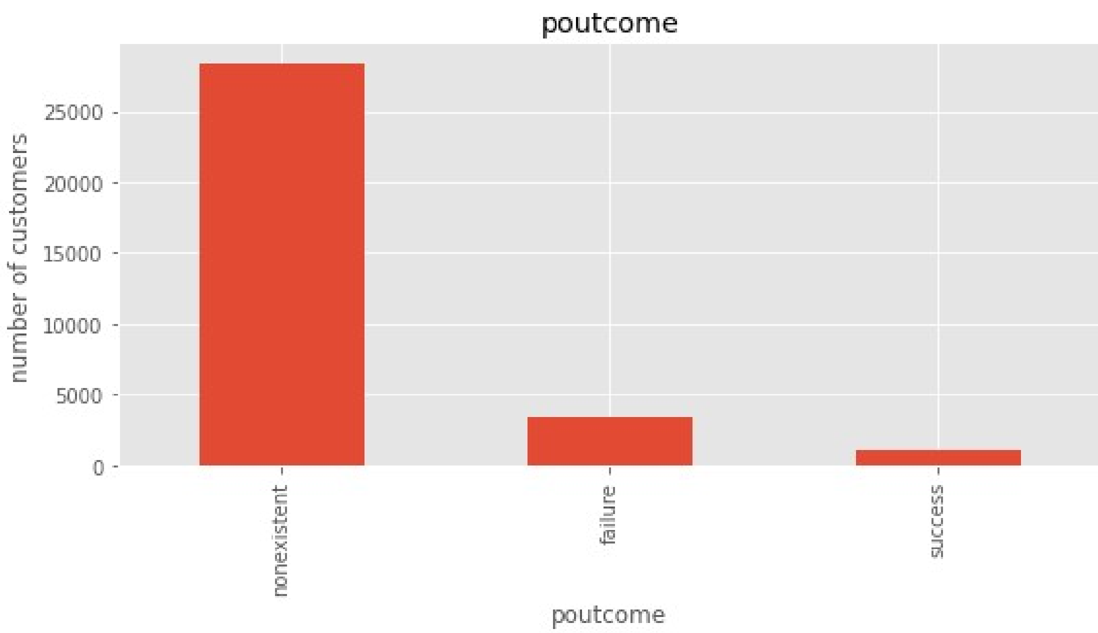


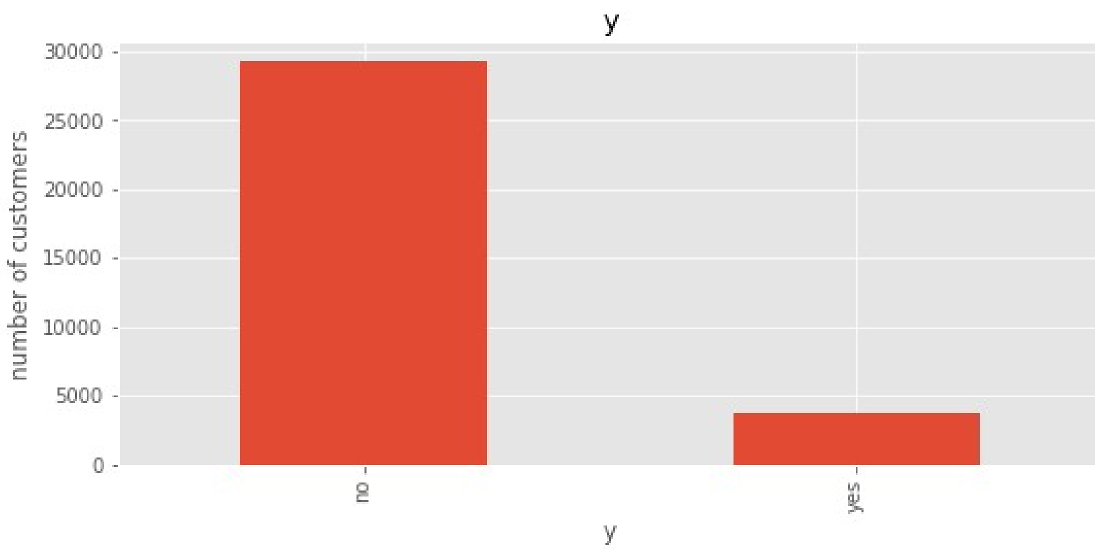
contact
number of customers
20000
17500
15000
12500
10000
7500
5000
2500
0
cellular
telephone
contact



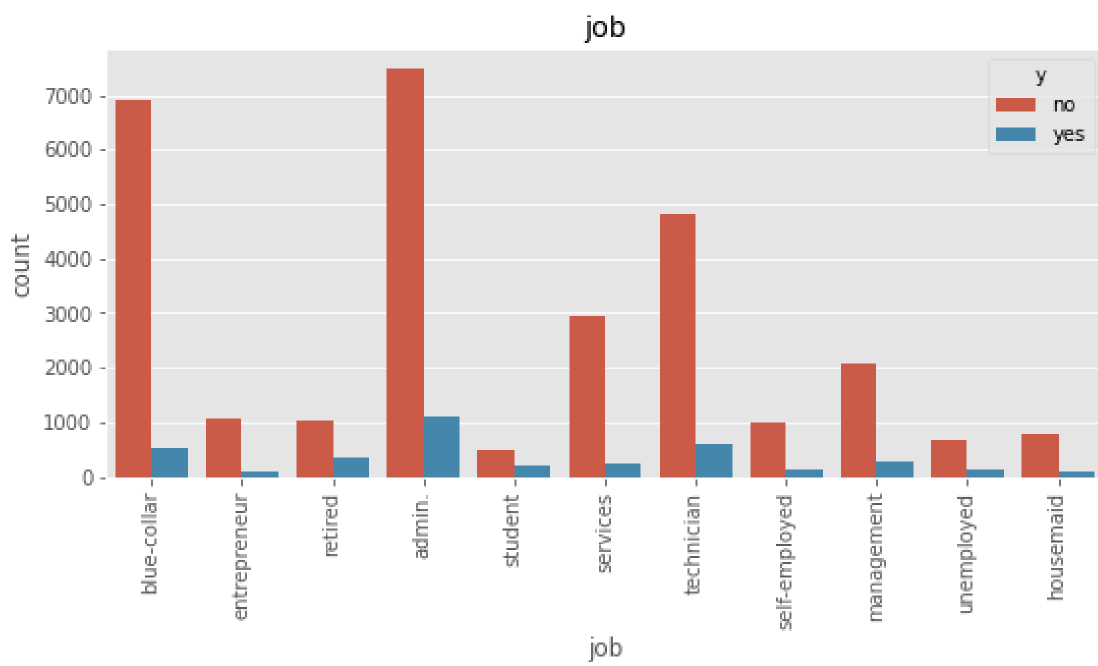
month
number of customers
10000
8000
6000
4000
2000
0
may
jul
aug
jun
nov
apr
oct
sep
mar
dec
month

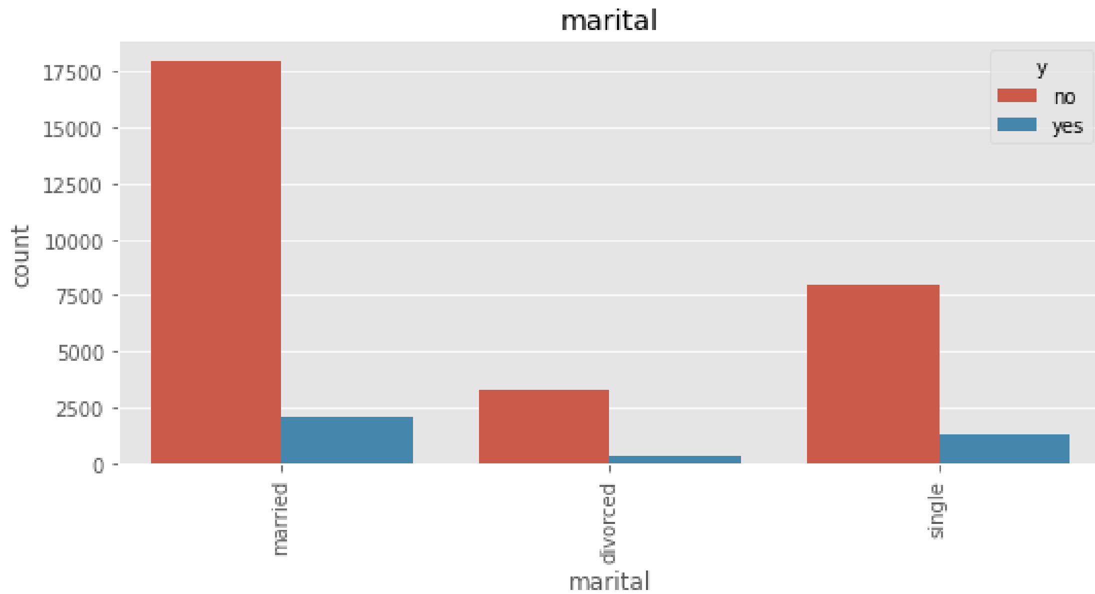

day_of_week
number of customers
7000
6000
5000
4000
3000
2000
1000
0
thu
mon
wed
tue
fri
day_of_week


poutcome
number of customers
25000
20000
15000
10000
5000
0
nonexistent
failure
success
poutcome

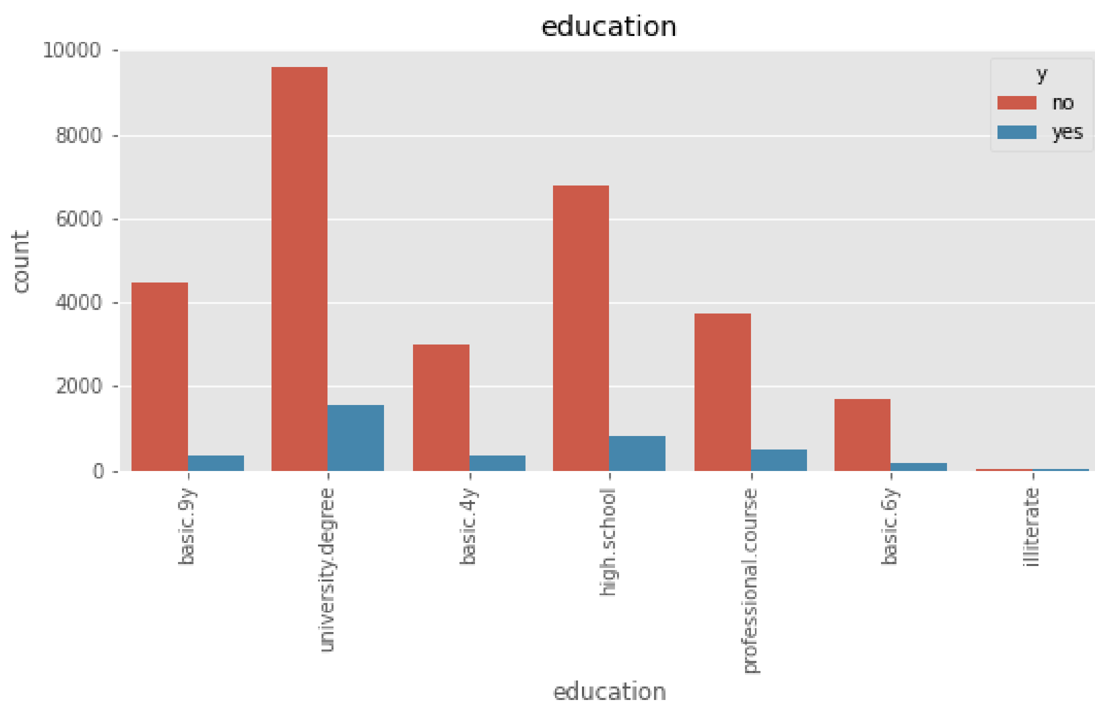



```python
# replacing "unknown" with the mode
for column in cat_var:
    mode= data[column].mode()[0]
    data[column]= data[column].replace("unknown", mode)

plt.style.use("ggplot")
for column in cat_var:
    plt.figure(figsize=(20,4))
    plt.subplot(121)
    sns.countplot(data[column], hue=data["y"])
    plt.title(column)
    plt.xticks(rotation=90)
```

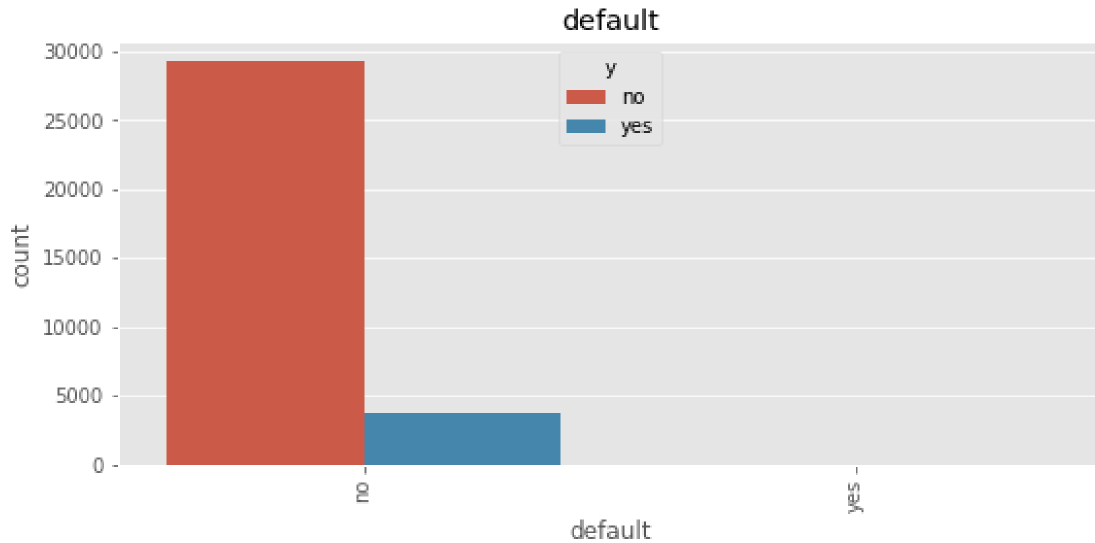


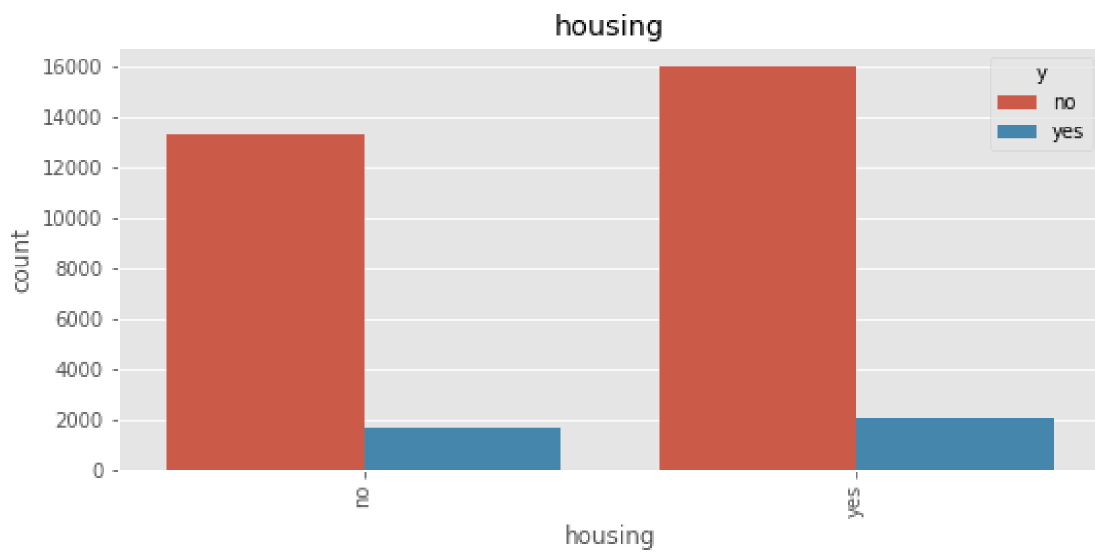


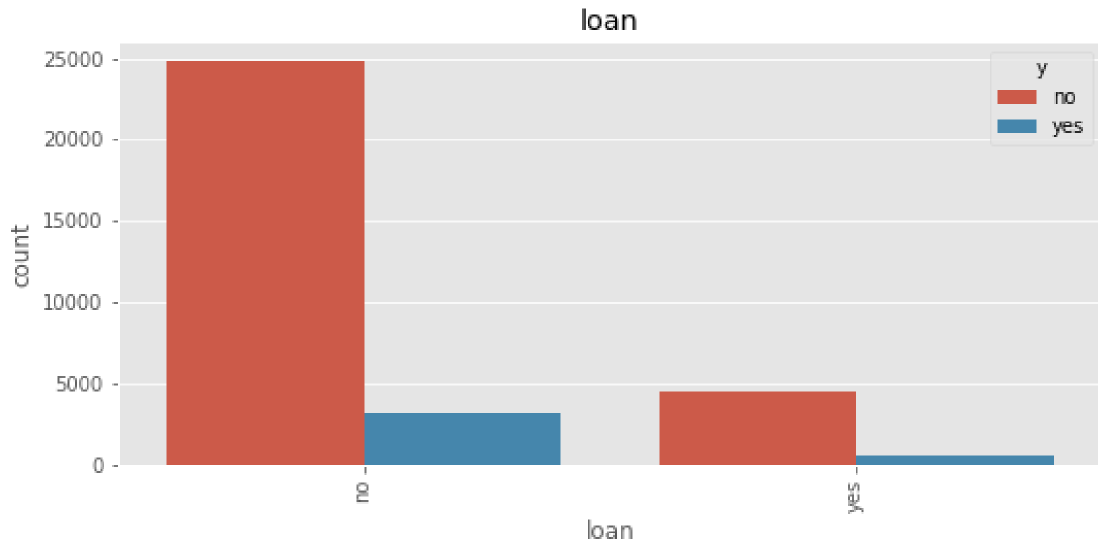
marital
y
no
yes
17500
15000
12500
10000
7500
5000
2500
0
count
married
divorced
single
marital

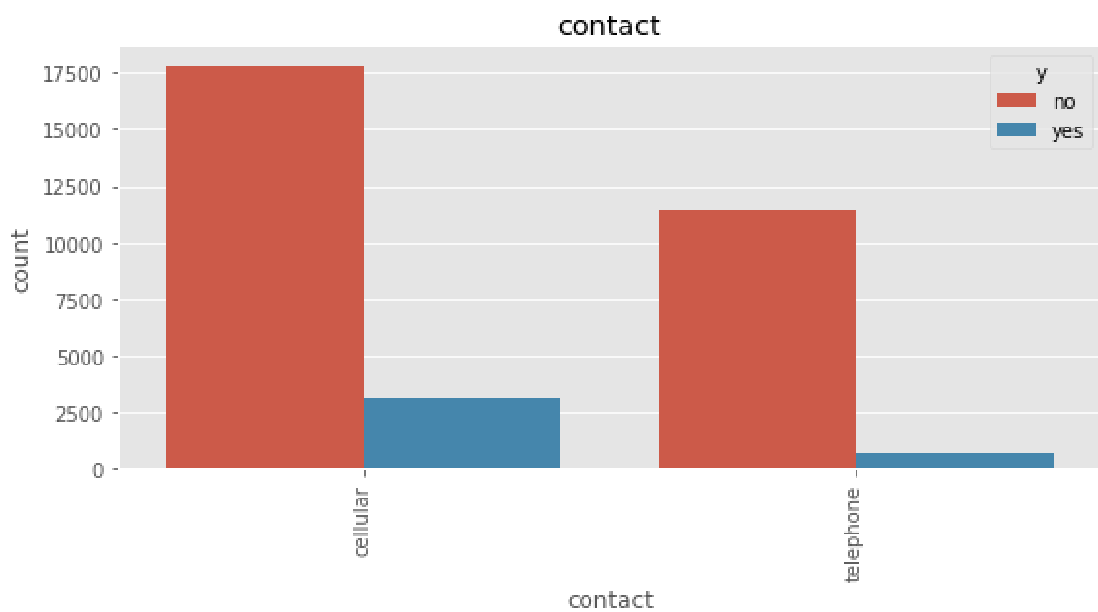


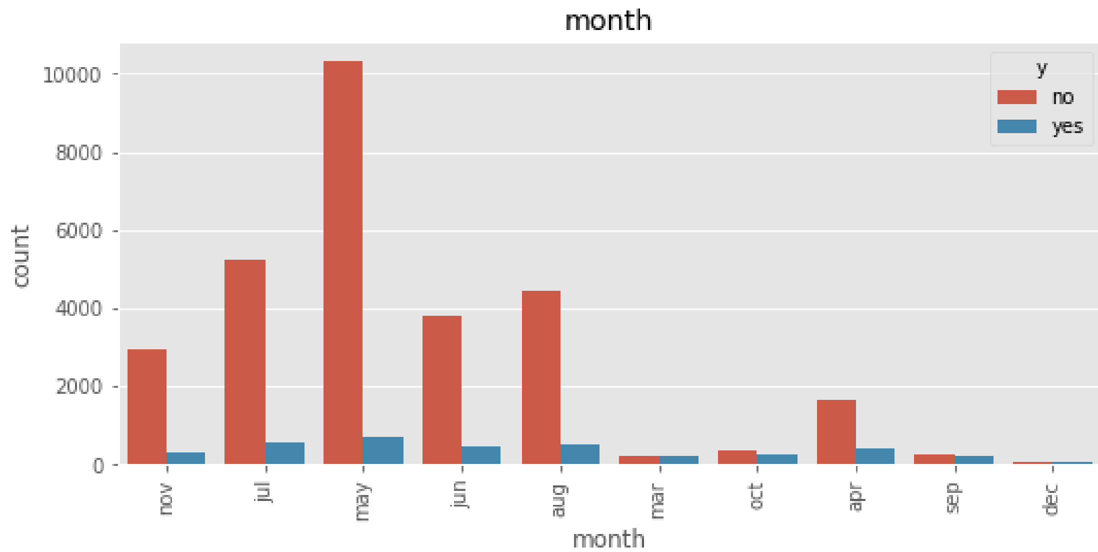
education
y
no
yes
10000
8000
6000
4000
2000
0
count
basic.9y
university.degree
basic.4y
high.school
professional.course
basic.6y
illiterate
education

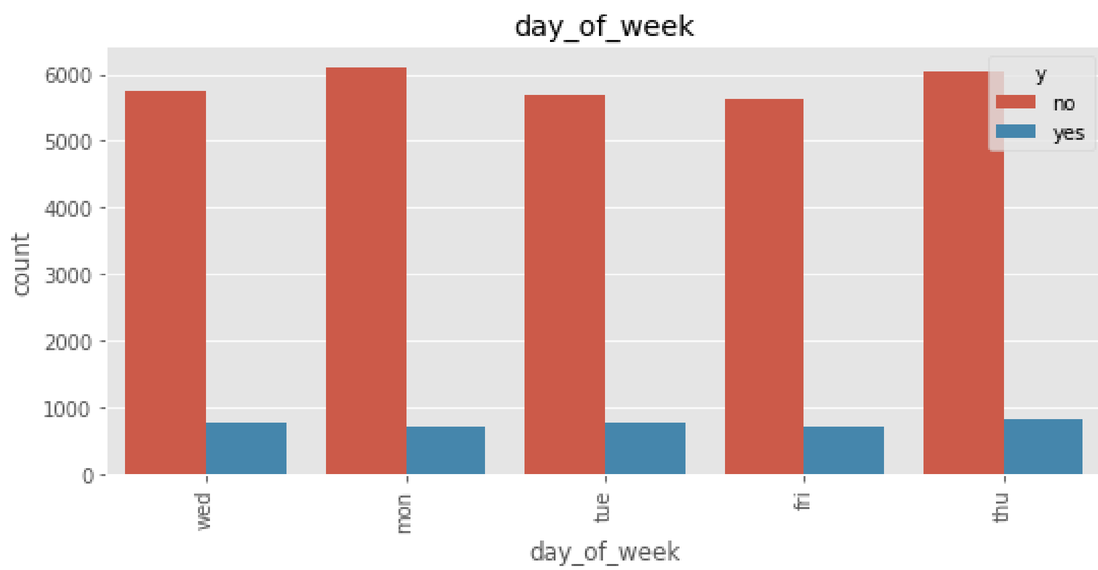

default
y
no
yes
30000
25000
20000
15000
10000
5000
0
count
no
yes
default

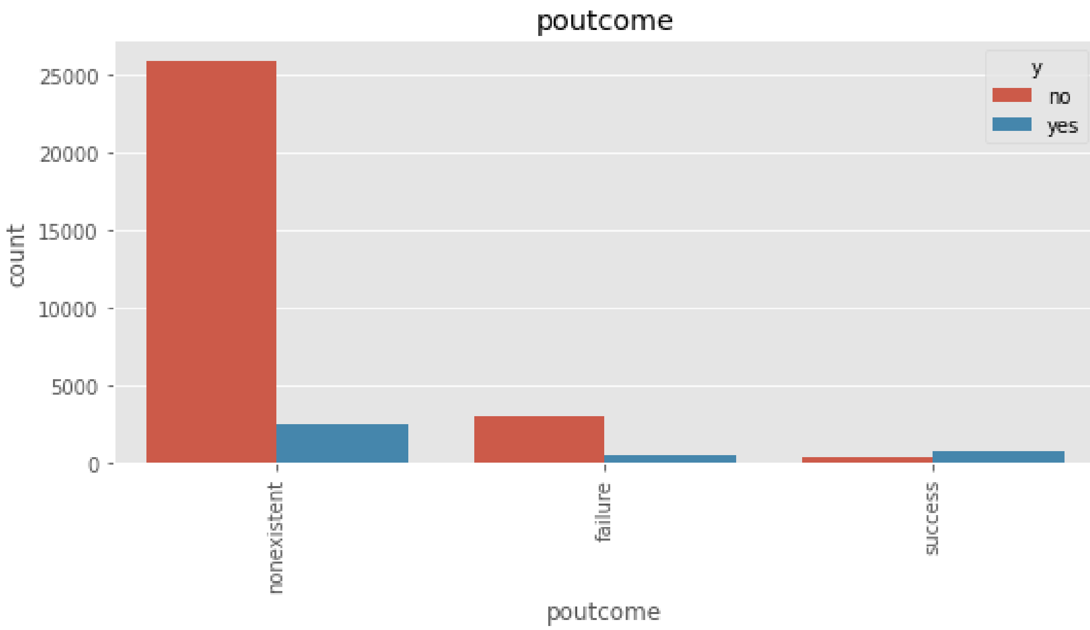

housing
y
no
yes
16000
14000
12000
10000
8000
6000
4000
2000
0
count
no
yes
housing

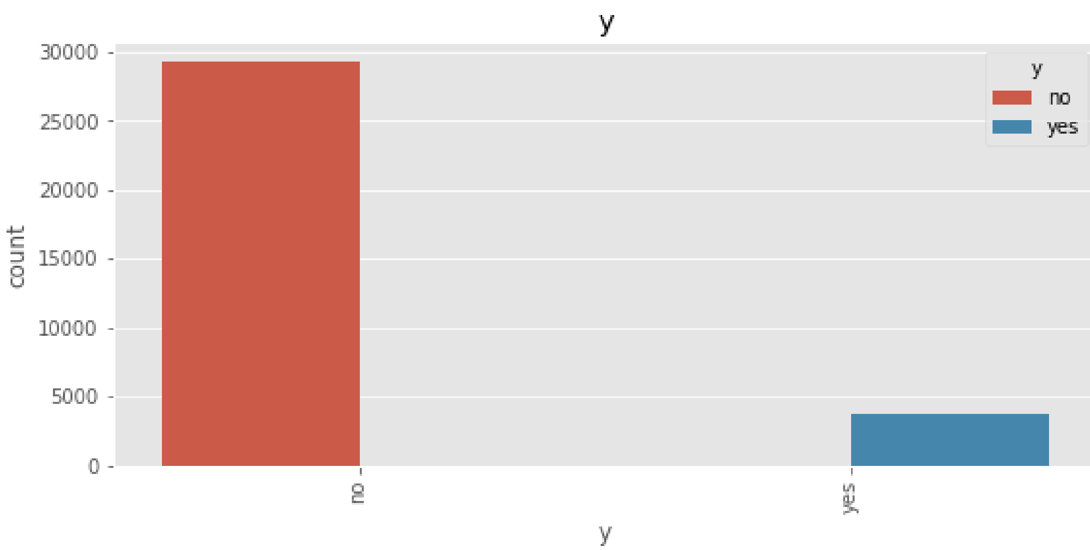

loan
y
no
yes
count
25000
20000
15000
10000
5000
0
no
yes
loan


contact
y
no
yes
count
17500
15000
12500
10000
7500
5000
2500
0
cellular
telephone
contact


month
y
no
yes
10000
8000
6000
4000
2000
0
count
nov
jul
may
jun
aug
mar
oct
apr
sep
dec
month


day_of_week
y
no
yes
6000
5000
4000
3000
2000
1000
0
count
wed
mon
tue
fri
thu
day_of_week



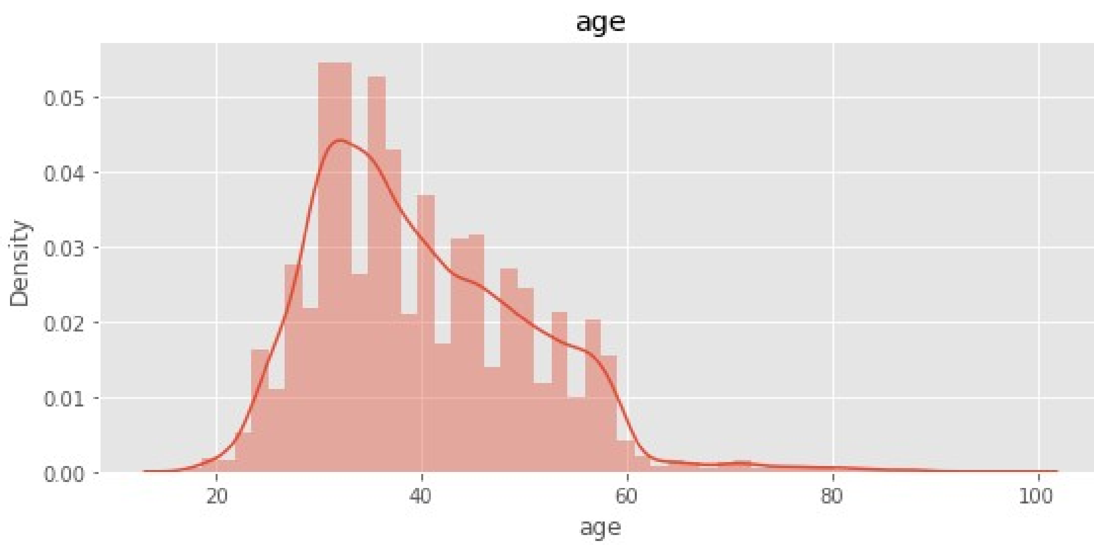


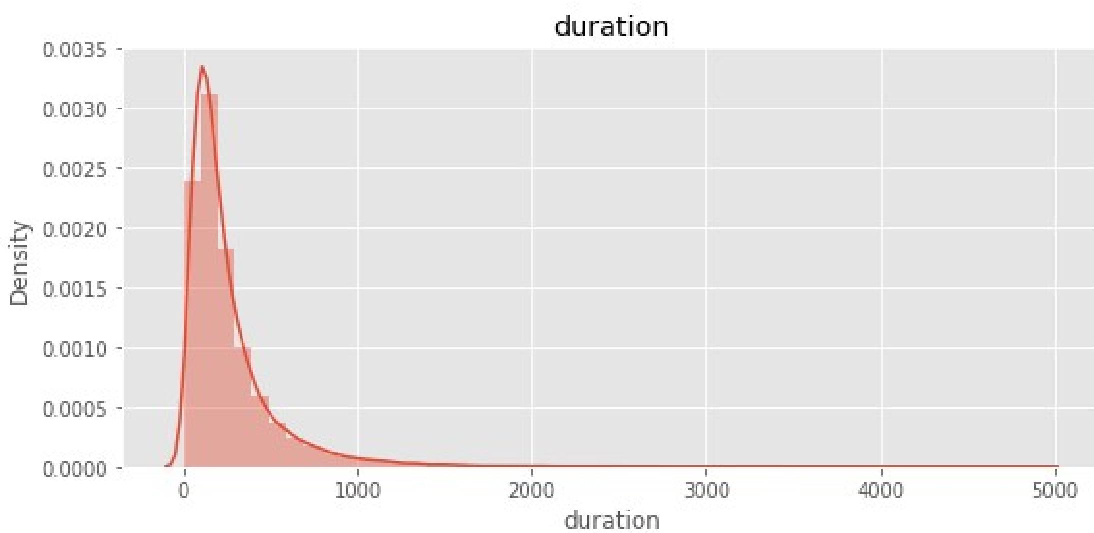

```
# indentifying the numerical variables
num_var= data.select_dtypes(include=np.number)
num_var.head()
```

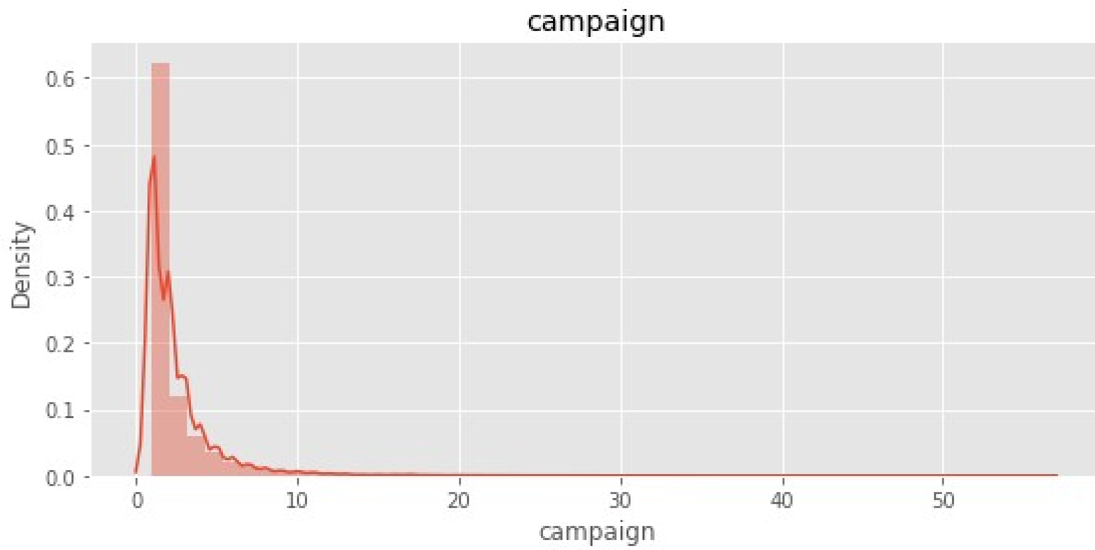
```
   age  duration  campaign  pdays  previous
0   49       227         4    999         0
1   37       202         2    999         1
2   78      1148         1    999         0
3   36       120         2    999         0
4   59       368         2    999         0
```

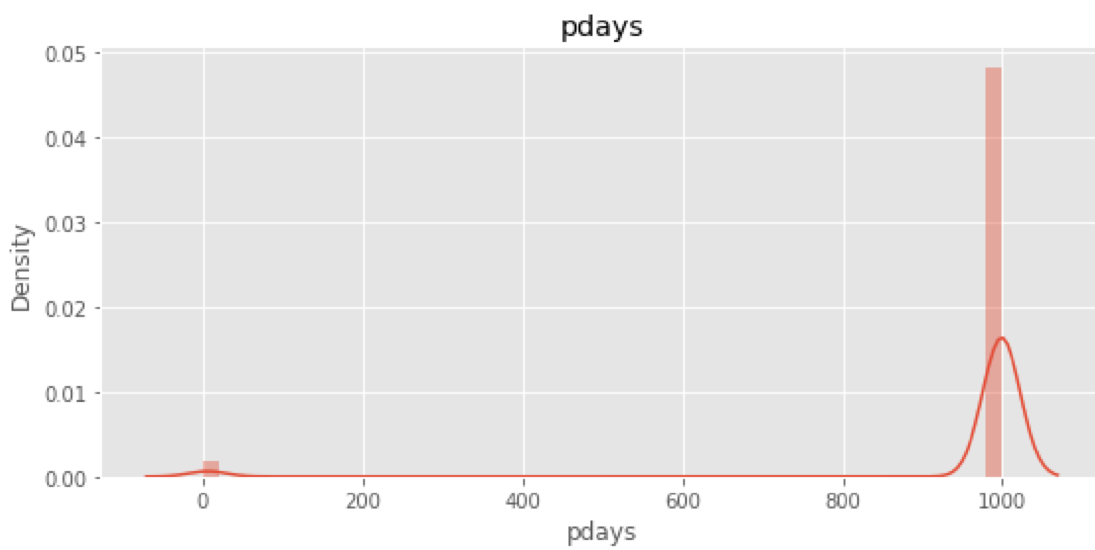
```
# plotting histogram for each numerical variable
plt.style.use("ggplot")
for column in ["age", "duration", "campaign", "pdays", "previous"]:
```

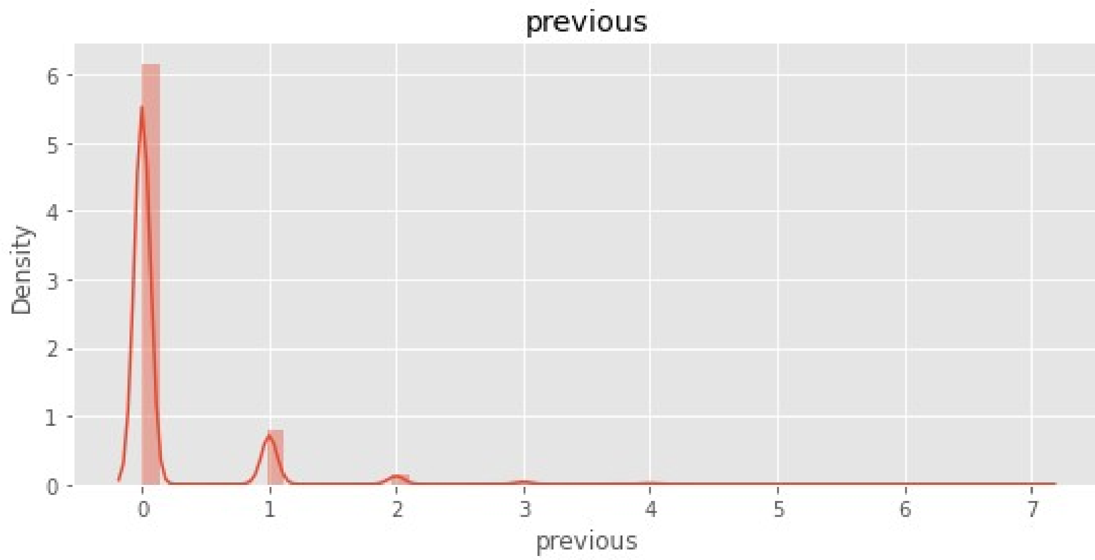
```
plt.figure(figsize=(20,4))
plt.subplot(121)
sns.distplot(data[column], kde=True)
plt.title(column)
```



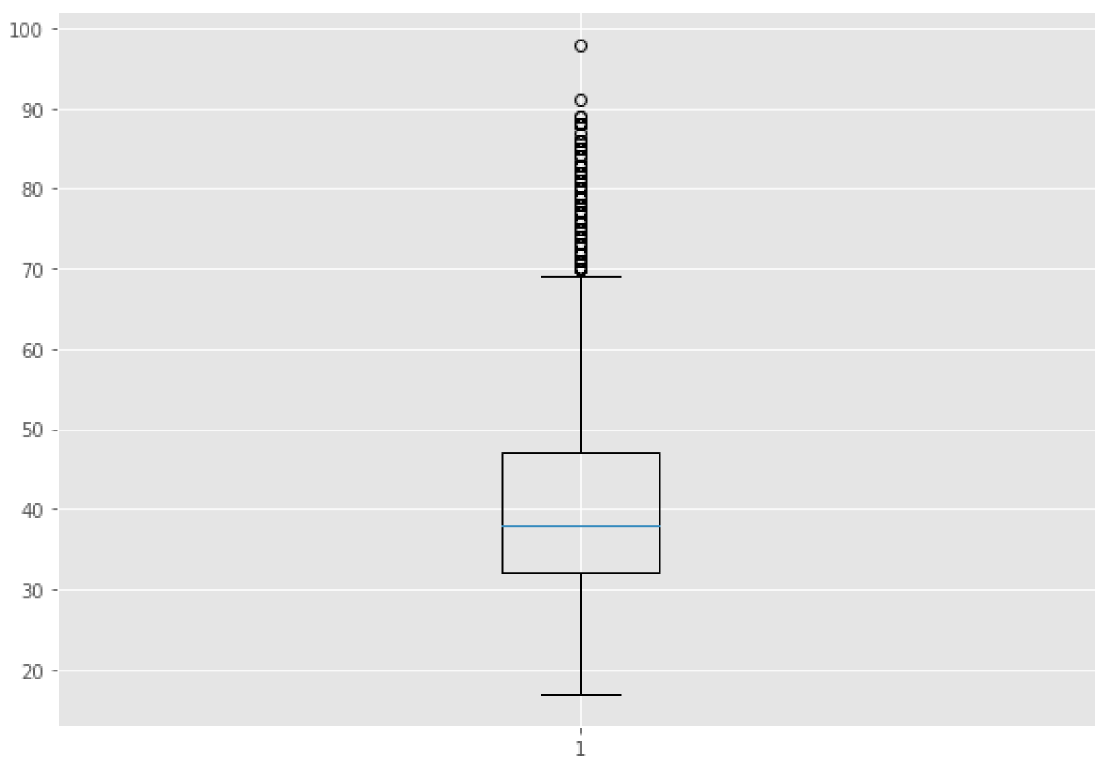



campaign
Density
0.6
0.5
0.4
0.3
0.2
0.1
0.0
0
10
20
30
40
50
campaign

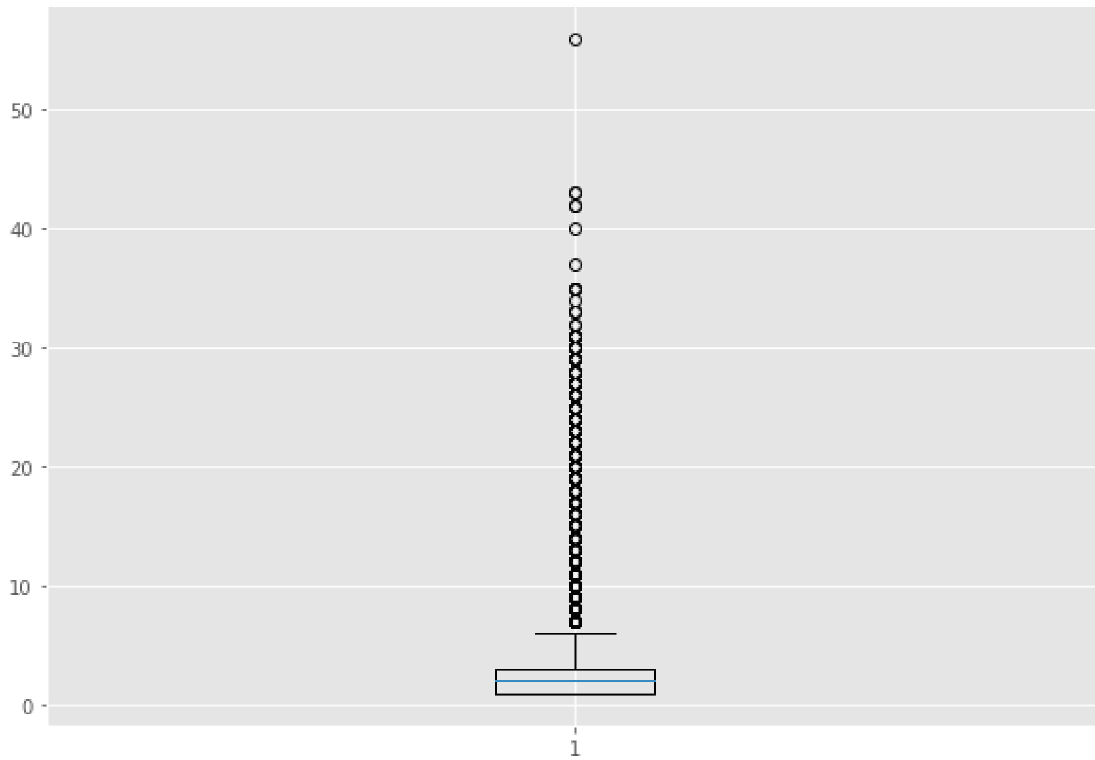

pdays
Density
0.05
0.04
0.03
0.02
0.01
0.00
0
200
400
600
800
1000
pdays



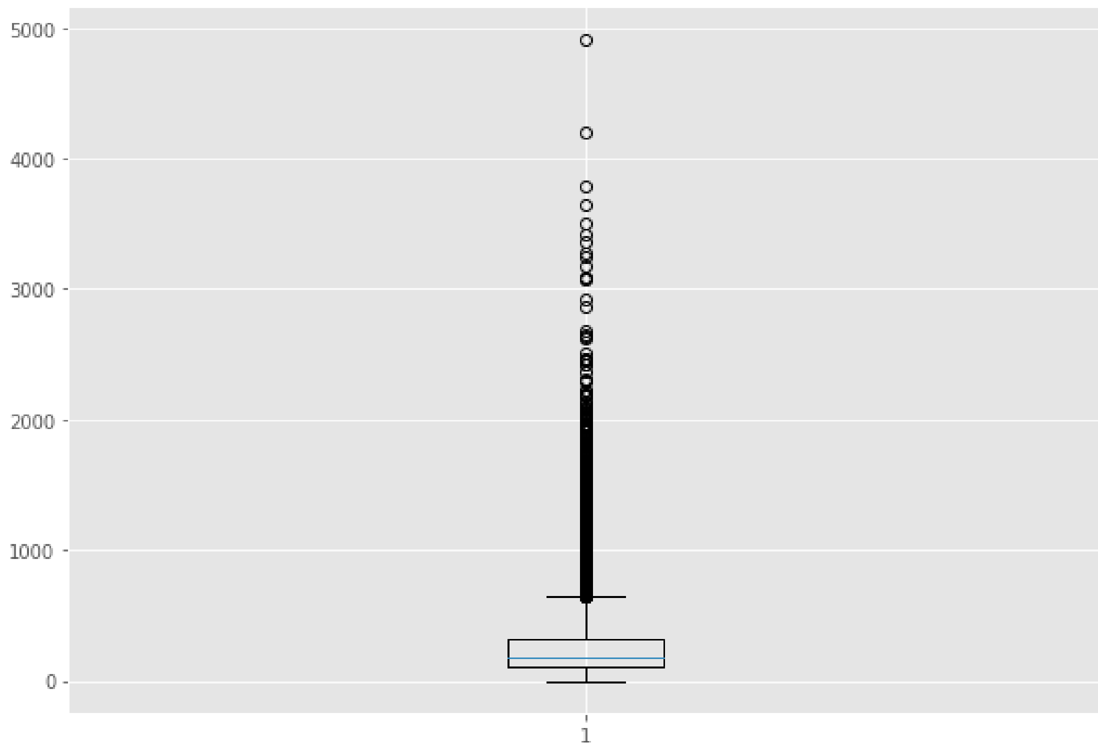

```
age = data["age"]

fig = plt.figure(figsize =(10, 7))

# Creating plot
plt.boxplot(age)

# show plot
plt.show()
```



```python
campaign = data["campaign"]

fig = plt.figure(figsize =(10, 7))

# Creating plot
plt.boxplot(campaign)

# show plot
plt.show()
```




```python
duration = data["duration"]

fig = plt.figure(figsize =(10, 7))

# Creating plot
plt.boxplot(duration)

# show plot
plt.show()
```




```
data.drop(columns=["pdays", "previous"], axis=1, inplace=True)

data.describe()
```

	age	duration	campaign
count	32950.000000	32950.000000	32950.000000
mean	40.014112	258.127466	2.560607
std	10.403636	258.975917	2.752326
min	17.000000	0.000000	1.000000
25%	32.000000	103.000000	1.000000
50%	38.000000	180.000000	2.000000
75%	47.000000	319.000000	3.000000
max	98.000000	4918.000000	56.000000

```
# compute interquantile range to calculate the boundaries
lower_boundries= []
upper_boundries= []
for i in ["age", "duration", "campaign"]:
    IQR= data[i].quantile(0.75) - data[i].quantile(0.25)
    lower_bound= data[i].quantile(0.25) - (1.5*IQR)
    upper_bound= data[i].quantile(0.75) + (1.5*IQR)

    print(i, ":", lower_bound, ",",  upper_bound)

    lower_boundries.append(lower_bound)
    upper_boundries.append(upper_bound)
```

```
age : 9.5 , 69.5
duration : -221.0 , 643.0
campaign : -2.0 , 6.0
```

```
lower_boundries
```

```
[9.5, -221.0, -2.0]
```

```
upper_boundries
```

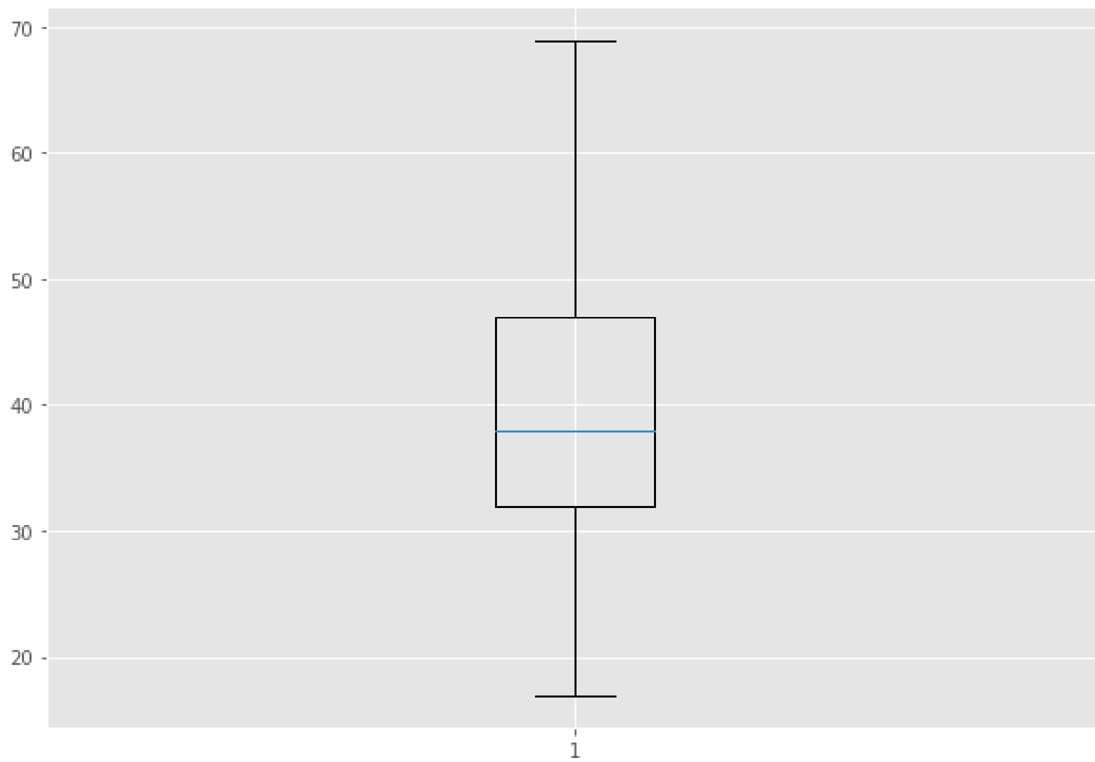
```
[69.5, 643.0, 6.0]
```

```
# replace the all the outliers which is greater then upper boundary by
upper boundary
j = 0
for i in ["age", "duration", "campaign"]:
    data.loc[data[i] > upper_boundries[j], i] =
int(upper_boundries[j])
    j = j + 1
```

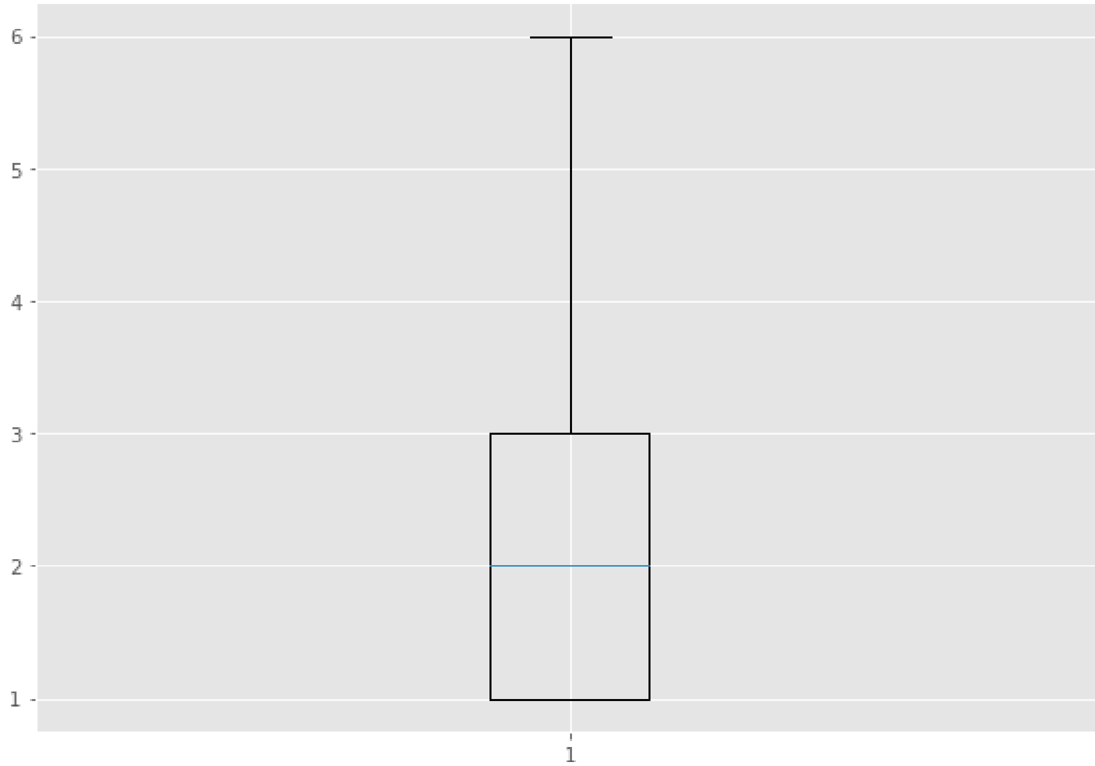
```
# without outliers
data.describe()
```

	age	duration	campaign
count	32950.000000	32950.000000	32950.000000
mean	39.929894	234.923915	2.271077
std	10.118566	176.854558	1.546302
min	17.000000	0.000000	1.000000
25%	32.000000	103.000000	1.000000
50%	38.000000	180.000000	2.000000
75%	47.000000	319.000000	3.000000
max	69.000000	643.000000	6.000000

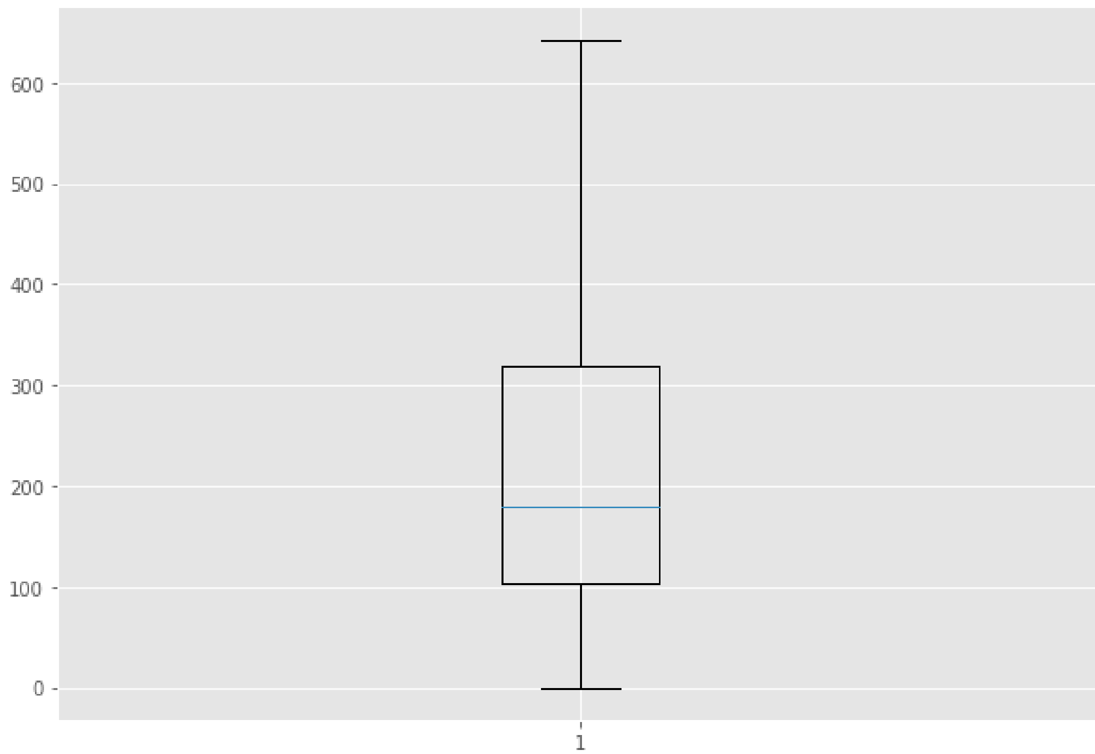
```
age = data["age"]

fig = plt.figure(figsize =(10, 7))

# Creating plot
plt.boxplot(age)

# show plot
plt.show()
```



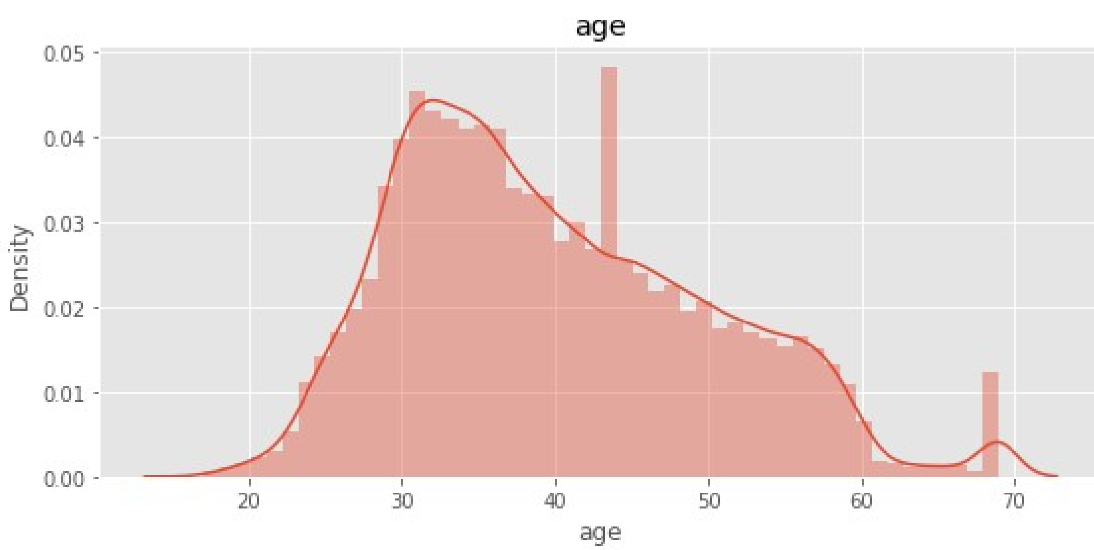

```
campaign = data["campaign"]

fig = plt.figure(figsize =(10, 7))

# Creating plot
plt.boxplot(campaign)

# show plot
plt.show()
```

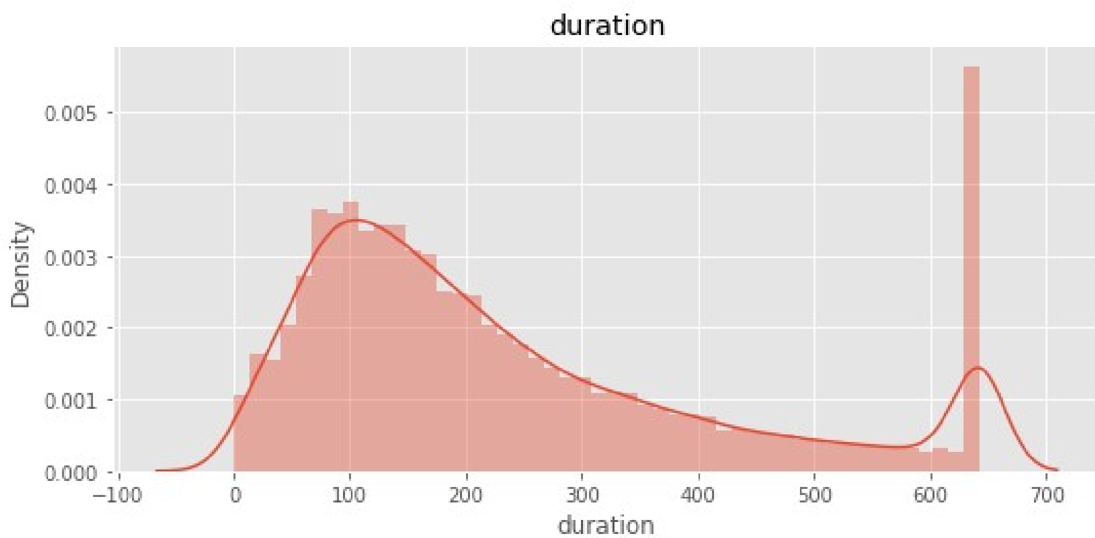


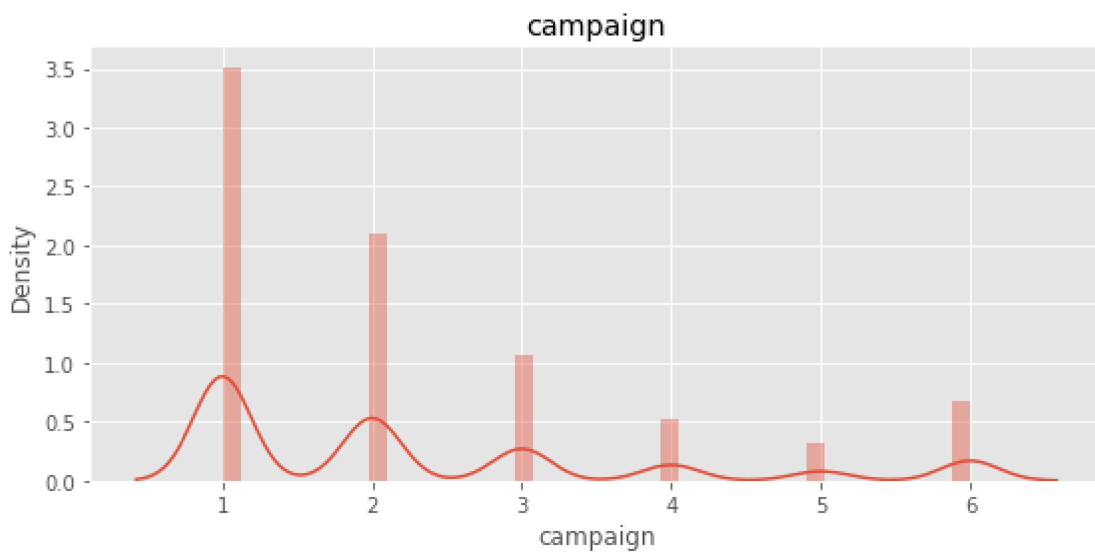

```
duration = data["duration"]

fig = plt.figure(figsize =(10, 7))

# Creating plot
plt.boxplot(duration)

# show plot
plt.show()
```




```
# plotting histogram for each numerical variable
plt.style.use("ggplot")
for column in ["age", "duration", "campaign"]:
    plt.figure(figsize=(20,4))
    plt.subplot(121)
    sns.distplot(data[column], kde=True)
    plt.title(column)
```








```
#categorical features
cat_var
```

```
Index(['job', 'marital', 'education', 'default', 'housing', 'loan',
'contact',
       'month', 'day_of_week', 'poutcome', 'y'],
      dtype='object')
```

```
# check categorical class
for i in cat_var:
    print(i, ":", data[i].unique())
```

```
job : ['blue-collar' 'entrepreneur' 'retired' 'admin.' 'student'
'services'
 'technician' 'self-employed' 'management' 'unemployed' 'housemaid']
marital : ['married' 'divorced' 'single']
education : ['basic.9y' 'university.degree' 'basic.4y' 'high.school'
```

```
 'professional.course' 'basic.6y' 'illiterate']
default : ['no' 'yes']
housing : ['no' 'yes']
loan : ['no' 'yes']
contact : ['cellular' 'telephone']
month : ['nov' 'jul' 'may' 'jun' 'aug' 'mar' 'oct' 'apr' 'sep' 'dec']
day_of_week : ['wed' 'mon' 'tue' 'fri' 'thu']
poutcome : ['nonexistent' 'failure' 'success']
y : ['no' 'yes']
```

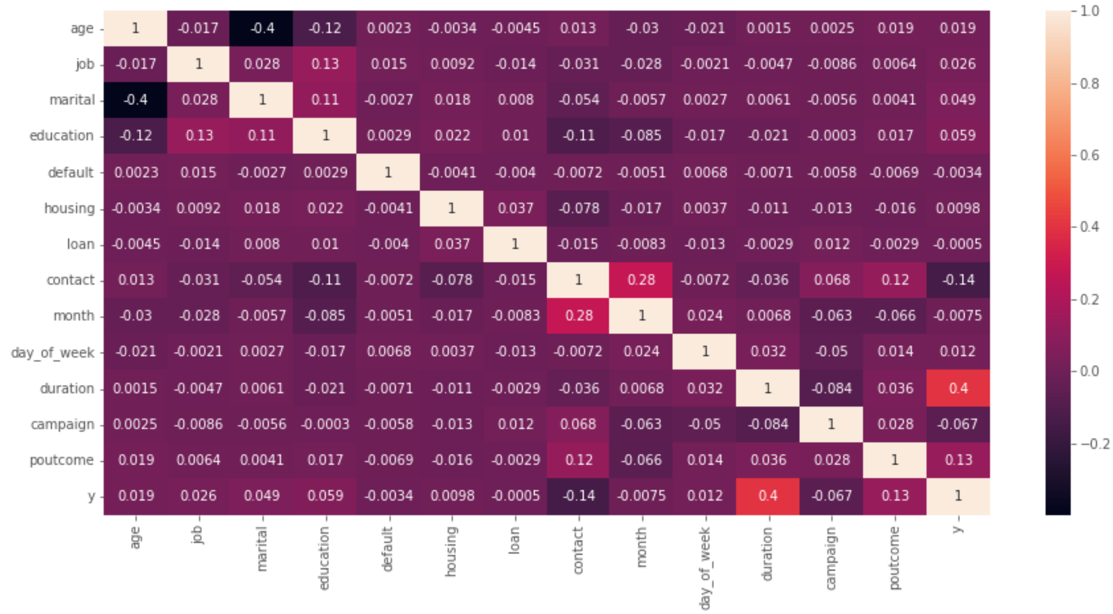
```
from sklearn.preprocessing import LabelEncoder

# initializing label encoder
le= LabelEncoder()

# iterating through each categorical feature and label encoding them
for feature in cat_var:
    data[feature]= le.fit_transform(data[feature])

# label encoded dataset
data.head()
```

```
   age  job  marital  education  default  housing  loan  contact
month  \
0   49    1        1          2        0        0     0        0
7
1   37    2        1          6        0        0     0        1
7
2   69    5        1          0        0        0     0        0
3
3   36    0        1          6        0        1     0        1
6
4   59    5        0          6        0        0     0        0
4

   day_of_week  duration  campaign  poutcome  y
0            4       227         4         1  0
1            4       202         2         0  0
2            1       643         1         1  1
3            1       120         2         1  0
4            3       368         2         1  0
```

```
# feature variables
x= data.iloc[:, :-1]

# target variable
y= data.iloc[:, -1]
```

```
plt.figure(figsize=(15,7))
sns.heatmap(data.corr(), annot=True)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f708aa93710>
```




```
#initialising oversampling
smote= SMOTETomek(0.75)

#implementing oversampling to training data
x_sm, y_sm= smote.fit_resample(x,y)

# x_sm and y_sm are the resampled data

# target class count of resampled dataset
y_sm.value_counts()
```

```
0    28961
1    21651
Name: y, dtype: int64
```

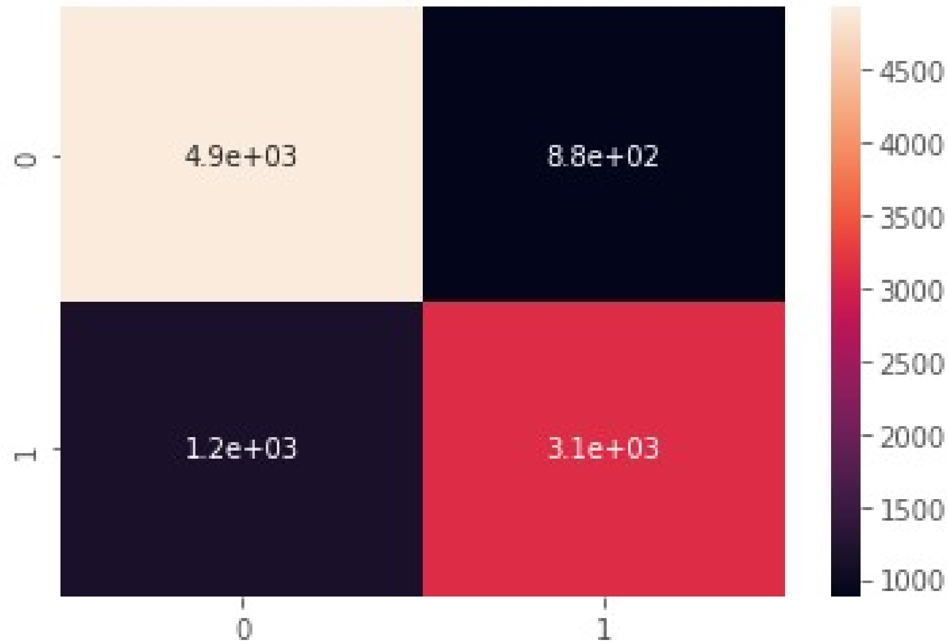
```
x_train, x_test, y_train, y_test= train_test_split(x_sm, y_sm,
test_size=0.2, random_state=42)

# selecting the classifier
log_reg= LogisticRegression()

# selecting hyperparameter tuning
log_param= {"C": 10.0**np.arange(-2,3), "penalty": ["l1", "l2"]}

# defining stratified Kfold cross validation
cv_log= StratifiedKFold(n_splits=5)

# using gridsearch for respective parameters
gridsearch_log= GridSearchCV(log_reg, log_param, cv=cv_log, scoring=
"f1_macro", n_jobs=-1, verbose=2)
```

```python
# fitting the model on resampled data
gridsearch_log.fit(x_train, y_train)
```

```
Fitting 5 folds for each of 10 candidates, totalling 50 fits

GridSearchCV(cv=StratifiedKFold(n_splits=5, random_state=None,
shuffle=False),
             estimator=LogisticRegression(), n_jobs=-1,
             param_grid={'C': array([1.e-02, 1.e-01, 1.e+00, 1.e+01,
1.e+02]),
                         'penalty': ['l1', 'l2']},
             scoring='f1_macro', verbose=2)
```

```python
# checking model performance
y_predicted= gridsearch_log.predict(x_test)

cm= confusion_matrix(y_test, y_predicted)
sns.heatmap(cm, annot=True)
print("Accuracy of Logistic Regression:",accuracy_score(y_test,
y_predicted))
print(classification_report(y_test, y_predicted))
```

```
Accuracy of Logistic Regression: 0.797095722611874
              precision    recall  f1-score   support

           0       0.81      0.85      0.83      5813
           1       0.78      0.73      0.75      4310

    accuracy                           0.80     10123
   macro avg       0.79      0.79      0.79     10123
weighted avg       0.80      0.80      0.80     10123
```

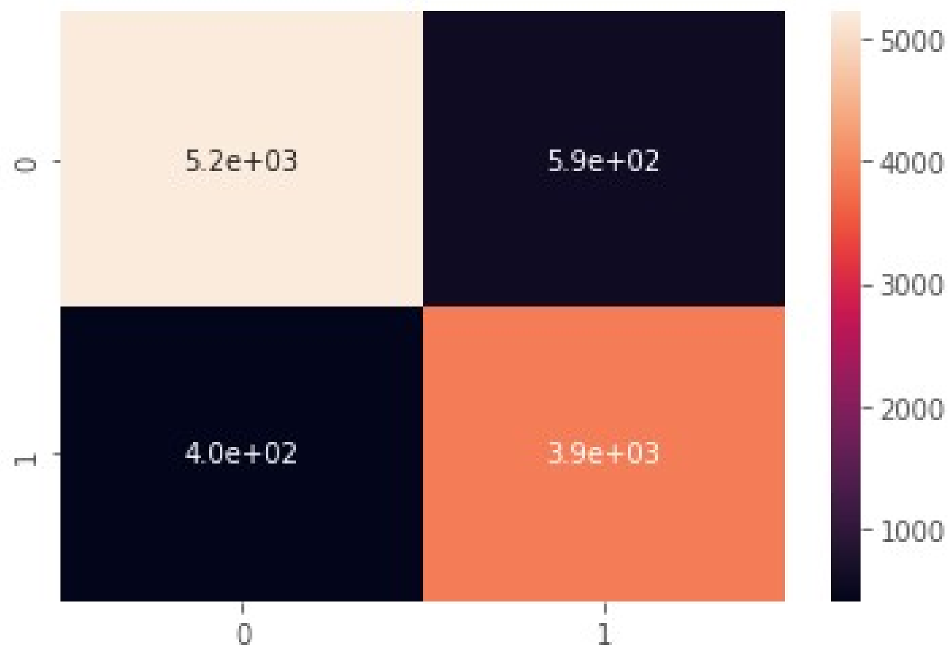



```
# random forest
rf= RandomForestClassifier()

rf_param= {
            "n_estimators": [int(x) for x in np.linspace(start=100,
stop=1000, num=10)],
            "max_features": ["auto", "sqrt", "log2"],
#             "max_depth": [4,5,6,7,8],
            "max_depth": [int(x) for x in np.linspace(start=5, stop=30,
num=6)],
            "min_samples_split": [5,10,15,100],
            "min_samples_leaf": [1,2,5,10],
            "criterion":['gini', 'entropy']
          }

cv_rf= StratifiedKFold(n_splits=5)

randomsearch_rf= RandomizedSearchCV(rf, rf_param, cv=cv_rf, scoring=
"f1_macro", n_jobs=-1, verbose=2, n_iter=10)

randomsearch_rf.fit(x_train, y_train)
```

```
Fitting 5 folds for each of 10 candidates, totalling 50 fits

RandomizedSearchCV(cv=StratifiedKFold(n_splits=5, random_state=None,
shuffle=False),
                   estimator=RandomForestClassifier(), n_jobs=-1,
                   param_distributions={'criterion': ['gini',
'entropy'],
                                        'max_depth': [5, 10, 15, 20,
```

```
25, 30],
                                        'max_features': ['auto',
'sqrt',
                                                         'log2'],
                                        'min_samples_leaf': [1, 2, 5,
10],
                                        'min_samples_split': [5, 10,
15, 100],
                                        'n_estimators': [100, 200,
300, 400,
                                                         500, 600,
700, 800,
                                                         900, 1000]},
                   scoring='f1_macro', verbose=2)

# checking model performance
y_predicted_rf= randomsearch_rf.predict(x_test)
sns.heatmap(confusion_matrix(y_test, y_predicted_rf), annot=True)
print("Accuracy of Random Forest Model:",accuracy_score(y_test,
y_predicted_rf))
print(classification_report(y_test, y_predicted_rf))
```

```
Accuracy of Random Forest Model: 0.9015114096611676
              precision    recall  f1-score   support

           0       0.93      0.90      0.91      5813
           1       0.87      0.91      0.89      4310

    accuracy                           0.90     10123
   macro avg       0.90      0.90      0.90     10123
weighted avg       0.90      0.90      0.90     10123
```




```
#Artificial Neural Network
ANN_Classifier=Sequential()
ANN_Classifier.add(Dense(units = 6, kernel_initializer = 'uniform',
activation = 'relu', input_dim = 13))
ANN_Classifier.add(Dense(units = 6, kernel_initializer = 'uniform',
activation = 'relu'))
ANN_Classifier.add(Dense(units = 1, kernel_initializer = 'uniform',
activation = 'sigmoid'))
ANN_Classifier.compile(optimizer = 'adam', loss =
'binary_crossentropy', metrics = ['accuracy'])
ANN_Classifier.fit(x_train, y_train, batch_size = 10, epochs = 20)
ANN_Classifier.predict(x_test)
```

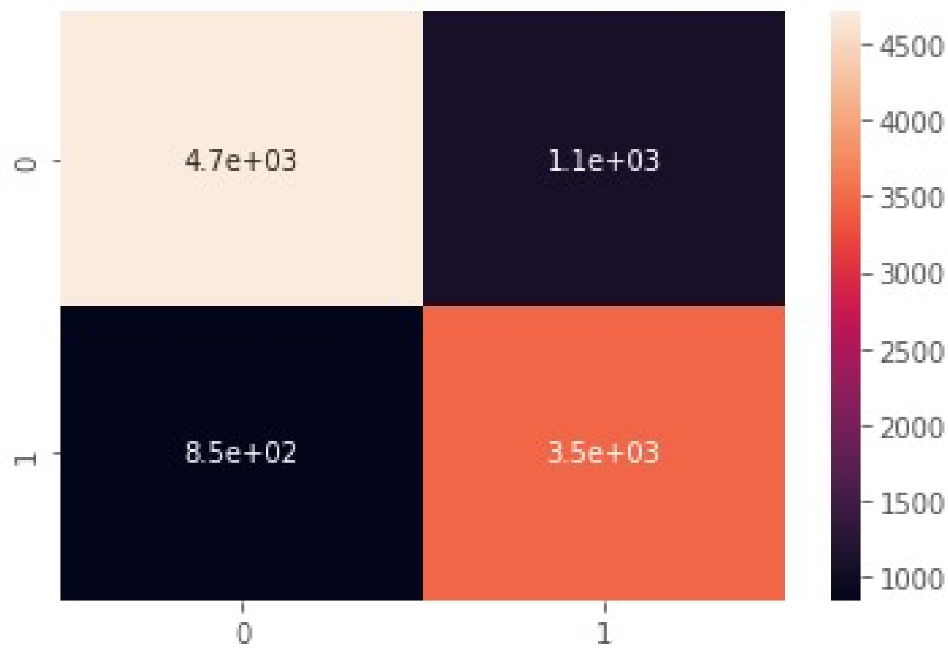
```
Epoch 1/20
4049/4049 [==============================] - 12s 3ms/step - loss:
0.4667 - accuracy: 0.7735
Epoch 2/20
4049/4049 [==============================] - 11s 3ms/step - loss:
0.4201 - accuracy: 0.8025
Epoch 3/20
4049/4049 [==============================] - 12s 3ms/step - loss:
0.4162 - accuracy: 0.8027
Epoch 4/20
4049/4049 [==============================] - 11s 3ms/step - loss:
0.4157 - accuracy: 0.8046
Epoch 5/20
4049/4049 [==============================] - 11s 3ms/step - loss:
0.4135 - accuracy: 0.8044
Epoch 6/20
4049/4049 [==============================] - 11s 3ms/step - loss:
```

```
0.4121 - accuracy: 0.8046
Epoch 7/20
4049/4049 [==============================] - 22s 5ms/step - loss:
0.4115 - accuracy: 0.8041
Epoch 8/20
4049/4049 [==============================] - 11s 3ms/step - loss:
0.4093 - accuracy: 0.8072
Epoch 9/20
4049/4049 [==============================] - 11s 3ms/step - loss:
0.4089 - accuracy: 0.8056
Epoch 10/20
4049/4049 [==============================] - 11s 3ms/step - loss:
0.4072 - accuracy: 0.8074
Epoch 11/20
4049/4049 [==============================] - 12s 3ms/step - loss:
0.4060 - accuracy: 0.8065
Epoch 12/20
4049/4049 [==============================] - 11s 3ms/step - loss:
0.4051 - accuracy: 0.8067
Epoch 13/20
4049/4049 [==============================] - 11s 3ms/step - loss:
0.4056 - accuracy: 0.8075
Epoch 14/20
4049/4049 [==============================] - 11s 3ms/step - loss:
0.4047 - accuracy: 0.8071
Epoch 15/20
4049/4049 [==============================] - 11s 3ms/step - loss:
0.4036 - accuracy: 0.8071
Epoch 16/20
4049/4049 [==============================] - 13s 3ms/step - loss:
0.4040 - accuracy: 0.8069
Epoch 17/20
4049/4049 [==============================] - 11s 3ms/step - loss:
0.4035 - accuracy: 0.8071
Epoch 18/20
4049/4049 [==============================] - 10s 3ms/step - loss:
0.4032 - accuracy: 0.8083
Epoch 19/20
4049/4049 [==============================] - 11s 3ms/step - loss:
0.4022 - accuracy: 0.8090
Epoch 20/20
4049/4049 [==============================] - 10s 3ms/step - loss:
0.4020 - accuracy: 0.8085

array([[0.23497224],
       [0.00383079],
       [0.21346164],
       ...,
       [0.6979944 ],
```

```
       [0.33189636],
       [0.9060904 ]], dtype=float32)
```

```
y_predicted_rf= ANN_Classifier.predict(x_test)
y_predicted_rf = (y_predicted_rf > 0.5)
confusion_matrix(y_test, y_predicted_rf)
sns.heatmap(confusion_matrix(y_test, y_predicted_rf), annot=True)
print("Accuracy of ANN Model:",accuracy_score(y_test, y_predicted_rf))
print(classification_report(y_test, y_predicted_rf))
```

```
Accuracy of ANN Model: 0.8073693569100069
              precision    recall  f1-score   support

           0       0.85      0.81      0.83      5813
           1       0.76      0.80      0.78      4310

    accuracy                           0.81     10123
   macro avg       0.80      0.81      0.80     10123
weighted avg       0.81      0.81      0.81     10123
```




```
test_data= pd.read_csv("bank_test.csv")
test_data.head()
```

```
   age  job  marital  education  default  housing  loan  contact
month  \
0   32    4        0          6        0        0     0        0
3
1   37   10        3          6        0        0     0        0
4
```

```
2   55    5        0          5        1        2     0        0
3
3   44    2        1          0        1        0     0        1
4
4   28    0        2          3        0        0     0        0
5

   day_of_week  duration  campaign  poutcome
0            3       131         5         1
1            3       100         1         1
2            2       131         2         1
3            3        48         2         1
4            0       144         2         1
```

```
x_test = x_test.to_numpy()
x_train = x_train.to_numpy()
```

```
x_train.shape
```

```
(40489, 13)
```

```
x_train  = np.reshape(x_train, (x_train.shape[0], 1,
x_train.shape[1]))
x_test = np.reshape(x_test, (x_test.shape[0], 1, x_test.shape[1]))
batch_size = 32
```

```
#LSTM Model
model = Sequential()
model.add(LSTM(4,input_dim=13))
model.add(Dropout(0.1))
model.add(Dense(1))
model.add(Activation('sigmoid'))
```

```
model.summary()
```

```
Model: "sequential_5"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 lstm_1 (LSTM)               (None, 4)                 288

 dropout_1 (Dropout)         (None, 4)                 0

 dense_13 (Dense)            (None, 1)                 5

 activation_1 (Activation)   (None, 1)                 0

=================================================================
Total params: 293
Trainable params: 293
Non-trainable params: 0
_________________________________________________________________
```

```python
model.compile(loss='binary_crossentropy',optimizer='adam',metrics=['ac
curacy'])
checkpointer = callbacks.ModelCheckpoint(filepath="checkpoint-
{epoch:02d}.hdf5", verbose=1, save_best_only=True,
monitor='val_acc',mode='max')
model.fit(x_train, y_train, batch_size=batch_size, epochs=10,
validation_data=(x_test, y_test))
```

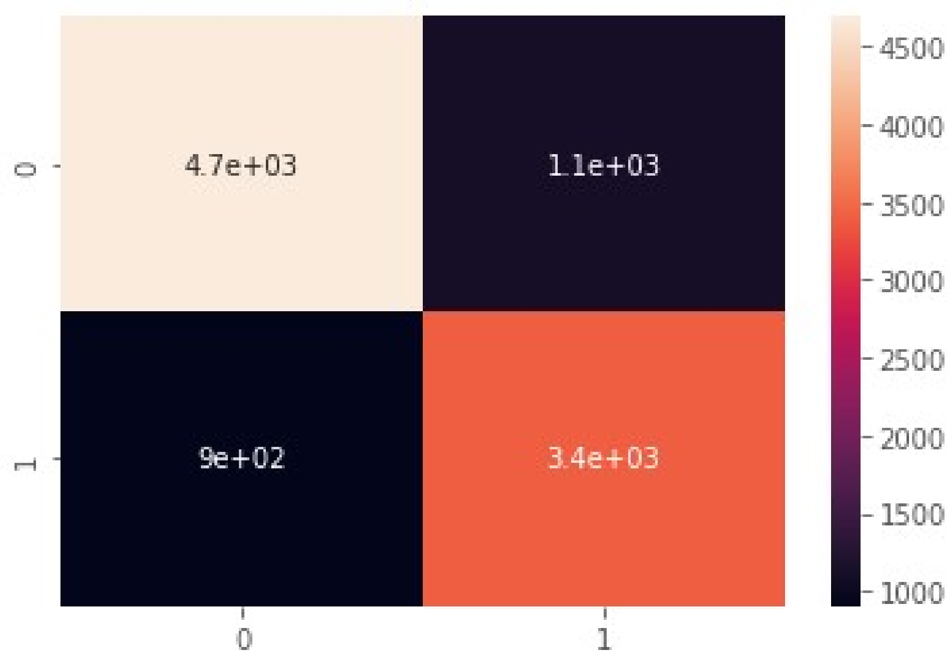
```
Epoch 1/10
1266/1266 [==============================] - 10s 5ms/step - loss:
0.6076 - accuracy: 0.6864 - val_loss: 0.5762 - val_accuracy: 0.7382
Epoch 2/10
1266/1266 [==============================] - 5s 4ms/step - loss:
0.5486 - accuracy: 0.7322 - val_loss: 0.5092 - val_accuracy: 0.7435
Epoch 3/10
1266/1266 [==============================] - 5s 4ms/step - loss:
0.4973 - accuracy: 0.7574 - val_loss: 0.4687 - val_accuracy: 0.7746
Epoch 4/10
1266/1266 [==============================] - 5s 4ms/step - loss:
0.4753 - accuracy: 0.7766 - val_loss: 0.4476 - val_accuracy: 0.7915
Epoch 5/10
1266/1266 [==============================] - 6s 4ms/step - loss:
0.4681 - accuracy: 0.7765 - val_loss: 0.4479 - val_accuracy: 0.7837
Epoch 6/10
1266/1266 [==============================] - 6s 4ms/step - loss:
0.4651 - accuracy: 0.7744 - val_loss: 0.4394 - val_accuracy: 0.7781
Epoch 7/10
1266/1266 [==============================] - 6s 5ms/step - loss:
0.4609 - accuracy: 0.7628 - val_loss: 0.4372 - val_accuracy: 0.7936
Epoch 8/10
1266/1266 [==============================] - 6s 5ms/step - loss:
0.4561 - accuracy: 0.7593 - val_loss: 0.4312 - val_accuracy: 0.8000
Epoch 9/10
1266/1266 [==============================] - 5s 4ms/step - loss:
0.4555 - accuracy: 0.7593 - val_loss: 0.4317 - val_accuracy: 0.7975
Epoch 10/10
1266/1266 [==============================] - 5s 4ms/step - loss:
0.4540 - accuracy: 0.7637 - val_loss: 0.4300 - val_accuracy: 0.7998
```

```
<keras.callbacks.History at 0x7f708bfc6f50>
```

```python
loss, accuracy = model.evaluate(x_test, y_test)
print("Accuracy of LSTM Model: %.2f%%" % ( accuracy*100))
y_pred = model.predict(x_test)
y_pred = (y_pred > 0.5)
confusion_matrix(y_test, y_pred)
sns.heatmap(confusion_matrix(y_test, y_pred), annot=True)
print(classification_report(y_test, y_pred))
```

```
317/317 [==============================] - 1s 3ms/step - loss: 0.4300
- accuracy: 0.7998
```

```
Accuracy of LSTM Model: 79.98%
              precision    recall  f1-score   support

           0       0.84      0.81      0.82      5813
           1       0.75      0.79      0.77      4310

    accuracy                           0.80     10123
   macro avg       0.80      0.80      0.80     10123
weighted avg       0.80      0.80      0.80     10123
```



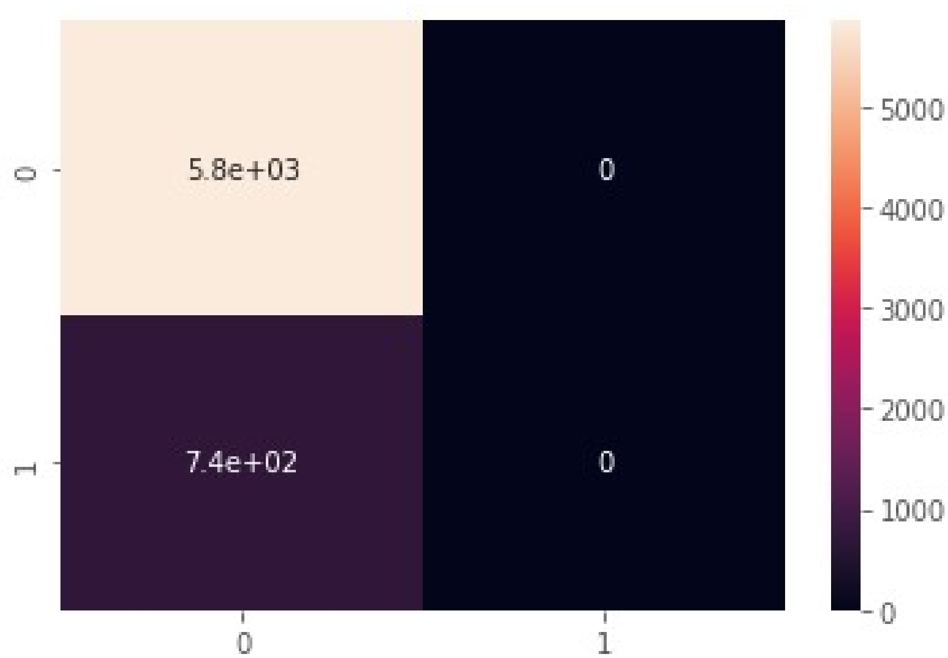

```python
training_set, test_set = train_test_split(data, test_size = 0.2,
random_state = 1)

x_train = training_set.iloc[:,0:13].values
y_train = training_set.iloc[:,13].values
x_test = test_set.iloc[:,0:13].values
y_test = test_set.iloc[:,13].values

#SVM Model
classifier = SVC(kernel='rbf', random_state = 1)
classifier.fit(x_train,y_train)
```

```
SVC(random_state=1)
```

```python
y_pred = classifier.predict(x_test)

test_set["Predictions"] = y_pred

from sklearn.metrics import confusion_matrix
cm = confusion_matrix(y_test,y_pred)
```

```
accuracy = float(cm.diagonal().sum())/len(y_test)
print("\nAccuracy Of SVM For The Given Dataset : ", accuracy)
sns.heatmap(confusion_matrix(y_test, y_pred), annot=True)
print(classification_report(y_test, y_pred))
```

```
Accuracy Of SVM For The Given Dataset :  0.887556904400607
              precision    recall  f1-score   support

           0       0.89      1.00      0.94      5849
           1       0.00      0.00      0.00       741

    accuracy                           0.89      6590
   macro avg       0.44      0.50      0.47      6590
weighted avg       0.79      0.89      0.83      6590
```




```
# predicting the test data
y_predicted= randomsearch_rf.predict(test_data)
y_predicted
```

```
array([0, 0, 0, ..., 1, 0, 0])
```

```
# dataset of predicted values for target variable y
prediction= pd.DataFrame(y_predicted, columns=["y_predicted"])
prediction_dataset= pd.concat([test_data, prediction], axis=1)
prediction_dataset['y_predicted'] =
prediction_dataset['y_predicted'].map({1: 'yes', 0: 'no'})
prediction_dataset.to_csv('Output.csv')
prediction_dataset
```

```
      age  job  marital  education  default  housing  loan  contact
month  \
0      32    4        0          6        0        0     0        0
3
1      37   10        3          6        0        0     0        0
4
2      55    5        0          5        1        2     0        0
3
3      44    2        1          0        1        0     0        1
4
4      28    0        2          3        0        0     0        0
5
...   ...  ...      ...        ...      ...      ...   ...      ...
...
8233   48    4        1          2        0        2     0        0
6
8234   30    7        2          3        0        2     0        0
6
8235   33    7        1          3        0        0     0        0
4
8236   44    1        1          1        0        2     2        1
6
8237   42    1        1          2        1        2     0        0
6

      day_of_week  duration  campaign  poutcome y_predicted
0               3       131         5         1          no
1               3       100         1         1          no
2               2       131         2         1          no
3               3        48         2         1          no
4               0       144         2         1          no
...           ...       ...       ...       ...         ...
8233            3       554         1         1         yes
8234            0       159         1         1          no
8235            1       472         1         0         yes
8236            1       554         5         1          no
8237            3        83         5         1          no

[8238 rows x 14 columns]
```