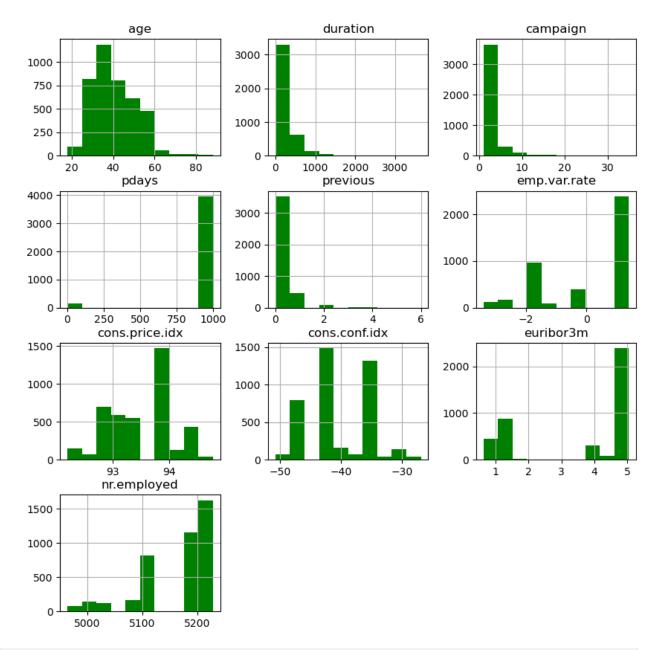
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
%matplotlib inline
df = pd.read csv('/Users/aaryanbabuta/Documents/Prodigy DS Internship
June 2024/bank+marketing/bank-additional/bank-
additional.csv',delimiter=';')
df.rename(columns={'y':'deposit'}, inplace=True)
df.head()
                                       education default housing
                job
                     marital
   age
loan \
    30 blue-collar
                     married
                                        basic.9y
                                                      no
                                                              yes
no
                                     high.school
1
    39
           services
                      single
                                                      no
                                                               no
no
2
    25
           services
                     married
                                     high.school
                                                      no
                                                              yes
no
    38
           services
                     married
                                        basic.9y
3
                                                      no
                                                          unknown
unknown
    47
             admin.
                     married university.degree
                                                      no
                                                              yes
no
     contact month day_of_week ... campaign pdays
                                                       previous
poutcome \
                                                  999
    cellular
                           fri
                                                              0
               may
nonexistent
                           fri
                                                  999
                                                              0
  telephone
               may
nonexistent
                                                              0
  telephone
                                                  999
               jun
                           wed
nonexistent
  telephone
                           fri
                                                  999
                                                              0
               jun
nonexistent
    cellular
               nov
                           mon
                                                  999
                                                              0
nonexistent
  emp.var.rate cons.price.idx cons.conf.idx euribor3m nr.employed
deposit
0
          -1.8
                        92.893
                                         -46.2
                                                    1.313
                                                                5099.1
no
           1.1
                        93.994
                                         -36.4
                                                    4.855
                                                                5191.0
1
no
           1.4
                        94.465
                                         -41.8
                                                    4.962
2
                                                                5228.1
no
```

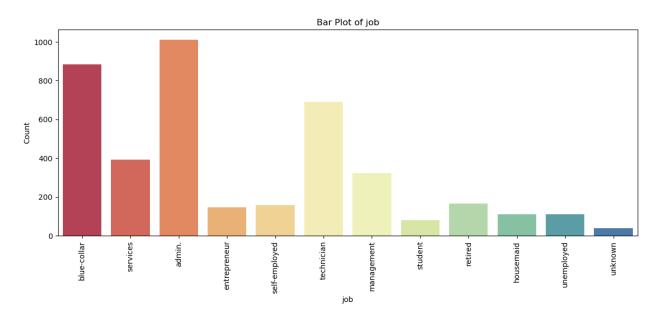
3	1.4	94.465	-41.8	4.959	5228.1
no 4	-0.1	93.200	-42.0	4.191	5195.8
no	· · -	00.200			5_55.5
[5 rows x 21 columns]					
df.head()				
age loan \	job	marital	educati	on default	housing
	blue-collar	married	basic.	9y no	yes
no		. ,			-
1 39 no	services	single	high.scho	ol no	no
2 25	services	married	high.scho	ol no	yes
no 3 38	services	married	basic.	9y no	unknown
unknown	Services	marrieu	Dasic.	9y 110	ulikilowii
4 47	admin.	married u	niversity.degr	ee no	yes
no					
contact month day_of_week campaign pdays previous					
<pre>poutcome 0 cell</pre>	ular may	fri	2	999	Θ
nonexist	,	111	2	333	U
1 telep	_	fri	4	999	0
nonexist 2 telep		wed	1	999	0
nonexist	ent				
<pre>3 telep nonexist</pre>		fri	3	999	0
	ular nov	mon	1	999	0
nonexistent					
<pre>emp.var.rate cons.price.idx cons.conf.idx euribor3m nr.employed deposit</pre>					
0	-1.8	92.893	-46.2	1.313	5099.1
no 1	1.1	93.994	-36.4	4.855	5191.0
no	1.1	93.994	-30.4	4.033	5191.0
2	1.4	94.465	-41.8	4.962	5228.1
no 3	1.4	94.465	-41.8	4.959	5228.1
no					
4 no	-0.1	93.200	-42.0	4.191	5195.8
[5 rows x 21 columns]					

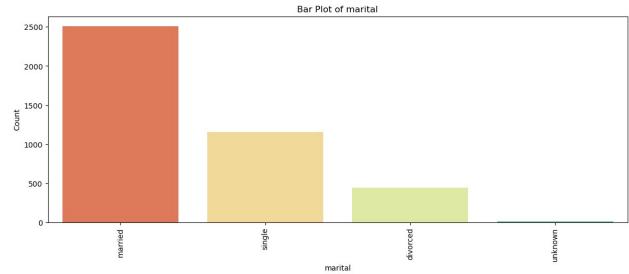
```
df.shape
(4119, 21)
df.columns
Index(['age', 'job', 'marital', 'education', 'default', 'housing',
'loan',
       'contact', 'month', 'day of week', 'duration', 'campaign',
'pdays'
        previous', 'poutcome', 'emp.var.rate', 'cons.price.idx',
       'cons.conf.idx', 'euribor3m', 'nr.employed', 'deposit'],
      dtype='object')
df.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4119 entries, 0 to 4118
Data columns (total 21 columns):
     Column
                     Non-Null Count
                                     Dtype
0
                     4119 non-null
                                     int64
     age
                     4119 non-null
 1
     iob
                                     object
 2
     marital
                     4119 non-null
                                     object
 3
     education
                     4119 non-null
                                     object
4
     default
                     4119 non-null
                                     object
 5
                     4119 non-null
     housing
                                     object
 6
    loan
                     4119 non-null
                                     object
 7
     contact
                     4119 non-null
                                     object
 8
                     4119 non-null
     month
                                     object
 9
     day_of_week
                     4119 non-null
                                     obiect
 10 duration
                     4119 non-null
                                     int64
 11 campaign
                     4119 non-null
                                     int64
 12
                     4119 non-null
    pdays
                                     int64
 13 previous
                     4119 non-null
                                     int64
 14
    poutcome
                     4119 non-null
                                     object
 15 emp.var.rate
                     4119 non-null
                                     float64
 16 cons.price.idx
                     4119 non-null
                                     float64
 17 cons.conf.idx
                     4119 non-null
                                     float64
 18 euribor3m
                     4119 non-null
                                     float64
 19
    nr.employed
                     4119 non-null
                                     float64
20
     deposit
                     4119 non-null
                                     object
dtypes: float64(5), int64(5), object(11)
memory usage: 675.9+ KB
df.dtypes.value counts()
object
           11
            5
int64
            5
float64
Name: count, dtype: int64
```

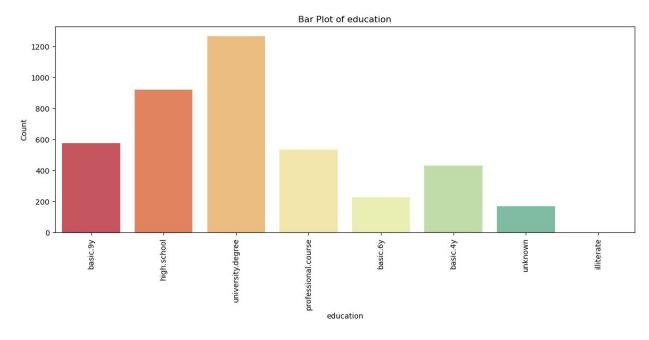
```
df.duplicated().sum()
0
df.isna().sum().any()
False
cat cols = df.select dtypes(include='object').columns
num cols = df.select dtypes(exclude='object').columns
print(cat cols,"\n")
print(num cols)
Index(['job', 'marital', 'education', 'default', 'housing', 'loan',
'contact',
       'month', 'day_of_week', 'poutcome', 'deposit'],
      dtype='object')
Index(['age', 'duration', 'campaign', 'pdays', 'previous',
'emp.var.rate',
       'cons.price.idx', 'cons.conf.idx', 'euribor3m', 'nr.employed'],
      dtype='object')
df.hist(figsize=(10,10),color='Green')
plt.show()
```

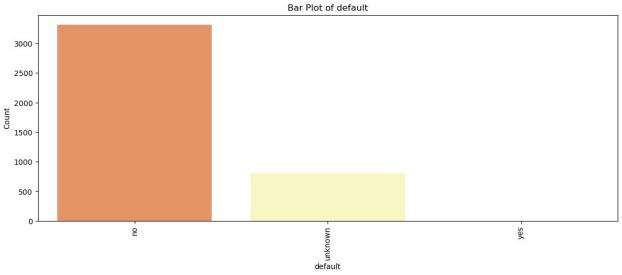


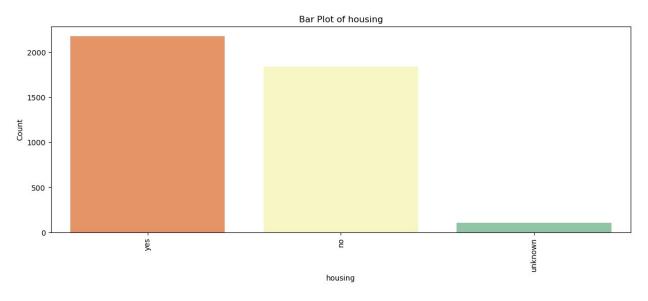
```
for feature in cat_cols:
    plt.figure(figsize=(14,5)) # Adjust the figure size as needed
    sns.countplot(x=feature, data=df, palette='Spectral')
    plt.title(f'Bar Plot of {feature}')
    plt.xlabel(feature)
    plt.ylabel('Count')
    plt.xticks(rotation=90)
    plt.show()
```

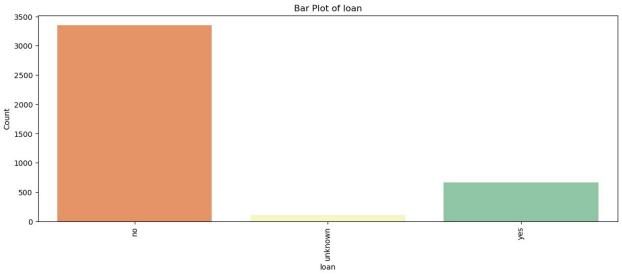


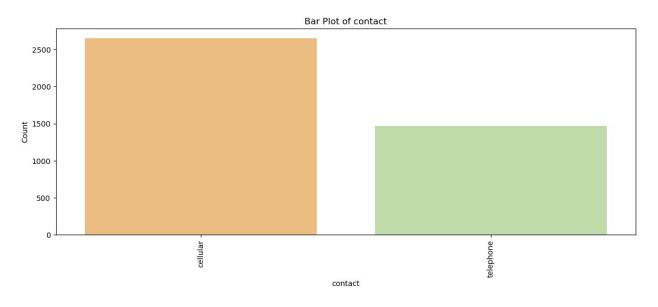


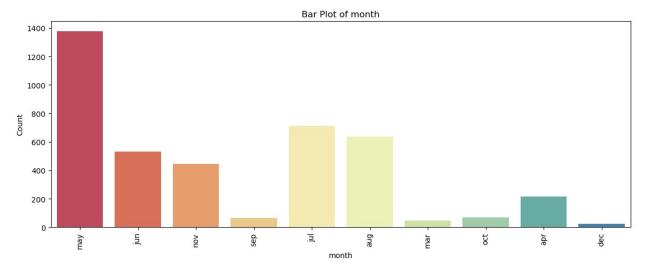


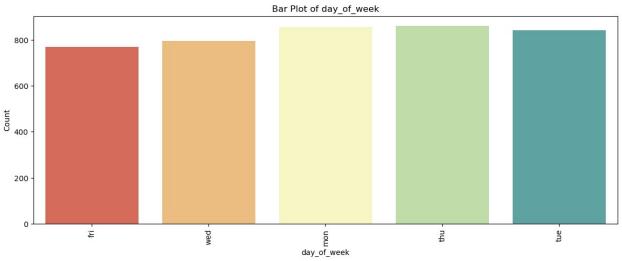


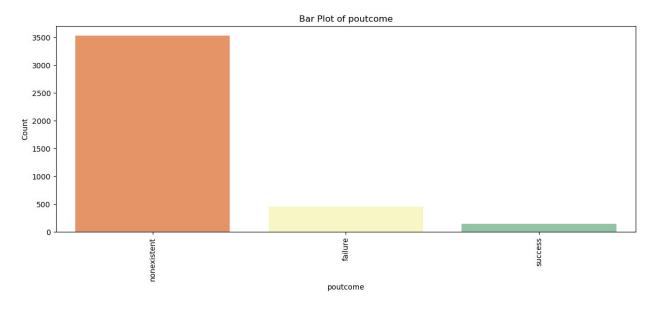


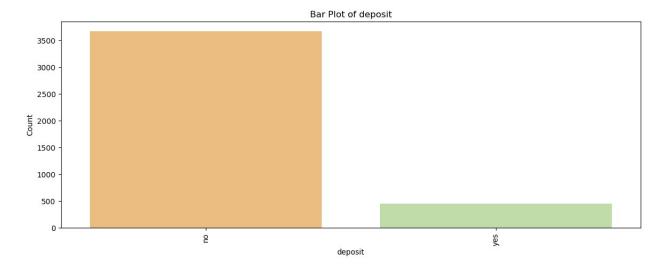




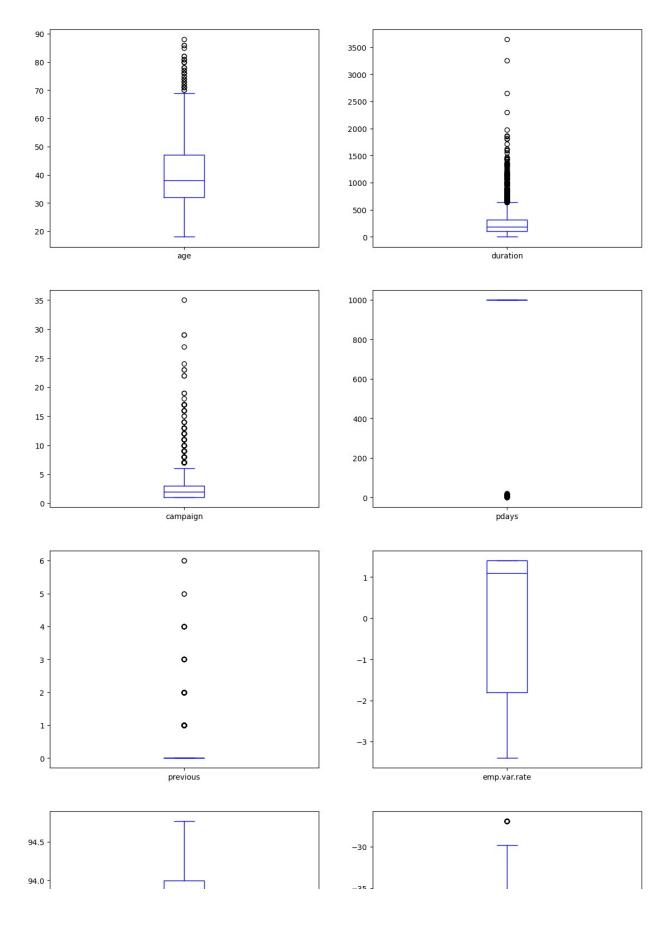






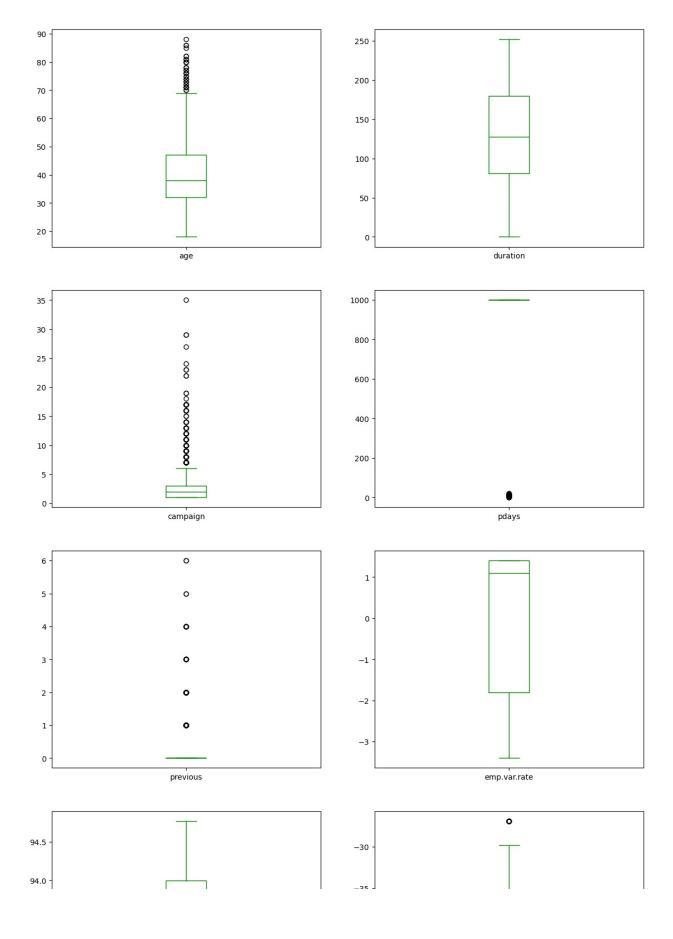


```
df.plot(kind='box', subplots=True,
layout=(5,2),figsize=(14,30),color='Blue')
plt.show()
```

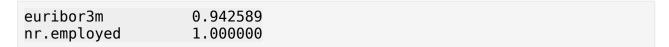


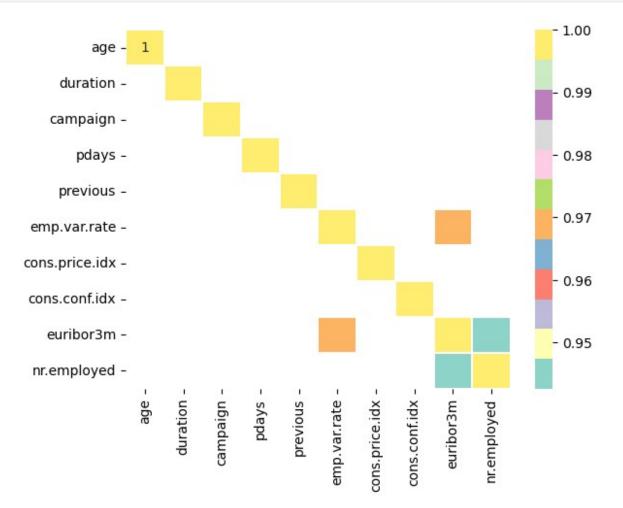
```
column = df[['age','campaign','duration']]
q1 = np.percentile(column, 25)
q3 = np.percentile(column, 75)
iqr = q3 - q1
lower_bound = q1 - 1.5 * iqr
upper_bound = q3 + 1.5 * iqr
df[['age','campaign','duration']] = column[(column > lower_bound) &
(column < upper_bound)]

df.plot(kind='box', subplots=True,
layout=(5,2),figsize=(14,30),color='Green')
plt.show()</pre>
```



```
numeric df = df.select dtypes(include=[np.number])
corr = numeric df.corr()
print(corr)
corr = corr[abs(corr) >= 0.90]
sns.heatmap(corr,annot=True,cmap='Set3',linewidths=0.2)
plt.show()
                          duration
                     age
                                     campaign
                                                  pdays
                                                         previous
age
                1.000000
                          0.014048 -0.014169 -0.043425
                                                         0.050931
duration
                0.014048
                          1.000000 -0.218111 -0.093694
                                                         0.094206
campaign
               -0.014169 -0.218111
                                     1.000000
                                               0.058742 -0.091490
               -0.043425 -0.093694
                                     0.058742
                                               1.000000 -0.587941
pdays
                          0.094206 -0.091490 -0.587941
previous
                0.050931
                                                         1.000000
               -0.019192 -0.063870
                                     0.176079
                                               0.270684 -0.415238
emp.var.rate
cons.price.idx -0.000482 -0.013338
                                     0.145021
                                               0.058472 -0.164922
cons.conf.idx
                                     0.007882 -0.092090 -0.051420
                0.098135
                         0.045889
euribor3m
               -0.015033 -0.067815
                                     0.159435
                                               0.301478 -0.458851
               -0.041936 -0.097339
                                     0.161037
                                               0.381983 -0.514853
nr.employed
                emp.var.rate cons.price.idx
                                               cons.conf.idx
                                                               euribor3m
\
age
                   -0.019192
                                    -0.000482
                                                    0.098135
                                                               -0.015033
duration
                    -0.063870
                                    -0.013338
                                                    0.045889
                                                               -0.067815
campaign
                    0.176079
                                     0.145021
                                                    0.007882
                                                                0.159435
                    0.270684
                                     0.058472
                                                   -0.092090
                                                                0.301478
pdays
previous
                    -0.415238
                                    -0.164922
                                                   -0.051420
                                                               -0.458851
emp.var.rate
                    1.000000
                                     0.755155
                                                    0.195022
                                                                0.970308
cons.price.idx
                    0.755155
                                     1.000000
                                                    0.045835
                                                                0.657159
cons.conf.idx
                    0.195022
                                     0.045835
                                                    1.000000
                                                                0.276595
euribor3m
                    0.970308
                                     0.657159
                                                    0.276595
                                                                1.000000
nr.employed
                    0.897173
                                     0.472560
                                                    0.107054
                                                                0.942589
                nr.employed
                  -0.041936
age
                  -0.097339
duration
                   0.161037
campaign
pdays
                   0.381983
                  -0.514853
previous
emp.var.rate
                   0.897173
cons.price.idx
                   0.472560
cons.conf.idx
                   0.107054
```



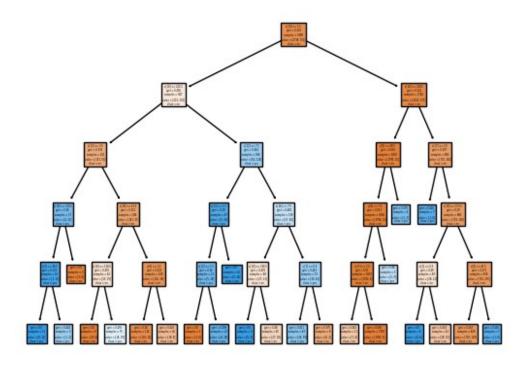


```
from sklearn.preprocessing import LabelEncoder
lb = LabelEncoder()
df_encoded = df1.apply(lb.fit_transform)
df encoded
      age job marital education default housing loan contact
month
       12
                                    2
                                              0
                                                        2
6
1
       21
                        2
                                    3
                                                        0
                                                              0
                                                                        1
6
2
        7
                                    3
                                                        2
                                                              0
                                                                        1
              7
4
3
       20
                                    2
                                                        1
                                                              1
                                                                        1
4
4
       29
                                                        2
                                                              0
                                                                        0
              0
                                    6
                                              0
7
       12
4114
              0
                                    1
                                                        2
                                                              2
                                                                        0
4115
       21
                                                        2
                                                              0
                                                                        1
3
4116
                                                                        0
       9
                                                              0
4117
       40
              0
                                    3
                                                        0
                                                              0
                                                                        0
1
                                              0
                                                        2
4118
       16
              4
                        2
                                    3
                                                              0
                                                                        0
      day_of_week ... campaign pdays
                                             previous
                                                       poutcome
emp.var.rate \
                                  1
                                        20
                                                     0
                                                                1
3
1
                                  3
                                        20
                                                     0
                                                                1
8
2
                                        20
                                                     0
                                                                1
9
3
                                  2
                                        20
                                                     0
                                                                1
9
4
                                                                1
                                  0
                                        20
                                                     0
7
. . .
4114
                 2
                                  0
                                        20
                                                     0
                                                                1
4115
                                        20
                                                                1
9
4116
                                        20
                                                               0
                                  1
                                                     1
```

```
4117
                 0
                                       20
                                                   0
                                                              1
9
4118
                 4
                                 0
                                       20
                                                   0
                                                              1
                                       euribor3m
      cons.price.idx cons.conf.idx
                                                   nr.employed
                                                                 deposit
0
                                              156
                                                              6
1
                                   16
                                              207
                                                              8
                   18
                                                                        0
2
                   23
                                                             10
                                                                        0
                                    8
                                              225
3
                   23
                                    8
                                              222
                                                             10
                                                                        0
                                    7
4
                   11
                                              201
                                                              9
                                                                        0
                                              . . .
                                  . . .
4114
                   17
                                    6
                                              221
                                                             10
                                                                        0
4115
                   17
                                    6
                                              222
                                                             10
                                                                        0
                                    4
                                                                        0
4116
                    8
                                              160
                                                              6
4117
                   13
                                   17
                                              229
                                                             10
                                                                        0
                                              199
                                                                        0
4118
                   11
                                    7
                                                              9
[4119 rows \times 21 columns]
df encoded['deposit'].value counts()
deposit
     3668
      451
Name: count, dtype: int64
x = df encoded.drop('deposit',axis=1) # independent variable
y = df encoded['deposit']
                                         # dependent variable
print(x.shape)
print(y.shape)
print(type(x))
print(type(y))
(4119, 20)
(4119,)
<class 'pandas.core.frame.DataFrame'>
<class 'pandas.core.series.Series'>
from sklearn.model selection import train test split
print(4119*0.25)
1029.75
x_train,x_test,y_train,y_test =
train test_split(x,y,test_size=0.25,random_state=1)
print(x train.shape)
print(x_test.shape)
print(y_train.shape)
print(y test.shape)
```

```
(3089, 20)
(1030, 20)
(3089,)
(1030,)
from sklearn.metrics import
confusion matrix, classification report, accuracy score
def eval model(y_test,y_pred):
    acc = accuracy_score(y_test,y_pred)
    print('Accuracy_Score',acc)
    cm = confusion matrix(y test,y pred)
    print('Confusion Matrix\n',cm)
    print('Classification Report\
n',classification report(y test,y pred))
def mscore(model):
    train score = model.score(x train,y train)
    test score = model.score(x test,y test)
    print('Training Score',train_score)
    print('Testing Score', test score)
from sklearn.tree import DecisionTreeClassifier
dt =
DecisionTreeClassifier(criterion='gini', max depth=5, min samples split=
10)
dt.fit(x train,y train)
DecisionTreeClassifier(max depth=5, min samples split=10)
mscore(dt)
Training Score 0.9219812236969893
Testing Score 0.9087378640776699
ypred dt = dt.predict(x test)
print(ypred dt)
[0 \ 0 \ 1 \ \dots \ 1 \ 0 \ 0]
eval model(y test,ypred dt)
Accuracy Score 0.9087378640776699
Confusion Matrix
 [[902 28]
 [ 66 34]]
Classification Report
               precision
                             recall f1-score
                                                support
           0
                   0.93
                              0.97
                                        0.95
                                                    930
           1
                   0.55
                              0.34
                                        0.42
                                                    100
```

```
0.91
                                                  1030
    accuracy
                                        0.69
                                                  1030
   macro avg
                   0.74
                             0.65
weighted avg
                   0.89
                             0.91
                                        0.90
                                                  1030
from sklearn.tree import plot tree
cn = ['no','yes']
fn = x_train.columns
print(fn)
print(cn)
Index(['age', 'job', 'marital', 'education', 'default', 'housing',
'loan',
       'contact', 'month', 'day of week', 'duration', 'campaign',
'pdays'
        previous', 'poutcome', 'emp.var.rate', 'cons.price.idx',
       'cons.conf.idx', 'euribor3m', 'nr.employed'],
      dtype='object')
['no', 'yes']
plot_tree(dt,class_names=cn,filled=True)
plt.show()
```



dt1 =
DecisionTreeClassifier(criterion='entropy',max_depth=4,min_samples_spl

```
it=15)
dt1.fit(x_train,y_train)
DecisionTreeClassifier(criterion='entropy', max depth=4,
min samples split=15)
mscore(dt1)
Training Score 0.915182907089673
Testing Score 0.9106796116504854
ypred_dt1 = dt1.predict(x_test)
eval model(y test,ypred dt1)
Accuracy_Score 0.9106796116504854
Confusion Matrix
 [[896 34]
 [ 58 42]]
Classification Report
               precision
                            recall f1-score
                                               support
           0
                   0.94
                             0.96
                                       0.95
                                                  930
           1
                   0.55
                             0.42
                                       0.48
                                                   100
                                       0.91
                                                  1030
    accuracy
                                                  1030
   macro avq
                   0.75
                             0.69
                                       0.71
weighted avg
                   0.90
                             0.91
                                       0.91
                                                  1030
plt.figure(figsize=(15,15))
plot tree(dt1,class names=cn,filled=True)
plt.show()
```

