```
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('/content/bank-additional.csv',delimiter=';')
df.rename(columns={'y':'deposit'}, inplace=True)
df.head()
```

	age jo		marital	education	default housing		loan	contact	month	day
0	30	blue- collar	married	basic.9y	no	yes	no	cellular	may	
1	39	services	single	high.school	no	no	no	telephone	may	
2	25	services	married	high.school	no	yes	no	telephone	jun	
3	38	services	married	basic.9y	no	unknown	unknown	telephone	jun	
4	47	admin.	married	university.degree	no	yes	no	cellular	nov	
5 rc	ws ×	21 column	S							

df.head()

	age	job marital		education	default housing		loan contact		month	day
0	30	blue- collar	married	basic.9y	no	yes	no	cellular	may	
1	39	services	single	high.school	no	no	no	telephone	may	
2	25	services	married	high.school	no	yes	no	telephone	jun	
3	38	services	married	basic.9y	no	unknown	unknown	telephone	jun	
4	47	admin.	married	university.degree	no	yes	no	cellular	nov	
5 rows × 21 columns										

df.tail()

	age	job	marital	education	default	housing	loan	contact	month	day_
4114	30	admin.	married	basic.6y	no	yes	yes	cellular	jul	
4115	39	admin.	married	high.school	no	yes	no	telephone	jul	
4116	27	student	single	high.school	no	no	no	cellular	may	
4117	58	admin.	married	high.school	no	no	no	cellular	aug	
4118	34	management	single	high.school	no	yes	no	cellular	nov	
5 rows	× 21 d	columns								

```
df.shape (4119, 21)
```

df.columns

```
df.dtypes
```

int64 age job object marital object education object object default housing object loan object contact object month obiect day\_of\_week object duration int64 int64 campaign int64 pdays previous int64 object poutcome emp.var.rate float64 cons.price.idx float64 cons.conf.idx float64 float64 euribor3m nr.employed float64 deposit object dtype: object

df.dtypes.value\_counts()

object 11 int64 5 float64 5 dtype: int64

df.info

```
job
<bound method DataFrame.info of</pre>
                                                             marital
                                                                               education default housing
                                                                                                                 loan \
           blue-collar married
                                             basic.9y
0
       30
                                                             no
                                                                     yes
                                                                                no
       39
               services
                           single
                                          high.school
                                                             no
                                                                                no
2
       25
               services
                          married
                                          high.school
                                                             no
                                                                     yes
                                                                                no
                                             basic.9y
3
       38
               services
                          married
                                                             no
                                                                 unknown
                                                                           unknown
4
       47
                 admin.
                          married
                                    university.degree
                                                             no
                                                                     yes
                                                                                no
                     . . .
                                                            . . .
                                             basic.6y
                          married
4114
       30
                 admin.
                                                             no
                                                                     ves
                                                                               ves
4115
       39
                 admin.
                          married
                                          high.school
                                                             no
                                                                     yes
                                                                                no
                                          high.school
4116
       27
                student
                          single
                                                             no
                                                                                no
                                                                       no
4117
       58
                 admin.
                          married
                                          high.school
                                                             no
                                                                      no
                                                                                no
                                          high.school
4118
       34
             management
                          single
                                                             nο
                                                                     yes
                                                                                nο
        contact month day_of_week
                                                      pdays
                                           campaign
                                                              previous
                                      . . .
0
                                                        999
       cellular
                   may
                                fri
                                                   2
                                                                     0
                                      . . .
                                                        999
1
      telephone
                   may
                                fri
                                                   4
                                                                     0
                                      ...
2
      telephone
                                                        999
                                                                     0
                   jun
                                wed
                                      . . .
3
      telephone
                                fri
                                                   3
                                                        999
                                                                     0
                   jun
                                      . . .
4
       cellular
                   nov
                                mon
                                      . . .
                                                   1
                                                        999
                                                                     0
                                      . . .
4114
       cellular
                   jul
                                thu
                                                        999
                                                                     0
                                                  1
                                      . . .
4115
      telephone
                   iul
                                fri
                                                        999
                                                                     a
                                      . . .
                                                   1
4116
       cellular
                   may
                                mon
                                      . . .
                                                   2
                                                        999
                                                                     1
4117
       cellular
                   aug
                                fri
                                                   1
                                                        999
                                                                     0
                                      . . .
4118
       cellular
                                                        999
                   nov
                                wed
                                      . . .
         poutcome emp.var.rate
                                  cons.price.idx cons.conf.idx
                                                                    euribor3m
0
      nonexistent
                            -1.8
                                           92.893
                                                             -46.2
                                                                         1.313
                                           93.994
                                                             -36.4
      nonexistent
                             1.1
                                                                         4.855
1
2
      nonexistent
                             1.4
                                           94.465
                                                             -41.8
                                                                         4.962
      nonexistent
                             1.4
                                           94.465
                                                             -41.8
                                                                         4.959
      nonexistent
                            -0.1
                                           93.200
                                                             -42.0
                                                                         4.191
4
                                           93.918
                                                             -42.7
                                                                         4.958
4114
      nonexistent
                             1.4
                                           93.918
                                                             -42.7
                                                                         4.959
4115
      nonexistent
                             1.4
                                           92.893
                                                             -46.2
                                                                         1.354
4116
          failure
                            -1.8
4117
      nonexistent
                             1.4
                                           93.444
                                                             -36.1
                                                                         4.966
                            -0.1
                                           93.200
                                                             -42.0
                                                                         4.120
4118
      nonexistent
      nr.employed deposit
0
            5099.1
                          no
            5191.0
1
                          no
2
            5228.1
                          no
3
            5228.1
                          no
4
            5195.8
                          no
```

5228.1

4114

```
1/14/24, 7:15 PM
      4115
               5228.1
                         no
      4116
               5099.1
                         no
               5228.1
      4117
                         no
      4118
               5195.8
      [4119 rows x 21 columns]>
   df.duplicated().sum()
      0
   df.isna().sum()
      age
      job
                    0
      marital
                    0
      education
                    0
      default
                    0
      housing
                    0
      loan
                    0
      contact
                    0
      month
      day_of_week
                    0
      duration
                    0
      campaign
                    0
                    0
      pdays
      previous
                    0
      poutcome
                    0
      emp.var.rate
                    0
      cons.price.idx
                    0
      cons.conf.idx
                    0
      euribor3m
                    0
      nr.employed
                    0
      deposit
                    0
      dtype: int64
   cat_cols = df.select_dtypes(include='object').columns
   print(cat_cols)
   num_cols = df.select_dtypes(exclude='object').columns
   print(num_cols)
```

df.describe()

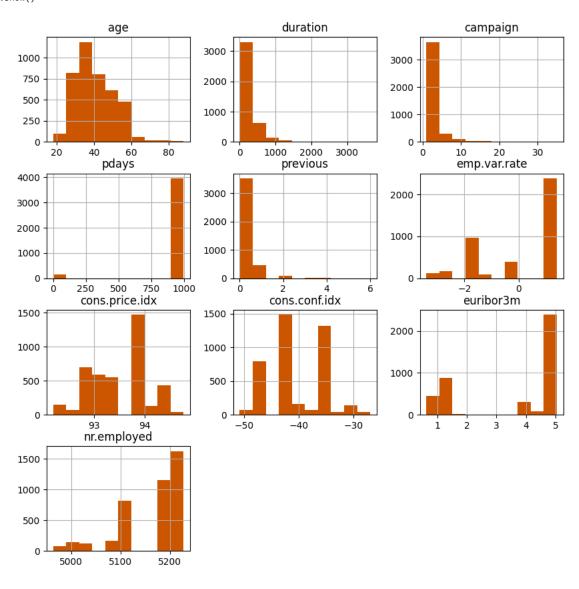
dtype='object')

	age	duration	campaign	pdays	previous	emp.var.rate	cons.price.idx	cons.conf.idx	euribor3m	nr.employe
count	4119.000000	4119.000000	4119.000000	4119.000000	4119.000000	4119.000000	4119.000000	4119.000000	4119.000000	4119.00000
mean	40.113620	256.788055	2.537266	960.422190	0.190337	0.084972	93.579704	-40.499102	3.621356	5166.48169
std	10.313362	254.703736	2.568159	191.922786	0.541788	1.563114	0.579349	4.594578	1.733591	73.66790
min	18.000000	0.000000	1.000000	0.000000	0.000000	-3.400000	92.201000	-50.800000	0.635000	4963.60000
25%	32.000000	103.000000	1.000000	999.000000	0.000000	-1.800000	93.075000	-42.700000	1.334000	5099.10000
50%	38.000000	181.000000	2.000000	999.000000	0.000000	1.100000	93.749000	-41.800000	4.857000	5191.00000
75%	47.000000	317.000000	3.000000	999.000000	0.000000	1.400000	93.994000	-36.400000	4.961000	5228.10000
max	88.000000	3643.000000	35.000000	999.000000	6.000000	1.400000	94.767000	-26.900000	5.045000	5228.10000

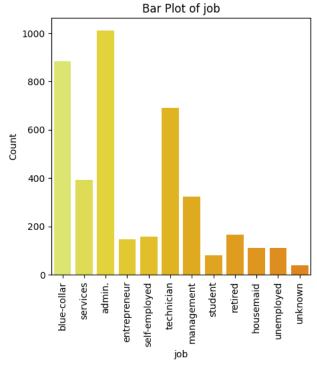
df.describe(include='object')

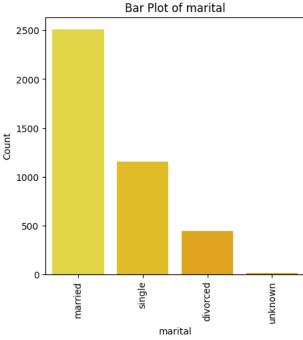
	job	marital	education	default	housing	loan	contact	month	day_of_week	poutcome	deposit
count	4119	4119	4119	4119	4119	4119	4119	4119	4119	4119	4119
unique	12	4	8	3	3	3	2	10	5	3	2
top	admin.	married	university.degree	no	yes	no	cellular	may	thu	nonexistent	no
freq	1012	2509	1264	3315	2175	3349	2652	1378	860	3523	3668

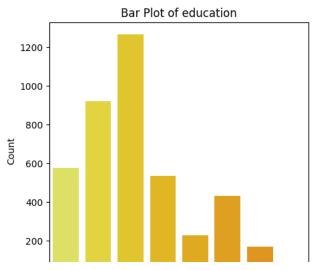
df.hist(figsize=(10,10),color='#cc5500')
plt.show()

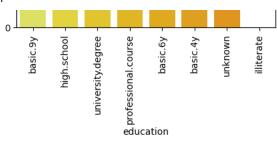


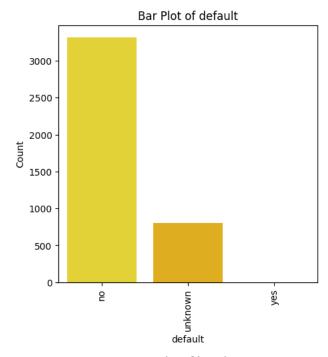
```
for feature in cat_cols:
   plt.figure(figsize=(5,5)) # Adjust the figure size as needed
   sns.countplot(x=feature, data=df, palette='Wistia')
   plt.title(f'Bar Plot of {feature}')
   plt.xlabel(feature)
   plt.ylabel('Count')
   plt.xticks(rotation=90)
   plt.show()
```

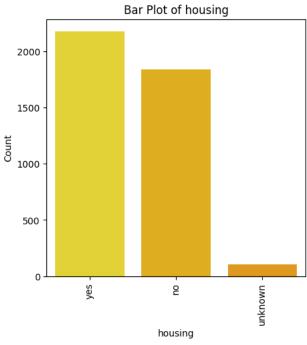




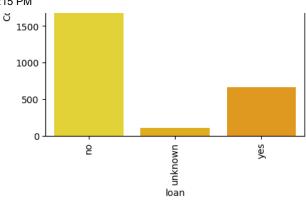


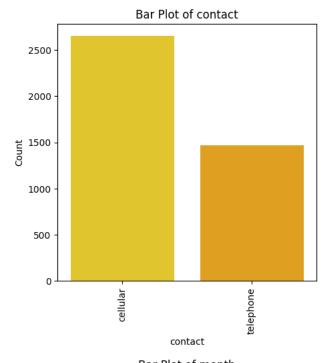


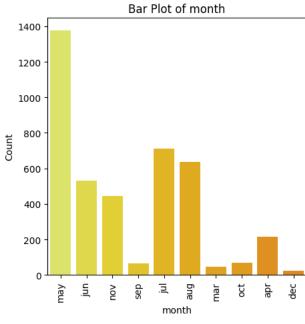


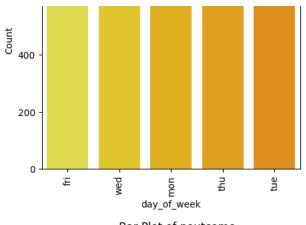


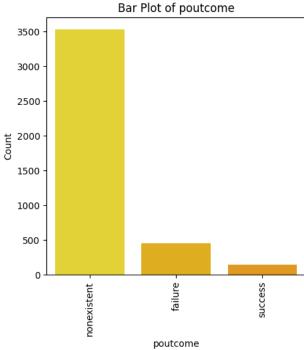


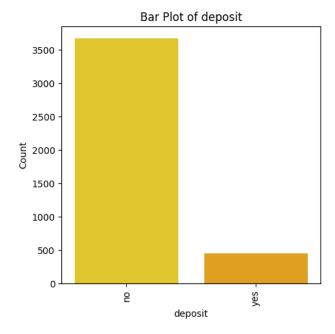


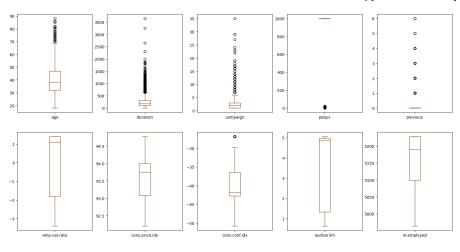






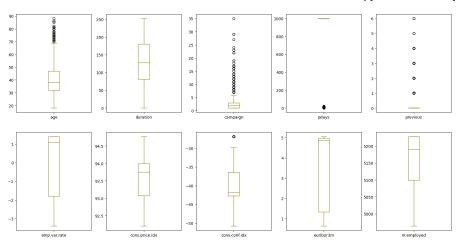






```
column = df[['age','campaign','duration']]
q1 = np.percentile(column, 25)
q3 = np.percentile(column, 75)
iqr = q3 - q1
lower_bound = q1 - 1.5 * iqr
upper_bound = q3 + 1.5 * iqr
df[['age','campaign','duration']] = column[(column > lower_bound) & (column < upper_bound)]

df.plot(kind='box', subplots=True, layout=(2,5),figsize=(20,10),color='#808000')
plt.show()</pre>
```



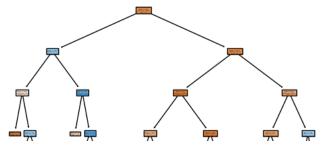
```
corr = df.corr()
print(corr)
corr = corr[abs(corr)>=0.90]
sns.heatmap(corr,annot=True,cmap='Set3',linewidths=0.2)
plt.show()
```

```
duration campaign
                                                    pdays previous \
                      age
age
                1.000000
                           0.014048 -0.014169 -0.043425
                                                           0.050931
                0.014048
                          1.000000 -0.218111 -0.093694
                                                           0.094206
duration
                -0.014169 -0.218111 1.000000 0.058742 -0.091490
campaign
pdays
                -0.043425 -0.093694 0.058742
                                                1.000000 -0.587941
                0.050931 0.094206
                                     -0.091490
                                               -0.587941 1.000000
previous
                                                0.270684 -0.415238
emp.var.rate
                -0.019192 -0.063870
                                     0.176079
cons.price.idx -0.000482 -0.013338
                                     0.145021
                                                0.058472 -0.164922
cons.conf.idx
                0.098135 0.045889
                                     0.007882 -0.092090 -0.051420
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 \
                                     -0.000482
                    -0.019192
                                                      0.098135
                                                                 -0.015033
age
                    -0.063870
                                     -0.013338
                                                      0.045889
                                                                -0.067815
duration
                    0.176079
                                                      0.007882
                                                                 0.159435
campaign
                                      0.145021
pdays
                    0.270684
                                      0.058472
                                                     -0.092090
                                                                 0.301478
previous
                    -0.415238
                                     -0.164922
                                                     -0.051420
                                                                -0.458851
                    1.000000
                                      0.755155
                                                      0.195022
                                                                 0.970308
emp.var.rate
cons.price.idx
                     0.755155
                                      1.000000
                                                      0.045835
                                                                 0.657159
                                                      1.000000
                                                                 0.276595
cons.conf.idx
                     0.195022
                                      0.045835
                                                      0.276595
                                                                 1.000000
                     0.970308
                                      0.657159
euribor3m
nr.employed
                    0.897173
                                      0.472560
                                                      0.107054
                                                                 0.942589
                nr.employed
                   -0.041936
age
duration
                   -0.097339
                    0.161037
campaign
                    0.381983
pdays
previous
                   -0.514853
emp.var.rate
                    0.897173
cons.price.idx
                    0.472560
                    0.107054
cons.conf.idx
euribor3m
                    0.942589
                    1.000000
nr.employed
                                                                              1.00
           age - 1
      duration -
                                                                              0.99
     campaign -
                             1
                                  1
         pdays -
                                                                              0.98
                                        1
      previous -
                                                                              0.97
                                                            0.97
  emp.var.rate -
                                             1
                                                   1
 cons.price.idx -
                                                                              0.96
  cons.conf.idx -
                                                        1
    euribor3m -
                                            0.97
                                                                  0.94
                                                             1
                                                                              0.95
                                                            0.94
  nr.employed -
                                                                   1
                            ampaign
                                  pdays
                                             .var.rate
                                                             uribor3m
                                       previous
                                                  price.idx
                                                        s.conf.idx
                                                                   mployed
```

	age	job	marital	education	default	housing	loan	contact	month	day_of_week	duration	campaign	pdays	previous	poutcome	cc
0	12	1	1	2	0	2	0	0	6	0	250	1	20	0	1	
1	21	7	2	3	0	0	0	1	6	0	250	3	20	0	1	
2	7	7	1	3	0	2	0	1	4	4	224	0	20	0	1	
3	20	7	1	2	0	1	1	1	4	0	14	2	20	0	1	
4	29	0	1	6	0	2	0	0	7	1	55	0	20	0	1	
4114	12	0	1	1	0	2	2	0	3	2	50	0	20	0	1	
4115	21	0	1	3	0	2	0	1	3	0	216	0	20	0	1	
4116	9	8	2	3	0	0	0	0	6	1	61	1	20	1	0	
4117	40	0	1	3	0	0	0	0	1	0	250	0	20	0	1	
4118	16	4	2	3	0	2	0	0	7	4	172	0	20	0	1	
4119 rc	ws ×	18 col	umns													•

```
df_encoded['deposit'].value_counts()
     0
          3668
          451
     Name: deposit, 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, 17)
     (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, 17)
     (1030, 17)
     (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
     DecisionTreeClassifier(max_depth=5, min_samples_split=10)
mscore(dt)
     Training Score 0.9148591777274199
     Testing Score 0.8990291262135922
ypred_dt = dt.predict(x_test)
print(ypred_dt)
     [0 0 1 ... 0 0 0]
eval_model(y_test,ypred_dt)
     Accuracy_Score 0.8990291262135922
     Confusion Matrix
      [[905 25]
      [ 79 21]]
     Classification Report
                               recall f1-score
                   precision
                                                 support
               0
                       0.92
                                0.97
                                          0.95
                                                     930
                       0.46
                                0.21
                                          0.29
                                                     100
        accuracy
                                          9.99
                                                    1030
        macro avg
                       0.69
                                0.59
                                          0.62
                                                    1030
     weighted avg
                       0.87
                                0.90
                                          0.88
                                                    1030
from sklearn.tree import plot_tree
cn = ['no','yes']
fn = x_train.columns
print(fn)
print(cn)
    'previous', 'poutcome', 'cons.price.idx', 'cons.conf.idx'],
          dtype='object')
     ['no', 'yes']
plot_tree(dt,class_names=cn,filled=True)
plt.show()
```



dt1 = DecisionTreeClassifier(criterion='entropy',max\_depth=4,min\_samples\_split=15)
dt1.fit(x\_train,y\_train)

```
DecisionTreeClassifier
DecisionTreeClassifier(criterion='entropy', max_depth=4, min_samples_split=15)
```

mscore(dt1)

Training Score 0.9080608611201036 Testing Score 0.9048543689320389

ypred\_dt1 = dt1.predict(x\_test)

eval\_model(y\_test,ypred\_dt1)

0	0.92	0.98	0.95	930
1	0.53	0.17	0.26	100
accuracy macro avg weighted avg	0.72 0.88	0.58 0.90	0.90 0.60 0.88	1030 1030 1030

plt.figure(figsize=(15,15))
plot\_tree(dt1,class\_names=cn,filled=True)
plt.show()

 $\square$