```
#Importing Necessary Libaraies
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("C:\\Users\\jayaraman\\OneDrive\\Pictures\\Desktop\\
Data science intership\\bank-additional\\bank-
additional.csv",delimiter=';')
df.rename(columns={'y':'deposit'}, inplace=True)
df.head()
```

```
   age          job  marital          education default  housing
loan  \
0   30  blue-collar  married           basic.9y      no      yes
no
1   39     services   single        high.school      no       no
no
2   25     services  married        high.school      no      yes
no
3   38     services  married           basic.9y      no  unknown
unknown
4   47       admin.  married  university.degree      no      yes
no

     contact month day_of_week  ...  campaign  pdays  previous
poutcome  \
0   cellular   may         fri  ...         2    999         0
nonexistent
1  telephone   may         fri  ...         4    999         0
nonexistent
2  telephone   jun         wed  ...         1    999         0
nonexistent
3  telephone   jun         fri  ...         3    999         0
nonexistent
4   cellular   nov         mon  ...         1    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          1.1          93.994          -36.4      4.855       5191.0
no
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         -0.1          93.200          -42.0      4.191       5195.8
no

[5 rows x 21 columns]
```

```
df.head()
```

```
   age          job  marital          education default  housing
loan  \
0   30  blue-collar  married           basic.9y      no      yes
no
1   39     services   single        high.school      no       no
no
2   25     services  married        high.school      no      yes
no
3   38     services  married           basic.9y      no  unknown
unknown
4   47       admin.  married  university.degree      no      yes
no

     contact month day_of_week  ...  campaign  pdays  previous
poutcome  \
0   cellular   may         fri  ...         2    999         0
nonexistent
1  telephone   may         fri  ...         4    999         0
nonexistent
2  telephone   jun         wed  ...         1    999         0
nonexistent
3  telephone   jun         fri  ...         3    999         0
nonexistent
4   cellular   nov         mon  ...         1    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          1.1          93.994          -36.4      4.855       5191.0
no
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         -0.1          93.200          -42.0      4.191       5195.8
no

[5 rows x 21 columns]
```

```
df.tail()

      age          job  marital    education default housing loan
contact  \
4114   30      admin.  married     basic.6y      no     yes  yes
cellular
4115   39      admin.  married  high.school      no     yes   no
telephone
4116   27     student   single  high.school      no      no   no
cellular
4117   58      admin.  married  high.school      no      no   no
cellular
4118   34  management   single  high.school      no     yes   no
cellular

     month day_of_week  ...  campaign  pdays  previous     poutcome  \
4114   jul         thu  ...         1    999         0  nonexistent
4115   jul         fri  ...         1    999         0  nonexistent
4116   may         mon  ...         2    999         1      failure
4117   aug         fri  ...         1    999         0  nonexistent
4118   nov         wed  ...         1    999         0  nonexistent

     emp.var.rate  cons.price.idx  cons.conf.idx  euribor3m
nr.employed  \
4114          1.4          93.918          -42.7      4.958
5228.1
4115          1.4          93.918          -42.7      4.959
5228.1
4116         -1.8          92.893          -46.2      1.354
5099.1
4117          1.4          93.444          -36.1      4.966
5228.1
4118         -0.1          93.200          -42.0      4.120
5195.8

      deposit
4114       no
4115       no
4116       no
4117       no
4118       no

[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.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
emp.var.rate      float64
cons.price.idx    float64
cons.conf.idx     float64
euribor3m         float64
nr.employed       float64
deposit            object
dtype: object
```

```
df.dtypes.value_counts()
```

```
object     11
int64       5
float64     5
Name: count, dtype: int64
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4119 entries, 0 to 4118
Data columns (total 21 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   age             4119 non-null   int64
 1   job             4119 non-null   object
 2   marital         4119 non-null   object
 3   education       4119 non-null   object
```

```
 4   default          4119 non-null   object
 5   housing          4119 non-null   object
 6   loan             4119 non-null   object
 7   contact          4119 non-null   object
 8   month            4119 non-null   object
 9   day_of_week      4119 non-null   object
 10  duration         4119 non-null   int64
 11  campaign         4119 non-null   int64
 12  pdays            4119 non-null   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.duplicated().sum()
```

```
0
```

```
df.isna().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
emp.var.rate      0
cons.price.idx    0
cons.conf.idx     0
euribor3m         0
nr.employed       0
deposit           0
dtype: int64
```

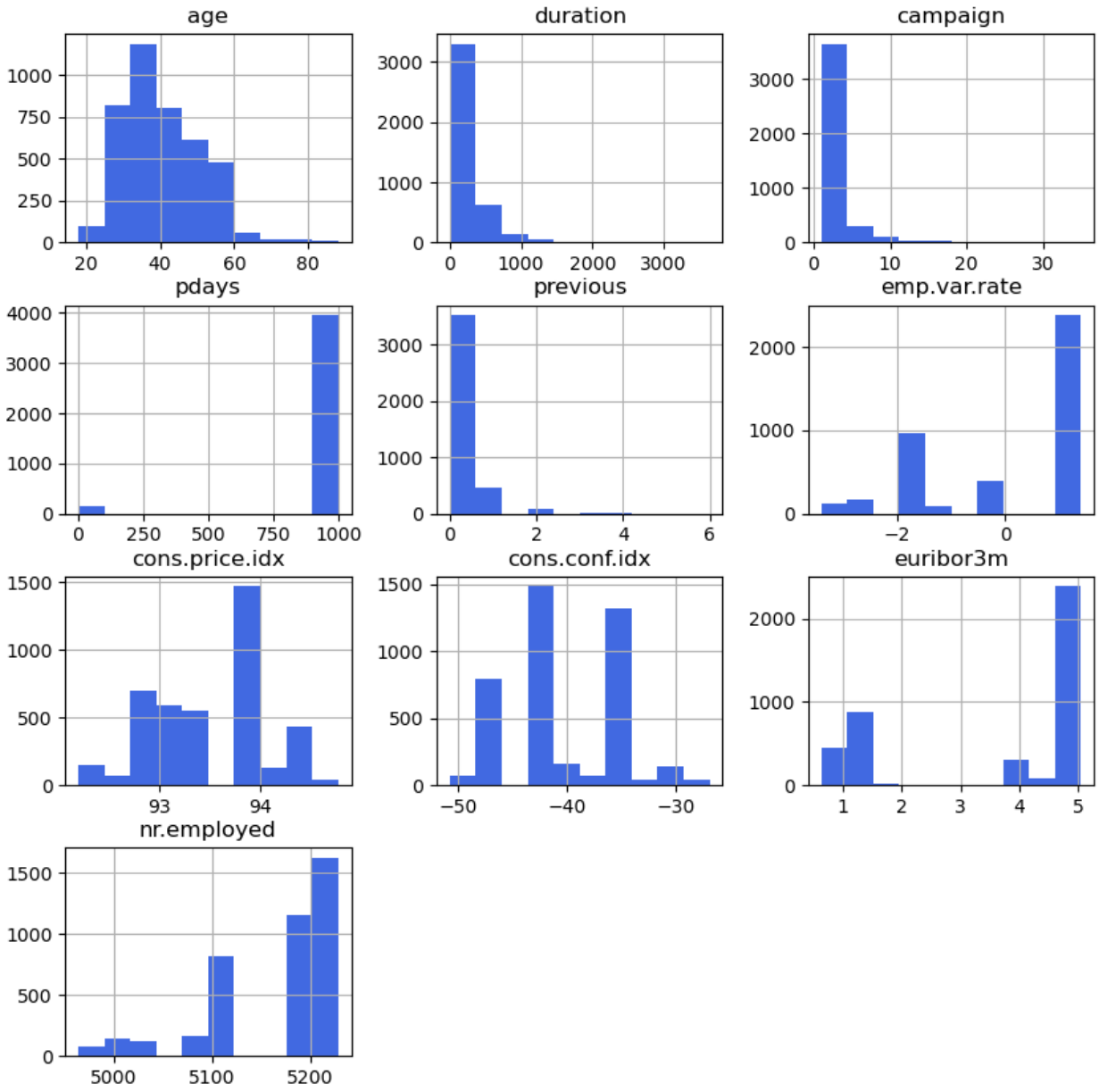
```
cat_cols = df.select_dtypes(include='object').columns
print(cat_cols)

num_cols = df.select_dtypes(exclude='object').columns
print(num_cols)
```

```
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')
```

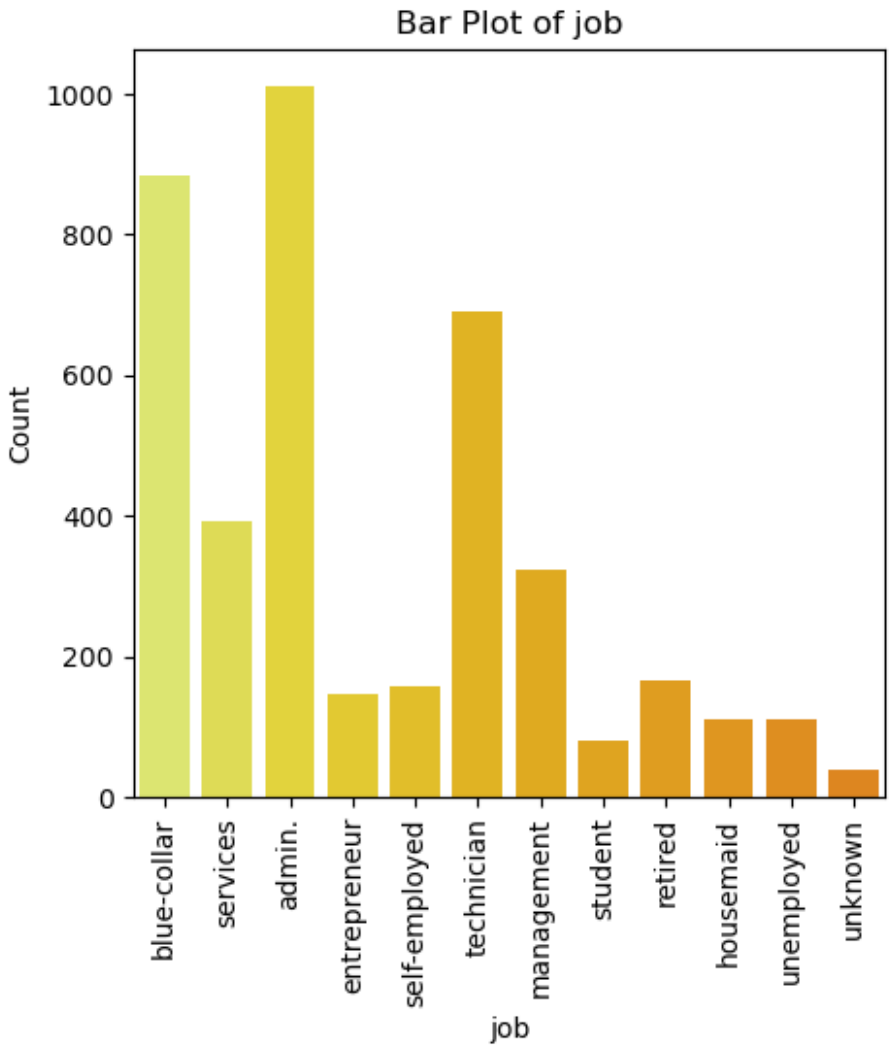
```
df.describe()
```

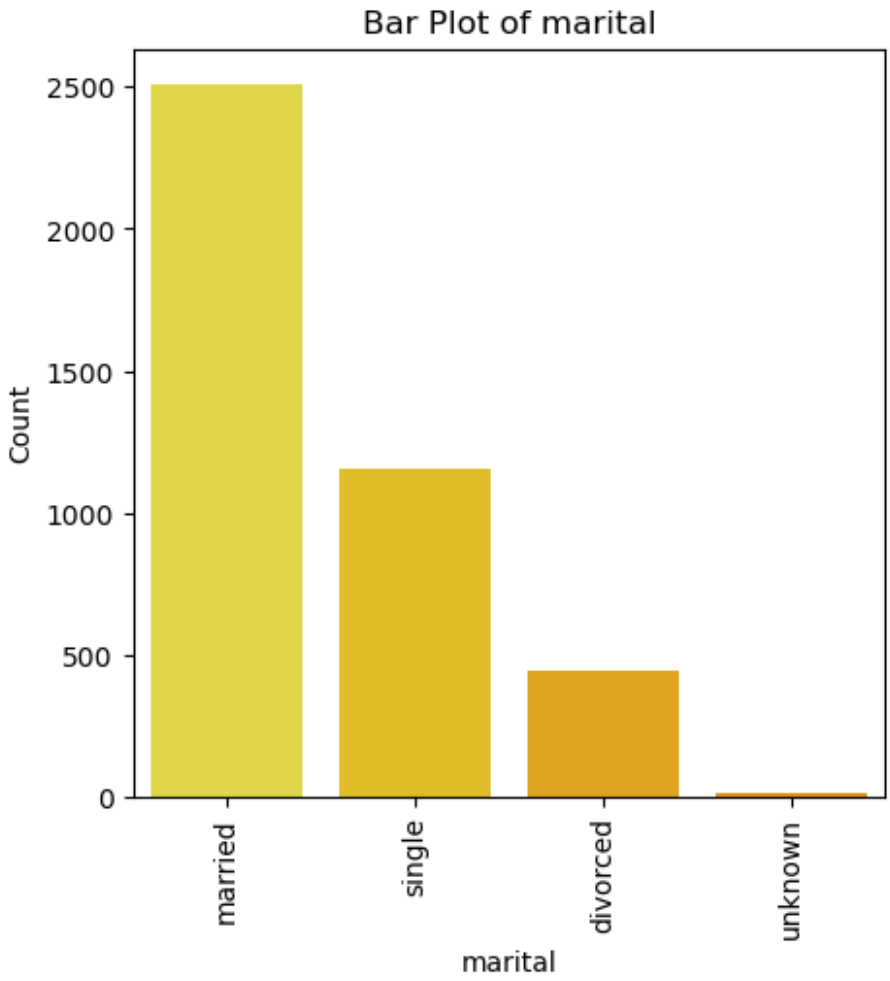
```
                age     duration     campaign        pdays     previous
\
count  4119.000000  4119.000000  4119.000000  4119.000000  4119.000000

mean     40.113620   256.788055     2.537266   960.422190     0.190337

std      10.313362   254.703736     2.568159   191.922786     0.541788

min      18.000000     0.000000     1.000000     0.000000     0.000000

25%      32.000000   103.000000     1.000000   999.000000     0.000000

50%      38.000000   181.000000     2.000000   999.000000     0.000000

75%      47.000000   317.000000     3.000000   999.000000     0.000000

max      88.000000  3643.000000    35.000000   999.000000     6.000000


       emp.var.rate  cons.price.idx  cons.conf.idx    euribor3m
nr.employed
count   4119.000000     4119.000000    4119.000000  4119.000000
4119.000000
mean       0.084972       93.579704     -40.499102     3.621356
5166.481695
std        1.563114        0.579349       4.594578     1.733591
73.667904
min       -3.400000       92.201000     -50.800000     0.635000
4963.600000
25%       -1.800000       93.075000     -42.700000     1.334000
5099.100000
50%        1.100000       93.749000     -41.800000     4.857000
5191.000000
75%        1.400000       93.994000     -36.400000     4.961000
```

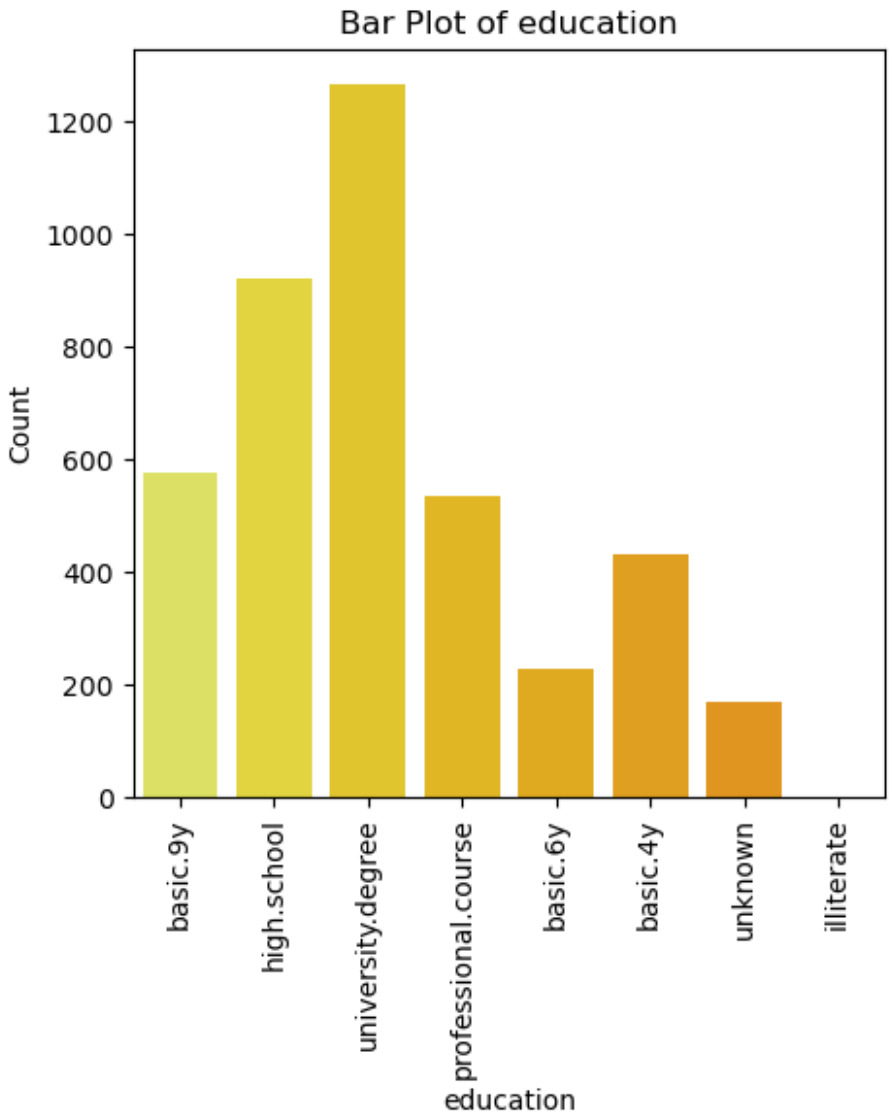
```
5228.100000
max        1.400000       94.767000     -26.900000      5.045000
5228.100000

df.describe(include='object')

           job  marital          education default housing  loan
contact  \
count     4119     4119               4119    4119    4119  4119
4119
unique      12        4                  8       3       3     3
2
top     admin.  married  university.degree      no     yes    no
cellular
freq      1012     2509               1264    3315    2175  3349
2652

       month day_of_week     poutcome deposit
count   4119        4119         4119    4119
unique    10           5            3       2
top      may         thu  nonexistent      no
freq    1378         860         3523    3668

df.hist(figsize=(10,10),color='#4169E1')
plt.show()
```

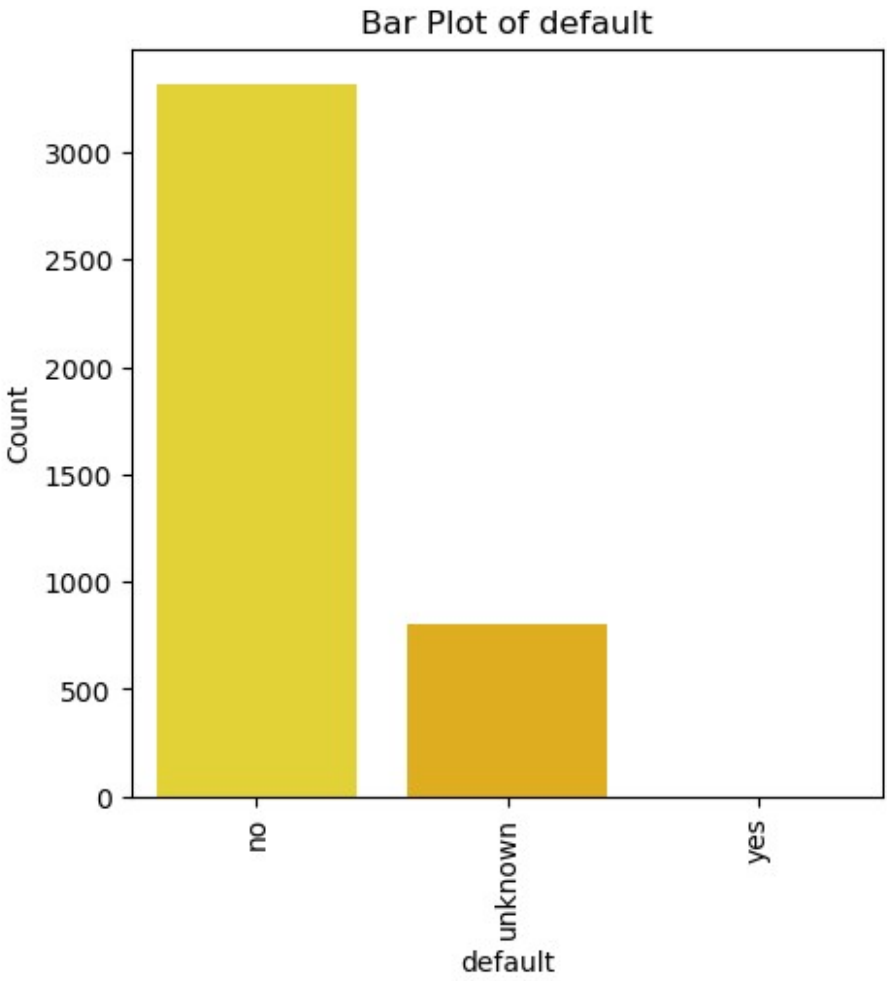


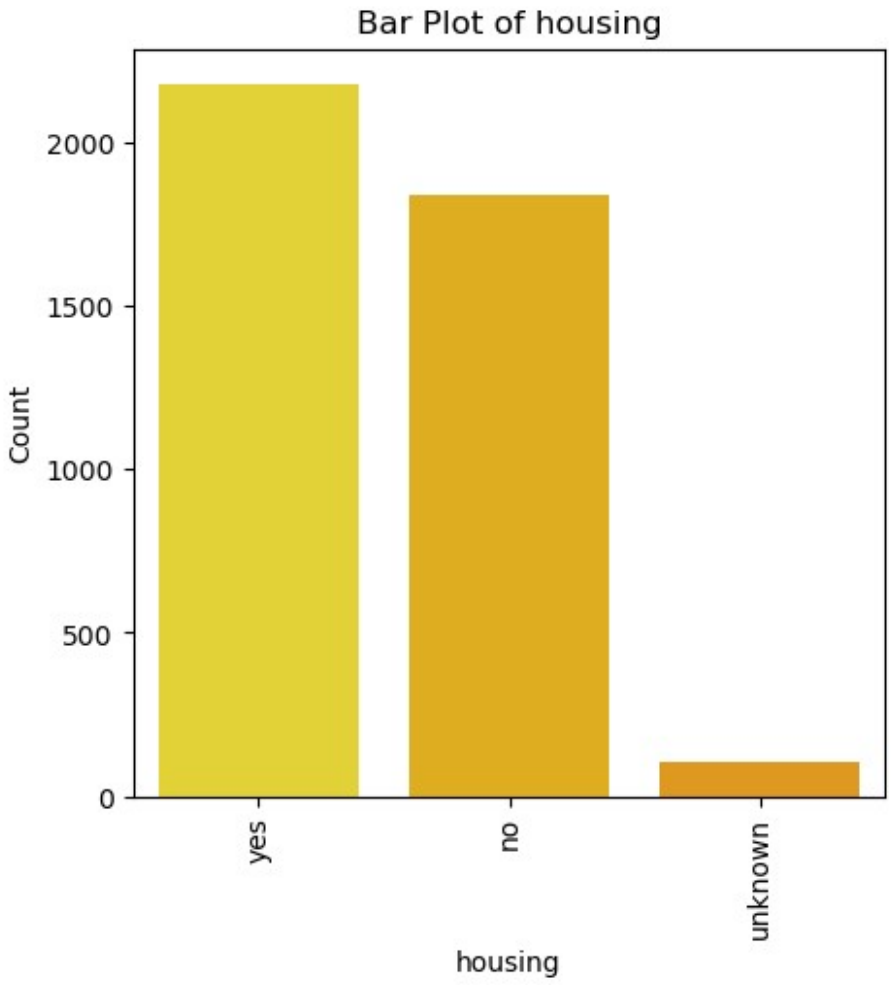

```
for feature in cat_cols:
    plt.figure(figsize=(5,5))  # Adjust the figure size as needed
    sns.countplot(x=feature, data=df, palette='Wistia')
    plt.title(f'Bar Plot of {feature}')
    plt.xlabel(feature)
    plt.ylabel('Count')
    plt.xticks(rotation=90)
    plt.show()
```

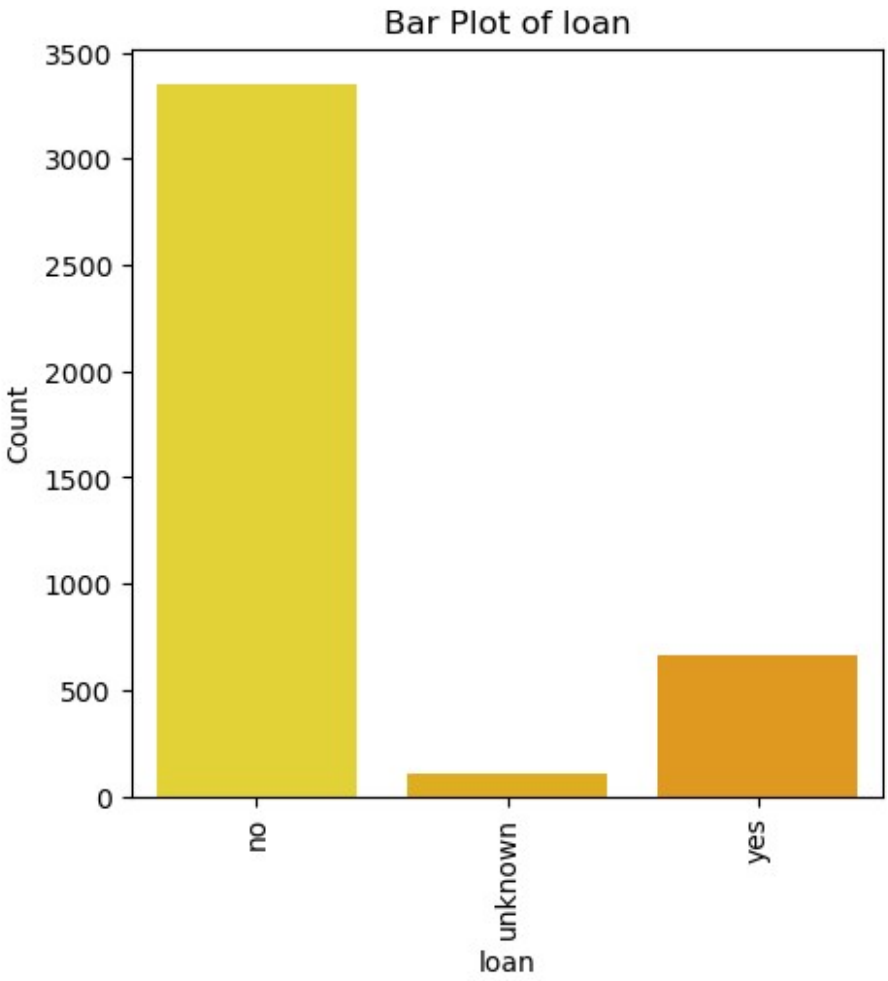

Bar Plot of job
Count
1000
800
600
400
200
0
blue-collar
services
admin.
entrepreneur
self-employed
technician
management
student
retired
housemaid
unemployed
unknown
job

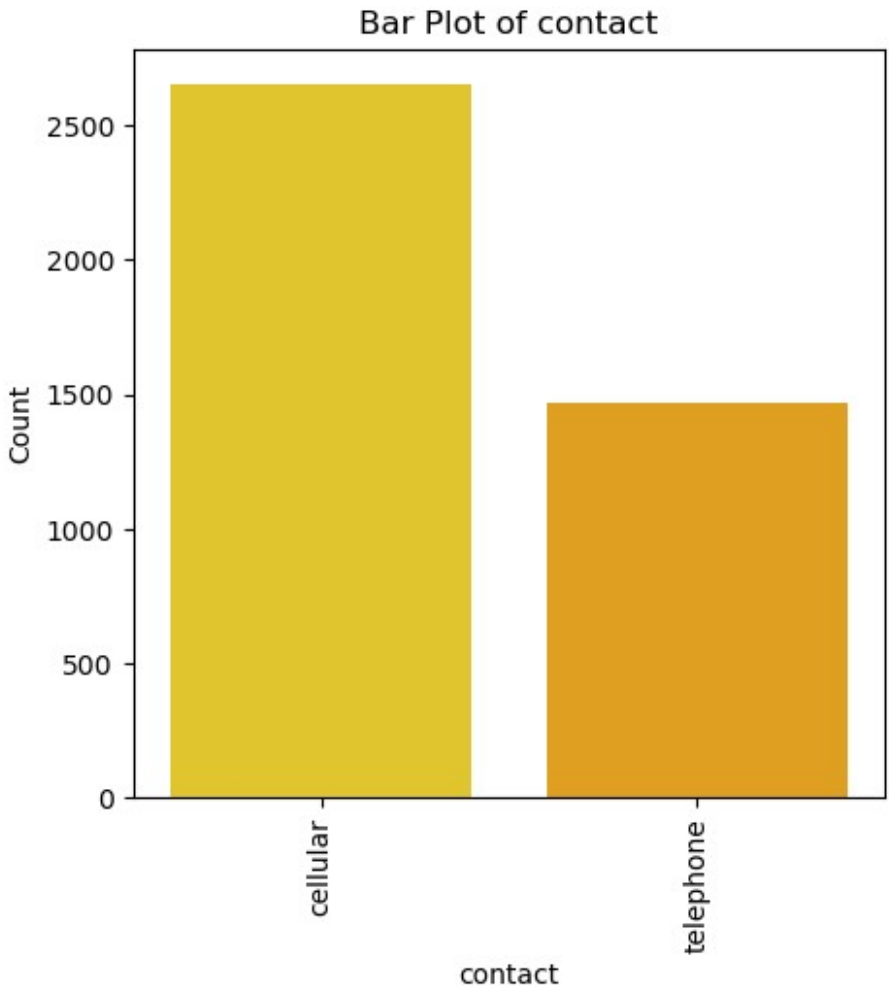

Bar Plot of marital
Count
2500
2000
1500
1000
500
0
married
single
divorced
unknown
marital

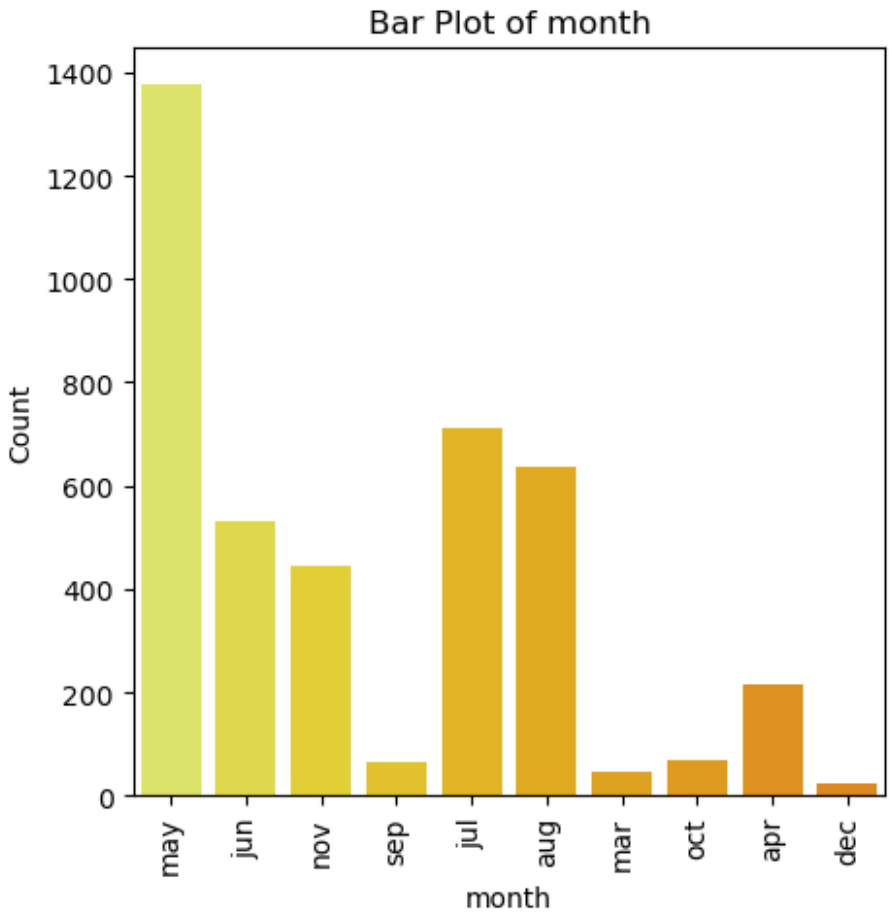

Bar Plot of education
Count
0
200
400
600
800
1000
1200
basic.9y
high.school
university.degree
professional.course
basic.6y
basic.4y
unknown
illiterate
education

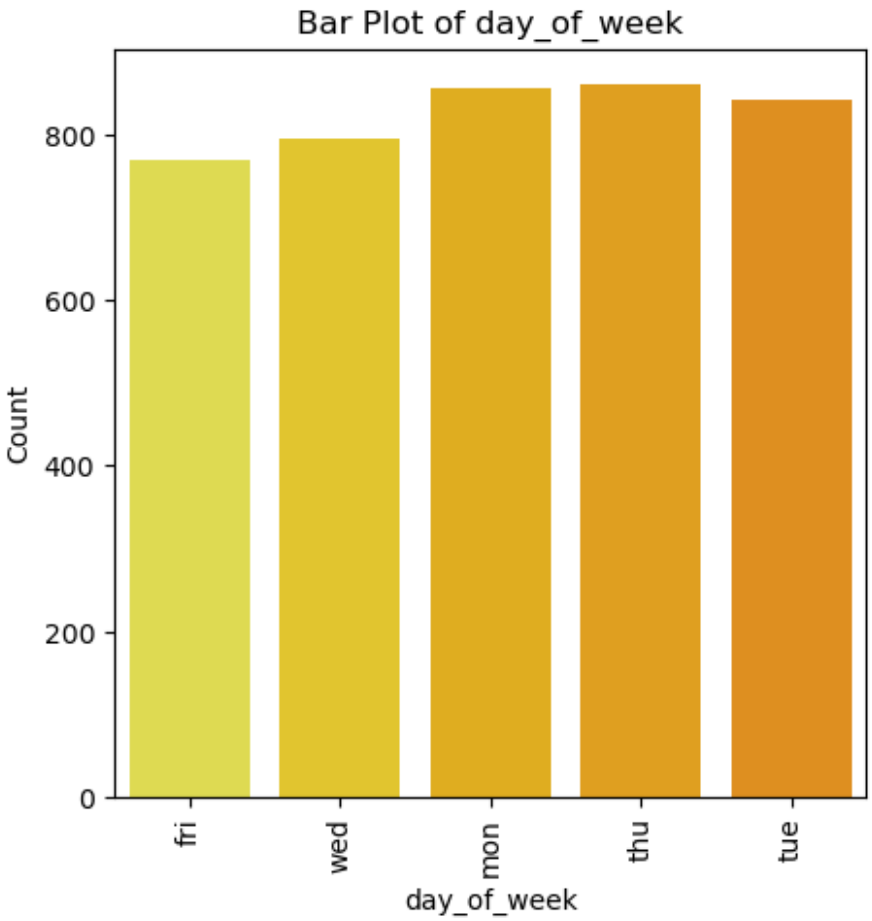

Bar Plot of default
Count
3000
2500
2000
1500
1000
500
0
no
unknown
yes
default

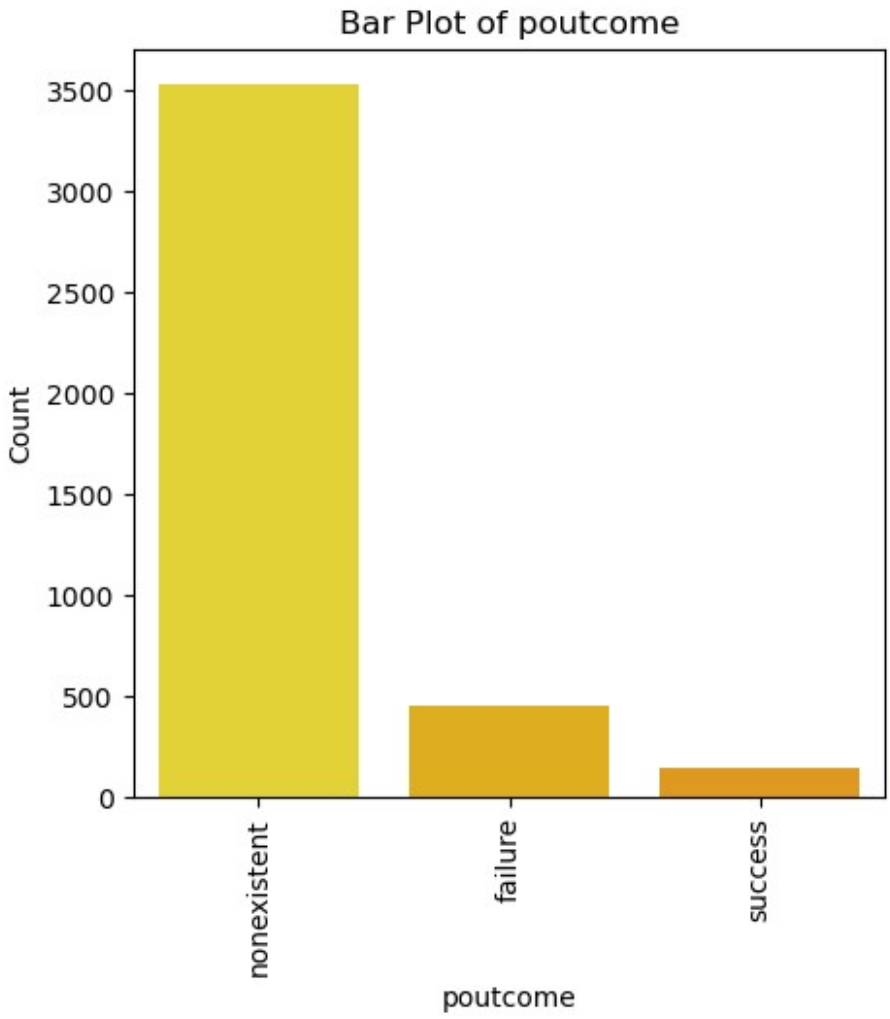

Bar Plot of housing
Count
2000
1500
1000
500
0
yes
no
unknown
housing

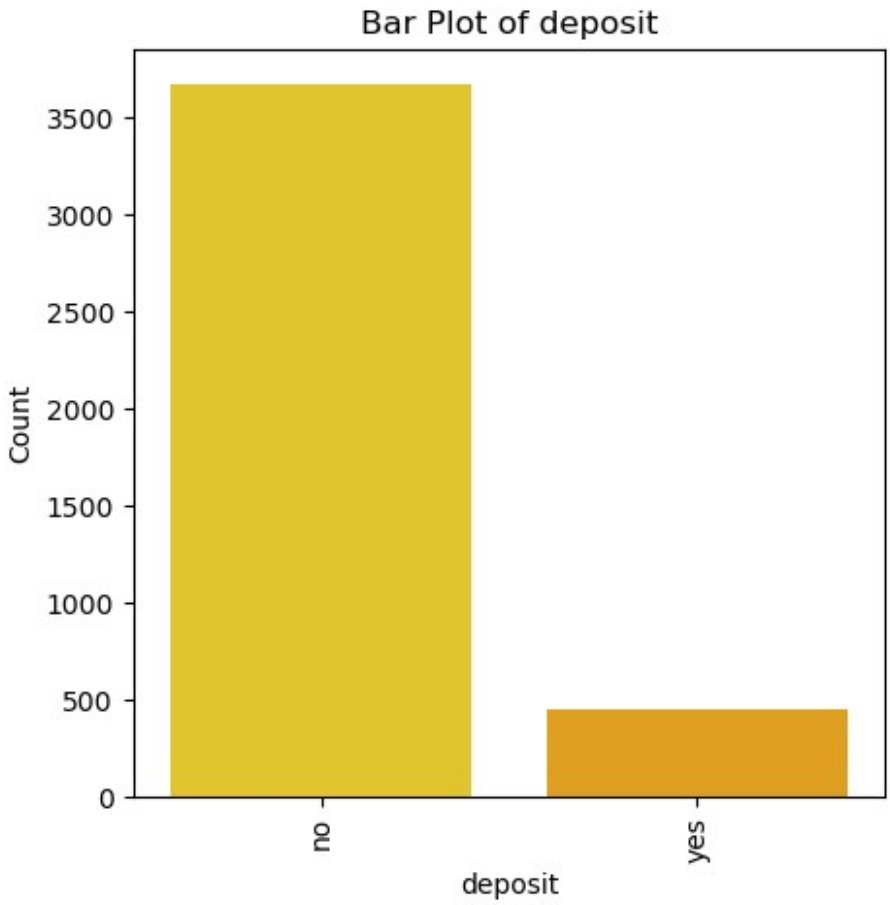

Bar Plot of loan
3500
3000
2500
2000
1500
1000
500
0
Count
no
unknown
yes
loan


Bar Plot of contact
Count
2500
2000
1500
1000
500
0
cellular
telephone
contact

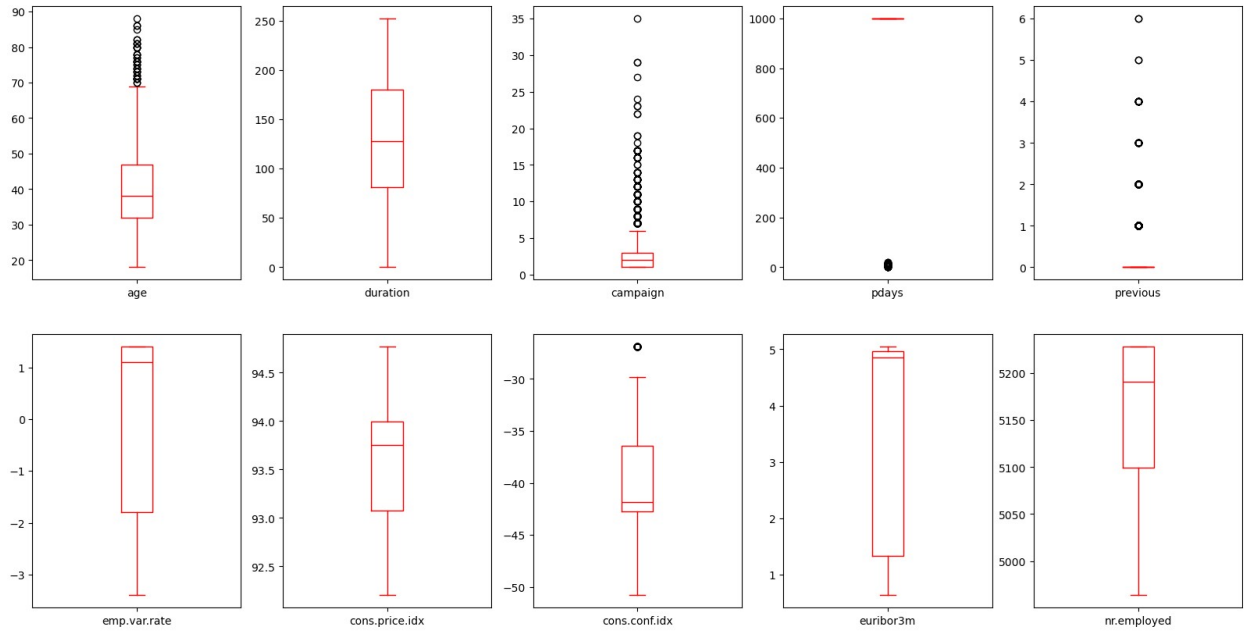

Bar Plot of month
Count
1400
1200
1000
800
600
400
200
0
may
jun
nov
sep
jul
aug
mar
oct
apr
dec
month


Bar Plot of day_of_week
Count
0
200
400
600
800
fri
wed
mon
thu
tue
day_of_week


Bar Plot of poutcome
Count
3500
3000
2500
2000
1500
1000
500
0
nonexistent
failure
success
poutcome




```
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='#FF0000')
plt.show()
```




```
high_corr_cols = ['emp.var.rate','euribor3m','nr.employed']

df1 = df.copy()
df1.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')

df1.drop(high_corr_cols,inplace=True,axis=1)  # axis=1 indicates
columns
df1.columns

Index(['age', 'job', 'marital', 'education', 'default', 'housing',
'loan',
       'contact', 'month', 'day_of_week', 'duration', 'campaign',
'pdays',
       'previous', 'poutcome', 'cons.price.idx', 'cons.conf.idx',
'deposit'],
      dtype='object')

df1.shape

(4119, 18)

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  \
0      12    1        1          2        0        2     0        0
6
1      21    7        2          3        0        0     0        1
6
2       7    7        1          3        0        2     0        1
4
3      20    7        1          2        0        1     1        1
4
4      29    0        1          6        0        2     0        0
7
...   ...  ...      ...        ...      ...      ...   ...      ...
...
4114   12    0        1          1        0        2     2        0
3
4115   21    0        1          3        0        2     0        1
3
4116    9    8        2          3        0        0     0        0
6
4117   40    0        1          3        0        0     0        0
1
4118   16    4        2          3        0        2     0        0
7

      day_of_week  duration  campaign  pdays  previous  poutcome  \
0               0       250         1     20         0         1
1               0       250         3     20         0         1
2               4       224         0     20         0         1
3               0        14         2     20         0         1
4               1        55         0     20         0         1
...           ...       ...       ...    ...       ...       ...
4114            2        50         0     20         0         1
4115            0       216         0     20         0         1
4116            1        61         1     20         1         0
4117            0       250         0     20         0         1
4118            4       172         0     20         0         1

      cons.price.idx  cons.conf.idx  deposit
0                  8              4        0
1                 18             16        0
2                 23              8        0
3                 23              8        0
4                 11              7        0
...              ...            ...      ...
4114              17              6        0
4115              17              6        0
```

```
4116                8              4        0
4117               13             17        0
4118               11              7        0

[4119 rows x 18 columns]
```

```
df_encoded['deposit'].value_counts()
```

```
deposit
0    3668
1     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, 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
```

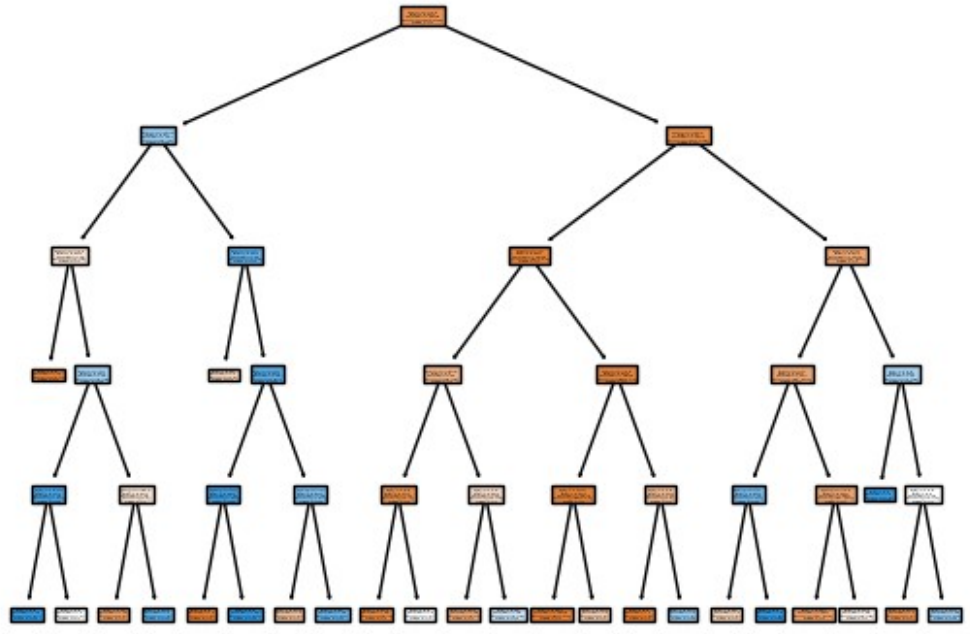
```
x_train,x_test,y_train,y_test =
train_test_split(x,y,test_size=0.25,random_state=1)
print(x_train.shape)
print(x_test.shape)
print(y_train.shape)
print(y_test.shape)
```

```
(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\
```

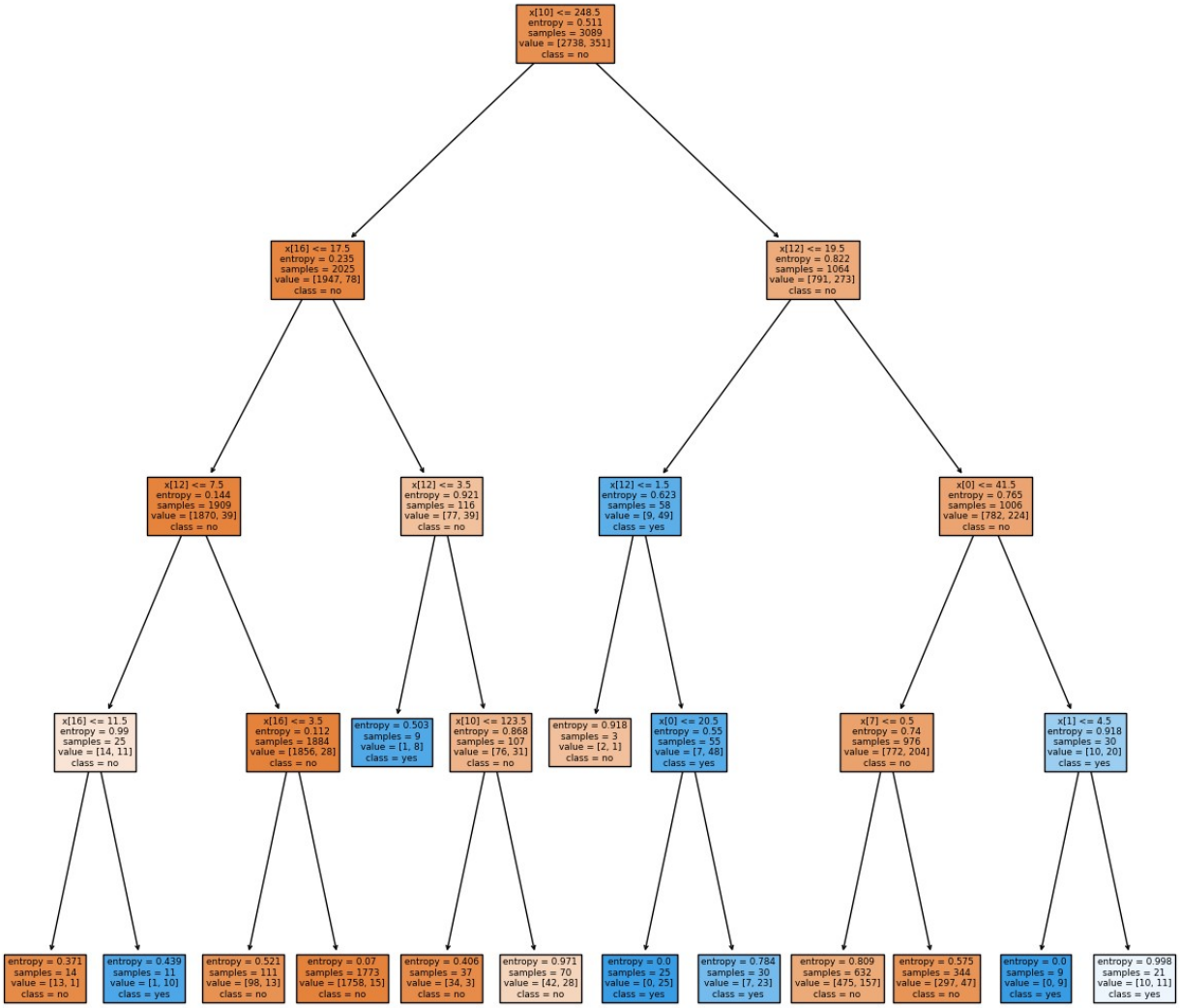
```
n',classification_report(y_test,y_pred))

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(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
              precision    recall  f1-score   support

           0       0.92      0.97      0.95       930
           1       0.46      0.21      0.29       100

    accuracy                           0.90      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)
```

```
Index(['age', 'job', 'marital', 'education', 'default', 'housing',
'loan',
       'contact', 'month', 'day_of_week', 'duration', 'campaign',
'pdays',
       '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_spl
it=15)
dt1.fit(x_train,y_train)

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)
```

```
Accuracy_Score 0.9048543689320389
Confusion Matrix
 [[915  15]
 [ 83  17]]
Classification Report
              precision    recall  f1-score   support

           0       0.92      0.98      0.95       930
           1       0.53      0.17      0.26       100

    accuracy                           0.90      1030
   macro avg       0.72      0.58      0.60      1030
weighted avg       0.88      0.90      0.88      1030


plt.figure(figsize=(15,15))
plot_tree(dt1,class_names=cn,filled=True)
plt.show()
```


x[10] <= 248.5
entropy = 0.511
samples = 3089
value = [2738, 351]
class = no
x[16] <= 17.5
entropy = 0.235
samples = 2025
value = [1947, 78]
class = no
x[12] <= 19.5
entropy = 0.822
samples = 1064
value = [791, 273]
class = no
x[12] <= 7.5
entropy = 0.144
samples = 1909
value = [1870, 39]
class = no
x[12] <= 3.5
entropy = 0.921
samples = 116
value = [77, 39]
class = no
x[12] <= 1.5
entropy = 0.623
samples = 58
value = [9, 49]
class = yes
x[0] <= 41.5
entropy = 0.765
samples = 1006
value = [782, 224]
class = no
x[16] <= 11.5
entropy = 0.99
samples = 25
value = [14, 11]
class = no
x[16] <= 3.5
entropy = 0.112
samples = 1884
value = [1856, 28]
class = no
entropy = 0.503
samples = 9
value = [1, 8]
class = yes
x[10] <= 123.5
entropy = 0.868
samples = 107
value = [76, 31]
class = no
entropy = 0.918
samples = 3
value = [2, 1]
class = no
x[0] <= 20.5
entropy = 0.55
samples = 55
value = [7, 48]
class = yes
x[7] <= 0.5
entropy = 0.74
samples = 976
value = [772, 204]
class = no
x[1] <= 4.5
entropy = 0.918
samples = 30
value = [10, 20]
class = yes
entropy = 0.371
samples = 14
value = [13, 1]
class = no
entropy = 0.439
samples = 11
value = [1, 10]
class = yes
entropy = 0.521
samples = 111
value = [98, 13]
class = no
entropy = 0.07
samples = 1773
value = [1758, 15]
class = no
entropy = 0.406
samples = 37
value = [34, 3]
class = no
entropy = 0.971
samples = 70
value = [42, 28]
class = no
entropy = 0.0
samples = 25
value = [0, 25]
class = yes
entropy = 0.784
samples = 30
value = [7, 23]
class = yes
entropy = 0.809
samples = 632
value = [475, 157]
class = no
entropy = 0.575
samples = 344
value = [297, 47]
class = no
entropy = 0.0
samples = 9
value = [0, 9]
class = yes
entropy = 0.998
samples = 21
value = [10, 11]
class = yes