bank1

April 20, 2024

[1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

import warnings
warnings.filterwarnings('ignore')

%matplotlib inline
```

[3]:
```
df = pd.read_csv('C:\\Users\\EL HASSANI␣
↪SAFAA\\Desktop\\Task3_dataset\\bank-additional\\bank-additional.
↪csv',delimiter=';')
df.rename(columns={'y':'deposit'}, inplace=True)
df.head()
```

[3]:

	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]

[4]:
```
df.head()
```

[4]:

	age	job	marital	education	default	housing	loan	contact	month	day_of_week	…	campaign	pdays	previous	poutcome	emp.var.rate	cons.price.idx	cons.conf.idx	euribor3m	nr.employed	deposit
0	30	blue-collar	married	basic.9y	no	yes	no	cellular	may	fri	…	2	999	0	nonexistent	-1.8	92.893	-46.2	1.313	5099.1	no
1	39	services	single	high.school	no	no	no	telephone	may	fri	…	4	999	0	nonexistent	1.1	93.994	-36.4	4.855	5191.0	no
2	25	services	married	high.school	no	yes	no	telephone	jun	wed	…	1	999	0	nonexistent	1.4	94.465	-41.8	4.962	5228.1	no
3	38	services	married	basic.9y	no	unknown	unknown	telephone	jun	fri	…	3	999	0	nonexistent	1.4	94.465	-41.8	4.959	5228.1	no
4	47	admin.	married	university.degree	no	yes	no	cellular	nov	mon	…	1	999	0	nonexistent	-0.1	93.200	-42.0	4.191	5195.8	no

[5 rows x 21 columns]

[5]:
```
df.tail()
```

[5]:

	age	job	marital	education	default	housing	loan	contact	month	day_of_week	…	campaign	pdays	previous	poutcome	emp.var.rate	cons.price.idx	cons.conf.idx	euribor3m	nr.employed
4114	30	admin.	married	basic.6y	no	yes	yes	cellular	jul	thu	…	1	999	0	nonexistent	1.4	93.918	-42.7	4.958	5228.1
4115	39	admin.	married	high.school	no	yes	no	telephone	jul	fri	…	1	999	0	nonexistent	1.4	93.918	-42.7	4.959	5228.1
4116	27	student	single	high.school	no	no	no	cellular	may	mon	…	2	999	1	failure	-1.8	92.893	-46.2	1.354	5099.1
4117	58	admin.	married	high.school	no	no	no	cellular	aug	fri	…	1	999	0	nonexistent	1.4	93.444	-36.1	4.966	5228.1
4118	34	management	single	high.school	no	yes	no	cellular	nov	wed	…	1	999	0	nonexistent	-0.1	93.200	-42.0	4.120	5195.8

```
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]
```

[6]:
```
df.shape
```

[6]:
```
(4119, 21)
```

[7]:
```
df.columns
```

[7]:
```
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')
```

[8]:
```
df.dtypes
```

[8]:
```
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
```

[9]:
```
df.dtypes.value_counts()
```

[9]:
```
object     11
int64       5
float64     5
Name: count, dtype: int64
```

[10]:
```
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
```

[11]:
```
df.duplicated().sum()
```

[11]:
```
0
```

[12]:
```
df.isna().sum()
```

[12]:
```
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
```

[13]:
```
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')
```

[14]:
```
df.describe()
```

[14]:

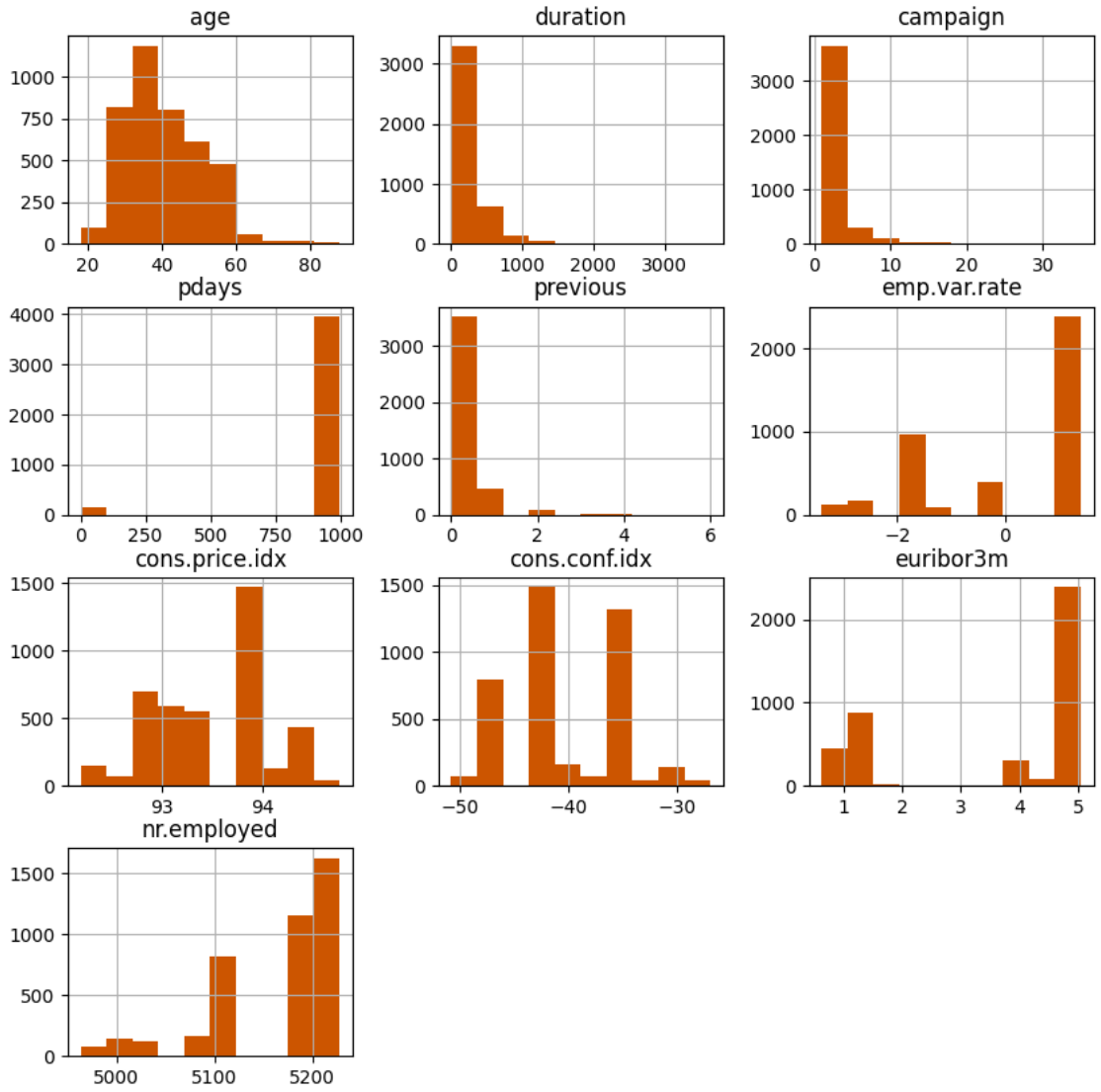
	age	duration	campaign	pdays	previous
count	4119.000000	4119.000000	4119.000000	4119.000000	4119.000000
mean	40.113620	256.788055	2.537266	960.422190	0.190337
std	10.313362	254.703736	2.568159	191.922786	0.541788
min	18.000000	0.000000	1.000000	0.000000	0.000000
25%	32.000000	103.000000	1.000000	999.000000	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
```

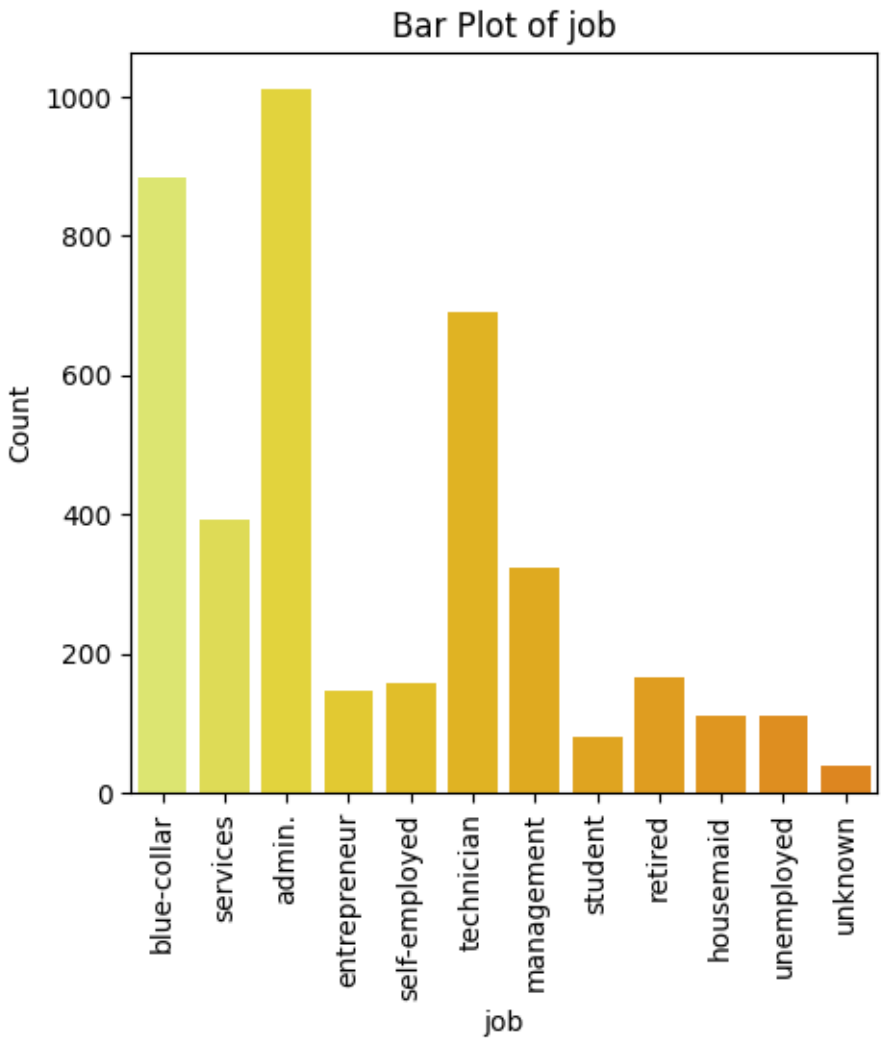
[15]:
```
df.describe(include='object')
```

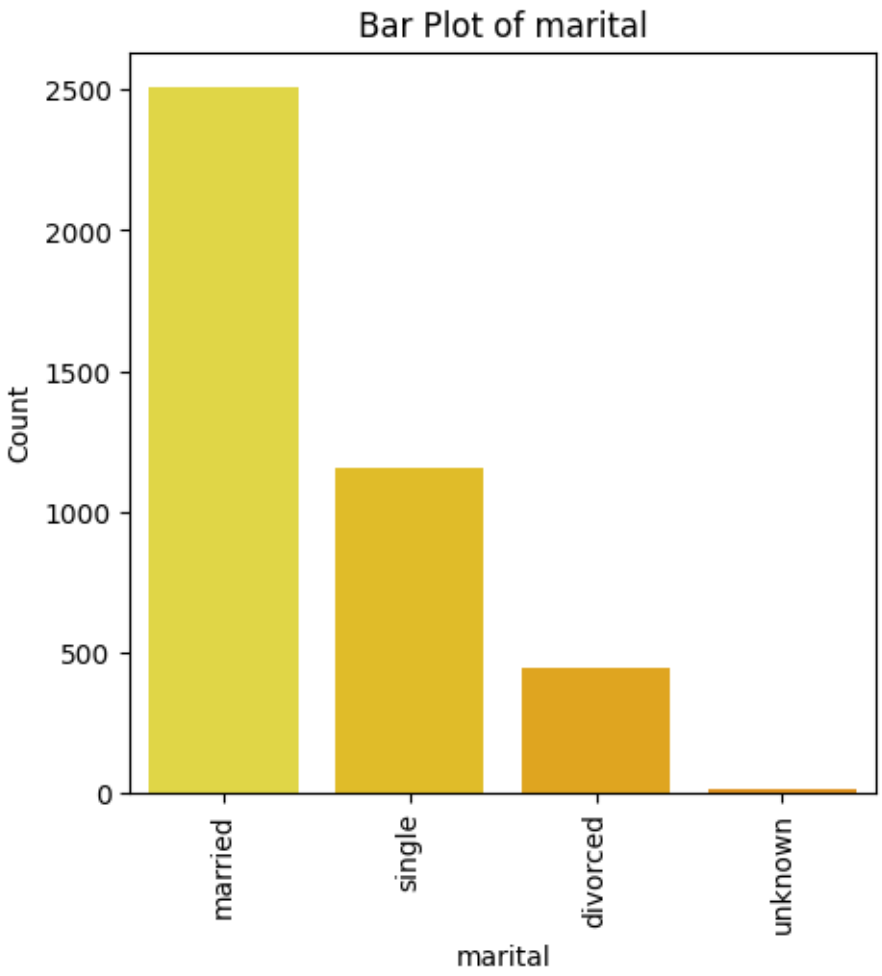
[15]:
```
           job  marital          education default housing  loan   contact  \
count     4119     4119               4119    4119    4119  4119      4119
unique      12        4                  8       3       3     3         2
top     admin.  married  university.degree      no     yes    no  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
```

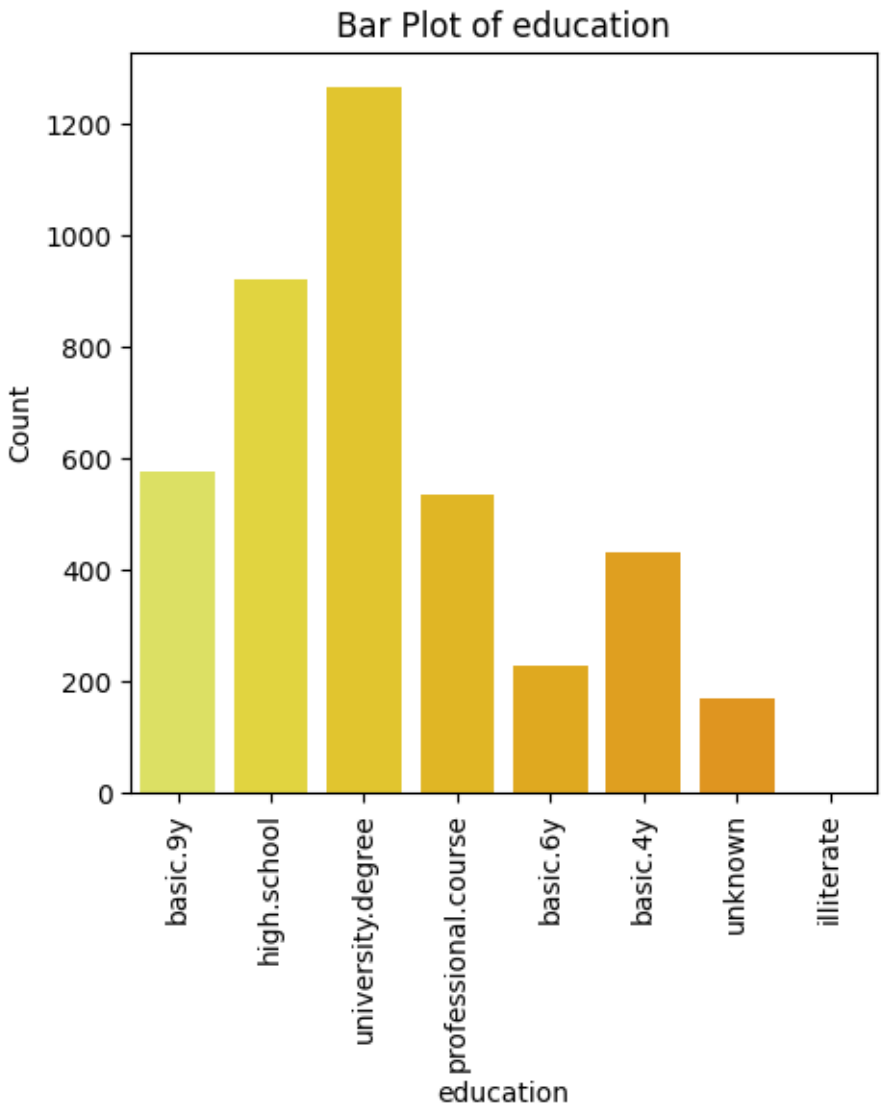
[16]:
```
df.hist(figsize=(10,10),color='#cc5500')
plt.show()
```

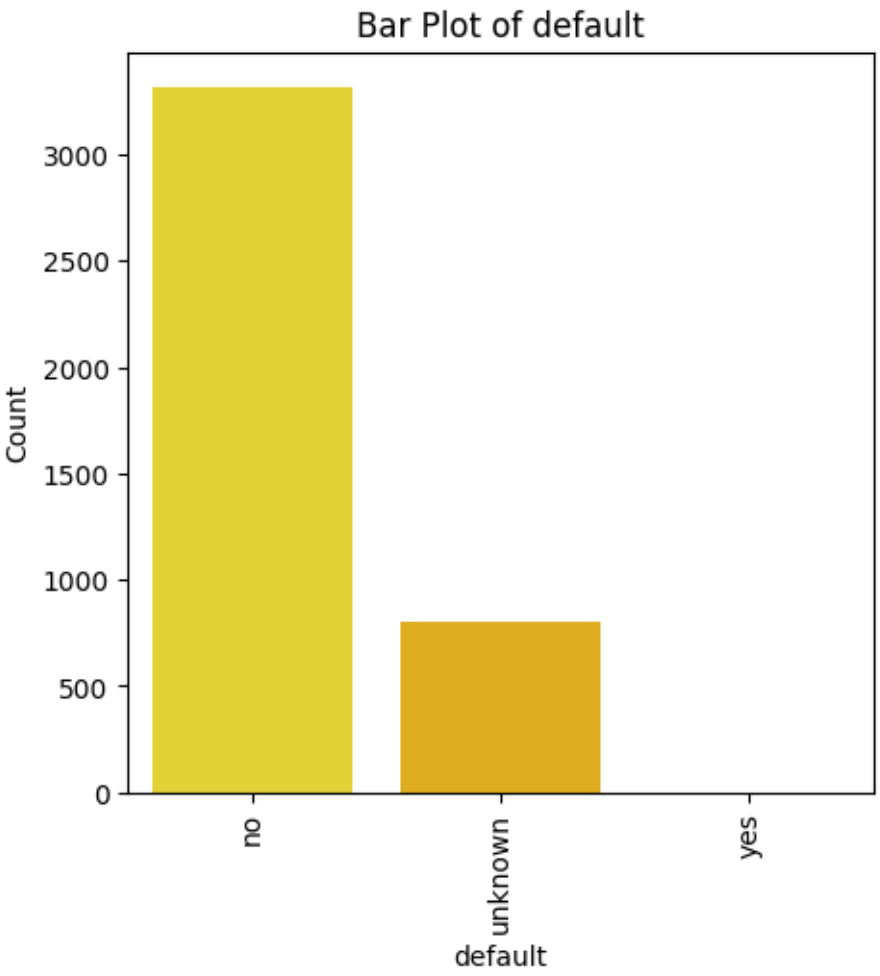


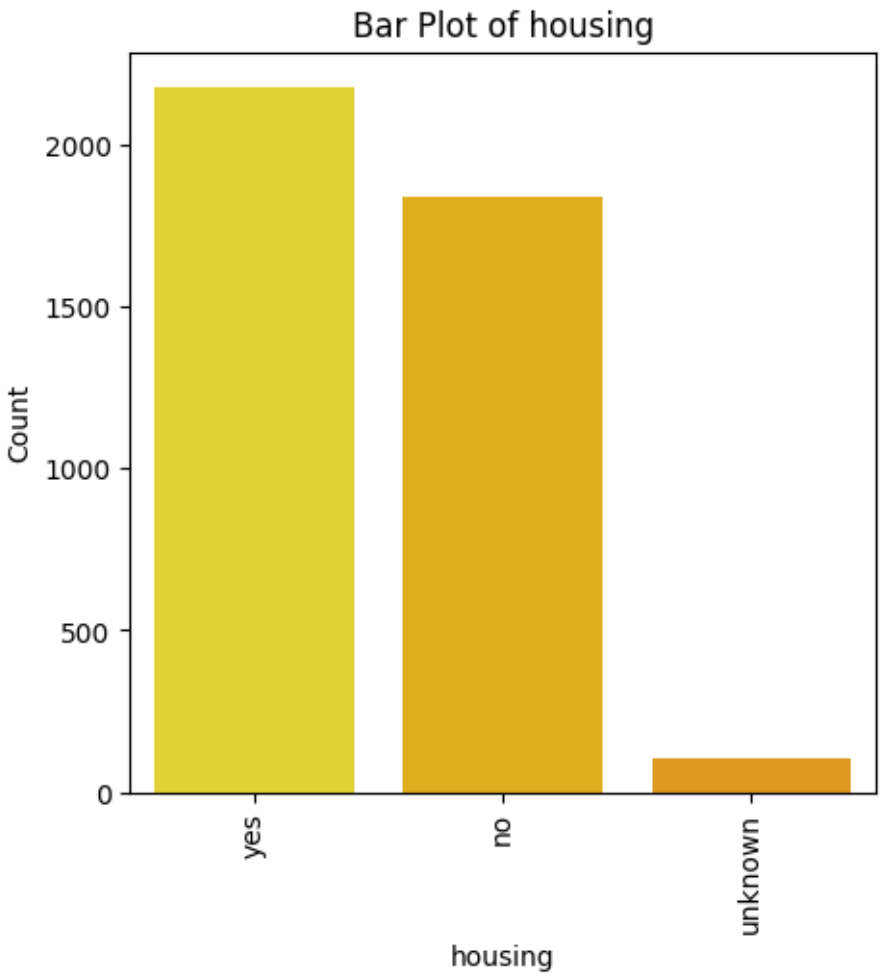
[17]:
```
for feature in cat_cols:
    plt.figure(figsize=(5,5))  # Adjust the figure size as needed
    sns.countplot(x=feature, data=df, palette='Wistia')
    plt.title(f'Bar Plot of {feature}')
    plt.xlabel(feature)
    plt.ylabel('Count')
    plt.xticks(rotation=90)
    plt.show()
```

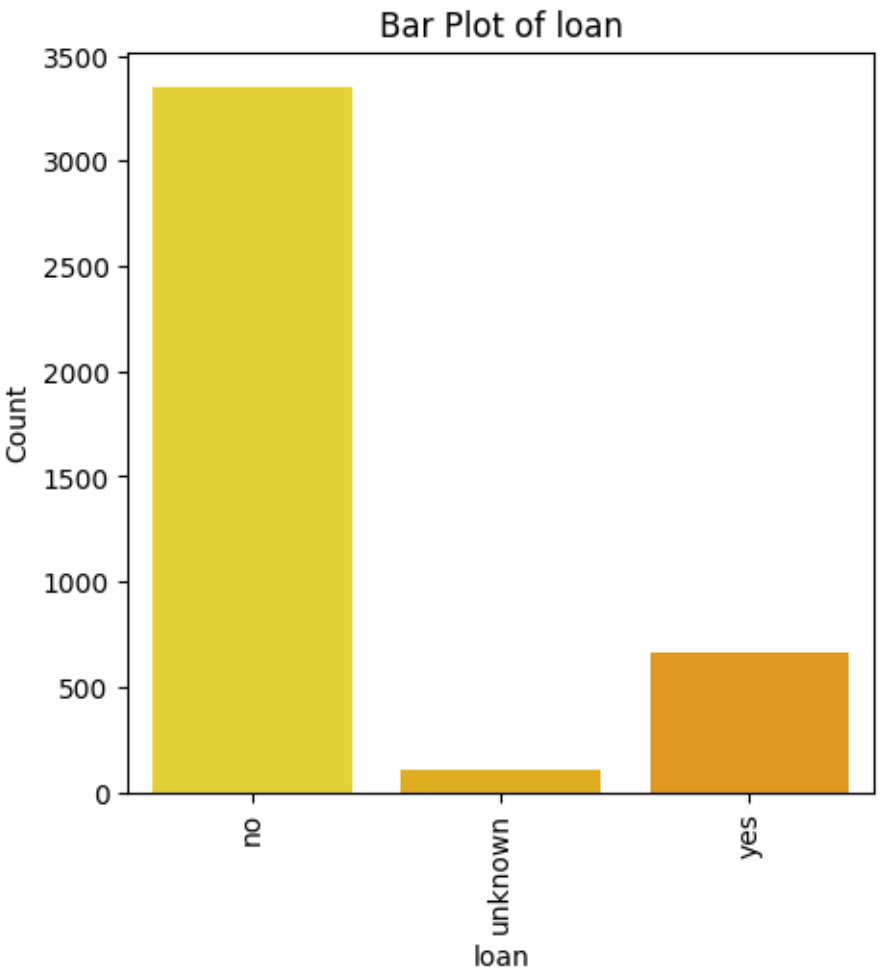

Bar Plot of job
Count
1000
800
600
400
200
0
blue-collar
services
admin.
entrepreneur
self-employed
technician
management
student
retired
housemaid
unemployed
unknown
job

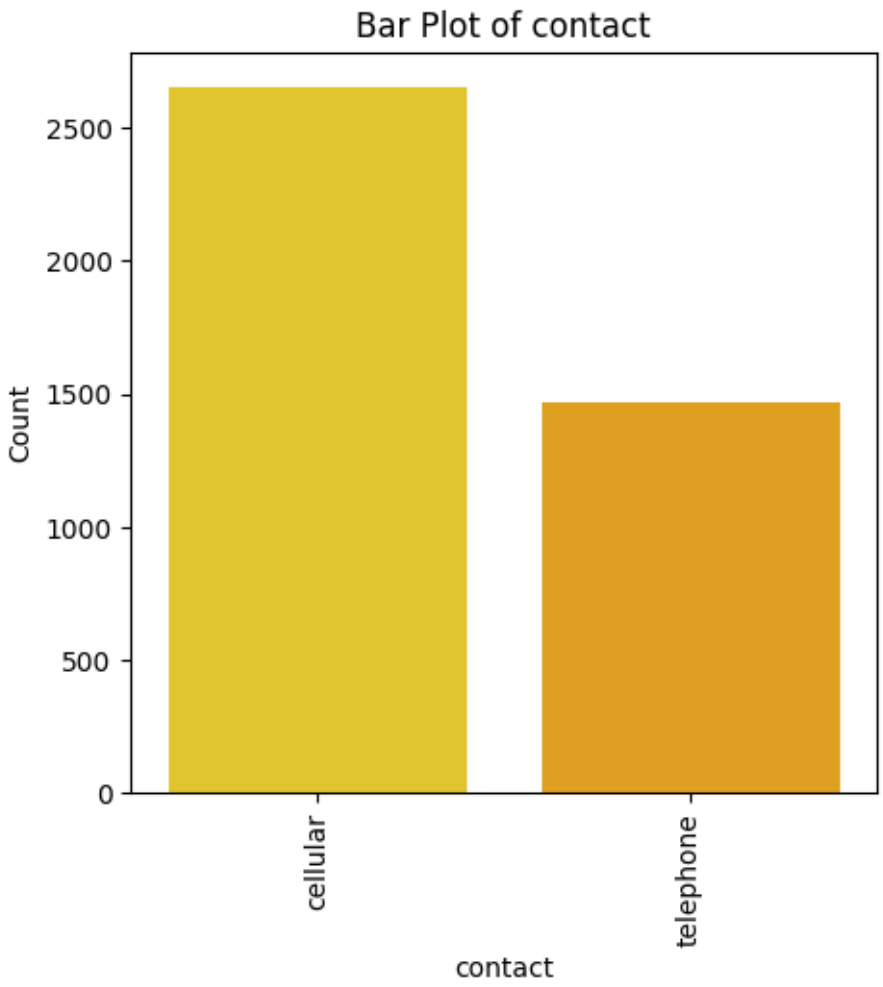

Bar Plot of marital
Count
2500
2000
1500
1000
500
0
married
single
divorced
unknown
marital

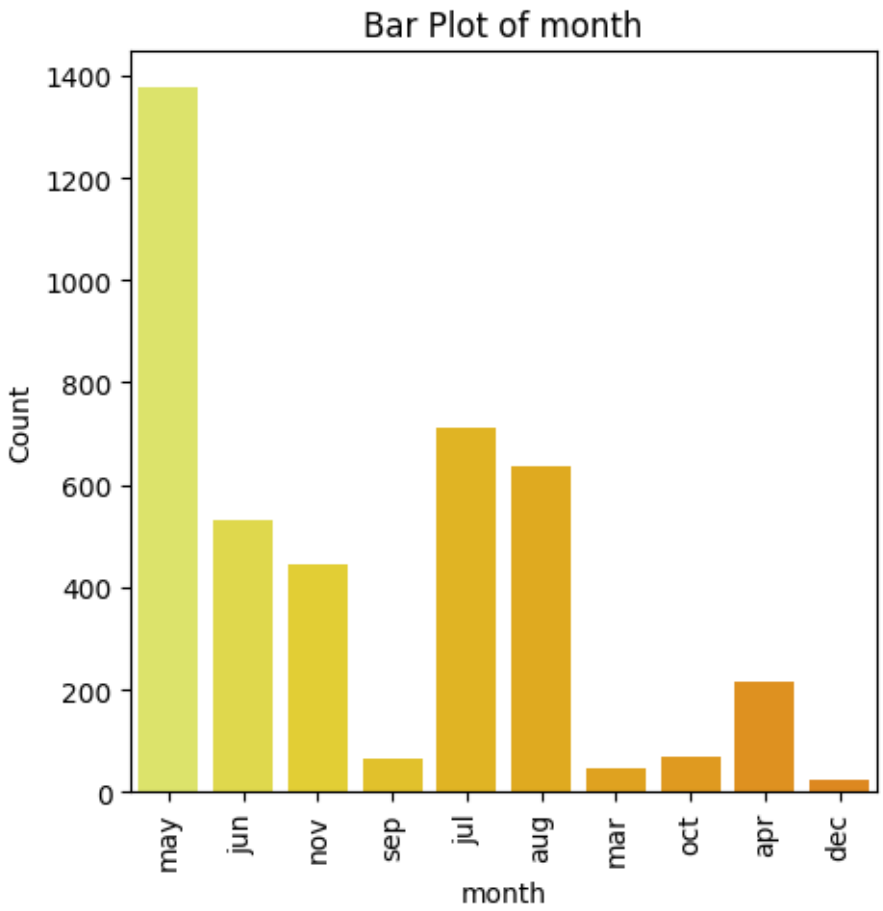

Bar Plot of education
Count
0
200
400
600
800
1000
1200
basic.9y
high.school
university.degree
professional.course
basic.6y
basic.4y
unknown
illiterate
education

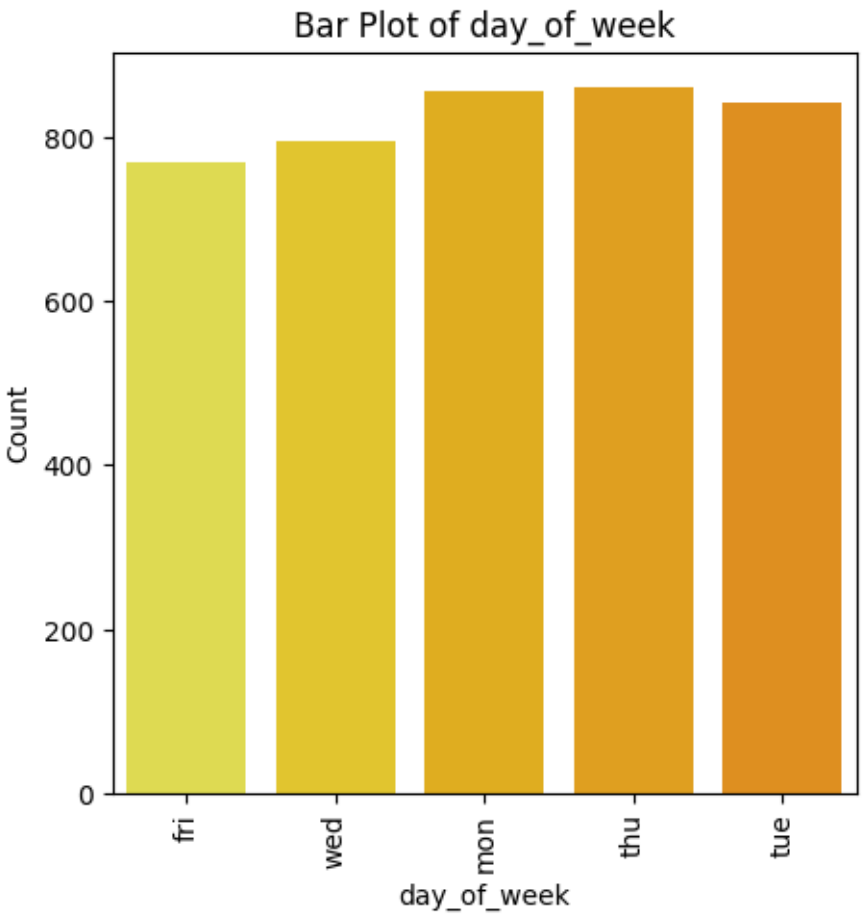

Bar Plot of default
Count
3000
2500
2000
1500
1000
500
0
no
unknown
yes
default

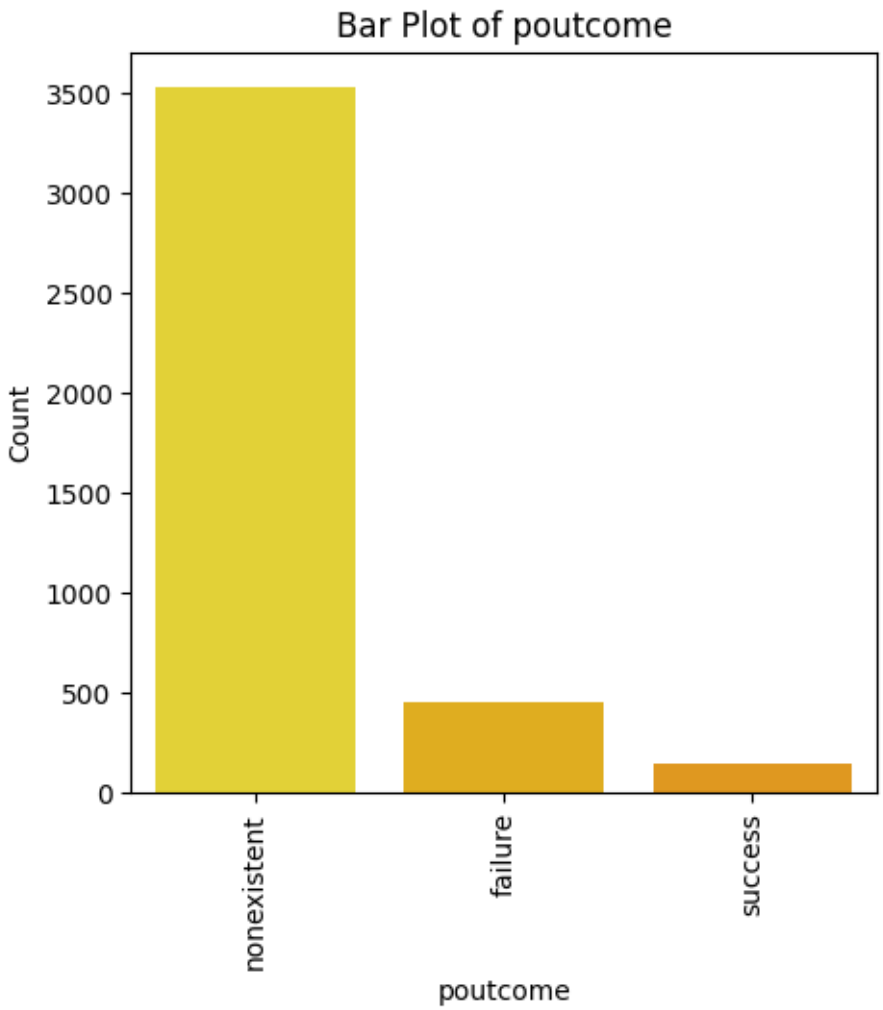

Bar Plot of housing
Count
2000
1500
1000
500
0
yes
no
unknown
housing

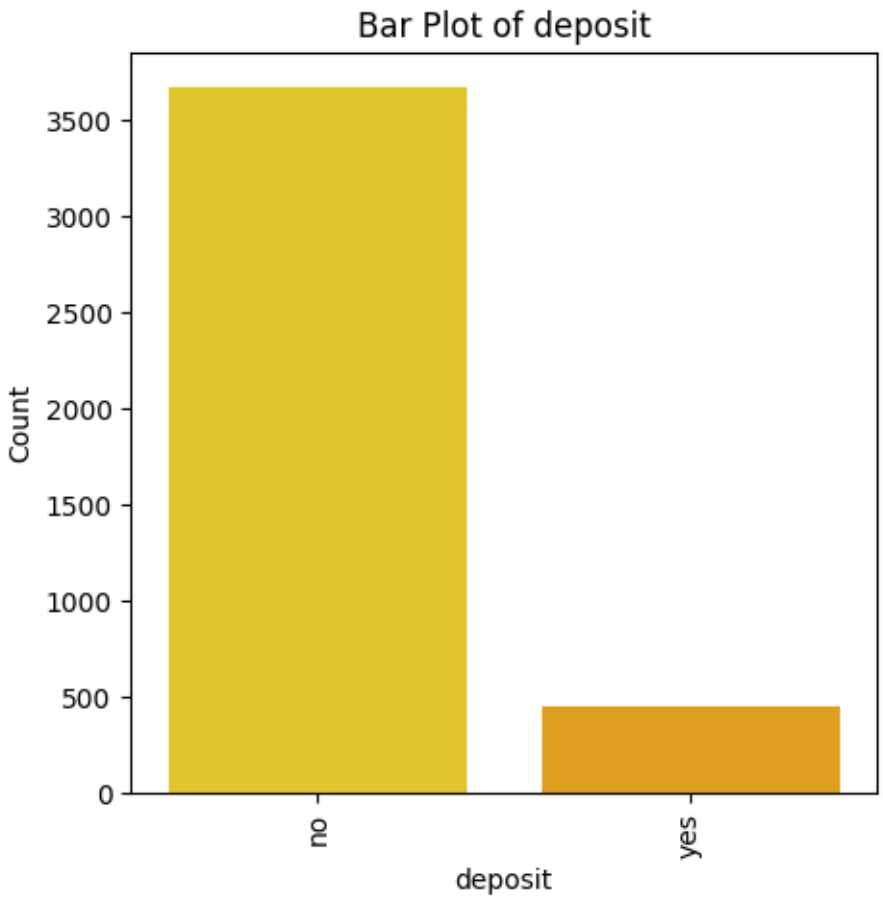

Bar Plot of loan
Count
3500
3000
2500
2000
1500
1000
500
0
no
unknown
yes
loan


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

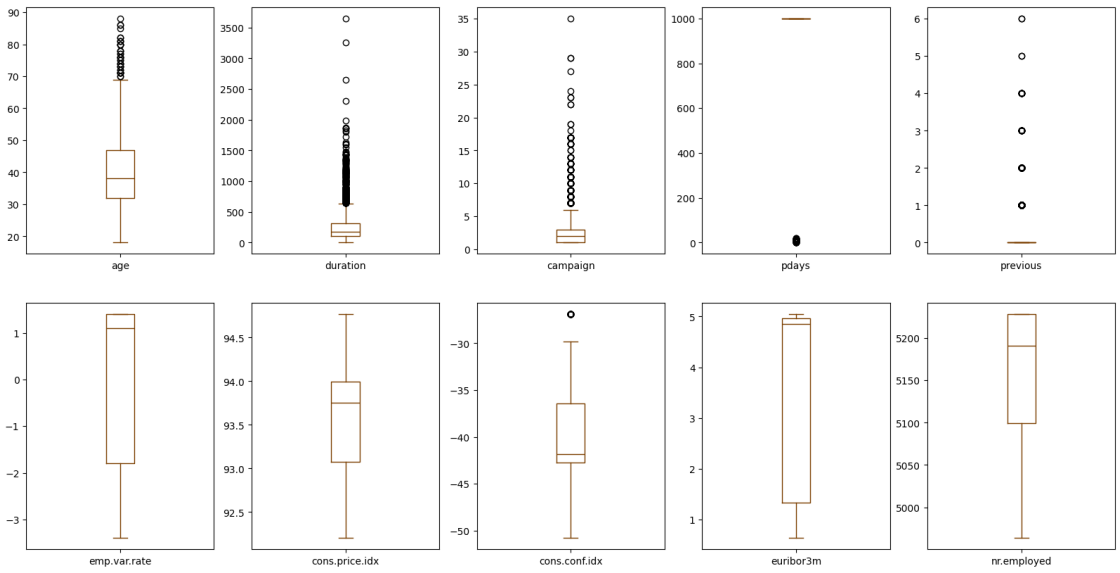

Bar Plot of month
Count
1400
1200
1000
800
600
400
200
0
may
jun
nov
sep
jul
aug
mar
oct
apr
dec
month


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

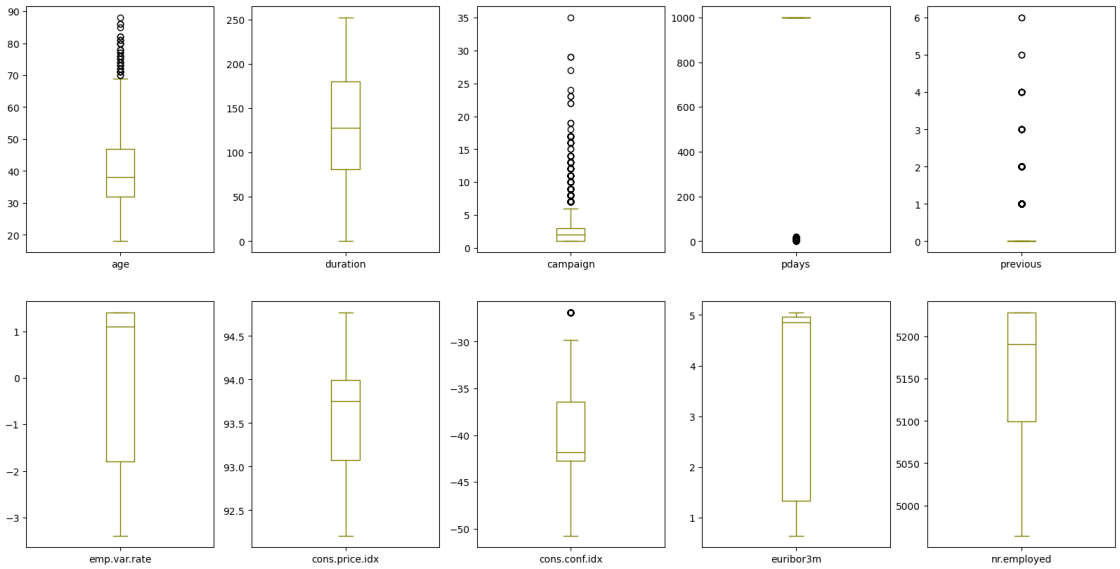


[18]:
```
df.plot(kind='box', subplots=True, layout=(2,5),figsize=(20,10),color='#7b3f00')
plt.show()
```



[19]:
```
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)]
```

[20]:
```
df.plot(kind='box', subplots=True, layout=(2,5),figsize=(20,10),color='#808000')
plt.show()
```



[25]:
```
high_corr_cols = ['emp.var.rate','euribor3m','nr.employed']
```

[26]:
```
df1 = df.copy()
df1.columns
```

[26]:
```
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')
```

[27]:
```
df1.drop(high_corr_cols,inplace=True,axis=1)  # axis=1 indicates columns
df1.columns
```

[27]:
```
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')
```

[28]:
```
df1.shape
```

[28]:
```
(4119, 18)
```

[29]:
```
from sklearn.preprocessing import LabelEncoder
lb = LabelEncoder()
df_encoded = df1.apply(lb.fit_transform)
df_encoded
```

[29]:

	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]
```

[30]:
```
df_encoded['deposit'].value_counts()
```

[30]:
```
deposit
0    3668
1     451
Name: count, dtype: int64
```

[31]:
```
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'>
```

[32]:
```
from sklearn.model_selection import train_test_split

print(4119*0.25)
```

```
1029.75
```

[33]:
```
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,)
```

[34]:
```
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)
```

[35]:
```
from sklearn.tree import DecisionTreeClassifier

dt = DecisionTreeClassifier(criterion='gini',max_depth=5,min_samples_split=10)
dt.fit(x_train,y_train)
```

[35]:
```
DecisionTreeClassifier(max_depth=5, min_samples_split=10)
```

[36]:
```
mscore(dt)
```

```
Training Score 0.9148591777274199
Testing Score 0.8990291262135922
```

[37]:
```
ypred_dt = dt.predict(x_test)
print(ypred_dt)
```

```
[0 0 1 … 0 0 0]
```

[38]:
```
eval_model(y_test,ypred_dt)
```

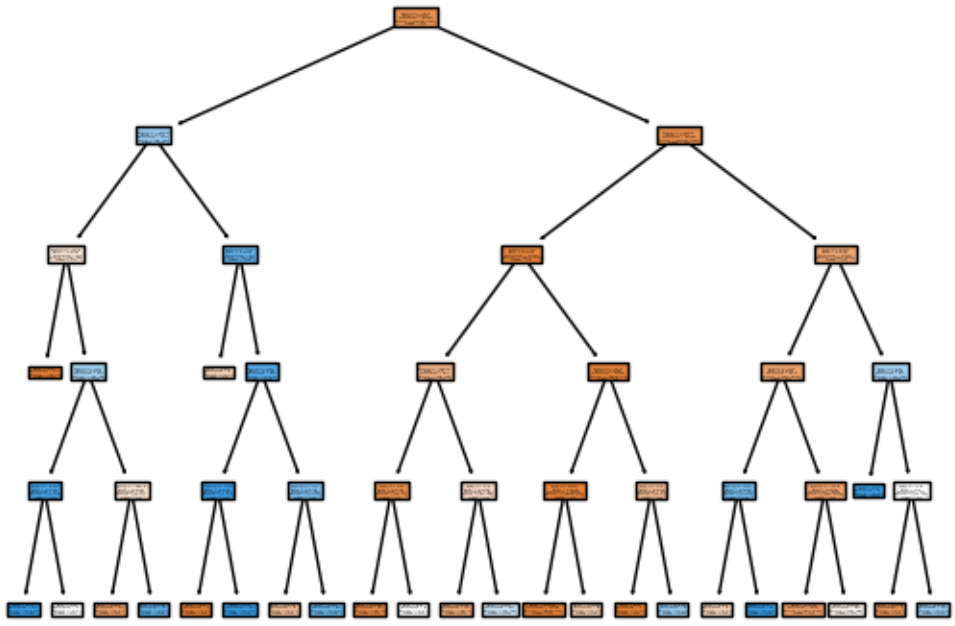
```
Accuracy_Score 0.8990291262135922
Confusion Matrix
 [[905  25]
 [ 79  21]]
Classification Report
              precision    recall  f1-score   support

           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
```

[39]:
```
from sklearn.tree import plot_tree
```

[40]:
```
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']
```

[41]:
```
plot_tree(dt,class_names=cn,filled=True)
plt.show()
```



[42]:
```
dt1 =␣
  ↪DecisionTreeClassifier(criterion='entropy',max_depth=4,min_samples_split=15)
dt1.fit(x_train,y_train)
```

[42]:
```
DecisionTreeClassifier(criterion='entropy', max_depth=4, min_samples_split=15)
```

[43]:
```
mscore(dt1)
```

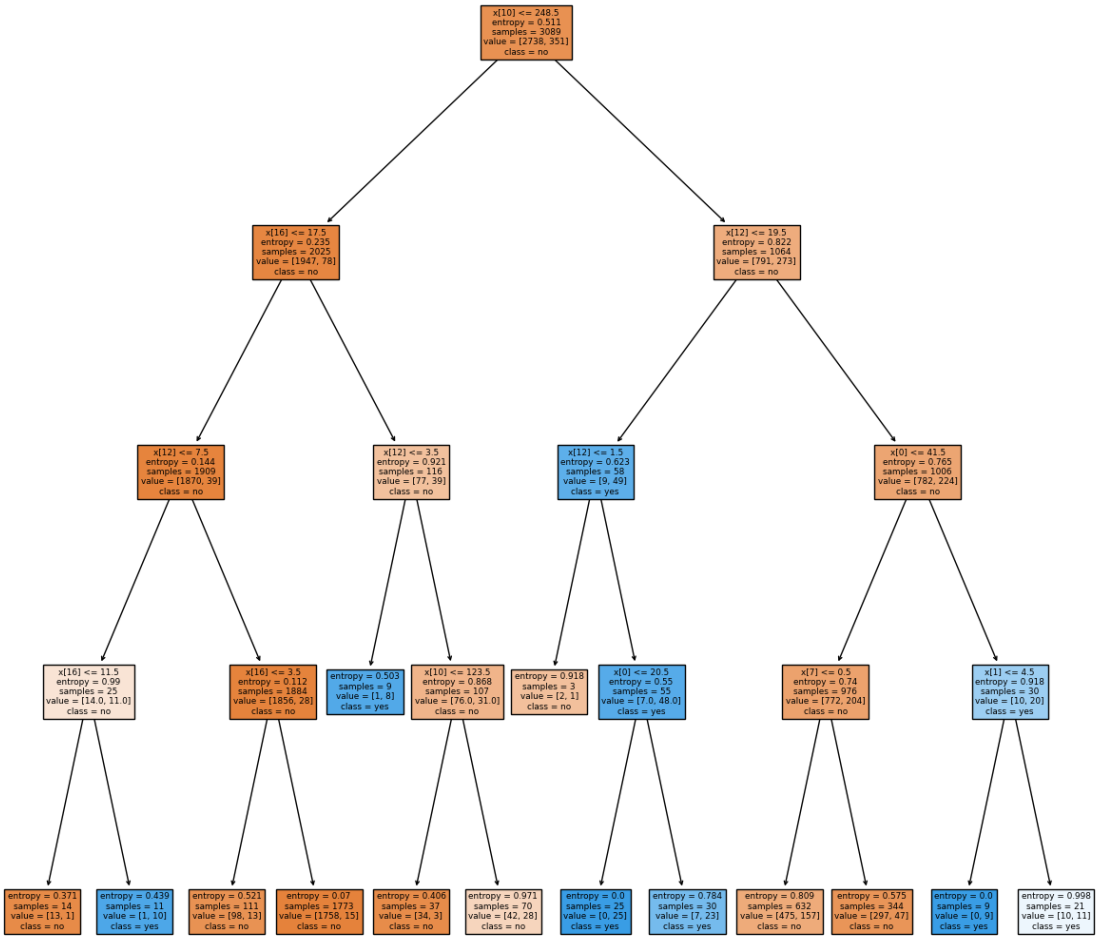
```
Training Score 0.9080608611201036
Testing Score 0.9048543689320389
```

[44]:
```
ypred_dt1 = dt1.predict(x_test)
```

[45]:
```
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
```

[46]:
```
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 = [14.0, 11.0]
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 = [76.0, 31.0]
class = no
entropy = 0.918
samples = 3
value = [2, 1]
class = no
x[0] <= 20.5
entropy = 0.55
samples = 55
value = [7.0, 48.0]
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

[ ]: