In [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
```

In [4]:

```
df = pd.read_csv('C:\\Users\\dheek\\Documents\\bank-additional\\bank-additional\\bank-additional.csv',delimiter=';')
df.rename(columns={'y':'deposit'}, inplace=True)
df.head()
```

Out[4]:

	age	job	marital	education	default	housing	loan	contact	month	day_of_week	...	campaign	pdays	previous	
0	30	blue-collar	married	basic.9y	no	yes	no	cellular	may	fri	...	2	999	0	r
1	39	services	single	high.school	no	no	no	telephone	may	fri	...	4	999	0	r
2	25	services	married	high.school	no	yes	no	telephone	jun	wed	...	1	999	0	r
3	38	services	married	basic.9y	no	unknown	unknown	telephone	jun	fri	...	3	999	0	r
4	47	admin.	married	university.degree	no	yes	no	cellular	nov	mon	...	1	999	0	r

5 rows × 21 columns

In [5]:

```
df.tail()
```

Out[5]:

	age	job	marital	education	default	housing	loan	contact	month	day_of_week	...	campaign	pdays	previous	p
4114	30	admin.	married	basic.6y	no	yes	yes	cellular	jul	thu	...	1	999	0	nc
4115	39	admin.	married	high.school	no	yes	no	telephone	jul	fri	...	1	999	0	nc
4116	27	student	single	high.school	no	no	no	cellular	may	mon	...	2	999	1	
4117	58	admin.	married	high.school	no	no	no	cellular	aug	fri	...	1	999	0	nc
4118	34	management	single	high.school	no	yes	no	cellular	nov	wed	...	1	999	0	nc

5 rows × 21 columns

In [6]:

```
df.shape
```

Out[6]:

```
(4119, 21)
```

In [7]:

```
df.columns
```

Out[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')
```

In [8]:

```
df.dtypes
```

Out[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
```

In [9]:

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

Out[9]:

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

In [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
```

In [11]:

```python
df.duplicated().sum()
```

Out[11]:

```
0
```

In [12]:

```python
df.isna().sum()
```

```
Out[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
```

In [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')
```

In [14]:

```
df.describe()
```

Out[14]:

	age	duration	campaign	pdays	previous	emp.var.rate	cons.price.idx	cons.conf.idx	euribor3m	nr.employ
count	4119.000000	4119.000000	4119.000000	4119.000000	4119.000000	4119.000000	4119.000000	4119.000000	4119.000000	4119.000
mean	40.113620	256.788055	2.537266	960.422190	0.190337	0.084972	93.579704	-40.499102	3.621356	5166.481
std	10.313362	254.703736	2.568159	191.922786	0.541788	1.563114	0.579349	4.594578	1.733591	73.667
min	18.000000	0.000000	1.000000	0.000000	0.000000	-3.400000	92.201000	-50.800000	0.635000	4963.600
25%	32.000000	103.000000	1.000000	999.000000	0.000000	-1.800000	93.075000	-42.700000	1.334000	5099.100
50%	38.000000	181.000000	2.000000	999.000000	0.000000	1.100000	93.749000	-41.800000	4.857000	5191.000
75%	47.000000	317.000000	3.000000	999.000000	0.000000	1.400000	93.994000	-36.400000	4.961000	5228.100
max	88.000000	3643.000000	35.000000	999.000000	6.000000	1.400000	94.767000	-26.900000	5.045000	5228.100

In [15]:

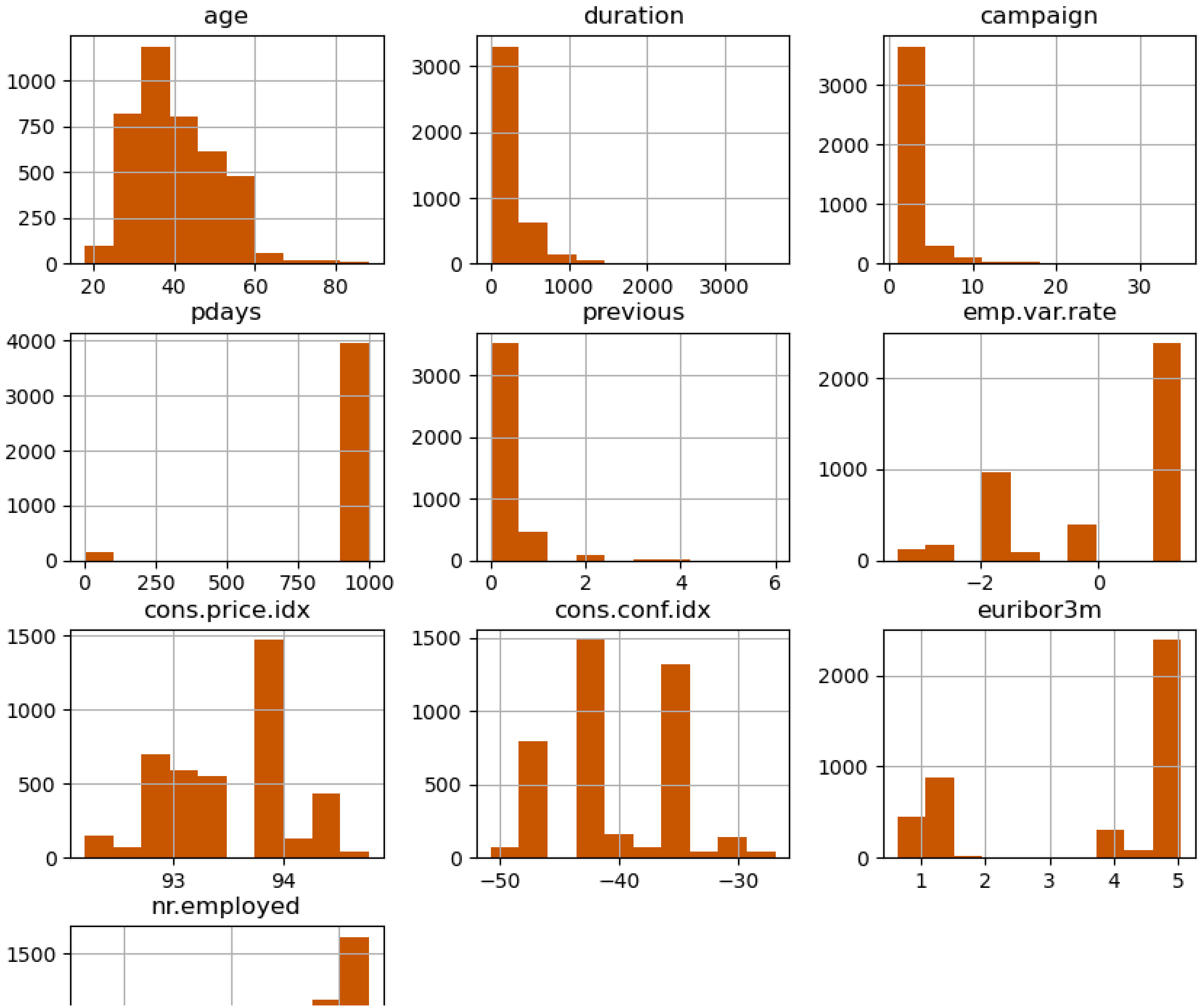
```
df.describe(include='object')
```

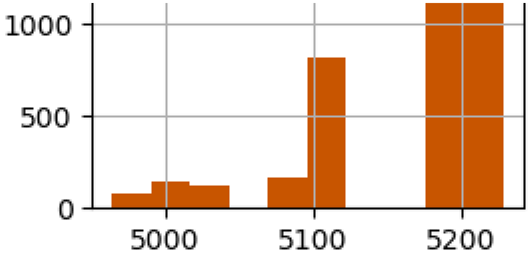
Out[15]:

	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

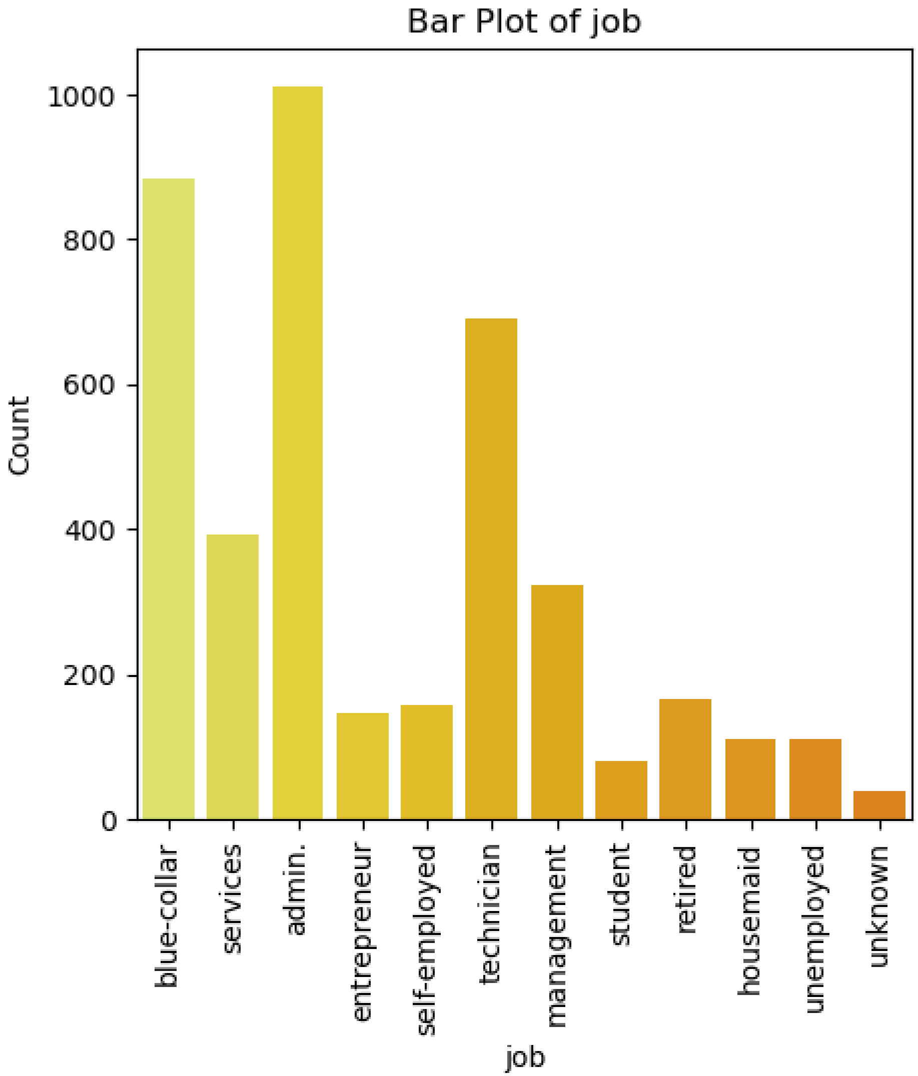
In [16]:

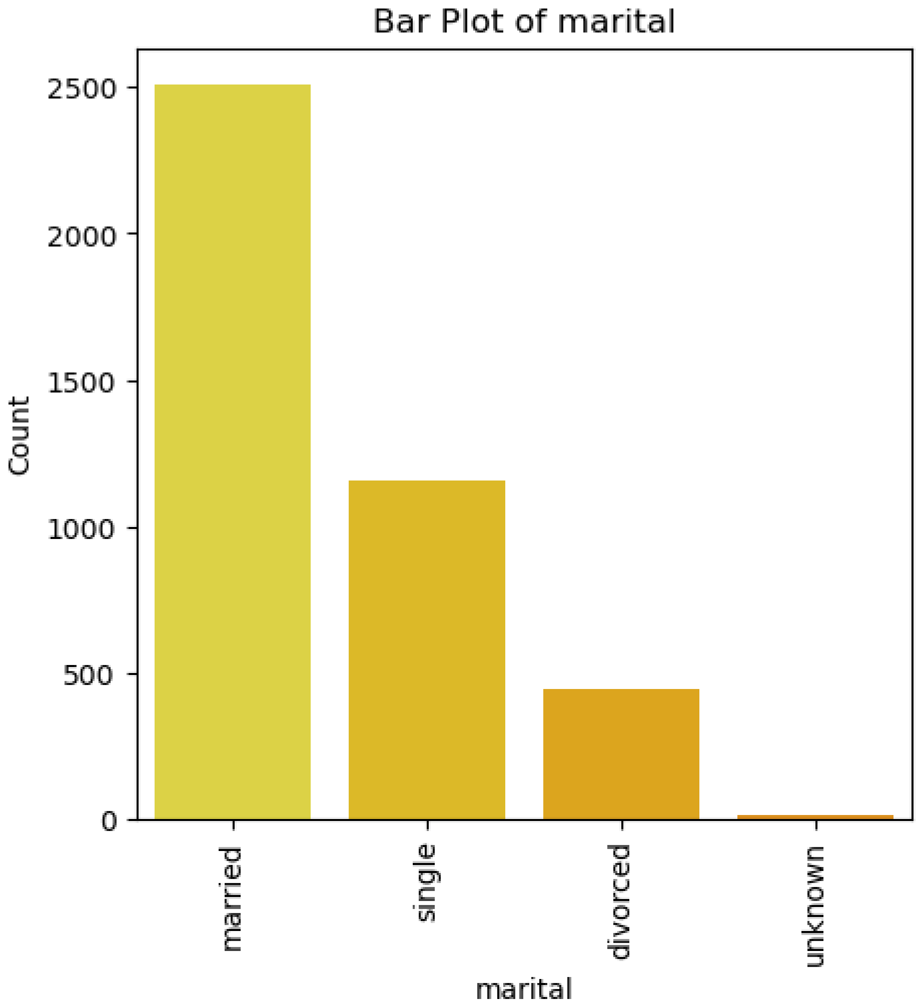
```
df.hist(figsize=(10,10),color='#cc5500')
plt.show()
```

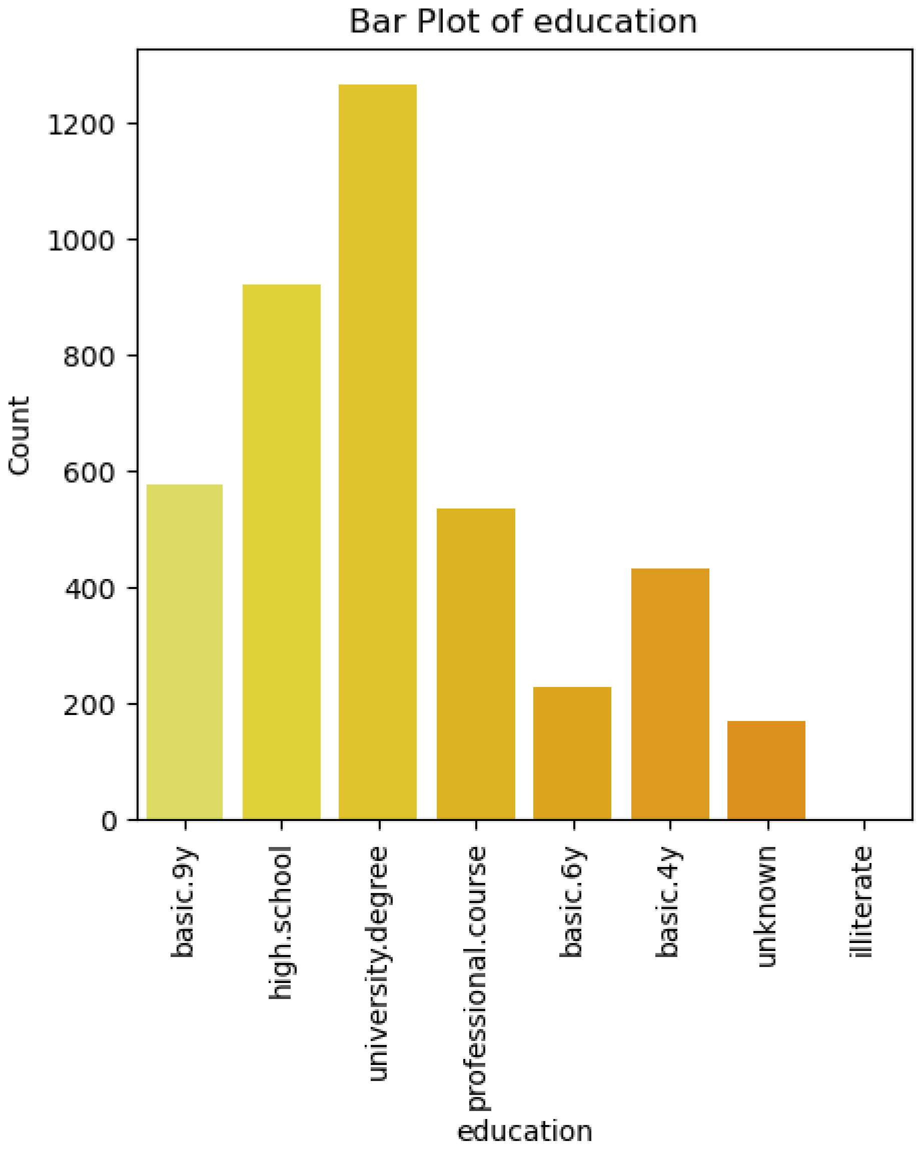

age
0
250
500
750
1000
20
40
60
80
duration
0
1000
2000
3000
0
1000
2000
3000
campaign
0
1000
2000
3000
0
10
20
30
pdays
0
1000
2000
3000
4000
0
250
500
750
1000
previous
0
1000
2000
3000
0
2
4
6
emp.var.rate
0
1000
2000
−2
0
cons.price.idx
0
500
1000
1500
93
94
cons.conf.idx
0
500
1000
1500
−50
−40
−30
euribor3m
0
1000
2000
1
2
3
4
5
nr.employed
1500

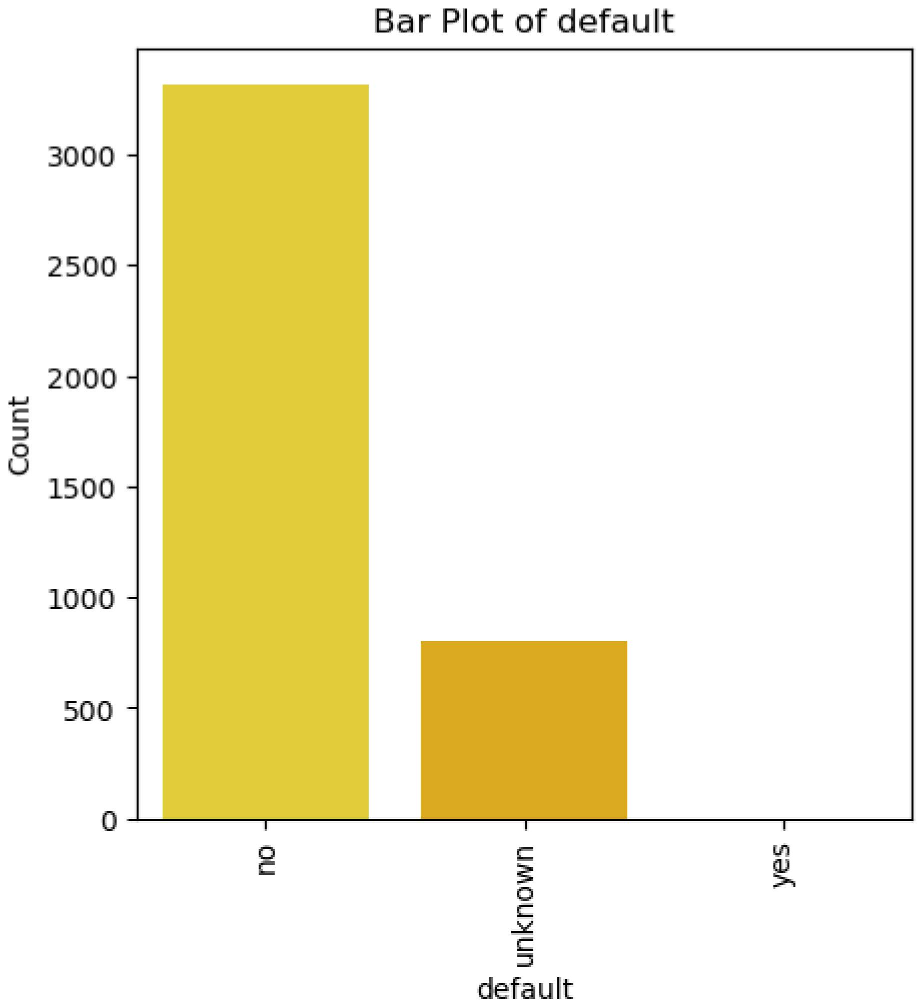


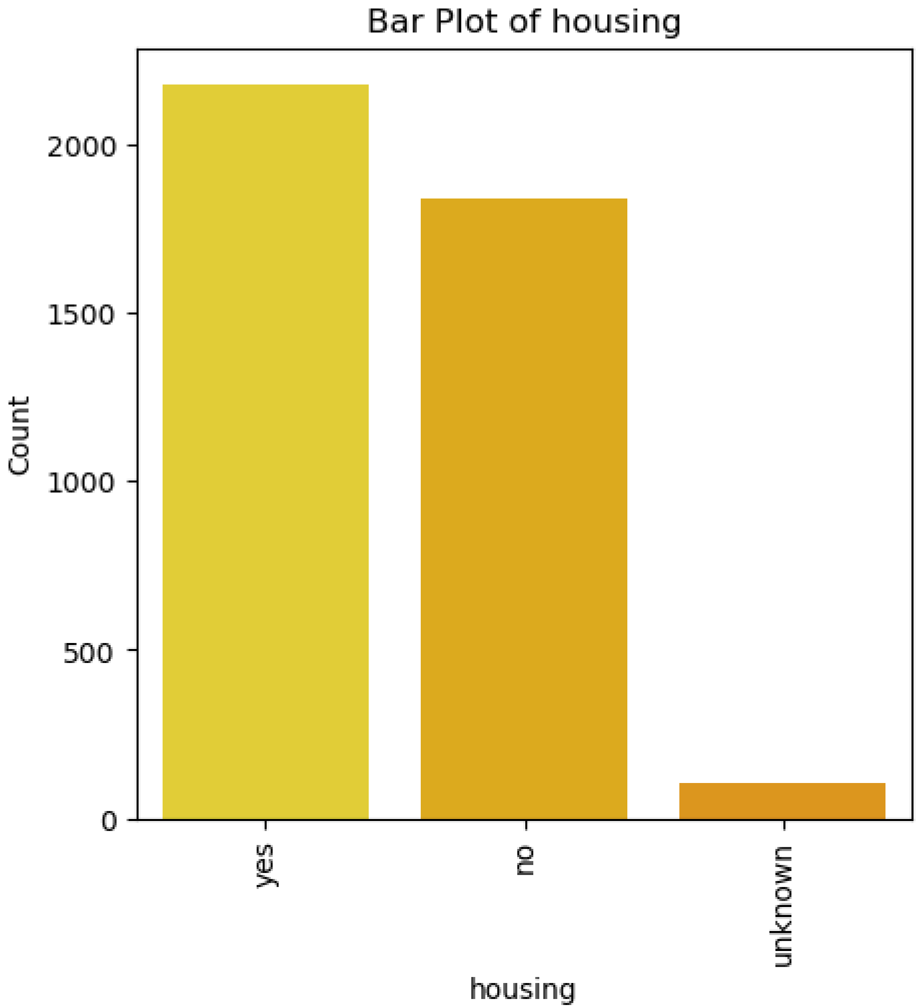
In [17]:
```
for feature in cat_cols:
    plt.figure(figsize=(5,5))  # Adjust the figure size as needed
    sns.countplot(x=feature, data=df, palette='Wistia')
    plt.title(f'Bar Plot of {feature}')
    plt.xlabel(feature)
    plt.ylabel('Count')
    plt.xticks(rotation=90)
    plt.show()
```

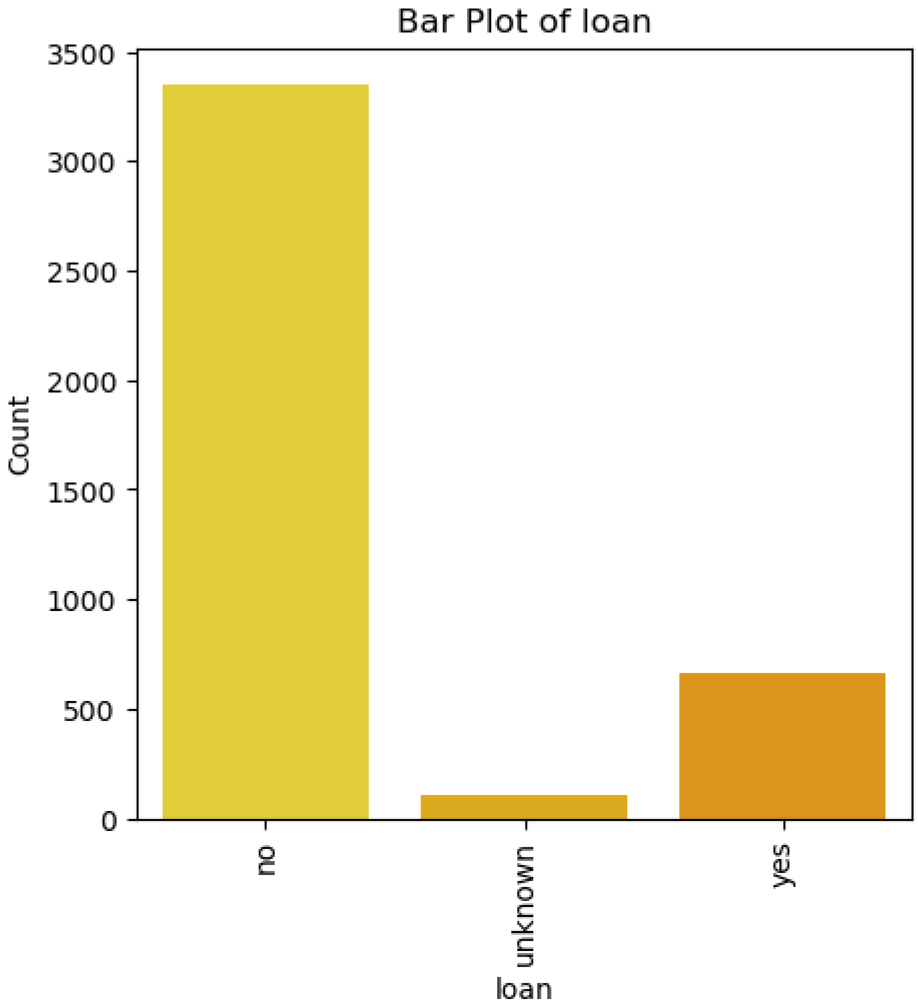

Bar Plot of job
Count
1000
800
600
400
200
0
blue-collar
services
admin.
entrepreneur
self-employed
technician
management
student
retired
housemaid
unemployed
unknown
job

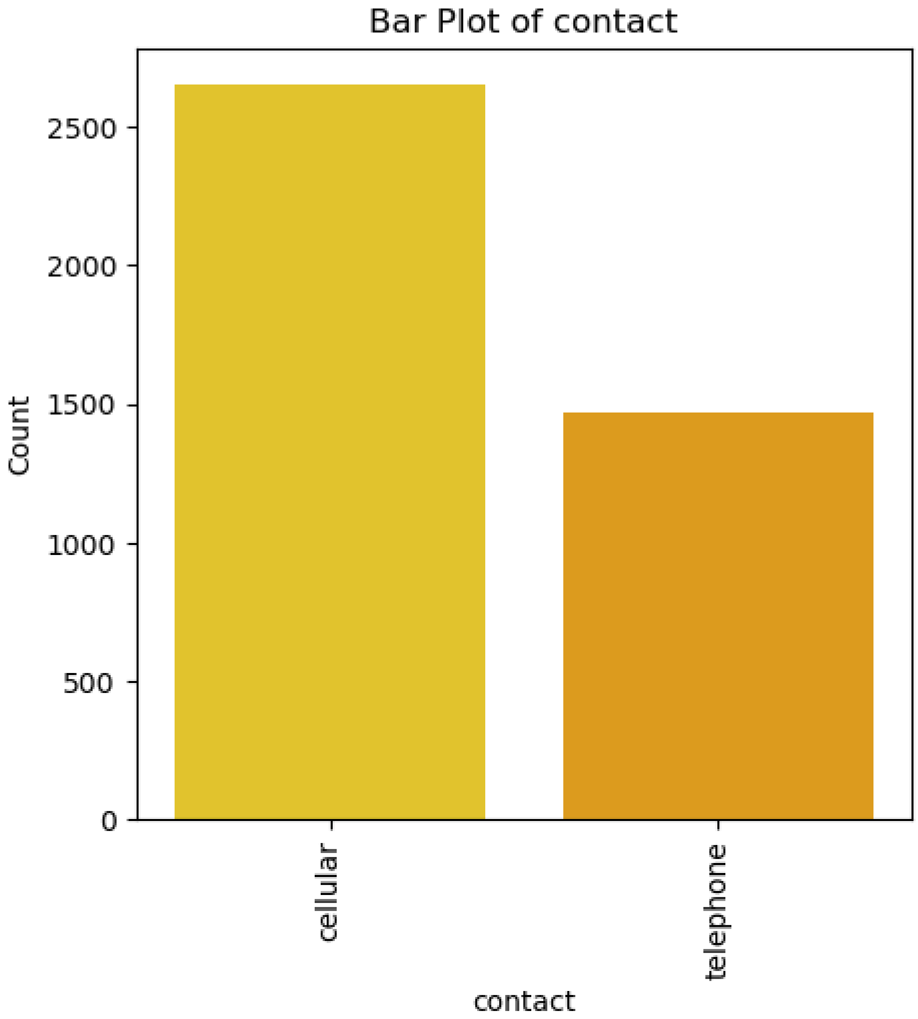

Bar Plot of marital
Count
2500
2000
1500
1000
500
0
married
single
divorced
unknown
marital

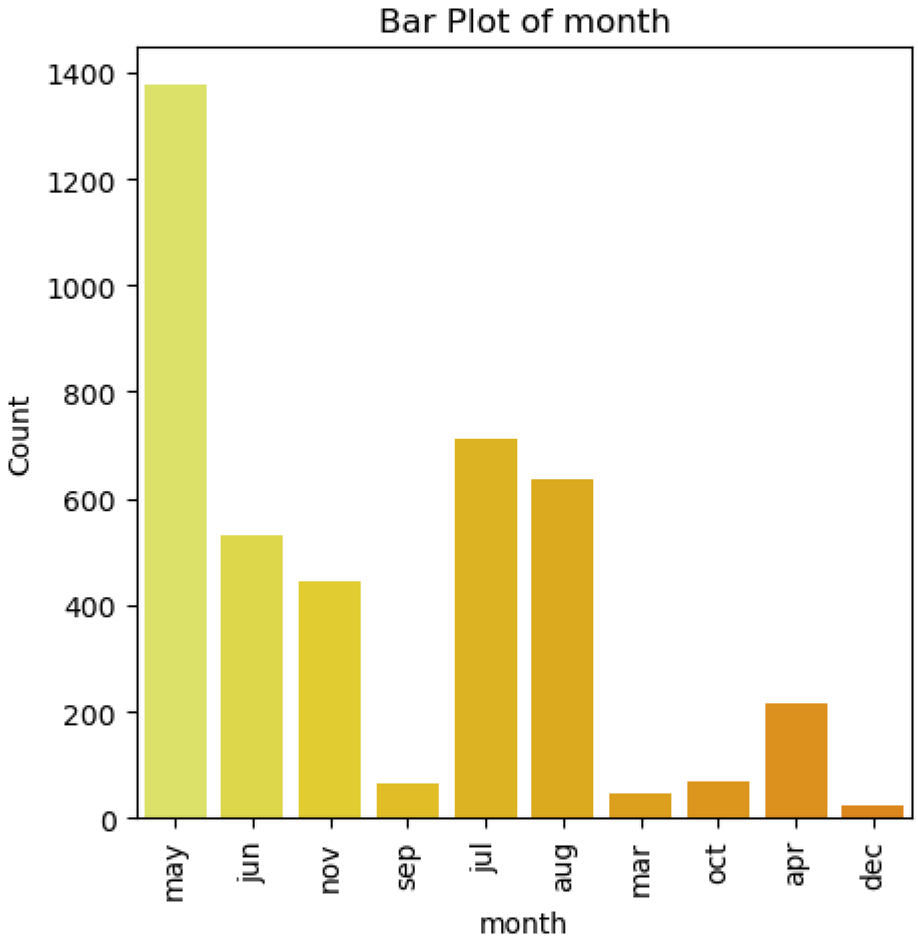

Bar Plot of education
Count
0
200
400
600
800
1000
1200
basic.9y
high.school
university.degree
professional.course
basic.6y
basic.4y
unknown
illiterate
education

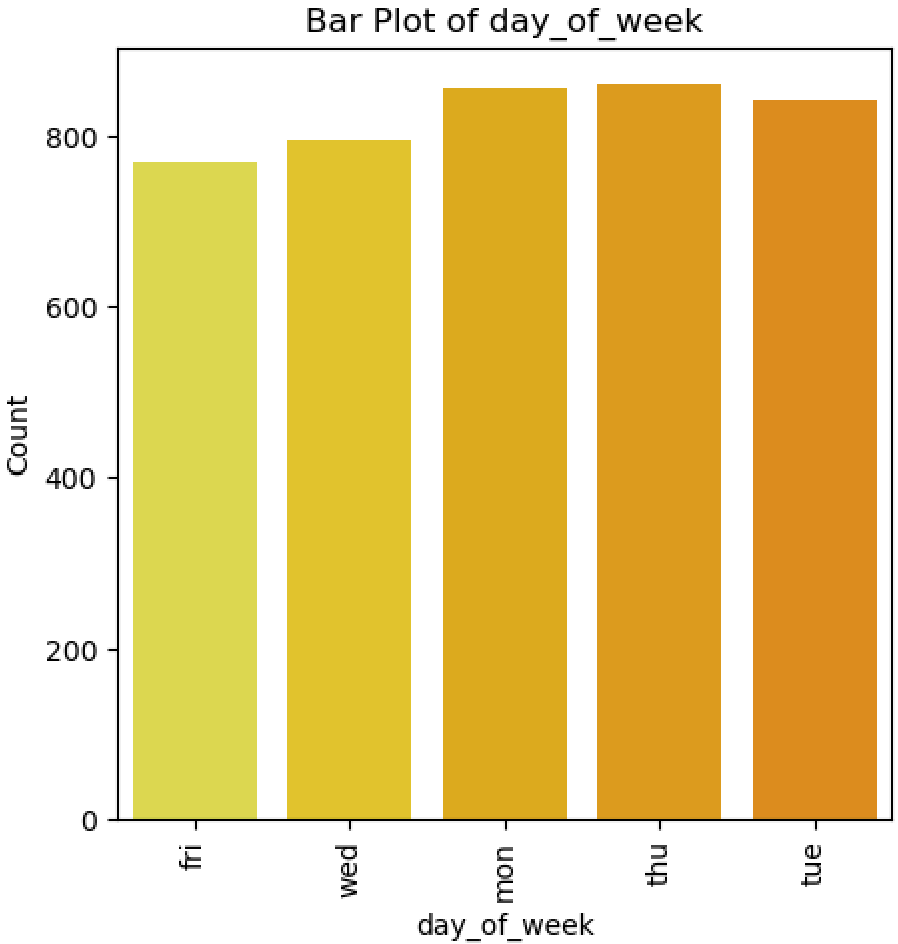

Bar Plot of default
Count
3000
2500
2000
1500
1000
500
0
no
unknown
yes
default


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

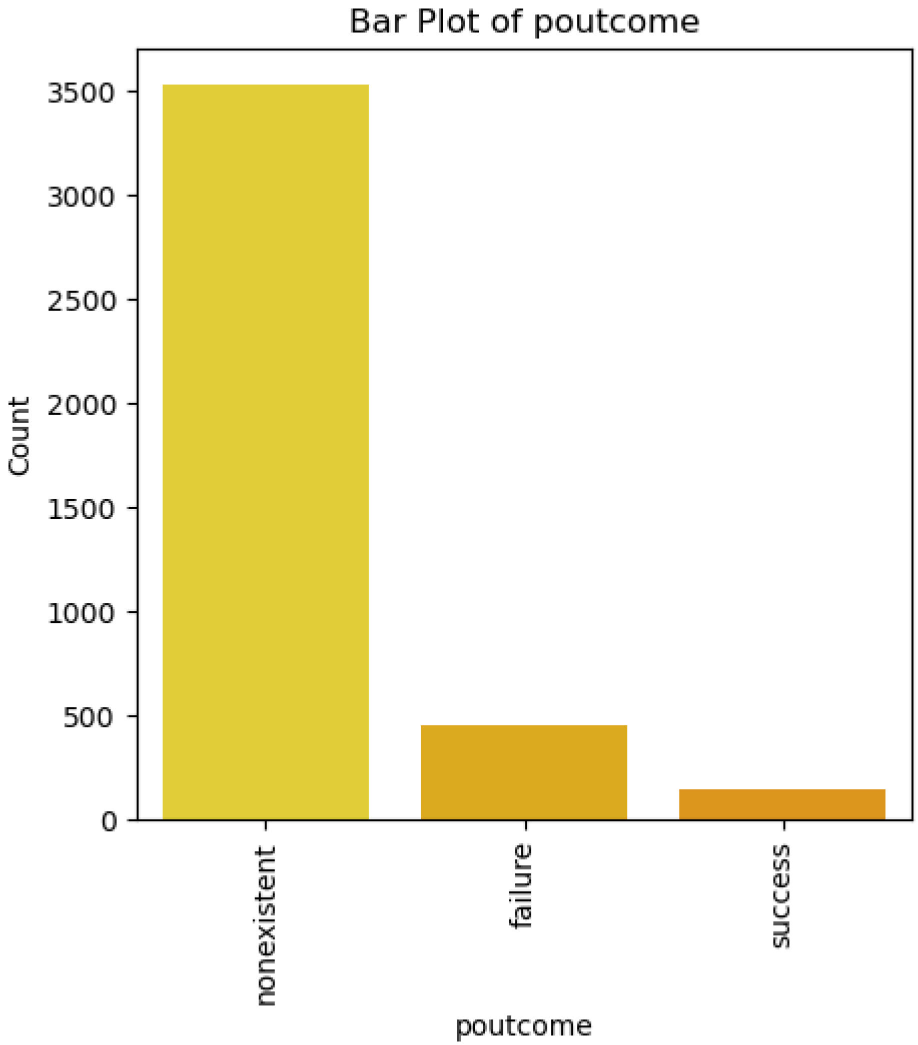

Bar Plot of loan
Count
3500
3000
2500
2000
1500
1000
500
0
no
unknown
yes
loan

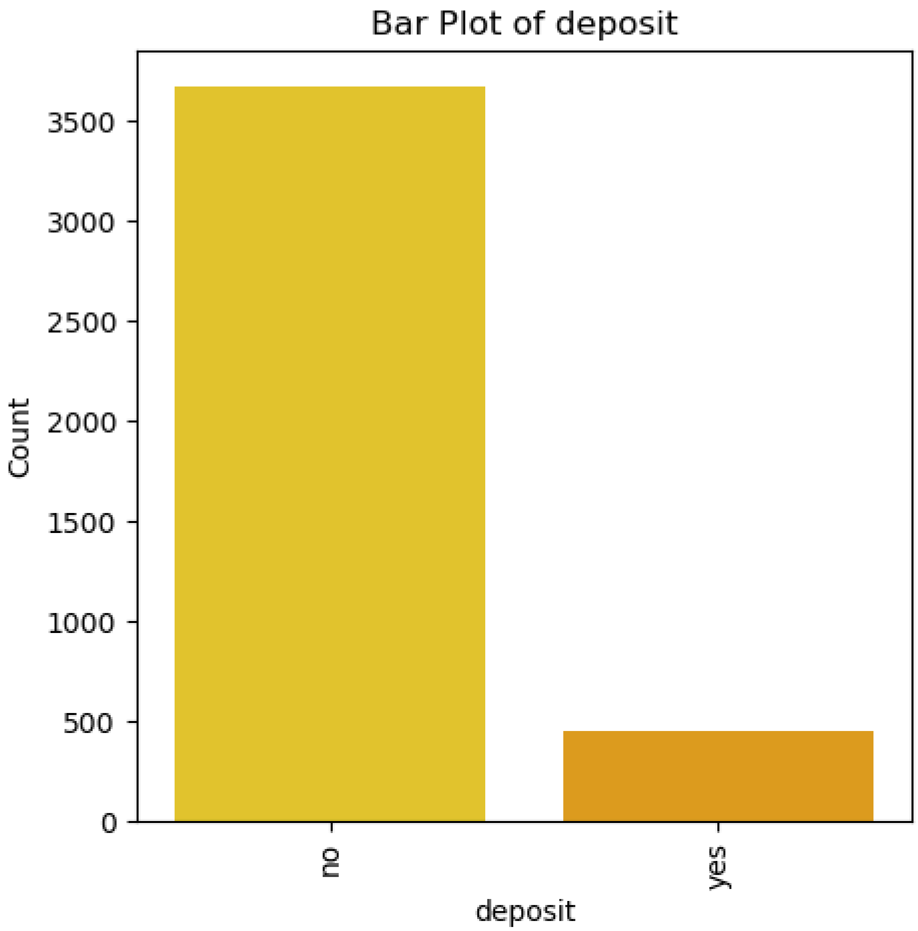

Bar Plot of contact
Count
2500
2000
1500
1000
500
0
cellular
telephone
contact


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

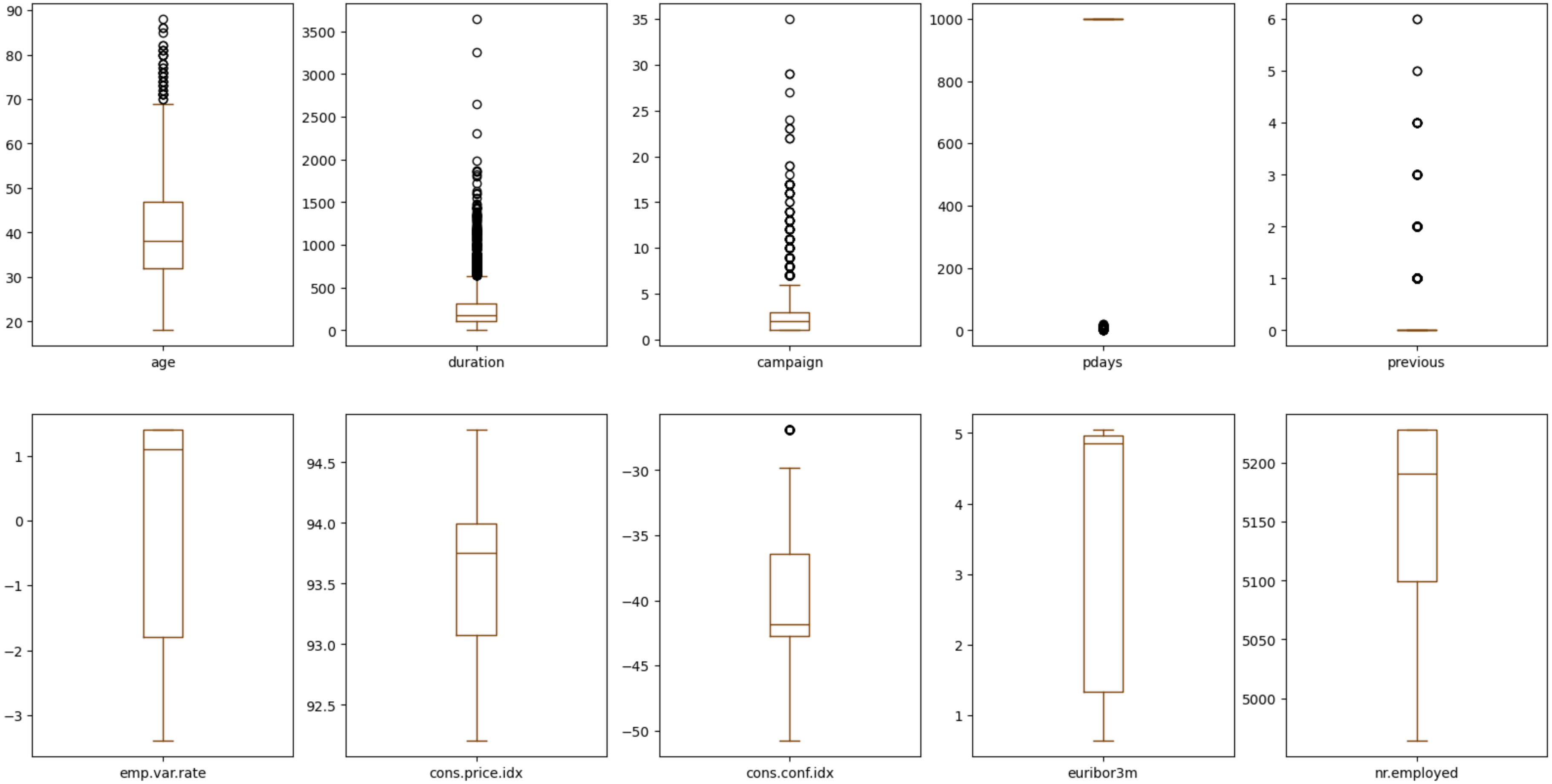


Bar Plot of day_of_week
Count
0
200
400
600
800
fri
wed
mon
thu
tue
day_of_week


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



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

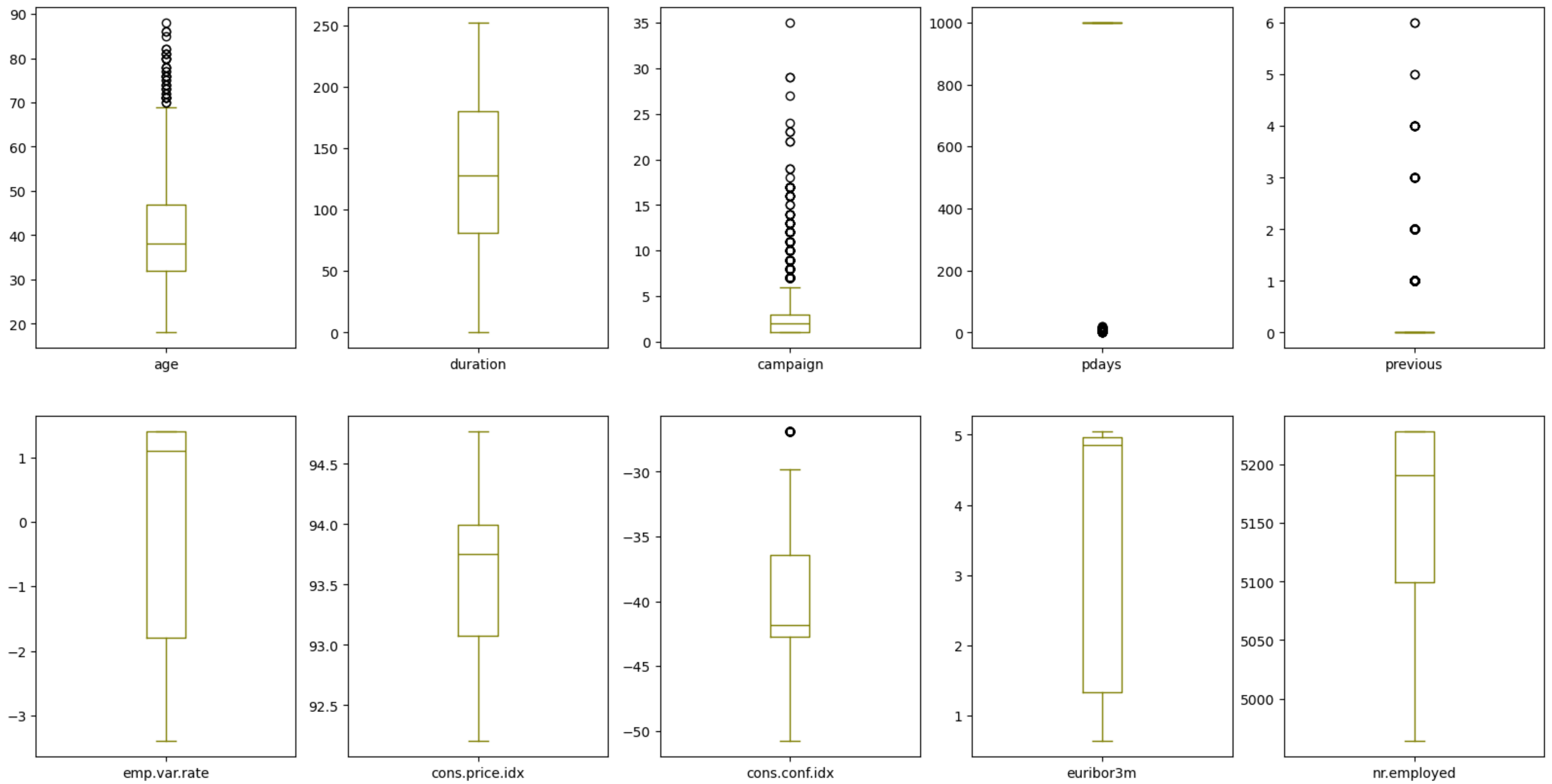


In [19]:

```
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)]
```

In [20]:

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



In [21]:
```
high_corr_cols = ['emp.var.rate','euribor3m','nr.employed']
```

In [22]:
```
df1 = df.copy()
df1.columns
```

Out[22]:
```
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')
```

In [23]:
```
df1.drop(high_corr_cols,inplace=True,axis=1)  # axis=1 indicates columns
df1.columns
```

Out[23]:
```
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')
```

In [24]:
```
df1.shape
```

Out[24]:
```
(4119, 18)
```

In [25]:
```
from sklearn.preprocessing import LabelEncoder
lb = LabelEncoder()
df_encoded = df1.apply(lb.fit_transform)
df_encoded
```

Out[25]:

	age	job	marital	education	default	housing	loan	contact	month	day_of_week	duration	campaign	pdays	previous	poutco
0	12	1	1	2	0	2	0	0	6	0	250	1	20	0	
1	21	7	2	3	0	0	0	1	6	0	250	3	20	0	
2	7	7	1	3	0	2	0	1	4	4	224	0	20	0	
3	20	7	1	2	0	1	1	1	4	0	14	2	20	0	
4	29	0	1	6	0	2	0	0	7	1	55	0	20	0	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
4114	12	0	1	1	0	2	2	0	3	2	50	0	20	0	
4115	21	0	1	3	0	2	0	1	3	0	216	0	20	0	
4116	9	8	2	3	0	0	0	0	6	1	61	1	20	1	
4117	40	0	1	3	0	0	0	0	1	0	250	0	20	0	
4118	16	4	2	3	0	2	0	0	7	4	172	0	20	0	

4119 rows × 18 columns

In [26]:

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

Out[26]:

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

In [27]:

```
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'>
```

In [28]:

```
from sklearn.model_selection import train_test_split

print(4119*0.25)
```

```
1029.75
```

In [29]:

```
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,)
```

In [30]:

```
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)
```

In [31]:

```
from sklearn.tree import DecisionTreeClassifier

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

```
Out[31]: ▾           DecisionTreeClassifier

         DecisionTreeClassifier(max_depth=5, min_samples_split=10)
```

```
In [32]: mscore(dt)
```

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

```
In [33]: ypred_dt = dt.predict(x_test)
         print(ypred_dt)
```

```
[0 0 1 ... 0 0 0]
```

```
In [34]: 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
```

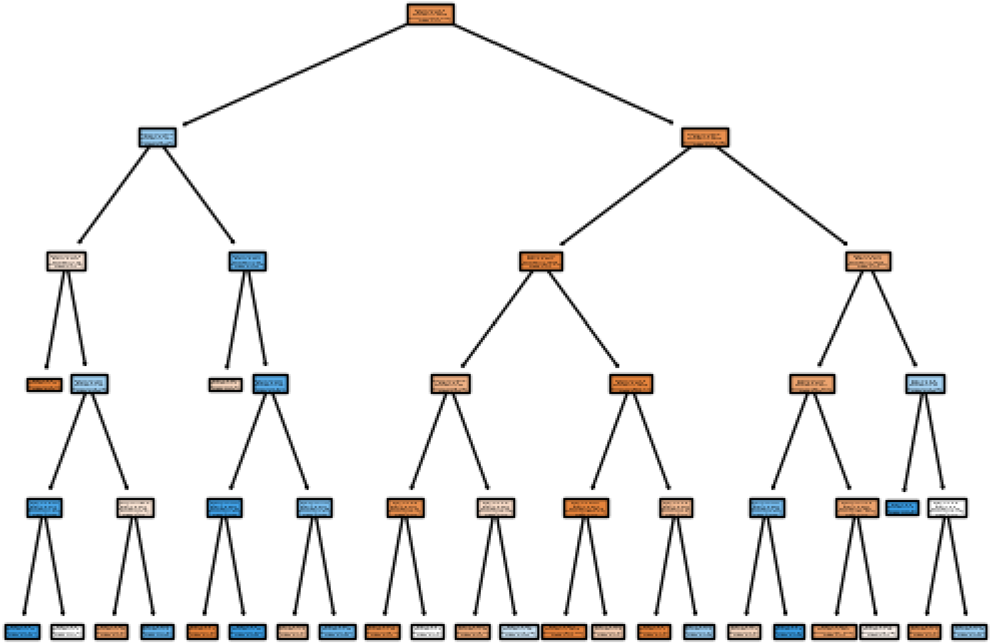
```
In [35]: from sklearn.tree import plot_tree
```

```
In [36]: 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']
```

In [37]:

```
plot_tree(dt,class_names=cn,filled=True)
plt.show()
```



In [38]:

```
dt1 = DecisionTreeClassifier(criterion='entropy',max_depth=4,min_samples_split=15)
dt1.fit(x_train,y_train)
```

Out[38]:

```
▾ DecisionTreeClassifier

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

In [39]:
```
mscore(dt1)
```

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

In [40]:
```
ypred_dt1 = dt1.predict(x_test)
```

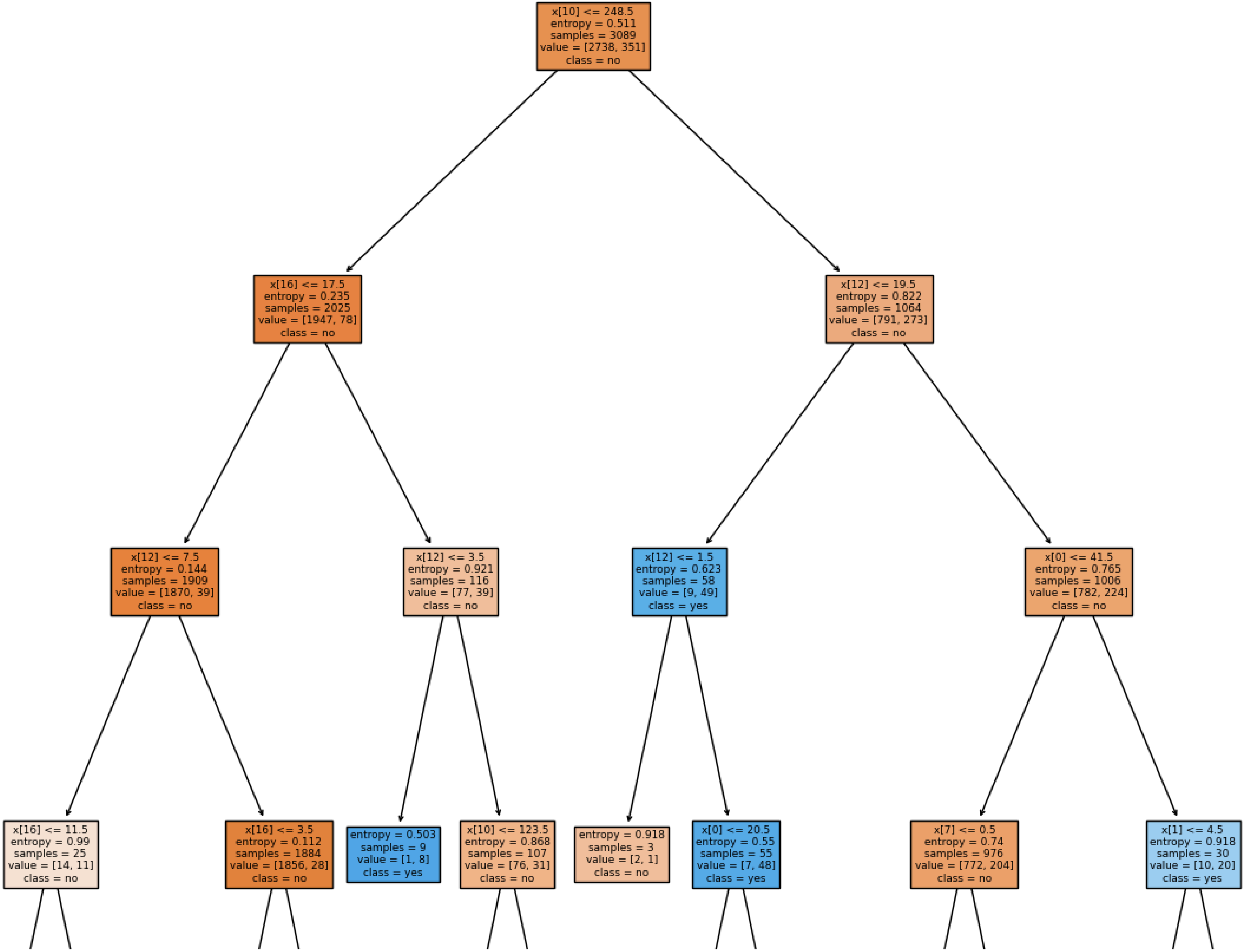
In [41]:
```
eval_model(y_test,ypred_dt1)
```

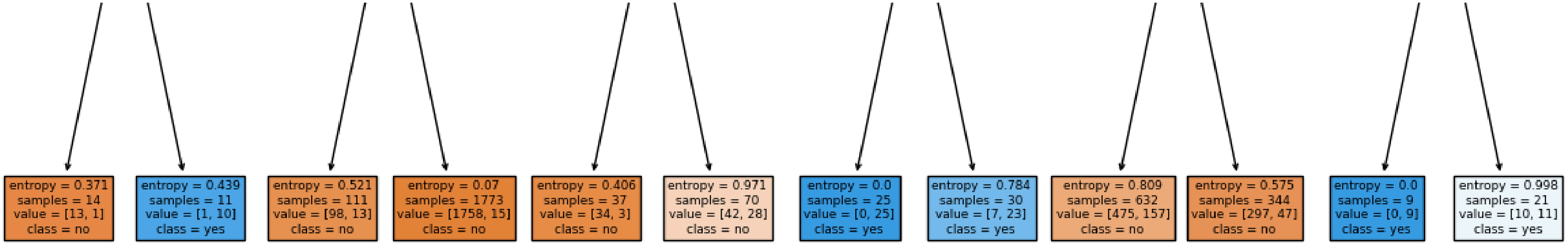
```
Accuracy_Score 0.9048543689320389
Confusion Matrix
 [[915  15]
 [ 83  17]]
Classification Report
               precision    recall  f1-score   support

           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
```

In [42]:
```
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

In [ ]: