In [1]:
```python
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 [2]:
```python
df = pd.read_csv('C:/Users/saswa/OneDrive/Desktop/Pinaki_Bank_Marketing/bank-additional/bank-additional/bank-addition
df.rename(columns={'y':'deposit'}, inplace=True)
df.head()
```

Out[2]:

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

5 rows × 21 columns

In [3]:
```python
df.head()
```

Out[3]:

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

5 rows × 21 columns

In [4]:
```python
df.tail()
```

Out[4]:

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

5 rows × 21 columns

In [5]:
```python
df.shape
```

Out[5]: (4119, 21)

In [6]:
```
df.columns
```

Out[6]:
```
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 [7]:
```
df.dtypes
```

Out[7]:
```
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
```

In [8]:
```
df.dtypes.value_counts()
```

Out[8]:
```
object     11
int64       5
float64     5
dtype: int64
```

In [9]:
```
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
```

In [10]:
```
df.duplicated().sum()
```
Out[10]:
```
0
```
In [11]:
```
df.isna().sum()
```
Out[11]:
```
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 [12]:
```
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 [13]:
```
df.describe()
```
Out[13]:

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

In [14]:

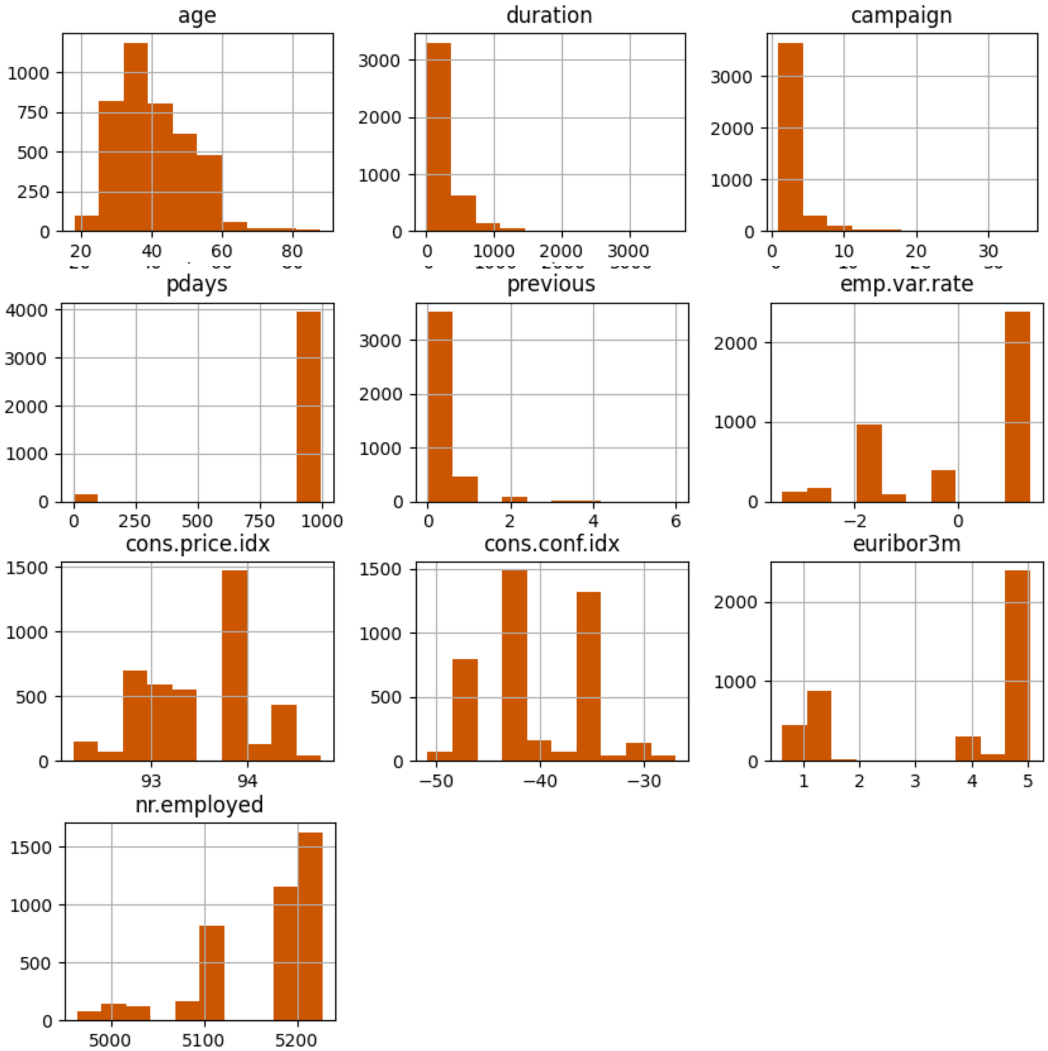
```
df.describe(include='object')
```

Out[14]:

	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

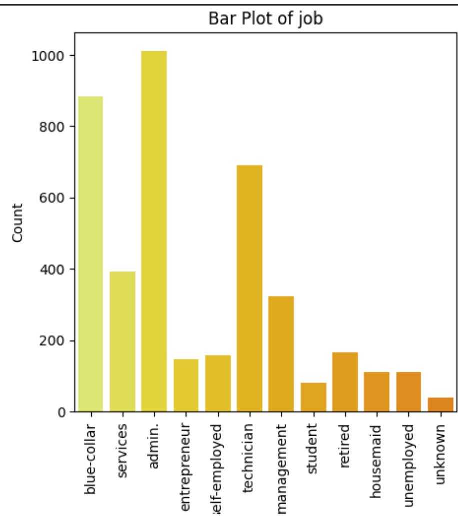
In [15]:

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

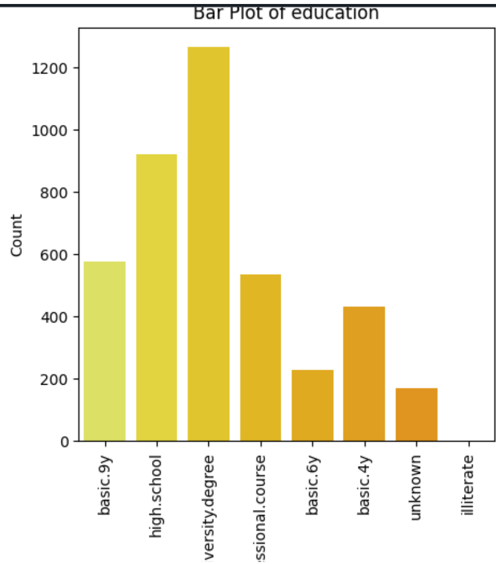


In [16]:

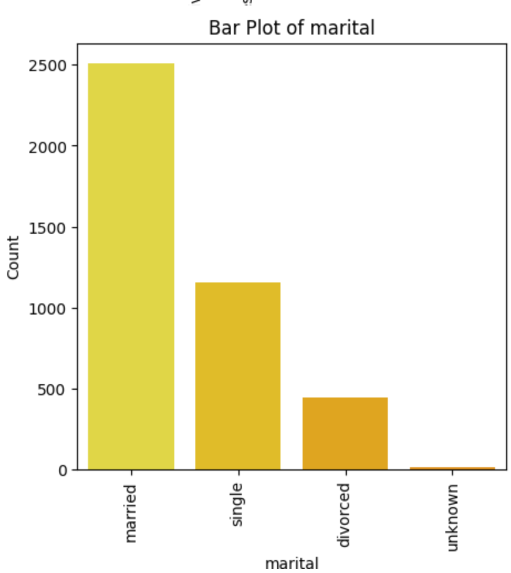
```
for feature in cat_cols:
    plt.figure(figsize=(5,5))  # Adjust the figure size as needed
    sns.countplot(x=feature, data=df, palette='Wistia')
    plt.title(f'Bar Plot of {feature}')
    plt.xlabel(feature)
    plt.ylabel('Count')
    plt.xticks(rotation=90)
    plt.show()
```



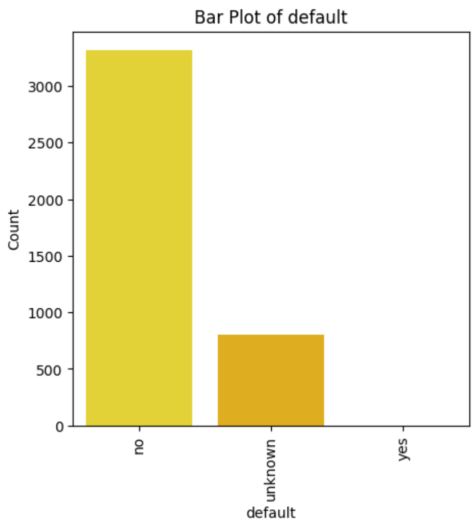
Bar Plot of job
Count
1000
800
600
400
200
0
blue-collar
services
admin.
entrepreneur
elf-employed
technician
management
student
retired
housemaid
unemployed
unknown

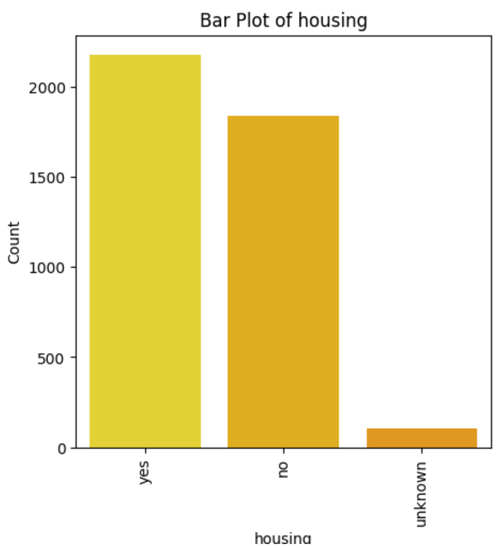


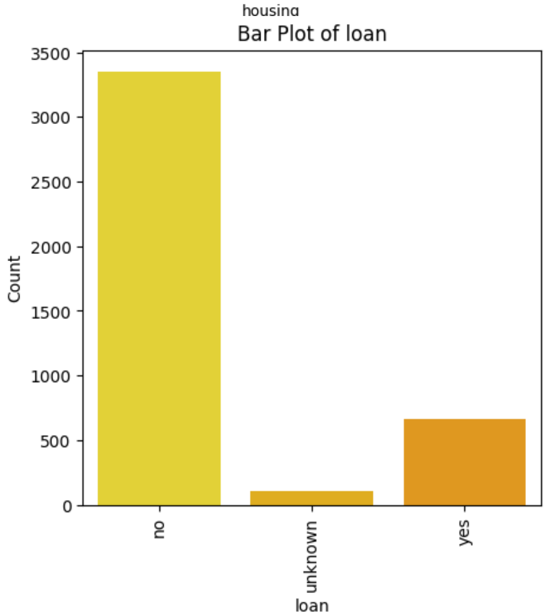
Bar Plot of education
Count
1200
1000
800
600
400
200
0
basic.9y
high.school
versity.degree
ssional.course
basic.6y
basic.4y
unknown
illiterate

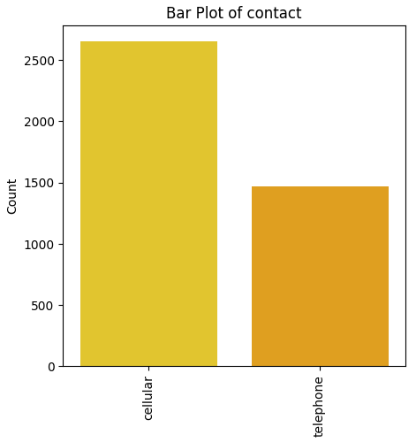


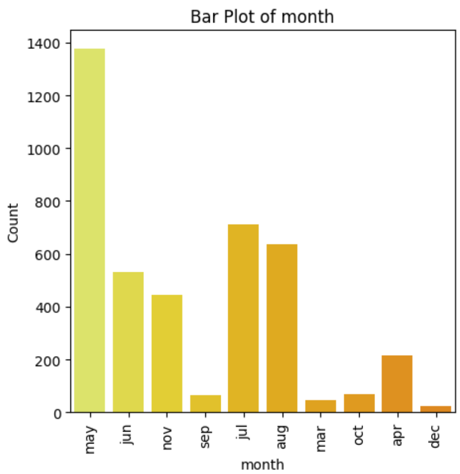
Bar Plot of marital
Count
2500
2000
1500
1000
500
0
married
single
divorced
unknown
marital

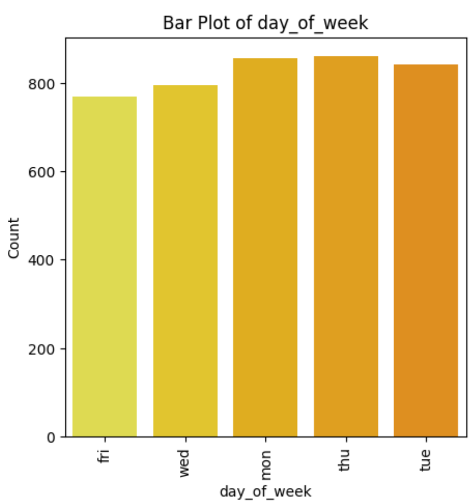

Bar Plot of default
Count
3000
2500
2000
1500
1000
500
0
no
unknown
yes
default

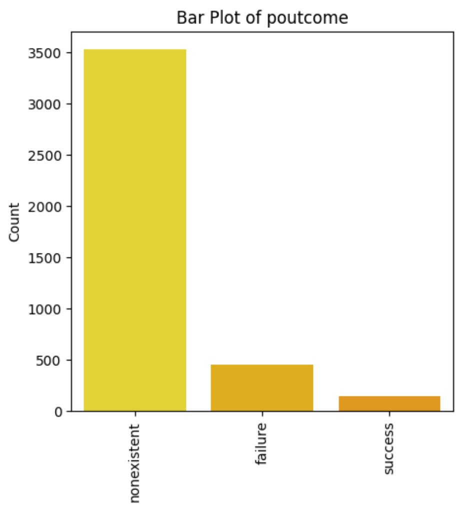

Bar Plot of housing
Count
2000
1500
1000
500
0
yes
no
unknown
housing

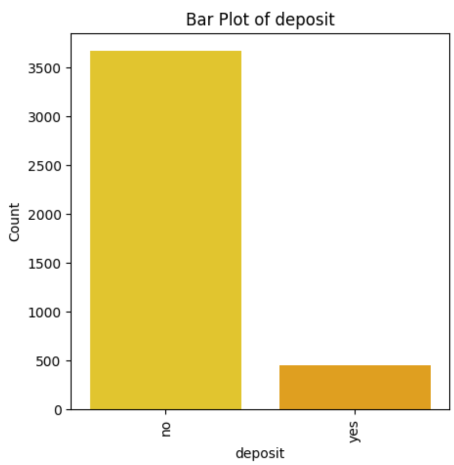

Bar Plot of loan
Count
3500
3000
2500
2000
1500
1000
500
0
no
unknown
yes
loan


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


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

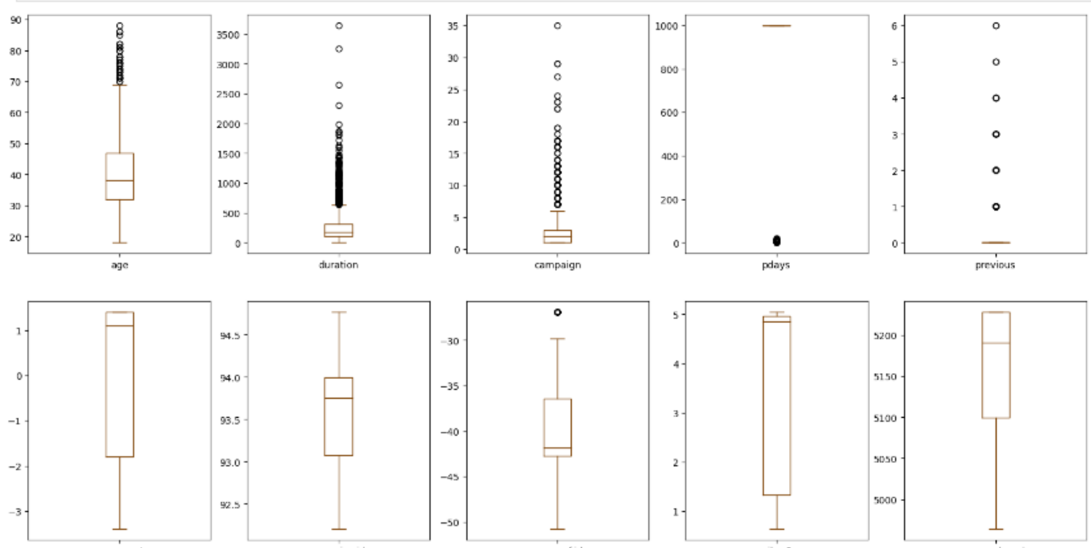

Bar Plot of day_of_week
Count
0
200
400
600
800
fri
wed
mon
thu
tue
day_of_week





In [17]:

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

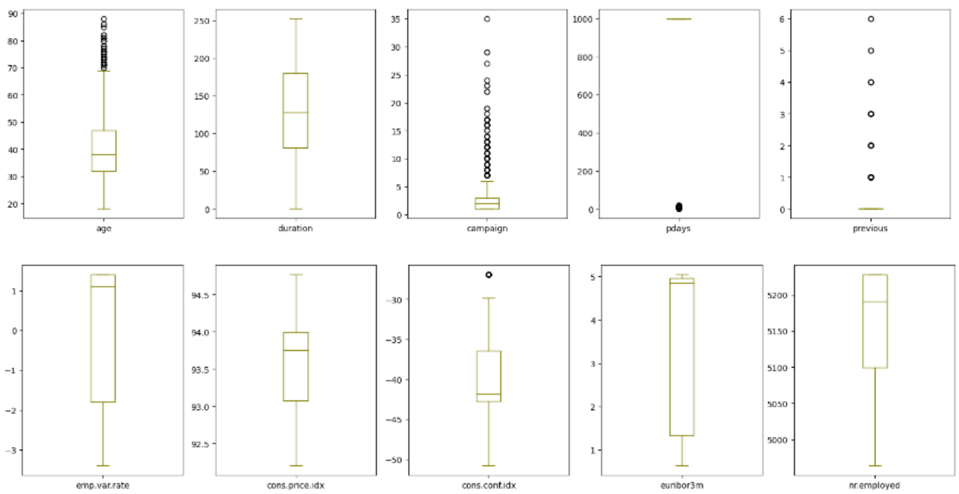


In [18]:

```python
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 [19]:

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



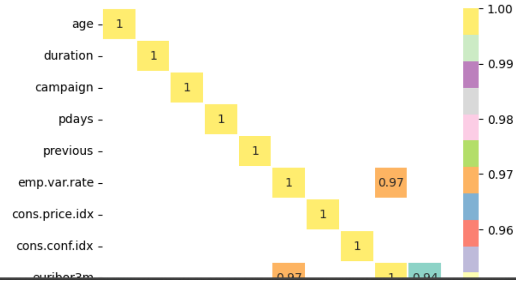
In [20]:

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

```
                     age  duration  campaign     pdays  previous  \
age             1.000000  0.014048 -0.014169 -0.043425  0.050931
duration        0.014048  1.000000 -0.218111 -0.093694  0.094206
campaign       -0.014169 -0.218111  1.000000  0.058742 -0.091490
pdays          -0.043425 -0.093694  0.058742  1.000000 -0.587941
previous        0.050931  0.094206 -0.091490 -0.587941  1.000000
emp.var.rate   -0.019192 -0.063870  0.176079  0.270684 -0.415238
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
nr.employed    -0.041936 -0.097339  0.161037  0.381983 -0.514853

                emp.var.rate  cons.price.idx  cons.conf.idx  euribor3m  \
age                -0.019192       -0.000482       0.098135  -0.015033
duration           -0.063870       -0.013338       0.045889  -0.067815
campaign            0.176079        0.145021       0.007882   0.159435
pdays               0.270684        0.058472      -0.092090   0.301478
previous           -0.415238       -0.164922      -0.051420  -0.458851
emp.var.rate        1.000000        0.755155       0.195022   0.970308
cons.price.idx      0.755155        1.000000       0.045835   0.657159
cons.conf.idx       0.195022        0.045835       1.000000   0.276595
euribor3m           0.970308        0.657159       0.276595   1.000000
nr.employed         0.897173        0.472560       0.107054   0.942589
```

```
              nr.employed
age             -0.041936
duration        -0.097339
campaign         0.161037
pdays            0.381983
previous        -0.514853
emp.var.rate     0.897173
cons.price.idx   0.472560
cons.conf.idx    0.107054
euribor3m        0.942589
nr.employed      1.000000
```



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

In [22]:
```python
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]:
```python
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]:
```python
df1.shape
```

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

In [25]:
```python
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
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]:
```python
df_encoded['deposit'].value_counts()
```
Out[26]:
```
0    3668
1     451
Name: deposit, dtype: int64
```
In [27]:
```python
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]:
```python
from sklearn.model_selection import train_test_split

print(4119*0.25)
```
```
1029.75
```
In [29]:
```python
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]:
```python
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)
```
```
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 [37]:
```python
from sklearn.tree import plot_tree
```
In [38]:
```python
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 [32]:
```
mscore(dt)
```

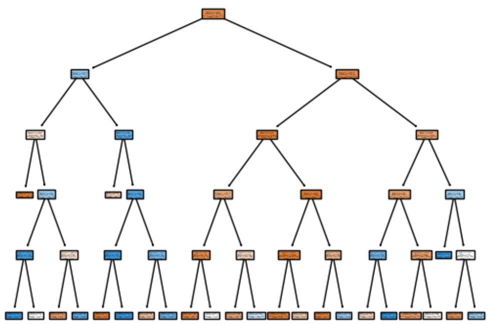
```
Training Score 0.9148591777274199
Testing Score 0.8990291262135922
```

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)
```

In [46]:
```
plot_tree(dt,class_names=cn,filled=True)
plt.show()
```



In [41]:
```
mscore(dt1)
```

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

In [42]:
```
ypred_dt1 = dt1.predict(x_test)
```

In [43]:
```
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
```

```
[[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 [47]:

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