PRODIGY_DS_03

September 20, 2024

1 TASK 3

Build a decision tree classifier to predict whether a customer will purchase a product or service based on their demographic and behavioral data. Use a dataset such as the Bank Marketing dataset from the UCI Machine Learning Repository

[3]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
%matplotlib inline
```

[5]:
```
df = pd.read_csv("bank-additional.csv",delimiter=';')
df.rename(columns={'y':'deposit'}, inplace=True)
df.head()
```

[5]:
```
   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]
```

[7]:
```python
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
```

[9]:
```python
df.tail()
```

[9]:
```
      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]
```

[11]:
```python
df.shape
```

[11]:
```
(4119, 21)
```

[13]:
```python
df.columns
```

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

[15]:
```python
df.dtypes
```

[15]:
```
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
```

[17]:
```
df.dtypes.value_counts()
```

[17]:
```
object     11
int64       5
float64     5
Name: count, dtype: int64
```

[19]:
```
df.duplicated().sum()
```

[19]: 0

[21]:
```
df.isna().sum()
```

[21]:
```
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
```

[23]:
```
cat_cols = df.select_dtypes(include='object').columns
print(cat_cols)
```

```python
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')
```

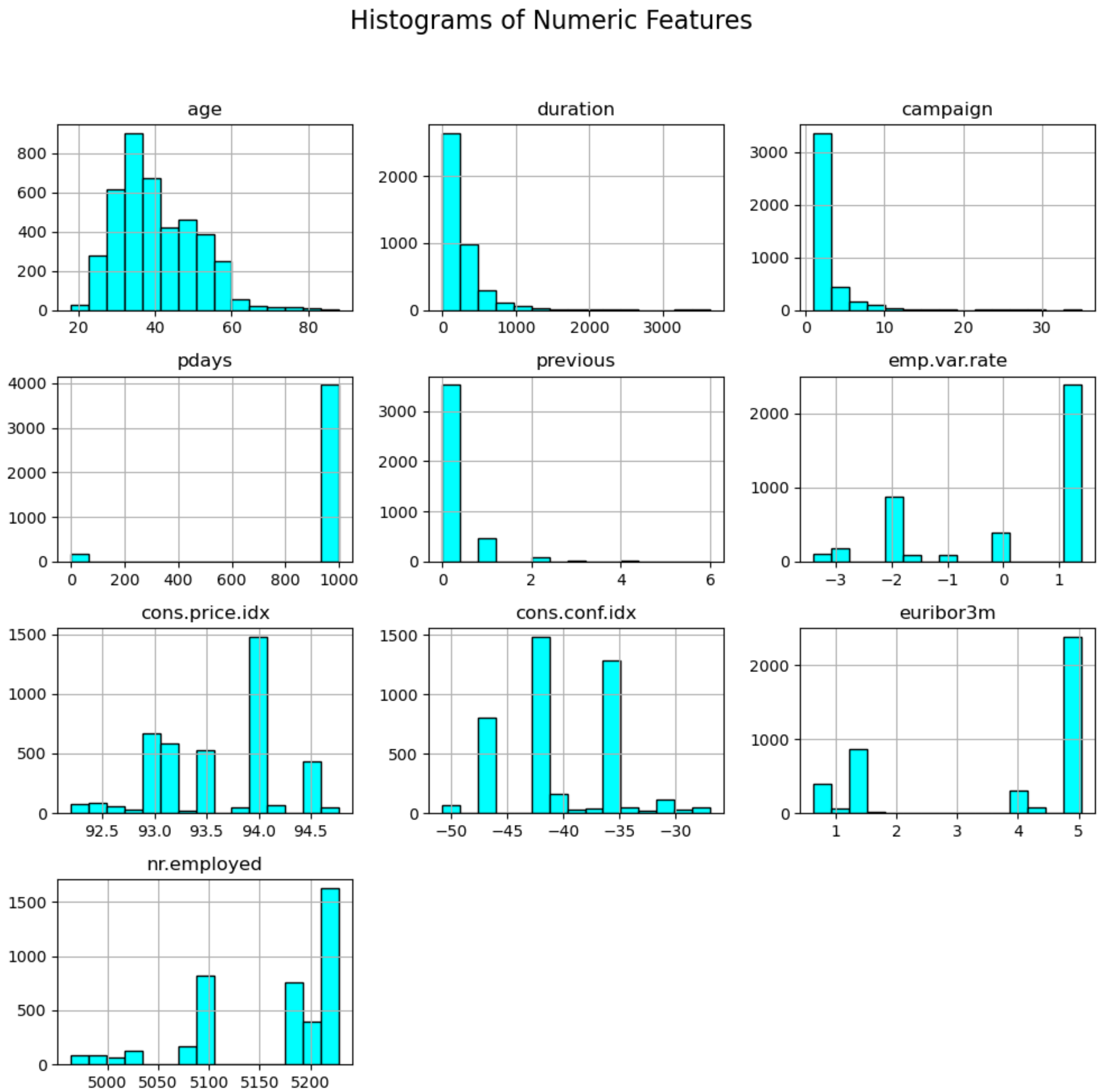
[25]:
```python
df.describe()
```

[25]:
```
               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
```

[27]:
```python
df.describe(include='object')
```

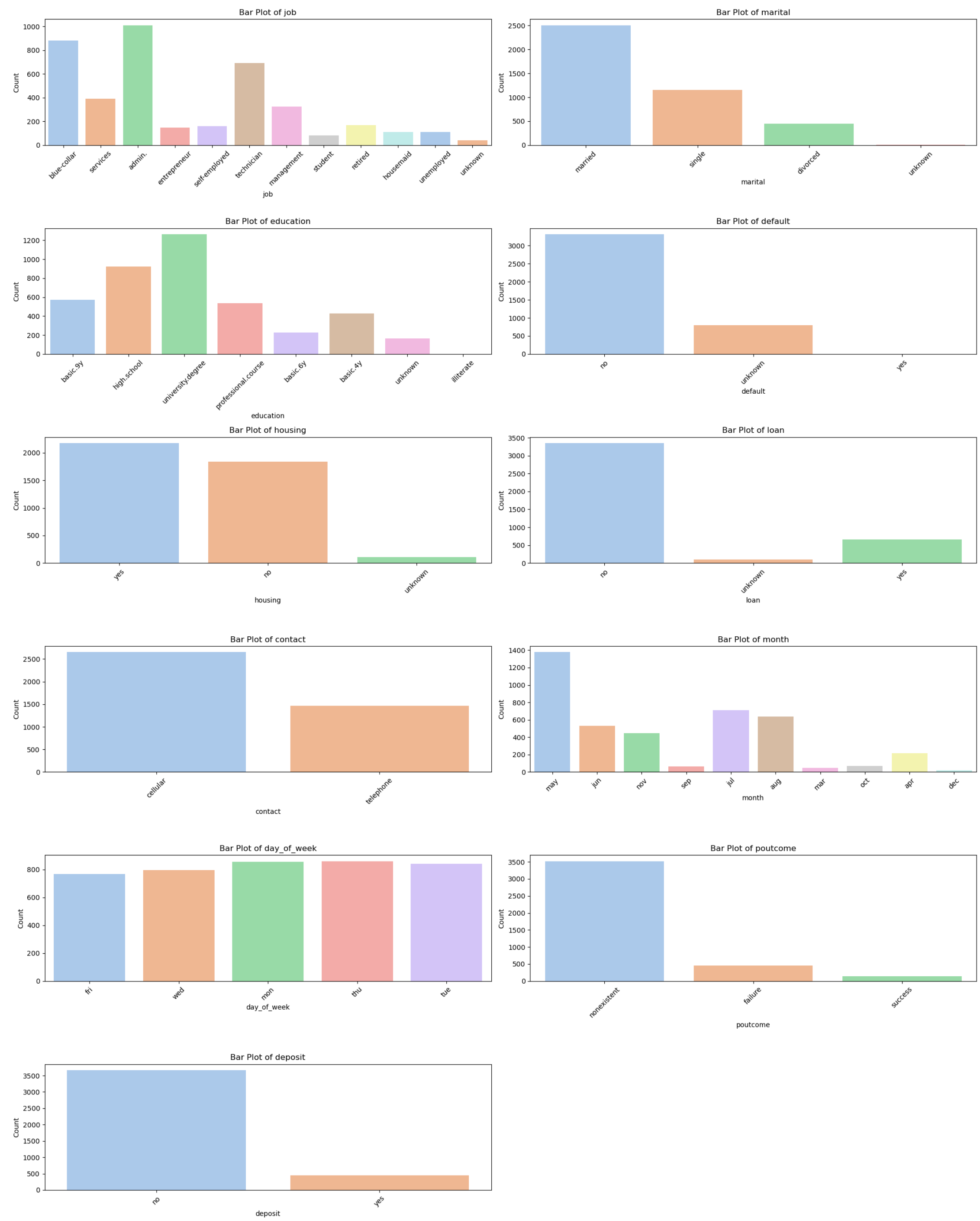
[27]:
```
           job  marital          education default housing  loan   contact  \
count     4119     4119               4119    4119    4119  4119      4119
unique      12        4                  8       3       3     3         2
top     admin.  married  university.degree      no     yes    no  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
```

[31]:
```python
import matplotlib.pyplot as plt
df.hist(figsize=(10, 10), color='#00FFFF', edgecolor='black', bins=15)
plt.suptitle('Histograms of Numeric Features', fontsize=16)
plt.xlabel('Value', fontsize=12)
plt.ylabel('Frequency', fontsize=12)
plt.tight_layout(rect=[0, 0, 1, 0.95])
plt.show()
```

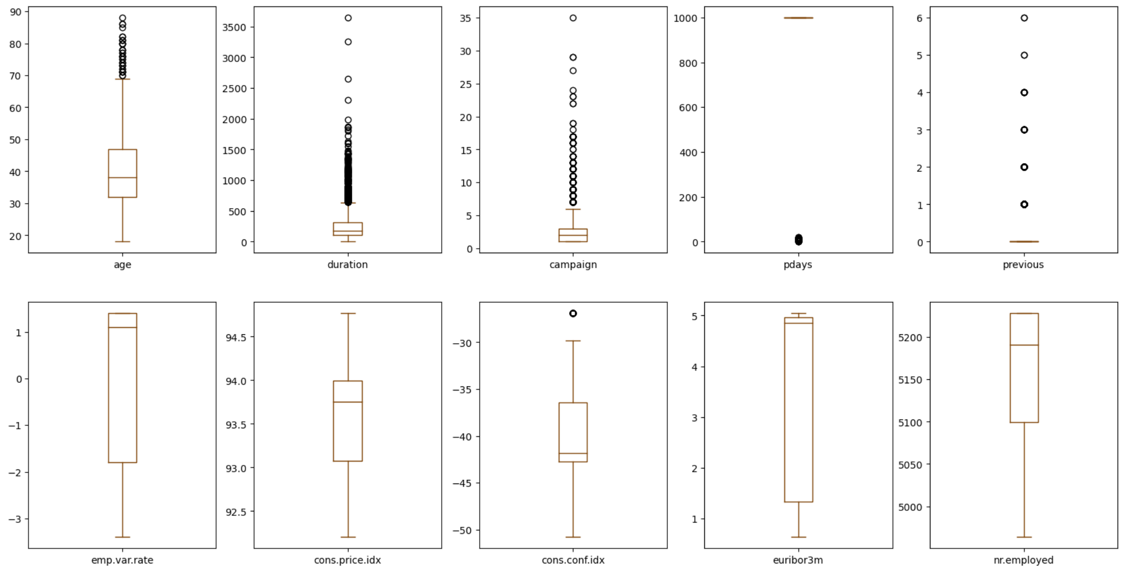


[65]:
```python
num_plots = len(cat_cols)
num_rows = (num_plots + 1) // 2
num_cols = 2

plt.figure(figsize=(20, 25))
```

```python
for i, feature in enumerate(cat_cols, 1):
    plt.subplot(num_rows, num_cols, i)
    sns.countplot(x=feature, data=df, palette='pastel')
    plt.title(f'Bar Plot of {feature}')
    plt.xlabel(feature)
    plt.ylabel('Count')
    plt.xticks(rotation=45)

plt.tight_layout()
plt.show()
```

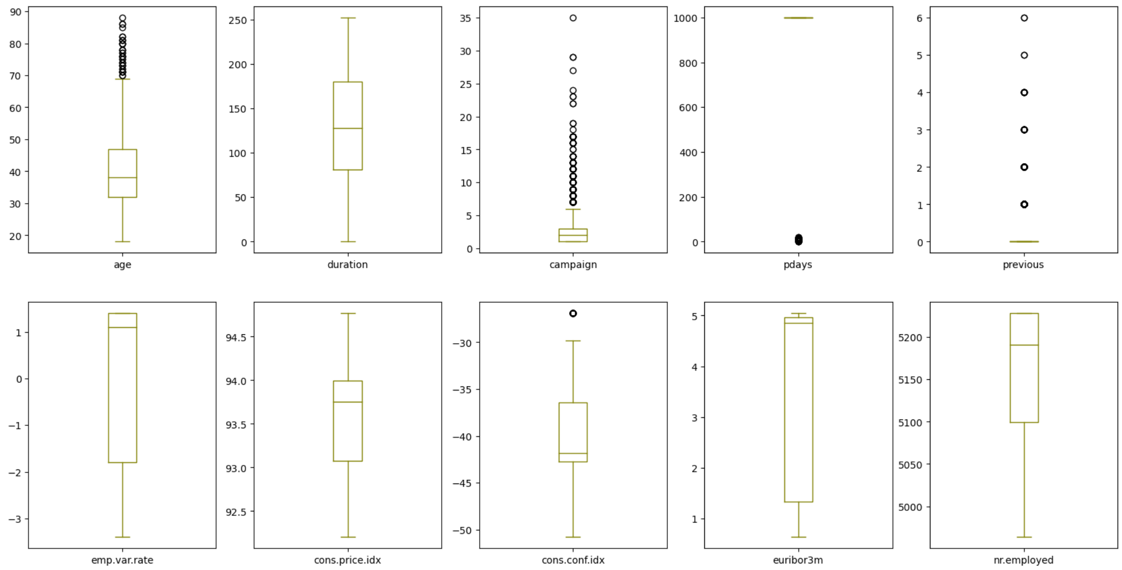


[33]:
```
df.plot(kind='box', subplots=True, layout=(2,5),figsize=(20,10),color='#7b3f00')
plt.show()
```



[35]:
```
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)]
```

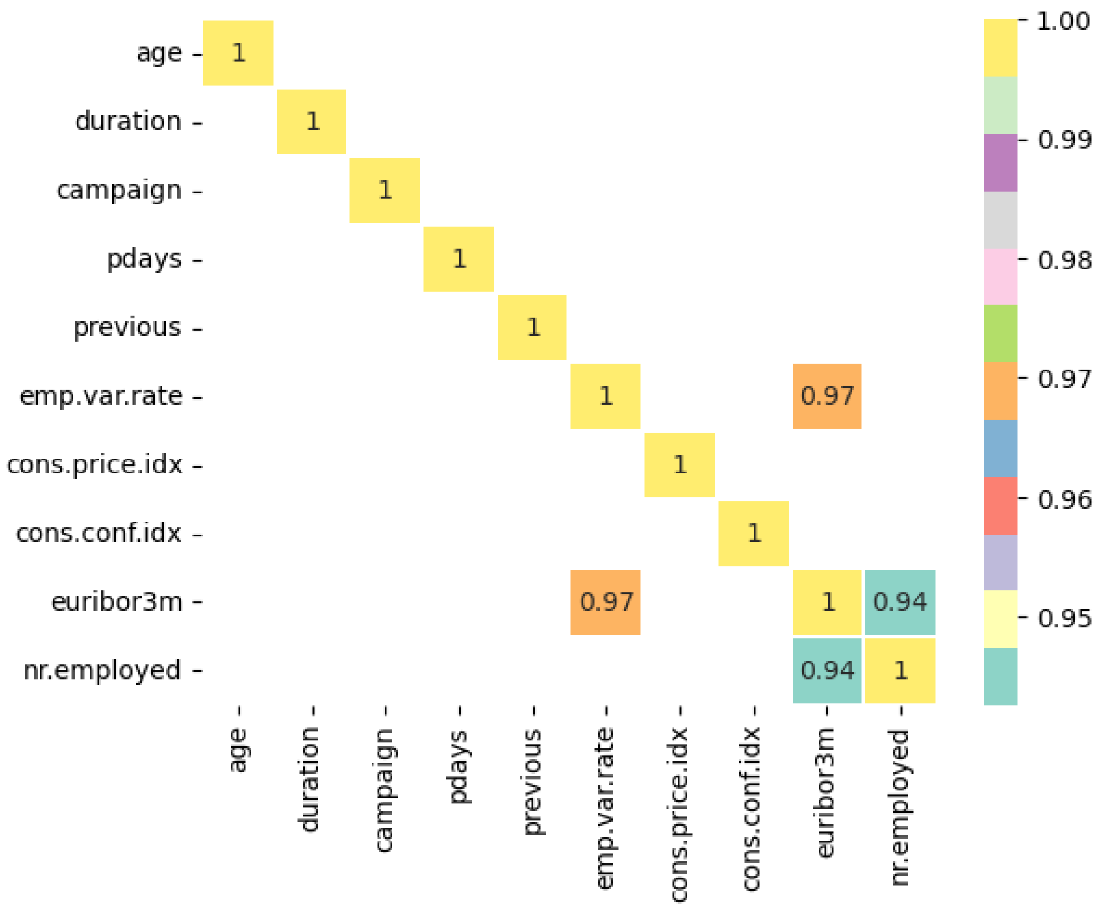
[37]:
```
df.plot(kind='box', subplots=True, layout=(2,5),figsize=(20,10),color='#808000')
plt.show()
```



[39]:

```
numeric_df = df.drop(columns=cat_cols)
corr = numeric_df.corr()
# Print the correlation matrix
print(corr)
# Filter correlations with absolute value >= 0.90
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
```



[41]:
```
high_corr_cols = ['emp.var.rate','euribor3m','nr.employed']
```

[43]:
```
df1 = df.copy()
df1.columns
```

[43]:
```
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')
```

[45]:
```
df1.drop(high_corr_cols,inplace=True,axis=1)   # axis=1 indicates columns
df1.columns
```

[45]:
```
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')
```

[47]:
```
df1.shape
```

[47]: (4119, 18)

[49]:
```
from sklearn.preprocessing import LabelEncoder
lb = LabelEncoder()
df_encoded = df1.apply(lb.fit_transform)
df_encoded
```

[49]:
```
      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]
```

[51]:
```
df_encoded['deposit'].value_counts()
```

[51]:
```
deposit
0    3668
1     451
Name: count, dtype: int64
```

[53]:
```
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'>
```

[27]:
```
from sklearn.model_selection import train_test_split
```

[28]:
```
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,)
```

[83]:
```
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)
```

[31]:
```
mscore(dt)
```

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

[32]:
```
ypred_dt = dt.predict(x_test)
print(ypred_dt)
```

```
[0 0 1 … 0 0 0]
```

[33]:
```
eval_model(y_test,ypred_dt)
```

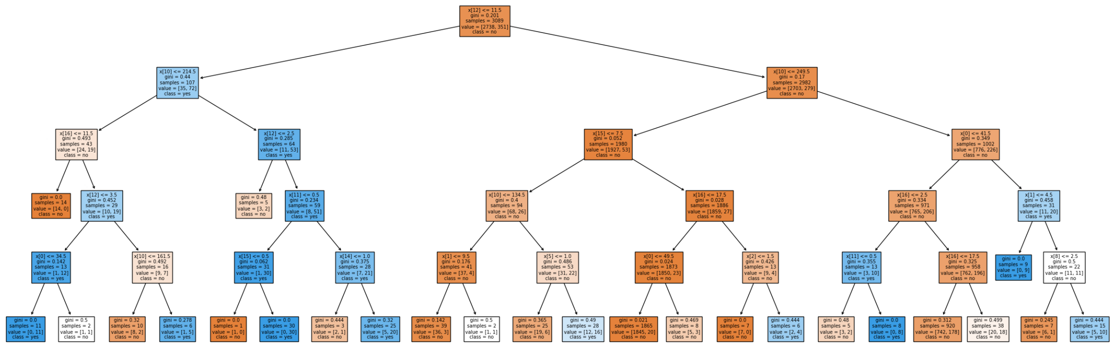
```
Accuracy_Score 0.8990291262135922
Confusion Matrix
 [[905  25]
 [ 79  21]]
Classification Report
               precision    recall  f1-score   support

           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
```

[34]:
```
from sklearn.tree import plot_tree
```

[35]:
```
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']
```

[79]:
```
plt.figure(figsize=(30,10))
plot_tree(dt,class_names=cn,filled=True)
plt.show()
```



[45]:
```
mscore(dt1)
```

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

[46]:
```
ypred_dt1 = dt1.predict(x_test)
```

[47]:
```
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
```