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

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

5 rows × 21 columns

+ Code + Text

```
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.tail()
```

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

5 rows × 21 columns

```
df.shape
```

```
(4119, 21)
```

```
df.dtypes
```

	0
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

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

```
0
```

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

	0
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

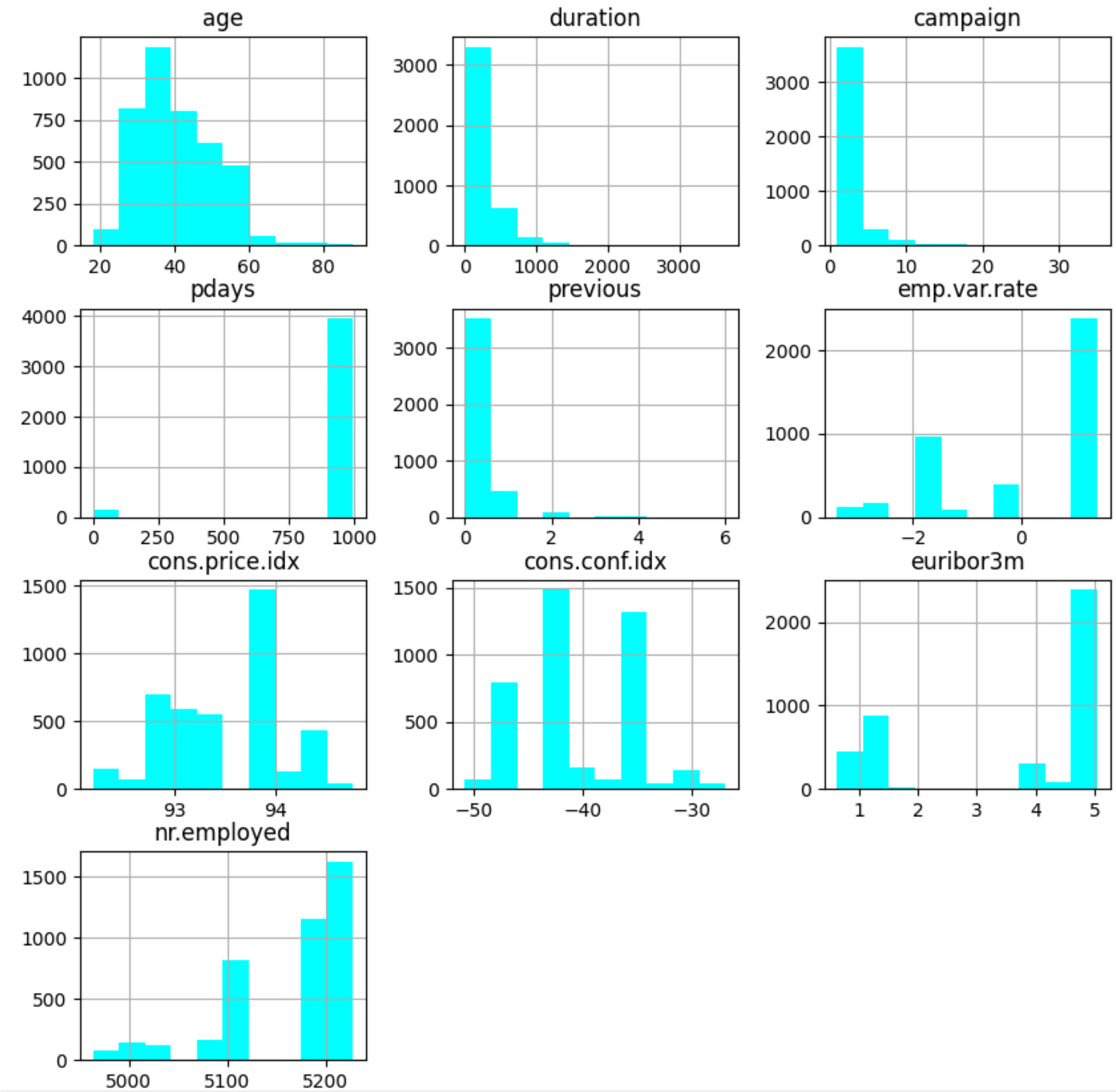
```
cat_cols = df.select_dtypes(include='object').columns
print(cat_cols)

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')
```

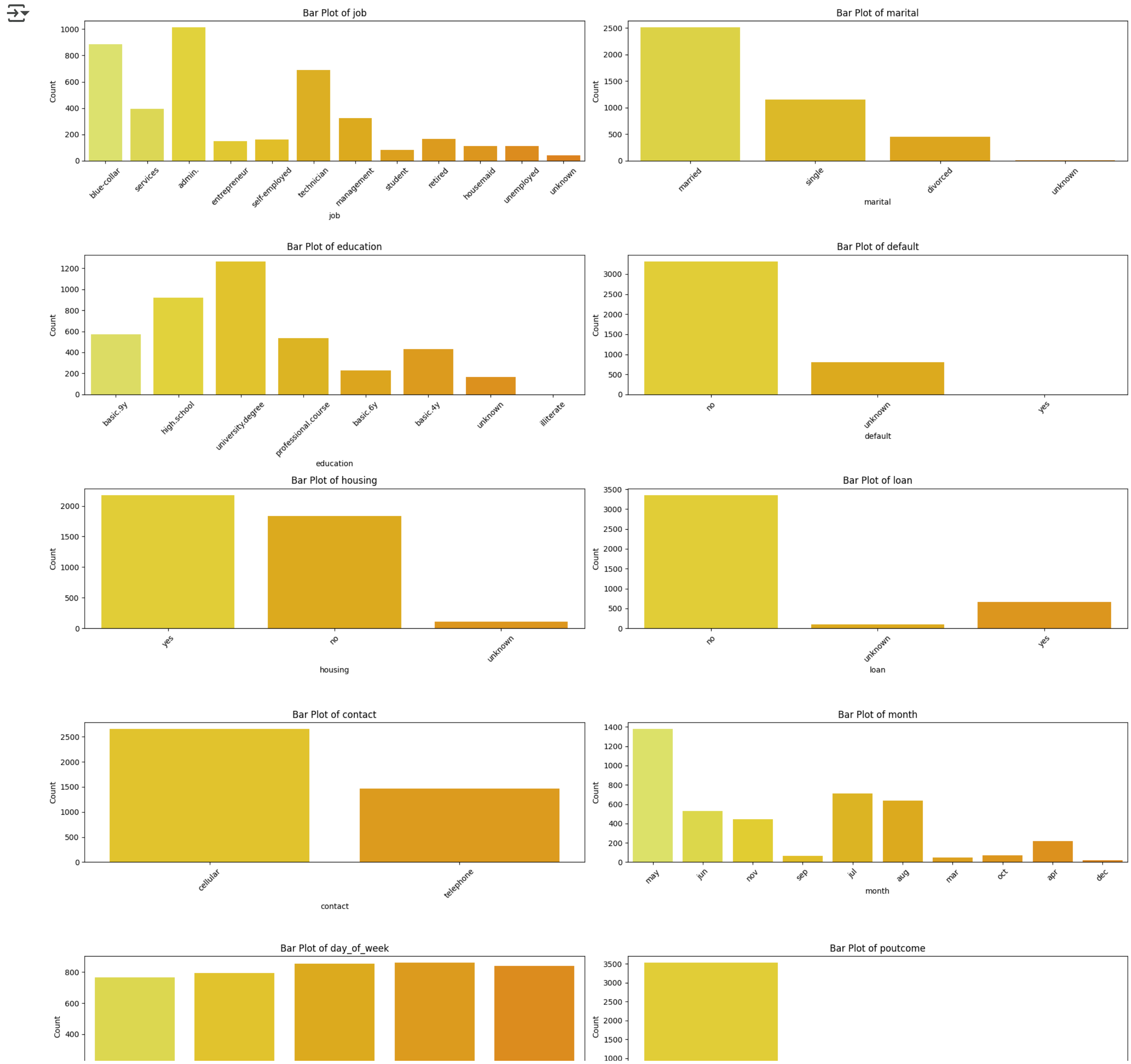
```
df.describe()
```

	age	duration	campaign	pdays	previous	emp.var.rate	cons.price.idx	cons.conf.idx	euribor3m	nr.employe
count	4119.000000	4119.000000	4119.000000	4119.000000	4119.000000	4119.000000	4119.000000	4119.000000	4119.000000	4119.00000
mean	40.113620	256.788055	2.537266	960.422190	0.190337	0.084972	93.579704	-40.499102	3.621356	5166.4816
std	10.313362	254.703736	2.568159	191.922786	0.541788	1.563114	0.579349	4.594578	1.733591	73.6679
min	18.000000	0.000000	1.000000	0.000000	0.000000	-3.400000	92.201000	-50.800000	0.635000	4963.6000
25%	32.000000	103.000000	1.000000	999.000000	0.000000	-1.800000	93.075000	-42.700000	1.334000	5099.1000
50%	38.000000	181.000000	2.000000	999.000000	0.000000	1.100000	93.749000	-41.800000	4.857000	5191.0000
75%	47.000000	317.000000	3.000000	999.000000	0.000000	1.400000	93.994000	-36.400000	4.961000	5228.1000
max	88.000000	3643.000000	35.000000	999.000000	6.000000	1.400000	94.767000	-26.900000	5.045000	5228.1000

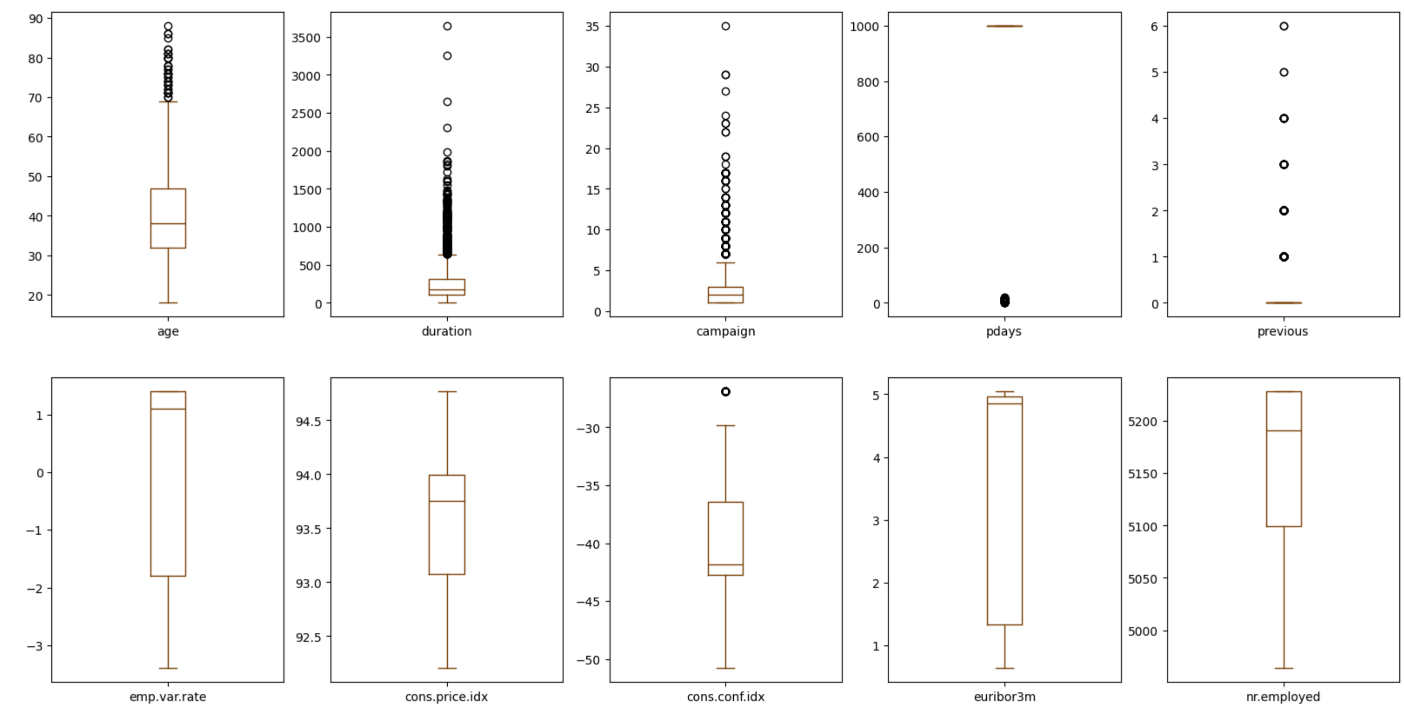
```
df.hist(figsize=(10,10),color='#00FFFF')
plt.show()
```




```
# Calculate the number of rows and columns for subplots
num_plots = len(cat_cols)
num_rows = (num_plots + 1) // 2  # Add 1 and divide by 2 to round up for odd numbers
num_cols = 2

# Create a new figure
plt.figure(figsize=(20, 25))  # Adjust the figure size as needed

# Loop through each feature and create a countplot
for i, feature in enumerate(cat_cols, 1):
    plt.subplot(num_rows, num_cols, i)
    sns.countplot(x=feature, data=df, palette='Wistia')
    plt.title(f'Bar Plot of {feature}')
    plt.xlabel(feature)
    plt.ylabel('Count')
    plt.xticks(rotation=45)

# Adjust layout to prevent overlap of subplots
plt.tight_layout()
plt.show()
```

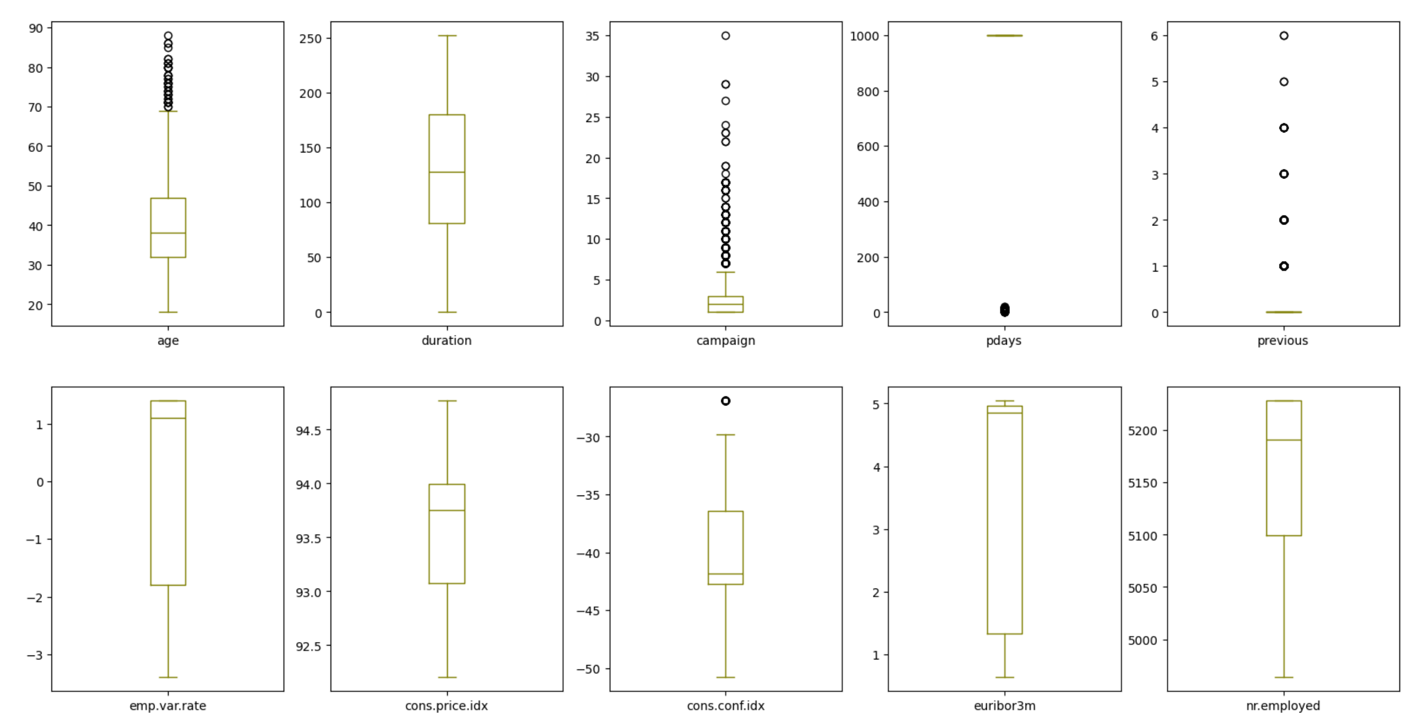



```
df.plot(kind='box', subplots=True, layout=(2,5),figsize=(20,10),color='#7b3f00')
plt.show()
```




```
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)]
```

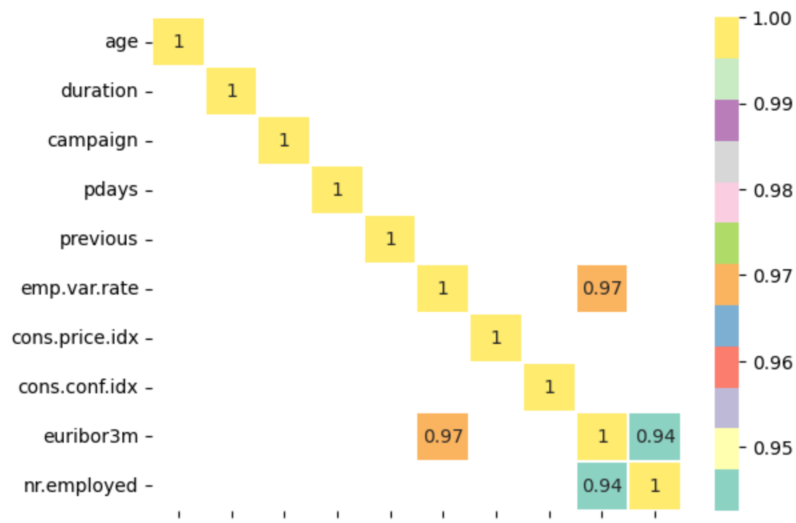
```
df.plot(kind='box', subplots=True, layout=(2,5),figsize=(20,10),color='#808000')
plt.show()
```




```
# Exclude non-numeric columns
numeric_df = df.drop(columns=cat_cols)
```

```
# Compute the correlation matrix
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
```




```
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')
```

```
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	day_of_week	...	campaign	pdays	previous	poutcome	emp.var
0	12	1	1	2	0	2	0	0	6	0	...	1	20	0	1	
1	21	7	2	3	0	0	0	1	6	0	...	3	20	0	1	
2	7	7	1	3	0	2	0	1	4	4	...	0	20	0	1	
3	20	7	1	2	0	1	1	1	4	0	...	2	20	0	1	
4	29	0	1	6	0	2	0	0	7	1	...	0	20	0	1	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
4114	12	0	1	1	0	2	2	0	3	2	...	0	20	0	1	
4115	21	0	1	3	0	2	0	1	3	0	...	0	20	0	1	
4116	9	8	2	3	0	0	0	0	6	1	...	1	20	1	0	
4117	40	0	1	3	0	0	0	0	1	0	...	0	20	0	1	
4118	16	4	2	3	0	2	0	0	7	4	...	0	20	0	1	

4119 rows × 21 columns

```
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.model_selection import train_test_split
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, 20)
(1030, 20)
(3089,)
(1030,)
```

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

	count
deposit	
0	3668
1	451

```
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, 20)
(4119,)
<class 'pandas.core.frame.DataFrame'>
<class 'pandas.core.series.Series'>
```

```
from sklearn.tree import DecisionTreeClassifier

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

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

```
mscore(dt)
```

```
Training Score 0.9219812236969893
Testing Score 0.9087378640776699
```

```
ypred_dt = dt.predict(x_test)
print(ypred_dt)
```

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

```
eval_model(y_test,ypred_dt)
```

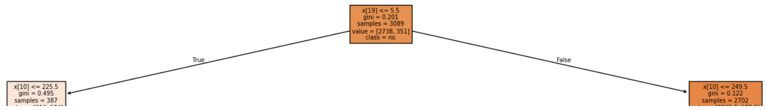
```
Accuracy_Score 0.9087378640776699
Confusion Matrix
 [[902  28]
 [ 66  34]]
Classification Report
               precision    recall  f1-score   support

           0       0.93      0.97      0.95       930
           1       0.55      0.34      0.42       100

    accuracy                           0.91      1030
   macro avg       0.74      0.65      0.69      1030
weighted avg       0.89      0.91      0.90      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', 'emp.var.rate', 'cons.price.idx',
       'cons.conf.idx', 'euribor3m', 'nr.employed'],
      dtype='object')
['no', 'yes']
```

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




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

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

```
mscore(dt1)
```

```
Training Score 0.915182907089673
Testing Score 0.9087378640776699
```

```
ypred_dt1 = dt1.predict(x_test)
```

```
eval_model(y_test,ypred_dt1)
```

```
Accuracy_Score 0.9087378640776699
Confusion Matrix
 [[894  36]
 [ 58  42]]
Classification Report
               precision    recall  f1-score   support
```