```
In [1]: import numpy as np
    import pandas as pd
    import seaborn as sns

In [5]: import pandas as pd
    df = pd.read_csv('D:/prodigy/task3 tree/bank-additional.csv', sep=';')

In [6]: print(df.head())
    print(df.columns)
    print(df.isnull().sum())
    print(df.describe())
```

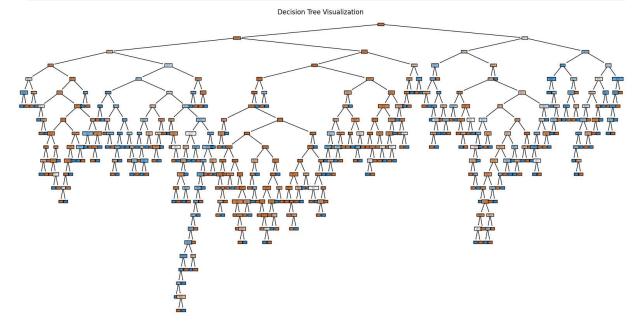
```
job marital
                                        education default housing
                                                                         loan
   age
0
    30
        blue-collar
                      married
                                         basic.9y
                                                        no
                                                                yes
                                                                           no
1
    39
           services
                                      high.school
                       single
                                                        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 \
                                  . . .
                                                                   nonexistent
    cellular
                                                    999
                may
                            fri
                                  . . .
                                              2
  telephone
                            fri
                                              4
                                                    999
1
                may
                                                                0
                                                                    nonexistent
2 telephone
                                              1
                                                    999
               jun
                            wed
                                                                0
                                                                    nonexistent
                                  . . .
3
  telephone
               jun
                            fri
                                  . . .
                                              3
                                                    999
                                                                 0
                                                                    nonexistent
4
    cellular
                                              1
                                                    999
               nov
                            mon
                                  . . .
                                                                    nonexistent
  emp.var.rate cons.price.idx
                                  cons.conf.idx
                                                  euribor3m
                                                             nr.employed
                                                                            У
          -1.8
                         92.893
                                          -46.2
                                                      1.313
                                                                   5099.1
0
                                                                           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]
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', 'y'],
      dtype='object')
age
                   0
                   0
job
marital
                   0
                   0
education
default
                   0
                   0
housing
                   0
loan
                   0
contact
                   0
month
day of week
                   0
duration
                   0
                   0
campaign
                   0
pdays
                   0
previous
poutcome
                   0
emp.var.rate
                   0
cons.price.idx
                   0
                   0
cons.conf.idx
                   0
euribor3m
nr.employed
                   0
                   0
dtype: int64
                                                       pdays
                        duration
                                      campaign
                                                                  previous \
                age
count
       4119.000000
                     4119.000000
                                   4119.000000
                                                4119.000000
                                                              4119.000000
         40.113620
                      256.788055
                                      2.537266
mean
                                                  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
                                                  999.000000
                                                                  0.000000
                                      2.000000
```

```
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
               4119.000000
                               4119.000000
                                              4119.000000 4119.000000 4119.000000
       count
                  0.084972
                                 93.579704
                                               -40.499102
                                                               3.621356 5166.481695
       mean
       std
                  1.563114
                                  0.579349
                                                 4.594578
                                                              1.733591
                                                                          73.667904
                 -3.400000
                                 92.201000
                                               -50.800000
                                                              0.635000 4963.600000
       min
       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
                  1.400000
                                 94.767000
                                               -26.900000
                                                               5.045000 5228.100000
       max
In [7]: df.dropna(inplace=True)
        df encoded = pd.get dummies(df, columns=['job', 'marital', 'education', 'default',
        X = df encoded.drop('y', axis=1)
        y = df encoded['y']
        from sklearn.model selection import train test split
        X train, X test, y train, y test = train test split(X, y, test size=0.2, random sta
In [8]: from sklearn.tree import DecisionTreeClassifier
        from sklearn.metrics import accuracy_score, classification_report, confusion_matrix
        dt = DecisionTreeClassifier(random state=42)
        dt.fit(X train, y train)
Out[8]:
                DecisionTreeClassifier
        DecisionTreeClassifier(random state=42)
In [9]: y pred = dt.predict(X test)
        accuracy = accuracy_score(y_test, y_pred)
        print(f'Accuracy: {accuracy:.2f}')
        print(classification_report(y_test, y_pred))
        print(confusion_matrix(y_test, y_pred))
       Accuracy: 0.87
                     precision
                                  recall f1-score
                                                     support
                 no
                          0.93
                                    0.92
                                              0.93
                                                         732
                                    0.47
                                              0.45
                                                          92
                          0.44
                yes
                                              0.87
                                                          824
           accuracy
          macro avg
                          0.69
                                    0.70
                                              0.69
                                                         824
       weighted avg
                          0.88
                                    0.87
                                              0.88
                                                         824
       [[677 55]
        [ 49 43]]
```

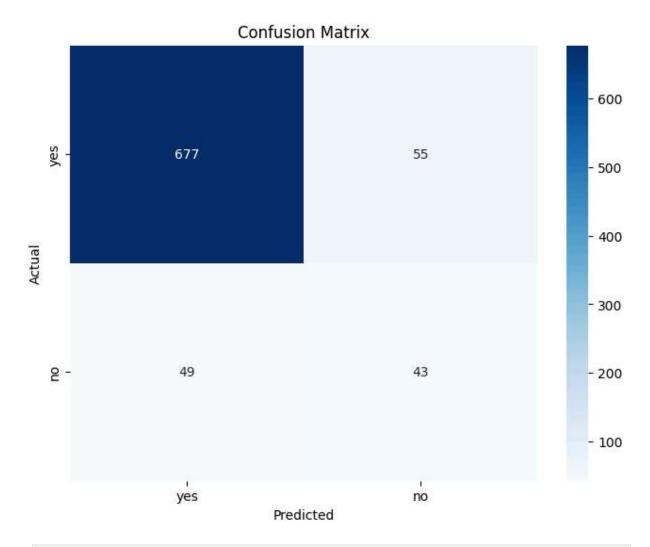
In [11]: #our output suggests that our decision tree classifier achieved an accuracy of 0.87
#when predicting whether customers would subscribe to a term deposit based on their
#The precision and recall for both classes ('yes' and 'no') are also provided, indi

#This performance indicates a reasonably good fit for predicting customer behavior
#If you're satisfied with the accuracy and other metrics, it suggests that your dec

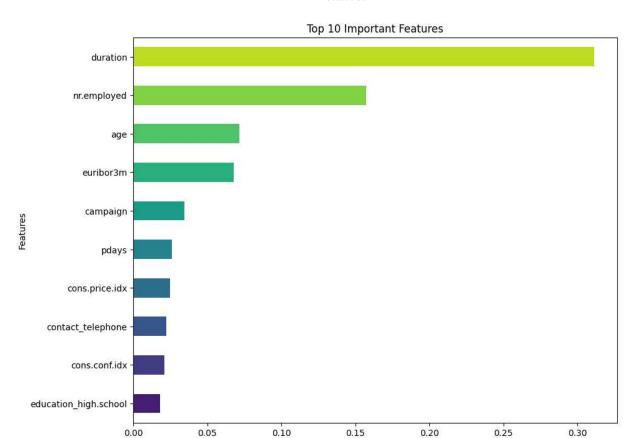
```
In [13]: from sklearn.tree import plot_tree
    import matplotlib.pyplot as plt
    cn = y.unique().astype(str)
    plt.figure(figsize=(20, 10))
    plot_tree(dt, filled=True, feature_names=X.columns, class_names=cn)
    plt.title('Decision Tree Visualization')
    plt.show()
```



```
In [14]: from sklearn.metrics import confusion_matrix
    import seaborn as sns
    cn = ['yes', 'no']
    cm = confusion_matrix(y_test, y_pred)
    plt.figure(figsize=(8, 6))
    sns.heatmap(cm, annot=True, cmap='Blues', fmt='d', xticklabels=cn, yticklabels=cn)
    plt.title('Confusion Matrix')
    plt.xlabel('Predicted')
    plt.ylabel('Actual')
    plt.show()
```



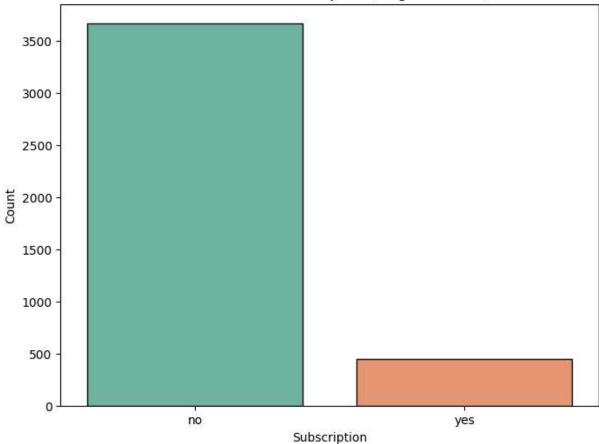
```
In [15]: plt.figure(figsize=(10, 8))
    feat_importances = pd.Series(dt.feature_importances_, index=X.columns)
    feat_importances.nlargest(10).sort_values().plot(kind='barh', color=sns.color_palet
    plt.title('Top 10 Important Features')
    plt.xlabel('Feature Importance')
    plt.ylabel('Features')
    plt.show()
```



Feature Importance

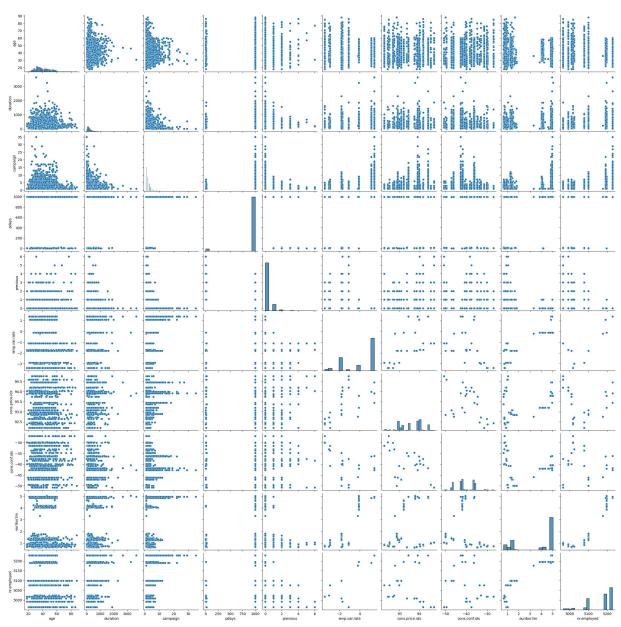
```
import seaborn as sns
import matplotlib.pyplot as plt
plt.figure(figsize=(8, 6))
sns.countplot(x='y', data=df, hue='y', palette='Set2', edgecolor='black', dodge=Fal
plt.title('Distribution of Subscription (Target Variable)')
plt.xlabel('Subscription')
plt.ylabel('Count')
plt.show()
```

## Distribution of Subscription (Target Variable)

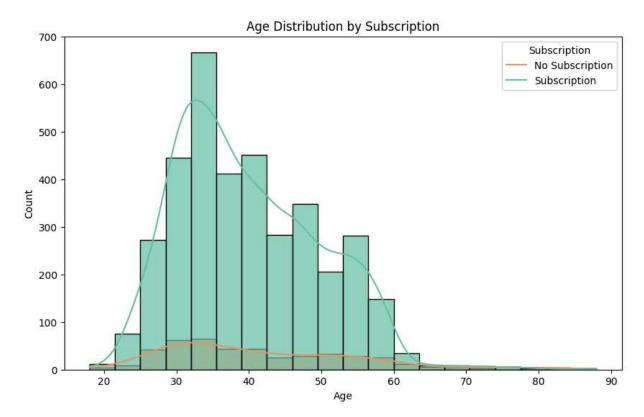


```
In [18]: num_features = df.select_dtypes(include=['int64', 'float64']).columns
    sns.pairplot(df[num_features])
    plt.suptitle('Pairplot of Numerical Features', y=1.02)
    plt.show()
```

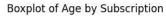
Pairplot of Numerical Feature

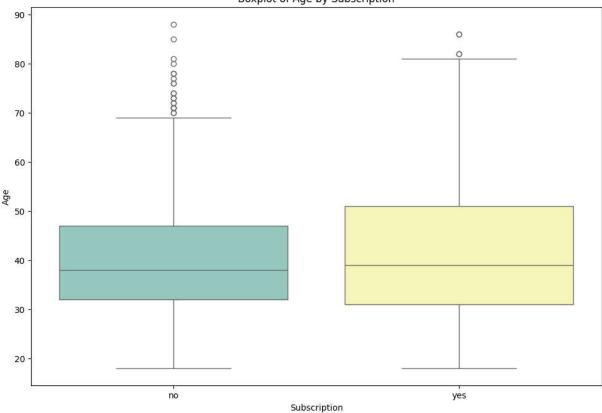


```
In [19]: plt.figure(figsize=(10, 6))
    sns.histplot(data=df, x='age', hue='y', bins=20, kde=True, palette='Set2', alpha=0.
    plt.title('Age Distribution by Subscription')
    plt.xlabel('Age')
    plt.ylabel('Count')
    plt.legend(labels=['No Subscription', 'Subscription'], title='Subscription')
    plt.show()
```

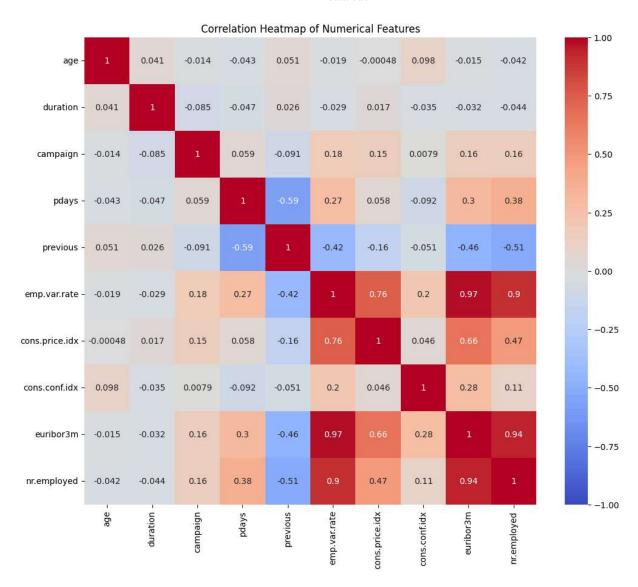


```
In [20]: plt.figure(figsize=(12, 8))
    sns.boxplot(data=df, x='y', y='age', palette='Set3', hue='y', dodge=False)
    plt.title('Boxplot of Age by Subscription')
    plt.xlabel('Subscription')
    plt.ylabel('Age')
    plt.show()
```





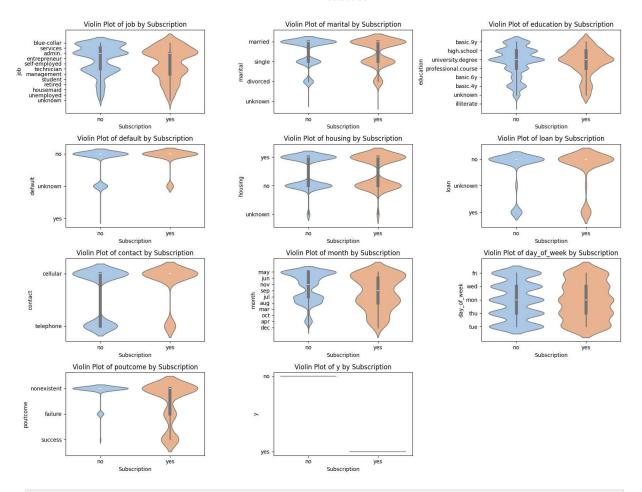
```
In [21]: numeric_cols = df.select_dtypes(include=np.number)
    plt.figure(figsize=(12, 10))
    sns.heatmap(numeric_cols.corr(), annot=True, cmap='coolwarm', vmin=-1, vmax=1)
    plt.title('Correlation Heatmap of Numerical Features')
    plt.show()
```



```
In [22]:
    cat_features = df.select_dtypes(include=['object']).columns
    num_cols = 3
    num_rows = (len(cat_features) // num_cols) + 1 # Calculate number of rows needed

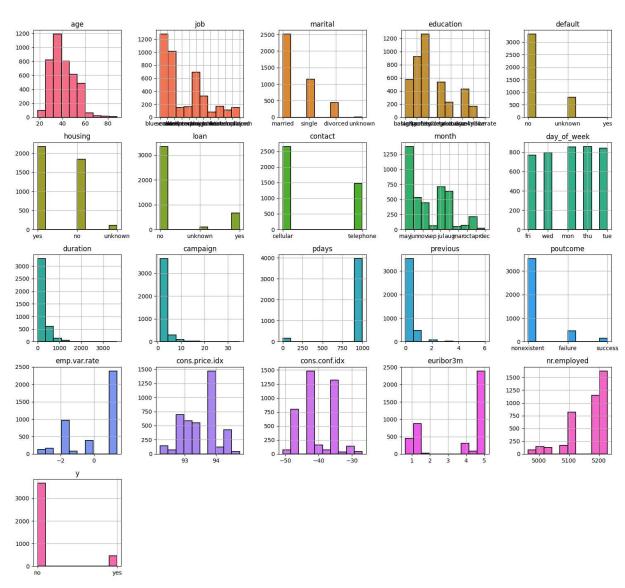
plt.figure(figsize=(16, 12))
    for i, col in enumerate(cat_features, 1):
        plt.subplot(num_rows, num_cols, i)
        sns.violinplot(x='y', y=col, data=df, hue='y', palette='pastel', legend=False)
        plt.title(f'Violin Plot of {col} by Subscription')
        plt.xlabel('Subscription')
        plt.ylabel(col)

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



```
In [23]: plt.figure(figsize=(15, 15))
    color_palette = sns.color_palette("husl", len(df.columns))
    for i, column in enumerate(df.columns):
        plt.subplot(5, 5, i + 1)
        df[column].hist(color=color_palette[i], edgecolor='black', linewidth=1.2)
        plt.title(column)
    plt.suptitle('Distribution of Features', size=20)
    plt.tight_layout(rect=[0, 0, 1, 0.95]) # Adjust Layout to make space for the main
    plt.show()
```

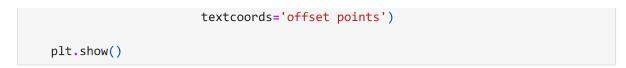
## Distribution of Features

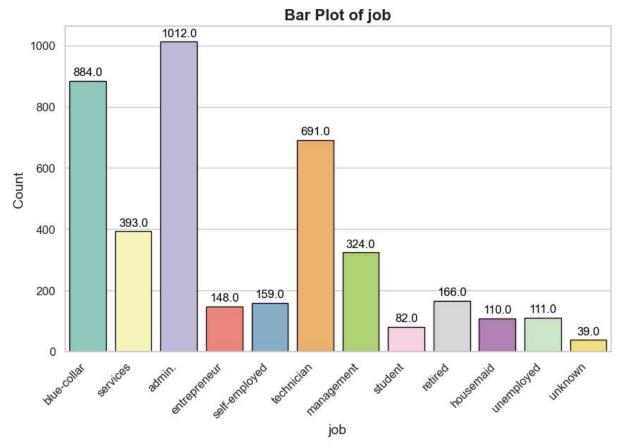


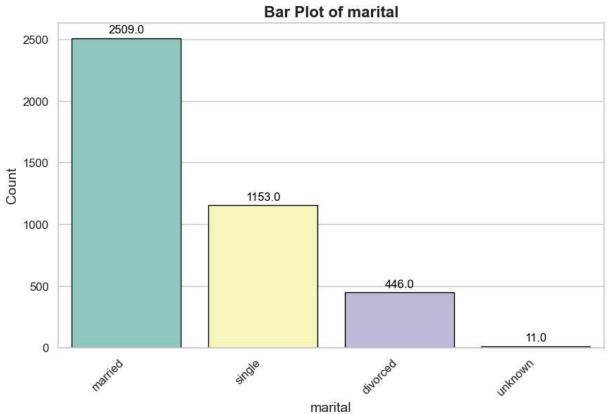
```
import seaborn as sns
import matplotlib.pyplot as plt
cat_cols = df.select_dtypes(include=['object']).columns
sns.set(style="whitegrid")
for feature in cat_cols:
    plt.figure(figsize=(10, 6)) # Adjust the figure size as needed
    barplot = sns.countplot(x=feature, hue=feature, data=df, palette='Set3', edgeco

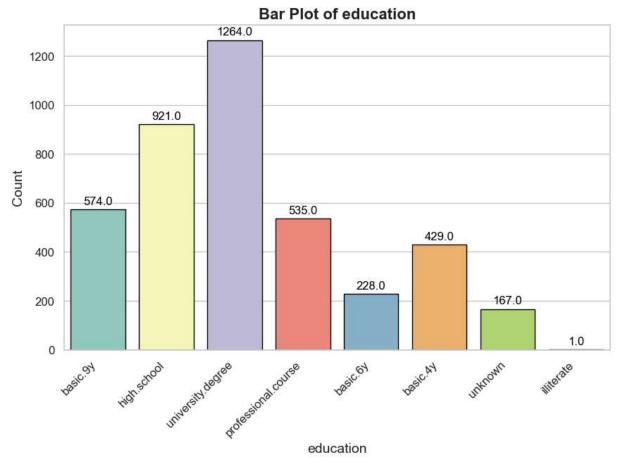
plt.title(f'Bar Plot of {feature}', fontsize=16, fontweight='bold')
    plt.xlabel(feature, fontsize=14)
    plt.ylabel('Count', fontsize=14)
    plt.xticks(rotation=45, fontsize=12, ha='right')
    plt.yticks(fontsize=12)

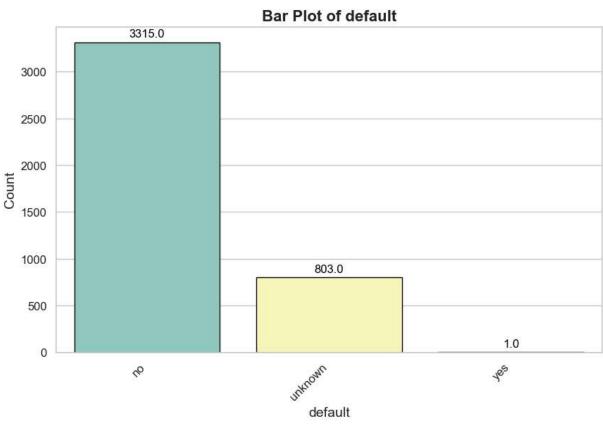
for p in barplot.patches:
    barplot.annotate(f'{p.get_height()}', (p.get_x() + p.get_width() / 2., p.
```

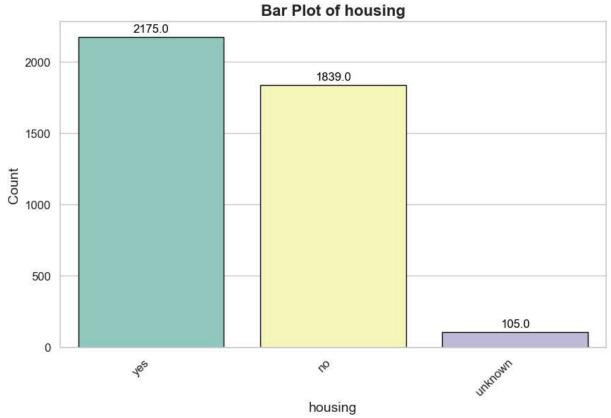


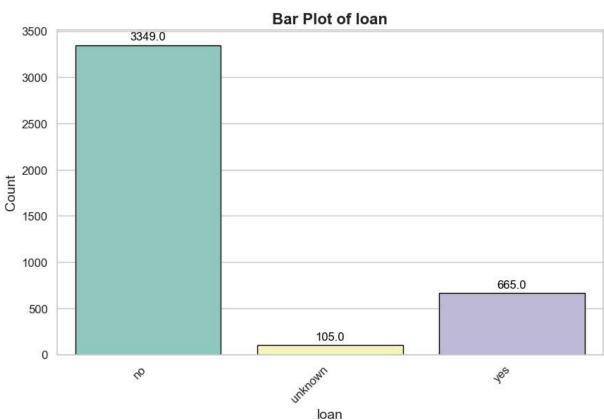


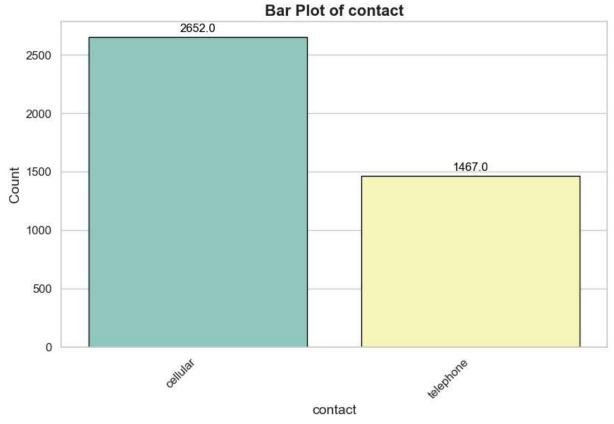


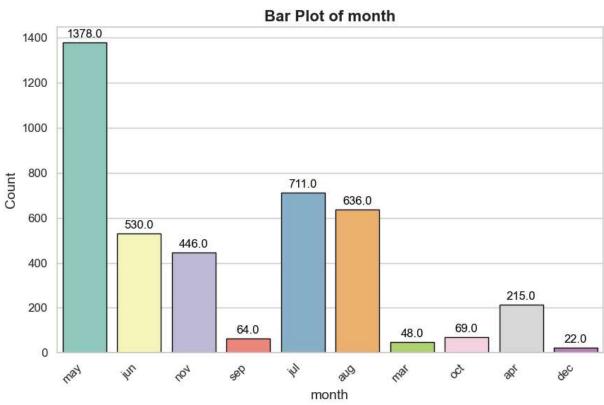


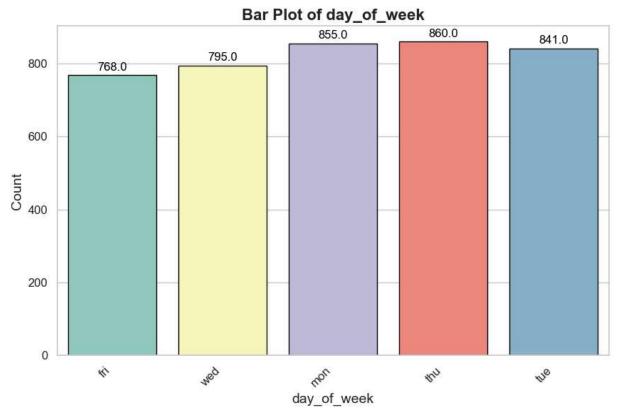


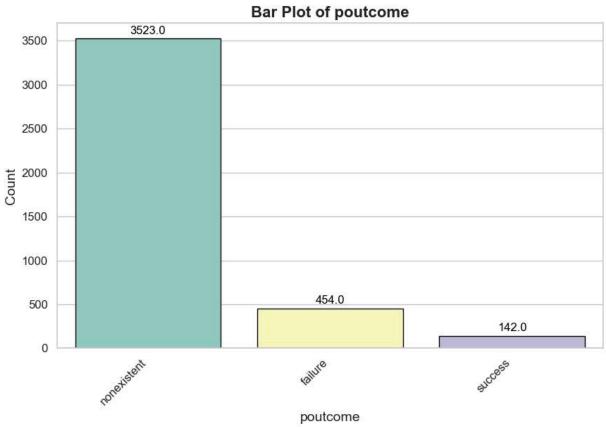


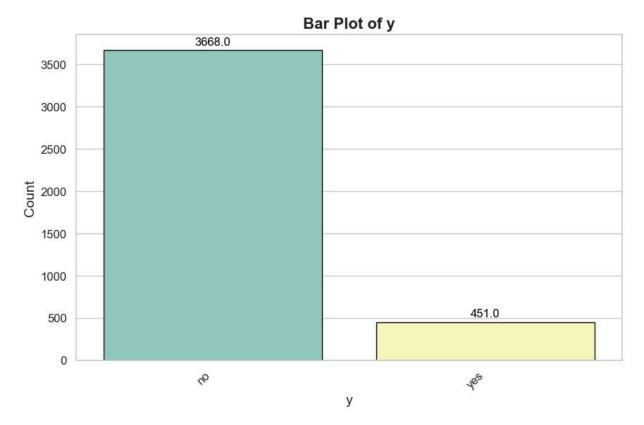












In [29]: df.plot(kind='box', subplots=True, layout=(2,5),figsize=(20,10),color='green')
 plt.suptitle('Boxplots of Numerical Features', fontsize=20)
 plt.show()

## **Boxplots of Numerical Features**

