# Nexus Bank

June 4, 2023

CUSTOMER SEGMENTATION AND DEPOSIT DETECTION SYSTEM CASE STUDY

[1]:
```
# Import necessary libraries

# Data analysis libraries
import pandas as pd
import numpy as np

# data visualization libraries
import matplotlib.pyplot as plt
import seaborn as sns

# data preprocessing
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import MinMaxScaler

# Clustering Libraries
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.cluster import KMeans
from scipy.cluster.hierarchy import dendrogram, linkage
from sklearn.metrics import silhouette_score, homogeneity_score
from IPython.display import Image

# Classifiers
from sklearn.linear_model import SGDClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.linear_model import LogisticRegression


# !pip install xgboost
!pip install xgboost

from xgboost import XGBClassifier
from sklearn.svm import SVC
```

```
from sklearn.svm import LinearSVC
from sklearn.naive_bayes import GaussianNB
from sklearn.tree import DecisionTreeClassifier

# Evaluation Metrics
from sklearn.metrics import accuracy_score, confusion_matrix,␣
↪classification_report, f1_score, precision_score, recall_score, roc_auc_score

import warnings
warnings.filterwarnings("ignore")
```

```
Requirement already satisfied: xgboost in c:\users\pc\anaconda3\lib\site-
packages (1.7.5)
Requirement already satisfied: numpy in c:\users\pc\anaconda3\lib\site-packages
(from xgboost) (1.21.5)
Requirement already satisfied: scipy in c:\users\pc\anaconda3\lib\site-packages
(from xgboost) (1.9.1)
```

[2]:
```
# Load the dataset

df = pd.read_csv(r"C:\Users\PC\Downloads\bank.csv")
```

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

[3]:
```
   age           job  marital  education default  balance housing loan  \
0   58    management  married   tertiary      no     2143     yes   no
1   44    technician   single  secondary      no       29     yes   no
2   33  entrepreneur  married  secondary      no        2     yes  yes
3   47   blue-collar  married    unknown      no     1506     yes   no
4   33       unknown   single    unknown      no        1      no   no

   contact  day month  duration  campaign  pdays  previous poutcome deposit
0  unknown    5   may       261         1     -1         0  unknown      no
1  unknown    5   may       151         1     -1         0  unknown      no
2  unknown    5   may        76         1     -1         0  unknown      no
3  unknown    5   may        92         1     -1         0  unknown      no
4  unknown    5   may       198         1     -1         0  unknown      no
```

Data Dictionary

- Age: This refers to the age of the customer who holds the bank account.
- Job: This feature indicates the type of job that the customer has.
- Marital: This feature indicates the marital status of the customer, which could be “married,” “divorced,” or “single”.
- Education: This refers to the education level of the customer, which could be “primary,” “secondary,” or “tertiary.”
- Default: This feature indicates whether the customer has previously defaulted on a loan or credit card payment, which could be “yes” or “no.“
- Balance: This feature represents the current balance in the customer’s account.

- Housing: This feature indicates whether the customer has a housing loan or not, which could be “yes” or “no.”
- Loan: This feature indicates whether the customer has a personal loan or not, which could be “yes” or “no.”
- Contact: This feature indicates the method of contact used to reach out to the customer, which could be “cellular,” “telephone,” or “unknown.“
- Day: This feature represents the day of the month when the customer was last contacted.
- Month: This feature represents the month of the year when the customer was last contacted.
- Duration: This feature represents the duration of the last contact with the customer, in seconds.
- Campaign: This feature represents the number of contacts made to the customer during this campaign.
- Pdays: This feature represents the number of days that passed by after the customer was last contacted from a previous campaign.
- Previous: This feature represents the number of contacts made to the customer before this campaign.
- Poutcome: This feature indicates the outcome of the previous marketing campaign, which could be “success,” “failure,” or “unknown.”
- Deposit: This feature indicates whether the customer has made a deposit, which could be “yes” or “no.”

[4]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 45211 entries, 0 to 45210
Data columns (total 17 columns):
 #   Column     Non-Null Count  Dtype
---  ------     --------------  -----
 0   age        45211 non-null  int64
 1   job        45211 non-null  object
 2   marital    45211 non-null  object
 3   education  45211 non-null  object
 4   default    45211 non-null  object
 5   balance    45211 non-null  int64
 6   housing    45211 non-null  object
 7   loan       45211 non-null  object
 8   contact    45211 non-null  object
 9   day        45211 non-null  int64
 10  month      45211 non-null  object
 11  duration   45211 non-null  int64
 12  campaign   45211 non-null  int64
 13  pdays      45211 non-null  int64
 14  previous   45211 non-null  int64
 15  poutcome   45211 non-null  object
 16  deposit    45211 non-null  object
dtypes: int64(7), object(10)
memory usage: 5.9+ MB
```

```
[5]: df.describe()
```

```
[5]:                 age        balance           day      duration      campaign  \
count  45211.000000   45211.000000  45211.000000  45211.000000  45211.000000
mean      40.936210    1362.272058     15.806419    258.163080      2.763841
std       10.618762    3044.765829      8.322476    257.527812      3.098021
min       18.000000   -8019.000000      1.000000      0.000000      1.000000
25%       33.000000      72.000000      8.000000    103.000000      1.000000
50%       39.000000     448.000000     16.000000    180.000000      2.000000
75%       48.000000    1428.000000     21.000000    319.000000      3.000000
max       95.000000  102127.000000     31.000000   4918.000000     63.000000

              pdays      previous
count  45211.000000  45211.000000
mean      40.197828      0.580323
std      100.128746      2.303441
min       -1.000000      0.000000
25%       -1.000000      0.000000
50%       -1.000000      0.000000
75%       -1.000000      0.000000
max      871.000000    275.000000
```

```
[ ]:
```

# 1 Exploratory Data Analysis

## 1.1 Univariate Analysis

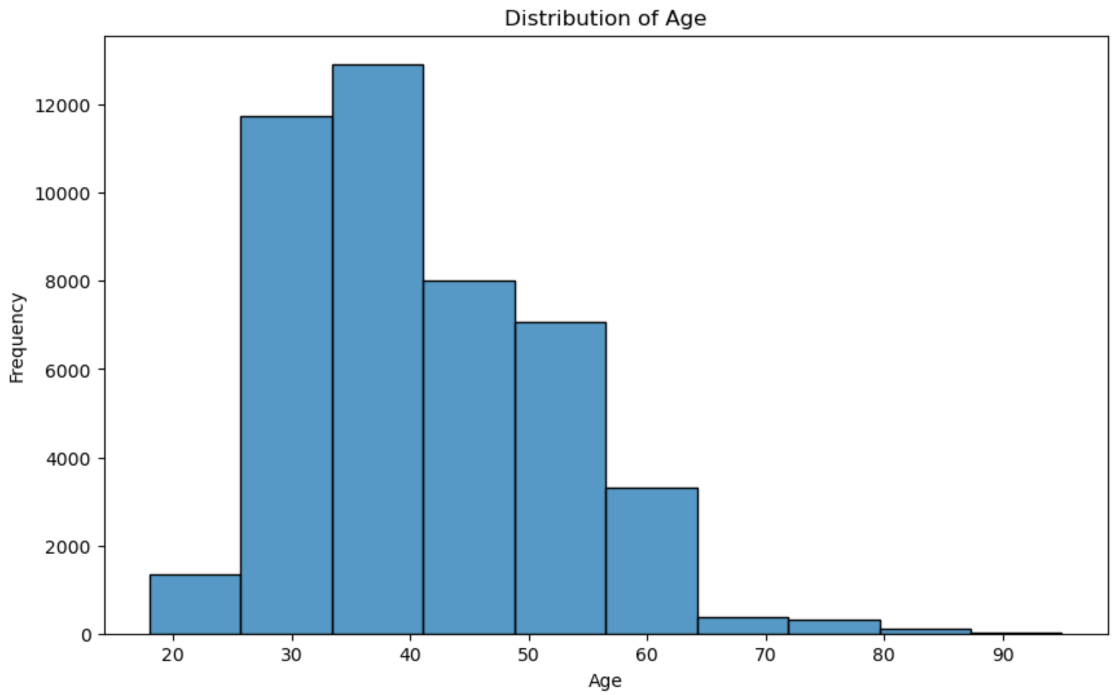
```
[6]: df.columns
```

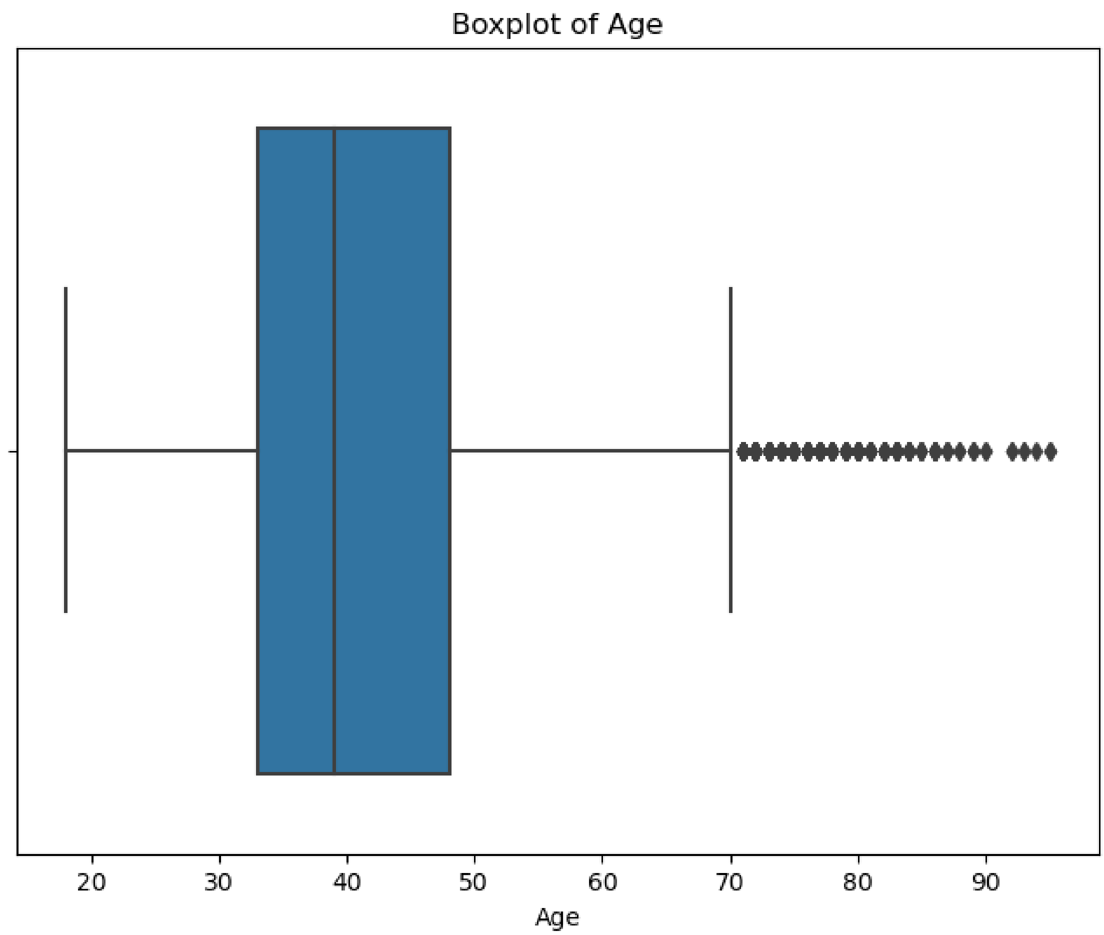
```
[6]: Index(['age', 'job', 'marital', 'education', 'default', 'balance', 'housing',
       'loan', 'contact', 'day', 'month', 'duration', 'campaign', 'pdays',
       'previous', 'poutcome', 'deposit'],
      dtype='object')
```

Age

```
[7]: # Descriptive statistics
df['age'].describe()

# Histogram
plt.figure(figsize=(10, 6))
sns.histplot(df['age'], bins=10)
plt.title('Distribution of Age')
plt.xlabel('Age')
plt.ylabel('Frequency')
plt.show()
```

```
# Boxplot
plt.figure(figsize=(8, 6))
sns.boxplot(df['age'])
plt.title('Boxplot of Age')
plt.xlabel('Age')
plt.show()
```

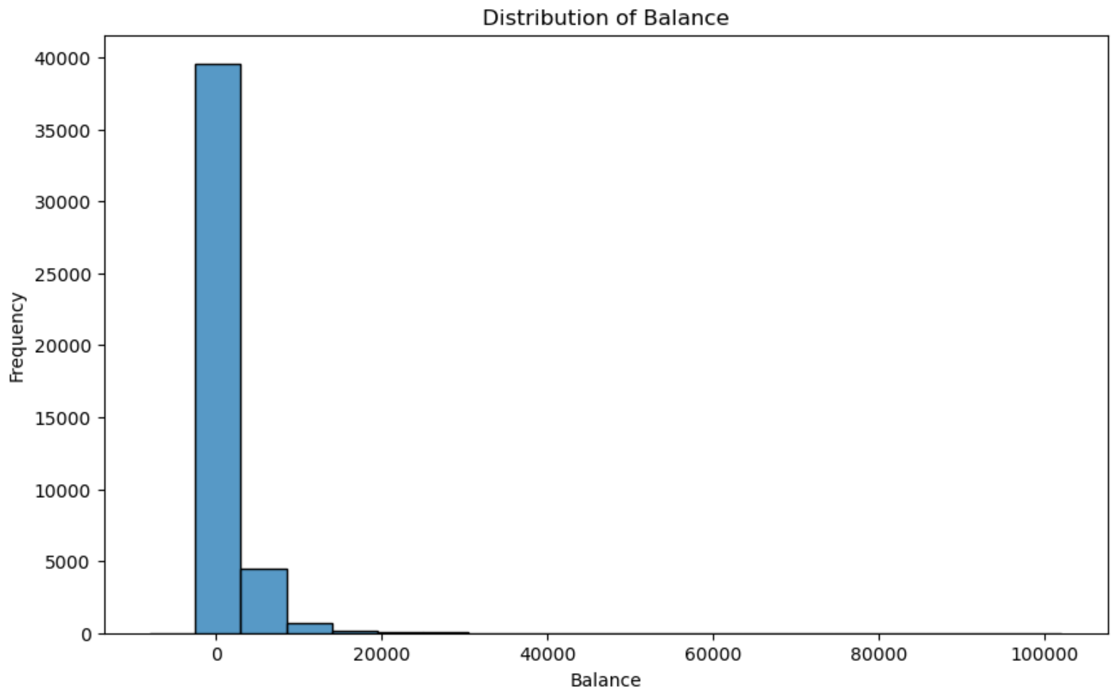


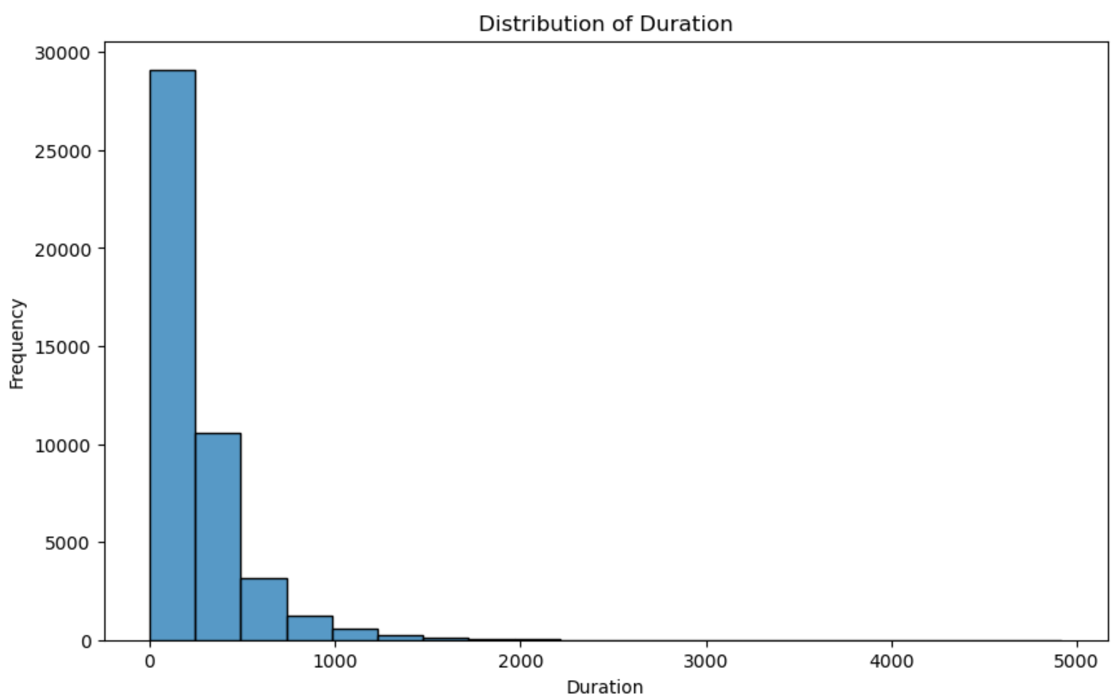


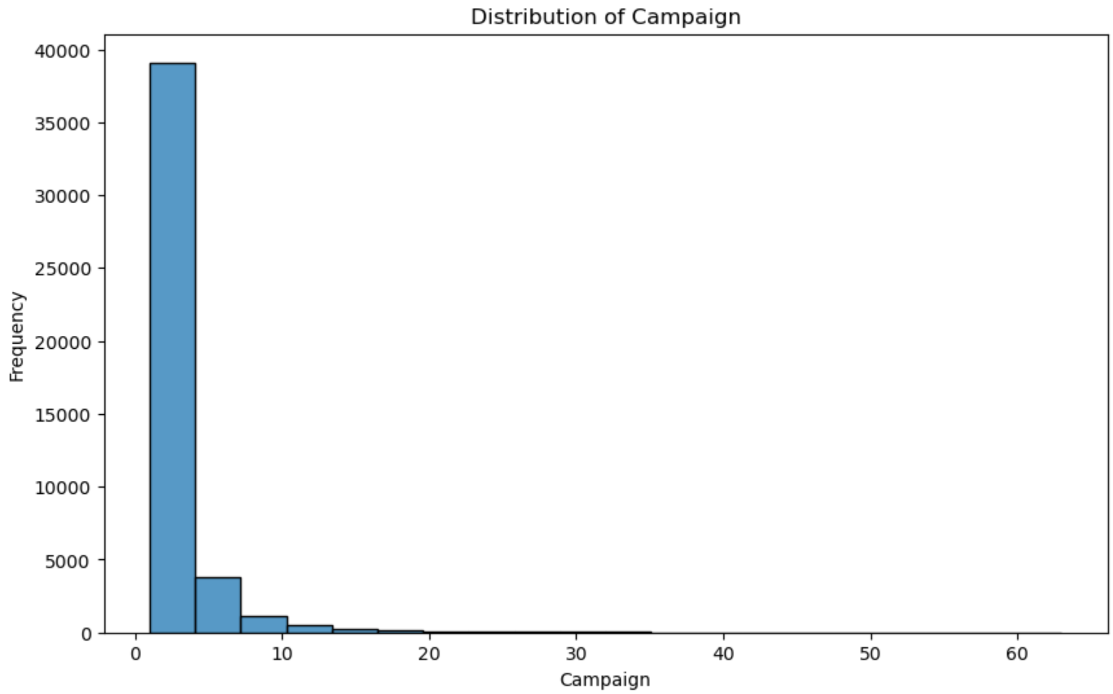

[8]:
```
# Histograms
plt.figure(figsize=(10, 6))
sns.histplot(df['balance'], bins=20)
plt.title('Distribution of Balance')
plt.xlabel('Balance')
plt.ylabel('Frequency')
plt.show()

plt.figure(figsize=(10, 6))
sns.histplot(df['duration'], bins=20)
plt.title('Distribution of Duration')
plt.xlabel('Duration')
plt.ylabel('Frequency')
plt.show()

plt.figure(figsize=(10, 6))
sns.histplot(df['campaign'], bins=20)
```

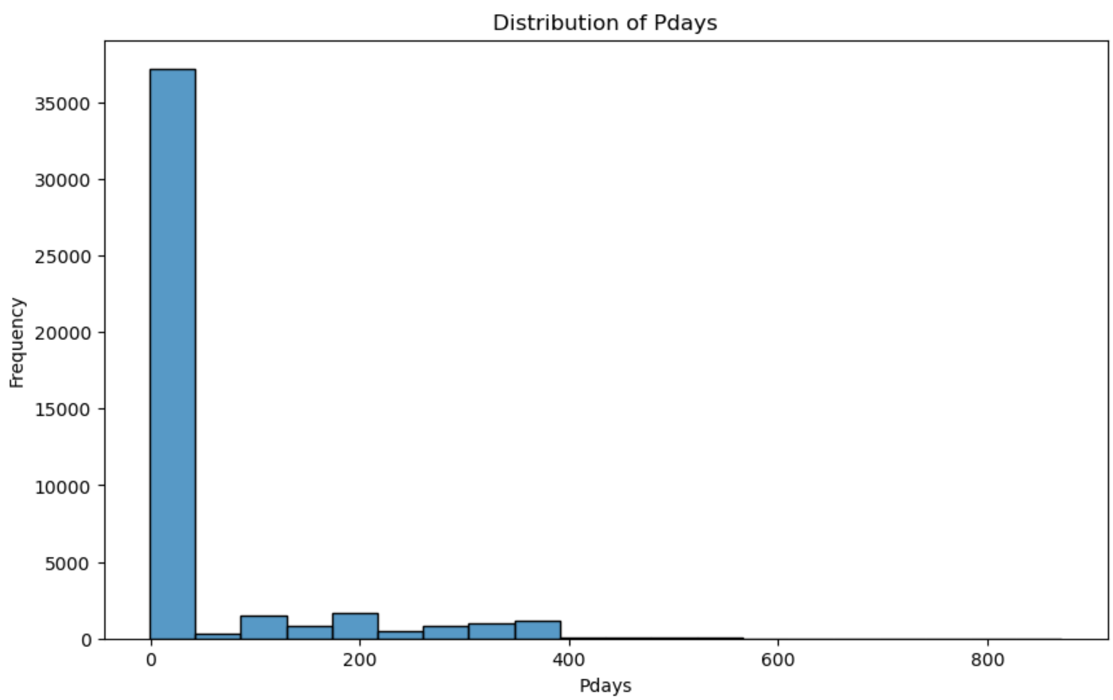
```python
plt.title('Distribution of Campaign')
plt.xlabel('Campaign')
plt.ylabel('Frequency')
plt.show()

plt.figure(figsize=(10, 6))
sns.histplot(df['pdays'], bins=20)
plt.title('Distribution of Pdays')
plt.xlabel('Pdays')
plt.ylabel('Frequency')
plt.show()

plt.figure(figsize=(10, 6))
sns.histplot(df['previous'], bins=20)
plt.title('Distribution of Previous')
plt.xlabel('Previous')
plt.ylabel('Frequency')
plt.show()

# Boxplots
plt.figure(figsize=(8, 6))
sns.boxplot(df['balance'])
plt.title('Boxplot of Balance')
plt.xlabel('Balance')
plt.show()

plt.figure(figsize=(8, 6))
sns.boxplot(df['duration'])
plt.title('Boxplot of Duration')
plt.xlabel('Duration')
plt.show()

plt.figure(figsize=(8, 6))
sns.boxplot(df['campaign'])
plt.title('Boxplot of Campaign')
plt.xlabel('Campaign')
plt.show()

plt.figure(figsize=(8, 6))
sns.boxplot(df['pdays'])
plt.title('Boxplot of Pdays')
plt.xlabel('Pdays')
plt.show()

plt.figure(figsize=(8, 6))
sns.boxplot(df['previous'])
plt.title('Boxplot of Previous')
```

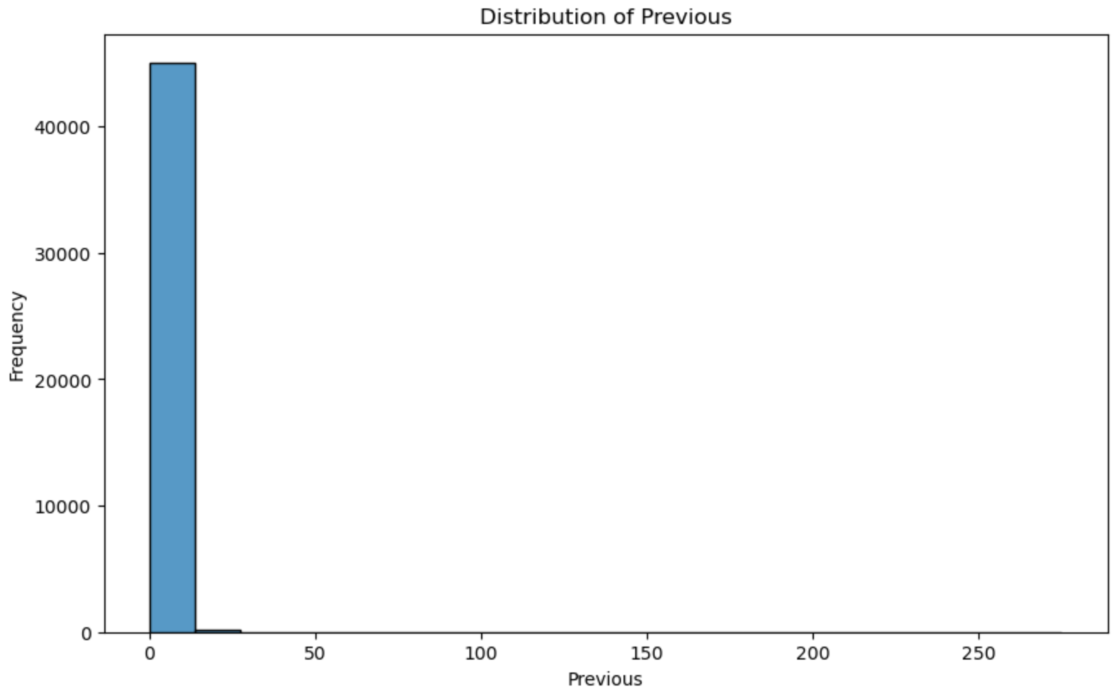
```
plt.xlabel('Previous')
plt.show()
```



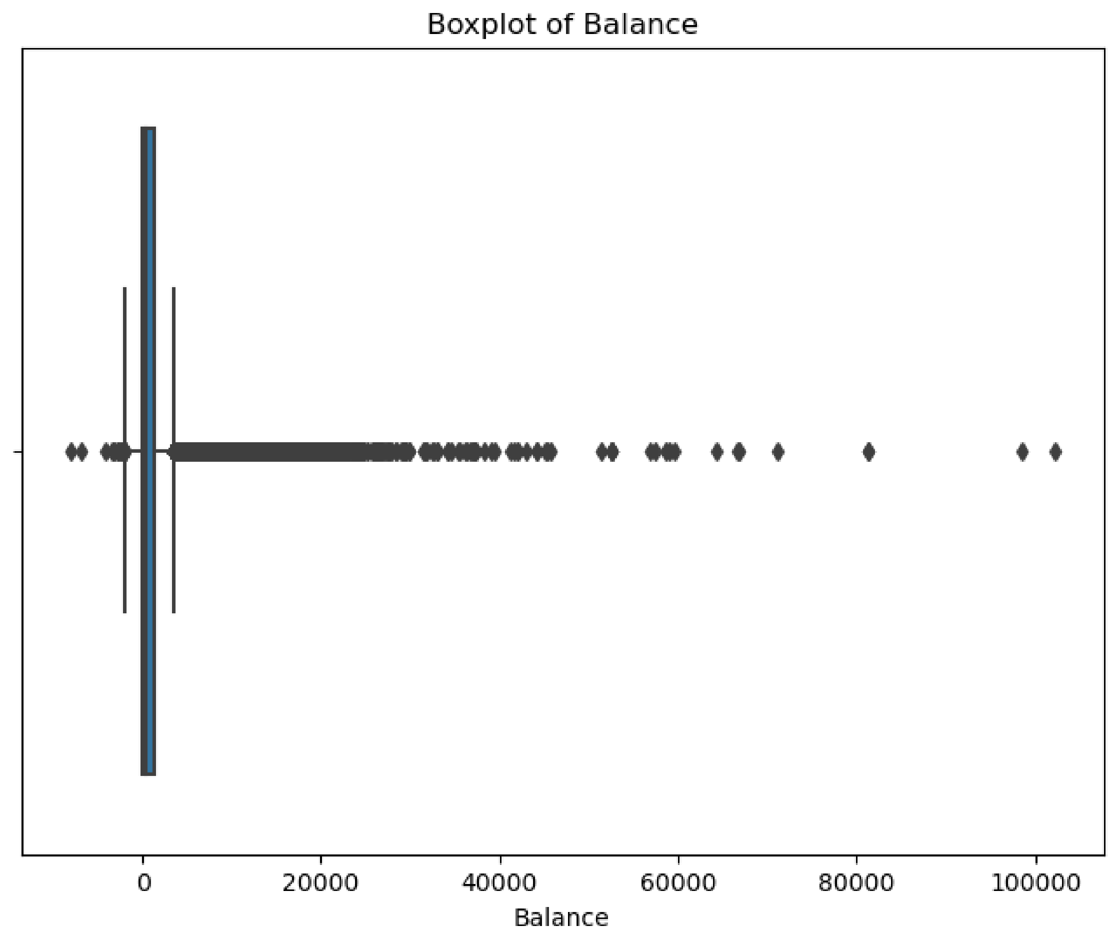



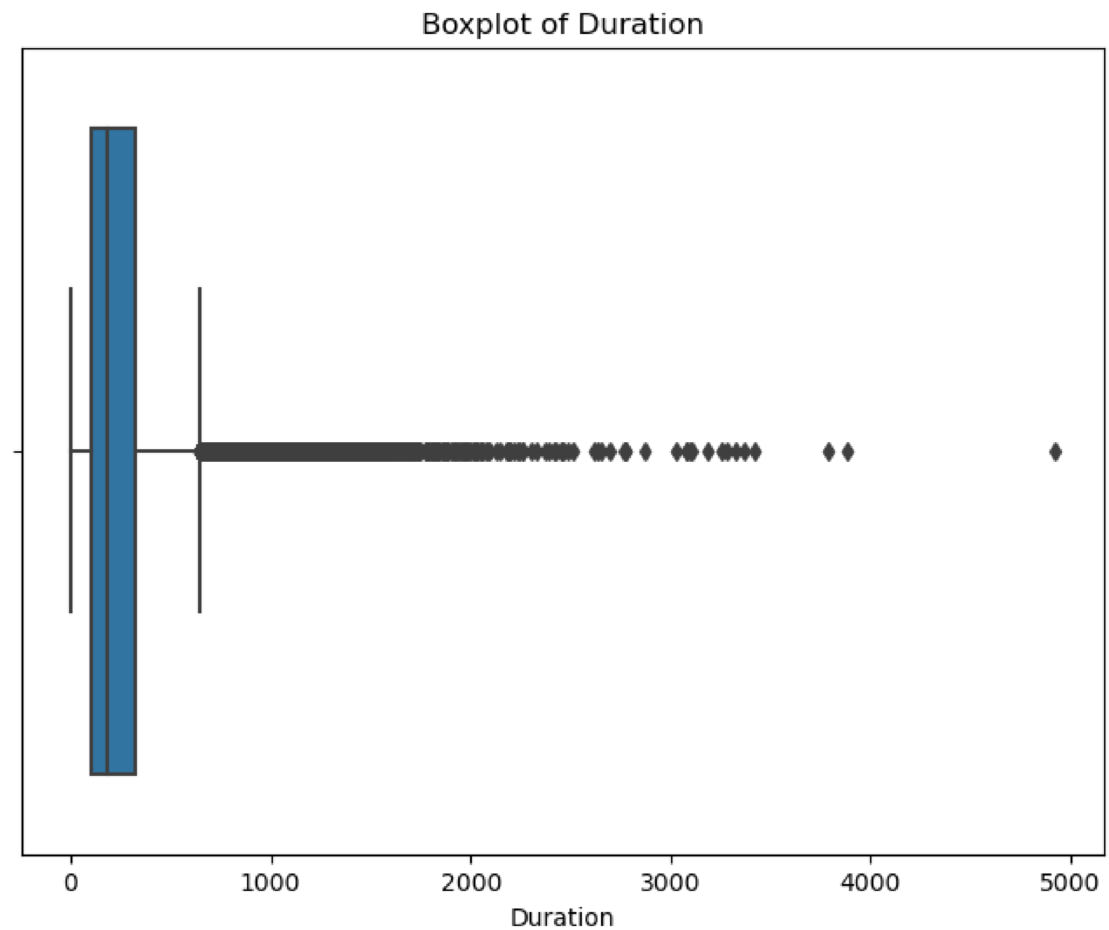

Distribution of Campaign
Frequency
Campaign
40000
35000
30000
25000
20000
15000
10000
5000
0
0
10
20
30
40
50
60

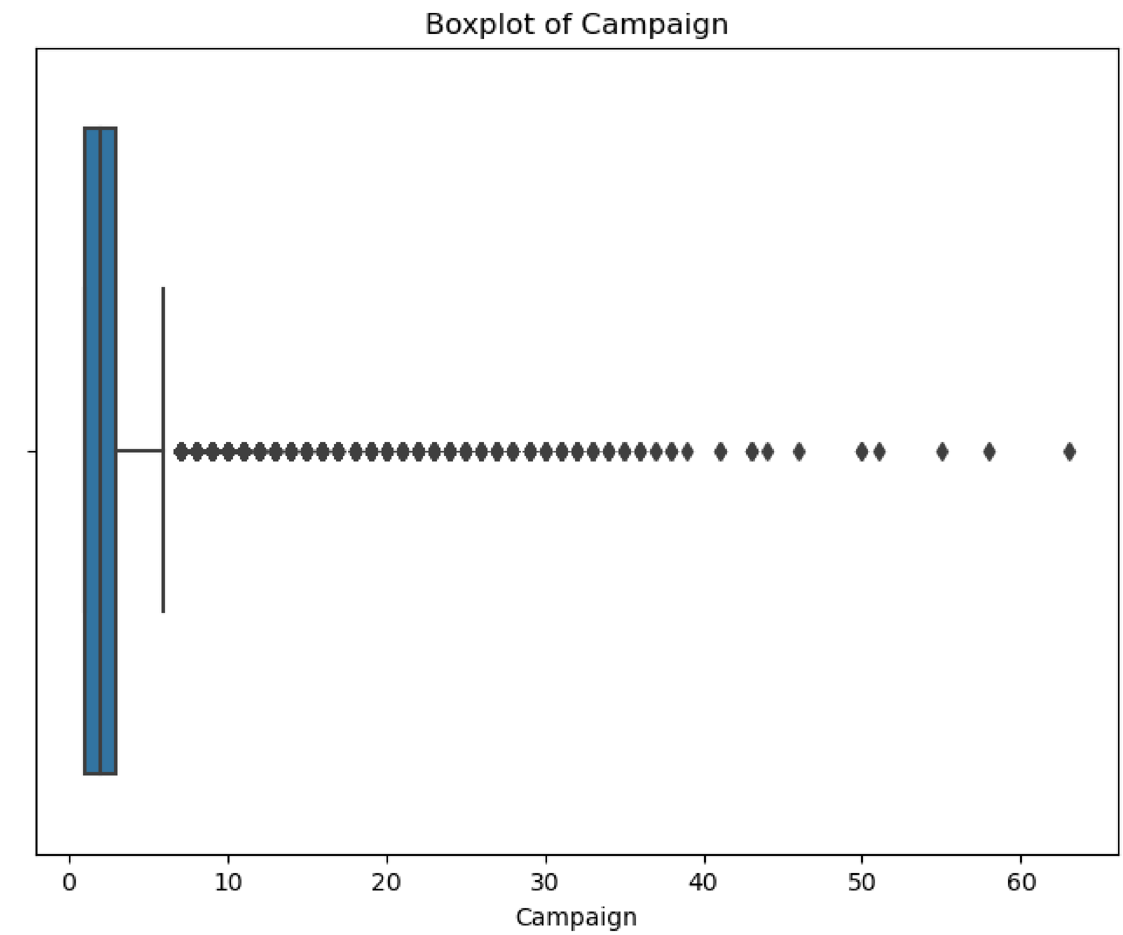

Distribution of Pdays
Frequency
Pdays
35000
30000
25000
20000
15000
10000
5000
0
0
200
400
600
800

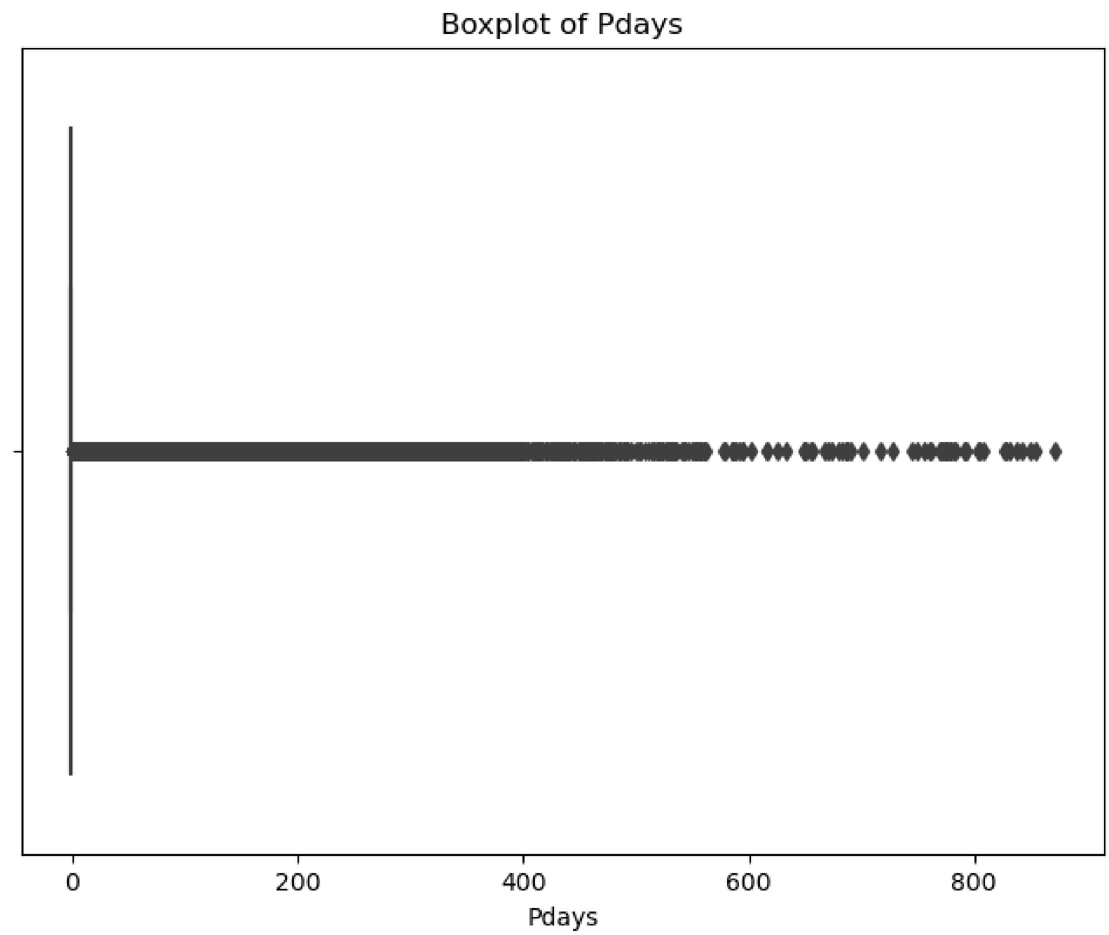


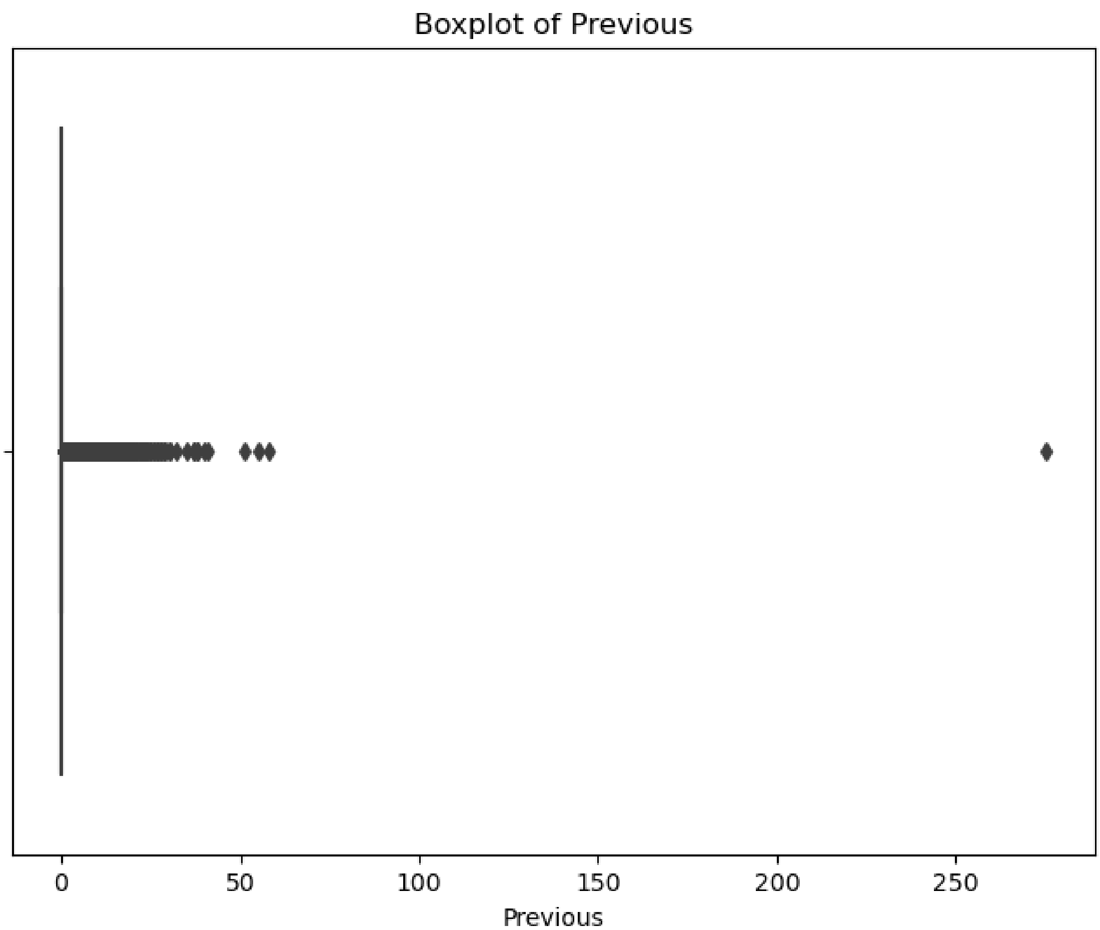
Distribution of Previous
Frequency
40000
30000
20000
10000
0
0
50
100
150
200
250
Previous


Boxplot of Balance
0
20000
40000
60000
80000
100000
Balance


Boxplot of Duration
0
1000
2000
3000
4000
5000
Duration


Boxplot of Campaign
0
10
20
30
40
50
60
Campaign


Boxplot of Pdays
0
200
400
600
800
Pdays




## 1.2 Bivariate Analysis

[9]:
```
df.head()
```

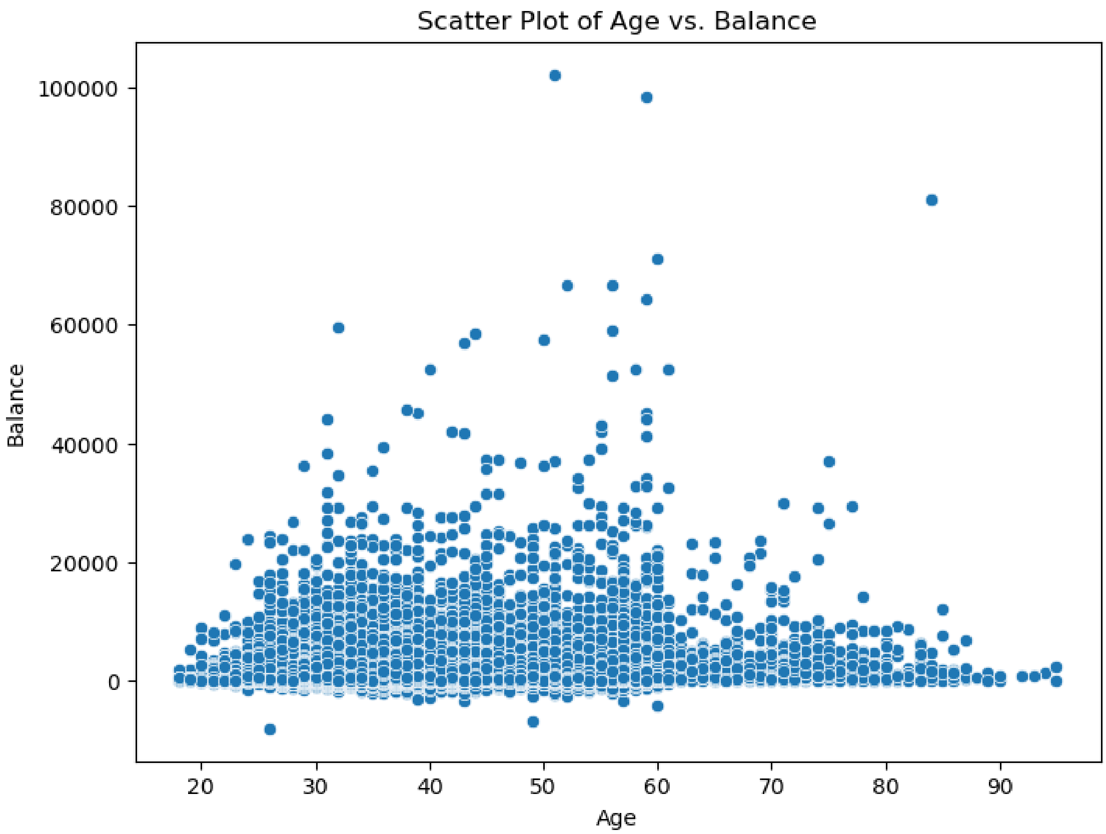
[9]:

| | age | job | marital | education | default | balance | housing | loan |
|---|---|---|---|---|---|---|---|---|
| 0 | 58 | management | married | tertiary | no | 2143 | yes | no |
| 1 | 44 | technician | single | secondary | no | 29 | yes | no |
| 2 | 33 | entrepreneur | married | secondary | no | 2 | yes | yes |
| 3 | 47 | blue-collar | married | unknown | no | 1506 | yes | no |
| 4 | 33 | unknown | single | unknown | no | 1 | no | no |

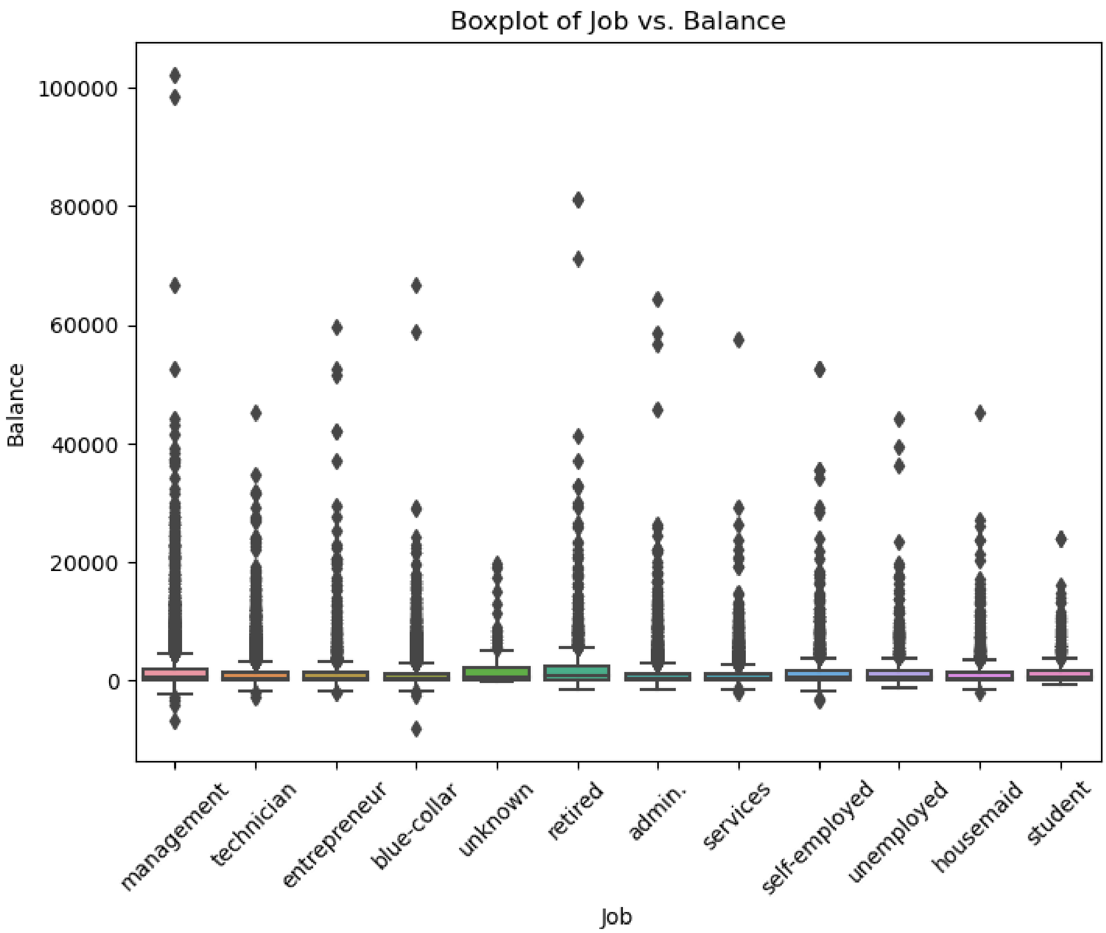
| | contact | day | month | duration | campaign | pdays | previous | poutcome | deposit |
|---|---|---|---|---|---|---|---|---|---|
| 0 | unknown | 5 | may | 261 | 1 | -1 | 0 | unknown | no |
| 1 | unknown | 5 | may | 151 | 1 | -1 | 0 | unknown | no |
| 2 | unknown | 5 | may | 76 | 1 | -1 | 0 | unknown | no |
| 3 | unknown | 5 | may | 92 | 1 | -1 | 0 | unknown | no |
| 4 | unknown | 5 | may | 198 | 1 | -1 | 0 | unknown | no |

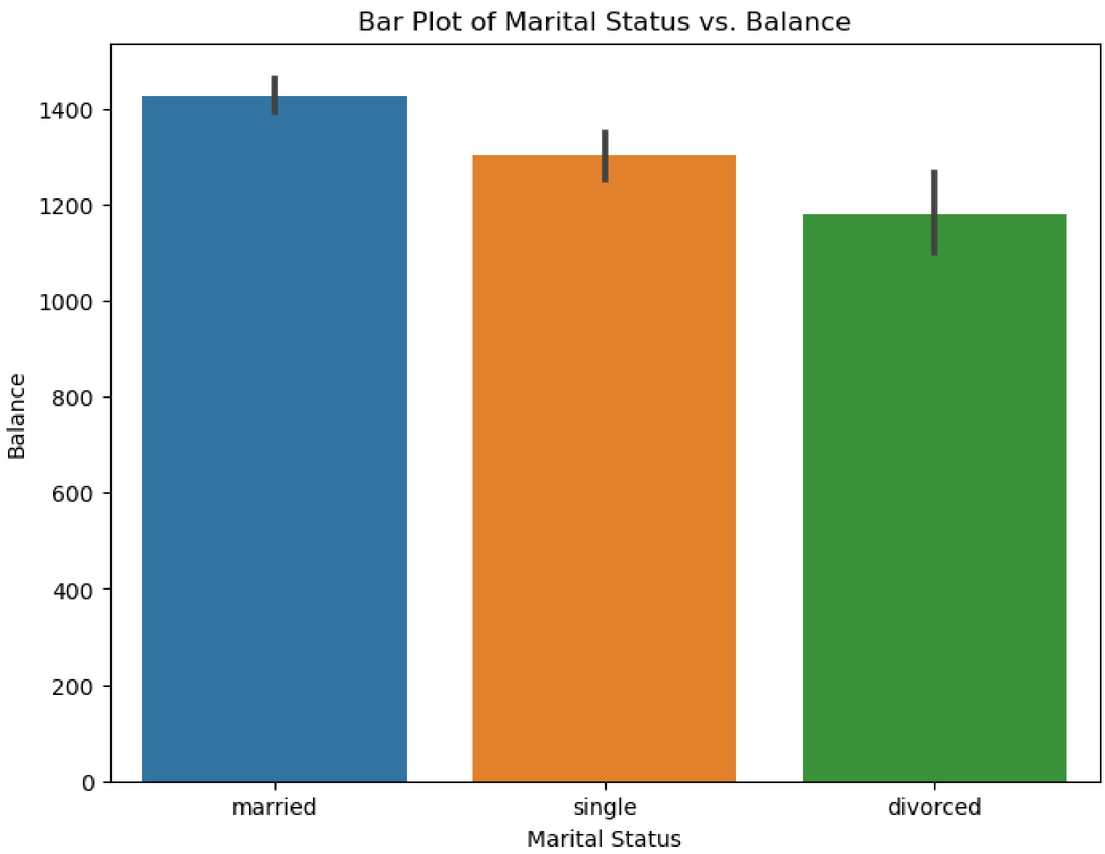
[10]:

```
# Scatter plot
plt.figure(figsize=(8, 6))
sns.scatterplot(x='age', y='balance', data=df)
plt.title('Scatter Plot of Age vs. Balance')
plt.xlabel('Age')
plt.ylabel('Balance')
plt.show()

# Boxplot
plt.figure(figsize=(8, 6))
sns.boxplot(x='job', y='balance', data=df)
plt.title('Boxplot of Job vs. Balance')
plt.xlabel('Job')
plt.ylabel('Balance')
plt.xticks(rotation=45)
plt.show()

# Bar plot
plt.figure(figsize=(8, 6))
sns.barplot(x='marital', y='balance', data=df)
plt.title('Bar Plot of Marital Status vs. Balance')
plt.xlabel('Marital Status')
plt.ylabel('Balance')
plt.show()
```



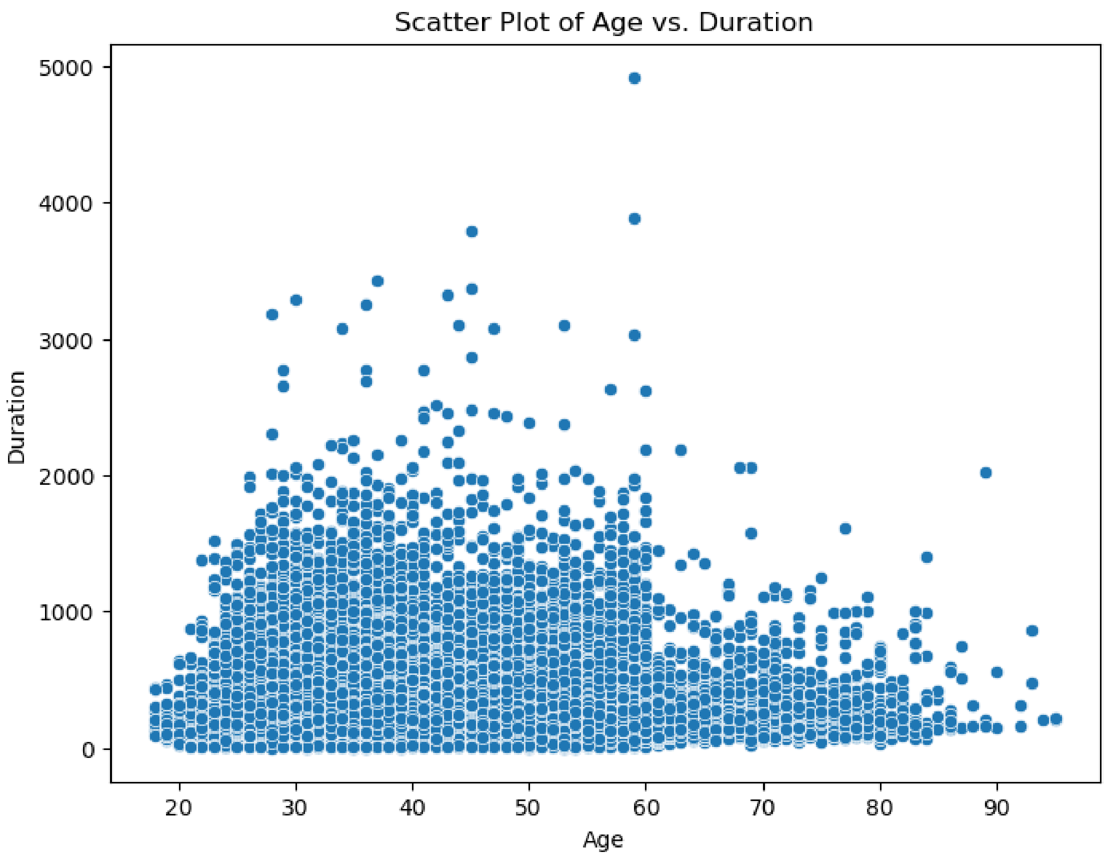
Scatter Plot of Age vs. Balance
Balance
Age
100000
80000
60000
40000
20000
0
20
30
40
50
60
70
80
90

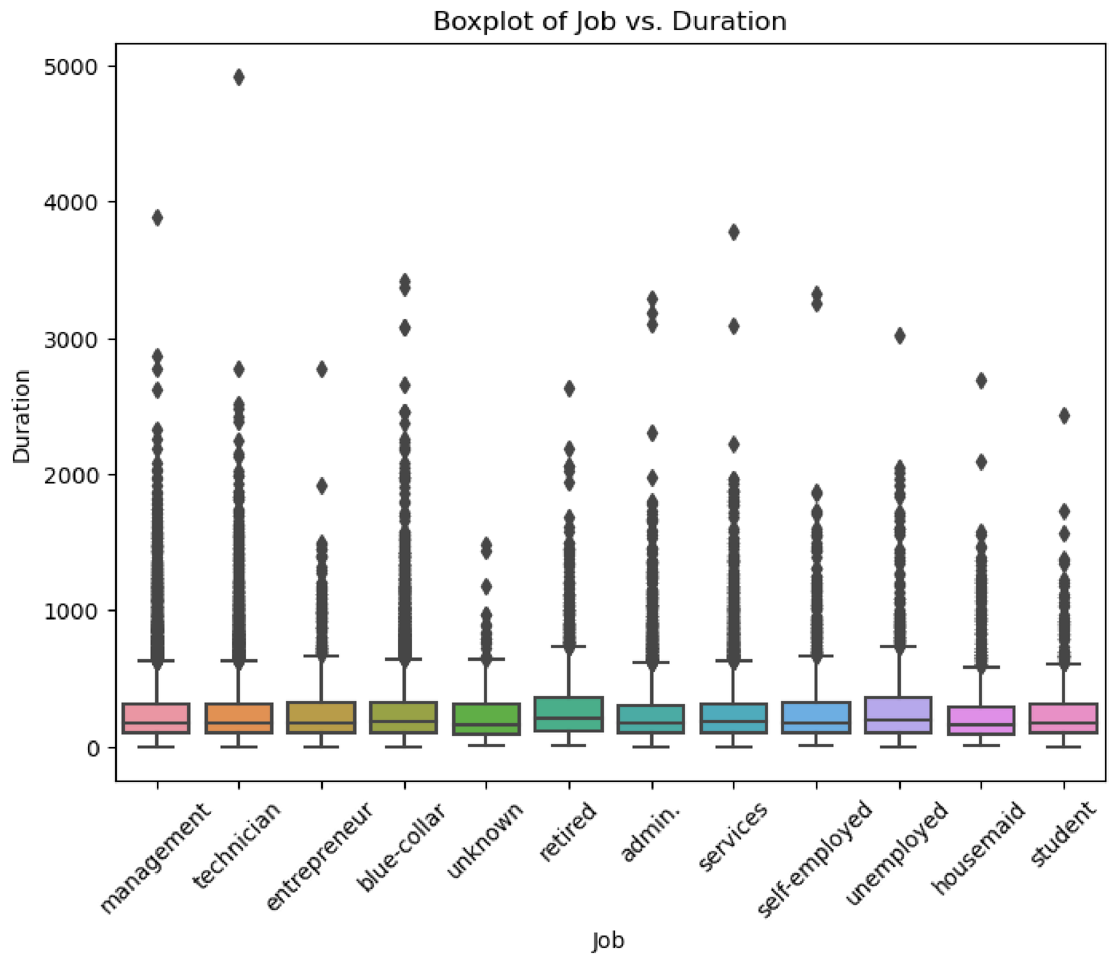

Boxplot of Job vs. Balance
100000
80000
60000
40000
20000
0
Balance
management
technician
entrepreneur
blue-collar
unknown
retired
admin.
services
self-employed
unemployed
housemaid
student
Job

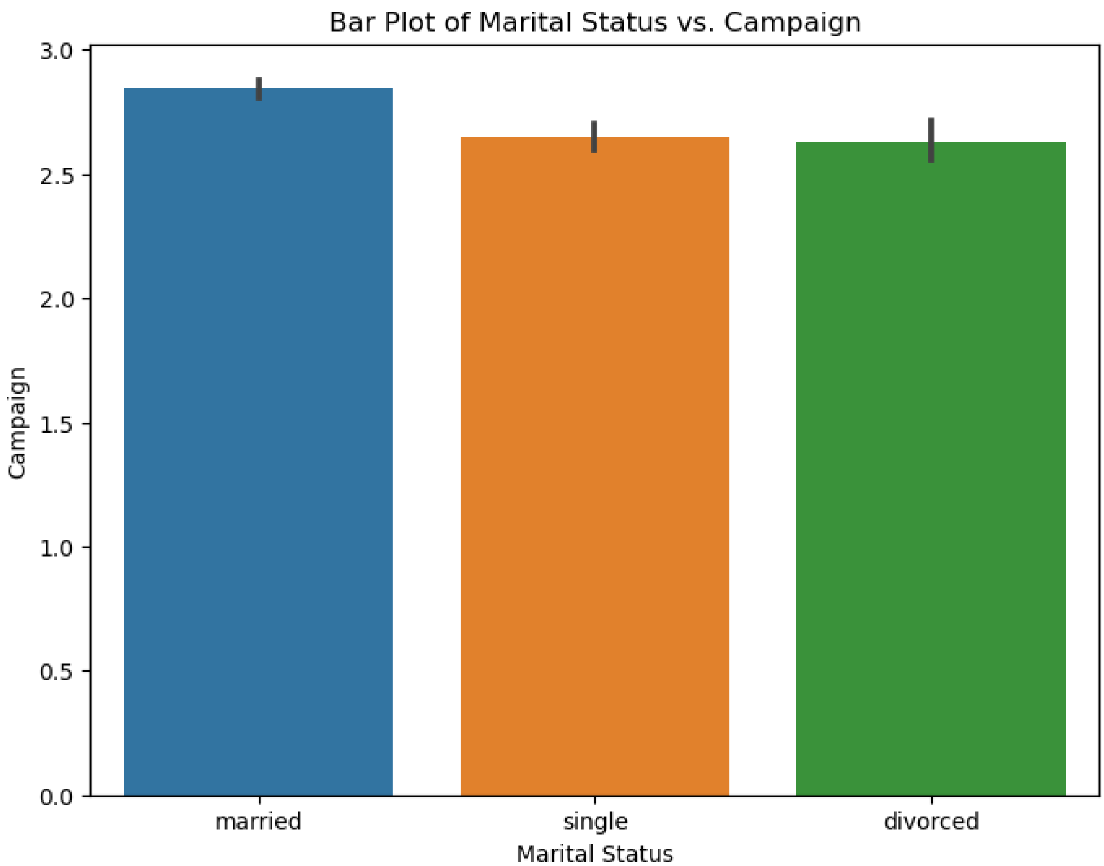



[11]:
```
# Scatter plot: Age vs. Duration
plt.figure(figsize=(8, 6))
sns.scatterplot(x='age', y='duration', data=df)
plt.title('Scatter Plot of Age vs. Duration')
plt.xlabel('Age')
plt.ylabel('Duration')
plt.show()

# Boxplot: Job vs. Duration
plt.figure(figsize=(8, 6))
sns.boxplot(x='job', y='duration', data=df)
plt.title('Boxplot of Job vs. Duration')
plt.xlabel('Job')
plt.ylabel('Duration')
plt.xticks(rotation=45)
plt.show()

# Bar plot: Marital vs. Campaign
plt.figure(figsize=(8, 6))
sns.barplot(x='marital', y='campaign', data=df)
```

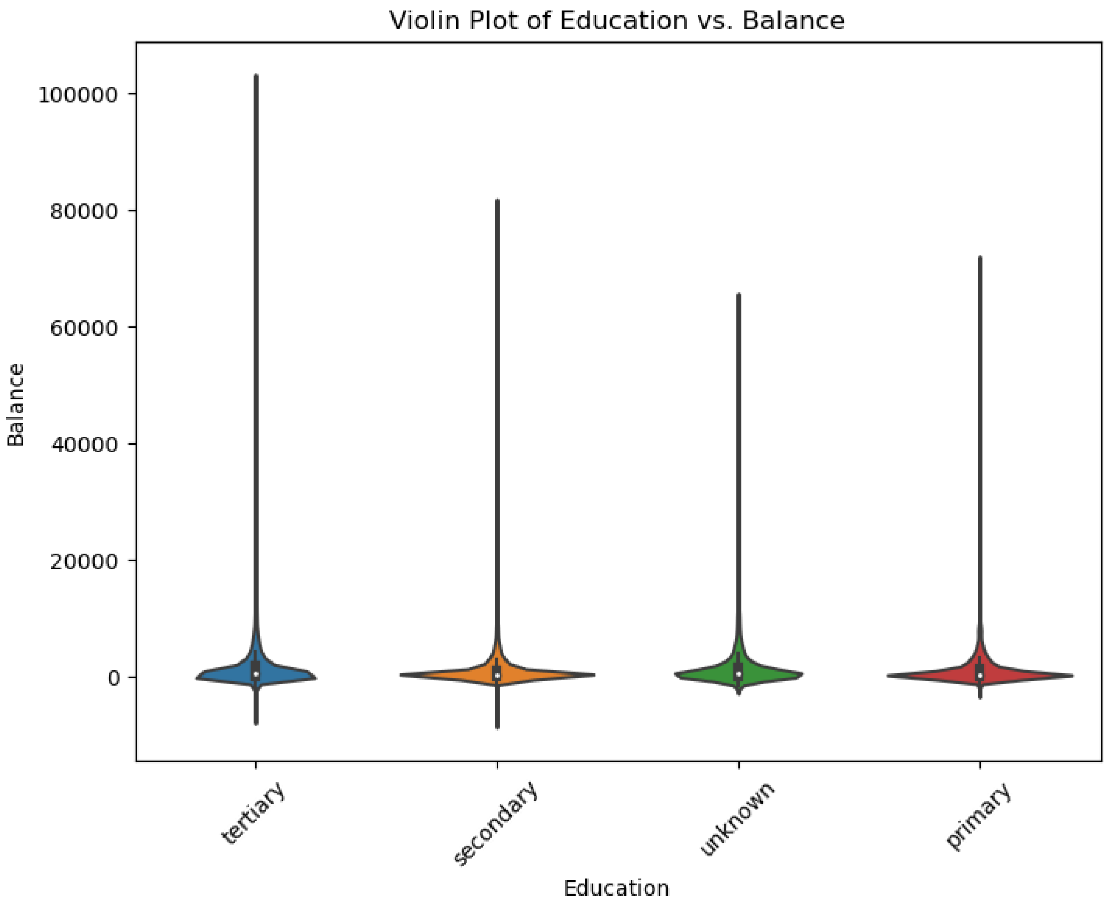
```
plt.title('Bar Plot of Marital Status vs. Campaign')
plt.xlabel('Marital Status')
plt.ylabel('Campaign')
plt.show()

# Violin plot: Education vs. Balance
plt.figure(figsize=(8, 6))
sns.violinplot(x='education', y='balance', data=df)
plt.title('Violin Plot of Education vs. Balance')
plt.xlabel('Education')
plt.ylabel('Balance')
plt.xticks(rotation=45)
plt.show()
```




Boxplot of Job vs. Duration
5000
4000
3000
2000
1000
0
Duration
management
technician
entrepreneur
blue-collar
unknown
retired
admin.
services
self-employed
unemployed
housemaid
student
Job



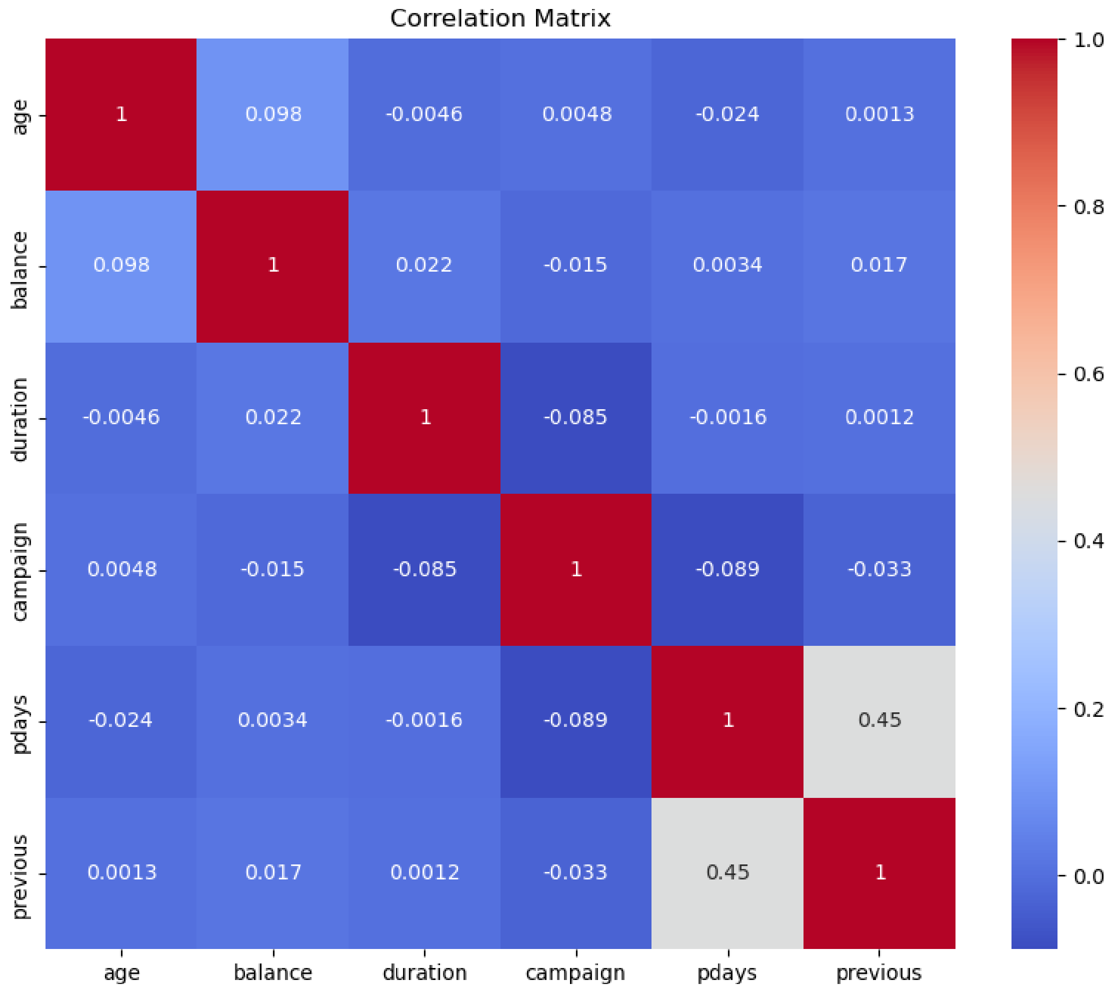
Bar Plot of Marital Status vs. Campaign
Campaign
3.0
2.5
2.0
1.5
1.0
0.5
0.0
married
single
divorced
Marital Status

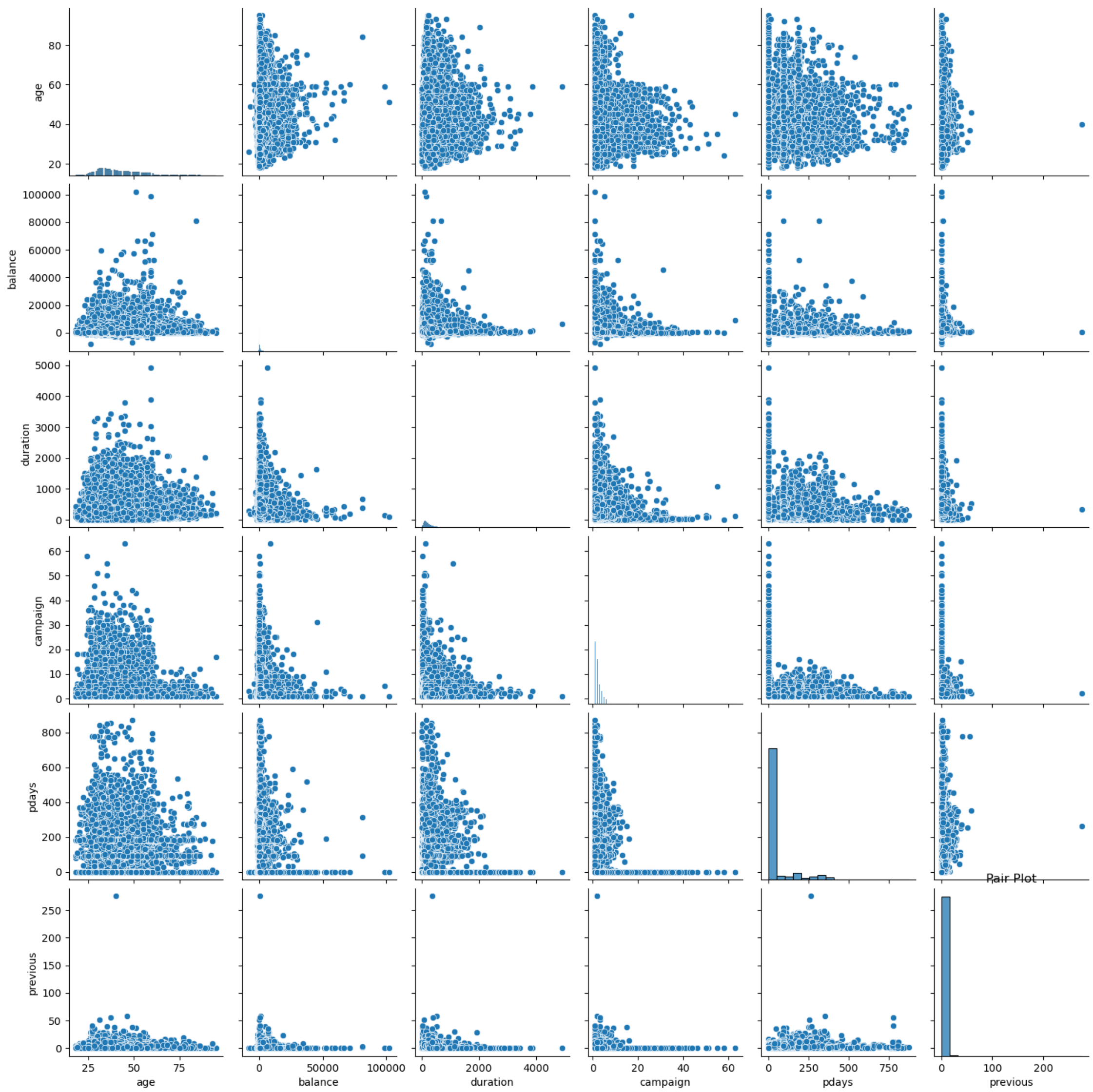



### 1.3 Multivariate Analysis

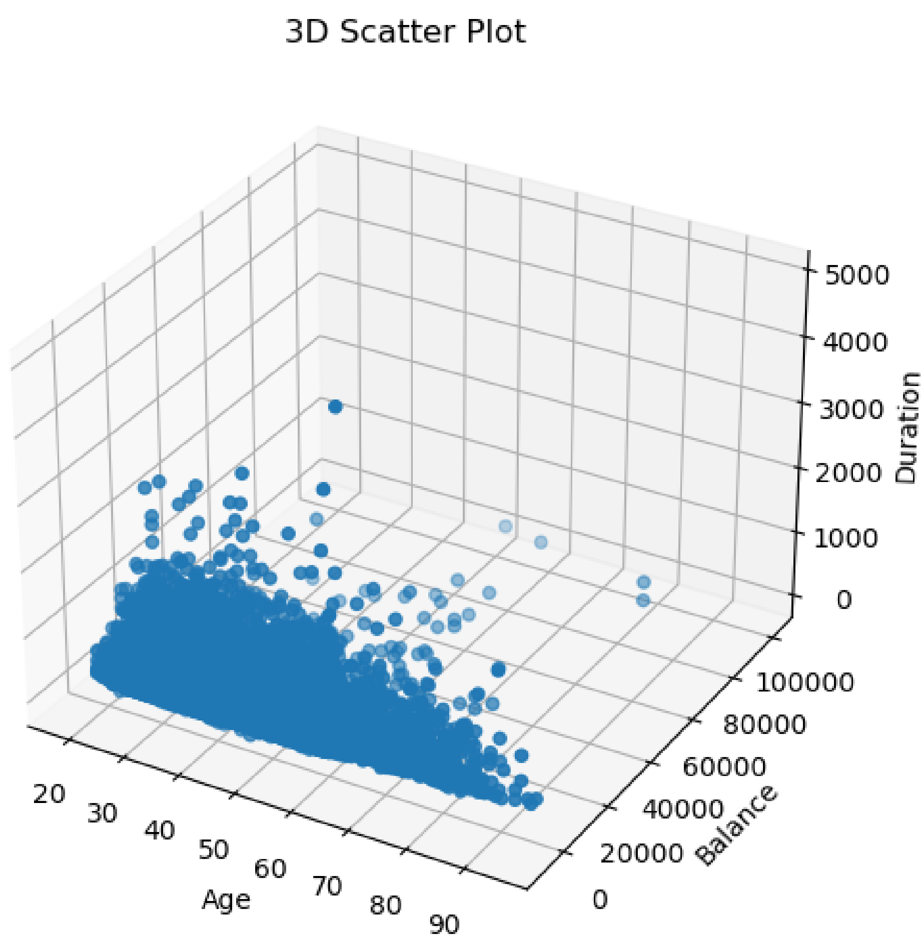
[12]:
```python
# Select the columns for multivariate analysis
columns = ['age', 'balance', 'duration', 'campaign', 'pdays', 'previous']

# Create a subset DataFrame with the selected columns
subset_df = df[columns]

# Compute the correlation matrix
corr_matrix = subset_df.corr()

# Visualize the correlation matrix
plt.figure(figsize=(10, 8))
sns.heatmap(corr_matrix, annot=True, cmap='coolwarm', square=True)
plt.title('Correlation Matrix')
plt.show()

# Pair plot
```

```
sns.pairplot(subset_df)
plt.title('Pair Plot')
plt.show()
```






```
[13]: from mpl_toolkits.mplot3d import Axes3D

fig = plt.figure(figsize=(8, 6))
ax = fig.add_subplot(111, projection='3d')
ax.scatter(df['age'], df['balance'], df['duration'])
ax.set_xlabel('Age')
ax.set_ylabel('Balance')
ax.set_zlabel('Duration')
plt.title('3D Scatter Plot')
plt.show()
```




## 2 Unsupervised Learning

CLustering

### 2.1 Data preprocessing

[14]:
```
df.head()
```

[14]:
```
   age            job  marital  education default  balance housing loan  \
0   58     management  married   tertiary      no     2143     yes   no
1   44     technician   single  secondary      no       29     yes   no
2   33   entrepreneur  married  secondary      no        2     yes  yes
3   47    blue-collar  married    unknown      no     1506     yes   no
4   33        unknown   single    unknown      no        1      no   no

   contact  day month  duration  campaign  pdays  previous poutcome deposit
0  unknown    5   may       261         1     -1         0  unknown      no
```

```
1  unknown    5   may       151          1     -1          0  unknown      no
2  unknown    5   may        76          1     -1          0  unknown      no
3  unknown    5   may        92          1     -1          0  unknown      no
4  unknown    5   may       198          1     -1          0  unknown      no
```

[15]:

```python
# Clustering Libraries
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.cluster import KMeans
from scipy.cluster.hierarchy import dendrogram, linkage
from sklearn.metrics import silhouette_score, homogeneity_score
from IPython.display import Image



from sklearn.preprocessing import LabelEncoder
```

[16]:

```python
# Checking for duplicates

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

```
0
```

[17]:

```python
# label encoding
encoder = LabelEncoder()

# looping for columns except survived
for c in df.columns[1:]:
    if(df[c].dtype=='object'):

        df[c] = encoder.fit_transform(df[c])
    else:
        df[c] = df[c]
```

[18]:

```python
df.head()
```

[18]:

```
   age  job  marital  education  default  balance  housing  loan  contact  \
0   58    4        1          2        0     2143        1     0        2
1   44    9        2          1        0       29        1     0        2
2   33    2        1          1        0        2        1     1        2
3   47    1        1          3        0     1506        1     0        2
4   33   11        2          3        0        1        0     0        2

   day  month  duration  campaign  pdays  previous  poutcome  deposit
0    5      8       261         1     -1         0         3        0
1    5      8       151         1     -1         0         3        0
```

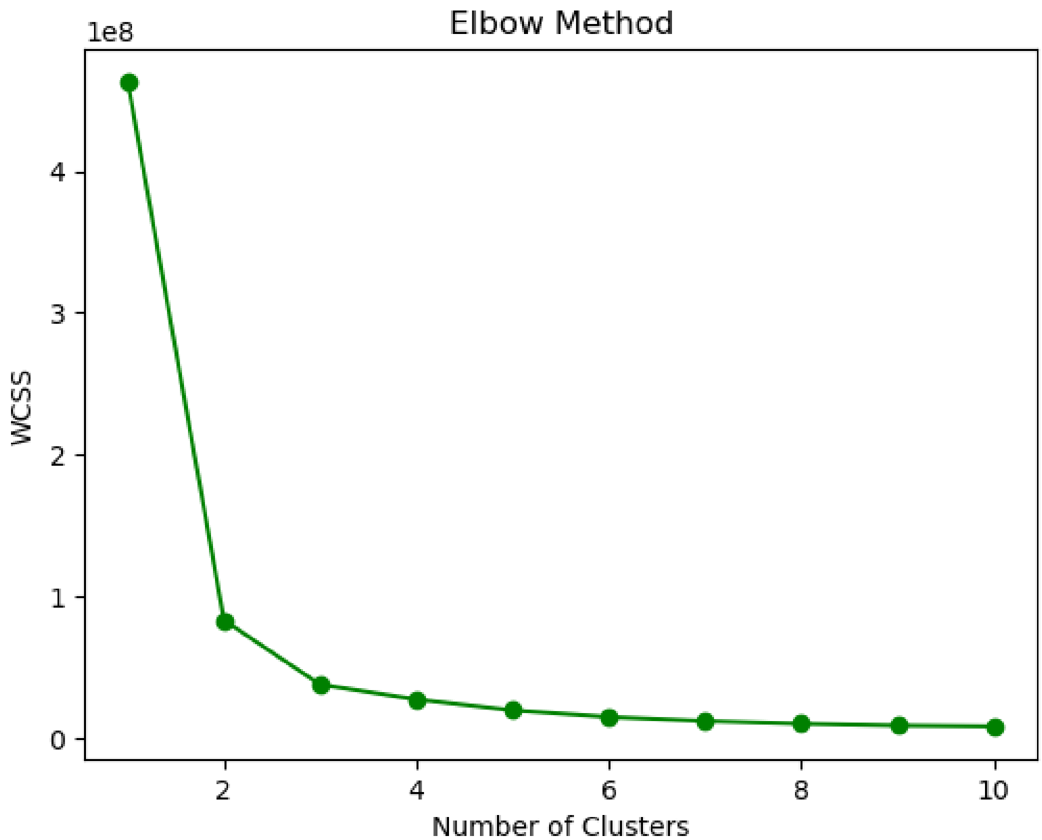
```
2     5      8        76          1     -1          0          3         0
3     5      8        92          1     -1          0          3         0
4     5      8       198          1     -1          0          3         0
```

[19]:
```python
from sklearn.preprocessing import MinMaxScaler

def min_max_scale_numeric(df, columns):
    scaler = MinMaxScaler()
    df[columns] = scaler.fit_transform(df[columns])
    return df

# Select the columns to be scaled
scaled_columns = ['balance', 'duration']

# Perform min-max scaling on selected columns
scaled_data = min_max_scale_numeric(df, scaled_columns)

# Print the scaled data
scaled_data.head()
```

[19]:
```
   age  job  marital  education  default   balance  housing  loan  contact  \
0   58    4        1          2        0  0.092259        1     0        2
1   44    9        2          1        0  0.073067        1     0        2
2   33    2        1          1        0  0.072822        1     1        2
3   47    1        1          3        0  0.086476        1     0        2
4   33   11        2          3        0  0.072812        0     0        2

   day  month  duration  campaign  pdays  previous  poutcome  deposit
0    5      8  0.053070         1     -1         0         3        0
1    5      8  0.030704         1     -1         0         3        0
2    5      8  0.015453         1     -1         0         3        0
3    5      8  0.018707         1     -1         0         3        0
4    5      8  0.040260         1     -1         0         3        0
```

[20]:
```python
# using elbow method to determine tyhe optimal number of clusters for thuis␣
 ↪dataset
wcss = []
max_clusters = 10
for n_clusters in range(1, max_clusters+1):
    kmeans = KMeans(n_clusters=n_clusters, random_state=42)
    kmeans.fit(scaled_data)
    wcss.append(kmeans.inertia_)

# Plot the WCSS against the number of clusters
plt.plot(range(1, max_clusters+1), wcss, color='green', marker='o')
plt.xlabel('Number of Clusters')
plt.ylabel('WCSS')
```

```
plt.title('Elbow Method')
plt.show()
```




[21]:
```
n_clusters = 3  # Optimum number of clusters
kmeans = KMeans(n_clusters=n_clusters, random_state=42)
kmeans.fit(scaled_data)

# Add cluster labels to the dataset
scaled_data['cluster_label'] = kmeans.labels_

# Print the dataset with cluster labels
scaled_data.head()
```

[21]:

| | age | job | marital | education | default | balance | housing | loan | contact | \ |
|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 58 | 4 | 1 | 2 | 0 | 0.092259 | 1 | 0 | 2 | |
| 1 | 44 | 9 | 2 | 1 | 0 | 0.073067 | 1 | 0 | 2 | |
| 2 | 33 | 2 | 1 | 1 | 0 | 0.072822 | 1 | 1 | 2 | |
| 3 | 47 | 1 | 1 | 3 | 0 | 0.086476 | 1 | 0 | 2 | |
| 4 | 33 | 11 | 2 | 3 | 0 | 0.072812 | 0 | 0 | 2 | |

```
   day  month  duration  campaign  pdays  previous  poutcome  deposit  \
0    5      8  0.053070         1     -1         0         3        0
1    5      8  0.030704         1     -1         0         3        0
2    5      8  0.015453         1     -1         0         3        0
3    5      8  0.018707         1     -1         0         3        0
4    5      8  0.040260         1     -1         0         3        0

   cluster_label
0              0
1              0
2              0
3              0
4              0
```

[22]:
```
# Running K means on 5 clusters

kmeans = KMeans(n_clusters=3, random_state=2)
kmeans = kmeans.fit(scaled_data)


kmeans.labels_

# "predictions" for new data
predictions = kmeans.predict(scaled_data)

# calculating the Counts of the cluster
unique, counts = np.unique(predictions, return_counts=True)
counts = counts.reshape(1,3)

# Creating a datagrame"Clust
countscldf = pd.DataFrame(counts, columns = ["Cluster 0","Cluster 1","Cluster␣
 ↪2"])

# display
countscldf
```

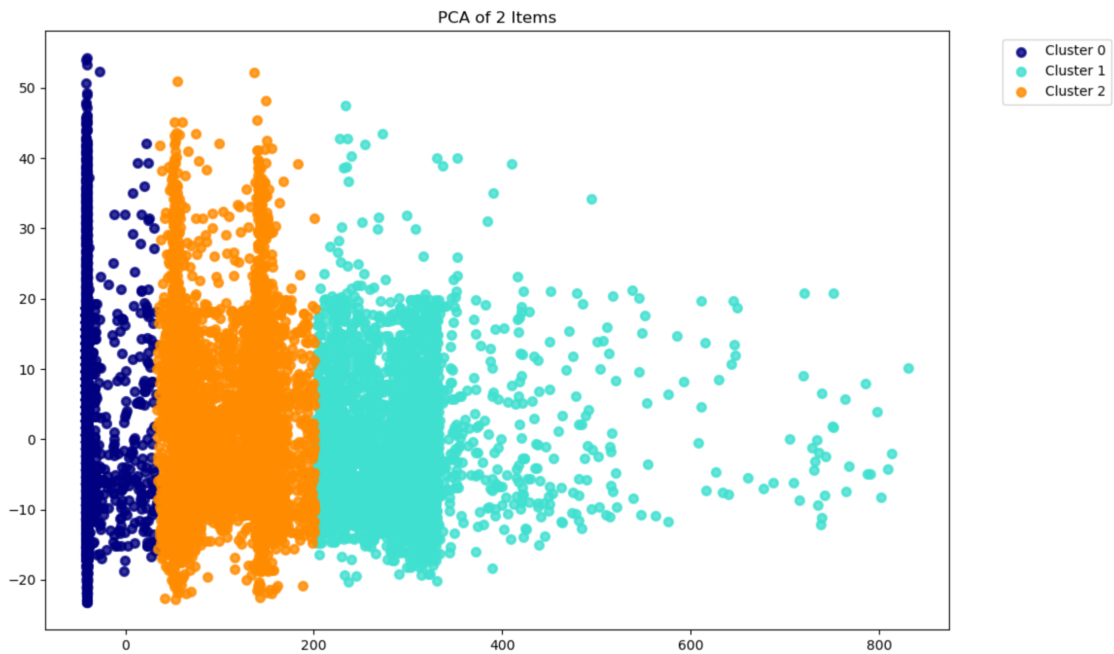
[22]:
```
   Cluster 0  Cluster 1  Cluster 2
0      37315       3588       4308
```

[23]:
```
# Running PCA to Visualize the data

from sklearn.decomposition import PCA
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis

X = scaled_data
y_num = predictions
```

```python
target_names = ["Cluster 0","Cluster 1","Cluster 2"]

pca = PCA(n_components=2, random_state = 453)
X_r = pca.fit(X).transform(X)


# Percentage of variance explained for each components
print('Explained variance ratio (first two components): %s' % str(pca.
 ↪explained_variance_ratio_))

# Plotting the data
plt.figure()
plt.figure(figsize=(12,8))
colors = ['navy', 'turquoise', 'darkorange']
lw = 2


for color, i, target_name in zip(colors, [0, 1, 2], target_names):
    plt.scatter(X_r[y_num == i, 0], X_r[y_num == i, 1], color=color, alpha=.8,␣
 ↪lw=lw,label=target_name)

plt.legend(loc='best', shadow=False, scatterpoints=1)
plt.legend(bbox_to_anchor=(1.05, 1), loc=2, borderaxespad=0.6)
plt.title('PCA of 2 Items')
plt.show()
```

```
Explained variance ratio (first two components): [0.97877637 0.01101072]
```

```
<Figure size 640x480 with 0 Axes>
```

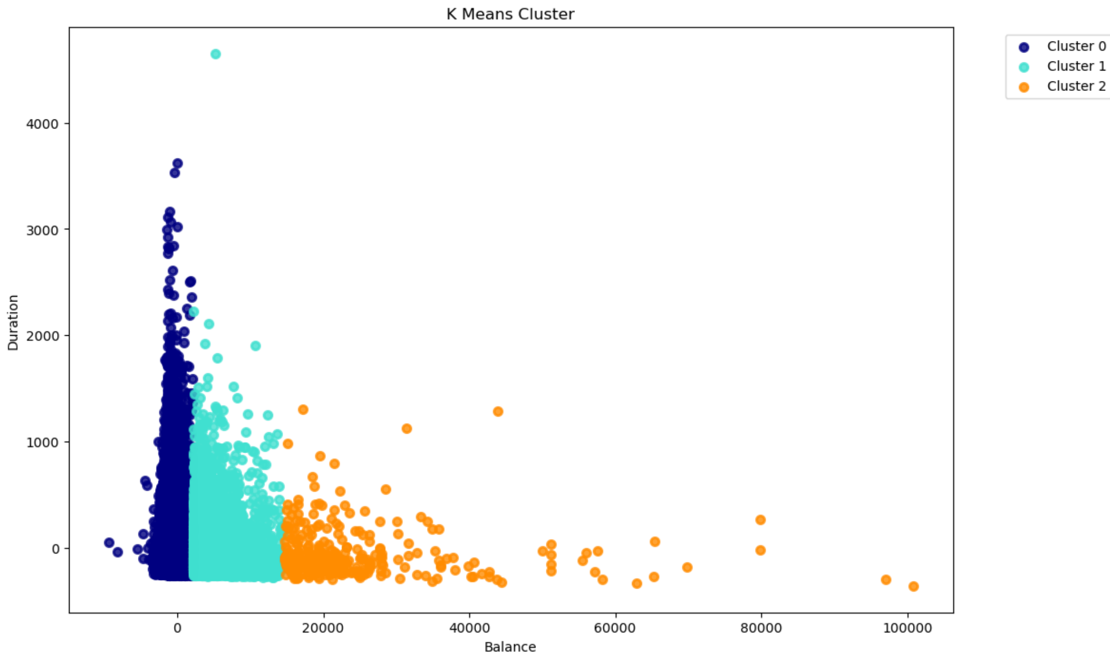


[62]:

```
# Running K means on 3 clusters

kmeans = KMeans(n_clusters=3, random_state=2)
kmeans = kmeans.fit(X)

predictions = kmeans.predict(X)

# Running PCA to Visualize the data

from sklearn.decomposition import PCA
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis

X = X
y_num = predictions

target_names = ["Cluster 0","Cluster 1","Cluster 2"]

pca = PCA(n_components=2, random_state = 453)
X_r = pca.fit(X).transform(X)


# Percentage of variance explained for each components
print('Explained variance ratio (first two components): %s' % str(pca.
 ↪explained_variance_ratio_))

# Plotting the data
plt.figure()
plt.figure(figsize=(12,8))
colors = ['navy', 'turquoise', 'darkorange']
lw = 2


for color, i, target_name in zip(colors, [0, 1, 2], target_names):
    plt.scatter(X_r[y_num == i, 0], X_r[y_num == i, 1], color=color, alpha=.8,␣
 ↪lw=lw,label=target_name)

plt.legend(loc='best', shadow=False, scatterpoints=1)
plt.legend(bbox_to_anchor=(1.05, 1), loc=2, borderaxespad=0.6)
plt.title('K Means Cluster')
plt.xlabel('Balance')
plt.ylabel('Duration')
plt.show()
```

```
Explained variance ratio (first two components): [0.99181208 0.00709196]
```

```
<Figure size 640x480 with 0 Axes>
```




[27]:
```python
pca = PCA(n_components=2)
X_pca = pca.fit_transform(X)

# Get the feature names
feature_names = X.columns

# Get the weights of the original features for the first two principal␣
↪components
component_weights = pd.DataFrame(pca.components_, columns=feature_names[:])

# Calculate the percentage contribution of each feature for each component
total_weights = component_weights.abs().sum(axis=1)
component_weights_percentages = (component_weights.abs() / total_weights[:,␣
↪None]) * 100

# Print the weights as percentages for the first two principal components
print("Weights as percentages for the first two principal components:")
print(component_weights_percentages.iloc[0])
print(component_weights_percentages.iloc[1])
```

```
Weights as percentages for the first two principal components:
age                0.244535
job                0.076834
marital            0.011247
```

```
education        0.000050
default          0.003825
balance          0.000090
housing          0.059191
loan             0.008003
contact          0.210774
day              0.747683
month            0.095474
duration         0.000077
campaign         0.263826
pdays           96.005207
previous         1.004962
poutcome         0.814059
deposit          0.031941
cluster_label    0.422221
Name: 0, dtype: float64
age             91.351579
job              0.703089
marital          2.113954
education        0.694859
default          0.021437
balance          0.023215
housing          0.782810
loan             0.051490
contact          0.156286
day              2.084874
month            1.160765
duration         0.001886
campaign         0.007389
pdays            0.213653
previous         0.253901
poutcome         0.113646
deposit          0.077356
cluster_label    0.187809
Name: 1, dtype: float64
```

[40]:
```
df = pd.read_csv(r"C:\Users\PC\Downloads\bank.csv")
```

[41]:
```
df.head()
```

[41]:
```
   age           job  marital  education default  balance housing loan  \
0   58    management  married   tertiary      no     2143     yes   no
1   44    technician   single  secondary      no       29     yes   no
2   33  entrepreneur  married  secondary      no        2     yes  yes
3   47   blue-collar  married    unknown      no     1506     yes   no
4   33       unknown   single    unknown      no        1      no   no
```

```
  contact  day month  duration  campaign  pdays  previous poutcome deposit
0  unknown    5   may       261         1     -1         0  unknown      no
1  unknown    5   may       151         1     -1         0  unknown      no
2  unknown    5   may        76         1     -1         0  unknown      no
3  unknown    5   may        92         1     -1         0  unknown      no
4  unknown    5   may       198         1     -1         0  unknown      no
```

[42]:
```python
from sklearn.preprocessing import LabelEncoder

# Assuming your data is stored in a pandas DataFrame called 'df'
label_encoder = LabelEncoder()

# Iterate over each column
for col in df.columns:
    # Check if the column contains non-numerical values
    if df[col].dtype == 'object':
        # Apply label encoding
        df[col] = label_encoder.fit_transform(df[col])

# 'data' now contains numerical values for non-numerical columns
```

[43]:
```python
df.head()
```

[43]:
```
   age  job  marital  education  default  balance  housing  loan  contact  \
0   58    4        1          2        0     2143        1     0        2
1   44    9        2          1        0       29        1     0        2
2   33    2        1          1        0        2        1     1        2
3   47    1        1          3        0     1506        1     0        2
4   33   11        2          3        0        1        0     0        2

   day  month  duration  campaign  pdays  previous  poutcome  deposit
0    5      8       261         1     -1         0         3        0
1    5      8       151         1     -1         0         3        0
2    5      8        76         1     -1         0         3        0
3    5      8        92         1     -1         0         3        0
4    5      8       198         1     -1         0         3        0
```

[44]:
```python
# Separate the target label from the features
y = df['deposit']
X = df.drop('deposit', axis=1)

# 'X' contains the features (all columns except the target label)
# 'y' contains the target label column
```

[45]:
```python
y.head(
)
```

[45]:
```
0    0
1    0
2    0
3    0
4    0
Name: deposit, dtype: int32
```

[46]:
```python
X.head(
)
```

[46]:
```
   age  job  marital  education  default  balance  housing  loan  contact  \
0   58    4        1          2        0     2143        1     0        2
1   44    9        2          1        0       29        1     0        2
2   33    2        1          1        0        2        1     1        2
3   47    1        1          3        0     1506        1     0        2
4   33   11        2          3        0        1        0     0        2

   day  month  duration  campaign  pdays  previous  poutcome
0    5      8       261         1     -1         0         3
1    5      8       151         1     -1         0         3
2    5      8        76         1     -1         0         3
3    5      8        92         1     -1         0         3
4    5      8       198         1     -1         0         3
```

[55]:
```python
from sklearn.preprocessing import MinMaxScaler

# Create a scaler object
scaler = MinMaxScaler()

# Fit the scaler on the features
scaler.fit(X)

# Transform the features to the scaled representation
X_scaled = scaler.transform(X)
import pandas as pd

# Assuming your scaled data is stored in 'X_scaled'
scaled_df = pd.DataFrame(X_scaled, columns=X.columns)  # Convert to DataFrame
 ↪with column names

scaled_df.head() # Print the first few rows of the scaled data frame
```

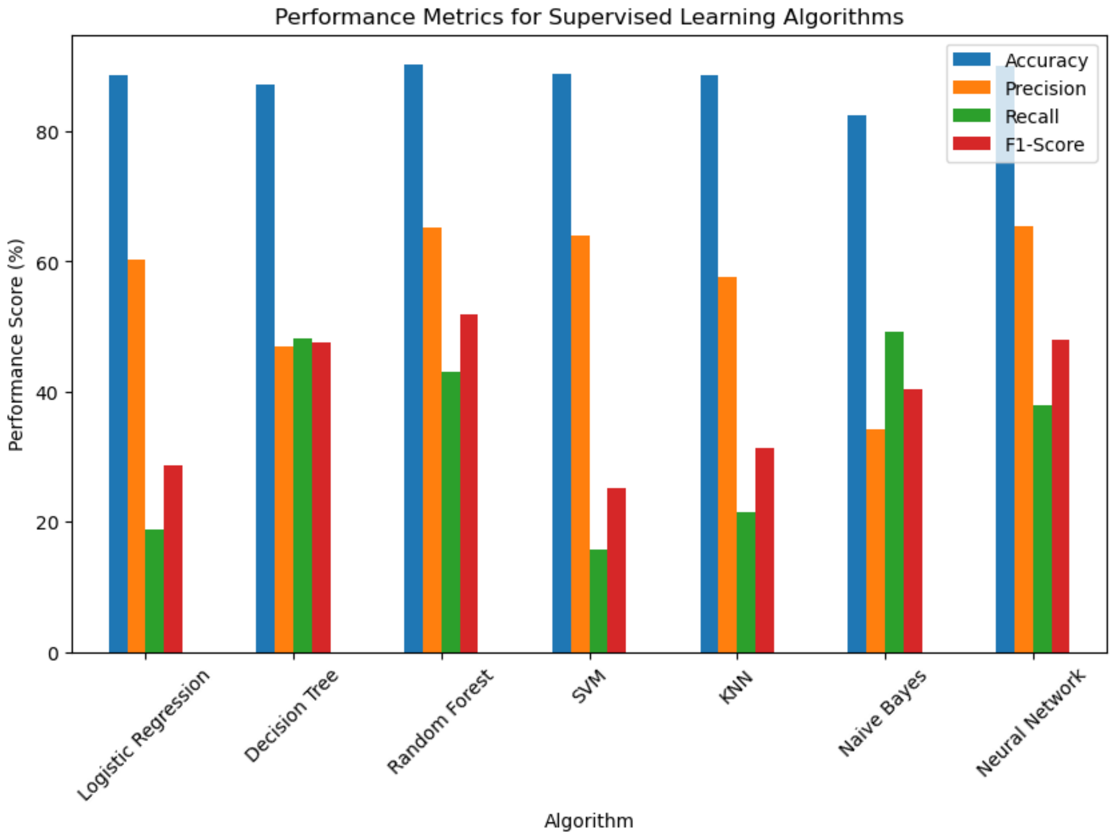
[55]:
```
        age       job  marital  education  default   balance  housing  loan  \
0  0.519481  0.363636      0.5   0.666667      0.0  0.092259      1.0   0.0
1  0.337662  0.818182      1.0   0.333333      0.0  0.073067      1.0   0.0
2  0.194805  0.181818      0.5   0.333333      0.0  0.072822      1.0   1.0
3  0.376623  0.090909      0.5   1.000000      0.0  0.086476      1.0   0.0
```

```
4  0.194805  1.000000      1.0   1.000000      0.0  0.072812      0.0   0.0

   contact       day     month  duration  campaign  pdays  previous  poutcome
0      1.0  0.133333  0.727273  0.053070       0.0    0.0       0.0       1.0
1      1.0  0.133333  0.727273  0.030704       0.0    0.0       0.0       1.0
2      1.0  0.133333  0.727273  0.015453       0.0    0.0       0.0       1.0
3      1.0  0.133333  0.727273  0.018707       0.0    0.0       0.0       1.0
4      1.0  0.133333  0.727273  0.040260       0.0    0.0       0.0       1.0
```

[58]:

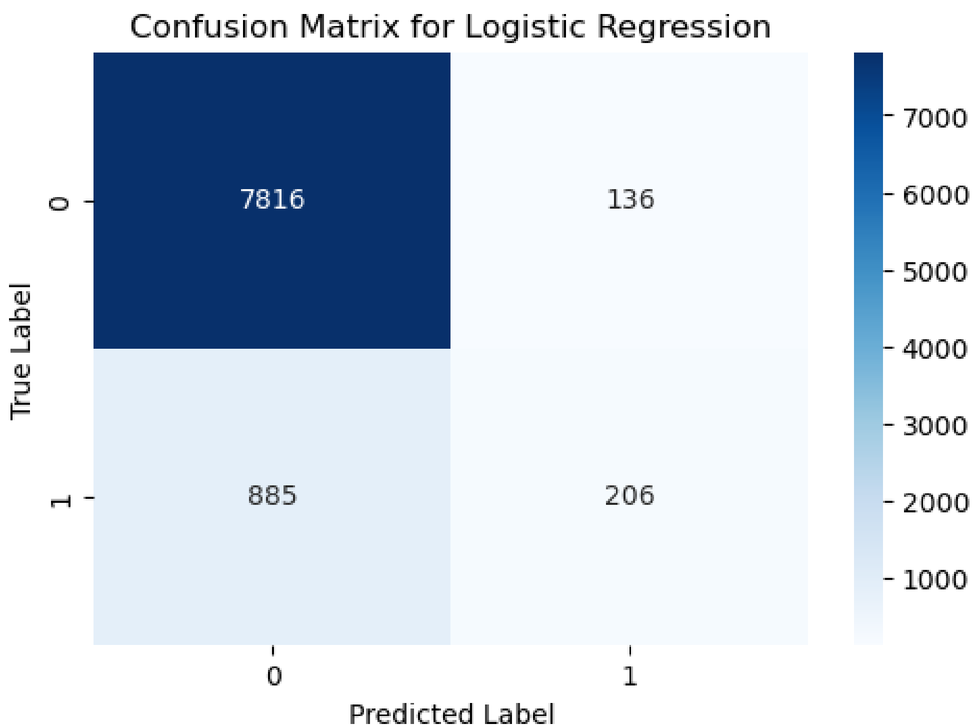
```python
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import MinMaxScaler
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.svm import SVC
from sklearn.neighbors import KNeighborsClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.neural_network import MLPClassifier
from sklearn.metrics import accuracy_score, precision_score, recall_score,␣
 ↪f1_score
import matplotlib.pyplot as plt

# Assuming your scaled features are stored in 'X_scaled' and target label in 'y'
# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X_scaled, y, test_size=0.2,␣
 ↪random_state=42)

# Define a list of algorithms
algorithms = [
    ("Logistic Regression", LogisticRegression()),
    ("Decision Tree", DecisionTreeClassifier()),
    ("Random Forest", RandomForestClassifier()),
    ("SVM", SVC()),
    ("KNN", KNeighborsClassifier()),
    ("Naive Bayes", GaussianNB()),
    ("Neural Network", MLPClassifier()),
]

# Initialize lists to store performance metrics
accuracy_scores = []
precision_scores = []
recall_scores = []
f1_scores = []

# Iterate over each algorithm, fit the model, and calculate performance metrics
for name, algorithm in algorithms:
```

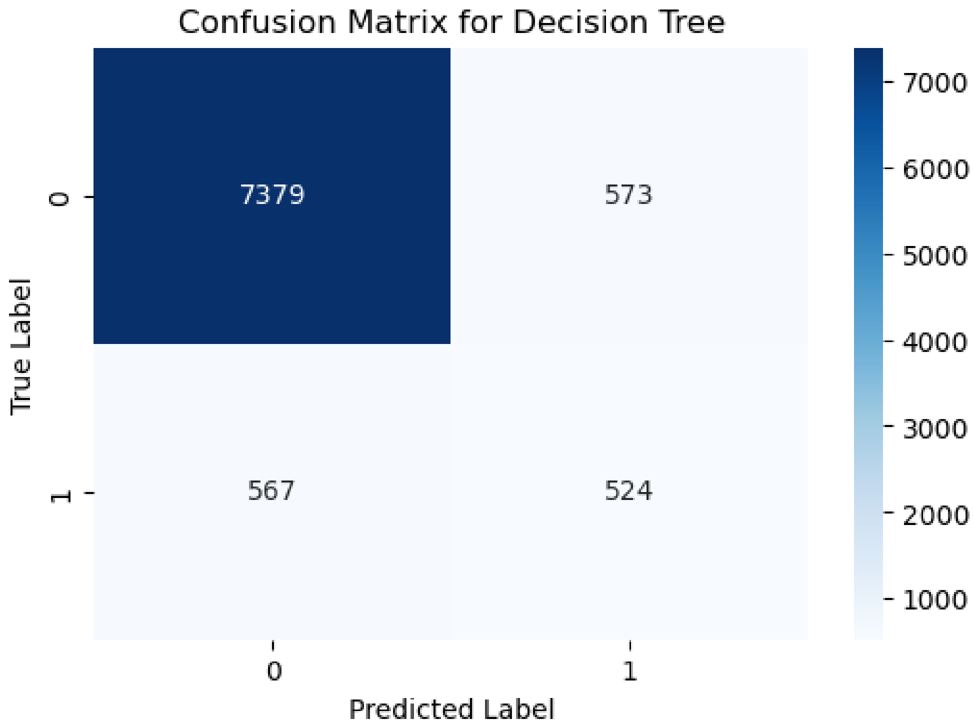
```
    model = algorithm
    model.fit(X_train, y_train)
    y_pred = model.predict(X_test)

    # Calculate performance metrics
    accuracy = accuracy_score(y_test, y_pred)
    precision = precision_score(y_test, y_pred)
    recall = recall_score(y_test, y_pred)
    f1 = f1_score(y_test, y_pred)

    # Append performance metrics to the respective lists
    accuracy_scores.append(accuracy)
    precision_scores.append(precision)
    recall_scores.append(recall)
    f1_scores.append(f1)

# Create a dataframe to store the performance scores
performance_df = pd.DataFrame({
    "Algorithm": [name for name, _ in algorithms],
    "Accuracy": accuracy_scores,
    "Precision": precision_scores,
    "Recall": recall_scores,
    "F1-Score": f1_scores
})

# Convert performance scores to percentages
performance_df["Accuracy"] *= 100
performance_df["Precision"] *= 100
performance_df["Recall"] *= 100
performance_df["F1-Score"] *= 100

# Plot the performance metrics in a column chart
performance_df.plot(x="Algorithm", kind="bar", figsize=(10, 6), rot=45)
plt.ylabel("Performance Score (%)")
plt.title("Performance Metrics for Supervised Learning Algorithms")
plt.show()
```

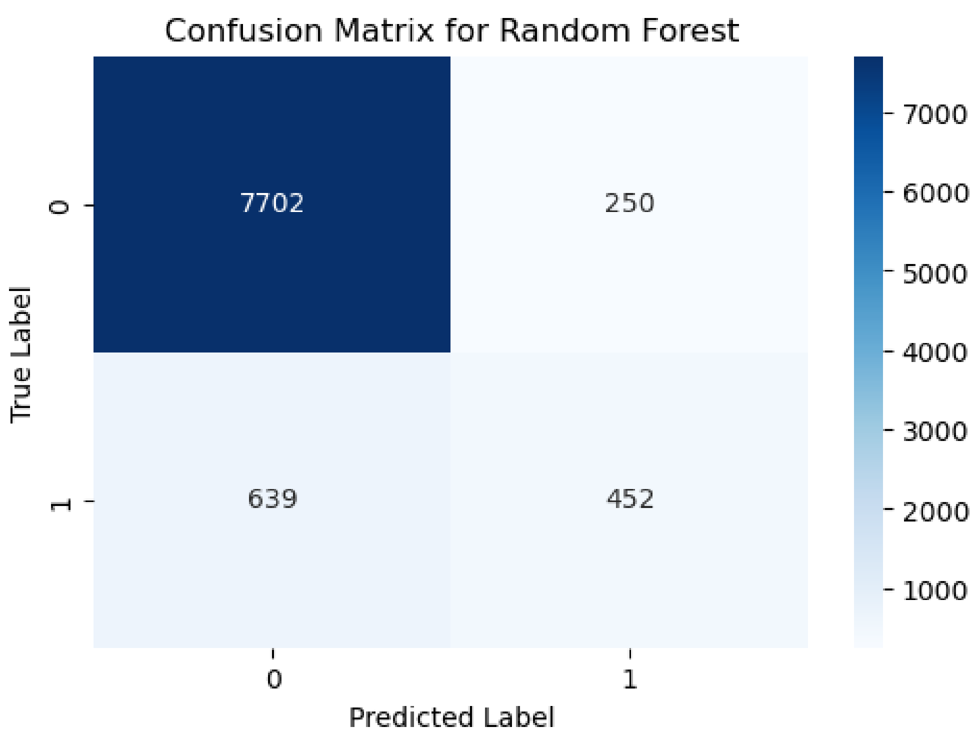


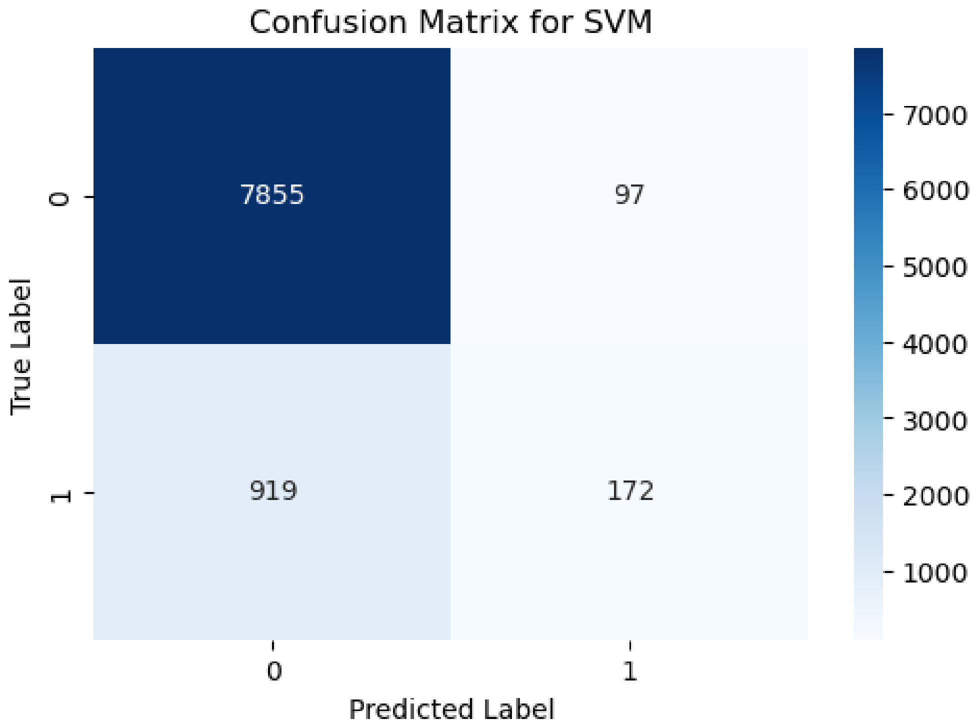

[59]:
```python
# Define a list of algorithms
algorithms = [
    ("Logistic Regression", LogisticRegression()),
    ("Decision Tree", DecisionTreeClassifier()),
    ("Random Forest", RandomForestClassifier()),
    ("SVM", SVC()),
    ("KNN", KNeighborsClassifier()),
    ("Naive Bayes", GaussianNB()),
    ("Neural Network", MLPClassifier()),
]

# Iterate over each algorithm, fit the model, and compute the confusion matrix
for name, algorithm in algorithms:
    model = algorithm
    model.fit(X_train, y_train)
    y_pred = model.predict(X_test)

    # Compute the confusion matrix
    cm = confusion_matrix(y_test, y_pred)
```

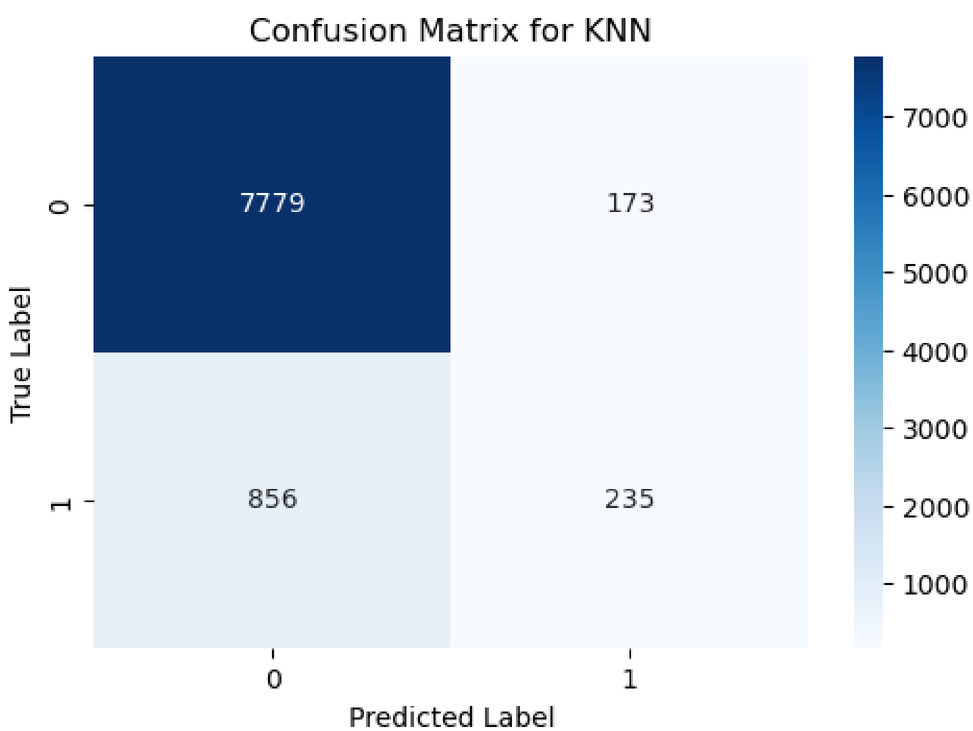
```python
# Plot the confusion matrix
plt.figure(figsize=(6, 4))
sns.heatmap(cm, annot=True, fmt="d", cmap="Blues")
plt.title(f"Confusion Matrix for {name}")
plt.xlabel("Predicted Label")
plt.ylabel("True Label")
plt.show()
```

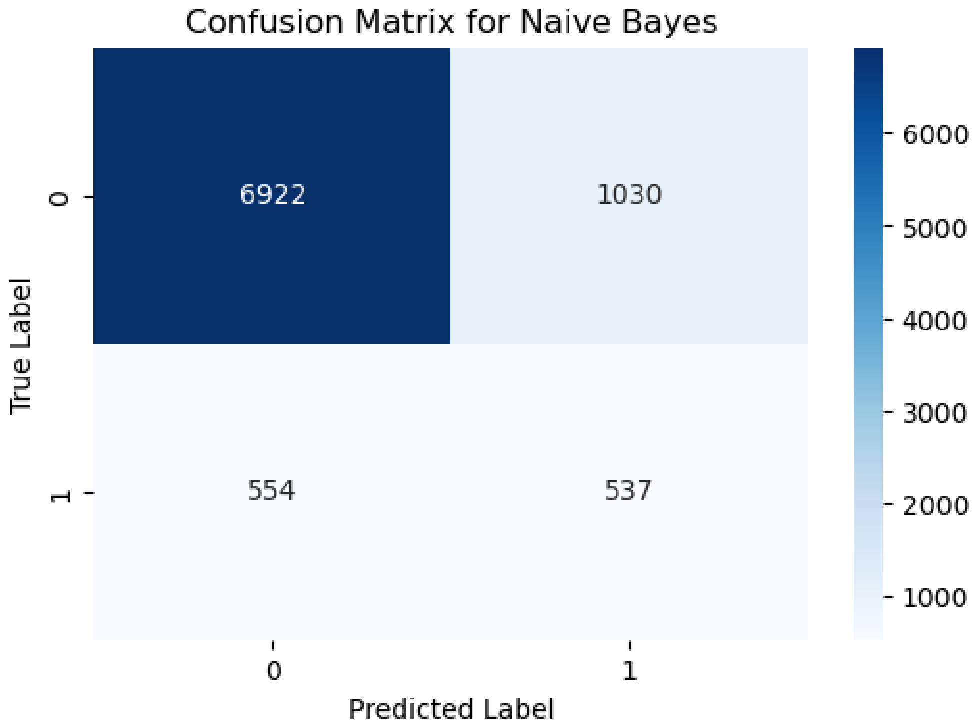


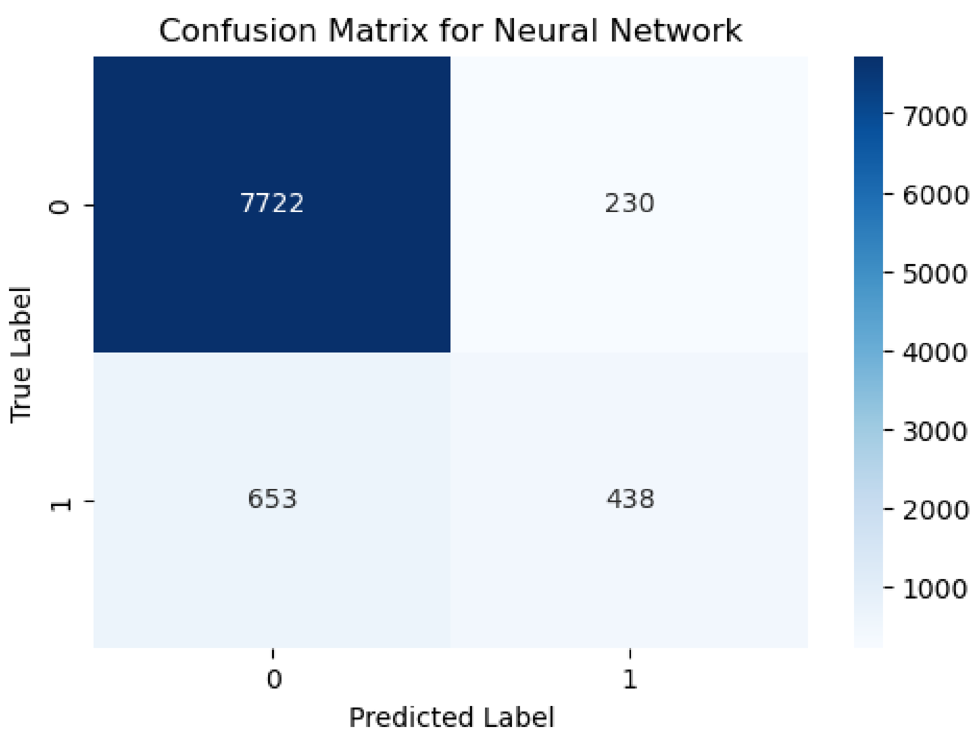

Confusion Matrix for Decision Tree
7379
573
567
524
True Label
Predicted Label
0
1
0
1
7000
6000
5000
4000
3000
2000
1000


Confusion Matrix for Random Forest
7702
250
639
452
True Label
Predicted Label
0
1
0
1
7000
6000
5000
4000
3000
2000
1000


Confusion Matrix for SVM
7855
97
919
172
True Label
Predicted Label
0
1
0
1
7000
6000
5000
4000
3000
2000
1000


Confusion Matrix for KNN
7779
173
856
235
True Label
Predicted Label
0
1
0
1
7000
6000
5000
4000
3000
2000
1000


Confusion Matrix for Naive Bayes
6922
1030
554
537
True Label
Predicted Label
0
1
0
1
6000
5000
4000
3000
2000
1000


Confusion Matrix for Neural Network
7722
230
653
438
True Label
Predicted Label
0
1
0
1
7000
6000
5000
4000
3000
2000
1000

[63]:
```
pip install hide_code
```

```
Collecting hide_codeNote: you may need to restart the kernel to use updated
packages.

  Downloading hide_code-0.7.0-py3-none-any.whl (67 kB)
     -------------------------------------- 67.9/67.9 kB 915.7 kB/s eta 0:00:00
Collecting pdfkit<2.0.0,>=1.0.0
  Downloading pdfkit-1.0.0-py3-none-any.whl (12 kB)
Requirement already satisfied: notebook<7.0.0,>=6.4.12 in
c:\users\pc\anaconda3\lib\site-packages (from hide_code) (6.4.12)
Requirement already satisfied: jupyter<2.0.0,>=1.0.0 in
c:\users\pc\anaconda3\lib\site-packages (from hide_code) (1.0.0)
Requirement already satisfied: qtconsole in c:\users\pc\anaconda3\lib\site-
packages (from jupyter<2.0.0,>=1.0.0->hide_code) (5.2.2)
Requirement already satisfied: ipykernel in c:\users\pc\anaconda3\lib\site-
packages (from jupyter<2.0.0,>=1.0.0->hide_code) (6.15.2)
Requirement already satisfied: nbconvert in c:\users\pc\anaconda3\lib\site-
packages (from jupyter<2.0.0,>=1.0.0->hide_code) (6.4.4)
Requirement already satisfied: ipywidgets in c:\users\pc\anaconda3\lib\site-
packages (from jupyter<2.0.0,>=1.0.0->hide_code) (7.6.5)
Requirement already satisfied: jupyter-console in
c:\users\pc\anaconda3\lib\site-packages (from jupyter<2.0.0,>=1.0.0->hide_code)
(6.4.3)
Requirement already satisfied: pyzmq>=17 in c:\users\pc\anaconda3\lib\site-
packages (from notebook<7.0.0,>=6.4.12->hide_code) (23.2.0)
Requirement already satisfied: nest-asyncio>=1.5 in
c:\users\pc\anaconda3\lib\site-packages (from
notebook<7.0.0,>=6.4.12->hide_code) (1.5.5)
Requirement already satisfied: jinja2 in c:\users\pc\anaconda3\lib\site-packages
(from notebook<7.0.0,>=6.4.12->hide_code) (2.11.3)
Requirement already satisfied: Send2Trash>=1.8.0 in
c:\users\pc\anaconda3\lib\site-packages (from
notebook<7.0.0,>=6.4.12->hide_code) (1.8.0)
Requirement already satisfied: nbformat in c:\users\pc\anaconda3\lib\site-
packages (from notebook<7.0.0,>=6.4.12->hide_code) (5.5.0)
Requirement already satisfied: jupyter-core>=4.6.1 in
c:\users\pc\anaconda3\lib\site-packages (from
notebook<7.0.0,>=6.4.12->hide_code) (4.11.1)
Requirement already satisfied: jupyter-client>=5.3.4 in
c:\users\pc\anaconda3\lib\site-packages (from
notebook<7.0.0,>=6.4.12->hide_code) (7.3.4)
Requirement already satisfied: ipython-genutils in
c:\users\pc\anaconda3\lib\site-packages (from
notebook<7.0.0,>=6.4.12->hide_code) (0.2.0)
Requirement already satisfied: tornado>=6.1 in c:\users\pc\anaconda3\lib\site-
packages (from notebook<7.0.0,>=6.4.12->hide_code) (6.1)
Requirement already satisfied: terminado>=0.8.3 in
```

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c:\users\pc\anaconda3\lib\site-packages (from
notebook<7.0.0,>=6.4.12->hide_code) (0.13.1)
Requirement already satisfied: prometheus-client in
c:\users\pc\anaconda3\lib\site-packages (from
notebook<7.0.0,>=6.4.12->hide_code) (0.14.1)
Requirement already satisfied: argon2-cffi in c:\users\pc\anaconda3\lib\site-
packages (from notebook<7.0.0,>=6.4.12->hide_code) (21.3.0)
Requirement already satisfied: traitlets>=4.2.1 in
c:\users\pc\anaconda3\lib\site-packages (from
notebook<7.0.0,>=6.4.12->hide_code) (5.1.1)
Requirement already satisfied: python-dateutil>=2.8.2 in
c:\users\pc\anaconda3\lib\site-packages (from jupyter-
client>=5.3.4->notebook<7.0.0,>=6.4.12->hide_code) (2.8.2)
Requirement already satisfied: entrypoints in c:\users\pc\anaconda3\lib\site-
packages (from jupyter-client>=5.3.4->notebook<7.0.0,>=6.4.12->hide_code) (0.4)
Requirement already satisfied: pywin32>=1.0 in c:\users\pc\anaconda3\lib\site-
packages (from jupyter-core>=4.6.1->notebook<7.0.0,>=6.4.12->hide_code) (302)
Requirement already satisfied: defusedxml in c:\users\pc\anaconda3\lib\site-
packages (from nbconvert->jupyter<2.0.0,>=1.0.0->hide_code) (0.7.1)
Requirement already satisfied: pygments>=2.4.1 in
c:\users\pc\anaconda3\lib\site-packages (from
nbconvert->jupyter<2.0.0,>=1.0.0->hide_code) (2.11.2)
Requirement already satisfied: testpath in c:\users\pc\anaconda3\lib\site-
packages (from nbconvert->jupyter<2.0.0,>=1.0.0->hide_code) (0.6.0)
Requirement already satisfied: mistune<2,>=0.8.1 in
c:\users\pc\anaconda3\lib\site-packages (from
nbconvert->jupyter<2.0.0,>=1.0.0->hide_code) (0.8.4)
Requirement already satisfied: bleach in c:\users\pc\anaconda3\lib\site-packages
(from nbconvert->jupyter<2.0.0,>=1.0.0->hide_code) (4.1.0)
Requirement already satisfied: nbclient<0.6.0,>=0.5.0 in
c:\users\pc\anaconda3\lib\site-packages (from
nbconvert->jupyter<2.0.0,>=1.0.0->hide_code) (0.5.13)
Requirement already satisfied: beautifulsoup4 in c:\users\pc\anaconda3\lib\site-
packages (from nbconvert->jupyter<2.0.0,>=1.0.0->hide_code) (4.11.1)
Requirement already satisfied: pandocfilters>=1.4.1 in
c:\users\pc\anaconda3\lib\site-packages (from
nbconvert->jupyter<2.0.0,>=1.0.0->hide_code) (1.5.0)
Requirement already satisfied: jupyterlab-pygments in
c:\users\pc\anaconda3\lib\site-packages (from
nbconvert->jupyter<2.0.0,>=1.0.0->hide_code) (0.1.2)
Requirement already satisfied: MarkupSafe>=0.23 in
c:\users\pc\anaconda3\lib\site-packages (from
jinja2->notebook<7.0.0,>=6.4.12->hide_code) (2.0.1)
Requirement already satisfied: jsonschema>=2.6 in
c:\users\pc\anaconda3\lib\site-packages (from
nbformat->notebook<7.0.0,>=6.4.12->hide_code) (4.16.0)
Requirement already satisfied: fastjsonschema in c:\users\pc\anaconda3\lib\site-
packages (from nbformat->notebook<7.0.0,>=6.4.12->hide_code) (2.16.2)
```

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Requirement already satisfied: pywinpty>=1.1.0 in
c:\users\pc\anaconda3\lib\site-packages (from
terminado>=0.8.3->notebook<7.0.0,>=6.4.12->hide_code) (2.0.2)
Requirement already satisfied: argon2-cffi-bindings in
c:\users\pc\anaconda3\lib\site-packages (from
argon2-cffi->notebook<7.0.0,>=6.4.12->hide_code) (21.2.0)
Requirement already satisfied: ipython>=7.23.1 in
c:\users\pc\anaconda3\lib\site-packages (from
ipykernel->jupyter<2.0.0,>=1.0.0->hide_code) (7.31.1)
Requirement already satisfied: debugpy>=1.0 in c:\users\pc\anaconda3\lib\site-
packages (from ipykernel->jupyter<2.0.0,>=1.0.0->hide_code) (1.5.1)
Requirement already satisfied: matplotlib-inline>=0.1 in
c:\users\pc\anaconda3\lib\site-packages (from
ipykernel->jupyter<2.0.0,>=1.0.0->hide_code) (0.1.6)
Requirement already satisfied: psutil in c:\users\pc\anaconda3\lib\site-packages
(from ipykernel->jupyter<2.0.0,>=1.0.0->hide_code) (5.9.0)
Requirement already satisfied: packaging in c:\users\pc\anaconda3\lib\site-
packages (from ipykernel->jupyter<2.0.0,>=1.0.0->hide_code) (21.3)
Requirement already satisfied: jupyterlab-widgets>=1.0.0 in
c:\users\pc\anaconda3\lib\site-packages (from
ipywidgets->jupyter<2.0.0,>=1.0.0->hide_code) (1.0.0)
Requirement already satisfied: widgetsnbextension~=3.5.0 in
c:\users\pc\anaconda3\lib\site-packages (from
ipywidgets->jupyter<2.0.0,>=1.0.0->hide_code) (3.5.2)
Requirement already satisfied: prompt-toolkit!=3.0.0,!=3.0.1,<3.1.0,>=2.0.0 in
c:\users\pc\anaconda3\lib\site-packages (from jupyter-
console->jupyter<2.0.0,>=1.0.0->hide_code) (3.0.20)
Requirement already satisfied: qtpy in c:\users\pc\anaconda3\lib\site-packages
(from qtconsole->jupyter<2.0.0,>=1.0.0->hide_code) (2.2.0)
Requirement already satisfied: colorama in c:\users\pc\anaconda3\lib\site-
packages (from ipython>=7.23.1->ipykernel->jupyter<2.0.0,>=1.0.0->hide_code)
(0.4.5)
Requirement already satisfied: decorator in c:\users\pc\anaconda3\lib\site-
packages (from ipython>=7.23.1->ipykernel->jupyter<2.0.0,>=1.0.0->hide_code)
(5.1.1)
Requirement already satisfied: jedi>=0.16 in c:\users\pc\anaconda3\lib\site-
packages (from ipython>=7.23.1->ipykernel->jupyter<2.0.0,>=1.0.0->hide_code)
(0.18.1)
Requirement already satisfied: setuptools>=18.5 in
c:\users\pc\anaconda3\lib\site-packages (from
ipython>=7.23.1->ipykernel->jupyter<2.0.0,>=1.0.0->hide_code) (63.4.1)
Requirement already satisfied: pickleshare in c:\users\pc\anaconda3\lib\site-
packages (from ipython>=7.23.1->ipykernel->jupyter<2.0.0,>=1.0.0->hide_code)
(0.7.5)
Requirement already satisfied: backcall in c:\users\pc\anaconda3\lib\site-
packages (from ipython>=7.23.1->ipykernel->jupyter<2.0.0,>=1.0.0->hide_code)
(0.2.0)
Requirement already satisfied: attrs>=17.4.0 in c:\users\pc\anaconda3\lib\site-
```

```
packages (from jsonschema>=2.6->nbformat->notebook<7.0.0,>=6.4.12->hide_code)
(21.4.0)
Requirement already satisfied: pyrsistent!=0.17.0,!=0.17.1,!=0.17.2,>=0.14.0 in
c:\users\pc\anaconda3\lib\site-packages (from
jsonschema>=2.6->nbformat->notebook<7.0.0,>=6.4.12->hide_code) (0.18.0)
Requirement already satisfied: wcwidth in c:\users\pc\anaconda3\lib\site-
packages (from prompt-toolkit!=3.0.0,!=3.0.1,<3.1.0,>=2.0.0->jupyter-
console->jupyter<2.0.0,>=1.0.0->hide_code) (0.2.5)
Requirement already satisfied: six>=1.5 in c:\users\pc\anaconda3\lib\site-
packages (from python-dateutil>=2.8.2->jupyter-
client>=5.3.4->notebook<7.0.0,>=6.4.12->hide_code) (1.16.0)
Requirement already satisfied: cffi>=1.0.1 in c:\users\pc\anaconda3\lib\site-
packages (from argon2-cffi-
bindings->argon2-cffi->notebook<7.0.0,>=6.4.12->hide_code) (1.15.1)
Requirement already satisfied: soupsieve>1.2 in c:\users\pc\anaconda3\lib\site-
packages (from beautifulsoup4->nbconvert->jupyter<2.0.0,>=1.0.0->hide_code)
(2.3.1)
Requirement already satisfied: webencodings in c:\users\pc\anaconda3\lib\site-
packages (from bleach->nbconvert->jupyter<2.0.0,>=1.0.0->hide_code) (0.5.1)
Requirement already satisfied: pyparsing!=3.0.5,>=2.0.2 in
c:\users\pc\anaconda3\lib\site-packages (from
packaging->ipykernel->jupyter<2.0.0,>=1.0.0->hide_code) (3.0.9)
Requirement already satisfied: pycparser in c:\users\pc\anaconda3\lib\site-
packages (from cffi>=1.0.1->argon2-cffi-
bindings->argon2-cffi->notebook<7.0.0,>=6.4.12->hide_code) (2.21)
Requirement already satisfied: parso<0.9.0,>=0.8.0 in
c:\users\pc\anaconda3\lib\site-packages (from
jedi>=0.16->ipython>=7.23.1->ipykernel->jupyter<2.0.0,>=1.0.0->hide_code)
(0.8.3)
Installing collected packages: pdfkit, hide_code
Successfully installed hide_code-0.7.0 pdfkit-1.0.0
```

[64]:
```
from IPython.display import display, HTML

# Function to hide code cells
def hide_code():
    display(HTML('''
        <script>
            code_show = false;
            function code_toggle() {
                if (code_show) {
                    $('div.input').hide();
                } else {
                    $('div.input').show();
                }
                code_show = !code_show
            }
```

```
            $(document).ready(code_toggle);
        </script>
        <form action="javascript:code_toggle()">
            <input type="submit" value="Click here to toggle code on/off">
        </form>
    '''))

# Call the function to hide code cells
hide_code()
```

<IPython.core.display.HTML object>

[ ]:

```

```