Customer Personality Analysis

Project Introduction

In this project, I employ K-Means and DBSCAN clustering algorithms to conduct a comprehensive Customer Personality Analysis on the provided dataset. By leveraging these algorithms, we aim to identify distinct customer segments based on their behaviors and preferences, allowing for a more targeted marketing approach.

The K-Means algorithm facilitates the partitioning of customers into predefined clusters, while DBSCAN offers the advantage of discovering clusters of varying shapes and densities without the need for prior knowledge of the number of clusters.

I'll evaluate the performance of these models using metrics such as silhouette score ensuring that our analysis not only enhances understanding of customer segments but also provides actionable insights for product modification and marketing strategies.

DataSet Link: https://www.google.com/url?q=https%3A%2F%2Fwww.kaggle.com%2Fdatasets%2Fimakash3011%2Fcustomer-personality-analysis%2Fdata

Literature Survey for Customer Personality Analysis Using Clustering Algorithms

Customer Personality Analysis is essential for businesses aiming to tailor their products and marketing strategies to meet the diverse needs of their customer base. This literature survey examines existing research on customer segmentation, focusing on the application of clustering algorithms like K-Means and DBSCAN. The survey highlights methodologies, findings, challenges, and future directions in the realm of customer analysis.

1. Customer Segmentation Techniques

Traditional Methods: Early segmentation strategies relied heavily on demographic data such as age, gender, and income. Smith (1956) proposed a typology of market segmentation based on demographic factors, which laid the foundation for more complex methods. Behavioral and Psychographic Segmentation: Recent studies emphasize the importance of behavioral (e.g., purchasing patterns) and psychographic (e.g., lifestyle, values) factors in segmentation. For instance, Wedel and Kamakura (2000) highlight that understanding consumer behavior leads to more meaningful segmentation.

2. Clustering Algorithms

K-Means Clustering-K-Means is one of the most commonly used clustering algorithms due to its simplicity and efficiency. It partitions data into K distinct clusters by minimizing the variance within each cluster. DBSCAN (Density-Based Spatial Clustering of Applications with Noise)-identifies clusters based on the density of data points, allowing it to find arbitrarily shaped clusters and handle noise effectively.

3. Model Evaluation Metrics

Silhouette Score: This metric measures how similar an object is to its own cluster compared to other clusters. Rousseeuw (1987) introduced the silhouette coefficient as a way to evaluate the quality of clustering.In this sceanrio we use this approach.

4. Applications in Marketing

Targeted Marketing: Research by Kumar et al. (2013) demonstrates how businesses can leverage clustering to identify high-value customer segments, allowing for more targeted marketing strategies. Product Development: Companies have utilized clustering to inform product development, tailoring offerings to meet the specific needs of identified customer segments (Farris et al., 2010).

DATASET DESCRIPTION

People

ID: Customer's unique identifier Year_Birth: Customer's birth year Education: Customer's education level Marital_Status: Customer's marital status Income: Customer's yearly household income Kidhome: Number of children in customer's household Teenhome: Number of teenagers in customer's household Dt_Customer: Date of customer's enrollment with the company Recency: Number of days since customer's last purchase Complain: 1 if the customer complained in the last 2 years, 0 otherwise

Product

MntWines: Amount spent on wine in last 2 years MntFruits: Amount spent on fruits in last 2 years MntMeatProducts: Amount spent on meat in last 2 years MntFishProducts: Amount spent on fish in last 2 years MntSweetProducts: Amount spent on sweets in last 2 years MntGoldProds: Amount spent on gold in last 2 years

Promotion

NumDealsPurchases: Number of purchases made with a discount AcceptedCmp1: 1 if customer accepted the offer in the 1st campaign, 0 otherwise AcceptedCmp2: 1 if customer accepted the offer in the 2nd campaign, 0 otherwise AcceptedCmp3: 1 if customer accepted the offer in the 3rd campaign, 0 otherwise AcceptedCmp4: 1 if customer accepted the offer in the 4th campaign, 0 otherwise AcceptedCmp5: 1 if customer accepted the offer in the 5th campaign, 0 otherwise Response: 1 if customer accepted the offer in the last campaign, 0 otherwise

Place

NumWebPurchases: Number of purchases made through the company's website NumCatalogPurchases: Number of purchases made using a catalogue NumStorePurchases: Number of purchases made directly in stores NumWebVisitsMonth: Number of visits to company's website in the last month

Target

Need to perform clustering to summarize customer segments

IMPORTING REQUIRED LIBRARIES

```
# Step 1: Import necessary libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import LabelEncoder, OrdinalEncoder, StandardScaler
from sklearn.cluster import KMeans
from google.colab import drive
from datetime import date
from datetime import datetime
from scipy.stats import zscore
from sklearn.metrics import silhouette_score
from sklearn.cluster import DBSCAN
from sklearn.decomposition import PCA

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

```
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

Dataset Description

```
# Step 2: Load the dataset
```

```
df = pd.read_csv("/content/drive/MyDrive/marketing_campaign_(1).csv", sep='\t')

data_prep = df.copy()
```

```
import pandas as pd

# Assuming df is already defined and has 'Year_Birth' and 'Dt_Customer' columns

# Step 1: Calculate Age more accurately
today = pd.to_datetime('today')
# Create a birth date using 1st Jan of Year_Birth
df['Birth_Date'] = pd.to_datetime(df['Year_Birth'].astype(str) + '-01-01')
df['Age'] = (today - df['Birth_Date']).dt.days / 365.25  # Age in years (float)
df['Age'] = df['Age'].astype(int)  # Optional: convert to integer

# Step 2: Convert Dt_Customer to datetime format
df['Dt_Customer'] = pd.to_datetime(df['Dt_Customer'], format='%d-%m-%Y')

# Step 3: Calculate customer tenure in years
df['Years_customer'] = (today - df['Dt_Customer']).dt.days / 365.25
```

```
df.head()
```

	ID	Year_Birth	Education	Marital_Status	Income	Kidhome	Teenhome	Dt_Customer
0	5524	1957	Graduation	Single	58138.0	0	0	2012-09-04
1	2174	1954	Graduation	Single	46344.0	1	1	2014-03-08
2	4141	1965	Graduation	Together	71613.0	0	0	2013-08-21
3	6182	1984	Graduation	Together	26646.0	1	0	2014-02-10
4	5324	1981	PhD	Married	58293.0	1	0	2014-01-19

5 rows × 32 columns

```
# Calculate total expenses and accepted campaign
df['Total_Expenses'] = (df['MntWines'] + df['MntFruits'] + df['MntMeatProducts'] +
                        df['MntFishProducts'] + df['MntSweetProducts'] + df['MntGoldProds'])
```

```
df['Total_Acc_Cmp'] = (df['AcceptedCmp1'] + df['AcceptedCmp2'] + df['AcceptedCmp3'] +
                       df['AcceptedCmp4'] + df['AcceptedCmp5'] + df['Response'])
```

Overview of the Dataset:

```
# Step 5: Explore the dataset
print(df.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2240 entries, 0 to 2239
Data columns (total 34 columns):
 #   Column               Non-Null Count  Dtype
---  ------               --------------  -----
 0   ID                   2240 non-null   int64
 1   Year_Birth           2240 non-null   int64
 2   Education            2240 non-null   object
 3   Marital_Status       2240 non-null   object
 4   Income               2216 non-null   float64
 5   Kidhome              2240 non-null   int64
 6   Teenhome             2240 non-null   int64
 7   Dt_Customer          2240 non-null   datetime64[ns]
 8   Recency              2240 non-null   int64
 9   MntWines             2240 non-null   int64
 10  MntFruits            2240 non-null   int64
 11  MntMeatProducts      2240 non-null   int64
 12  MntFishProducts      2240 non-null   int64
 13  MntSweetProducts     2240 non-null   int64
 14  MntGoldProds         2240 non-null   int64
 15  NumDealsPurchases    2240 non-null   int64
 16  NumWebPurchases      2240 non-null   int64
 17  NumCatalogPurchases  2240 non-null   int64
 18  NumStorePurchases    2240 non-null   int64
 19  NumWebVisitsMonth    2240 non-null   int64
 20  AcceptedCmp3         2240 non-null   int64
 21  AcceptedCmp4         2240 non-null   int64
 22  AcceptedCmp5         2240 non-null   int64
 23  AcceptedCmp1         2240 non-null   int64
 24  AcceptedCmp2         2240 non-null   int64
 25  Complain             2240 non-null   int64
 26  Z_CostContact        2240 non-null   int64
 27  Z_Revenue            2240 non-null   int64
 28  Response             2240 non-null   int64
 29  Birth_Date           2240 non-null   datetime64[ns]
 30  Age                  2240 non-null   int64
 31  Years_customer       2240 non-null   float64
 32  Total_Expenses       2240 non-null   int64
 33  Total_Acc_Cmp        2240 non-null   int64
dtypes: datetime64[ns](2), float64(2), int64(28), object(2)
memory usage: 595.1+ KB
None
```

```
df.describe()
```

	ID	Year_Birth	Income	Kidhome	Teenhome	Dt_Custom
count	2240.000000	2240.000000	2216.000000	2240.000000	2240.000000	22
mean	5592.159821	1968.805804	52247.251354	0.444196	0.506250	2013-07- 10:01:42.857142
min	0.000000	1893.000000	1730.000000	0.000000	0.000000	2012-07- 00:00:
25%	2828.250000	1959.000000	35303.000000	0.000000	0.000000	2013-01- 00:00:
50%	5458.500000	1970.000000	51381.500000	0.000000	0.000000	2013-07- 12:00:
75%	8427.750000	1977.000000	68522.000000	1.000000	1.000000	2013-12- 06:00:
max	11191.000000	1996.000000	666666.000000	2.000000	2.000000	2014-06- 00:00:
std	3246.662198	11.984069	25173.076661	0.538398	0.544538	Na

8 rows × 32 columns

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

```
np.int64(0)
```

```
df.shape
```

```
(2240, 34)
```

```
print(f"Unique IDs: {df['ID'].nunique()}")
```

```
Unique IDs: 2240
```

```
print("Number of unique values in Z_CostContact column:", df['Z_CostContact'].nunique())
print("Number of unique values in Z_Revenue column:", df["Z_Revenue"].nunique())
```

```
Number of unique values in Z_CostContact column: 1
Number of unique values in Z_Revenue column: 1
```

- Observations: 2,240 across 29 columns.
- Missing Values: 24 in the 'income' column.

- Column Types: Mostly numerical; three categorical: 'marital_status', 'education', 'Dt_customer' (to be converted to date).

Duplicates: None detected.

```
# Remove unnecessary columns ('Id' and columns with 1 unique value)
df.drop(['ID', 'Z_CostContact', 'Z_Revenue'], axis=1, inplace=True)
```

```
#string format to a datetime format.
df['Dt_Customer'] = pd.to_datetime(df.Dt_Customer, format="%d-%m-%Y")
latest_date = df['Dt_Customer'].max()
df['Days_is_client'] = (latest_date - df['Dt_Customer']).dt.days
```

```
# Count values in categorical columns
categorical_columns = df.select_dtypes('object')

for column in categorical_columns:
    value_counts = df[column].value_counts()
    print(value_counts)
    print("\n")
```

```
Education
Graduation    1127
PhD            486
Master         370
2n Cycle       203
Basic           54
Name: count, dtype: int64


Marital_Status
Married     864
Together    580
Single      480
Divorced    232
Widow        77
Alone         3
Absurd        2
YOLO          2
Name: count, dtype: int64
```

```
# Standardize 'Marital_Status' into 2 broader groups
df['Marital_Status'] = df['Marital_Status'].replace(['Married', 'Together'], 'Partner')
df['Marital_Status'] = df['Marital_Status'].replace(['Divorced', 'Widow', 'Alone', 'YOLO', '

# Standardize 'Education' into 3 broader groups
df['Education'] = df['Education'].replace(['PhD', 'Master'], 'Postgraduate')
df['Education'] = df['Education'].replace(['2n Cycle', 'Graduation'], 'Graduate')
```

```
df['Education'] = df['Education'].replace(['Basic'], 'Undergraduate')

for column in categorical_columns:
    print(f"Unique values in {column}:")
    print(df[column].unique())
    print("\n")
```

```
Unique values in Education:
['Graduate' 'Postgraduate' 'Undergraduate']


Unique values in Marital_Status:
['Single' 'Partner']
```

```
# Combining columns together to reduce the number of dimensions

df['Kids'] = df['Kidhome'] + df['Teenhome']
df['Expenses'] = df['MntWines'] + df['MntFruits'] + df['MntMeatProducts'] + df['MntFishProdu
df['TotalAcceptedCmp'] = df['AcceptedCmp1'] + df['AcceptedCmp2'] + df['AcceptedCmp3'] + df['
df['TotalNumPurchases'] = df['NumWebPurchases'] + df['NumCatalogPurchases'] + df['NumStorePu


data = df.copy()
df = df[['Education', 'Marital_Status', 'Income', 'Kids', 'Days_is_client', 'Recency', 'Expe
                 'TotalNumPurchases', 'TotalAcceptedCmp', 'Complain', 'Response']]


# Step 6: Handle duplicate values
df.drop_duplicates(inplace=True)

# Remove rows with any missing values (NaN)
df.dropna(inplace=True)

df.shape
```

```
(2031, 11)
```

```
# Categorize columns into three groups based on their data type

binary_columns = [col for col in df.columns if df[col].nunique() == 2]
categorical_columns = [col for col in df.columns if 2 < df[col].nunique() < 10]
numerical_columns = [col for col in df.select_dtypes(include=['number']).columns
                     if col not in binary_columns + categorical_columns]


## Detecting Outliers
import pandas as pd
from scipy import stats
# Calculate the z-scores for each column
z_scores = pd.DataFrame(stats.zscore(df[numerical_columns]), columns=numerical_columns)
```

```
# Generate descriptive statistics for the z-scores
print("Descriptive Statistics for Z-Scores before Outliers Removal")
display(z_scores.describe().round(3))
```

Descriptive Statistics for Z-Scores before Outliers Removal

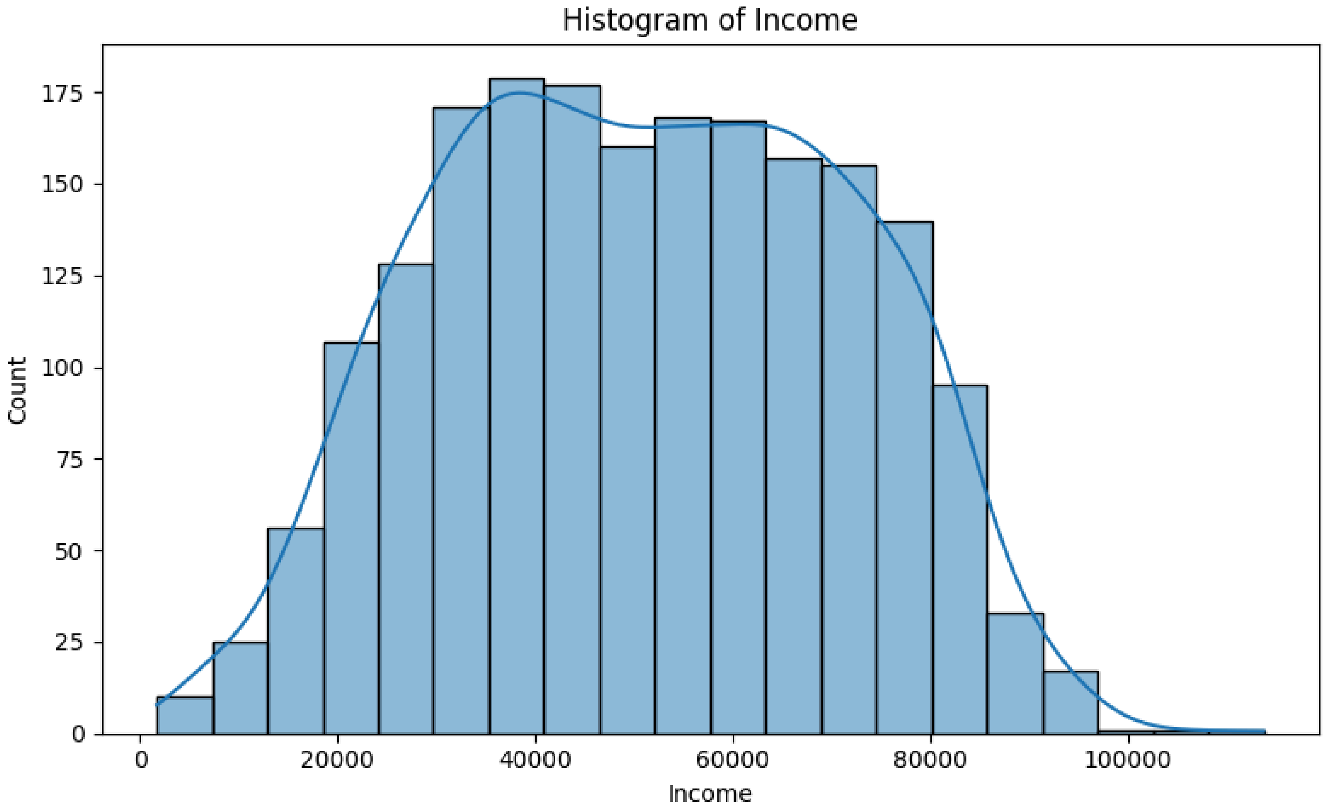
	Income	Days_is_client	Recency	Expenses	TotalNumPurchases
count	2031.000	2031.000	2031.000	2031.000	2031.000
mean	0.000	0.000	0.000	0.000	0.000
std	1.000	1.000	1.000	1.000	1.000
min	-1.984	-1.743	-1.688	-0.999	-1.945
25%	-0.660	-0.863	-0.859	-0.893	-0.900
50%	-0.032	-0.003	0.004	-0.350	0.014
75%	0.634	0.867	0.867	0.729	0.797
max	24.058	1.713	1.730	3.176	3.801

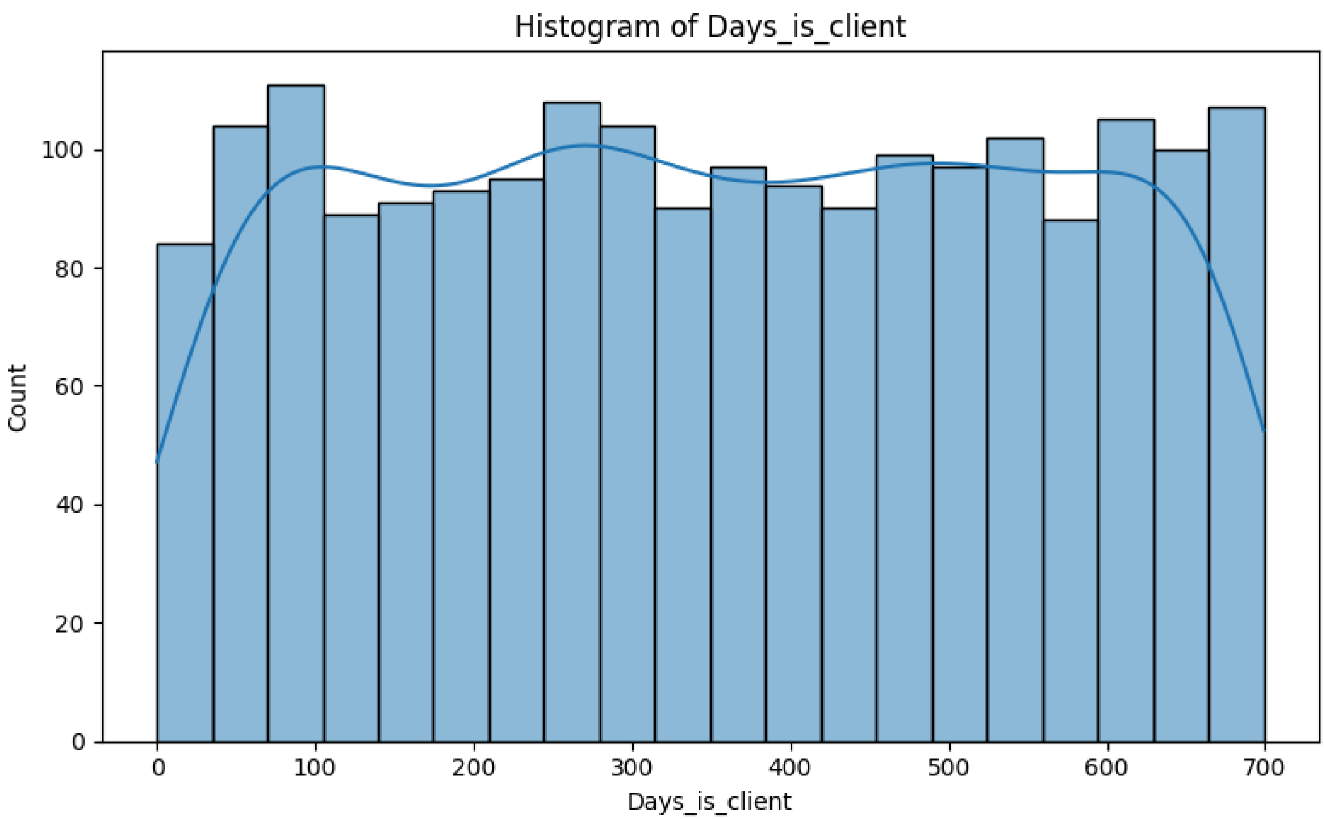
```
import numpy as np
from scipy import stats

# Step 1: Select only numeric columns for z-score calculation
numeric_cols = df.select_dtypes(include=[np.number])

# Step 2: Compute z-scores
z_scores = np.abs(stats.zscore(numeric_cols))

# Step 3: Convert to DataFrame with the same index as df
z_scores_df = pd.DataFrame(z_scores, columns=numeric_cols.columns, index=df.index)

# Step 4: Identify outliers (rows where any z-score > 3)
outliers = z_scores_df[(z_scores_df > 3).any(axis=1)]

# Step 5: Drop the rows from the original df
df = df.drop(outliers.index)
```

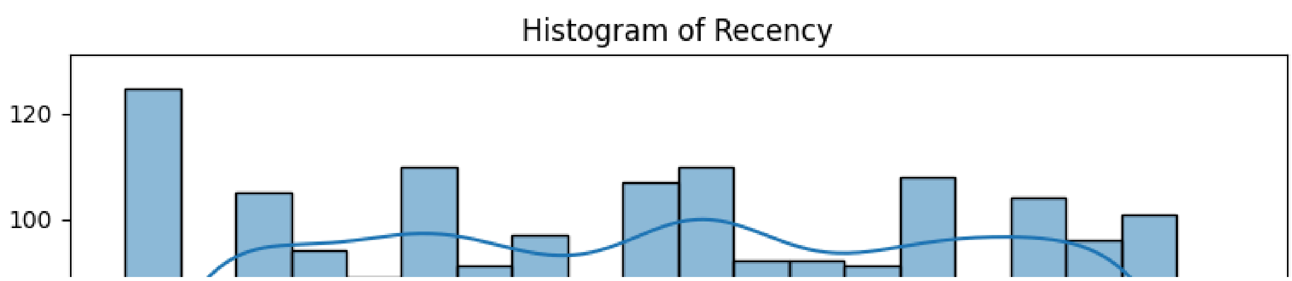
EDA

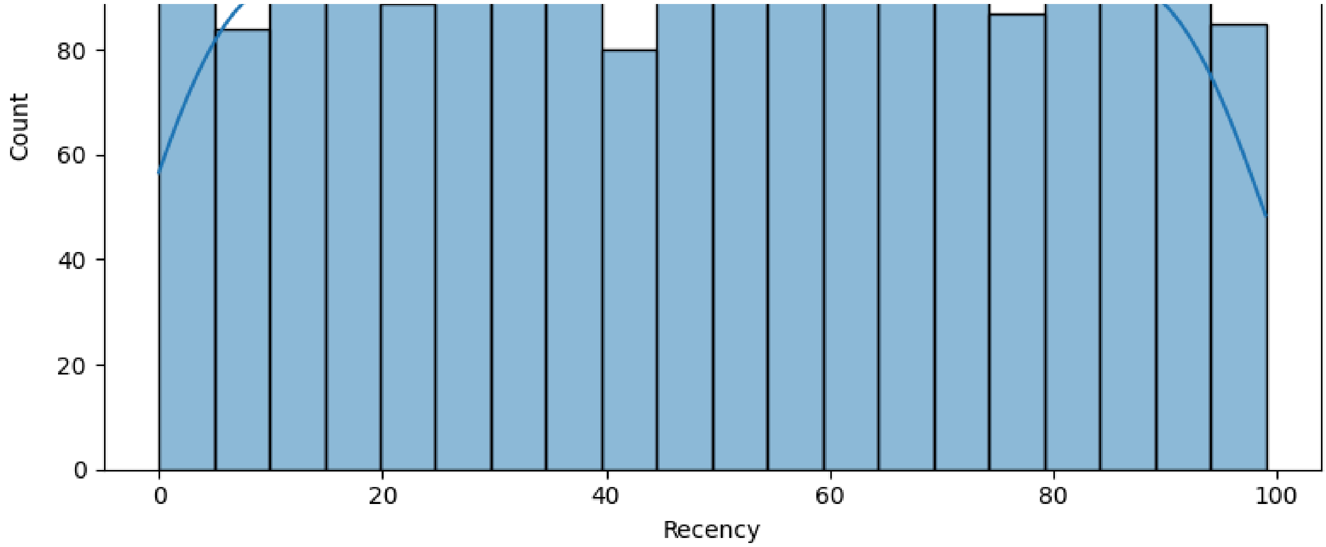
```
# Plot histograms for each numerical column
for column in numerical_columns:

    plt.figure(figsize=(8, 5))
    sns.histplot(data=df, x=column, kde=True, bins=20)
```

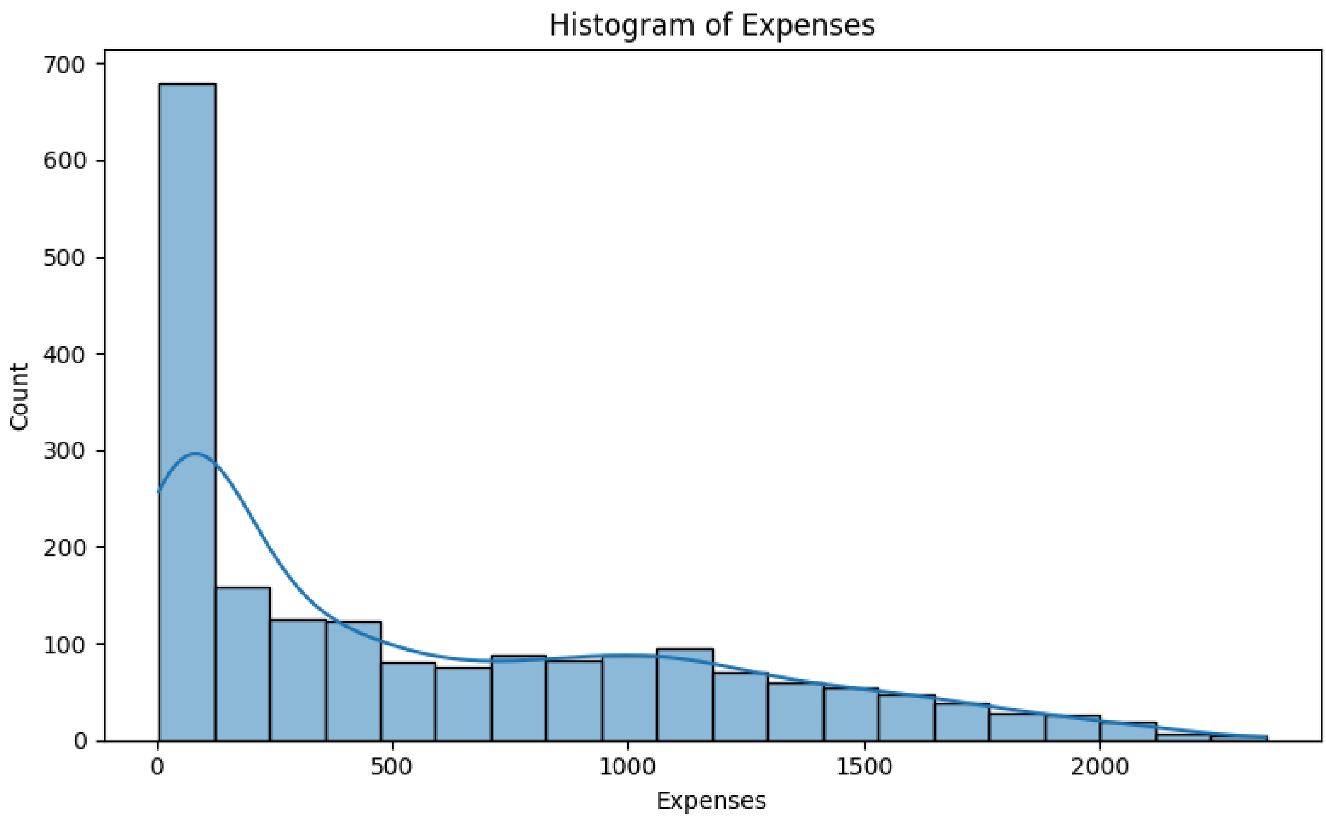
```
        plt.title(f'Histogram of {column}')

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

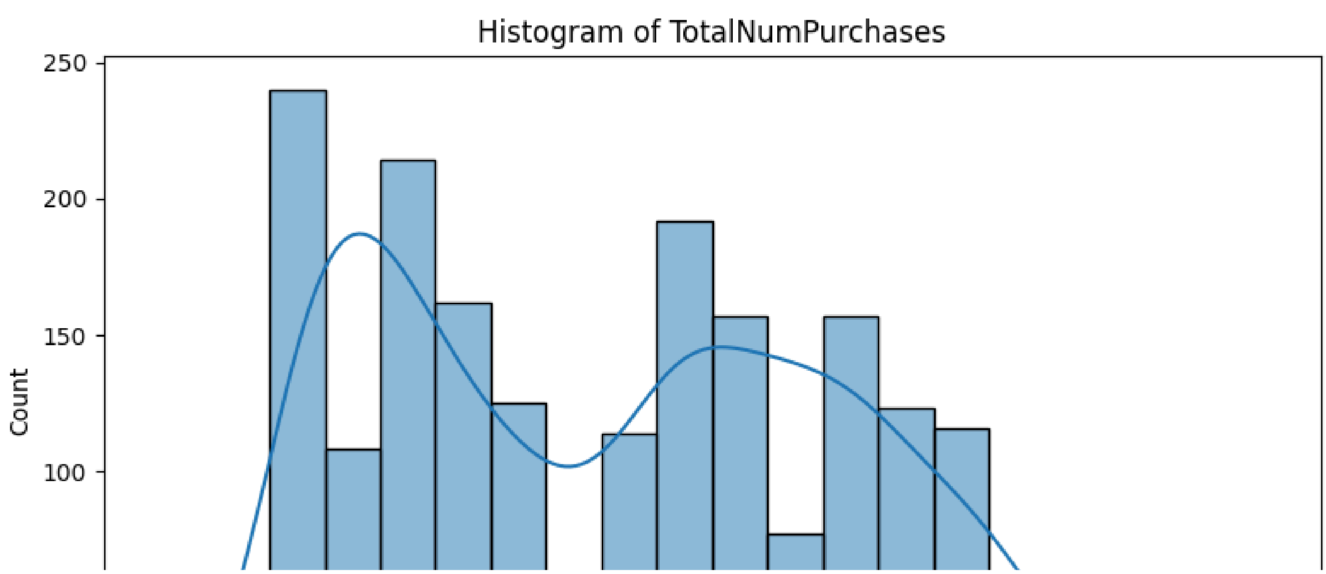

Histogram of Income
Count
Income
0
25
50
75
100
125
150
175
0
20000
40000
60000
80000
100000


Histogram of Days_is_client
Count
Days_is_client
0
20
40
60
80
100
0
100
200
300
400
500
600
700

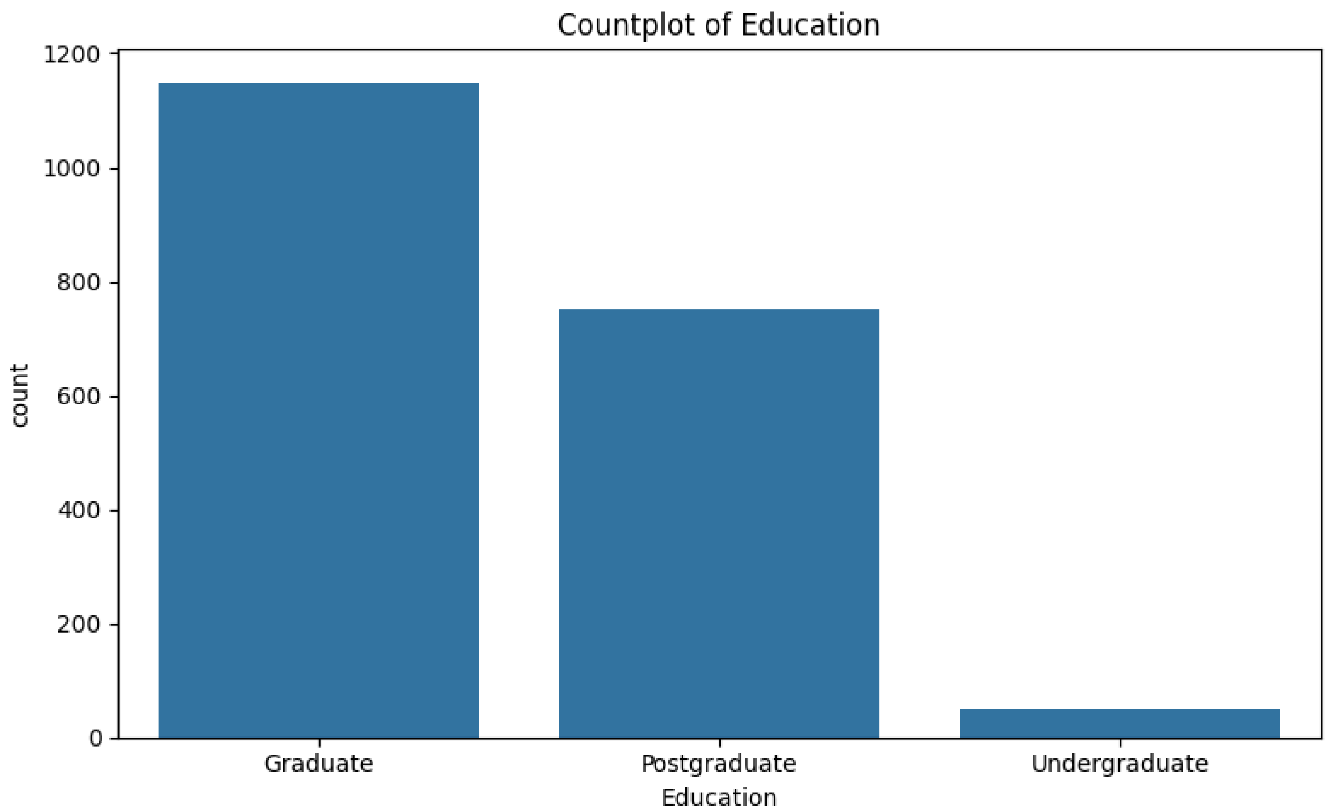

Histogram of Recency
100
120

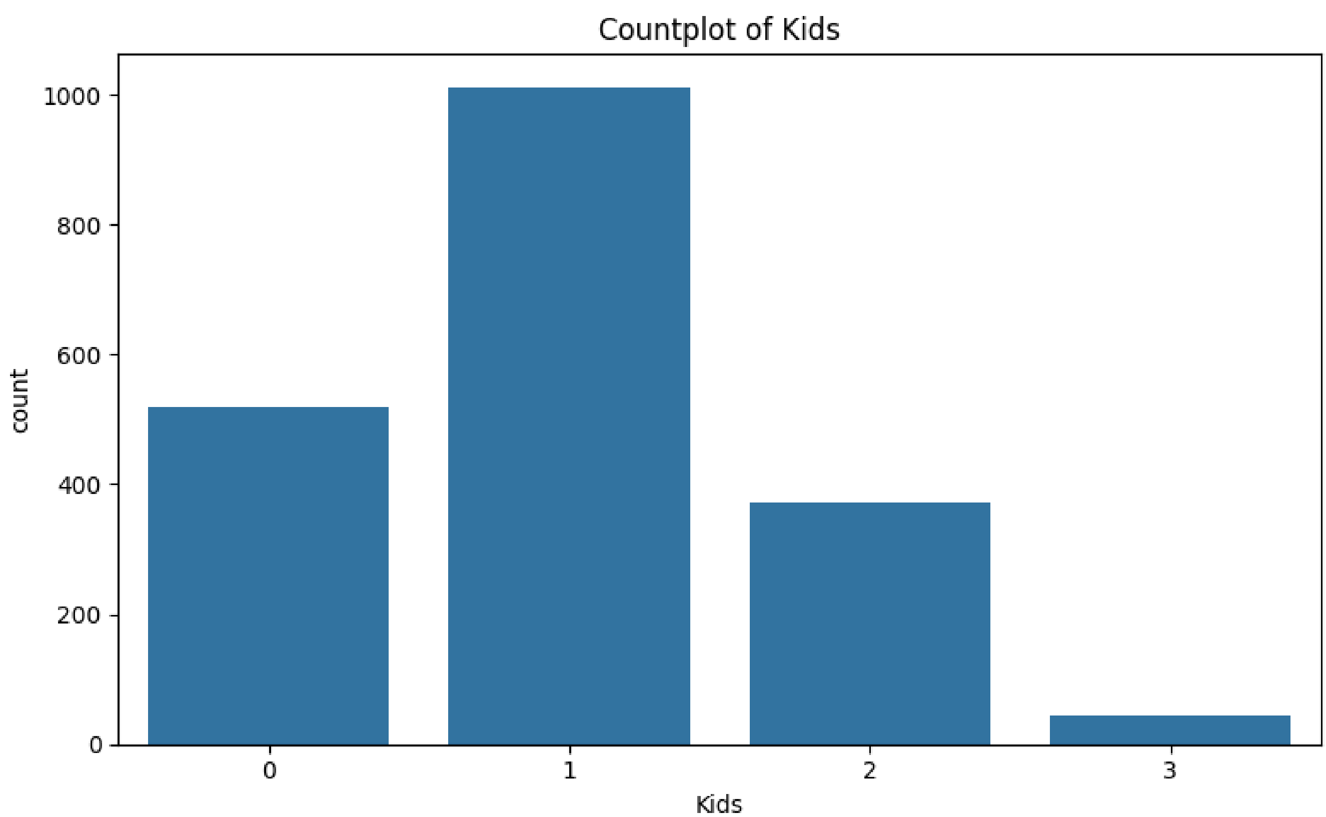

Count
Recency

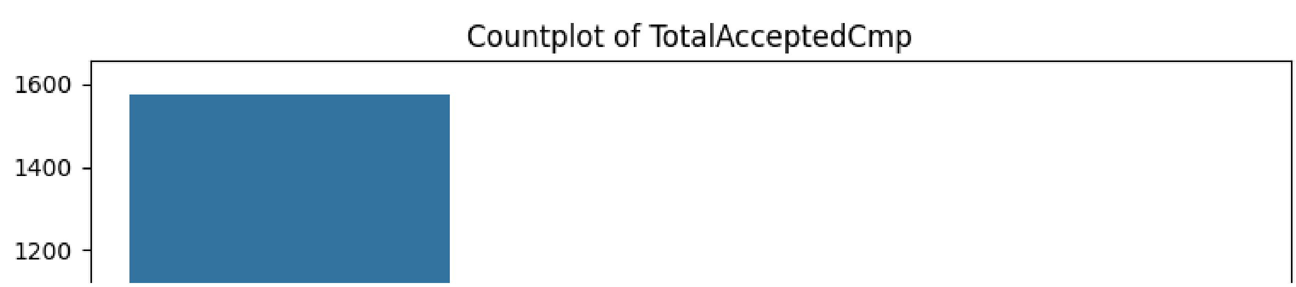

Histogram of Expenses
Count
Expenses

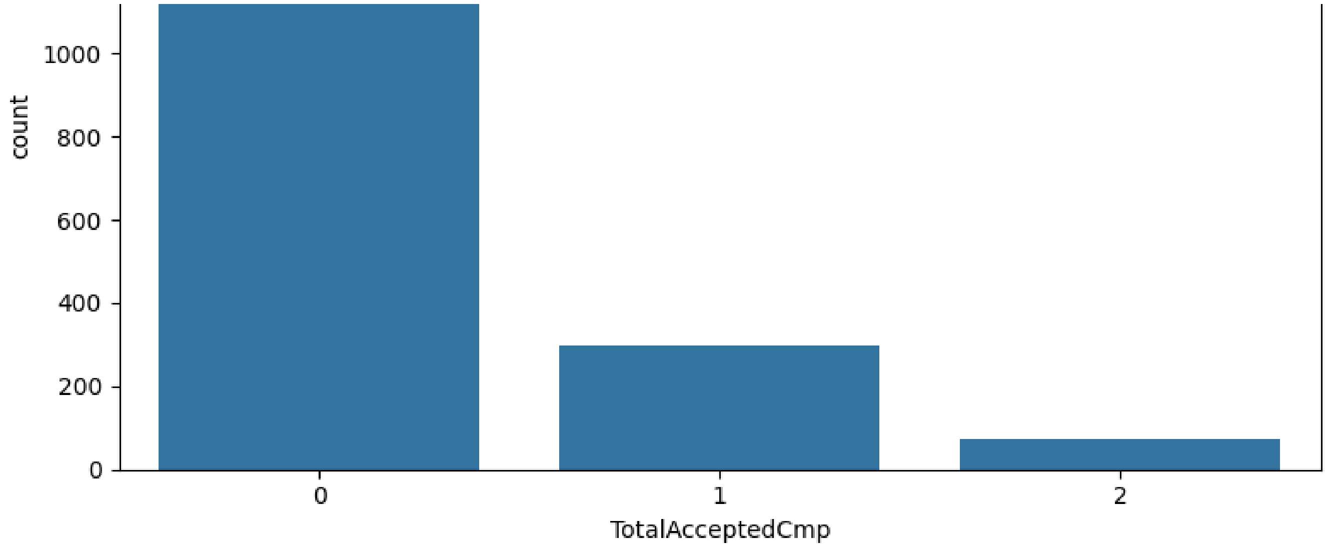

Histogram of TotalNumPurchases
Count

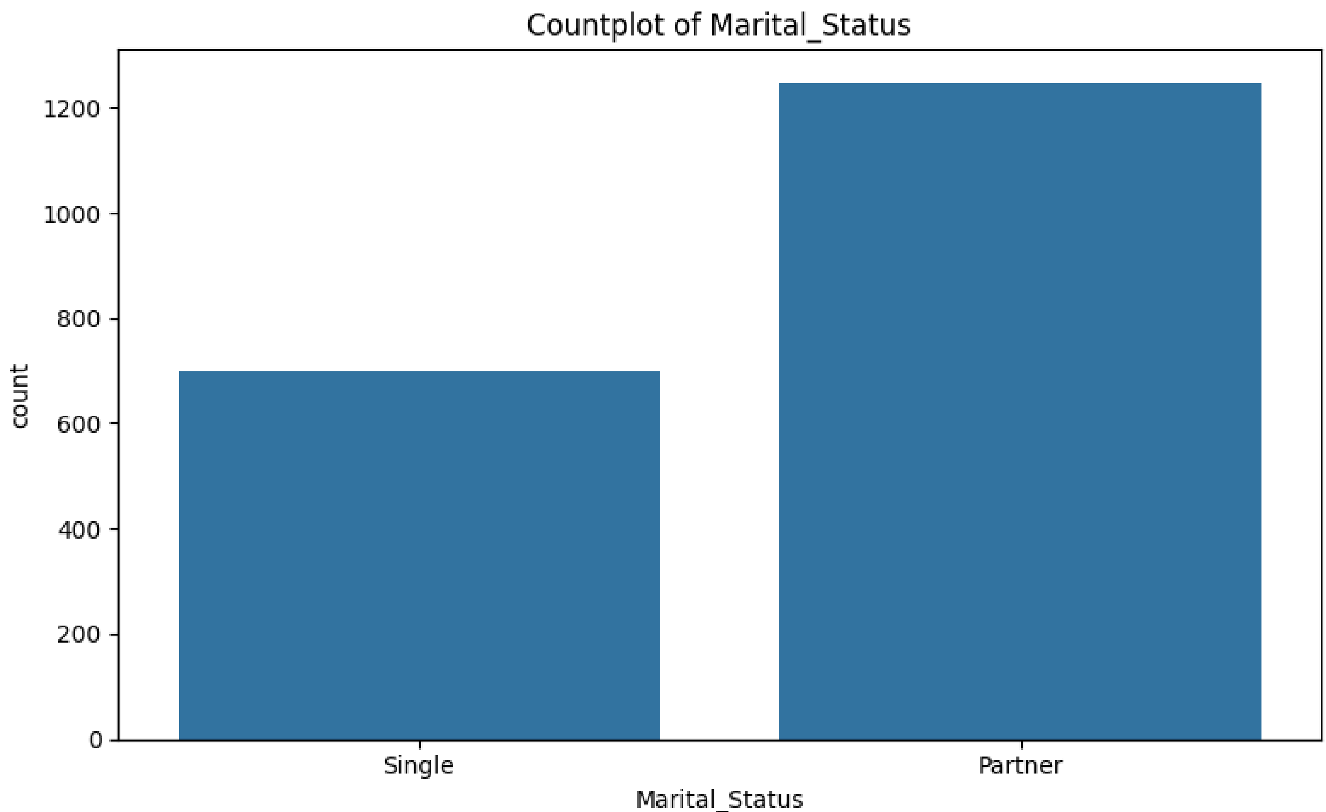
```
# Plot countplots for each categorical column
for column in categorical_columns + binary_columns:

    plt.figure(figsize=(8, 5))
    sns.countplot(data=df, x=column)
    plt.title(f'Countplot of {column}')

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

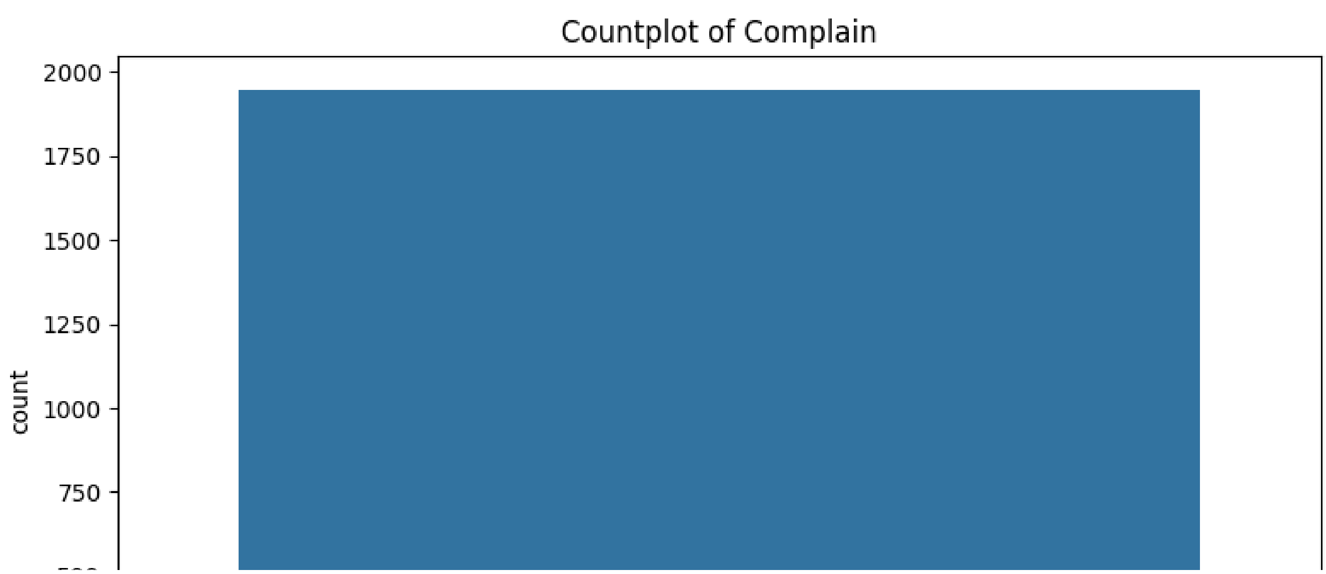

Countplot of Education
count
1200
1000
800
600
400
200
0
Graduate
Postgraduate
Undergraduate
Education


Countplot of Kids
count
1000
800
600
400
200
0
0
1
2
3
Kids

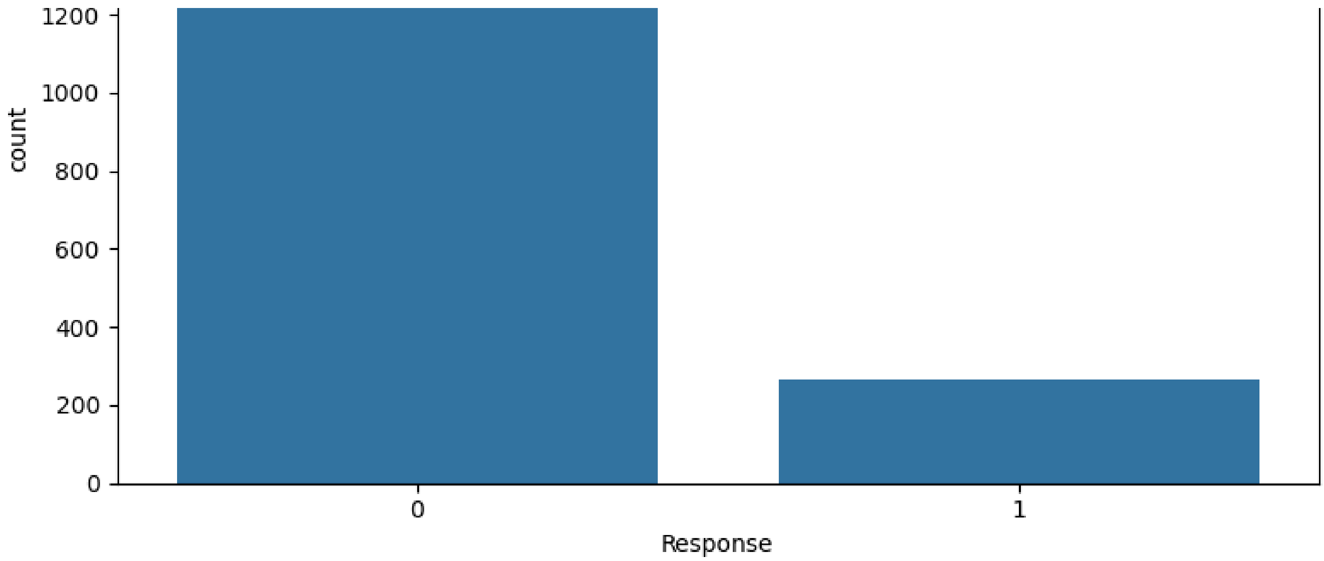

Countplot of TotalAcceptedCmp
1600
1400
1200


count
1000
800
600
400
200
0
0
1
2
TotalAcceptedCmp


Countplot of Marital_Status
count
1200
1000
800
600
400
200
0
Single
Partner
Marital_Status


Countplot of Complain
count
2000
1750
1500
1250
1000
750

```
from matplotlib.colors import LinearSegmentedColormap

colors = ["#A6393A", "#B7B5B9", "#1E4D4C"]

cmap = LinearSegmentedColormap.from_list("custom_cmap", colors)

# Example correlation matrix
corr_df= df.corr(numeric_only=True)

# Plotting the heatmap
plt.figure(figsize=(16,14))
sns.heatmap(corr_df, cmap=cmap, center=0, vmin=-1, annot=True)
plt.show()
```




Income
Kids
Days_is_client
Recency
Expenses
TotalNumPurchases
TotalAcceptedCmp
Complain
Response
1 -0.33 -0.016 -0.0017 0.82 0.7 0.31 0.11
-0.33 1 -0.037 0.032 -0.49 -0.25 -0.2 -0.14
-0.016 -0.037 1 0.028 0.19 0.22 -0.0084 0.2
-0.0017 0.032 0.028 1 0.012 0.005 -0.017 -0.21
0.82 -0.49 0.19 0.012 1 0.76 0.39 0.21
0.7 -0.25 0.22 0.005 0.76 1 0.24 0.12
0.31 -0.2 -0.0084 -0.017 0.39 0.24 1 0.32
0.11 -0.14 0.2 -0.21 0.21 0.12 0.32 1
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00

DATA PREPROCESSING

```
# Step 3: Clean and rename columns
df.columns = df.columns.str.strip()
```

```
print(df.isna().sum()) #
```

```
Education            0
Marital_Status       0
Income               0
Kids                 0
Days_is_client       0
Recency              0
Expenses             0
TotalNumPurchases    0
TotalAcceptedCmp     0
Complain             0
Response             0
dtype: int64
```

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

```
np.int64(0)
```

```
# Apply one-hot encoding directly with pandas
categorical_columns = df.select_dtypes(include=['object']).columns
```

```
X_encoded = pd.get_dummies(df, columns=categorical_columns, drop_first=True, dtype=int)
```

```
# Instantiate Scaler
scaler = StandardScaler()

# fit_transform
X_scaled = scaler.fit_transform(X_encoded)
X_scaled.shape
```

```
(1948, 12)
```

Model Implementation

K-means Clusturing

```
# Initialize the KMeans algorithm with 2 clusters and a maximum of 50 iterations
kmeans = KMeans(n_clusters=2, max_iter=50)

# Fit the KMeans algorithm
kmeans.fit(X_scaled)
y_kmeans = kmeans.fit_predict(X_scaled)

# Transform the scaled data back to its original scale using the inverse transformation
X_transformed = scaler.inverse_transform(X_scaled)
```

```
pd.DataFrame(X_transformed, columns=X_encoded.columns).head()
```

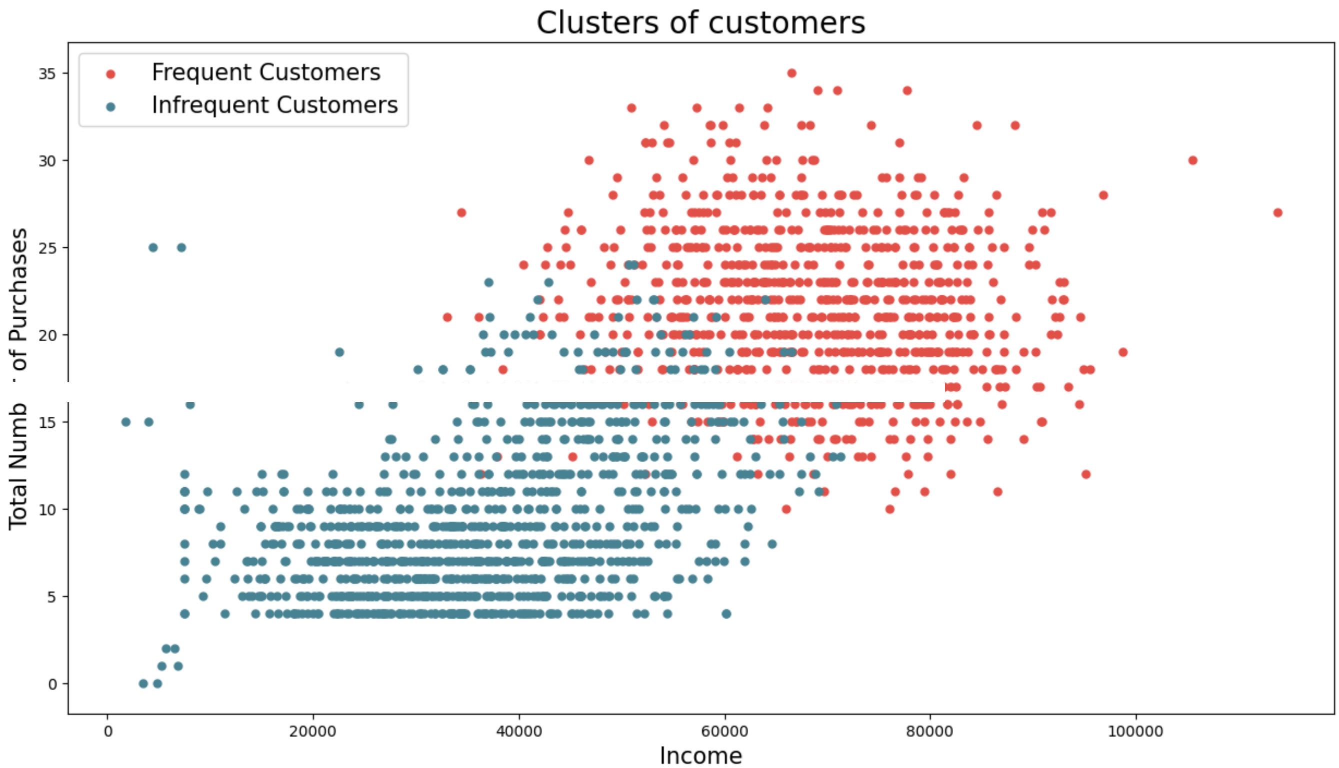
	Income	Kids	Days_is_client	Recency	Expenses	TotalNumPurchases	TotalAcceptedCmp
0	58138.0	0.0	663.0	58.0	1617.0	25.0	0.0
1	46344.0	2.0	113.0	38.0	27.0	6.0	0.0
2	71613.0	0.0	312.0	26.0	776.0	21.0	0.0
3	26646.0	1.0	139.0	26.0	53.0	8.0	0.0
4	58293.0	1.0	161.0	94.0	422.0	19.0	0.0

```
# Set the figure size for the plot
plt.figure(figsize=(15, 8))

# Plot the customers in Cluster 0 (High-Value Customers), using red color
plt.scatter(X_transformed[y_kmeans == 0, 0], X_transformed[y_kmeans == 0, 4], s=25, c='#E25

# Plot the customers in Cluster 1 (Low-Value Customers), using blue color
plt.scatter(X_transformed[y_kmeans == 1, 0], X_transformed[y_kmeans == 1, 4], s=25, c='#498

# Add title to the plot
plt.title('Clusters of customers', fontsize=20)

# Add label for the x-axis (Income)
plt.xlabel('Income', fontsize=15)

# Add label for the y-axis (Expenses)
plt.ylabel('Expenses', fontsize=15)

# Show the legend to identify each cluster
plt.legend(fontsize=15)

# Display the plot
plt.show()
```


```
# Set the figure size for the plot
plt.figure(figsize=(15, 8))

# Plot the customers in Cluster 0 (Frequent Customers), using red color
plt.scatter(X_transformed[y_kmeans == 0, 0], X_transformed[y_kmeans == 0, 5], s=25, c='#E25

# Plot the customers in Cluster 1 (Infrequent Customers), using blue color
plt.scatter(X_transformed[y_kmeans == 1, 0], X_transformed[y_kmeans == 1, 5], s=25, c='#498

# Add title to the plot
plt.title('Clusters of customers', fontsize=20)
```

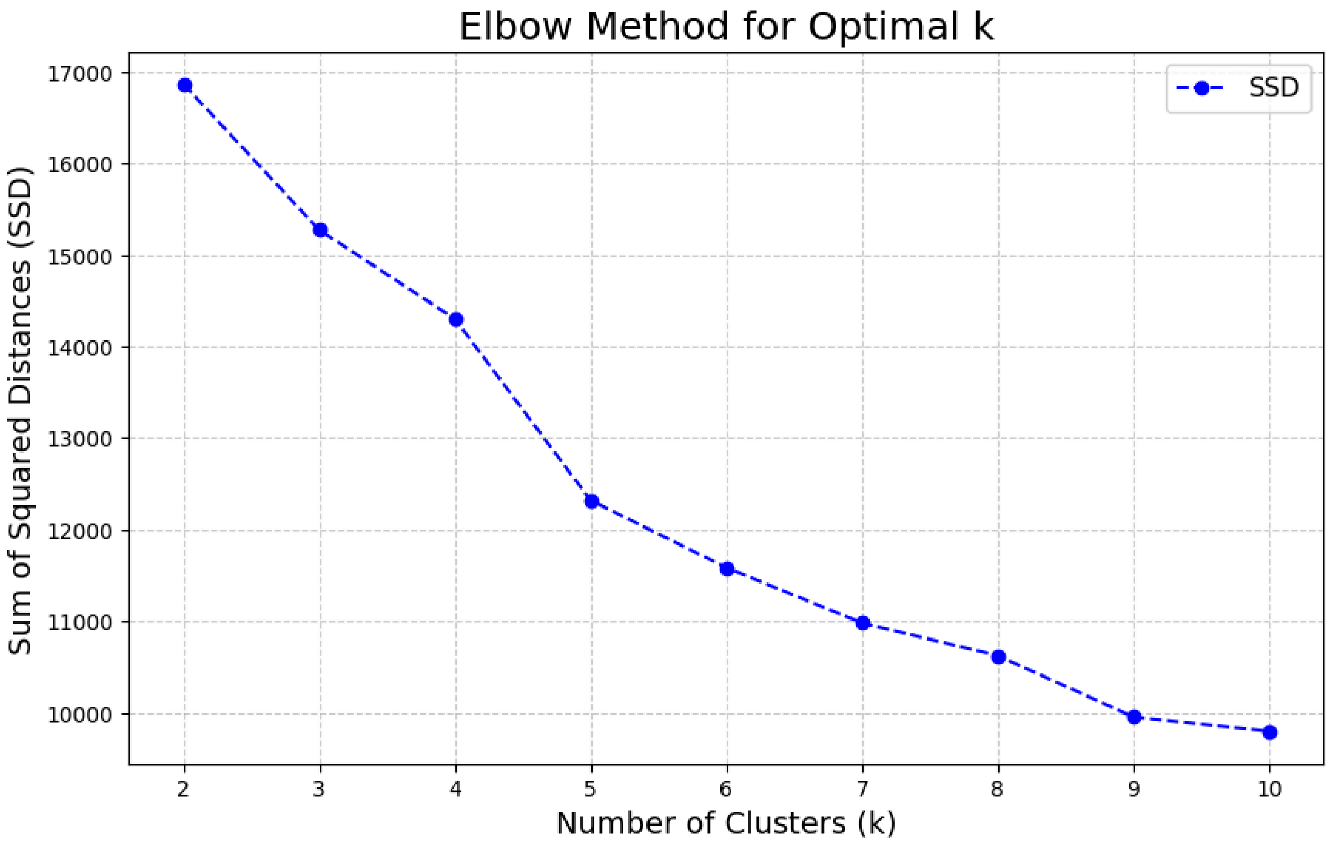
```
# Add label for the x-axis (Income)
plt.xlabel('Income', fontsize=15)

# Add label for the y-axis (Total Number of Purchases)
plt.ylabel('Total Number of Purchases', fontsize=15)

# Show the legend to identify each cluster
plt.legend(fontsize=15)

# Display the
```

```
<matplotlib.legend.Legend at 0x7d0c74c49b10>
```



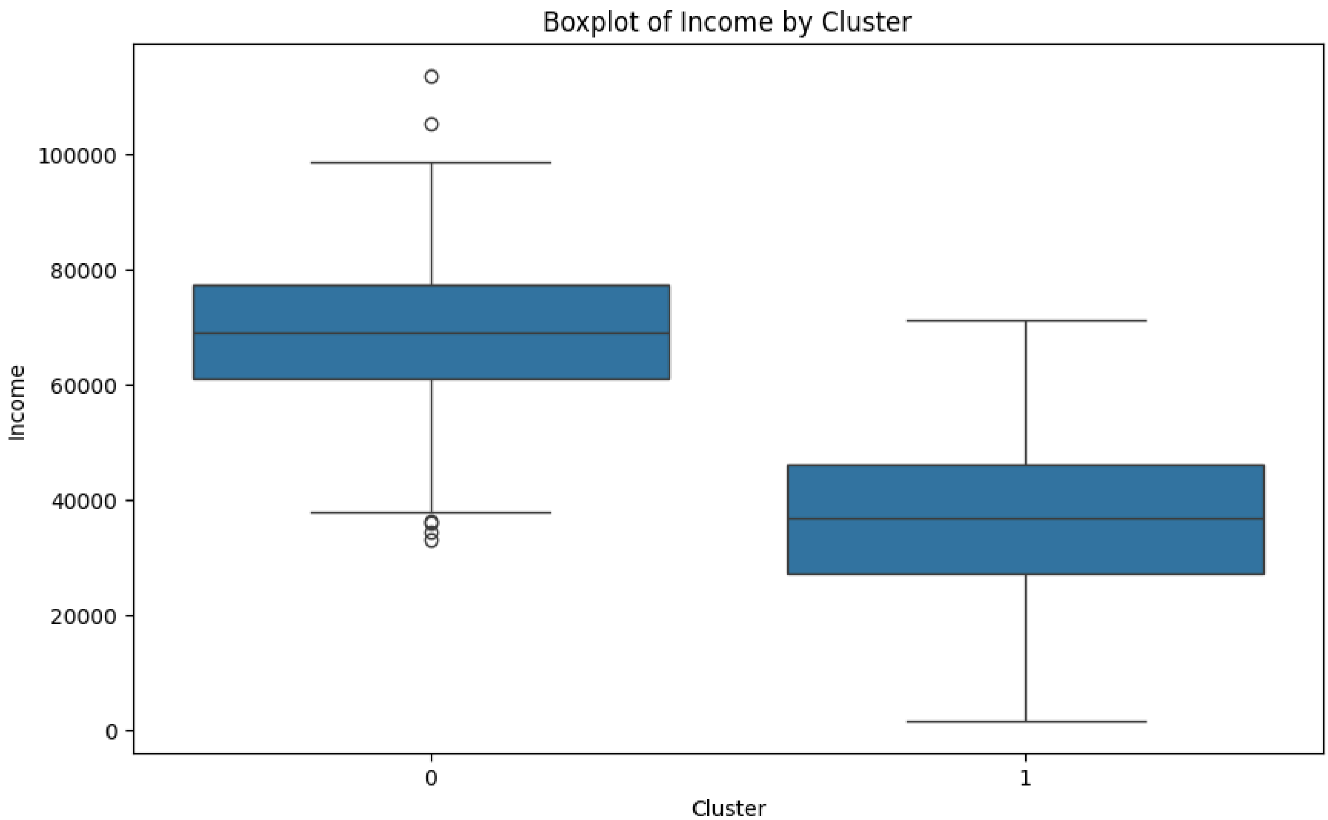
```
# Import necessary libraries
import matplotlib.pyplot as plt
from sklearn.cluster import KMeans

# Elbow-curve/SSD
ssd = []  # List to store the Sum of Squared Distances (SSD) for each k
range_n_clusters = range(2, 11)  # Range of k values from 2 to 10 for better insights

# Loop over the range of number of clusters (k)
for num_clusters in range_n_clusters:
    # Initialize the KMeans algorithm with current number of clusters and 300 maximum iterat
    kmeans = KMeans(n_clusters=num_clusters, max_iter=300, random_state=101)

    # Fit the KMeans model to the scaled data (X_scaled)
    kmeans.fit(X_scaled)

    # Append the inertia (SSD) for the current number of clusters to the list
    ssd.append(kmeans.inertia_)

    # Print the k value and its corresponding SSD
    print(f"Clusters: {num_clusters}, SSD: {kmeans.inertia_}")

# Find the "elbow" point (where SSD starts to decrease less dramatically)
# Compute the rate of change in SSD between consecutive points
ssd_diff = [ssd[i] - ssd[i-1] for i in range(1, len(ssd))]  # Difference between SSDs
ssd_diff_diff = [ssd_diff[i] - ssd_diff[i-1] for i in range(1, len(ssd_diff))]  # 2nd deriva

# The elbow is where the second derivative is the smallest (change in slope)
elbow_point = range_n_clusters[2 + ssd_diff_diff.index(min(ssd_diff_diff))]  # Add 2 because

print(f"The elbow point (optimal number of clusters) is: {elbow_point}")

# Plot the SSD values for each number of clusters (k)
plt.figure(figsize=(10, 6))  # Set the figure size for the plot
plt.plot(range_n_clusters, ssd, marker='o', linestyle='--', color='b', label="SSD")  # Plot

# Add labels and title to the plot
plt.title('Elbow Method for Optimal k', fontsize=18)
plt.xlabel('Number of Clusters (k)', fontsize=14)
plt.ylabel('Sum of Squared Distances (SSD)', fontsize=14)
plt.xticks(range_n_clusters)
plt.grid(True, linestyle='--', alpha=0.6)
plt.legend(fontsize=12)

# Show the plot
plt.show()
```

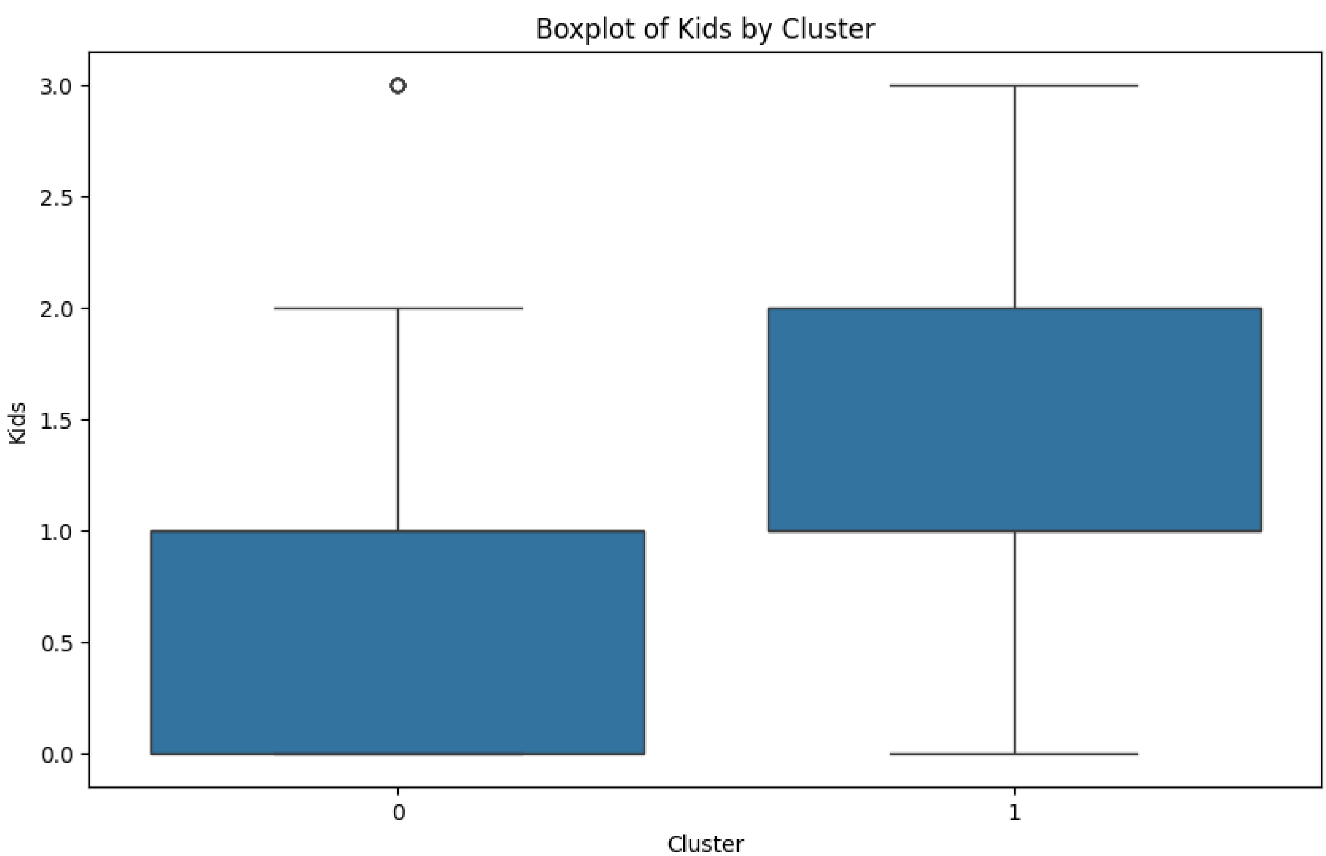
```
Clusters: 2, SSD: 16864.34473154984
Clusters: 3, SSD: 15271.712495748354
Clusters: 4, SSD: 14299.448911401352
Clusters: 5, SSD: 12319.260081044262
Clusters: 6, SSD: 11584.24959340387
Clusters: 7, SSD: 10979.817802305633
Clusters: 8, SSD: 10623.485811719496
Clusters: 9, SSD: 9953.406251272005
Clusters: 10, SSD: 9796.960213990236
The elbow point (optimal number of clusters) is: 5
```

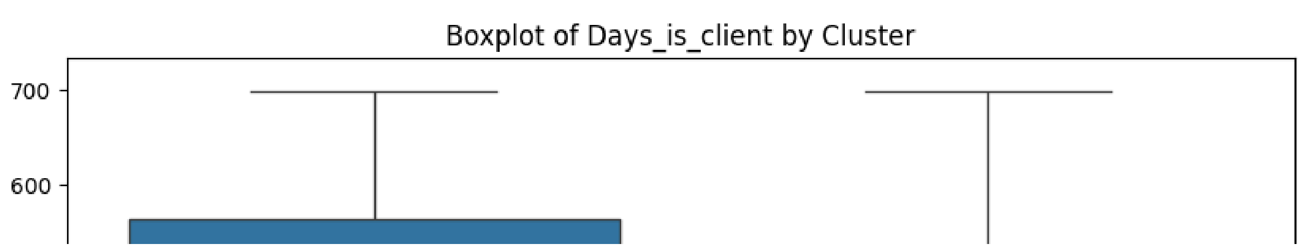


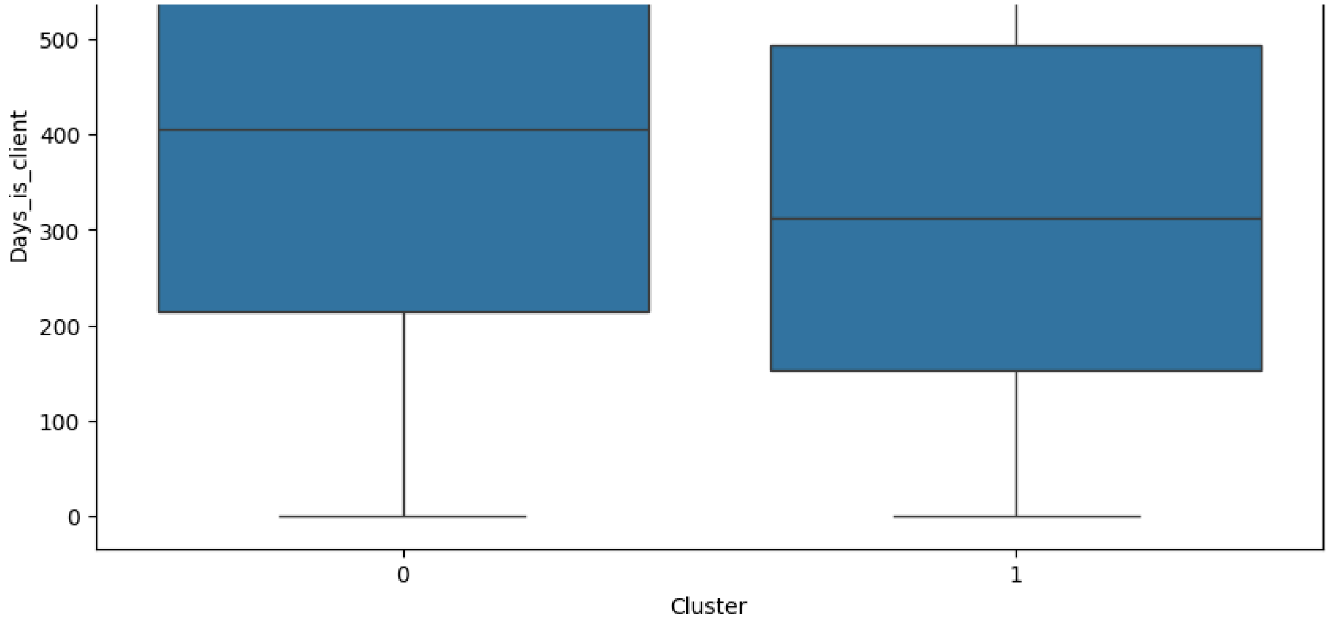

```
# Create a copy of the original DataFrame and add a new column 'Cluster'
df_clusters = df.copy()
df_clusters['Cluster'] = y_kmeans

# Select numerical columns to plot
columns_to_plot = ['Income', 'Kids', 'Days_is_client', 'Recency', 'Expenses', 'TotalNumPurch

# Plot boxplots for each numerical column
for column in columns_to_plot:
    plt.figure(figsize=(10, 6))
    sns.boxplot(x='Cluster', y=column, data=df_clusters)  # Adjust palette as needed
```

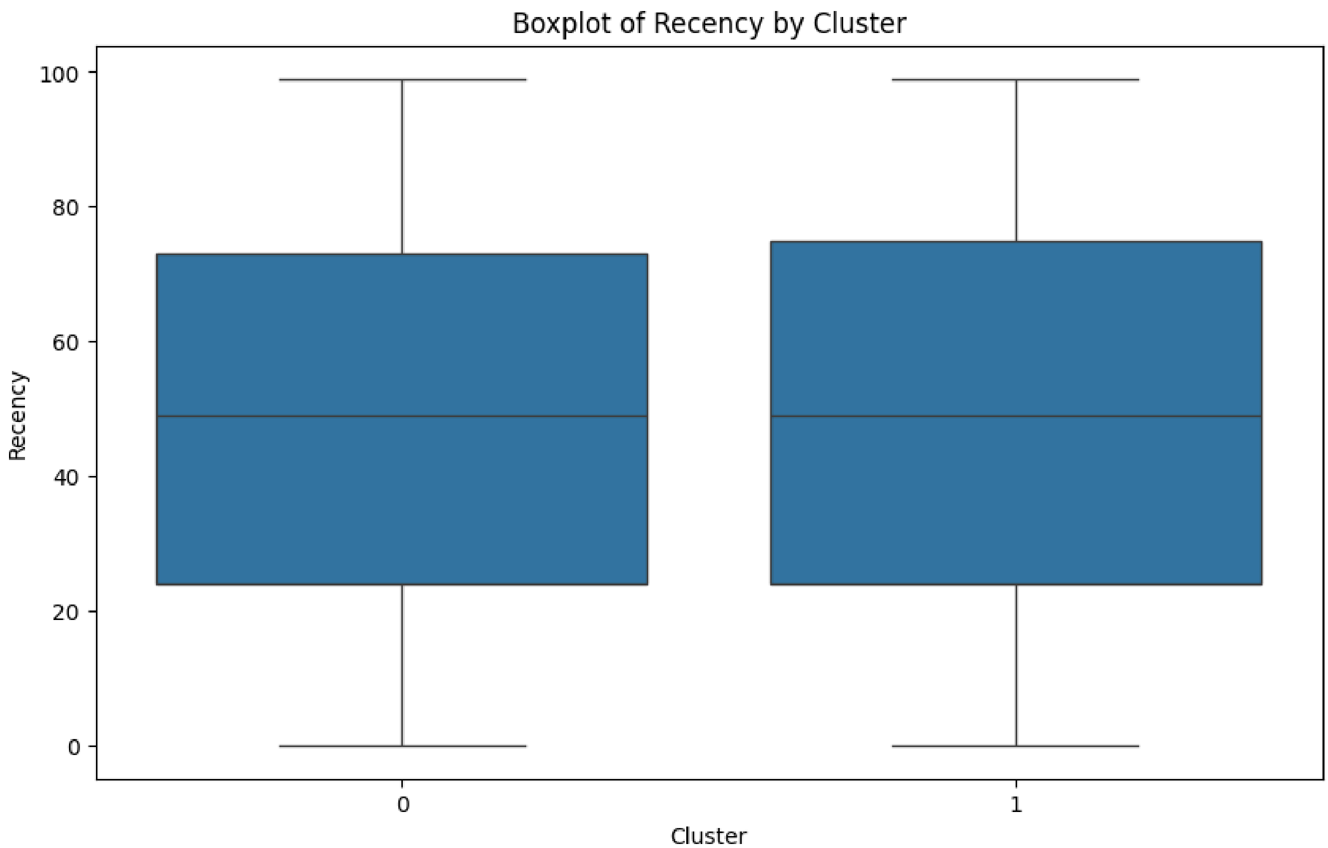
```
    plt.title(f'Boxplot of {column} by Cluster')
    plt.xlabel('Cluster')
    plt.ylabel(column)
    plt.show()
```

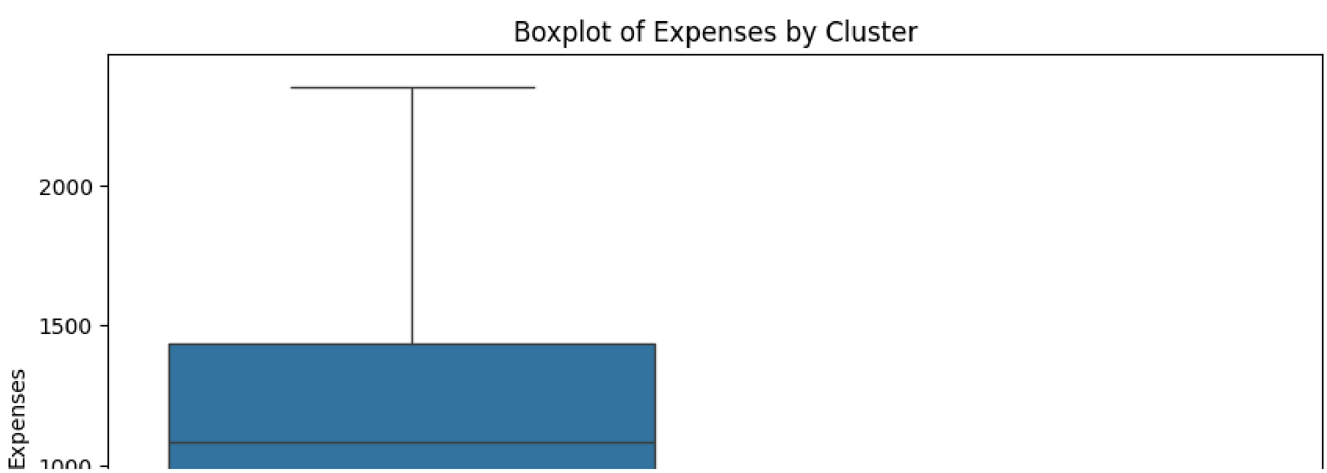

Boxplot of Income by Cluster
Income
Cluster
0
20000
40000
60000
80000
100000
0
1


Boxplot of Kids by Cluster
Kids
Cluster
0.0
0.5
1.0
1.5
2.0
2.5
3.0
0
1

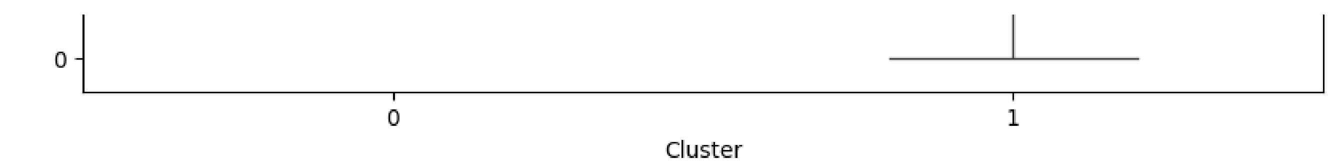

Boxplot of Days_is_client by Cluster
600
700

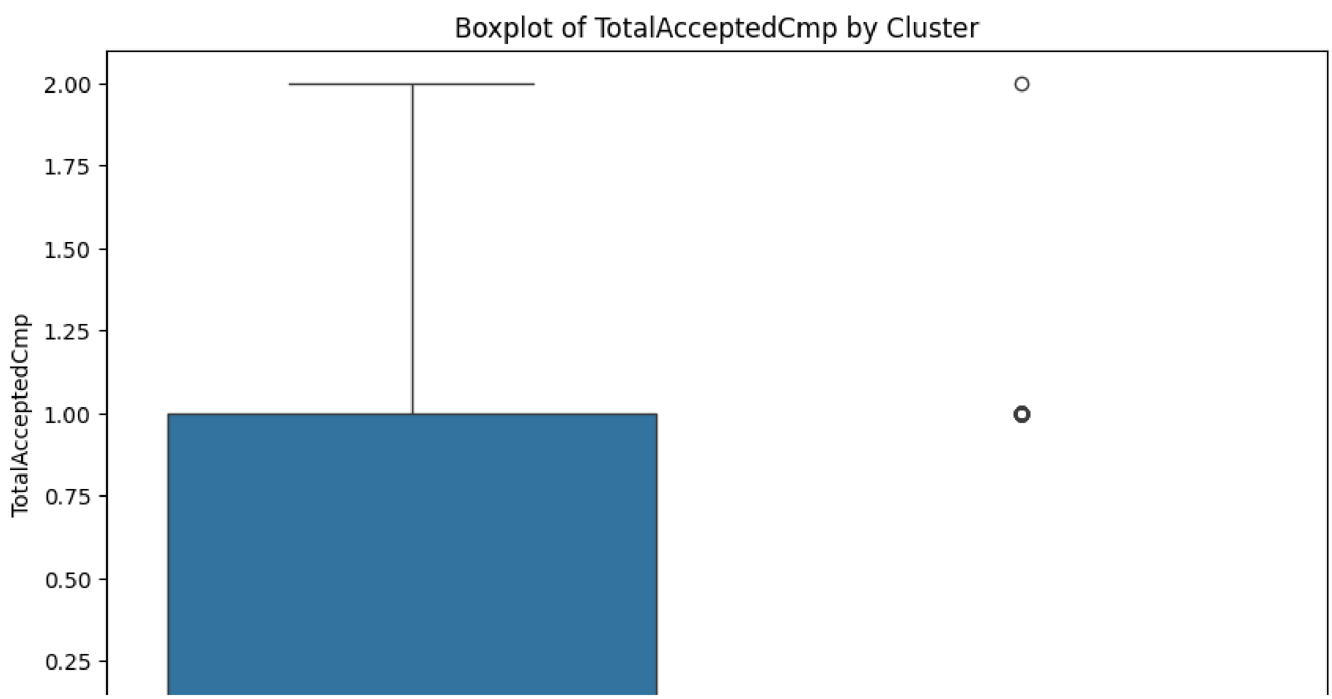

Days_is_client
500
400
300
200
100
0
0
1
Cluster

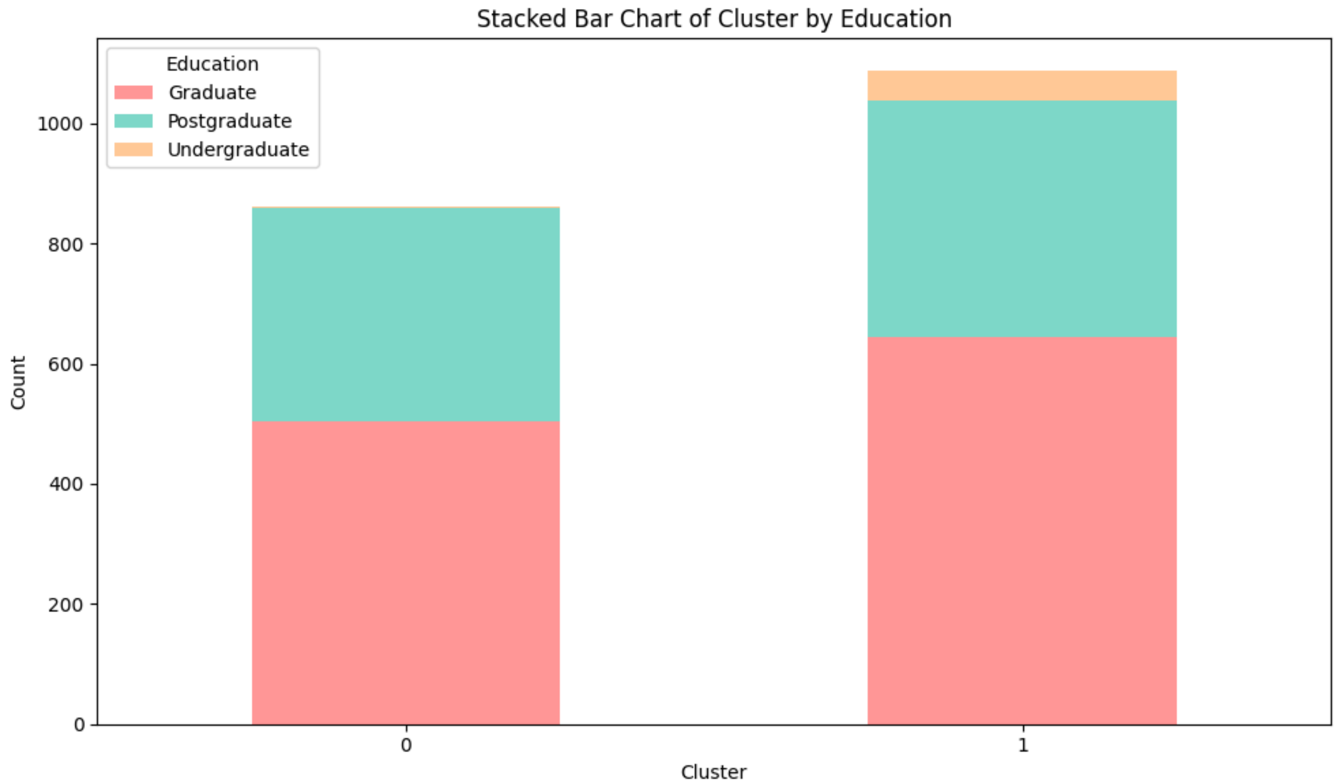

Boxplot of Recency by Cluster
Recency
100
80
60
40
20
0
0
1
Cluster

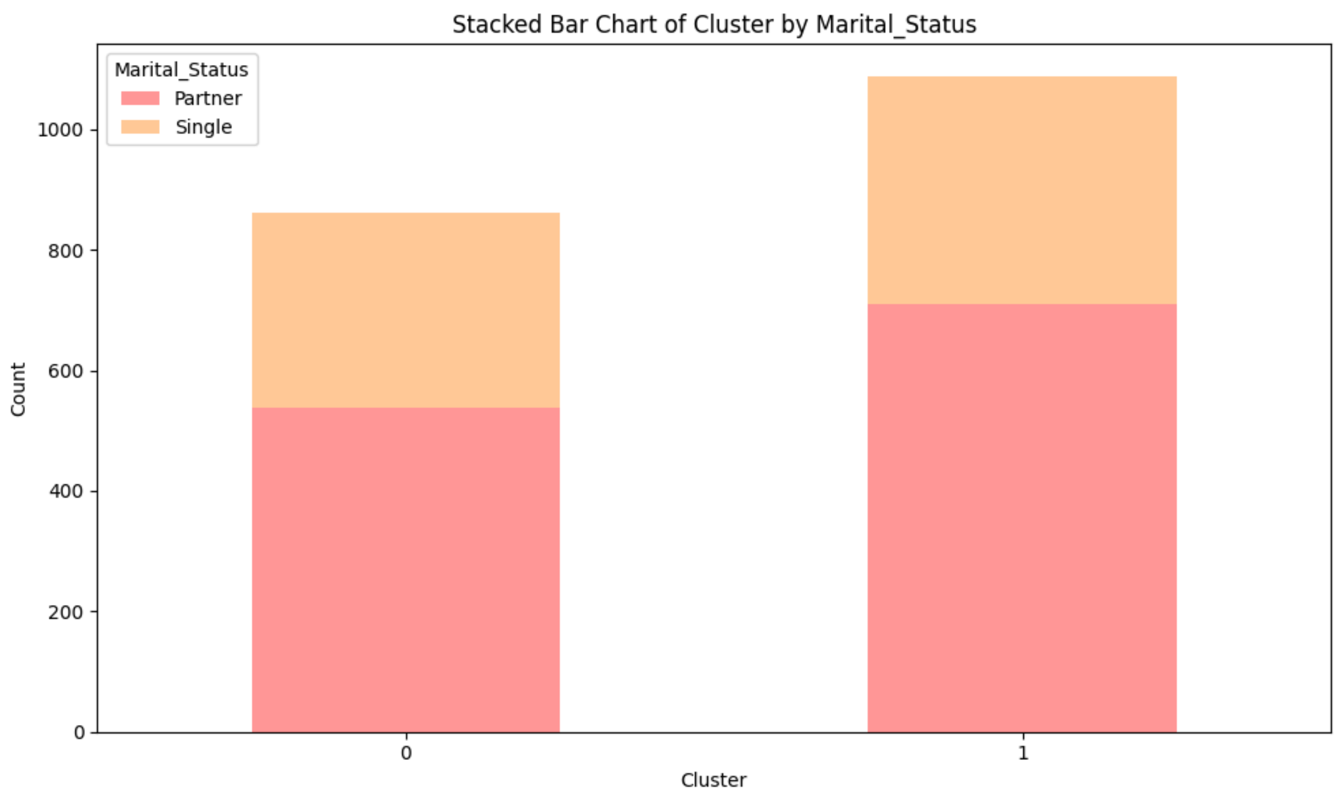

Boxplot of Expenses by Cluster
Expenses
2000
1500

```python
import pandas as pd
import matplotlib.pyplot as plt
from matplotlib.colors import LinearSegmentedColormap

# Define a custom color palette
custom_palette = ['#FF9999', '#66B3FF', '#99FF99', '#FFCC99']

# Create a custom colormap
cmap = LinearSegmentedColormap.from_list("custom_cmap", custom_palette)

# Assuming df_clusters is your DataFrame
# List of categorical columns to plot
categorical_columns = ['Education', 'Marital_Status']

for column in categorical_columns:
    # Prepare data
    data = df_clusters.groupby(['Cluster', column]).size().unstack().fillna(0)

    # Plot stacked bar chart
    data.plot(kind='bar', stacked=True, figsize=(10, 6), colormap=cmap)

    plt.title(f'Stacked Bar Chart of Cluster by {column}')
    plt.xlabel('Cluster')
    plt.ylabel('Count')
    plt.legend(title=column)
    plt.xticks(rotation=0)
    plt.tight_layout()
    plt.show()
```






Stacked Bar Chart of Cluster by Education
Education
Graduate
Postgraduate
Undergraduate
Count
0
200
400
600
800
1000
0
1
Cluster


Stacked Bar Chart of Cluster by Marital_Status
Marital_Status
Partner
Single
Count
0
200
400
600
800
1000
0
1
Cluster

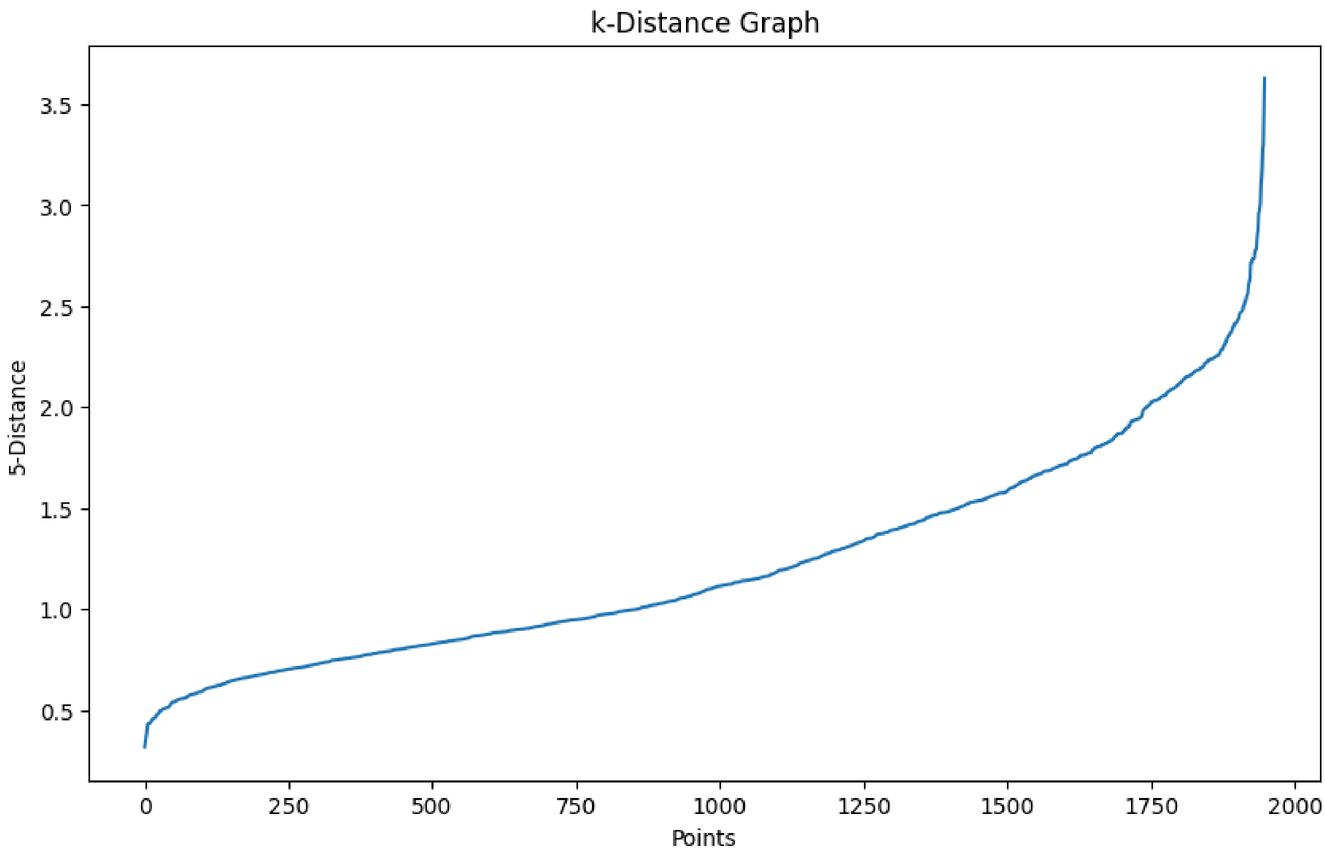
DBSCAN CLUSTURING

```
# Import necessary libraries
import pandas as pd
import numpy as np
from sklearn.preprocessing import StandardScaler # For normalizing data
from sklearn.cluster import DBSCAN
from sklearn.decomposition import PCA  # For reducing dimensions
import matplotlib.pyplot as plt
import seaborn as sns
from matplotlib.colors import LinearSegmentedColormap


# Step 1: Data Preprocessing
categorical_columns = df.select_dtypes(include=['object']).columns


# One-hot encode categorical variables
X_encoded = pd.get_dummies(df, columns=categorical_columns, drop_first=True, dtype=int)    #


# Scale the data
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X_encoded)  # omputes the mean and standard deviation for ea


# Before running the function

#prints the shape and summary statistics of the scaled datase
print("Data shape:", X_scaled.shape)
print("Data summary:")
print(pd.DataFrame(X_scaled).describe())
```

```
Data shape: (1948, 12)
Data summary:
                  0             1             2             3             4   \
count  1.948000e+03  1.948000e+03  1.948000e+03  1.948000e+03  1.948000e+03
mean   3.556361e-17 -2.553285e-17 -9.301252e-17  9.392441e-17  3.100417e-17
std    1.000257e+00  1.000257e+00  1.000257e+00  1.000257e+00  1.000257e+00
min   -2.432185e+00 -1.311394e+00 -1.736488e+00 -1.685360e+00 -9.945933e-01
25%   -7.909683e-01 -1.311394e+00 -8.587490e-01 -8.576661e-01 -8.856164e-01
50%   -9.777298e-03  4.024383e-02 -5.665219e-03  4.514498e-03 -3.649489e-01
75%    7.971440e-01  4.024383e-02  8.683758e-01  8.666951e-01  7.339017e-01
max    3.104606e+00  2.743519e+00  1.710365e+00  1.728876e+00  3.065229e+00

                  5             6       7             8             9   \
count  1.948000e+03  1.948000e+03  1948.0  1.948000e+03  1.948000e+03
mean   8.845309e-17 -4.377060e-17     0.0  3.282795e-17 -8.024610e-17
std    1.000257e+00  1.000257e+00     0.0  1.000257e+00  1.000257e+00
min   -1.949470e+00 -4.556251e-01     0.0 -3.968084e-01 -7.912290e-01
```

```
25%   -1.021585e+00 -4.556251e-01     0.0 -3.968084e-01 -7.912290e-01
50%    3.885467e-02 -4.556251e-01     0.0 -3.968084e-01 -7.912290e-01
75%    8.341845e-01 -4.556251e-01     0.0 -3.968084e-01  1.263857e+00
max    2.689954e+00  3.524455e+00     0.0  2.520108e+00  1.263857e+00

                 10            11
count  1.948000e+03  1.948000e+03
mean   5.106570e-17 -1.331356e-16
std    1.000257e+00  1.000257e+00
min   -1.606333e-01 -7.489309e-01
25%   -1.606333e-01 -7.489309e-01
50%   -1.606333e-01 -7.489309e-01
75%   -1.606333e-01  1.335237e+00
max    6.225360e+00  1.335237e+00
```

```
from sklearn.neighbors import NearestNeighbors  ## identifying the optimal value for eps
import matplotlib.pyplot as plt
import numpy as np

def k_distance_plot(X, k=5):
    nearest_neighbors = NearestNeighbors(n_neighbors=k)
    neighbors_fit = nearest_neighbors.fit(X)
    distances, indices = neighbors_fit.kneighbors(X)
    sorted_distances = np.sort(distances[:, -1])
    plt.figure(figsize=(10, 6))
    plt.plot(sorted_distances)
    plt.xlabel('Points')
    plt.ylabel(f'{k}-Distance')
    plt.title('k-Distance Graph')
    plt.show()

k_distance_plot(X_scaled, k=5)
```

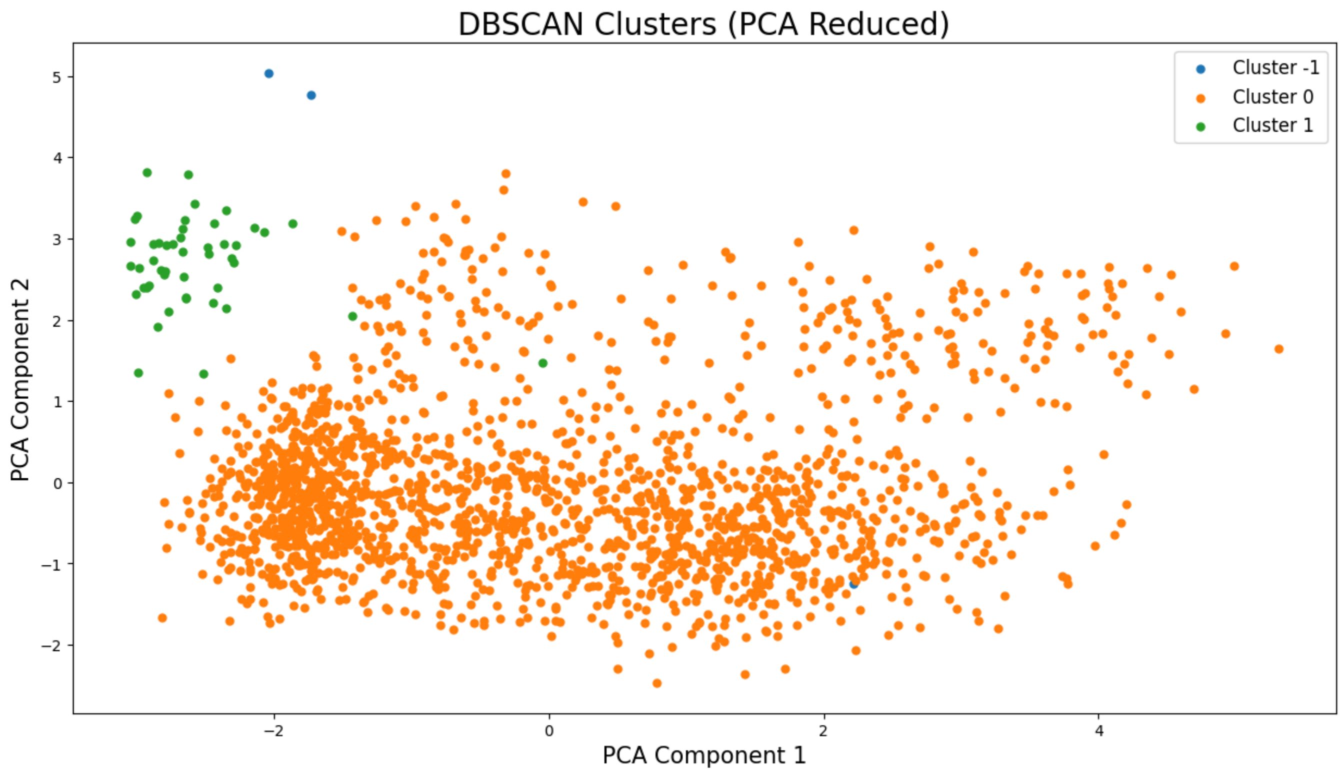



```
# Step 2: Implement DBSCAN Algorithm
from sklearn.cluster import DBSCAN

# Adjust eps and min_samples as per dataset for optimal results
dbscan = DBSCAN(eps=3, min_samples=11, metric='euclidean')
dbscan_labels = dbscan.fit_predict(X_scaled)

# Verify that the lengths match
print("Length of original DataFrame:", len(df))
print("Length of DBSCAN labels:", len(dbscan_labels))

# Add cluster labels to the DataFrame
if len(df) == len(dbscan_labels):
    df_clusters = df.copy()
    df_clusters['Cluster'] = dbscan_labels
else:
    # Adjust df to match X_scaled
    df_clusters = df.iloc[:len(dbscan_labels)].copy()
    df_clusters['Cluster'] = dbscan_labels
```

```
print(df_clusters.head())
```

```
Length of original DataFrame: 1948
Length of DBSCAN labels: 1948
     Education Marital_Status   Income  Kids  Days_is_client  Recency  \
0     Graduate         Single  58138.0     0             663       58
1     Graduate         Single  46344.0     2             113       38
2     Graduate        Partner  71613.0     0             312       26
3     Graduate        Partner  26646.0     1             139       26
4  Postgraduate       Partner  58293.0     1             161       94

   Expenses  TotalNumPurchases  TotalAcceptedCmp  Complain  Response  Cluster
0      1617                 25                 0         0         1        0
1        27                  6                 0         0         0        0
2       776                 21                 0         0         0        0
3        53                  8                 0         0         0        0
4       422                 19                 0         0         0        0
```

```
# Step 3: Visualize Clusters Using PCA
# Reduce dimensions for visualization
pca = PCA(n_components=2)
X_pca = pca.fit_transform(X_scaled)

plt.figure(figsize=(15, 8))
unique_labels = np.unique(dbscan_labels)

# Plot each cluster
for label in unique_labels:
    mask = dbscan_labels == label
    plt.scatter(X_pca[mask, 0], X_pca[mask, 1], label=f'Cluster {label}', s=25)

plt.title('DBSCAN Clusters (PCA Reduced)', fontsize=20)
plt.xlabel('PCA Component 1', fontsize=15)
plt.ylabel('PCA Component 2', fontsize=15)
plt.legend(fontsize=12)
plt.show()
```




```
print(df_clusters.columns)
```

```
Index(['Education', 'Marital_Status', 'Income', 'Kids', 'Days_is_client',
       'Recency', 'Expenses', 'TotalNumPurchases', 'TotalAcceptedCmp',
       'Complain', 'Response', 'Cluster'],
      dtype='object')
```

```
# Ensure 'Kids' column exists
if 'Kids' not in df_clusters.columns:
    df_clusters['Kids'] = df_clusters['Kidhome'] + df_clusters['Teenhome']
```

```
# Numerical columns for analysis
numerical_columns = ['Income', 'Kids', 'Days_is_client', 'Recency', 'Expenses', 'TotalNumPu

# Boxplot analysis
for column in numerical_columns:
    if column in df_clusters.columns:
        plt.figure(figsize=(10, 6))
        sns.boxplot(x='Cluster', y=column, data=df_clusters)
        plt.title(f'Boxplot of {column} by Cluster')
        plt.xlabel('Cluster')
        plt.ylabel(column)
        plt.show()
    else:
```