

```

1 import pandas as pd
2 import numpy as np
3 import matplotlib.pyplot as plt
4 import seaborn as sns
5 from sklearn.preprocessing import StandardScaler, OneHotEncoder
6 from sklearn.impute import SimpleImputer
7 from sklearn.compose import ColumnTransformer
8 from sklearn.pipeline import Pipeline
9 from sklearn.cluster import KMeans
10 from sklearn.metrics import silhouette_score
11 import scipy.cluster.hierarchy as sch
12 from scipy.spatial.distance import pdist, squareform
13 from sklearn.decomposition import PCA

```

```

1 # Configuración para visualizaciones
2 plt.style.use('seaborn-v0_8-whitegrid')
3 sns.set_palette("viridis")
4 plt.rcParams['figure.figsize'] = (12, 8)
5 plt.rcParams['font.size'] = 12

```

```

1 # prompt: carga de datos desde google drive
2
3 from google.colab import drive
4 drive.mount('/content/drive')

```

↗ Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount("/content/drive", force_remount=True).

```

1 # Specify the file path in your Google Drive
2 file_path = '/content/drive/MyDrive/BBDD_ParaInciar_MakDigital (1).xlsx' # Replace 'your_file.csv' with the actual file name and path

```

```

1 df = pd.read_excel(file_path)
2 df.columns
3

```

↗ /usr/local/lib/python3.11/dist-packages/openpyxl/worksheet/_reader.py:329: UserWarning: Unknown extension is not supported and will warn(msg)

```

Index(['IDENTIFICACION', 'NOMBRE', 'PERFILRIESGOENDEUDAMIENTO', 'EDAD', 'sexo',
      'estado_civil', 'MAXIMA_TARJETA', 'MAXIMO_CONSUMO', 'PAIS_DOM_CAL_DAT',
      'PROV_DOM_CAL_DAT', 'CIUDAD_DOM_CAL_DAT', 'DIR_DOM_CAL_DAT',
      'TEL_DOM_1_CAL_DAT', 'DIR_TRAB_1_CAL_DAT', 'TEL_TRA_1_CAL_DAT',
      'CELULAR_1', 'CELULAR_BAN', 'CORREO_BAN'],
      dtype='object')

```

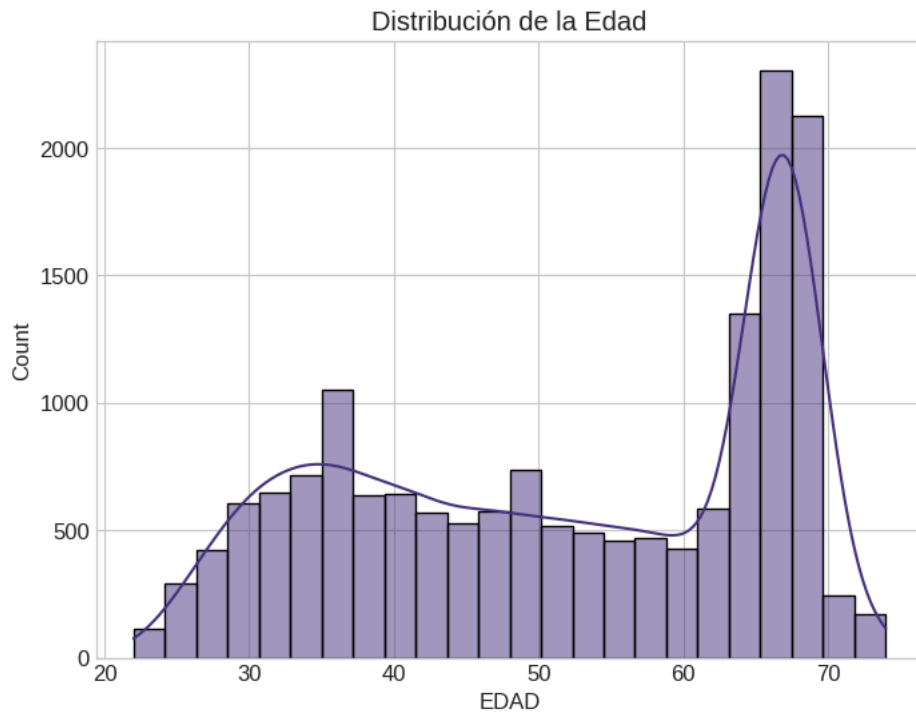
```

1 # Análisis exploratorio de variables seleccionadas
2
3 # Convertir 'EDAD' a numérica (si no lo está ya) y manejar valores no numéricos
4 df['EDAD'] = pd.to_numeric(df['EDAD'], errors='coerce')
5
6 # Análisis de la variable 'EDAD'
7 print("Análisis de la variable 'EDAD':")
8 print(df['EDAD'].describe())
9 plt.figure(figsize=(8, 6))
10 sns.histplot(df['EDAD'], kde=True)
11 plt.title('Distribución de la Edad')
12 plt.show()
13
14 # Análisis de la variable 'sexo'
15 print("\nAnálisis de la variable 'sexo':")
16 print(df['sexo'].value_counts())
17 plt.figure(figsize=(8, 6))
18 df['sexo'].value_counts().plot(kind='bar')
19 plt.title('Distribución del Sexo')
20 plt.show()
21
22 # Análisis de la variable 'estado_civil'
23 print("\nAnálisis de la variable 'estado_civil':")
24 print(df['estado_civil'].value_counts())
25 plt.figure(figsize=(8, 6))
26 df['estado_civil'].value_counts().plot(kind='bar')
27 plt.title('Distribución del Estado Civil')
28 plt.show()
29
30 # Análisis de la variable 'MAXIMA_TARJETA'
31 print("\nAnálisis de la variable 'MAXIMA_TARJETA':")
32 print(df['MAXIMA_TARJETA'].describe())
33 plt.figure(figsize=(8, 6))
34 sns.histplot(df['MAXIMA_TARJETA'], kde=True)

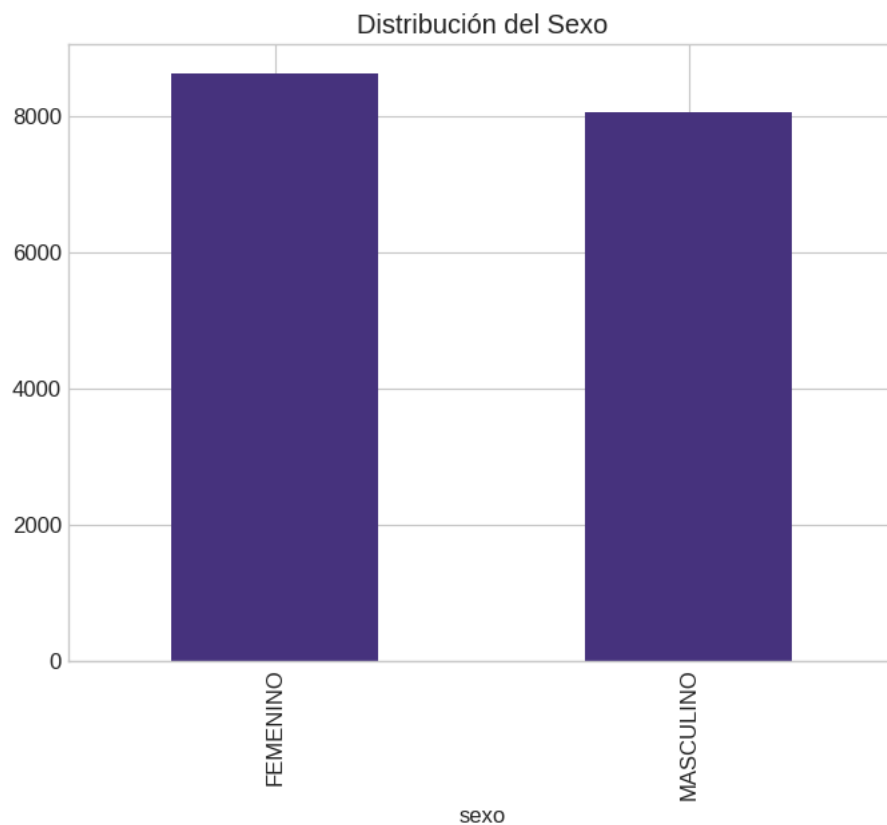
```

```
35 plt.title('Distribución del Máximo de Tarjeta')
36 plt.show()
37
38
39 # Análisis de la variable 'MAXIMO_CONSUMO'
40 print("\nAnálisis de la variable 'MAXIMO_CONSUMO':")
41 print(df['MAXIMO_CONSUMO'].describe())
42 plt.figure(figsize=(8, 6))
43 sns.histplot(df['MAXIMO_CONSUMO'], kde=True)
44 plt.title('Distribución del Máximo Consumo')
45 plt.show()
46
```

```
Análisis de la variable 'EDAD':  
count    16682.000000  
mean      51.917636  
std       14.487055  
min       22.000000  
25%       38.000000  
50%       54.000000  
75%       66.000000  
max       74.000000  
Name: EDAD, dtype: float64
```

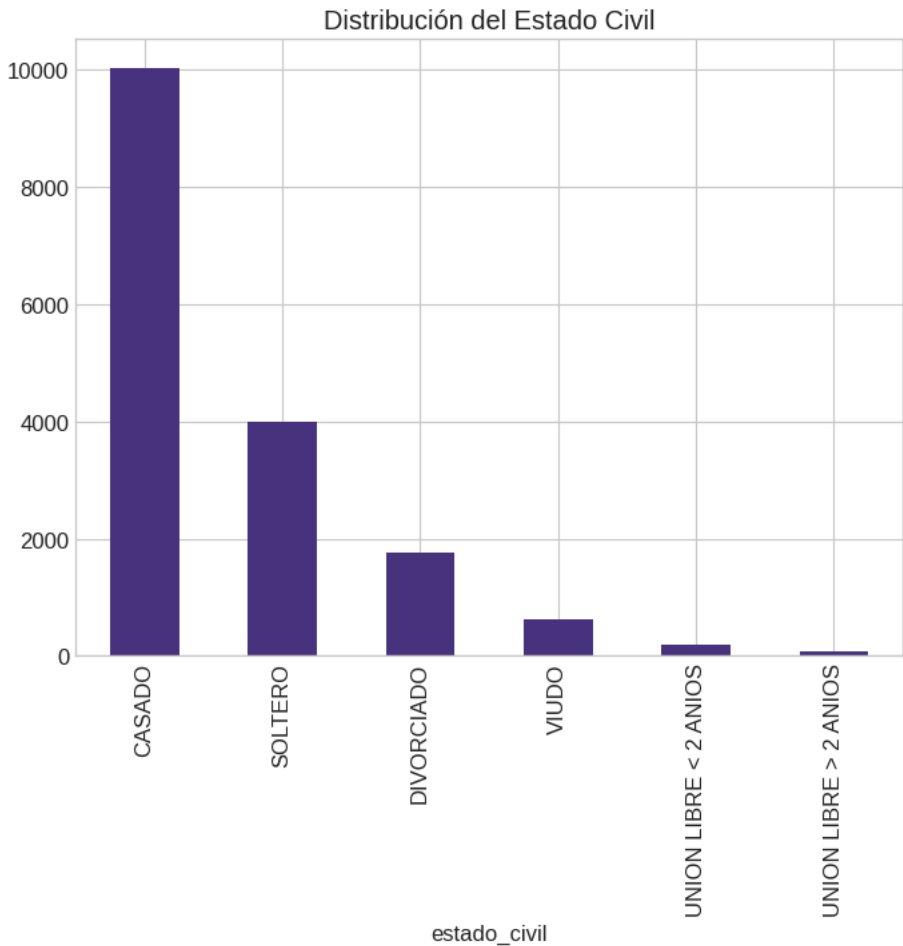


```
Análisis de la variable 'sexo':  
sexo  
FEMENINO    8624  
MASCULINO   8058  
Name: count, dtype: int64
```



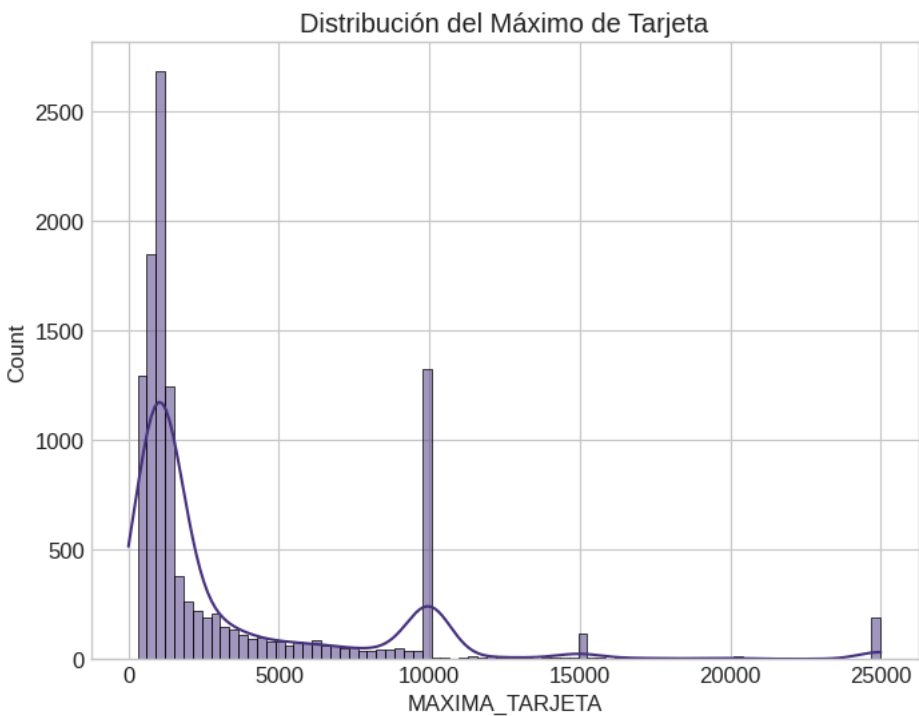
```
Análisis de la variable 'estado_civil':  
estado_civil  
CASADO      10019  
SOLTERO     4005  
DIVORCIADO  1754  
VIUDO       622
```

```
viudo      034
UNION LIBRE < 2 ANIOS    200
UNION LIBRE > 2 ANIOS    72
Name: count, dtype: int64
```



Análisis de la variable 'MAXIMA_TARJETA':

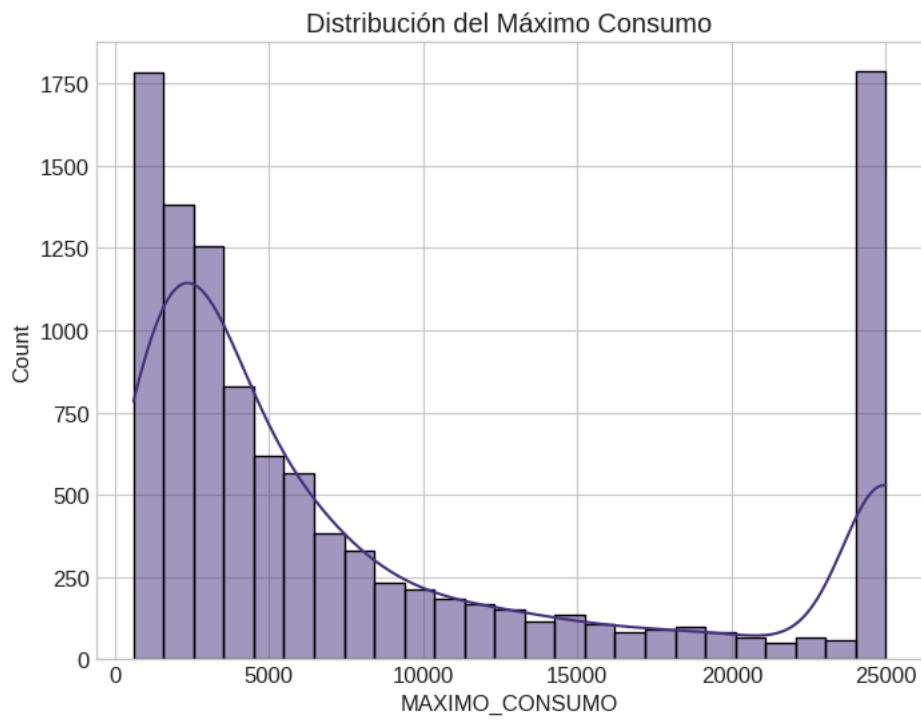
```
count    11859.000000
mean      3606.358040
std       4725.992054
min         0.000000
25%        900.000000
50%       1300.000000
75%       4400.000000
max      25000.000000
Name: MAXIMA_TARJETA, dtype: float64
```



Análisis de la variable 'MAXIMO_CONSUMO':

```
count    10838.000000
```

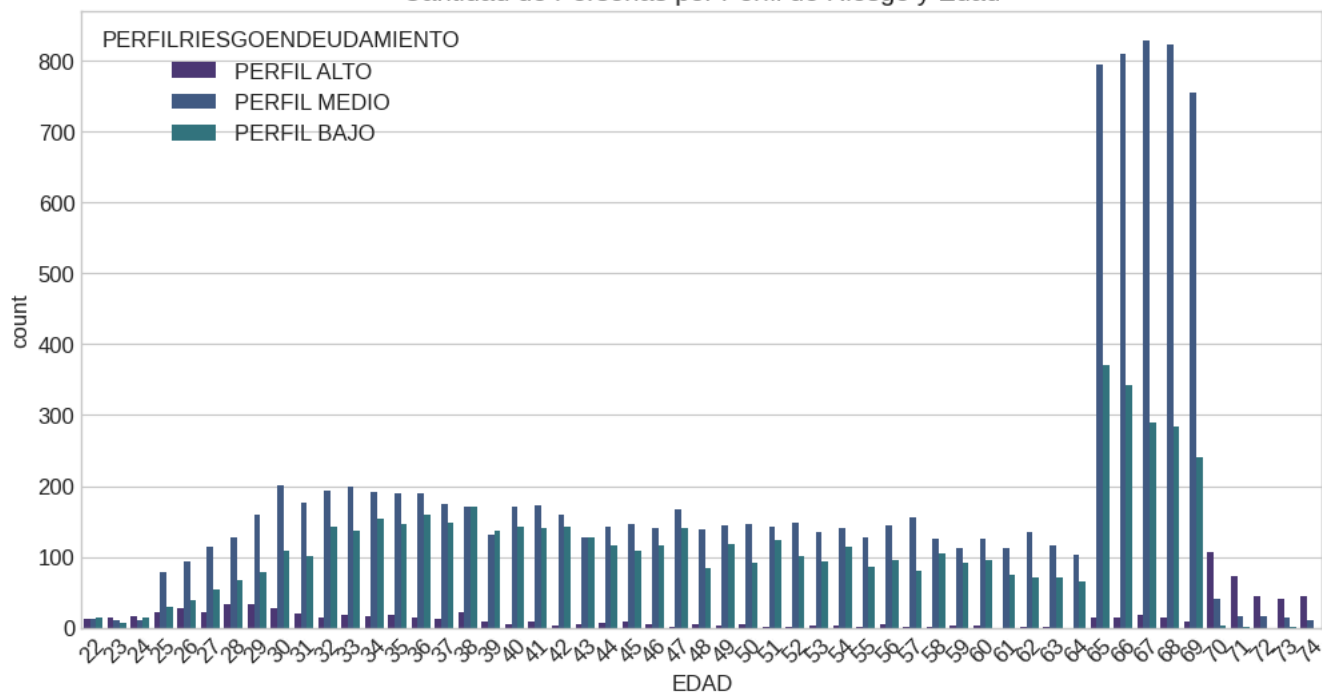
```
mean      8783.327182
std       8632.709979
min        600.000000
25%       2400.000000
50%       4800.000000
75%      13500.000000
max      25000.000000
Name: MAXIMO_CONSUMO, dtype: float64
```



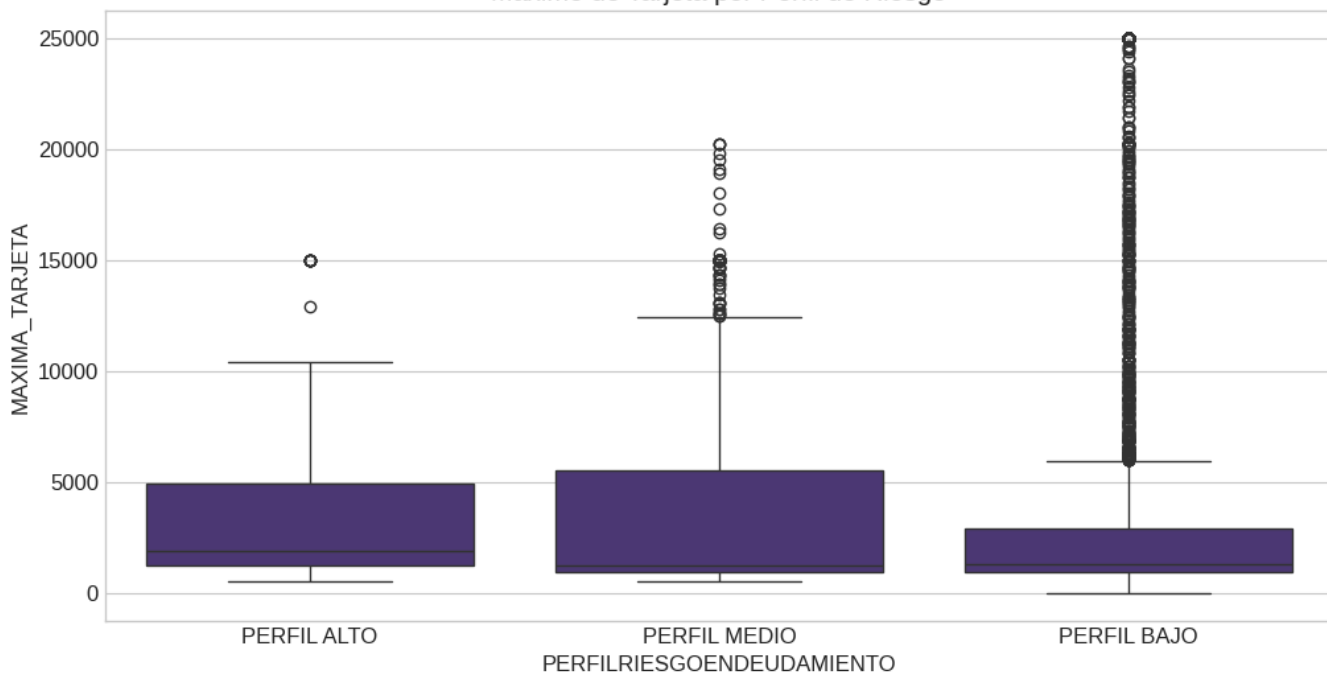
```
1 # Análisis de 'PERFILRIESGOENDEUDAMIENTO' vs. otras variables
2
3 # 1. Cantidad de personas por perfil de riesgo y edad
4 plt.figure(figsize=(12, 6))
5 sns.countplot(x='EDAD', hue='PERFILRIESGOENDEUDAMIENTO', data=df)
6 plt.title('Cantidad de Personas por Perfil de Riesgo y Edad')
7 plt.xticks(rotation=45)
8 plt.show()
9
10 # 2. Máximo de tarjeta por perfil de riesgo
11 plt.figure(figsize=(12, 6))
12 sns.boxplot(x='PERFILRIESGOENDEUDAMIENTO', y='MAXIMA_TARJETA', data=df)
13 plt.title('Máximo de Tarjeta por Perfil de Riesgo')
14 plt.show()
15
16 # 3. Máximo de consumo por perfil de riesgo
17 plt.figure(figsize=(12, 6))
18 sns.boxplot(x='PERFILRIESGOENDEUDAMIENTO', y='MAXIMO_CONSUMO', data=df)
19 plt.title('Máximo de Consumo por Perfil de Riesgo')
20 plt.show()
21
22
23 # 4. Estado civil por perfil de riesgo
24 plt.figure(figsize=(12, 6))
25 sns.countplot(x='estado_civil', hue='PERFILRIESGOENDEUDAMIENTO', data=df)
26 plt.title('Estado Civil por Perfil de Riesgo')
27 plt.xticks(rotation=45)
28 plt.show()
29
30 # Análisis adicionales (opcional)
31 # Puedes crear gráficos más específicos o combinar variables para un análisis más profundo:
32
33 # Ejemplo: Distribución de la edad para cada perfil de riesgo
34 for perfil in df['PERFILRIESGOENDEUDAMIENTO'].unique():
35     plt.figure(figsize=(8, 6))
36     sns.histplot(df[df['PERFILRIESGOENDEUDAMIENTO'] == perfil]['EDAD'], kde=True, label=perfil)
37     plt.title(f'Distribución de Edad para el perfil: {perfil}')
38     plt.legend()
39     plt.show()
40
```



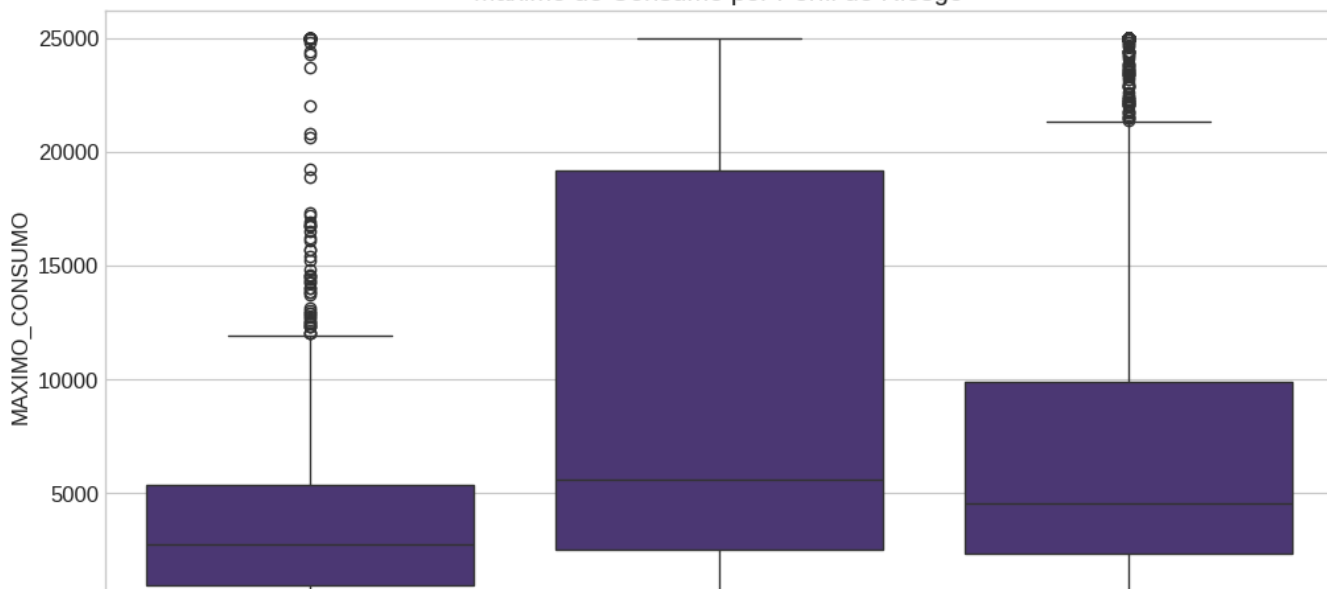
Cantidad de Personas por Perfil de Riesgo y Edad

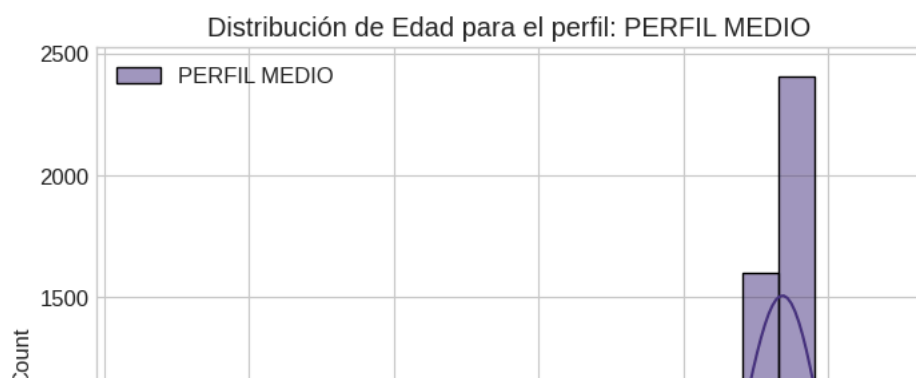
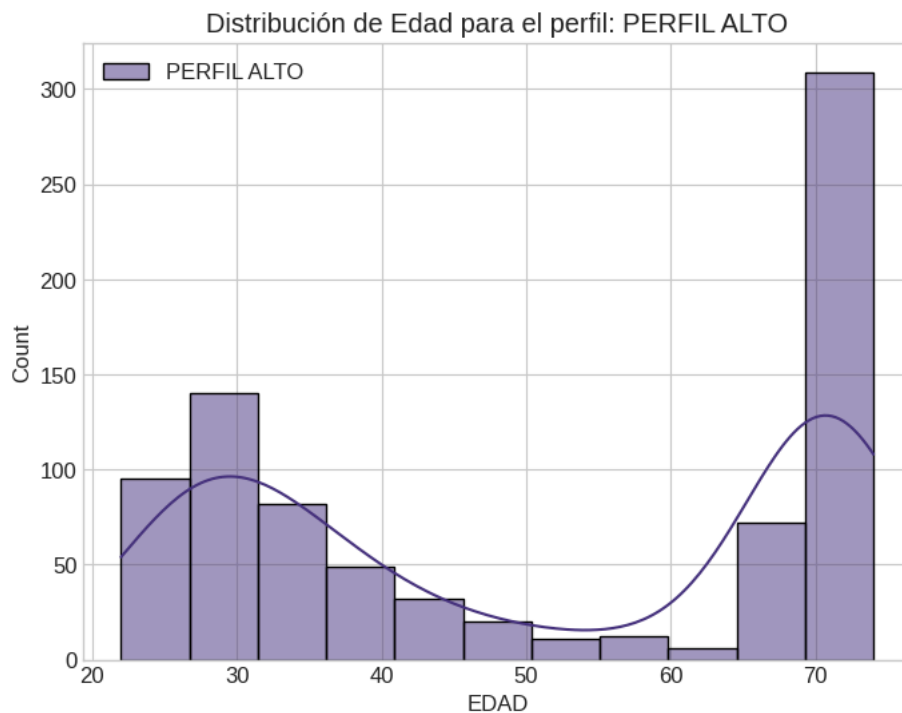
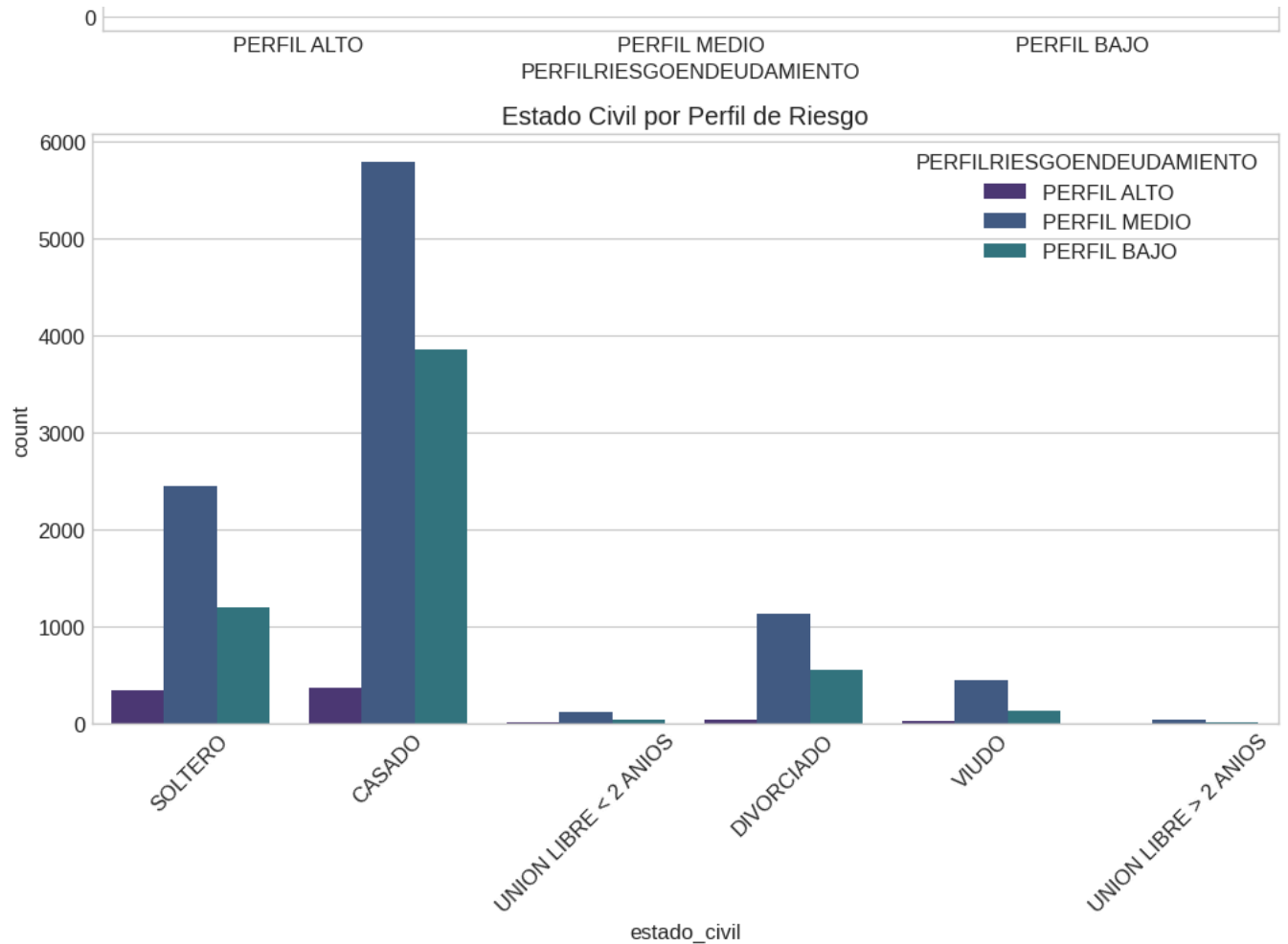


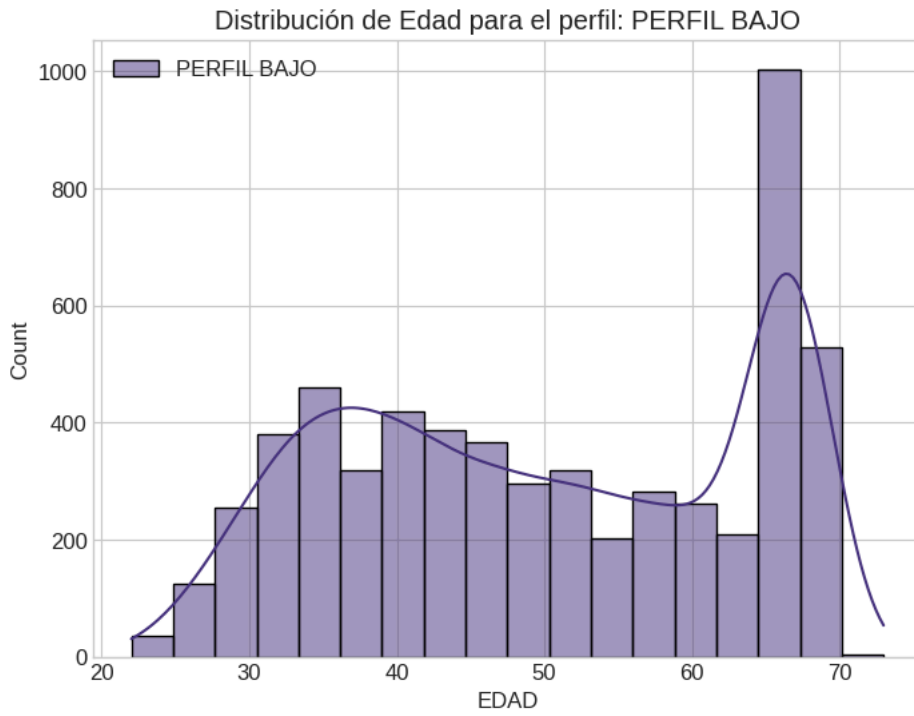
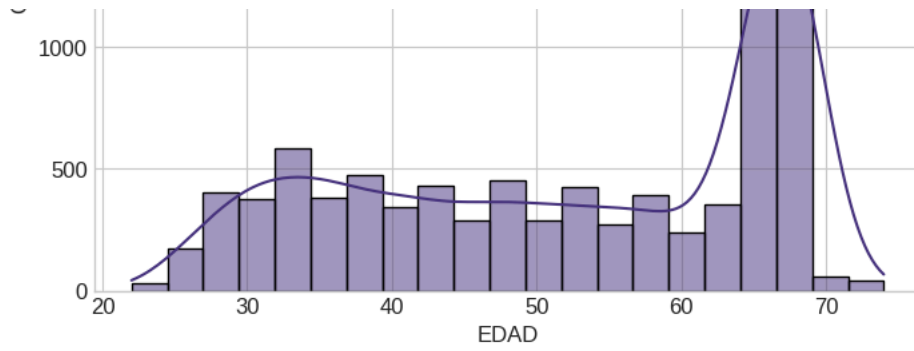
Máximo de Tarjeta por Perfil de Riesgo



Máximo de Consumo por Perfil de Riesgo



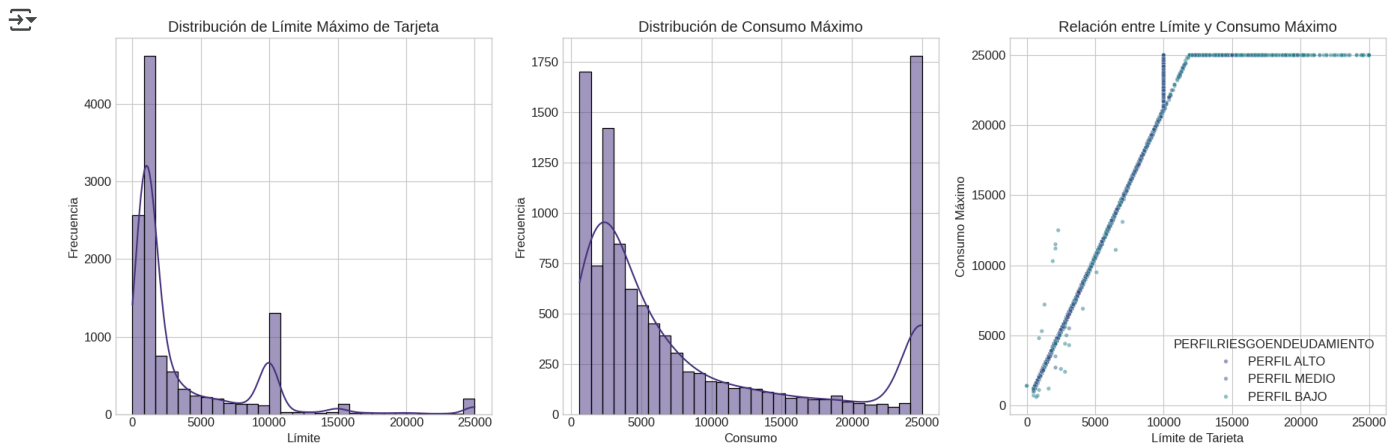




```

1 # 3.2 Análisis de variables financieras
2 plt.figure(figsize=(18, 6))
3
4 # Distribución del límite de tarjeta
5 plt.subplot(131)
6 sns.histplot(df['MAXIMA_TARJETA'], kde=True, bins=30)
7 plt.title('Distribución de Límite Máximo de Tarjeta')
8 plt.xlabel('Límite')
9 plt.ylabel('Frecuencia')
10
11 # Distribución del consumo máximo
12 plt.subplot(132)
13 sns.histplot(df['MAXIMO_CONSUMO'], kde=True, bins=30)
14 plt.title('Distribución de Consumo Máximo')
15 plt.xlabel('Consumo')
16 plt.ylabel('Frecuencia')
17
18 # Relación entre límite y consumo
19 plt.subplot(133)
20 sns.scatterplot(x='MAXIMA_TARJETA', y='MAXIMO_CONSUMO', data=df,
21               hue='PERFILRIESGOENDEUDAMIENTO', alpha=0.5, s=15)
22 plt.title('Relación entre Límite y Consumo Máximo')
23 plt.xlabel('Límite de Tarjeta')
24 plt.ylabel('Consumo Máximo')
25
26 plt.tight_layout()
27 plt.savefig('financieros.png')
28 plt.close()
29 from IPython.display import Image
30 display(Image('financieros.png'))

```



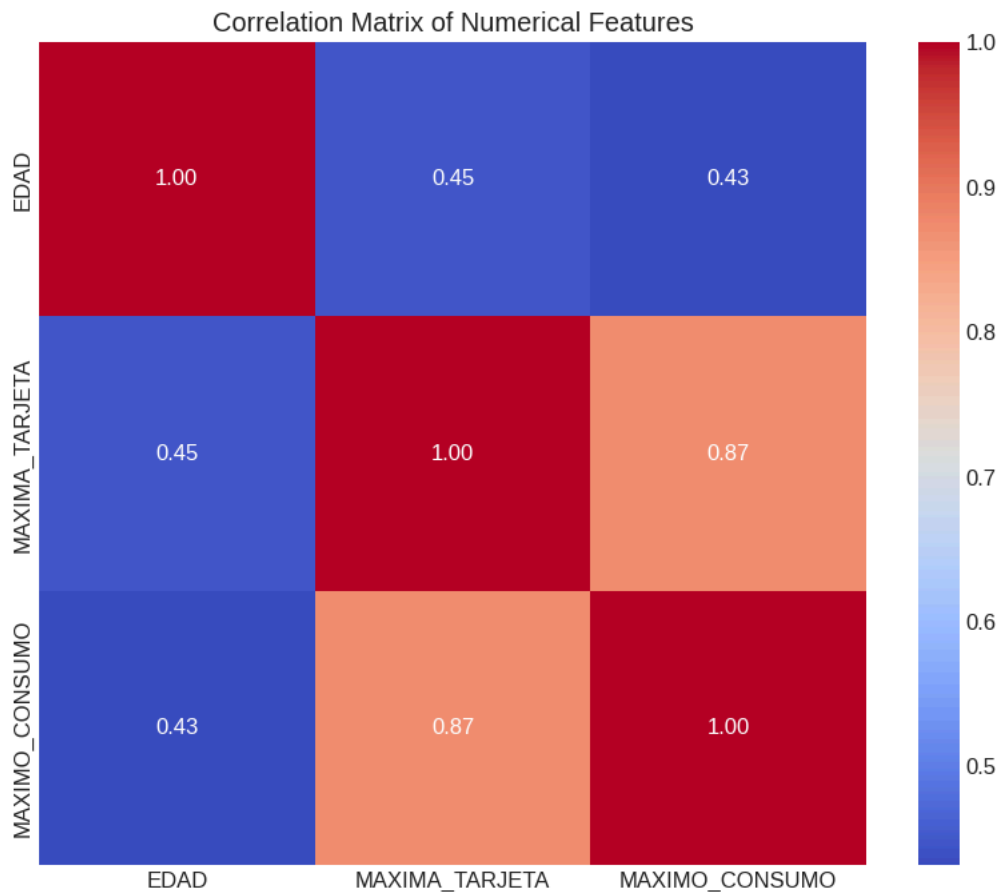
```

1 # Assuming 'df' is your DataFrame from the previous code
2
3 # Select numerical columns for correlation analysis
4 numerical_cols = ['EDAD', 'MAXIMA_TARJETA', 'MAXIMO_CONSUMO']
5 numerical_df = df[numerical_cols]
6
7 # Calculate the correlation matrix
8 correlation_matrix = numerical_df.corr()
9
10 # Display the correlation matrix
11 print(correlation_matrix)
12
13 # Visualize the correlation matrix using a heatmap
14 plt.figure(figsize=(10, 8))
15 sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt=".2f")
16 plt.title('Correlation Matrix of Numerical Features')
17 plt.show()
18

```



	EDAD	MAXIMA_TARJETA	MAXIMO_CONSUMO
EDAD	1.000000	0.445320	0.431907
MAXIMA_TARJETA	0.445320	1.000000	0.870249
MAXIMO_CONSUMO	0.431907	0.870249	1.000000



```

1 # prompt: remover del dataset las siguientes columnas: 'DIR_DOM_CAL_DAT', 'DIR_TRAB_1_CAL_DAT', 'NOMBRE'
2
3 # Remove specified columns
4 df = df.drop(columns=['DIR_DOM_CAL_DAT', 'DIR_TRAB_1_CAL_DAT', 'NOMBRE'], errors='ignore')
5

```

```

1 # Identify categorical columns
2 categorical_cols = df.select_dtypes(include=['object', 'category']).columns.tolist()
3
4 # Print the categorical columns
5 print("Categorical columns:")
6 categorical_cols
7

```



```

Categorical columns:
['PERFILRIESGOENDEUDAMIENTO',
 'sexo',
 'estado_civil',
 'PAIS_DOM_CAL_DAT',
 'PROV_DOM_CAL_DAT',
 'CIUDAD_DOM_CAL_DAT',
 'CORREO_BAN']

```

```

1 encoding_maps = {} # Diccionario para almacenar las bibliotecas de valores
2 for col in categorical_cols:
3     if col != 'IDENTIFICACION': # No transformar la columna 'IDENTIFICACION'
4         unique_values = df[col].unique()
5         encoding_map = {val: i for i, val in enumerate(unique_values)} # Asignar números consecutivos
6         df[col] = df[col].map(encoding_map)
7         encoding_maps[col] = encoding_map
8 # Mostrar las bibliotecas de valores y el DataFrame transformado
9 print("\nBibliotecas de valores:")
10 for col, map in encoding_maps.items():
11     print(f"{col}: {map}")
12 print("\nDataFrame transformado:")
13 # No usar decimales en la salida del DataFrame
14 with pd.option_context('display.float_format', '{:.0f}'.format):
15     print(df.head())
16

```



Bibliotecas de valores:

PERFILRIESGOENDEUDAMIENTO: {'PERFIL ALTO': 0, 'PERFIL MEDIO': 1, 'PERFIL BAJO': 2}

sexo: {'MASCULINO': 0, 'FEMENINO': 1}

estado_civil: {'SOLTERO': 0, 'CASADO': 1, 'UNION LIBRE < 2 ANIOS': 2, 'DIVORCIADO': 3, 'VIUDO': 4, 'UNION LIBRE > 2 ANIOS': 5}

PAIS_DOM_CAL_DAT: {'ECUADOR': 0}

PROV_DOM_CAL_DAT: {'PICHINCHA': 0}

CIUDAD_DOM_CAL_DAT: {'QUITO': 0}

CORREO_BAN: {'oliver_leo1994@hotmail.es': 0, 'rcristofer_dtb@hotmail.com': 1, 'andresquevedoandy@live.com.mx': 2, 'leojhongrefa@gmail.com': 3}

DataFrame transformado:

	IDENTIFICACION	PERFILRIESGOENDEUDAMIENTO	EDAD	sexo	estado_civil
0	2350359549	0	24	0	0
1	2300650476	0	23	0	0
2	2300107253	1	26	0	1
3	2200176531	0	25	0	0
4	2200046163	2	28	0	0

	MAXIMA_TARJETA	MAXIMO_CONSUMO	PAIS_DOM_CAL_DAT	PROV_DOM_CAL_DAT
0	NaN	2900	0	0
1	NaN	800	0	0
2	1000	NaN	0	0
3	NaN	800	0	0
4	1000	NaN	0	0

	CIUDAD_DOM_CAL_DAT	TEL_DOM_1_CAL_DAT	TEL_TRA_1_CAL_DAT	CELULAR_1
0	0	22420481	NaN	960605351
1	0	23447377	NaN	967428769
2	0	22441940	23971000	988676891
3	0	NaN	NaN	998645219
4	0	NaN	NaN	939070056

	CELULAR_BAN	CORREO_BAN
0	993931984	0
1	997398980	1
2	992510700	2
3	985945741	3
4	939983650	4

1 # Manejar valores faltantes

2 for column in df.columns:

3 df[column].fillna(df[column].mode()[0], inplace=True)

df[column].fillna(df[column].mode()[0], inplace=True)

<ipython-input-217-df6bc2e8bee9>:3: FutureWarning: A value is trying to be set on a copy of a DataFrame or Series through chained assignment. The behavior will change in pandas 3.0. This inplace method will never work because the intermediate object on which we are setting values is a copy.

For example, when doing 'df[col].method(value, inplace=True)', try using 'df.method({col: value}, inplace=True)' or df[col] = df

df[column].fillna(df[column].mode()[0], inplace=True)

<ipython-input-217-df6bc2e8bee9>:3: FutureWarning: A value is trying to be set on a copy of a DataFrame or Series through chained assignment. The behavior will change in pandas 3.0. This inplace method will never work because the intermediate object on which we are setting values is a copy.

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<ipython-input-217-df6bc2e8bee9>:3: FutureWarning: A value is trying to be set on a copy of a DataFrame or Series through chained assignment. The behavior will change in pandas 3.0. This inplace method will never work because the intermediate object on which we are setting values is a copy.

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<ipython-input-217-df6bc2e8bee9>:3: FutureWarning: A value is trying to be set on a copy of a DataFrame or Series through chained assignment. The behavior will change in pandas 3.0. This inplace method will never work because the intermediate object on which we are setting values is a copy.

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<ipython-input-217-df6bc2e8bee9>:3: FutureWarning: A value is trying to be set on a copy of a DataFrame or Series through chained assignment. The behavior will change in pandas 3.0. This inplace method will never work because the intermediate object on which we are setting values is a copy.

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<ipython-input-217-df6bc2e8bee9>:3: FutureWarning: A value is trying to be set on a copy of a DataFrame or Series through chained assignment. The behavior will change in pandas 3.0. This inplace method will never work because the intermediate object on which we are setting values is a copy.

For example, when doing 'df[col].method(value, inplace=True)', try using 'df.method({col: value}, inplace=True)' or df[col] = df

```
df[column].fillna(df[column].mode()[0], inplace=True)
<ipython-input-217-df6bc2e8bee9>:3: FutureWarning: A value is trying to be set on a copy of a DataFrame or Series through chained
The behavior will change in pandas 3.0. This inplace method will never work because the intermediate object on which we are setti
```

For example, when doing 'df[col].method(value, inplace=True)', try using 'df.method({col: value}, inplace=True)' or df[col] = df

```
df[column].fillna(df[column].mode()[0], inplace=True)
```

1
2

1 pip install pandas scikit-learn gower

```
Requirement already satisfied: pandas in /usr/local/lib/python3.11/dist-packages (2.2.2)
Requirement already satisfied: scikit-learn in /usr/local/lib/python3.11/dist-packages (1.6.1)
Requirement already satisfied: gower in /usr/local/lib/python3.11/dist-packages (0.1.2)
Requirement already satisfied: numpy>=1.23.2 in /usr/local/lib/python3.11/dist-packages (from pandas) (2.0.2)
Requirement already satisfied: python-dateutil>=2.8.2 in /usr/local/lib/python3.11/dist-packages (from pandas) (2.8.2)
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.11/dist-packages (from pandas) (2025.2)
Requirement already satisfied: tzdata>=2022.7 in /usr/local/lib/python3.11/dist-packages (from pandas) (2025.2)
Requirement already satisfied: scipy>=1.6.0 in /usr/local/lib/python3.11/dist-packages (from scikit-learn) (1.14.1)
Requirement already satisfied: joblib>=1.2.0 in /usr/local/lib/python3.11/dist-packages (from scikit-learn) (1.4.2)
Requirement already satisfied: threadpoolctl>=3.1.0 in /usr/local/lib/python3.11/dist-packages (from scikit-learn) (3.6.0)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.11/dist-packages (from python-dateutil>=2.8.2->pandas) (1.17.0)
```

```
1 # Separar variables numéricas y categóricas
2 numerical_features = df.select_dtypes(include=np.number).columns.tolist()
3 categorical_features = df.select_dtypes(exclude=np.number).columns.tolist()
4
5 # Transformación de variables categóricas (One-Hot Encoding)
6 encoder = OneHotEncoder(sparse_output=False, handle_unknown='ignore')
7 encoded_categorical = encoder.fit_transform(df[categorical_features])
8 encoded_categorical_df = pd.DataFrame(encoded_categorical, index=df.index)
9
10 # Get feature names from encoder
11 encoded_feature_names = encoder.get_feature_names_out(categorical_features)
12 encoded_categorical_df.columns = encoded_feature_names # Assign feature names to columns
13
14 df = pd.concat([df[numerical_features], encoded_categorical_df], axis=1)
15
16 # Replace infinite values with NaN
17 df.replace([np.inf, -np.inf], np.nan, inplace=True)
18
19 # Impute NaN values (if any) with the mean of the column
20 for col in numerical_features:
21     df[col].fillna(df[col].mean(), inplace=True)
22
23 # Ensure all column names are strings before scaling
24 df.columns = df.columns.astype(str)
25
26 # Escalar variables numéricas
27 scaler = StandardScaler()
28 df[numerical_features] = scaler.fit_transform(df[numerical_features])
```

```
<ipython-input-219-3883bf016583>:21: FutureWarning: A value is trying to be set on a copy of a DataFrame or Series through chained
The behavior will change in pandas 3.0. This inplace method will never work because the intermediate object on which we are setting
```

For example, when doing 'df[col].method(value, inplace=True)', try using 'df.method({col: value}, inplace=True)' or df[col] = df[col]

```
df[col].fillna(df[col].mean(), inplace=True)
```

```
1 # prompt: realizar algoritmo k-means para poder definir los clusters más logicos según el perfil de endeudamiento y maximo de consu
2
3 # Define features for clustering
4 features_to_cluster = ['PERFILRIESGOENDEUDAMIENTO', 'MAXIMA_TARJETA', 'MAXIMO_CONSUMO']
5
6 # Filter DataFrame for selected features
7 X = df[features_to_cluster]
8
9 # Determine optimal number of clusters using Silhouette analysis
10 range_n_clusters = [2, 3, 4, 5, 6, 7, 8]
11 silhouette_scores = []
12
13 for n_clusters in range_n_clusters:
```

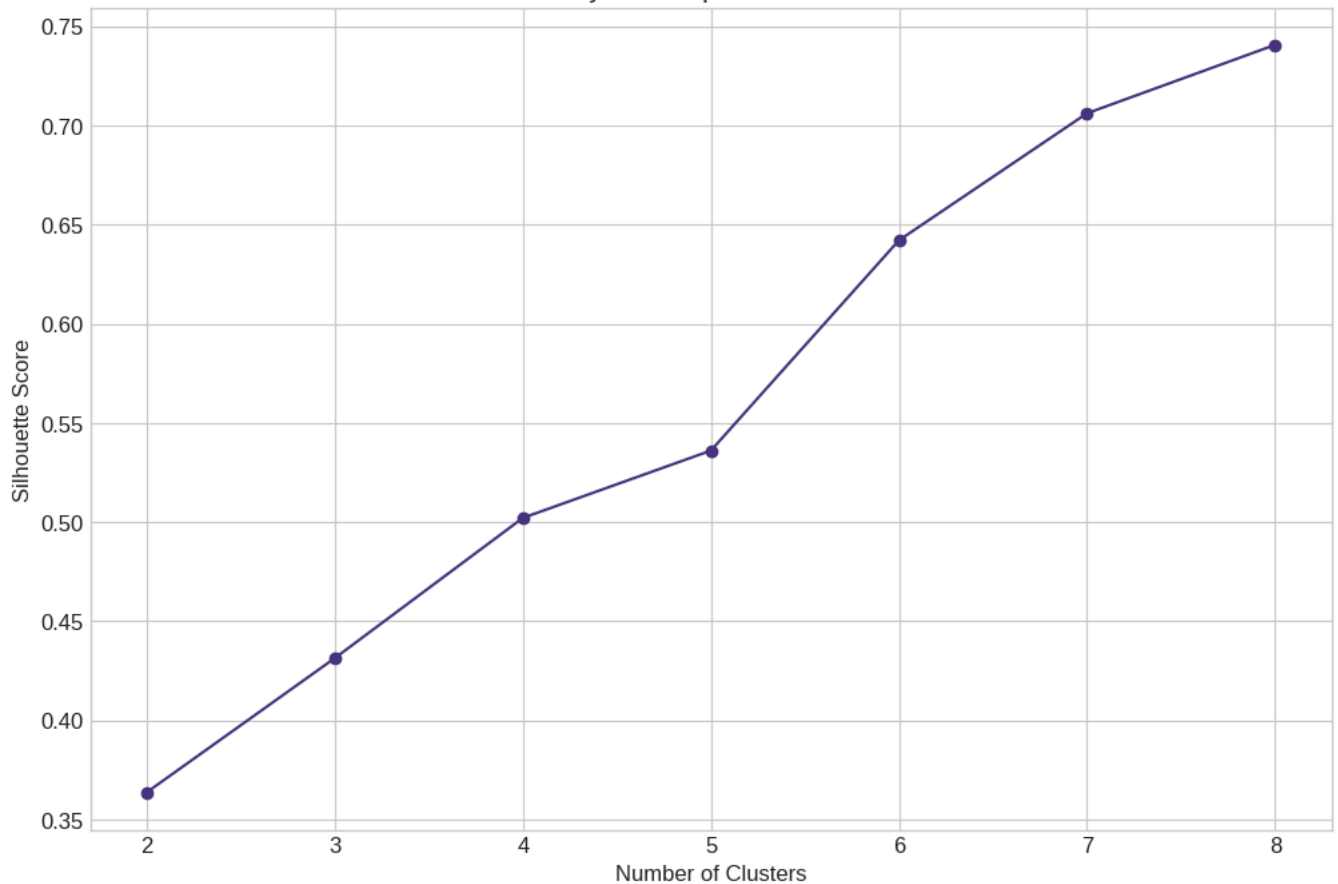
```
14 kmeans = KMeans(n_clusters=n_clusters, random_state=42)
15 cluster_labels = kmeans.fit_predict(X)
16 silhouette_avg = silhouette_score(X, cluster_labels)
17 silhouette_scores.append(silhouette_avg)
18 print(f"For n_clusters = {n_clusters}, the average silhouette_score is: {silhouette_avg}")
19
20 # Plot Silhouette scores
21 plt.plot(range_n_clusters, silhouette_scores, marker='o')
22 plt.xlabel("Number of Clusters")
23 plt.ylabel("Silhouette Score")
24 plt.title("Silhouette Analysis for Optimal Number of Clusters")
25 plt.show()
26
27 # Perform K-Means clustering with the optimal number of clusters (determined visually from the plot above)
28 optimal_n_clusters = 3 # Replace with the visually determined optimal k from the plot
29 kmeans = KMeans(n_clusters=optimal_n_clusters, random_state=42)
30 df['cluster'] = kmeans.fit_predict(X)
31
32 # Analyze and visualize the clusters
33 # Example: Calculate cluster means for each feature
34 cluster_means = df.groupby('cluster')[features_to_cluster].mean()
35 print("\nCluster Means:")
36 print(cluster_means)
37
38 plt.figure(figsize=(10, 6))
39 sns.scatterplot(data=df, x='PERFILRIESGOENDEUDAMIENTO', y='MAXIMO_CONSUMO', hue='cluster', palette='viridis')
40 plt.title('K-Means Clustering Visualization')
41 plt.xlabel('Perfil Riesgo Endeudamiento') # Updated x-axis label
42 plt.ylabel('Maximo Consumo')
43 plt.show()
```

```

↗ For n_clusters = 2, the average silhouette_score is: 0.3637257445503861
For n_clusters = 3, the average silhouette_score is: 0.43140390816397345
For n_clusters = 4, the average silhouette_score is: 0.5021076585191356
For n_clusters = 5, the average silhouette_score is: 0.5360789095668325
For n_clusters = 6, the average silhouette_score is: 0.642139587966258
For n_clusters = 7, the average silhouette_score is: 0.706183840023218
For n_clusters = 8, the average silhouette_score is: 0.7406880606947717

```

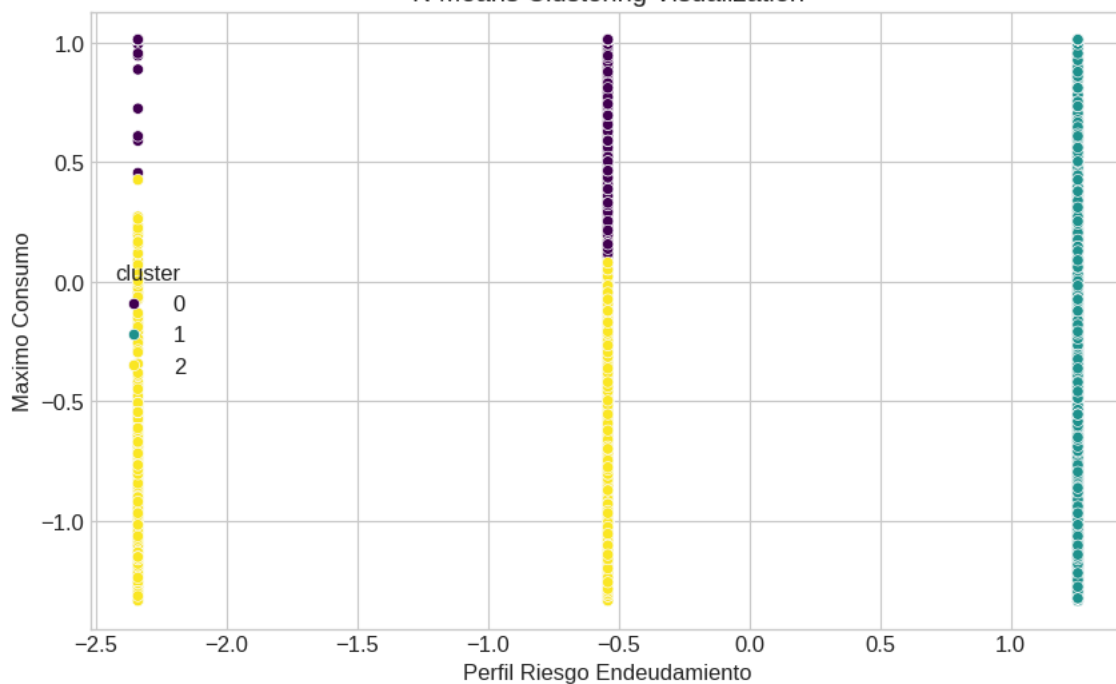
Silhouette Analysis for Optimal Number of Clusters



Cluster Means:

	PERFILRIESGOENDEUDAMIENTO	MAXIMA_TARJETA	MAXIMO_CONSUMO
cluster 0	-0.557605	-0.314335	0.968812
cluster 1	1.256783	0.185494	-0.094374
cluster 2	-0.810493	0.136323	-0.961597

K-Means Clustering Visualization



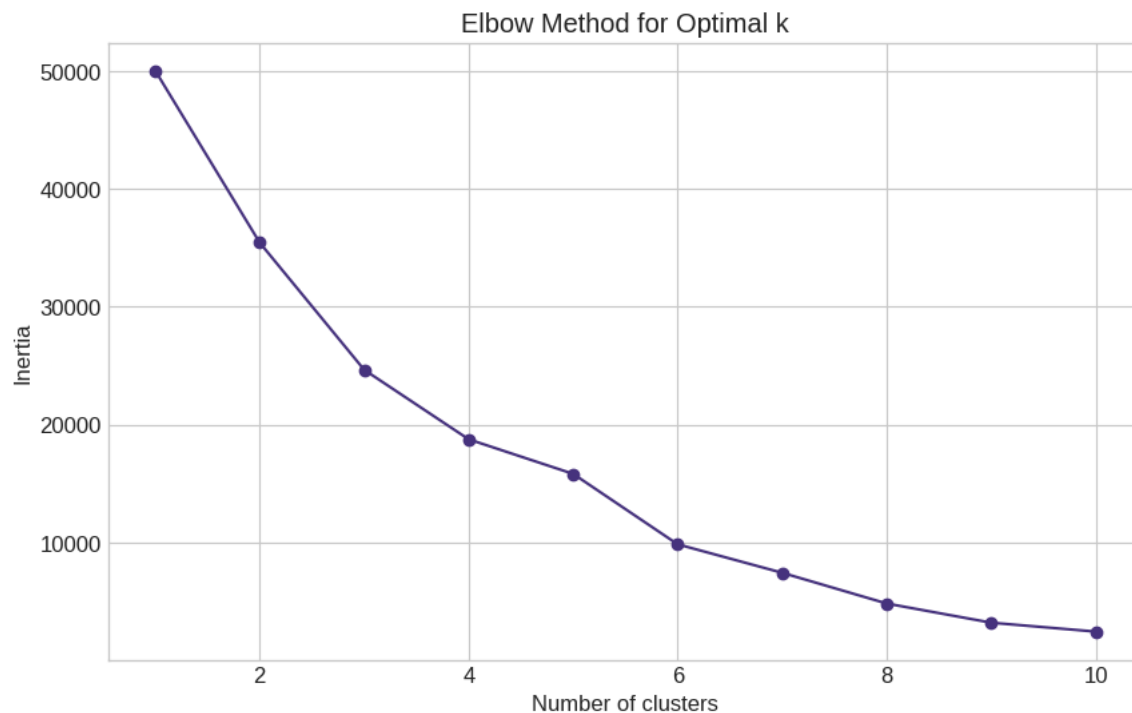
1 # prompt: grafico de codo

2

```

3 # Elbow Method for optimal k
4 inertia = []
5 for i in range(1, 11):
6     kmeans = KMeans(n_clusters=i, random_state=42)
7     kmeans.fit(X)
8     inertia.append(kmeans.inertia_)
9
10 plt.figure(figsize=(10, 6))
11 plt.plot(range(1, 11), inertia, marker='o')
12 plt.xlabel('Number of clusters')
13 plt.ylabel('Inertia')
14 plt.title('Elbow Method for Optimal k')
15 plt.show()
16

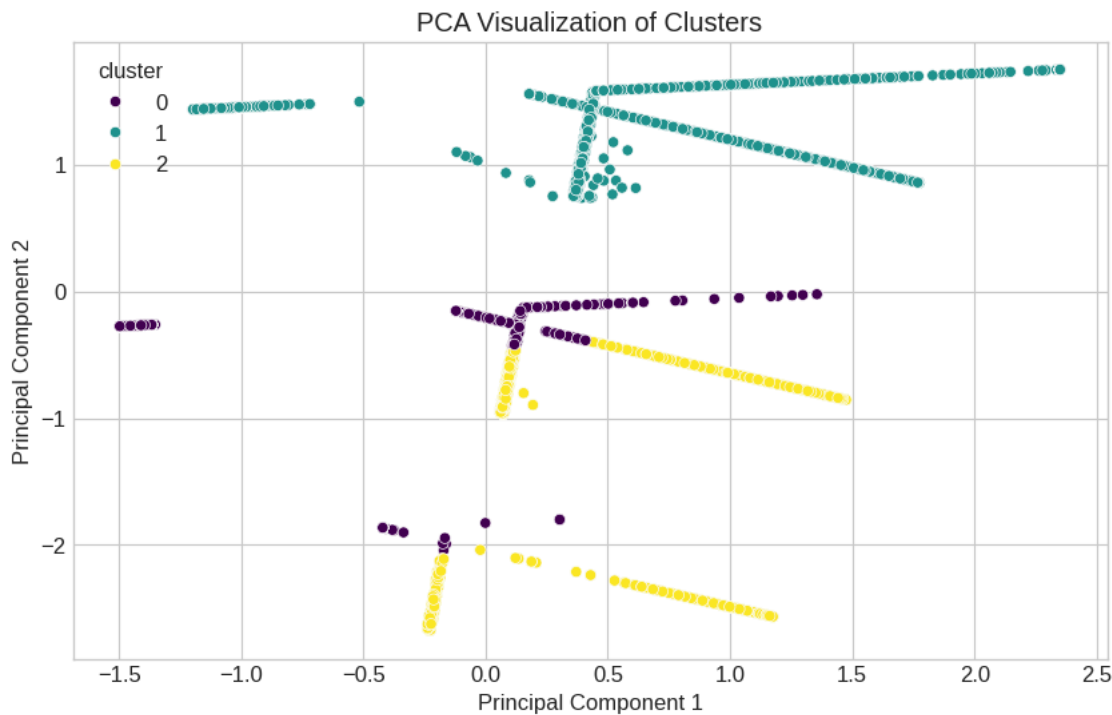
```



```

1 # Apply PCA
2 pca = PCA(n_components=2) # Reduce to 2 principal components
3 df_pca = pca.fit_transform(X)
4
5 # Create a DataFrame for the PCA results
6 df_pca = pd.DataFrame(data=df_pca, columns=['PC1', 'PC2'])
7 df_pca['cluster'] = df['cluster'] # Add the cluster labels
8
9 # Visualize the PCA results
10 plt.figure(figsize=(10, 6))
11 sns.scatterplot(data=df_pca, x='PC1', y='PC2', hue='cluster', palette='viridis')
12 plt.title('PCA Visualization of Clusters')
13 plt.xlabel('Principal Component 1')
14 plt.ylabel('Principal Component 2')
15 plt.show()
16
17 # Explained Variance Ratio
18 explained_variance_ratio = pca.explained_variance_ratio_
19 print(f"Explained Variance Ratio: {explained_variance_ratio}")
20 print(f"Total Explained Variance: {np.sum(explained_variance_ratio)}")
21

```

Explained Variance Ratio: [0.42833476 0.33762586]
Total Explained Variance: 0.7659606166129003

```
1 # Identify outliers using IQR method
2 def find_outliers_iqr(data):
3     Q1 = data.quantile(0.25)
4     Q3 = data.quantile(0.75)
5     IQR = Q3 - Q1
6     lower_bound = Q1 - 1.5 * IQR
7     upper_bound = Q3 + 1.5 * IQR
8     outliers = data[(data < lower_bound) | (data > upper_bound)]
9     return outliers
10
11 outlier_data = {}
12 for col in features_to_cluster:
13     outliers = find_outliers_iqr(df[col])
14     outlier_data[col] = outliers
15
16 # Create a DataFrame for outliers
17 outliers_df = pd.DataFrame(outlier_data)
18
19 # Download the outliers to a CSV file
20 outliers_df.to_csv('outliers.csv', index=False)
21 files.download('outliers.csv')
22
```



```
1 from sklearn.cluster import DBSCAN
2 # Suponiendo que 'df' es tu DataFrame y 'X' contiene las características numéricas para el clustering
3 # Por ejemplo:
4 X = df[['PERFILRIESGOENDEUDAMIENTO', 'MAXIMA_TARJETA', 'MAXIMO_CONSUMO']]
5
6 # Escalar los datos
7 scaler = StandardScaler()
8 X_scaled = scaler.fit_transform(X)
9
10 # Aplicar DBSCAN
11 dbscan = DBSCAN(eps=0.5, min_samples=5) # Ajustar eps y min_samples según tus datos
12 clusters = dbscan.fit_predict(X_scaled)
13
14 # Agregar los clusters al DataFrame
15 df['cluster'] = clusters
16
17 # Analizar los resultados
18 print(df['cluster'].value_counts())
19 # Visualizar los clusters (ejemplo con las primeras dos componentes principales)
20 pca = PCA(n_components=2)
21 X_pca = pca.fit_transform(X_scaled)
22
23 plt.figure(figsize=(8, 6))
24 plt.scatter(X_pca[:, 0], X_pca[:, 1], c=clusters, cmap='viridis')
```

```

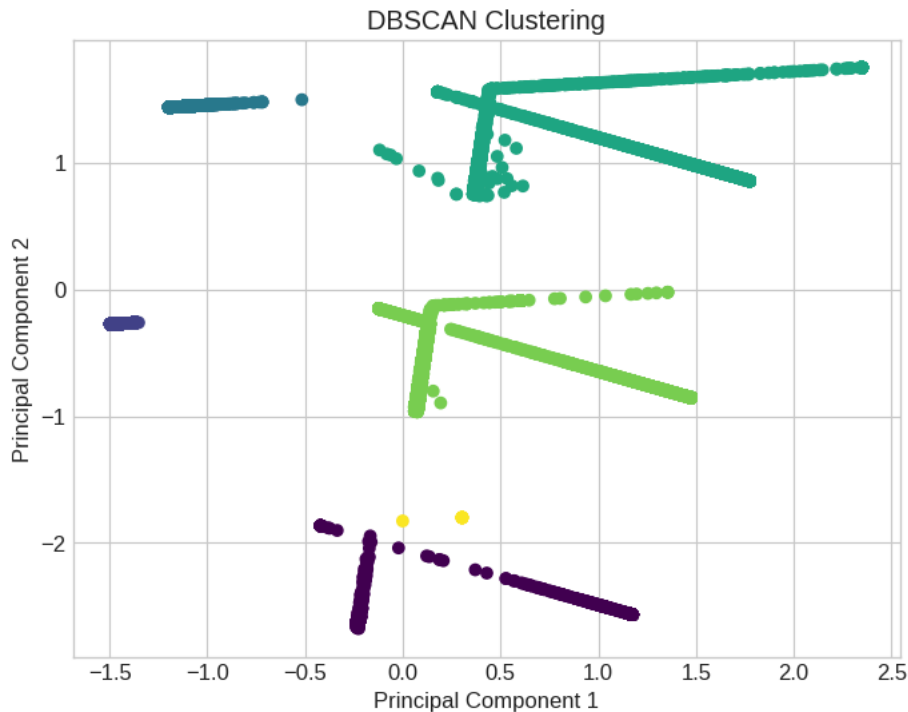
25 plt.title('DBSCAN Clustering')
26 plt.xlabel('Principal Component 1')
27 plt.ylabel('Principal Component 2')
28 plt.show()

```

```

cluster
4    6146
3    3864
1    3863
2    1981
0     819
5         9
Name: count, dtype: int64

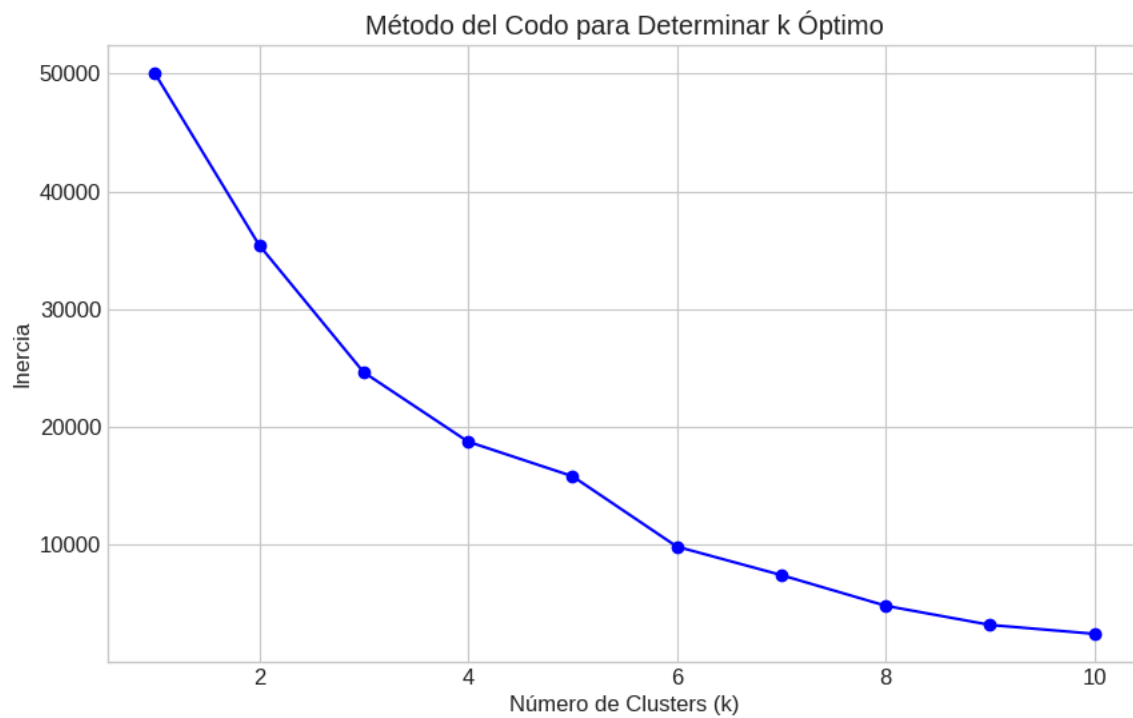
```



```

1 # 7. Exploración de patrones mediante clustering preliminar
2 # Seleccionamos las variables más relevantes para el clustering
3 X = df[['PERFILRIESGOENDEUDAMIENTO', 'MAXIMA_TARJETA', 'MAXIMO_CONSUMO']]
4
5 # Preprocesamiento: escalado de variables
6 scaler = StandardScaler()
7 X_scaled = scaler.fit_transform(X)
8
9 # 7.1 Determinación del número óptimo de clusters con el método del codo
10 inertias = []
11 K_range = range(1, 11)
12 for k in K_range:
13     kmeans = KMeans(n_clusters=k, random_state=42)
14     kmeans.fit(X_scaled)
15     inertias.append(kmeans.inertia_)
16
17 plt.figure(figsize=(10, 6))
18 plt.plot(K_range, inertias, 'bo-')
19 plt.title('Método del Codo para Determinar k Óptimo')
20 plt.xlabel('Número de Clusters (k)')
21 plt.ylabel('Inercia')
22 plt.grid(True)
23 plt.savefig('metodo_codo.png')
24 plt.close()
25 from IPython.display import Image
26 display(Image('metodo_codo.png'))

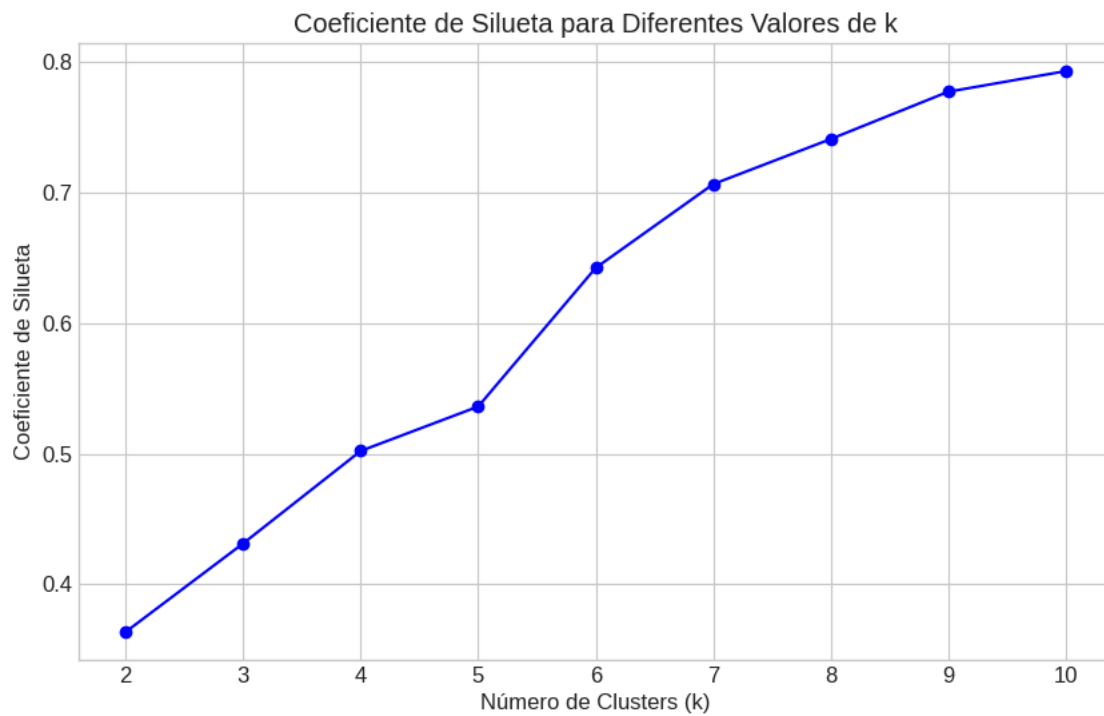
```



```

1 # 7.2 Evaluación con el coeficiente de silueta
2 silhouette_scores = []
3 for k in range(2, 11):
4     kmeans = KMeans(n_clusters=k, random_state=42)
5     cluster_labels = kmeans.fit_predict(X_scaled)
6     silhouette_avg = silhouette_score(X_scaled, cluster_labels)
7     silhouette_scores.append(silhouette_avg)
8
9 plt.figure(figsize=(10, 6))
10 plt.plot(range(2, 11), silhouette_scores, 'bo-')
11 plt.title('Coeficiente de Silueta para Diferentes Valores de k')
12 plt.xlabel('Número de Clusters (k)')
13 plt.ylabel('Coeficiente de Silueta')
14 plt.grid(True)
15 plt.savefig('silueta.png')
16 plt.close()
17 from IPython.display import Image
18 display(Image('silueta.png'))

```



```
1 optimal_k = 3 #Reemplaza con el valor optimo de k obtenido de las graficas
2 print(f"El número óptimo de clusters es: {optimal_k}")
3
```



El número óptimo de clusters es: 3

```
1 # 7.3 Aplicación preliminar de K-means con k=3 (valor asumido óptimo)
2 from sklearn.cluster import KMeans # Make sure KMeans is imported
3 from sklearn.preprocessing import StandardScaler
4
5 # Select features for clustering
6 X = df[['PERFILRIESGOENDEUDAMIENTO', 'MAXIMA_TARJETA', 'MAXIMO_CONSUMO']]
7
8 # Preprocessing: scaling features
9 scaler = StandardScaler()
10 X_scaled = scaler.fit_transform(X) # Define X_scaled here before using it
11
12 kmeans = KMeans(n_clusters=5, random_state=42)
13 df['cluster'] = kmeans.fit_predict(X_scaled)
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