Data Analyst Intern at Data Glacier

Week 10 Report

Project: Customer Segmentation

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Date:9th January, 2024

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I. Problem Description

XYZ Bank wants to segment its customers into no more than five distinct groups to send personalized Christmas offers. The goal is to automate the process, uncover hidden patterns in customer behavior, and improve campaign efficiency. The segmentation model should help target relevant customer groups with tailored offers, optimizing engagement and conversion rates.

II. Business Understanding

Problem Context: XYZ Bank is looking for a data-driven solution to divide its customer base into groups that have similar behaviors, so that they can create targeted offers.

Objective: Create a machine learning model to perform segmentation, aiming to group customers into 5 or fewer segments.

III. Project Lifecycle

Week 8 (26 Dec 2024): Submit data intake report with initial EDA.
Week 9 (2 Jan 2025): Deliver advanced EDA and feature engineering insights.
Week 10 (9 Jan 2025): Propose model-building plan and clustering approach.
Week 11 (16 Jan 2025): Present EDA findings and modeling technique.
Week 12 (23 Jan 2025): Finalize model, segmentation results, and dashboard.
Week 13 (30 Jan 2025): Submit final report and complete code repository.

1. Data Understanding

1.1. Data Size

The data contains 1000000 row and 48 columns.

```
In [2]: data
```

Out[2]:

	Unnamed: 0	fecha_dato	ncodpers	ind_empleado	pais_residencia	sexo	age	fecha_alta	ind_nuevo	antiguedad	...	ind_hip_fin_ult1	ind_plan_fin_ult1
0	0	2015-01-28	1375586	N	ES	H	35	2015-01-12	0.0	6	...	0	0
1	1	2015-01-28	1050611	N	ES	V	23	2012-08-10	0.0	35	...	0	0
2	2	2015-01-28	1050612	N	ES	V	23	2012-08-10	0.0	35	...	0	0
3	3	2015-01-28	1050613	N	ES	H	22	2012-08-10	0.0	35	...	0	0
4	4	2015-01-28	1050614	N	ES	V	23	2012-08-10	0.0	35	...	0	0
...	...	...	...	...	...	...	...	...	...	...	...	...	...
999995	999995	2015-02-28	1183296	N	ES	H	27	2013-09-25	0.0	22	...	0	0
999996	999996	2015-02-28	1183295	N	ES	H	56	2013-09-25	0.0	22	...	0	0
999997	999997	2015-02-28	1183294	N	ES	V	39	2013-09-25	0.0	22	...	0	0
999998	999998	2015-02-28	1183293	N	ES	V	36	2013-09-25	0.0	22	...	0	0
999999	999999	2015-02-28	1183289	N	ES	H	38	2013-09-25	0.0	22	...	0	0

1000000 rows × 48 columns

```
In [3]: data.shape
```

```
Out[3]: (1000000, 48)
```

```
duplicates = data.duplicated().sum()
print(f"\nNumber of Duplicate Rows: {duplicates}")
```

```
Number of Duplicate Rows: 0
```

1.2. Data Types

Data types include int64, object, float64

```
In [4]: print("Basic Dataset Information:")
        print(data.info())

        print("\nBasic Statistics:")
        print(data.describe())

        print("\nFirst 5 Rows of Dataset:")
        print(data.head())
```

```
Basic Dataset Information:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000000 entries, 0 to 999999
Data columns (total 48 columns):
 #   Column              Non-Null Count    Dtype
---  ------              --------------    -----
 0   Unnamed: 0          1000000 non-null  int64
 1   fecha_dato          1000000 non-null  object
 2   ncodpers            1000000 non-null  int64
 3   ind_empleado        989218 non-null   object
 4   pais_residencia     989218 non-null   object
 5   sexo                989214 non-null   object
 6   age                 1000000 non-null  object
 7   fecha_alta          989218 non-null   object
 8   ind_nuevo           989218 non-null   float64
 9   antiguedad          1000000 non-null  object
 10  indrel              989218 non-null   float64
 11  ult_fec_cli_1t      1101 non-null     object
 12  indrel_1mes         989218 non-null   float64
```

2. Data Cleaning

2.1. Renaming Unnecessary Columns

The column names were renamed for better understanding. The column description given by the company were used for the renaming.

```python
In [7]: # Define a dictionary with old column names as keys and new descriptive names as values
column_renames = {
    'fecha_dato': 'Partition_Date',
    'ncodpers': 'Customer_Code',
    'ind_empleado': 'Employee_Index',
    'pais_residencia': 'Country_Residence',
    'sexo': 'Gender',
    'age': 'Age',
    'fecha_alta': 'First_Contract_Date',
    'ind_nuevo': 'New_Customer_Index',
    'antiguedad': 'Customer_Seniority',
    'indrel': 'Primary_Customer_Status',
    'ult_fec_cli_1t': 'Last_Primary_Customer_Date',
    'indrel_1mes': 'Customer_Type_Begin_Month',
    'tiprel_1mes': 'Customer_Relation_Begin_Month',
    'indresi': 'Residence_Index',
    'indext': 'Foreigner_Index',
    'conyuemp': 'Spouse_Index',
    'canal_entrada': 'Joining_Channel',
    'indfall': 'Deceased_Index',
    'tipodom': 'Address_Type',
    'cod_prov': 'Province_Code',
    'nomprov': 'Province_Name',
    'ind_actividad_cliente': 'Customer_Activity_Index',
    'renta': 'Gross_Household_Income',
    'ind_ahor_fin_ult1': 'Saving_Account',
    'ind_aval_fin_ult1': 'Guarantees',
    'ind_cco_fin_ult1': 'Current_Accounts',
    'ind_cder_fin_ult1': 'Derivada_Account',
    'ind_cno_fin_ult1': 'Payroll_Account',
    'ind_ctju_fin_ult1': 'Junior_Account',
    'ind_ctma_fin_ult1': 'Más_Particular_Account',
    'ind_ctop_fin_ult1': 'Particular_Account',
    'ind_ctpp_fin_ult1': 'Particular_Plus_Account',
```

2.2. Data Mapping

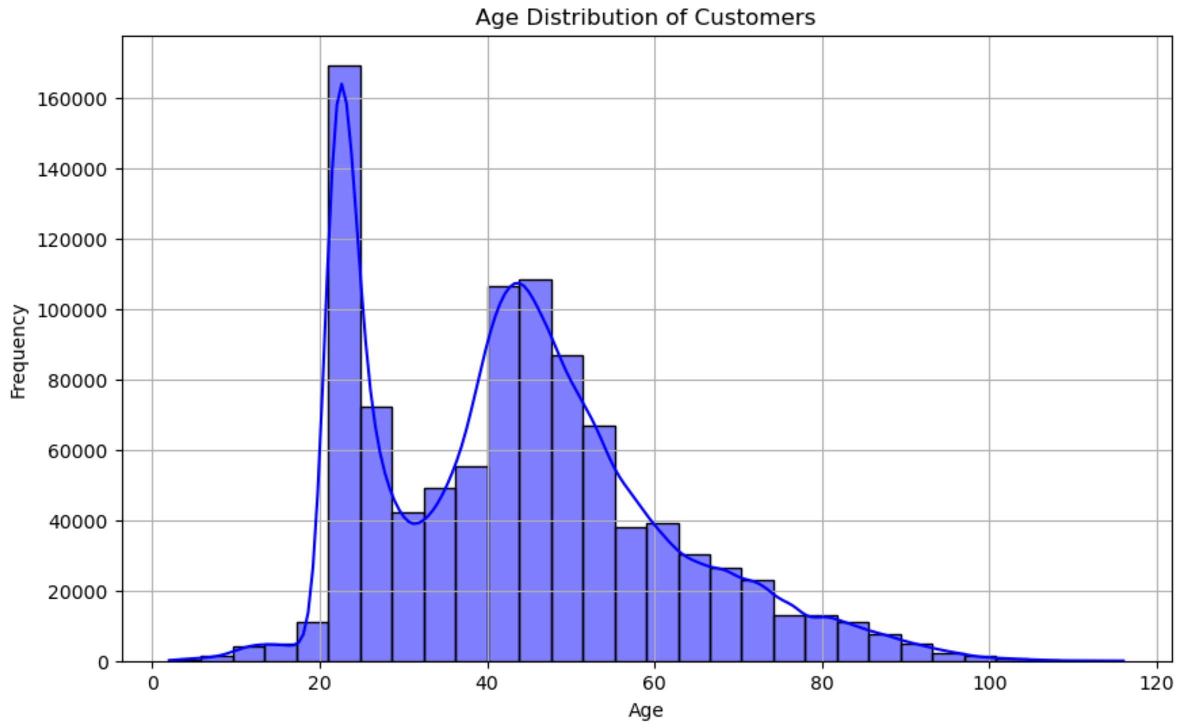
Categorical values were mapped in multiple columns to more meaningful labels for better readability and analysis. It converts encoded values for **Employee Index, Gender, Residence Index, Foreigner Index, and Deceased Index** into understandable terms.

In [8]:

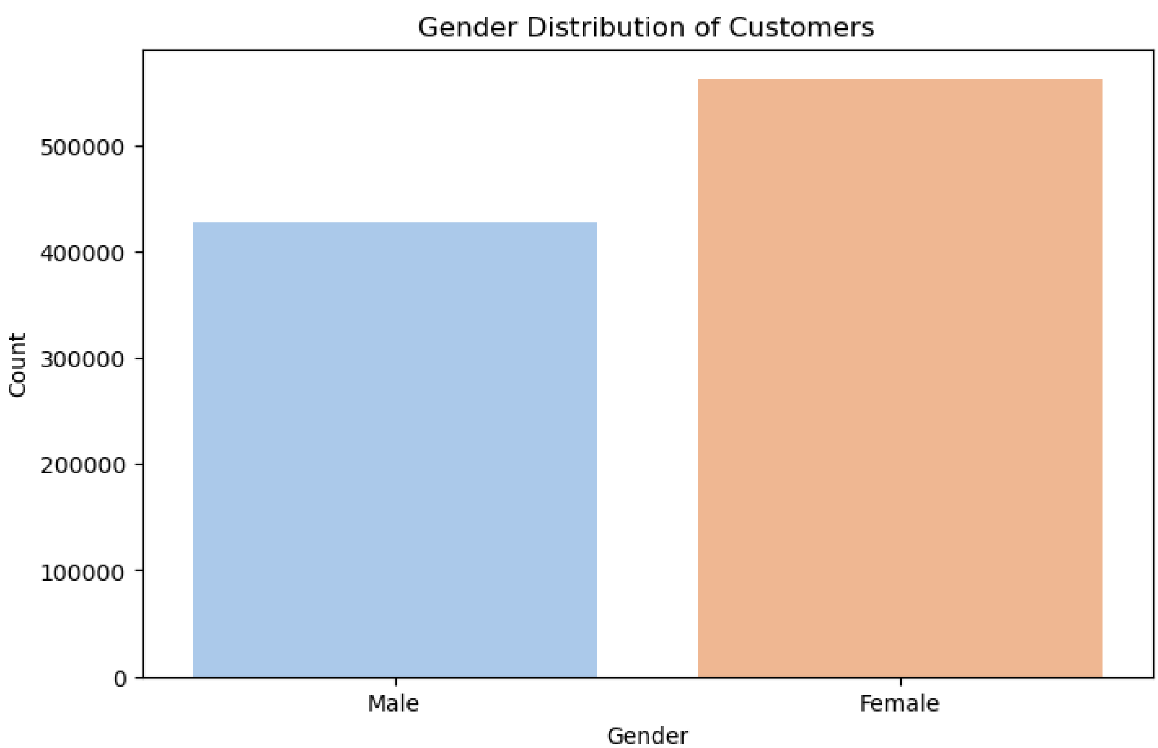
```python
# Map 'Employee_Index' values to meaningful labels
employee_index_map = {
    'A': 'Active',
    'B': 'Ex-Employee',
    'F': 'Filial',
    'N': 'Not_Employee',
    'P': 'Passive'
}

data['Employee_Index'] = data['Employee_Index'].map(employee_index_map)

# Map 'Gender' values to meaningful labels
gender_map = {
    'H': 'Male',
    'V': 'Female'
}

data['Gender'] = data['Gender'].map(gender_map)

# Map 'Residence_Index' values to meaningful labels
residence_index_map = {
    'S': 'Resident',
    'N': 'Non-Resident'
}

data['Residence_Index'] = data['Residence_Index'].map(residence_index_map)

# Map 'Foreigner_Index' values to meaningful labels
foreigner_index_map = {
    'S': 'Foreigner',
    'N': 'Local'
}

data['Foreigner_Index'] = data['Foreigner_Index'].map(foreigner_index_map)

# Map 'Deceased_Index' values to meaningful labels
deceased_index_map = {
    'S': 'Deceased',
```

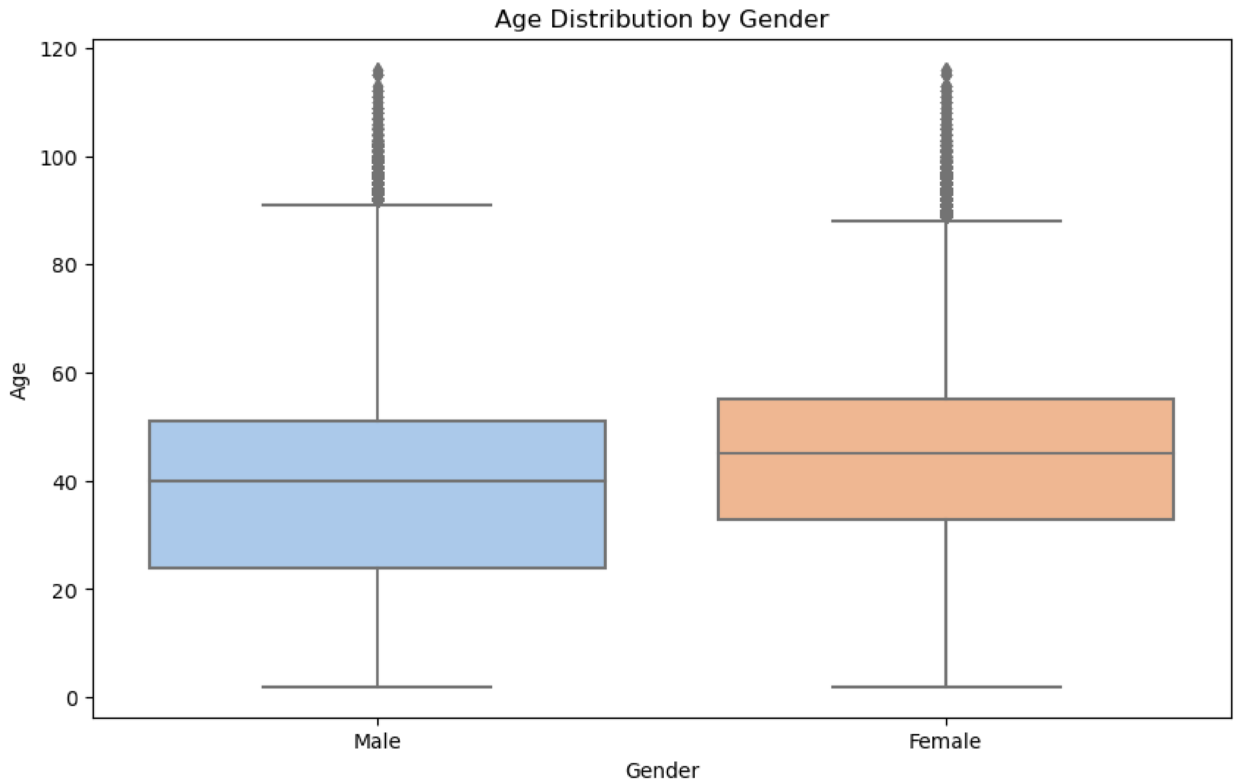
3. Exploratory Data Analysis

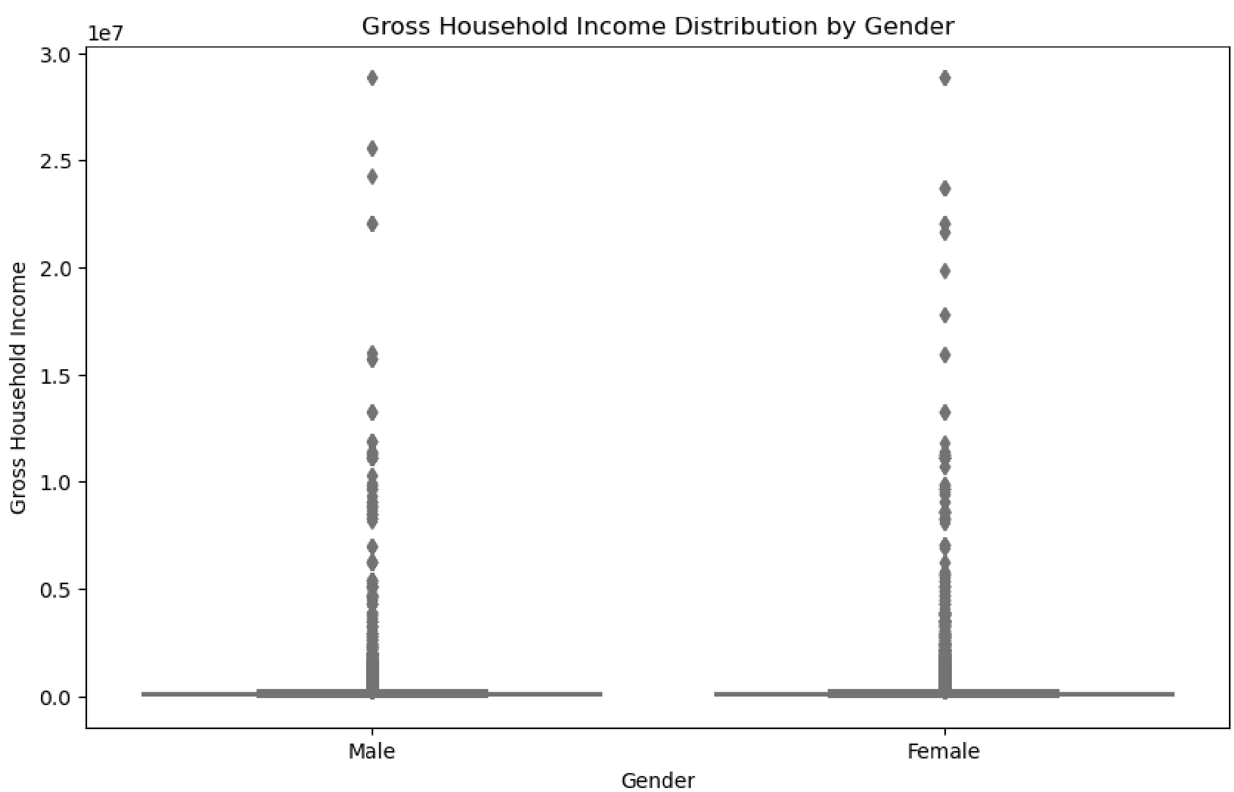
From the visualization below, we can see that most customers belong in the age range of 20-60. The number of adults is 42.8% higher than the rest of the population.

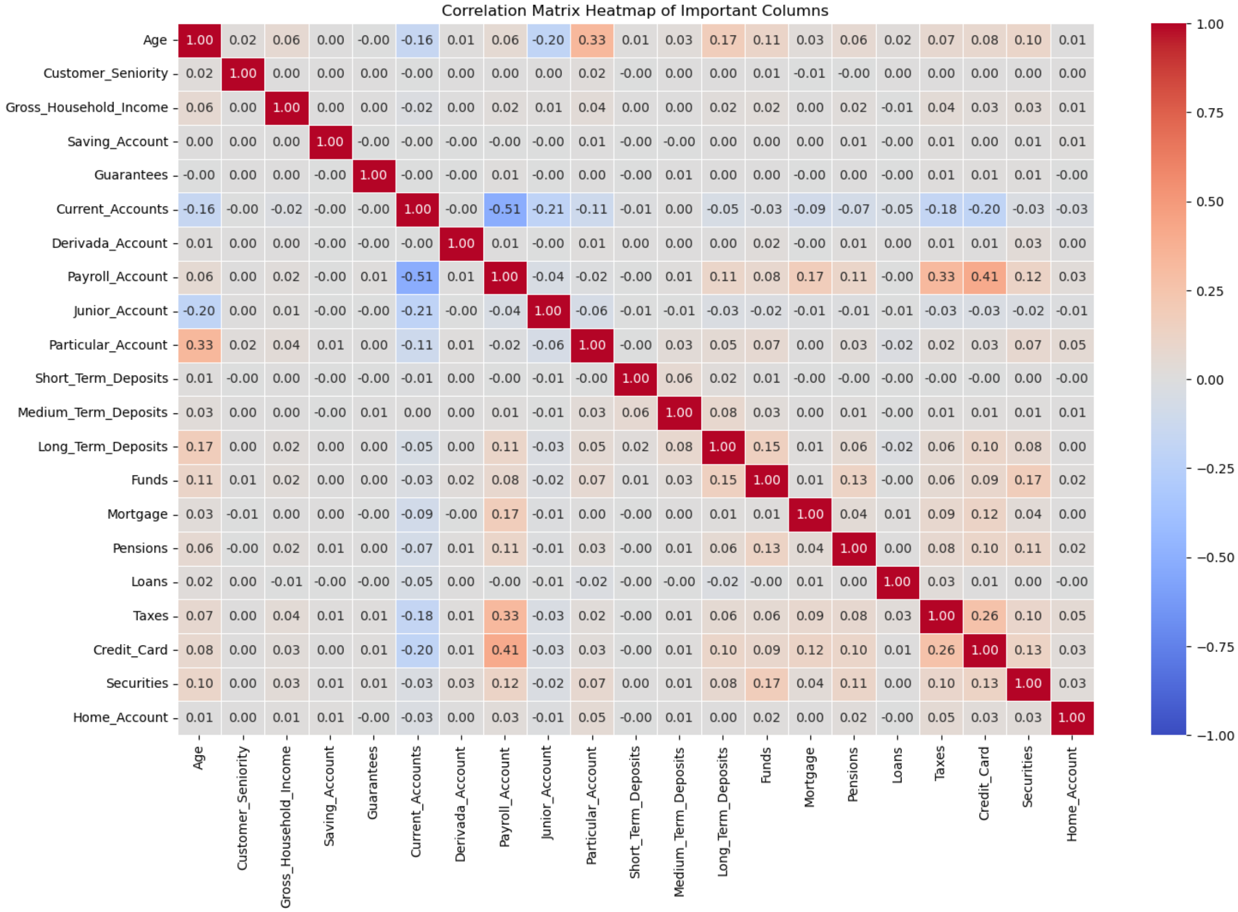


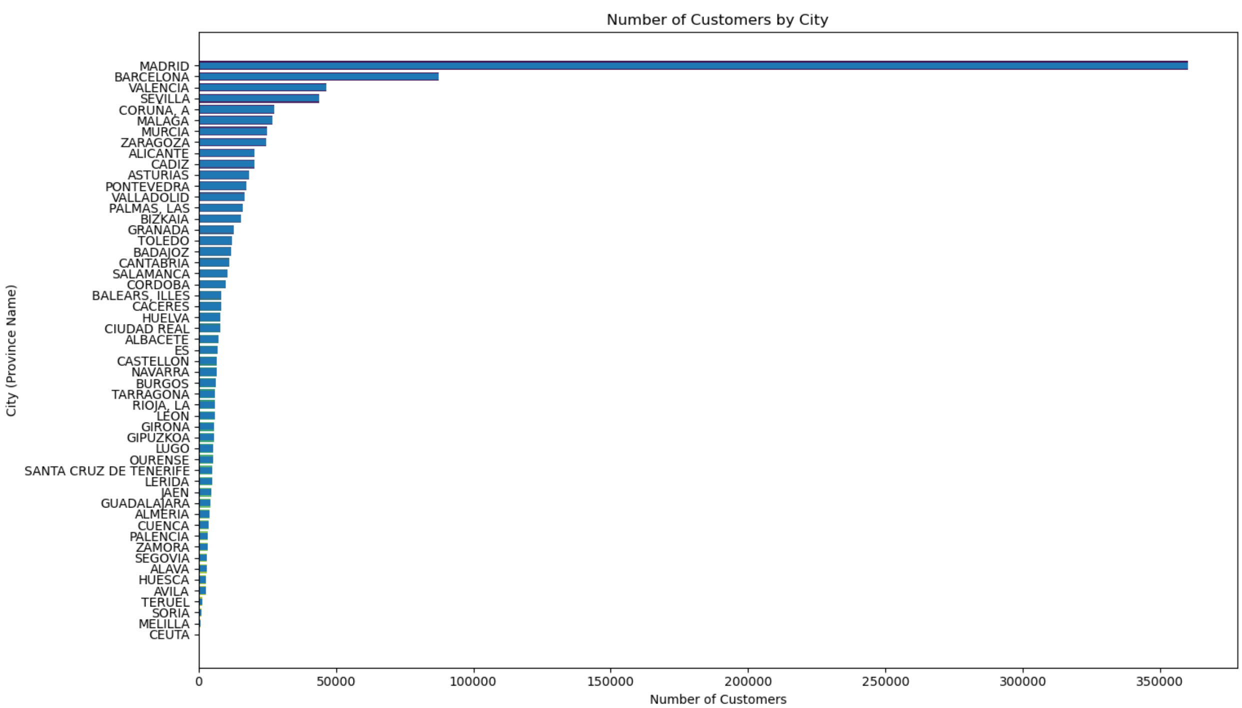
43.2% of customers are women and 56.8% are men.




Age Distribution by Gender
120
100
80
60
40
20
0
Age
Male
Female
Gender

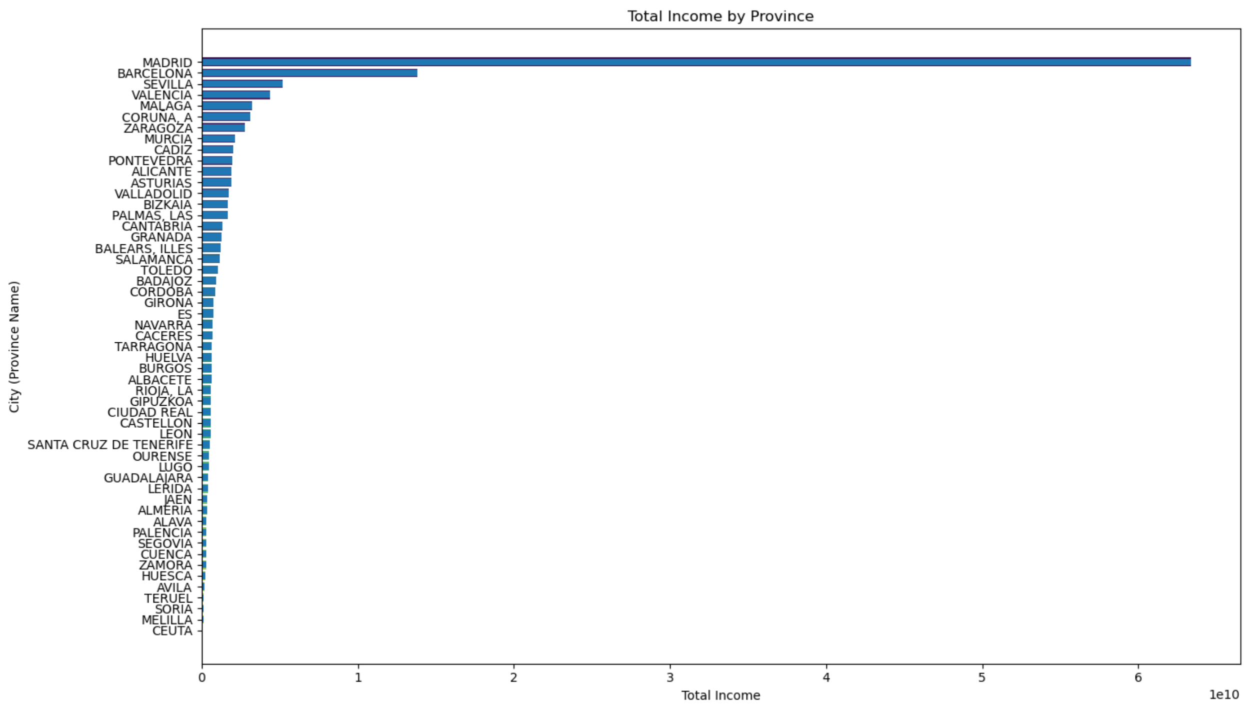

Gross Household Income Distribution by Gender
1e7
3.0
2.5
2.0
1.5
1.0
0.5
0.0
Gross Household Income
Male
Female
Gender


Correlation Matrix Heatmap of Important Columns
Age
Customer_Seniority
Gross_Household_Income
Saving_Account
Guarantees
Current_Accounts
Derivada_Account
Payroll_Account
Junior_Account
Particular_Account
Short_Term_Deposits
Medium_Term_Deposits
Long_Term_Deposits
Funds
Mortgage
Pensions
Loans
Taxes
Credit_Card
Securities
Home_Account
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00


Number of Customers by City
City (Province Name)
MADRID
BARCELONA
VALENCIA
SEVILLA
CORUNA, A
MALAGA
MURCIA
ZARAGOZA
ALICANTE
CADIZ
ASTURIAS
PONTEVEDRA
VALLADOLID
PALMAS, LAS
BIZKAIA
GRANADA
TOLEDO
BADAJOZ
CANTABRIA
SALAMANCA
CORDOBA
BALEARS, ILLES
CACERES
HUELVA
CIUDAD REAL
ALBACETE
ES
CASTELLON
NAVARRA
BURGOS
TARRAGONA
RIOJA, LA
LEON
GIRONA
GIPUZKOA
LUGO
OURENSE
SANTA CRUZ DE TENERIFE
LERIDA
JAEN
GUADALAJARA
ALMERIA
CUENCA
PALENCIA
ZAMORA
SEGOVIA
ALAVA
HUESCA
AVILA
TERUEL
SORIA
MELILLA
CEUTA
0
50000
100000
150000
200000
250000
300000
350000
Number of Customers

From the above visualization, Madrid, Barcelona and Valencia have the highest number of customers by City.

We can also see Madrid, Barcelona and Sevilla as the cities with the most income.



4. Final Recommendation

A model can be built using K-means and other techniques for customer segmentation. The Elbow method is employed to determine the optimal number of clusters. Additionally, a detailed analysis is conducted to evaluate clustering effectiveness, ensuring that customer groups are well-defined. Further, dimensionality reduction techniques such as PCA are applied to visualize the clusters, making the segmentation process more interpretable. This approach allows for meaningful insights into customer behavior, facilitating data-driven decision-making for personalized marketing strategies.