Data Glacier

Your Deep Learning Partner

Bank Customer Segmentation

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Date: Jan 15, 2025

Agenda

- Problem Description
- Data Understanding
- Data Cleaning
- EDA for Business
- Recommendations for Technical

Data Glacier
Your Deep Learning Partner

Batch:LISUM39

Week11: EDA Presentation and proposed modeling technique

Project: Bank Customer Segmentation

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Company: Omdena

Specialization: Data Analytics

Problem Description

XYZ Bank plans to enhance its marketing campaign as Christmas offers for its customers. However, instead of offering the same deal to all customers as generic, the bank wants to provide personalized offers to specific customer groups to fit their preferences. Identifying customer categories manually would be inefficient and fail to uncover hidden patterns in the data that could inform better segmentation. To address this, the bank has sought the assistance of Apple Analytics. Additionally, the bank has specified that customer segmentation should result in no more than 5 groups to ensure the campaign's efficiency.

Data Understanding

Tabular data details: cust_seg.csv.zip

Total number of observations	1,000,000
Total number of files	1
Total number of features	48
Base format of the file	csv.zip
Size of the data	19,483KB

Data Understanding

There are missing values.

Check the unique values and frequencies.

	count	unique	top	freq
fecha_dato	1000000	2	2015-01-28	625457
ind_empleado	989218	5	N	988260
pais_residencia	989218	113	ES	982264
sexo	989214	2	V	562000
age	1000000	115	22	51017
fecha_alta	989218	6238	2013-10-14	3920
antiguedad	1000000	249	21	34320
ult_fec_cli_1t	1101	22	2015-07-01	97
tiprel_1mes	989218	3	A	547800
indresi	989218	2	S	982264
indext	989218	2	N	946328
conyuemp	178	2	N	176
canal_entrada	989139	156	KAT	313944
indfall	989218	2	N	986107
nomprov	982266	52	MADRID	360131

```
<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
 13  tiprel_1mes            989218 non-null   object
 14  indresi                989218 non-null   object
 15  indext                 989218 non-null   object
 16  conyuemp               178 non-null      object
 17  canal_entrada          989139 non-null   object
 18  indfall                989218 non-null   object
 19  tipodom                989218 non-null   float64
 20  cod_prov               982266 non-null   float64
 21  nomprov                982266 non-null   object
 22  ind_actividad_cliente  989218 non-null   float64
 23  renta                  824817 non-null   float64
 24  ind_ahor_fin_ult1      1000000 non-null  int64
 25  ind_aval_fin_ult1      1000000 non-null  int64
 26  ind_cco_fin_ult1       1000000 non-null  int64
 27  ind_cder_fin_ult1      1000000 non-null  int64
 28  ind_cno_fin_ult1       1000000 non-null  int64
 29  ind_ctju_fin_ult1      1000000 non-null  int64
 30  ind_ctma_fin_ult1      1000000 non-null  int64
 31  ind_ctop_fin_ult1      1000000 non-null  int64
 32  ind_ctpp_fin_ult1      1000000 non-null  int64
 33  ind_deco_fin_ult1      1000000 non-null  int64
 34  ind_deme_fin_ult1      1000000 non-null  int64
 35  ind_dela_fin_ult1      1000000 non-null  int64
 36  ind_ecue_fin_ult1      1000000 non-null  int64
 37  ind_fond_fin_ult1      1000000 non-null  int64
 38  ind_hip_fin_ult1       1000000 non-null  int64
```

Data Understanding

Check the unique values each variables.

```
Unique values in fecha_dato are :
fecha_dato
2015-01-28    625457
2015-02-28    374543
Name: count, dtype: int64
****************************************
Unique values in ind_empleado are :
ind_empleado
N    988260
B       387
A       287
F       282
S         2
Name: count, dtype: int64
****************************************
Unique values in pais_residencia are :
pais_residencia
ES    982264
FR       546
AR       542
DE       487
GB       480
       ...
MM         2
ML         2
LV         2
BZ         2
AL         1
Name: count, Length: 113, dtype: int64
****************************************
Unique values in sexo are :
sexo
V    562000
H    427214
Name: count, dtype: int64
****************************************
Unique values in age are :
age
 22    51017
 23    45366
 24    38992
 21    34015
 44    28800
       ...
110       14
115       12
```

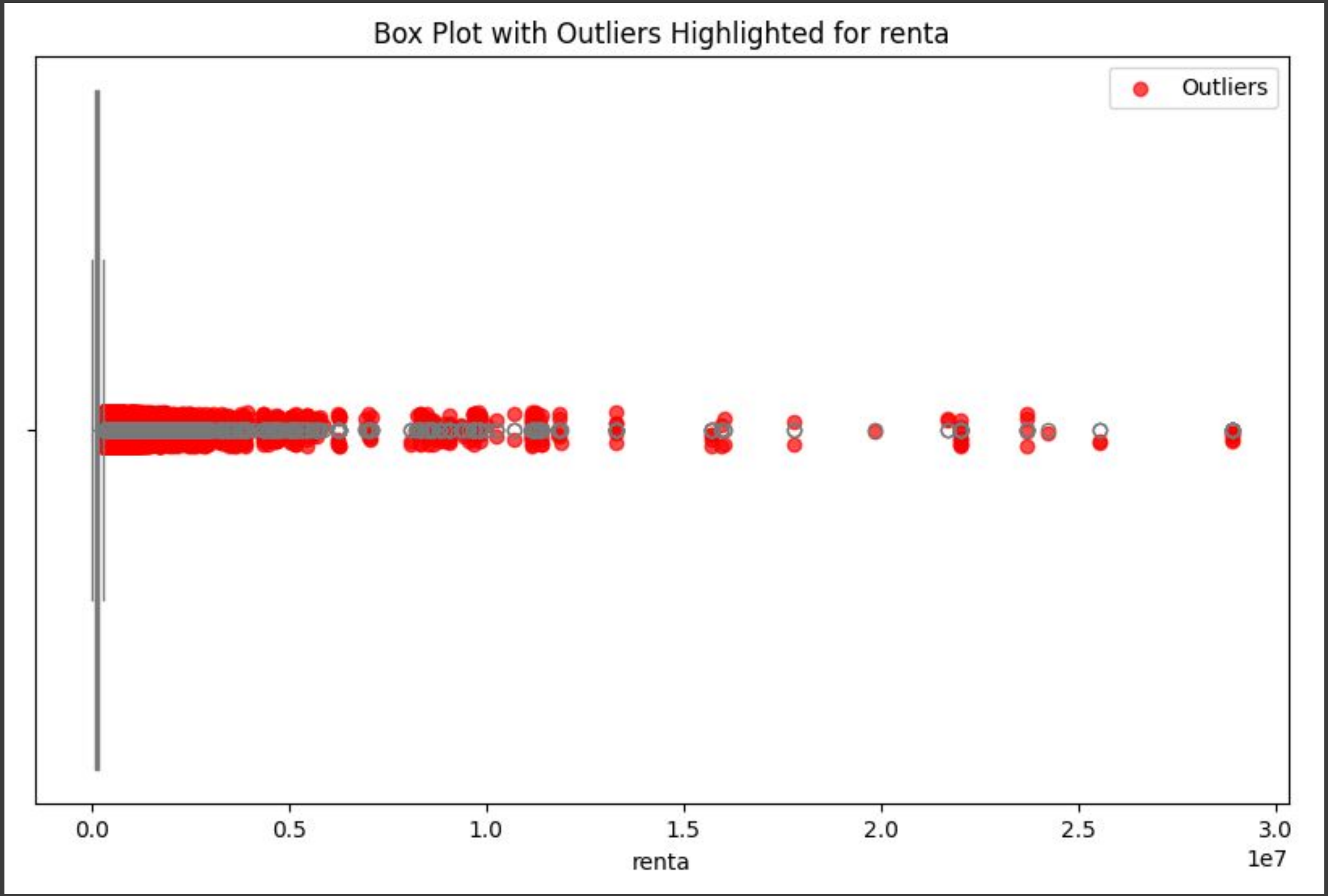
```
Name: count, Length: 115, dtype: int64
****************************************
Unique values in fecha_alta are :
fecha_alta
2013-10-14    3920
2013-08-03    3738
2014-07-28    3285
2014-10-03    2861
2013-10-11    2686
              ...
2015-02-17       1
2010-11-20       1
2010-11-21       1
2012-05-12       1
2011-02-05       1
Name: count, Length: 6238, dtype: int64
****************************************
Unique values in antiguedad are :
antiguedad
     21    34320
     23    23122
     24    20467
     12    19155
     20    18582
           ...
      0       49
      2       46
      1       37
      3       33
-999999        4
Name: count, Length: 249, dtype: int64
****************************************
Unique values in ult_fec_cli_1t are :
ult_fec_cli_1t
2015-07-01    97
2015-07-09    81
2015-07-06    76
2015-07-21    67
2015-07-07    63
2015-07-17    59
2015-07-28    57
2015-07-10    55
2015-07-15    54
2015-07-24    54
2015-07-20    53
2015-07-22    45
2015-07-03    42
```

Data Understanding

Check how many percent each variable has the missing values.

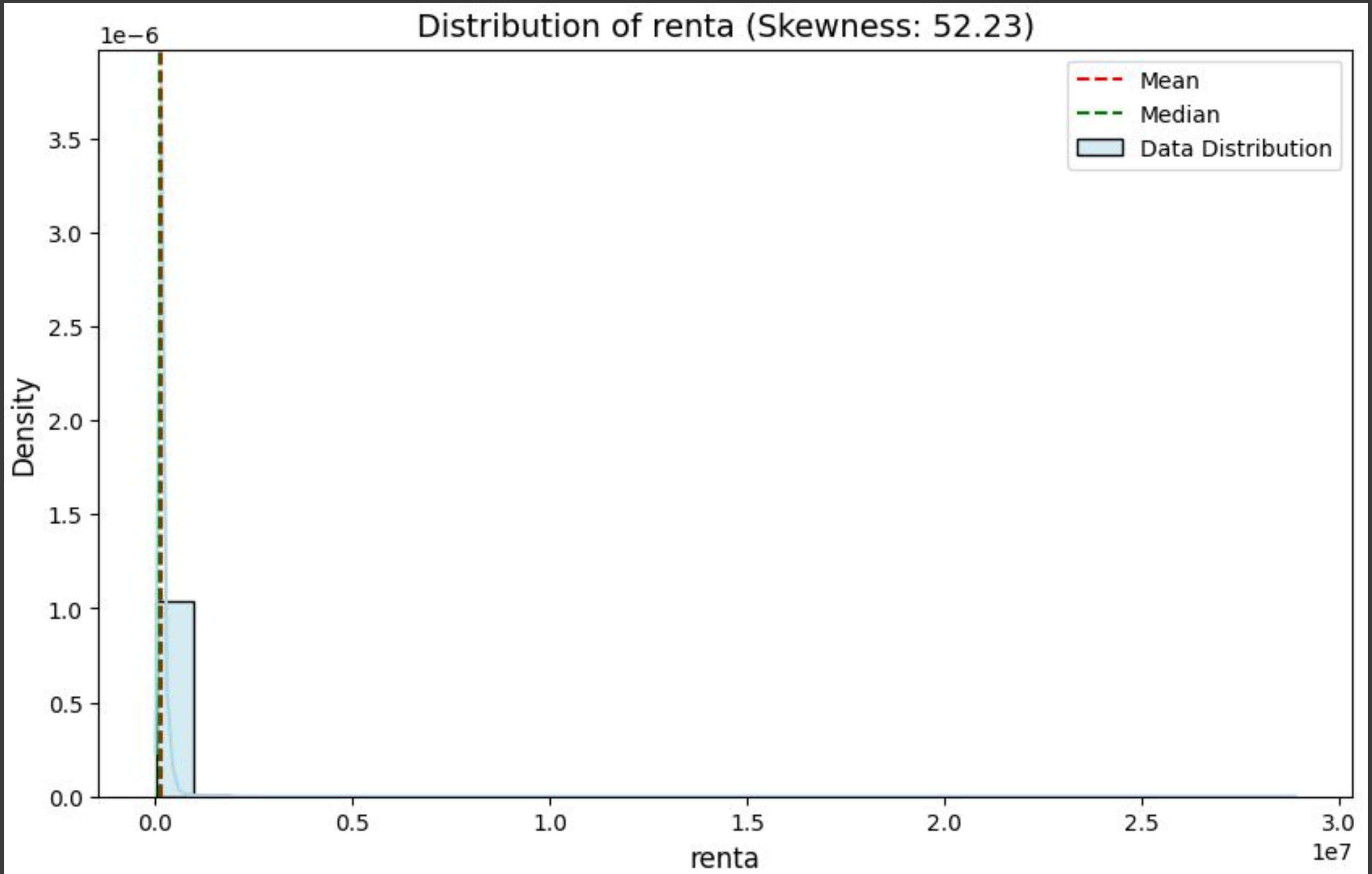
	Column_Name	aggregate	percent
0	conyuemp	999822	0.999822
1	ult_fec_cli_1t	998899	0.998899
2	renta	175183	0.175183
3	cod_prov	17734	0.017734
4	nomprov	17734	0.017734
5	canal_entrada	10861	0.010861
6	sexo	10786	0.010786
7	pais_residencia	10782	0.010782
8	indresi	10782	0.010782
9	tiprel_1mes	10782	0.010782
10	indext	10782	0.010782
11	ind_empleado	10782	0.010782
12	indrel_1mes	10782	0.010782
13	indrel	10782	0.010782
14	ind_nuevo	10782	0.010782
15	fecha_alta	10782	0.010782
16	tipodom	10782	0.010782
17	indfall	10782	0.010782
18	ind_actividad_cliente	10782	0.010782
19	ind_nom_pens_ult1	5402	0.005402
20	ind_nomina_ult1	5402	0.005402
21	ncodpers	0	0.000000
22	Unnamed: 0	0	0.000000
23	age	0	0.000000

Data Understanding



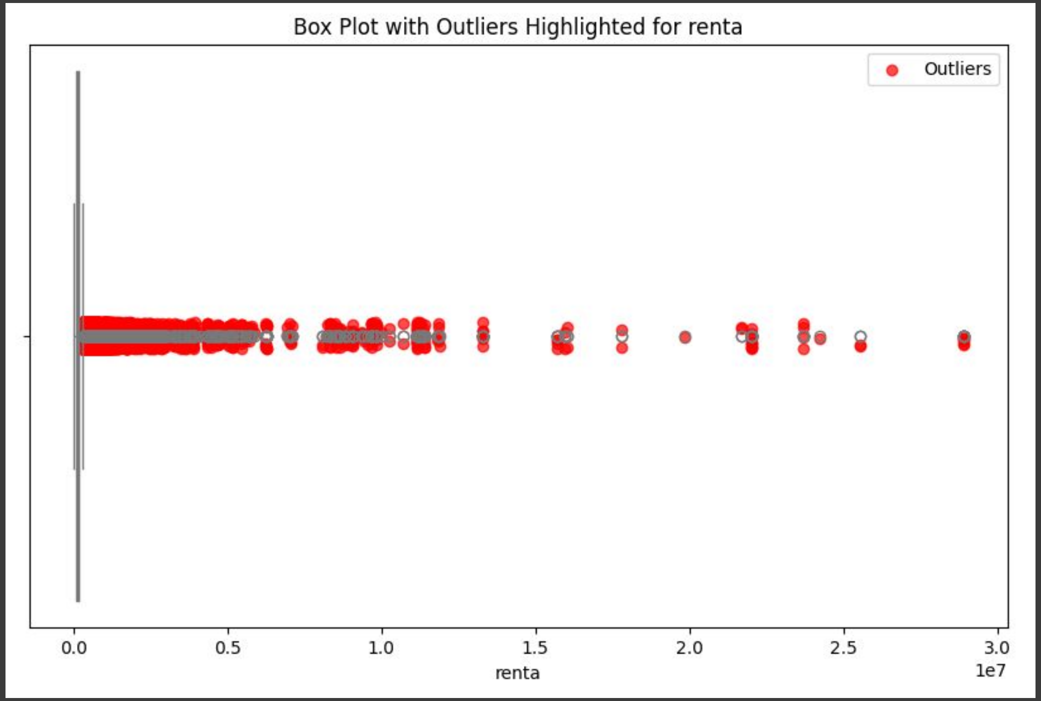
The variable ‘renta’ contains numerous outliers, with many of them representing individuals with high gross incomes.

Data Understanding



In the variable 'renta', Median and Mean is almost same point while there are many outliers.

Data Cleaning



Examined the outliers and skewness in the visualizations in the previous slide. It appears that the 'renta' variable, which represents the gross income of households, contains many outliers above the median and mean. These outliers correspond to high-income customers. Retaining these outliers may be beneficial for identifying specific trends within the high-income group, which could be useful for targeted campaigns. Therefore, while I am checking for outliers, I do not plan to omit them.

Data Cleaning

Impute Numerical missing values

1, fillna() median

Regarding **Renta**, the median and mean are almost same points and extremely skewed to right so applying **imputation with median**.

```
df['renta'] = df['renta'].fillna(df['renta'].median())
```

2, KNN Imputer method

Apply **KNN Imputer** to numerical values

Nearest Neighbor Imputation is a powerful technique that relies on the similarity between data points. It can provide more accurate imputations than simpler methods like mean or median imputation, especially when relationships between features are complex.

```
from sklearn.impute import KNNImputer

# Initialize KNNImputer with k=2 neighbors
imputer = KNNImputer(n_neighbors=2)

# Impute missing values
numeric_df = df.select_dtypes(include=[float, int]) #KNN impute only can apply for numerical values
imputed_data = imputer.fit_transform(numeric_df)

print(imputed_data)
```

```
[[0.000000e+00 1.375586e+06 0.000000e+00 ... 0.000000e+00 0.000000e+00
  0.000000e+00]
 [1.000000e+00 1.050611e+06 0.000000e+00 ... 0.000000e+00 0.000000e+00
```

Regarding 'renta', applied the method fillna() median.

Regarding other numerical missing values, applied KNN Imputation.

Data Cleaning

3, Impute Categorical missing values with fillna() mode

```
cols = df.select_dtypes(['object']).columns.tolist()
print(cols)
```

```
['fecha_dato', 'ind_empleado', 'pais_residencia', 'sexo', 'age', 'fecha_alta', 'antiguedad', 'tiprel_1mes', 'indresi', 'index
t', 'canal_entrada', 'indfall', 'nomprov']
```

```
for i in cols:
  df[i] = df[i].astype('category')
```

```
cat_cols = df.select_dtypes(['category']).columns.tolist()
print(cat_cols)
```

```
['fecha_dato', 'ind_empleado', 'pais_residencia', 'sexo', 'age', 'fecha_alta', 'antiguedad', 'tiprel_1mes', 'indresi', 'index
t', 'canal_entrada', 'indfall', 'nomprov']
```

```
for column in cat_cols:
  mode = df[column].mode()[0]
  df[column] = df[column].fillna(value=mode)
```

Regarding Categorical missing values, applied fillna() mode method.

Data Cleaning

Rename the column names to reader friendly

Drop the column with unnamed becuase it used be index

```
df.drop(columns=["Unnamed: 0"], inplace = True, axis = 1)
```

```
df.rename({'ancodpers': 'Customer_code', 'ind_empleado': 'Employee_index:_A_active_B_ex_employed_F_filial_N_not_employee_P
df
```

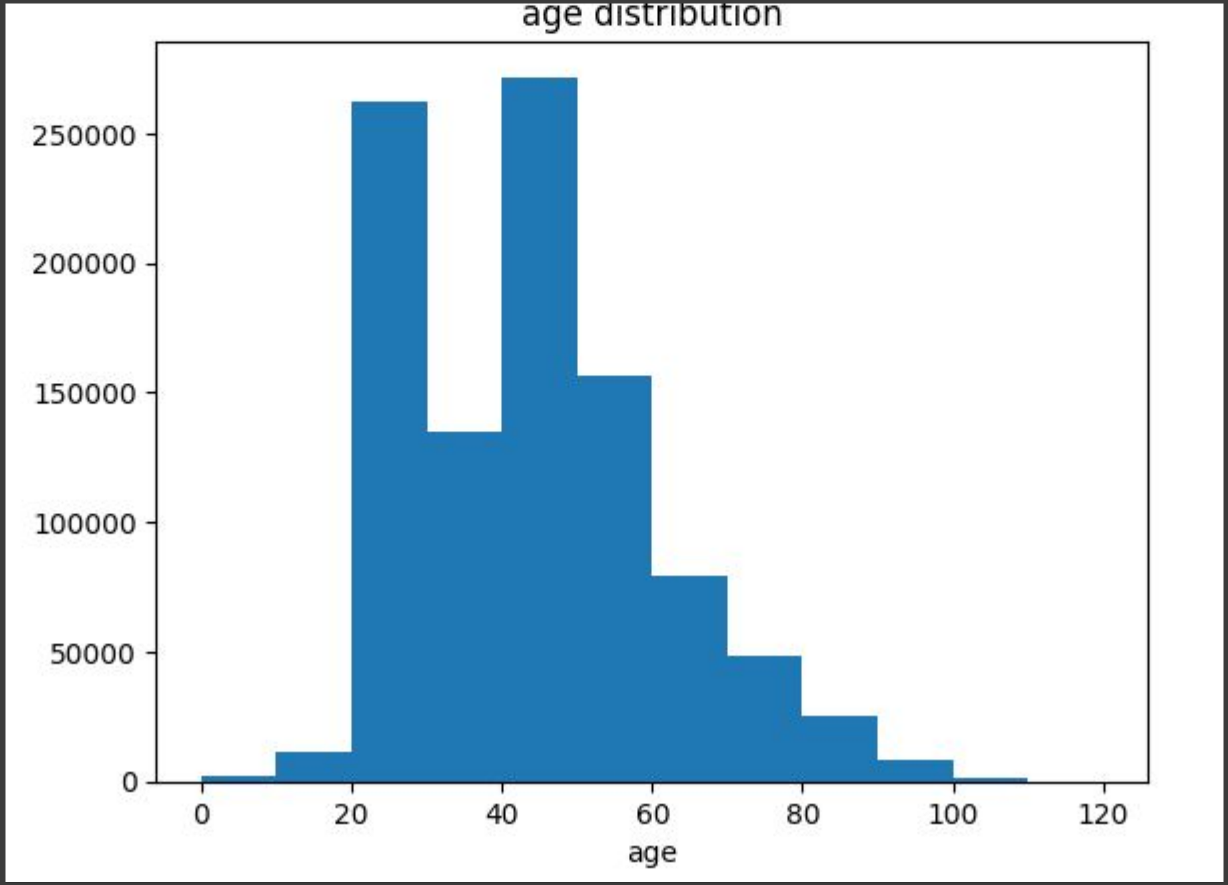
For readability in English, renamed the column name if it is hard to understand.

EDA

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000000 entries, 0 to 999999
Data columns (total 45 columns):
 #   Column                                        Non-Null Count    Dtype
---  ------                                        --------------    -----
 0   fecha_dato                                    1000000 non-null  object
 1   customer_id                                   1000000 non-null  int64
 2   Employee_or_not                               1000000 non-null  object
 3   Customer_s_Country_residence                  1000000 non-null  object
 4   sexo                                          1000000 non-null  object
 5   age                                           1000000 non-null  int64
 6   fecha_alta                                    1000000 non-null  object
 7   New_customer_Index                            1000000 non-null  int64
 8   Customer_seniority                            1000000 non-null  int64
 9   indrel                                        1000000 non-null  int64
 10  Customer_type_at_the_beginning_of_the_month   1000000 non-null  int64
 11  Customer_relation_type_at_the_beginning_of_the_month 1000000 non-null  object
 12  Residence_index                               1000000 non-null  object
 13  Foreigner_index                               1000000 non-null  object
 14  channel_used_by_the_customer_to_join          1000000 non-null  object
 15  Deceased_index                                1000000 non-null  object
 16  Addres_type                                   1000000 non-null  int64
 17  Province_code                                 1000000 non-null  int64
 18  Province_name                                 1000000 non-null  object
 19  Activity_index                                1000000 non-null  int64
 20  Gross_income_of_the_household                 1000000 non-null  float64
 21  Saving_Account                                1000000 non-null  int64
 22  Guarantees                                    1000000 non-null  int64
 23  Current_Accounts                              1000000 non-null  int64
 24  Derivada_Account                              1000000 non-null  int64
 25  Payroll_Account                               1000000 non-null  int64
 26  Junior_Account                                1000000 non-null  int64
 27  Más_particular_Account                        1000000 non-null  int64
 28  particular_Account                            1000000 non-null  int64
 29  particular_Plus_Account                       1000000 non-null  int64
 30  Short-term_deposits                           1000000 non-null  int64
 31  Medium-term_deposits                          1000000 non-null  int64
 32  Long-term_deposits                            1000000 non-null  int64
 33  e-account                                     1000000 non-null  int64
 34  Funds                                         1000000 non-null  int64
 35  Mortgage                                      1000000 non-null  int64
 36  Pensions                                      1000000 non-null  int64
 37  Loans                                         1000000 non-null  int64
 38  Taxes                                         1000000 non-null  int64
 39  Credit_Card                                   1000000 non-null  int64
 40  Securities                                    1000000 non-null  int64
```

Make sure the data type each variable and the number of data each variable.

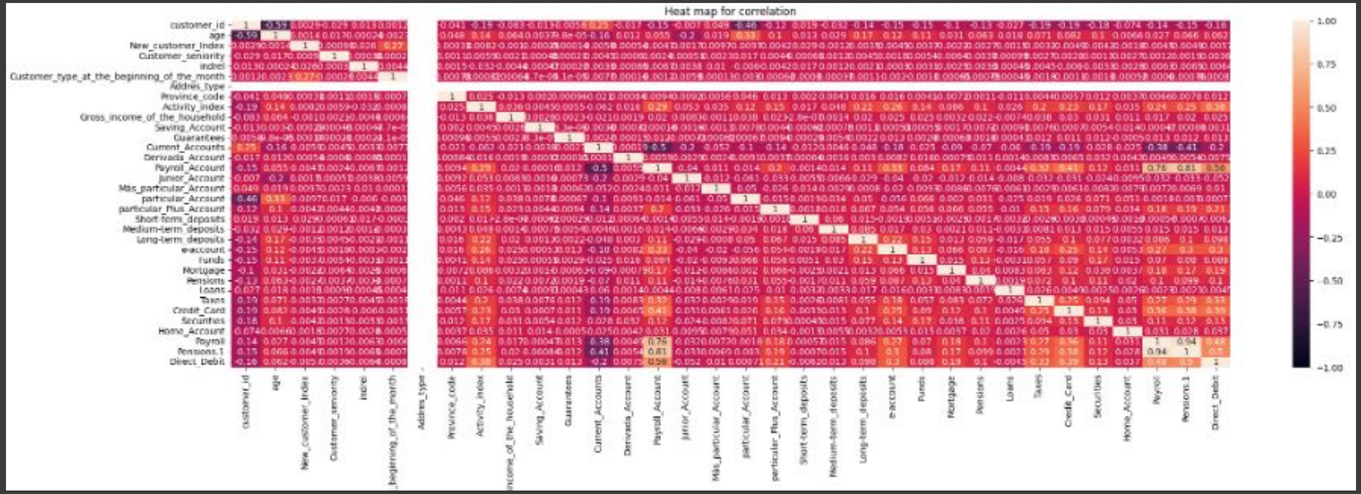
EDA



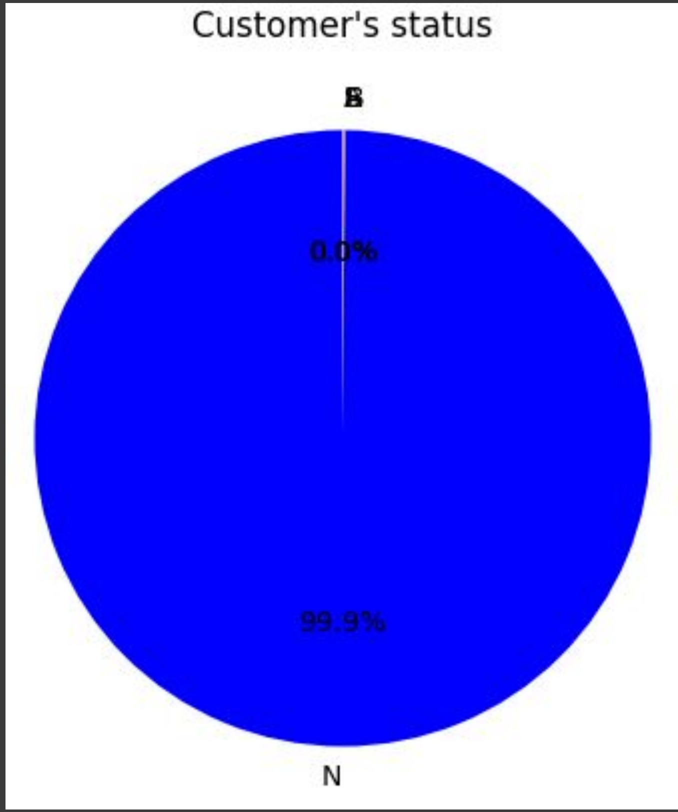
In the plot of Age Distribution, the majority of age group is from 20 years old to 60 years old.

EDA

There is no significantly related correlation.



EDA



Employee index:

A active

B ex employed

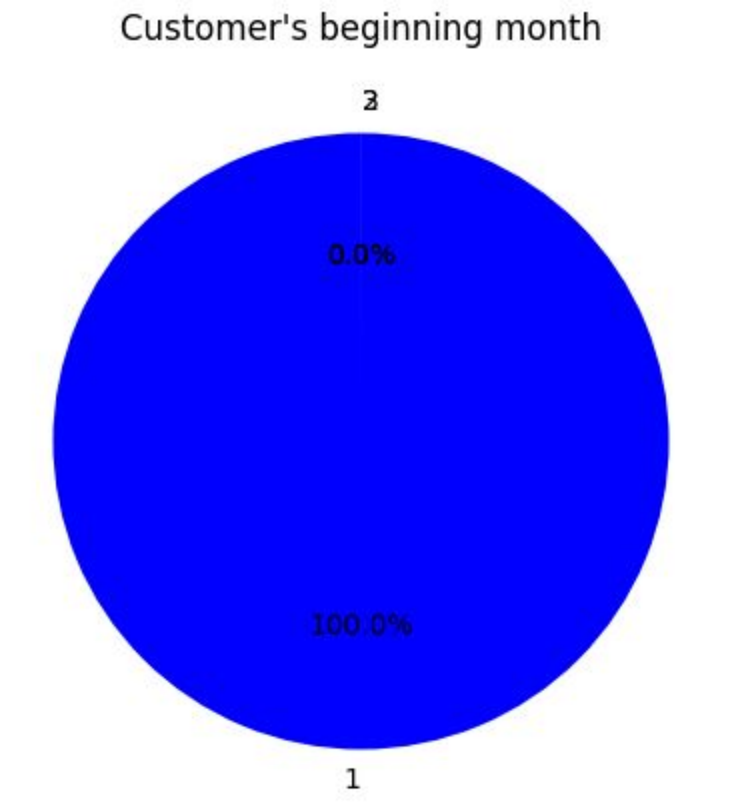
F filial

N not employee

P passive

Most of the customers are N as not employees.

EDA



Customer type at the beginning of the month

1 (First/Primary customer)

2 (co-owner)

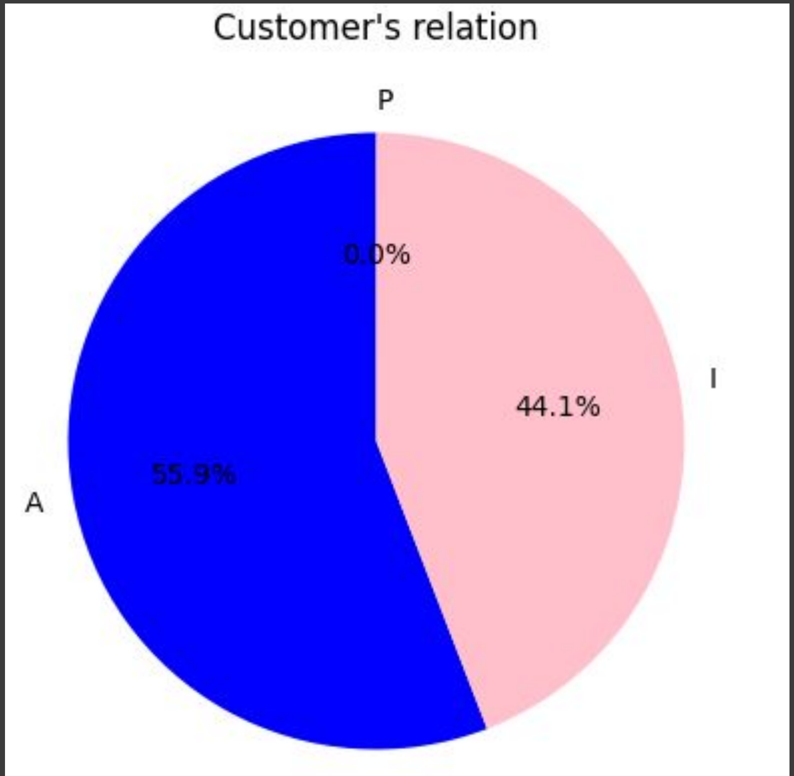
P (Potential)

3 (former primary)

4(former co-owner)

Most of customers are 1 (First/Primary customer)

EDA



Customer relation type at the beginning of the month

A (active)

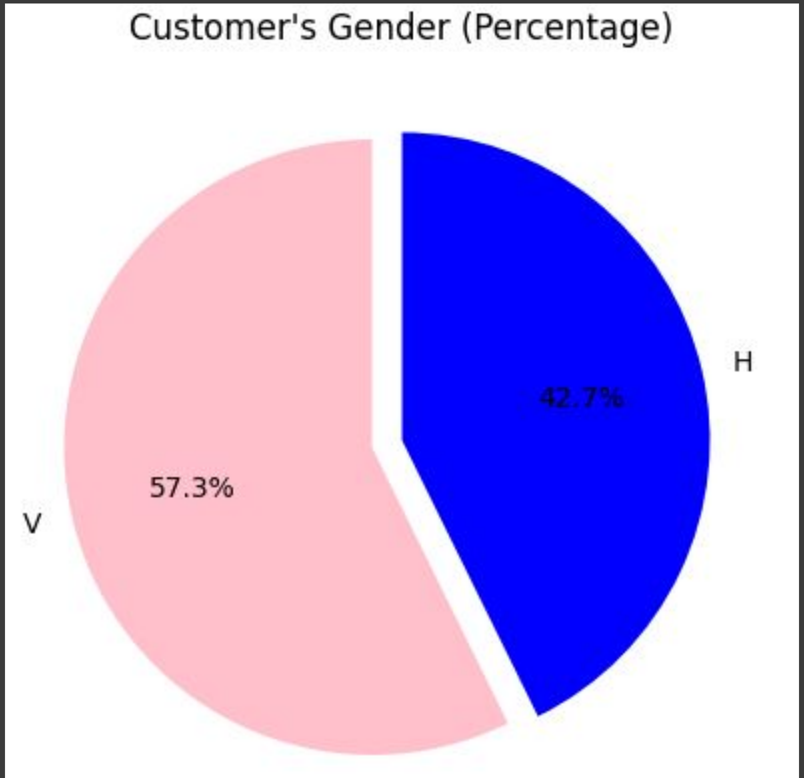
I (inactive)

P (former customer)

R (Potential)

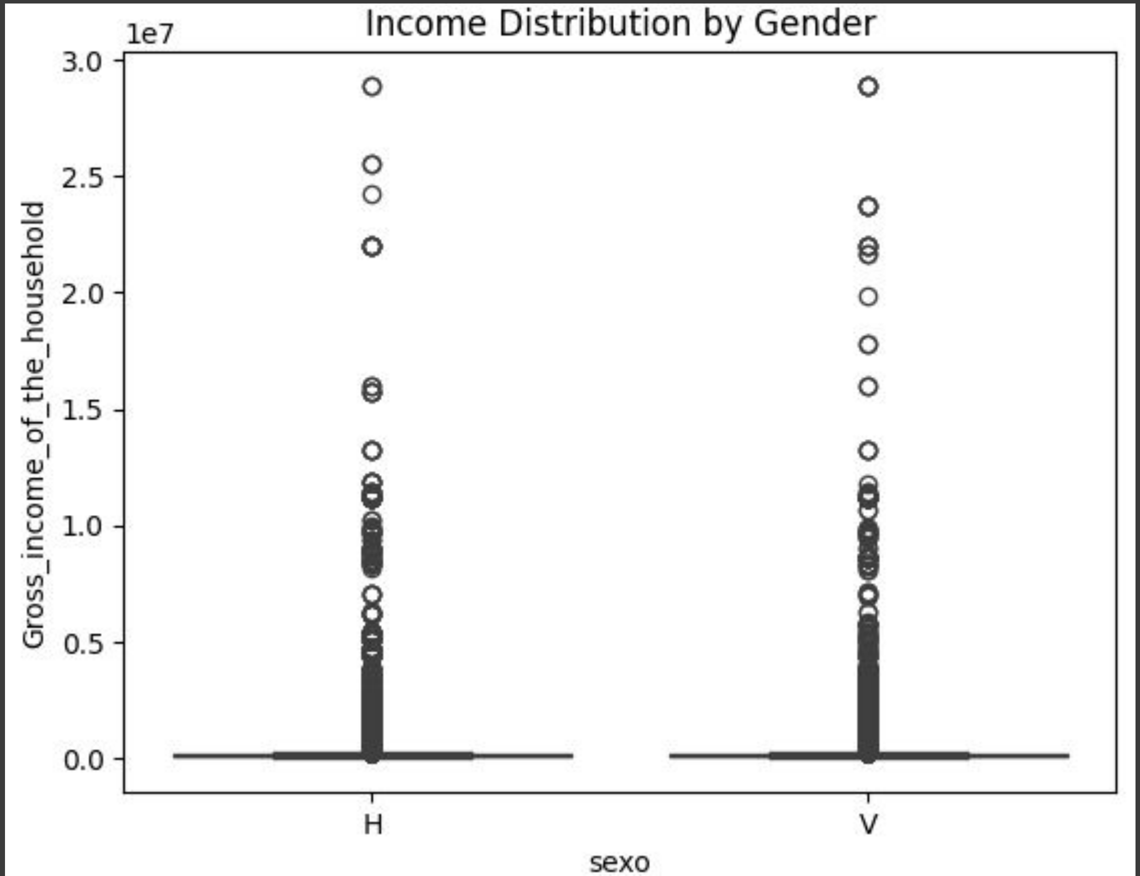
In Customer's relation, 55.9% of customers are active while 44.1% of customers are inactive.

EDA



Age distribution of customer are Make(H) shares 42.7% and Female(V) shares 57.3%.

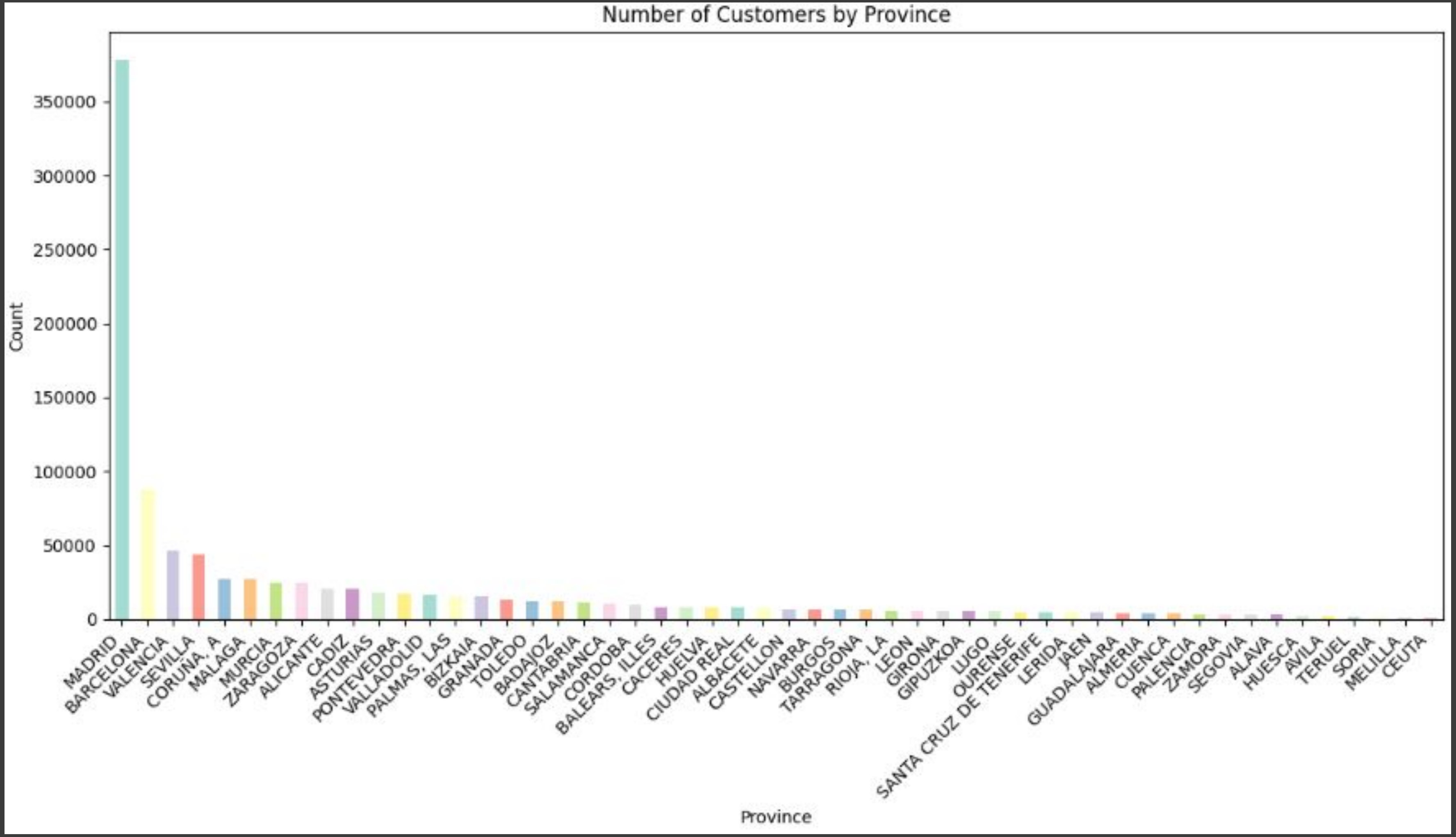
EDA



Checking the Outliers of Gender Distribution.

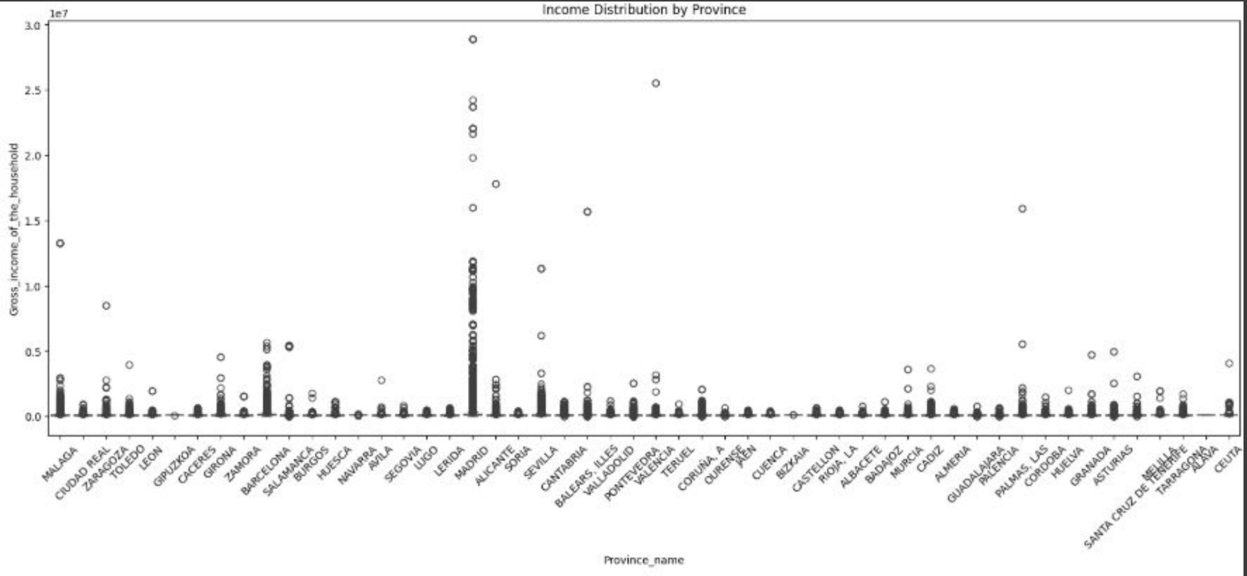
There are no significant differences in the distribution of gross income between Male(H) and Female(V). However, it seems slightly Female has more outliers concentrated above the median.

EDA



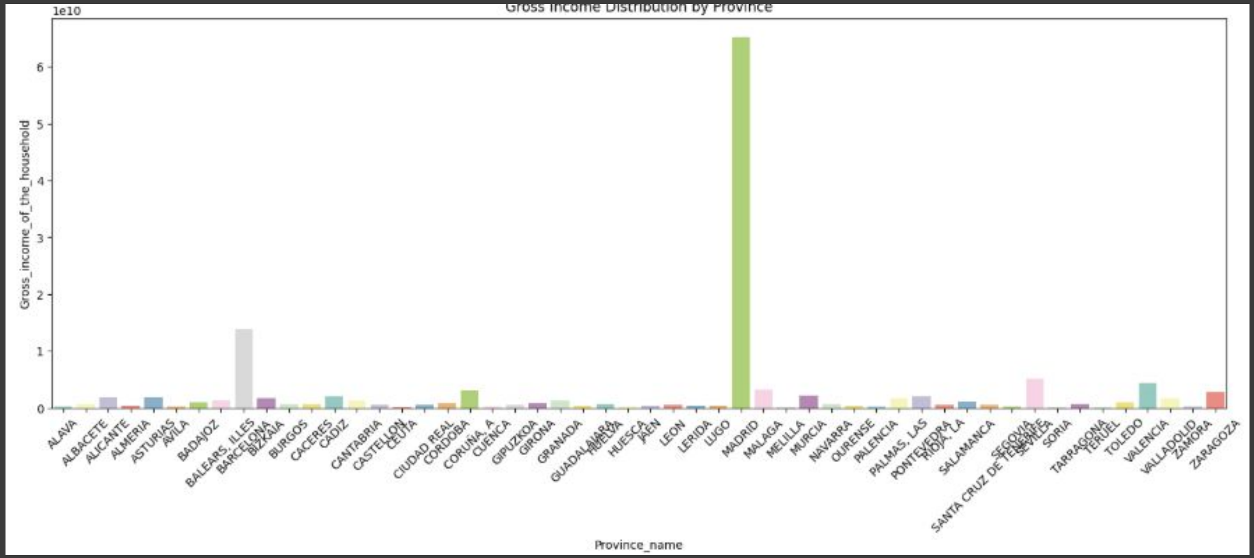
Madrid has the highest population of customers and the highest gross income household.

EDA



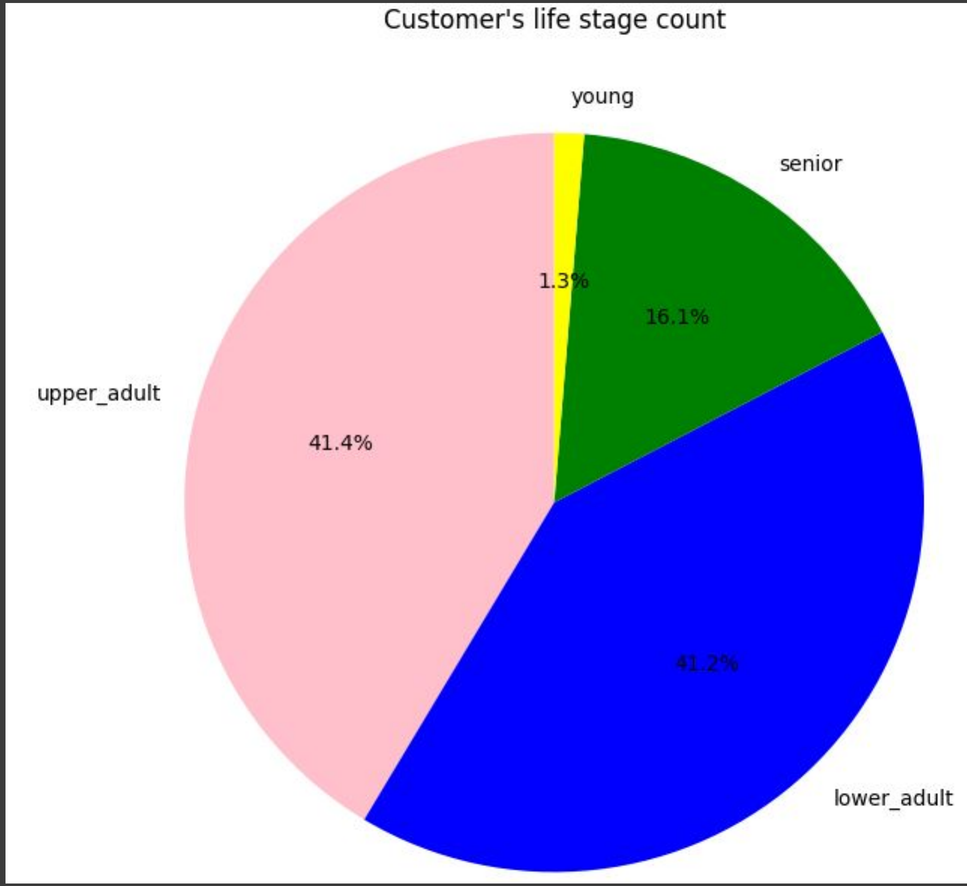
Regarding Income Distribution by Province in terms of outliers, Madrid has significant of amount of outliers.

EDA



Regarding Gross Income distribution by Province, Madrid has significant amount of income compared to other cities.

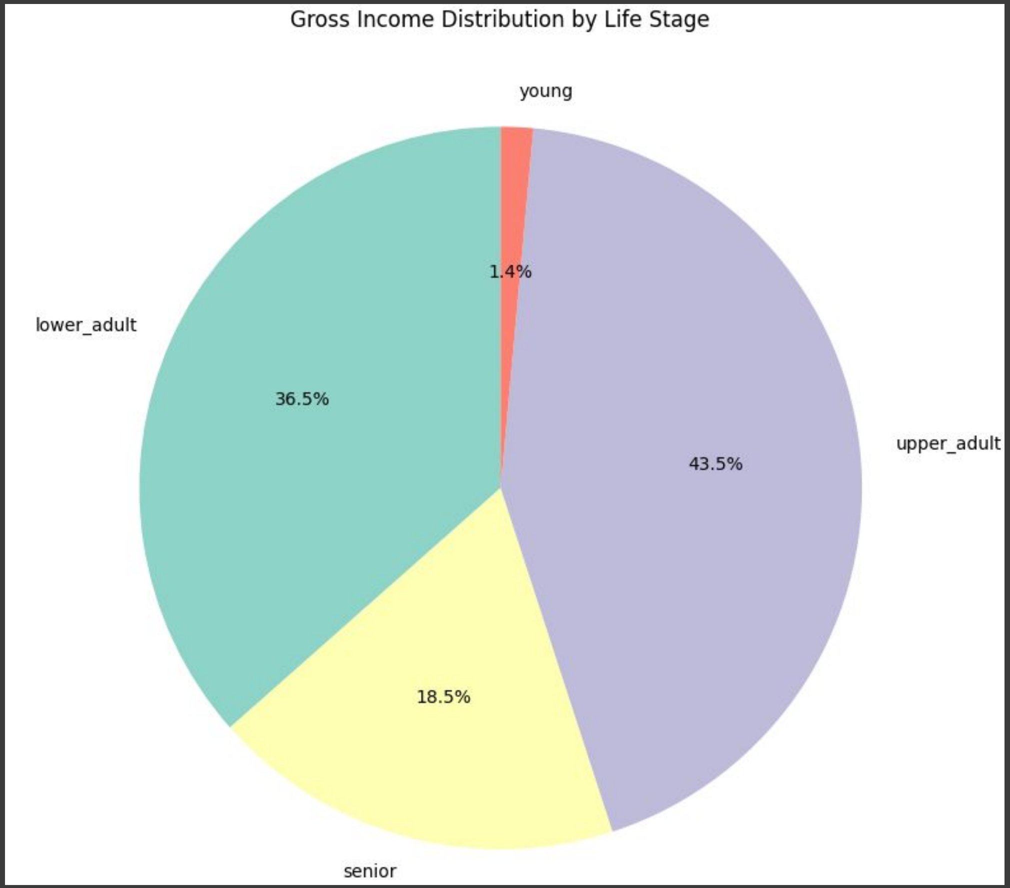
EDA



Majority of this bank customer is Adult(20-60 years old). On the other hand, Young(under 20 years old) is only 1.3% shared.

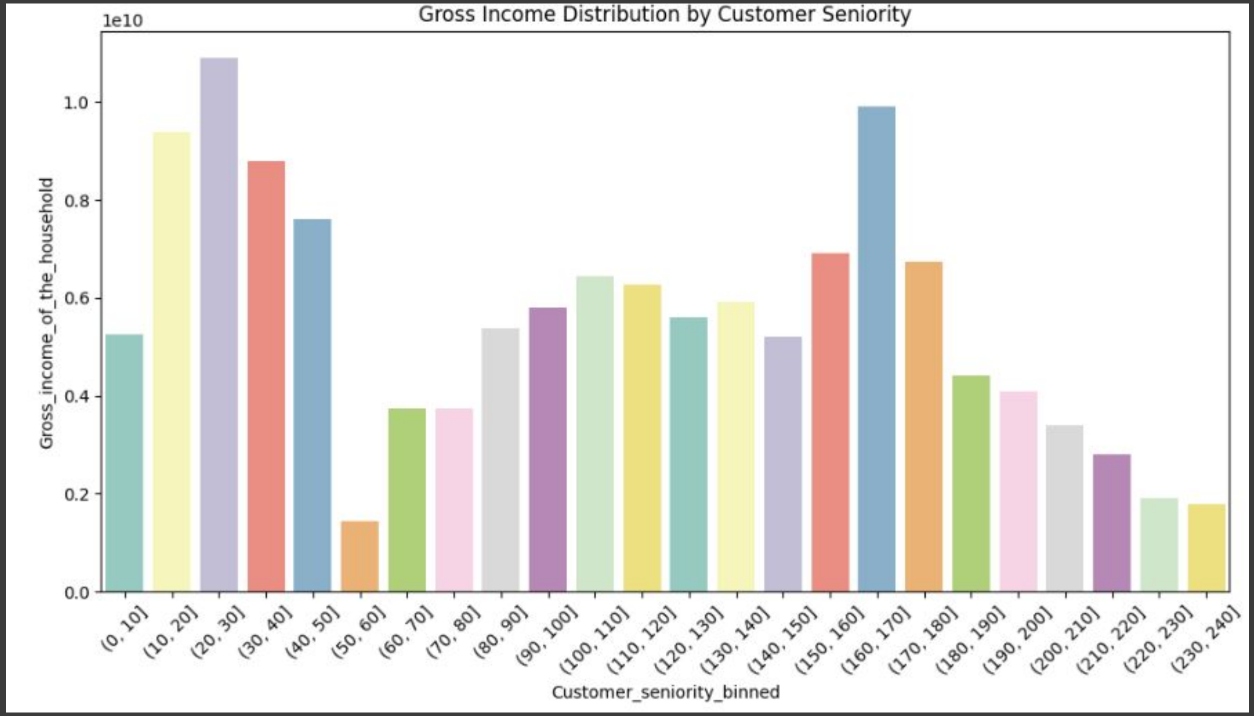
EDA

In term of the Gross Income Distribution by Life Stage, 43.5% is shared by Upper Adult and 36.5% is shared by Lower Adult.



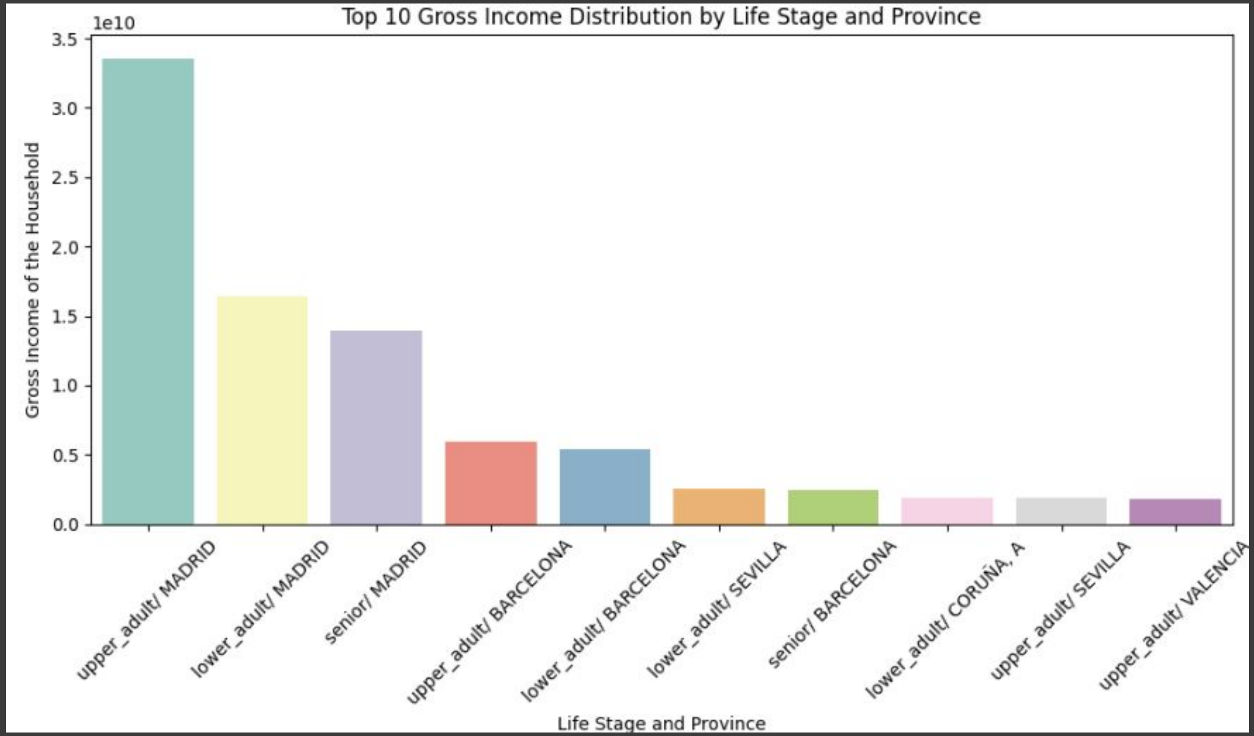
EDA

The highest group of customer seniority is 20-30 months. The next highest group is 160-170 months. The lowest group is 50-60 months. It may be some restrictions existing in this term such as some promotions being ended. From 180-240 months(15-20 years), there is a trend to decrease the number of seniority that indicates this bank cannot retain customers for the long term.



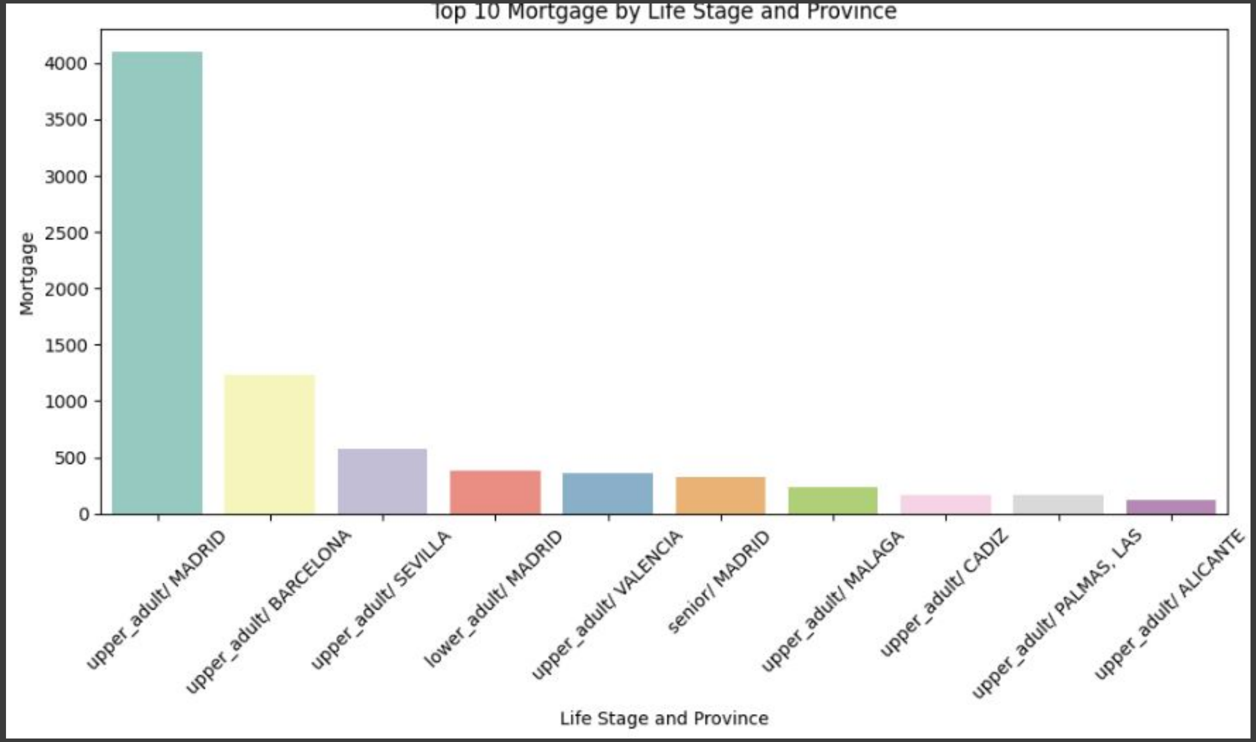
EDA

Regardless of the life stage group, customers who live in MADRID have the highest income. The customers who live in BARCELONA seem 2nd highest income group. But the life stage of the young is the minority in the any of provinces. There are no young life stage groups in this observation.



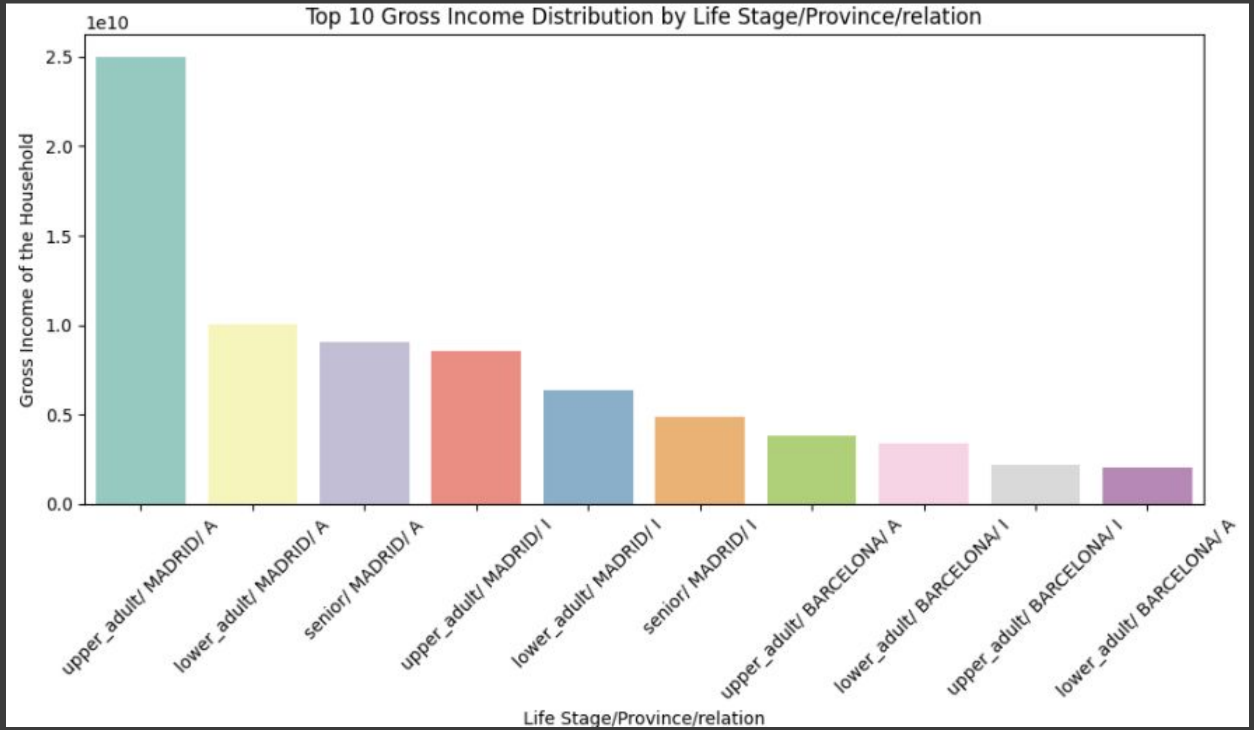
EDA

High income customers also have more Mortgage compared to low income customers. This plot relatively correlated to the plot of Gross Income Distribution by Life Stage and Province.



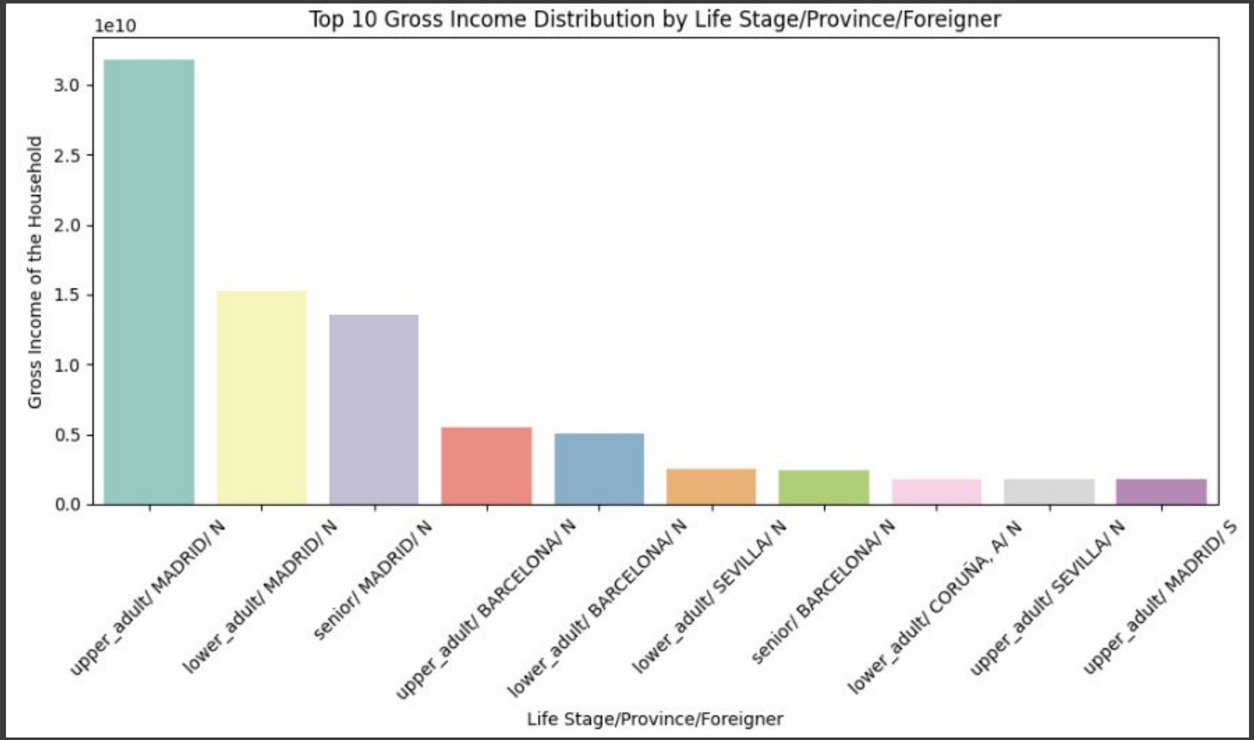
EDA

The group of Upper Adult/ Madrid is the most sharing the Active customers. Also, Upper Adult/ Madrid is the most sharing the Inactive customers.



EDA

The majority of high-income customers are from Residence (no foreigners) while upper_adult/MADRID/S shows they are foreigners.



Recommendation for technical users

K-Means Clustering Overview

K-Means Clustering is an unsupervised machine learning algorithm used to group data into **K clusters** based on their features. The algorithm iteratively assigns data points to clusters to minimize the variance within each cluster while maximizing the distance between clusters.

How It Works

1. **Initialization**:
   - Randomly select KKK initial cluster centroids (starting points for each cluster).
2. **Assignment**:
   - Assign each data point to the cluster whose centroid is closest based on a distance metric, typically **Euclidean distance**.
3. **Update**:
   - Recalculate the centroids as the mean of all data points assigned to each cluster.
4. **Repeat**:
   - Repeat the assignment and update steps until the centroids stabilize (i.e., no significant change in their positions) or a maximum number of iterations is reached.

Key Features

- **Number of Clusters**:
  - The number of clusters KKK must be specified beforehand. Techniques like the **Elbow Method** can help determine the optimal value of KKK.
- **Centroid-Based**:
  - Each cluster is represented by its centroid, which is the mean position of all points in the cluster.
- **Iterative Process**:
  - The algorithm continues to refine cluster assignments and centroids iteratively to minimize the **within-cluster sum of squares (WCSS)**.

Modeling

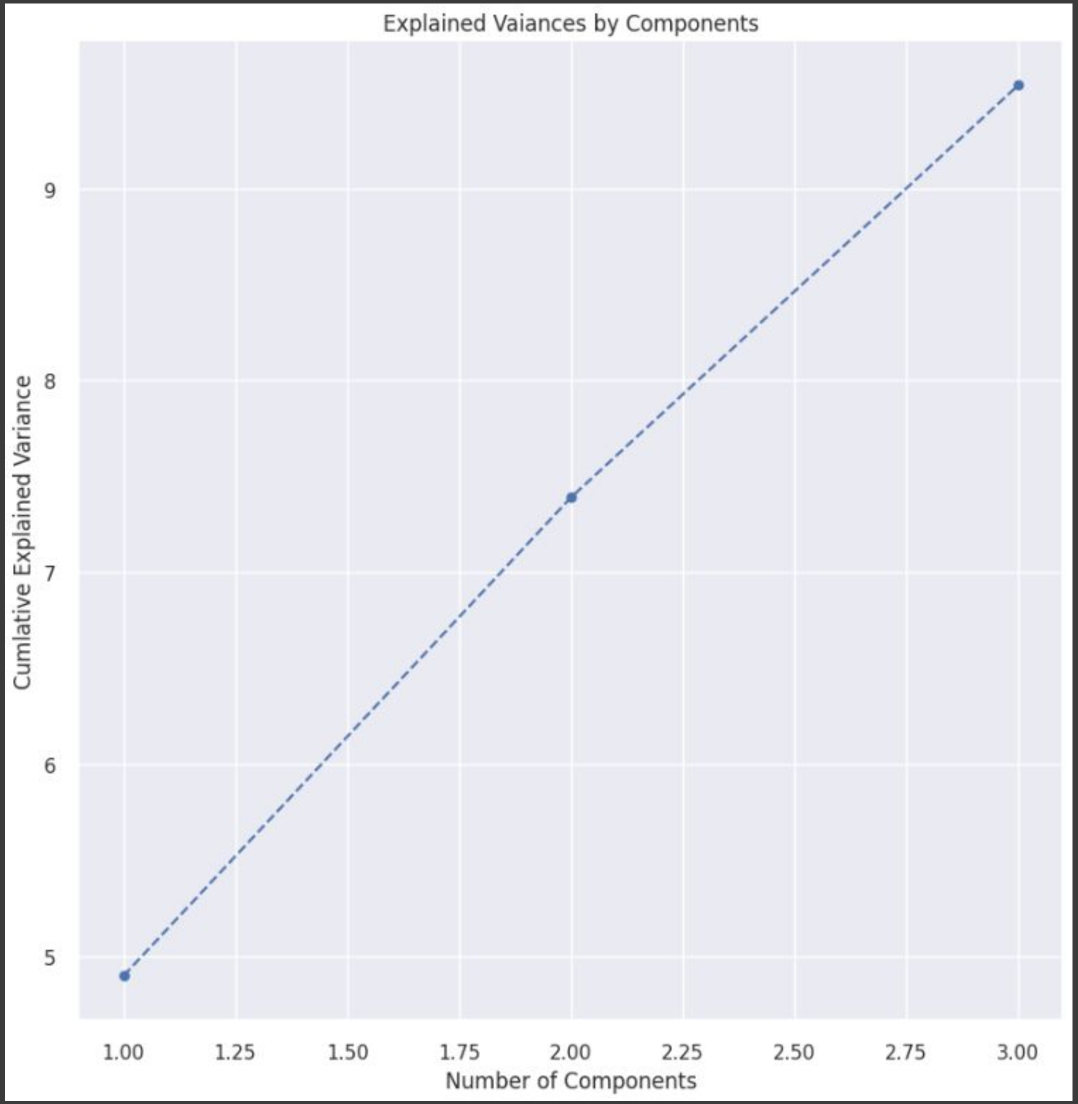
Before applying Kmeans, decided to apply PCA because the variables are many and there are not significantly correlated each variable.

By applying PCA, the variables can be efficient in terms of the calculation and it can reduce noises which would improve the result of Kmeans.

	PC1	PC2	PC3
0	-1.315076	-1.385793	-0.447665
1	-2.444797	-1.586799	-2.241275
2	-2.370449	-2.055705	-0.520818
3	-1.931309	-2.175039	-0.772620
4	-1.264435	-1.630508	-0.355673

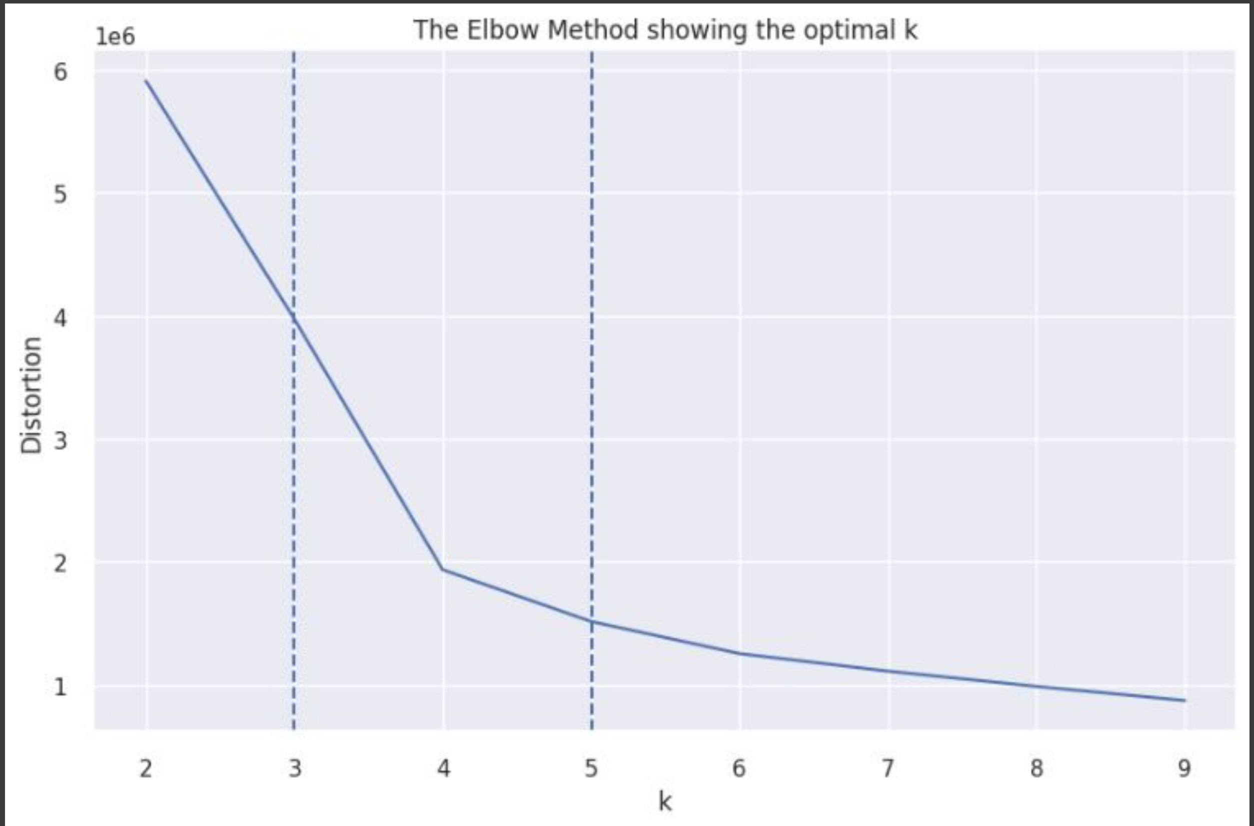
PCA

I have tried 3 components of PCA.



Elbow Method

The point that the elbow vending is the best for the segment. In this case, k = 4.



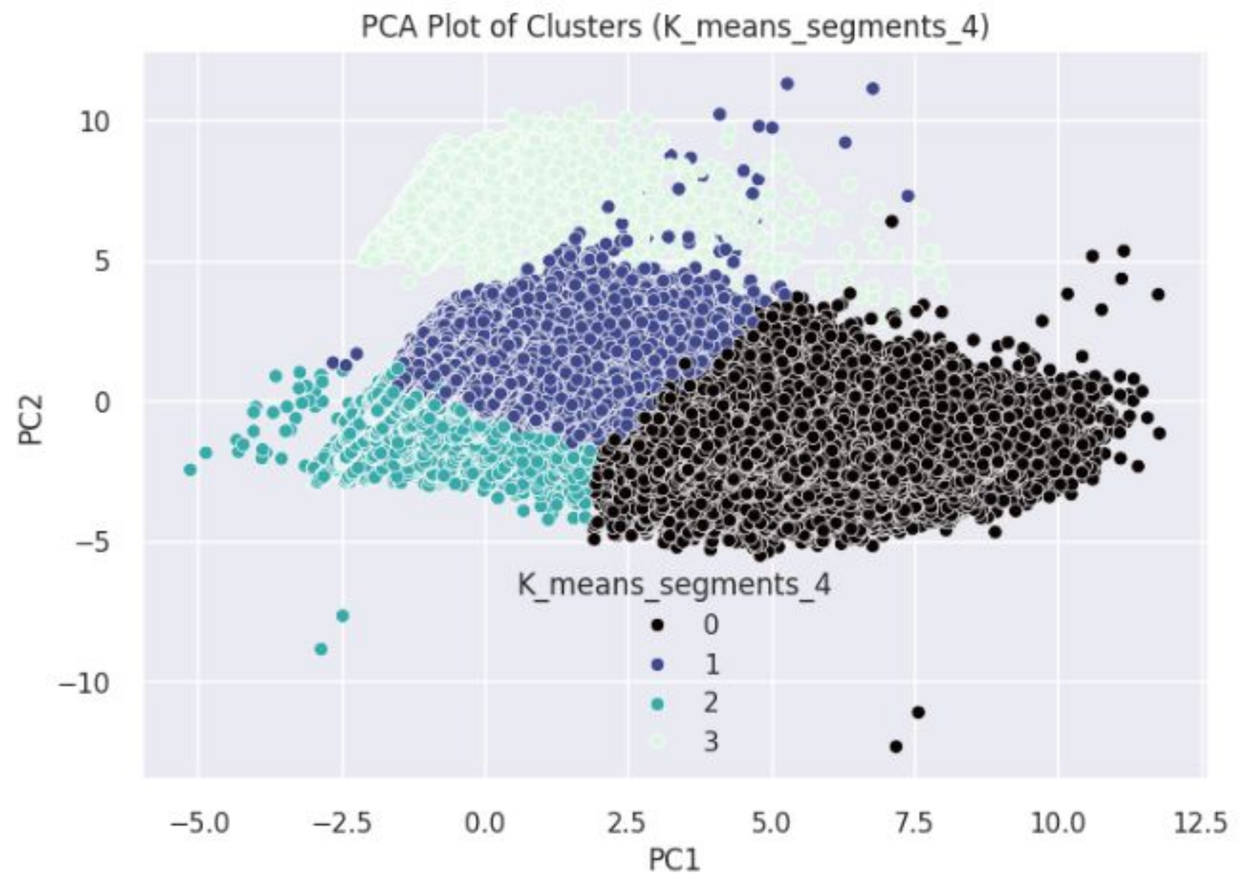
Elbow Method

With fit time, we can see how the fit time is getting longer if there is more clusters is increasing.

<Axes: title={'center': 'Distortion Score Elbow for KMeans Clustering'}, xlabel='k', ylabel='distortion score'>

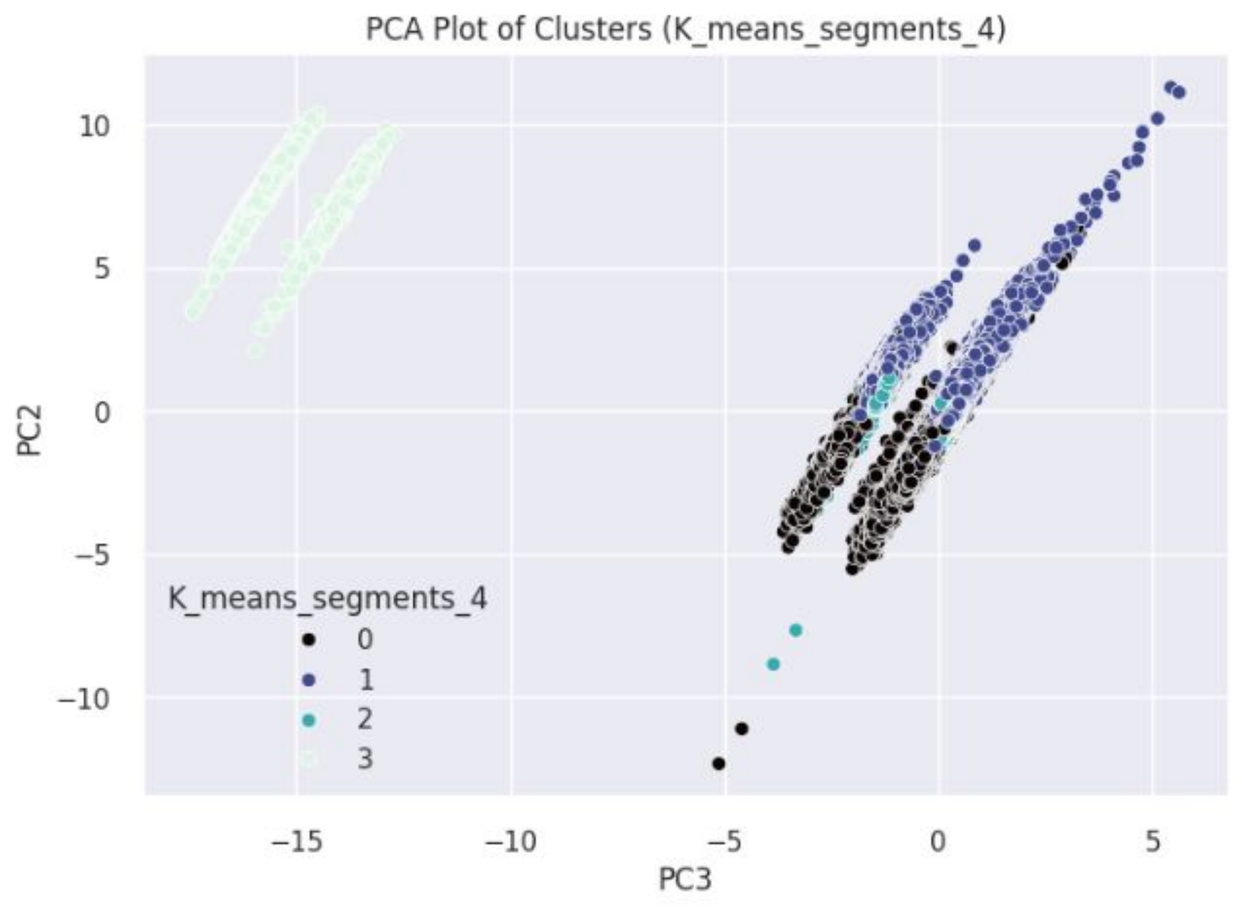
PCA

Separated segments by 4, there are clearly 4 segments between PC1 and PC2.



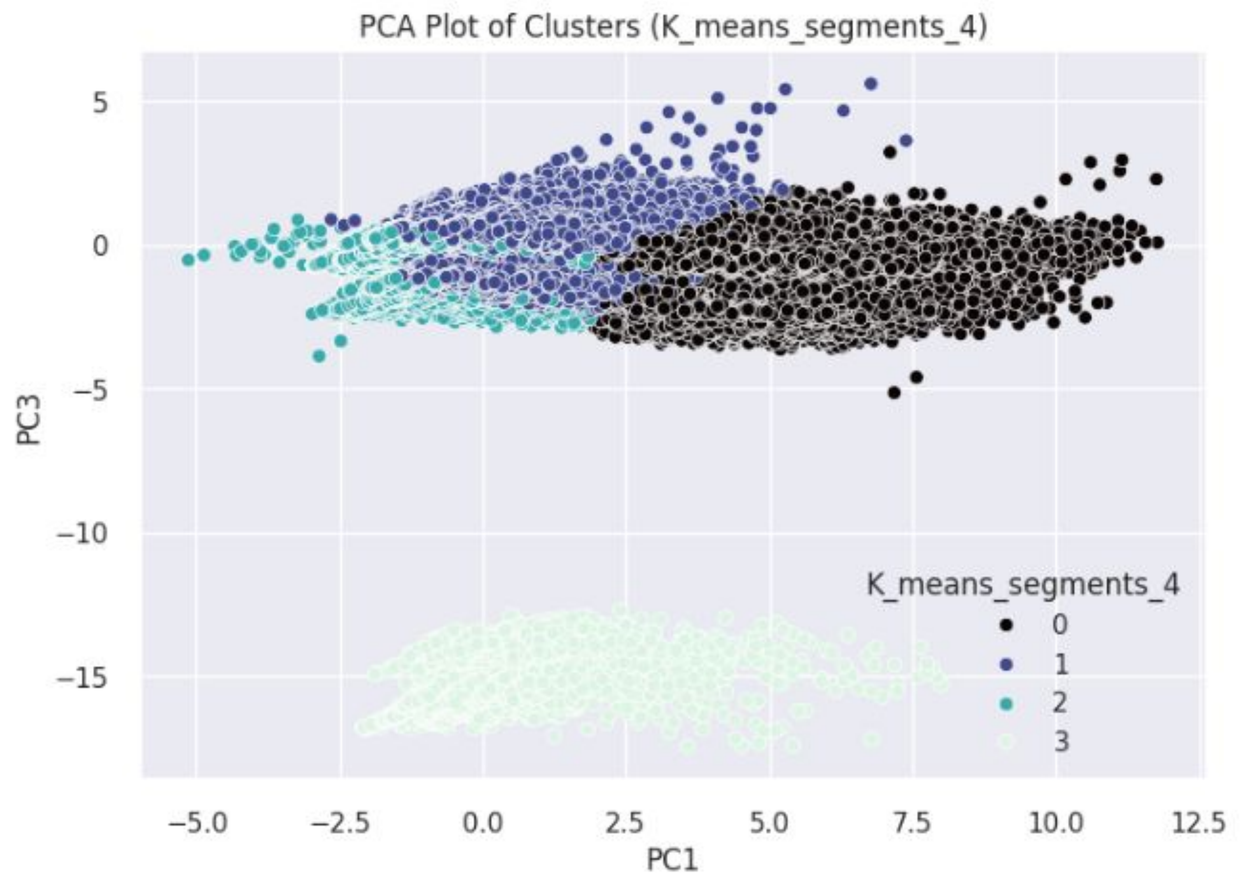
PCA

Separated segments by 4, there are clearly 4 segments between PC3 and PC2.



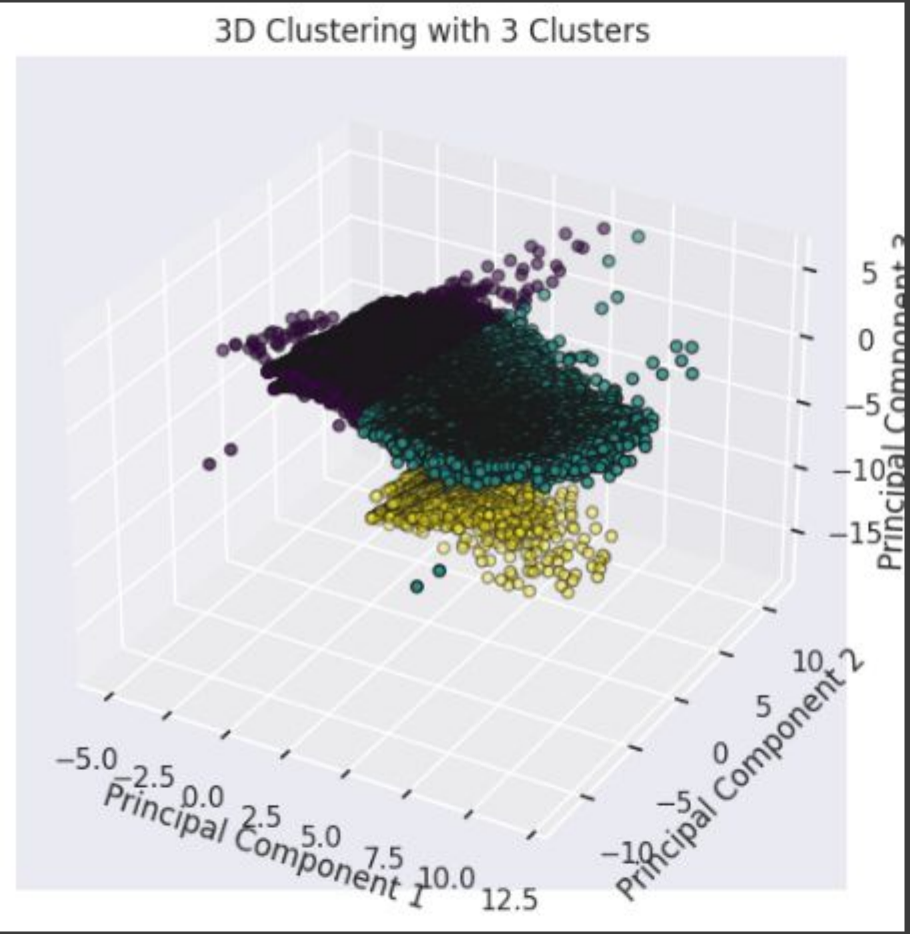
PCA

Separated segments by 4, there are clearly 4 segments between PC1 and PC3.



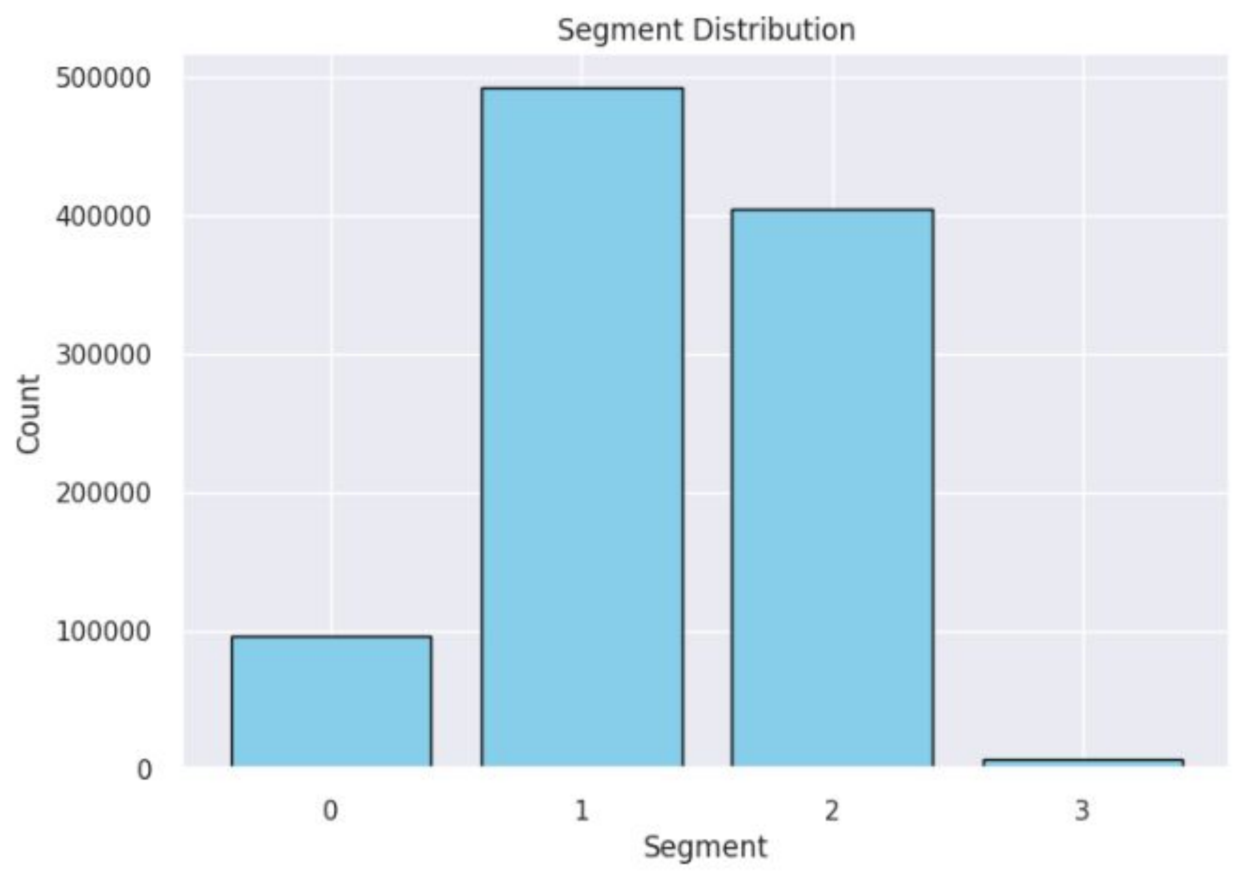
PCA

I have selected 3 segments in this 3D clustering.



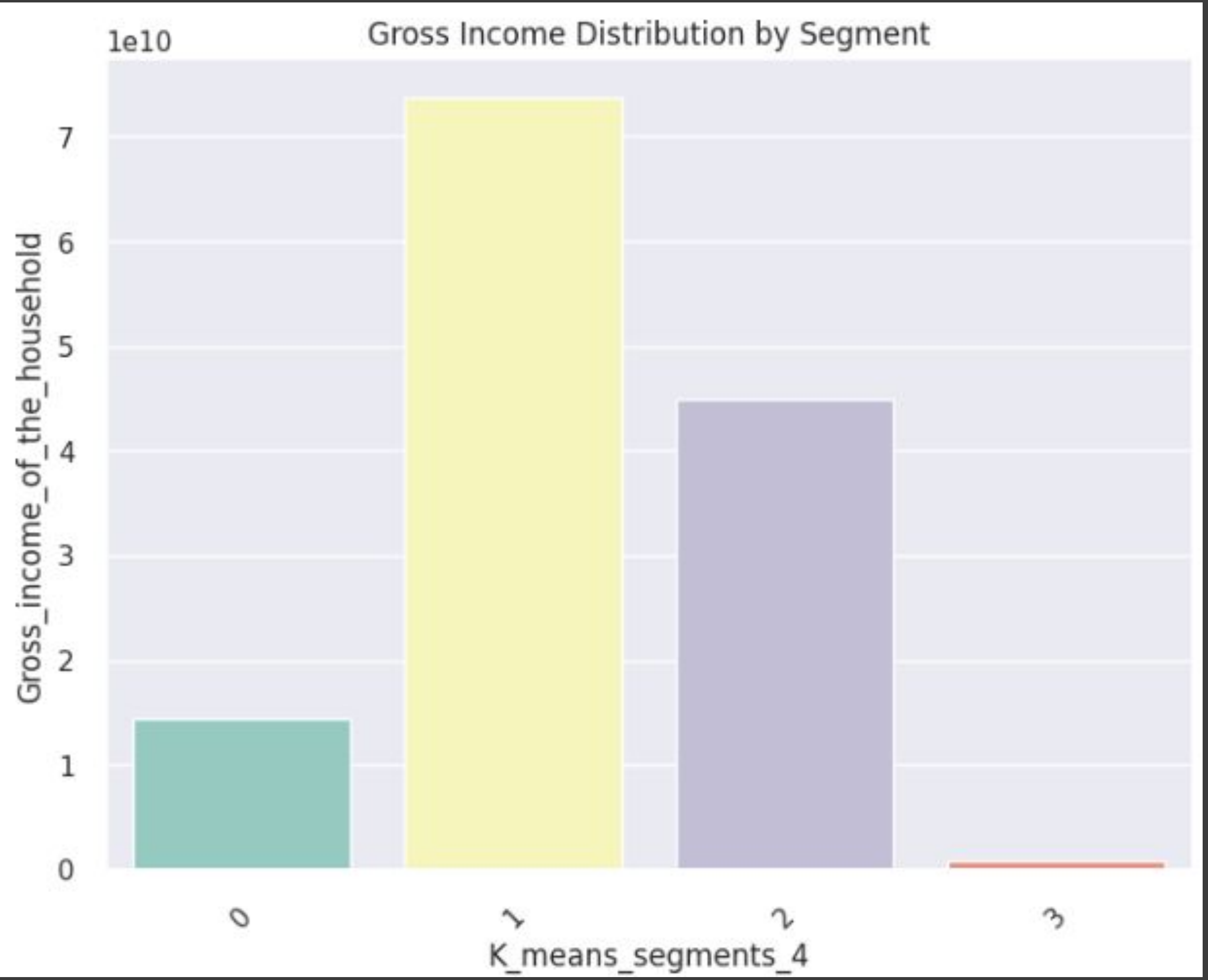
Segment Analysis

The amount of each segment, 1 is the largest segment. 3 is the smallest.



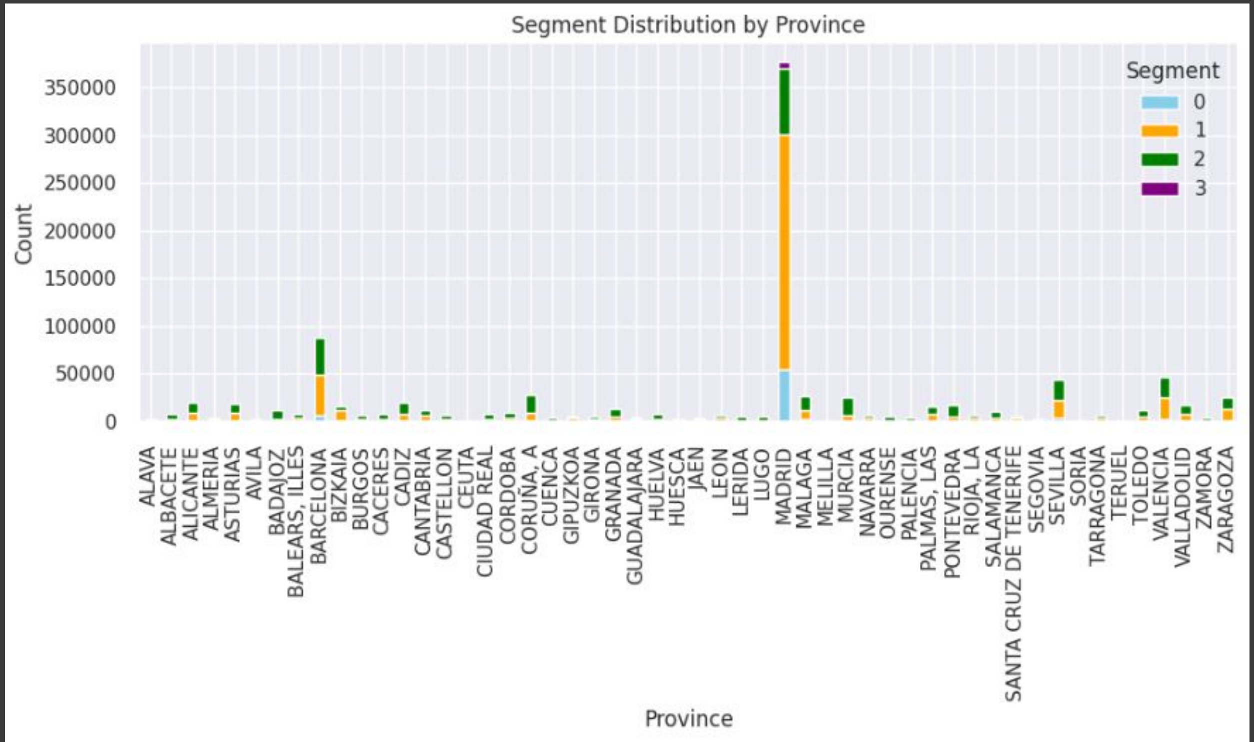
Segment Analysis

In the distribution of Gross income of the household, there is almost same result as the amount of the segments in the previous plot.



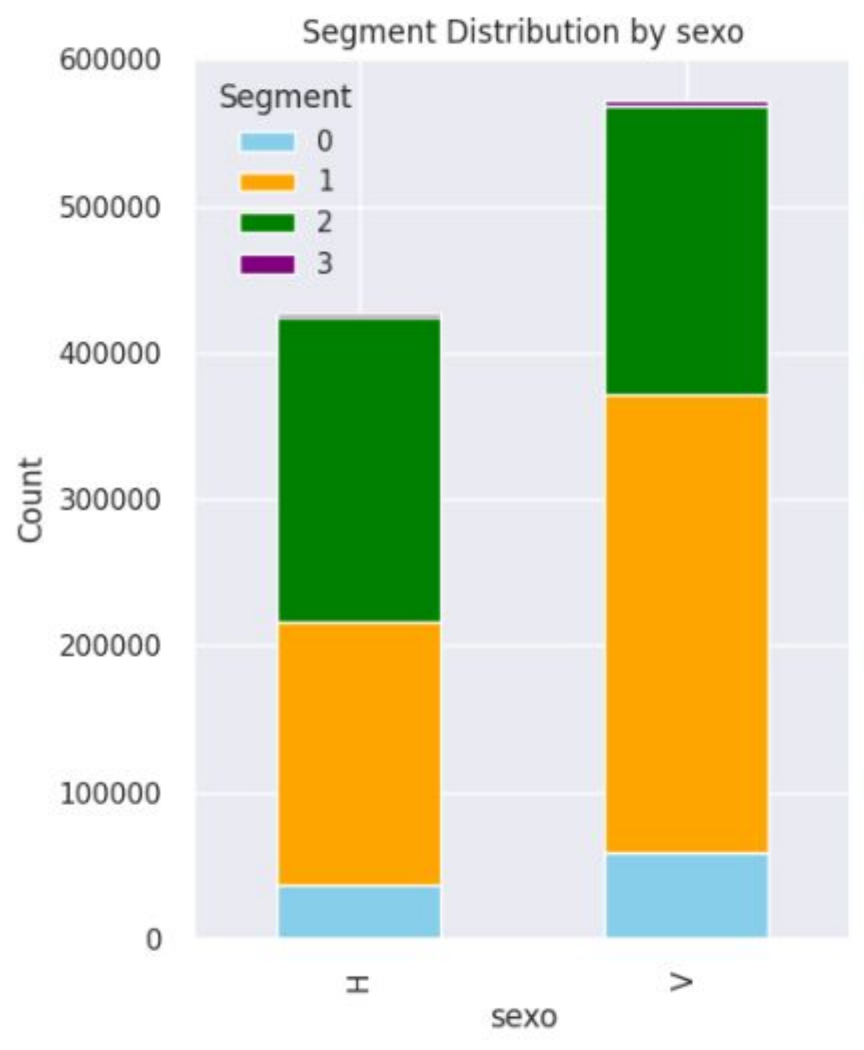
Segment Analysis

Madrid includes most of the segments regardless of the different type of the segments.



Segment Analysis

Female(V) has more segments compare to Male(H).



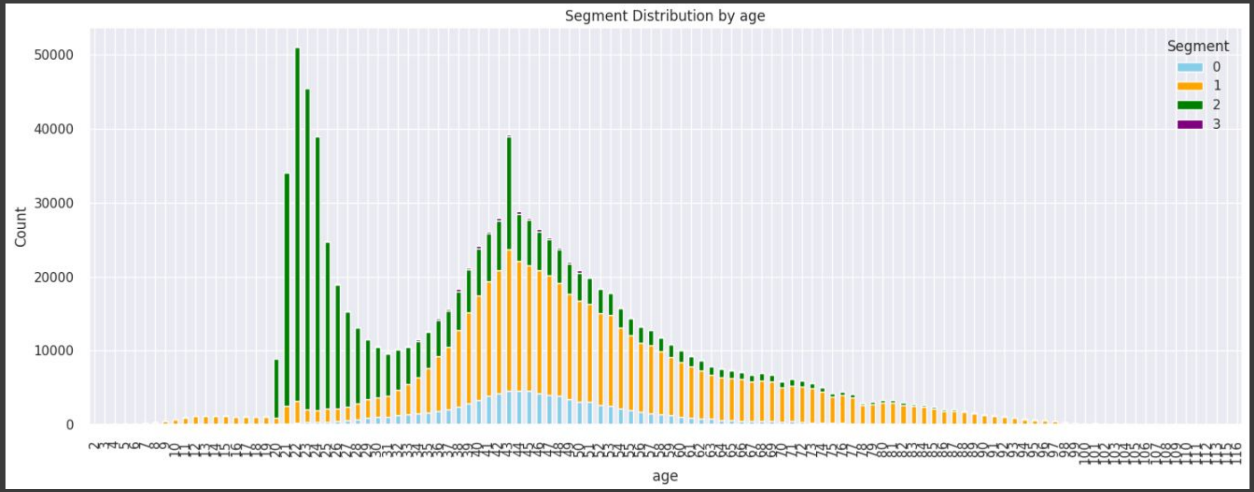
Segment Analysis

Activated customer has more segments.

Segment 0 located at activated bar.

Segment Analysis

Regardless the range of the age, each segment parse all over. But there is specific trends that segment 1 is located majority. And most of segment 2 located between age 20 and 40.



Conclusion

Utilizing unsupervised learning techniques, we applied Principal Component Analysis (PCA) and K-Means clustering to perform customer segmentation on the dataset. These methods proved highly effective due to the high dimensionality of the dataset and the absence of significant correlations among features.

Through the Elbow Method, we determined that the optimal number of customer segments is four. Based on these insights, the segmentation successfully identified four distinct customer groups. These groups provide actionable targets for the bank to implement more efficient and tailored marketing campaigns, optimizing resource allocation and improving campaign effectiveness.

Thank You