Data Glacier Data Scientist Internship

Batch: LISUM39

Week8: Deliverables

Project: Bank Customer Segmentation

Group name: Apple Analytics

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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 ABC 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:

The dataset includes various information for the bank customers. For segmentation analysis, we need to identify the specific groups with specific characteristics. To find the uniquenesses, unsupervised learning algorithms such as clustering are the best way to analyze.

What type of data have you got for analysis?

-The shape: 1000000 rows × 48 columns

Column Name	Description
fecha_dato	The table is partitioned for this column
ncodpers	Customer code
ind_empleado	Employee index: A active, B ex employed, F filial, N not employee, P pasive
pais_residencia	Customer's Country residence
sexo	Customer's sex
age	Age
fecha_alta	The date in which the customer became as the first holder of a contract in the bank
ind_nuevo	New customer Index. 1 if the customer registered in the last 6 months.
antiguedad	Customer seniority (in months)
indrel	1 (First/Primary), 99 (Primary customer during the month but not at the end of the month)
ult_fec_cli_1t	Last date as primary customer (if he isn't at the end of the month)
indrel_1mes	Customer type at the beginning of the month ,1 (First/Primary customer), 2 (co-owner),P (Potential),3 (former primary), 4(former co-owner)
tiprel_1mes	Customer relation type at the beginning of the month, A (active), I (inactive), P (former customer),R (Potential)
indresi	Residence index (S (Yes) or N (No) if the residence country is the same than the bank country)
indext	Foreigner index (S (Yes) or N (No) if the customer's birth country is different than the bank country)
conyuemp	Spouse index. 1 if the customer is spouse of an employee
canal_entrada	channel used by the customer to join
indfall	Deceased index. N/S

tipodom	**Addres type. 1, primary address**
cod_prov	**Province code (customer's address)**
nomprov	**Province name**
ind_actividad_cliente	**Activity index (1, active customer; 0, inactive customer)**
renta	**Gross income of the household**
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**
ind_deco_fin_ult1	**Short-term deposits**
ind_deme_fin_ult1	**Medium-term deposits**
ind_dela_fin_ult1	**Long-term deposits**
ind_ecue_fin_ult1	**e-account**
ind_fond_fin_ult1	**Funds**
ind_hip_fin_ult1	**Mortgage**
ind_plan_fin_ult1	**Pensions**
ind_pres_fin_ult1	**Loans**

ind_reca_fin_ult1	Taxes
ind_tjcr_fin_ult1	Credit Card
ind_valo_fin_ult1	Securities
ind_viv_fin_ult1	Home Account
ind_nomina_ult1	Payroll
ind_nom_pens_ult1	Pensions
ind_recibo_ult1	Direct Debit

-Data type in original

```
 #   Column              Non-Null Count    Dtype

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 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
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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
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 37  ind_fond_fin_ult1      1000000 non-null  int64

 38  ind_hip_fin_ult1       1000000 non-null  int64

 39  ind_plan_fin_ult1      1000000 non-null  int64

 40  ind_pres_fin_ult1      1000000 non-null  int64

 41  ind_reca_fin_ult1      1000000 non-null  int64

 42  ind_tjcr_fin_ult1      1000000 non-null  int64

 43  ind_valo_fin_ult1      1000000 non-null  int64

 44  ind_viv_fin_ult1       1000000 non-null  int64

 45  ind_nomina_ult1         994598 non-null   float64

 46  ind_nom_pens_ult1       994598 non-null   float64

 47  ind_recibo_ult1        1000000 non-null  int64

dtypes: float64(9), int64(24), object(15)
```
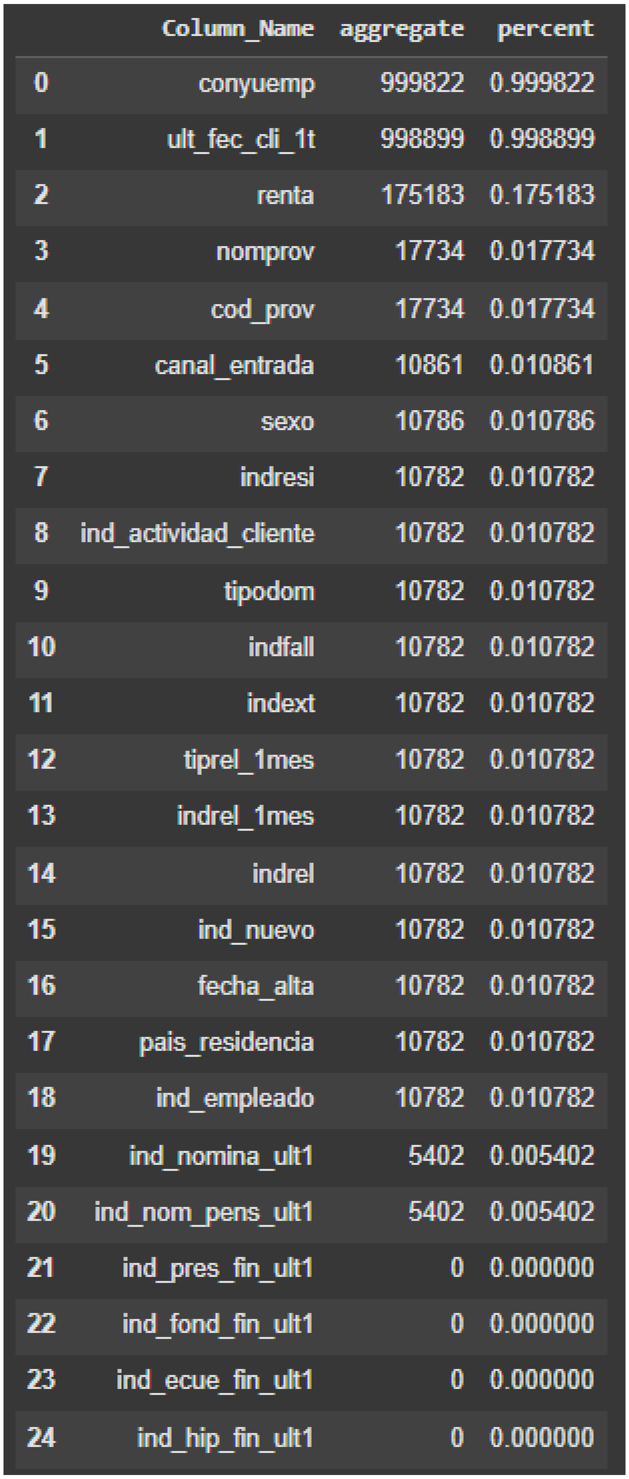
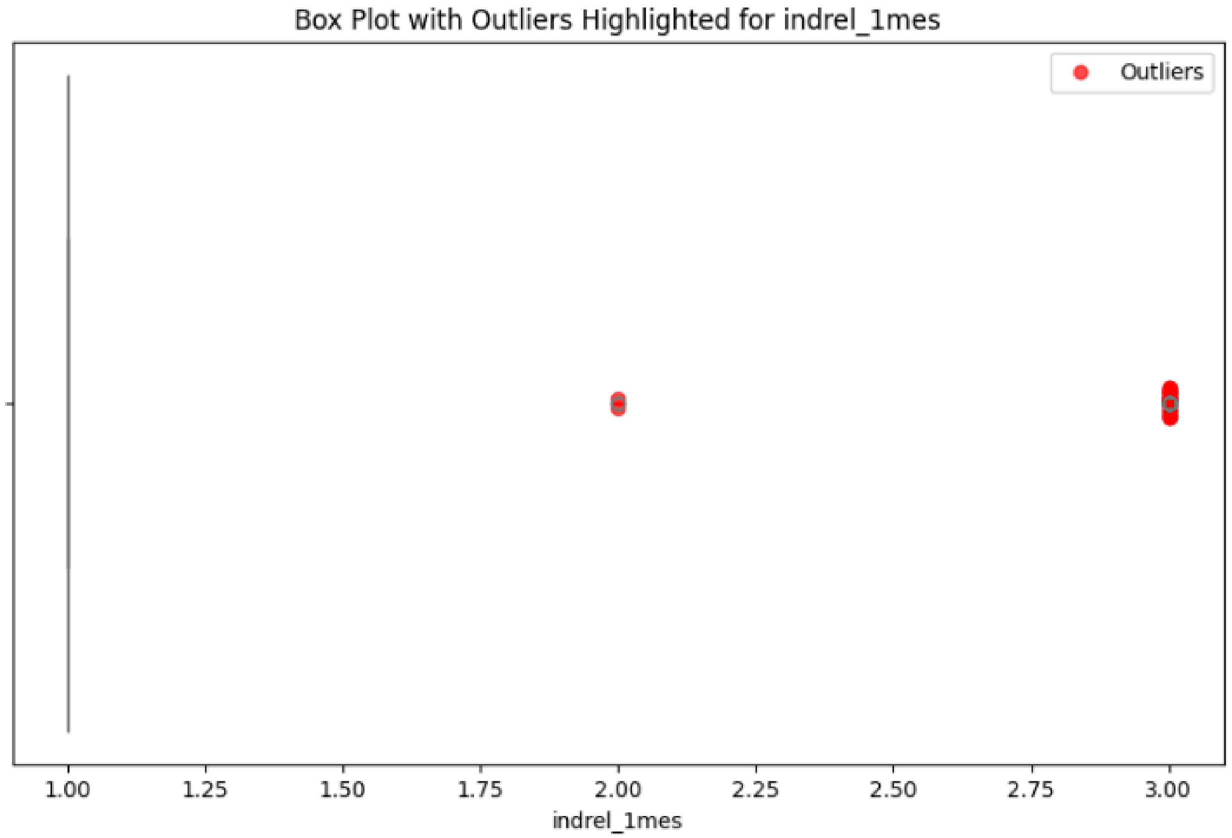

What are the problems in the data (number of NA values, outliers , skewed etc)

-The dataset has a lot of missing data (2,371,207 missing datas) as below.



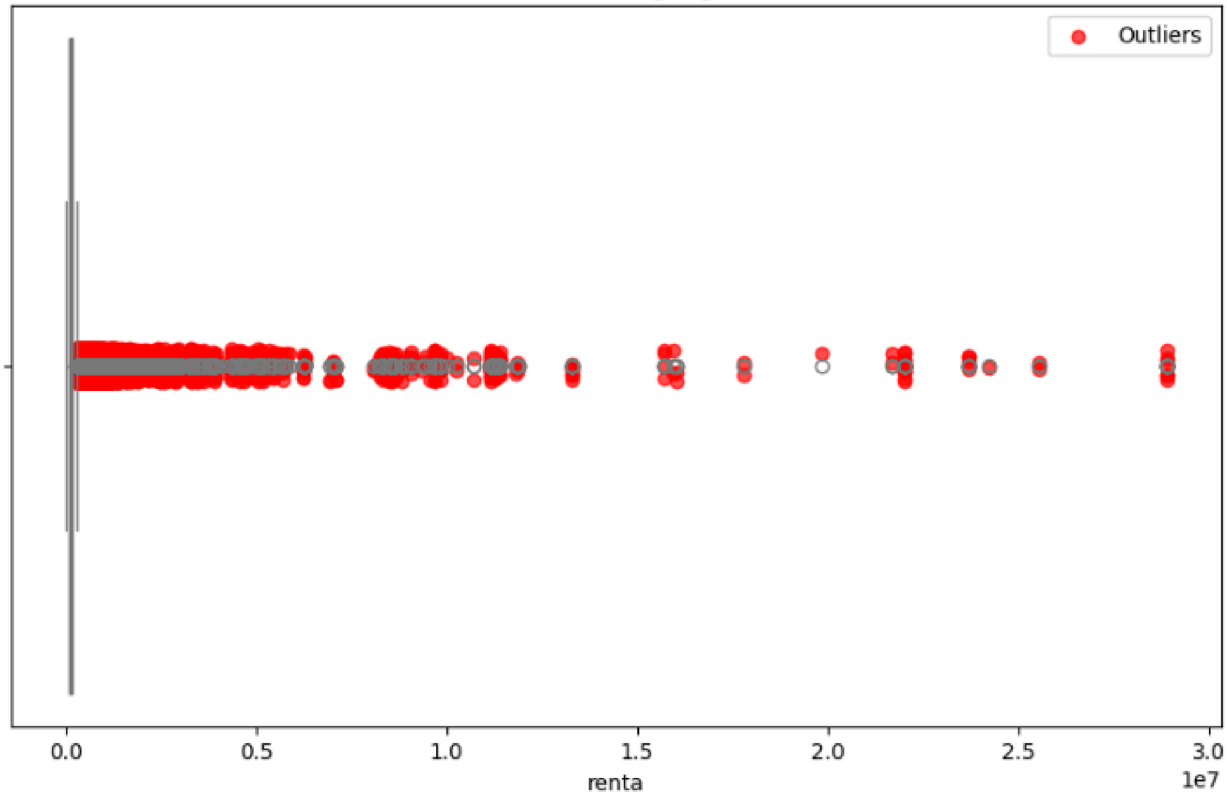
	Column_Name	aggregate	percent
0	conyuemp	999822	0.999822
1	ult_fec_cli_1t	998899	0.998899
2	renta	175183	0.175183
3	nomprov	17734	0.017734
4	cod_prov	17734	0.017734
5	canal_entrada	10861	0.010861
6	sexo	10786	0.010786
7	indresi	10782	0.010782
8	ind_actividad_cliente	10782	0.010782
9	tipodom	10782	0.010782
10	indfall	10782	0.010782
11	indext	10782	0.010782
12	tiprel_1mes	10782	0.010782
13	indrel_1mes	10782	0.010782
14	indrel	10782	0.010782
15	ind_nuevo	10782	0.010782
16	fecha_alta	10782	0.010782
17	pais_residencia	10782	0.010782
18	ind_empleado	10782	0.010782
19	ind_nomina_ult1	5402	0.005402
20	ind_nom_pens_ult1	5402	0.005402
21	ind_pres_fin_ult1	0	0.000000
22	ind_fond_fin_ult1	0	0.000000
23	ind_ecue_fin_ult1	0	0.000000
24	ind_hip_fin_ult1	0	0.000000

-Outliers


Box Plot with Outliers Highlighted for indrel_1mes
● Outliers
1.00
1.25
1.50
1.75
2.00
2.25
2.50
2.75
3.00
indrel_1mes

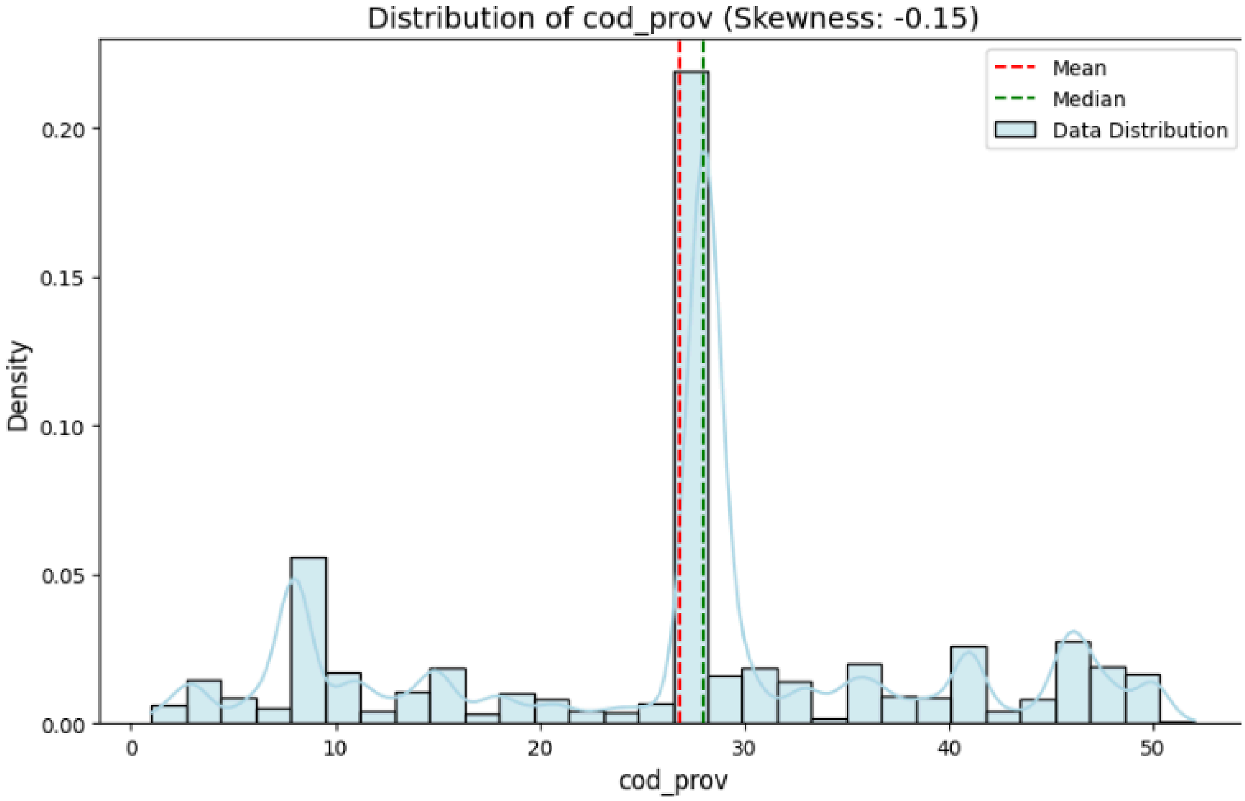
Regarding renta(Gross income of the household), there are so many outliers.

Box Plot with Outliers Highlighted for renta

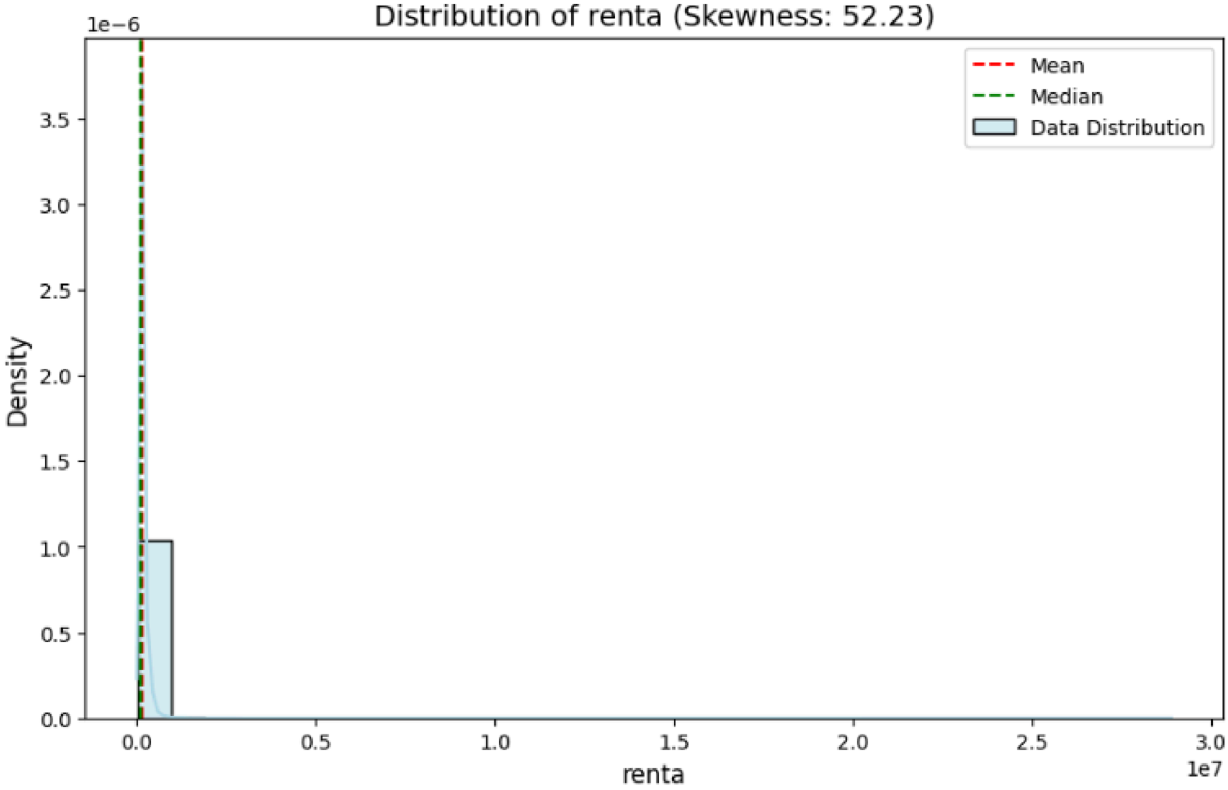


-Skewness

Regarding cod_prov(Province code (customer's address)), the median and the mean are around 27-28 and most of them were located to this bin.



Regarding renta(Gross income of the household), the median and the mean are skewed to right.



What approaches you are trying to apply on your data set to overcome problems like NA value, outlier etc and why?

-**NA value**: Future Engineering, Imputing method using mean, median, and mode, etc.. If there are too many NA values in a variable, then dropping the column itself may be the best method because assuming missing data cannot be predictable.

Additionally, using the algorithm is good for missing data treatment such as KNN imputation and MICE(Multiple Imputation by Chained Equations)

-**Outliers**: May apply to omit them. Depending on the case.

Identify based IQR, Zscore, and anomaly detection models such as Isolation Forest and OBSCAN.

If the outlier indicates significant characteristics, we apply robust scaling (log) and omit specific upper/ lower limits.

-**Skewness**: In this case, there are many like one hot encoding and categoricals. And we apply the cluster method. Adjusting skewness like normalization may not good idea.

Project life cycle along with deadline:

Project weeks	**Deadline**	**Lifecycle**
Week7	Dec 19, 2024	Problem statement, Pre-process
Week8	**Dec 26, 2024**	**Data process, understanding**
Week9	Jan 02, 2025	Data Cleaning, Merge, Review
Week10	Jan 09, 2025	EDA, Final recommendation
Week11	Jan 16, 2025	EDA presentation for business users
Week12	Jan 23, 2025	Model Selection and Model Building/Dashboard
Week13	Jan 30, 2025	Final Project Report and Code

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