Team Member Details

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Problem Description

In order to develop its promotional campaign, XYZ Bank needs to know the answers to the following questions:

- What is the best number of groups to divide customers into?
- What are the primary characteristics of each group?

To answer these questions, the k-means clustering algorithm will be used to segment the customers, and the inertia metric will be used to determine the optimal number of groups (k). Finally, the characteristics of each group will be summarized so that XYZ Bank can determine which offers to develop and target to each group.

Data Understanding and Types

The dataset consists of 1,000,000 observations across 48 features. The features include customer demographic information as well as details on the services the customer uses at the bank. The features, their datatypes, sample values, and the number of missing values are listed in the following table. Feature names were renamed to meaningful English names. The original Spanish names are listed in parentheses.

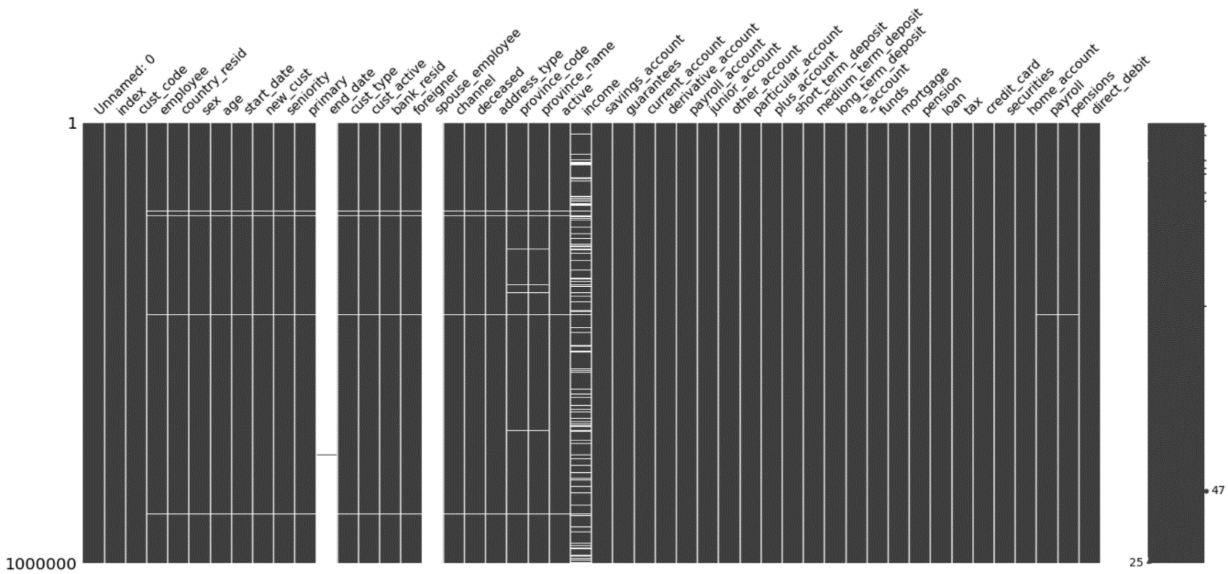
Feature Name	Feature Type	Datatype	Sample Values	Number of Missing Values
Unnamed: 0	index	integer	1, 999999	0
index (fecha_dato)	date	string	2015-01-28, 2015-02-28	0
cust_code (ncodpers)	numeric	integer	15889, 1379131	0
employee (indempleado)	categorical	string	N, S	10,782
country_resid (pais_residencia)	categorical	string	ES, AL	10,782
sex (sexo)	dichotomous categorical	string	V, H	10,786
age (age)	numeric	string	2, 116	10,782

start_date (fecha_alta)	date	string	1995-01-16, 2015-02-27	10,782
new_cust (ind_nuevo)	dichotomous categorical	float	0.0, 1.0	10,782
seniority (antiguedad)	numeric	string	-999999, 246	10,782
primary (indrel)	dichotomous categorical	float	1.0, 99.0	10,782
end_date (ult_fec_cli_1t)	date	string	2015-07-01, 2015-07-30	998,899
cust_type (indrel_1mes)	categorical	integer	1.0, 2.0	10,782
cust_active (tiprel_1mes)	categorical	string	A, I	10,782
bank_resid (indresi)	dichotomous categorical	string	S, N	10,782
foreigner (indext)	dichotomous categorical	string	S, N	10,782
spouse_employee (conyuemp)	dichotomous categorical	string	S, N	999,822
channel (canal_entrada)	categorical	string	KAT, KGC	10,861
deceased (indfall)	dichotomous categorical	string	S, N	10,782
address_type (tipodom)	categorical	float	1.0	10,782
province_code (cod_prov)	categorical	integer	1.0, 52.0	17,734
province_name (nom_prov)	categorical	string	AVILA, MADRID	17,734
active (ind_actividad_cliente)	dichotomous categorical	integer	0.0, 1.0	10,782
income (renta)	continuous numeric	float	1202.73, 28894395.51	175,183
savings_account (ind_ahor_fin_ult1)	dichotomous categorical	integer	0, 1	0
guarantees (ind_aval_fin_ult1)	dichotomous categorical	integer	0, 1	0
current_account (ind_cco_fin_ult1)	dichotomous categorical	integer	0, 1	0
derivative_account (ind_cder_fin_ult1)	dichotomous categorical	integer	0, 1	0
payroll_account (ind_cno_fin_ult1)	dichotomous categorical	integer	0, 1	0
junior_account (ind_ctju_fin_ult1)	dichotomous categorical	integer	0, 1	0

other_account (ind_ctma_fin_ult1)	dichotomous categorical	integer	0, 1	0
particular_account (ind_ctop_fin_ult1)	dichotomous categorical	integer	0, 1	0
plus_account (ind_ctpp_fin_ult1)	dichotomous categorical	integer	0, 1	0
short_term_deposit (ind_deco_fin_ult1)	dichotomous categorical	integer	0, 1	0
medium_term_deposit (ind_deme_fin_ult1)	dichotomous categorical	integer	0, 1	0
long_term_deposit (ind_dela_fin_ult1)	dichotomous categorical	integer	0, 1	0
e_account (ind_ecue_fin_ult1)	dichotomous categorical	integer	0, 1	0
funds (ind_fond_fin_ult1)	dichotomous categorical	integer	0, 1	0
mortgage (ind_hip_fin_ult1)	dichotomous categorical	integer	0, 1	0
pension (ind_pan_fin_ult1)	dichotomous categorical	integer	0, 1	0
loan (ind_pres_fin_ult1)	dichotomous categorical	integer	0, 1	0
tax (ind_reca_fin_ult1)	dichotomous categorical	integer	0, 1	0
credit_card (ind_tjcr_fin_ult1)	dichotomous categorical	integer	0, 1	0
securities (ind_valo_fin_ult1)	dichotomous categorical	integer	0, 1	0
home_account (ind_viv_fin_ult1)	dichotomous categorical	integer	0, 1	0
payroll (ind_nomina_ult1)	dichotomous categorical	integer	0, 1	5,402
pensions (ind_nom_pens_ult1)	dichotomous categorical	integer	0, 1	5,402
direct_debit (ind_recibo_ult1)	dichotomous categorical	integer	0, 1	0

Missing Data

It is notable that exactly 10,782 observations are missing from 14 features. The missing matrix suggests that these observations are all missing from the same rows:



These rows contain account information but not customer demographic information. Examining these rows further, there does not appear to be a pattern between types of accounts and the missingness of the data. The 10,782 rows account for only about 1.08% of the total data and do not provide useful customer demographic information for the purpose of clustering. Therefore, these rows were dropped from the dataset.

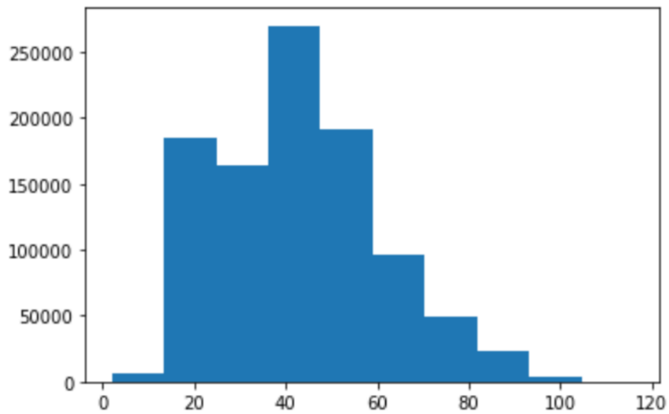
After these rows were dropped, some missing values remained. These will each be treated differently depending on the column as follows:

- sex (4 missing): Impute with the mode (male).
- end_date (988,117 missing): Drop the column. It does not provide useful information for grouping the customers.
- spouse_employee (989,040 missing): Impute missing numbers as N (not spouse). Assume that the number of spouses of employees is low and that the missing values should be interpreted as non-spouses.
- channel (79 missing): Drop the column. It does not provide useful information for grouping the customers due to the high number of channel values (156 different channels).
- province_code and province_name (6,952 missing values in each): Drop the column. It does not provide useful information for grouping the customers due to the high number of provinces (52 different provinces).
- income (164,401 missing): Examine the distribution of the column and impute with either the mean (if normal) or median (if skewed).
- payroll (100 missing): Impute with the mode (0).
- pensions (100 missing): Impute with the mode (0).

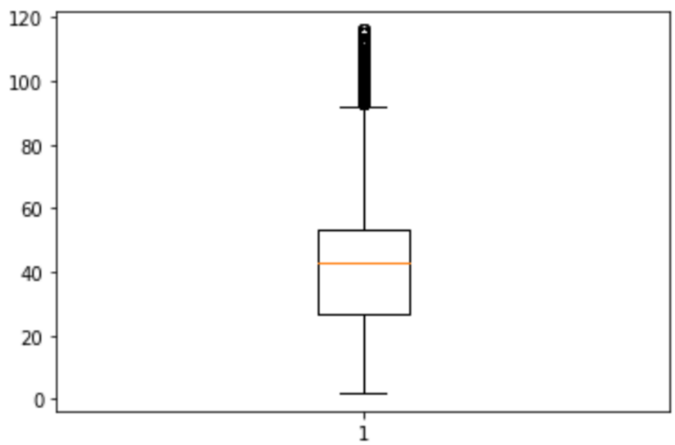
Distribution, Outliers, and Skew

The age column

The age column appears to be positively skewed:



There are outliers on the high end:

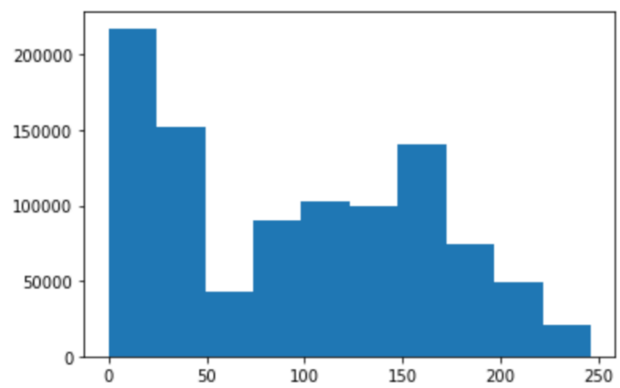


There is no reason to suspect that the outliers are unreasonable (for example, outside the expected age range for people) or otherwise incorrect. They will be retained.

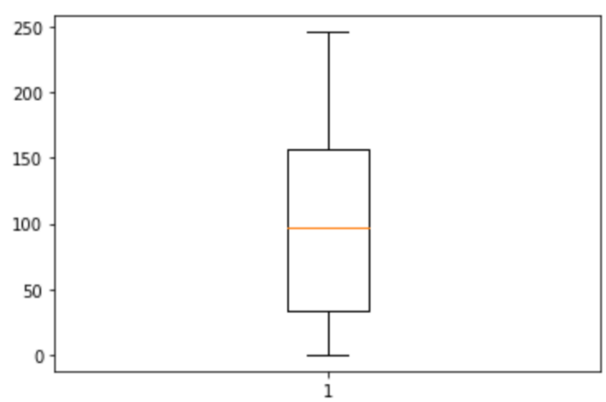
The seniority column

The seniority column contains many negative values, which do not make sense. The column is intended to represent the number of months the customer has been with the company. Because negative numbers do not make sense, any negative values in this column were changed to equal zero.

After this, the data appear to be positively skewed:

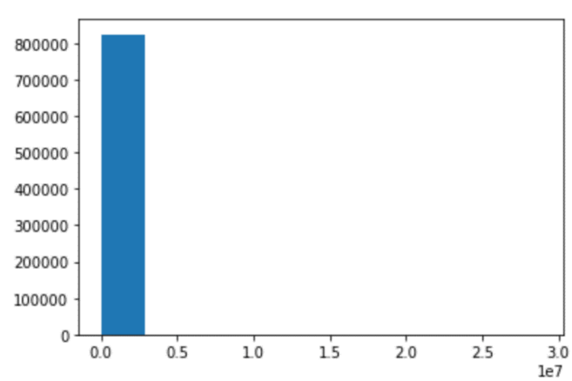


There are no outliers:

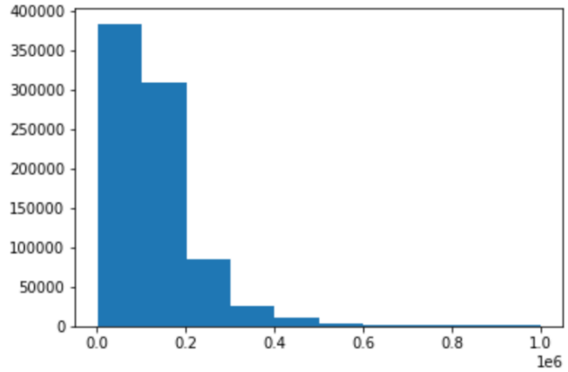


The income column

The distribution of the income column is positively skewed, which is typical of incomes, with very few values at the very high end:

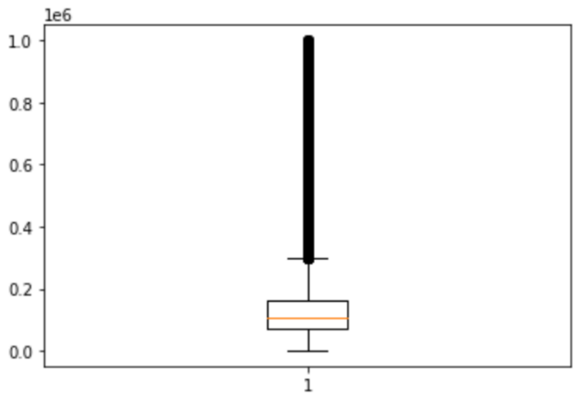


Excluding the 166,499 values above 10,000,000 (note that units of income are unknown) gives a clearer sense of the distribution:



Because of the skew, the missing values should be imputed with the median, not the mean.

There are many significant outliers at the high end. The boxplot shows those for incomes less than 10,000,000:



There is no indication that the outliers are mistakes in the data, so they will be retained.

Github Repository Link

[ebanning/DataGlacierProject: This is a customer segmentation project for the DataGlacier Data Science virtual internship. (github.com)]