

Data Analyst: Cross selling recommendation

1. Team member's details

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2. Problem description

XYZ Credit union in Latin America is performing very well in selling Banking products (Credit card , deposit amount, retirement account, safe deposit box), but their existing customer is not buying more than 1 product which means bank is not performing good in cross selling (Banks is not able to sell their other offering to existing customers). XYZ credit union decided to approach ABC analytics to solve their problem.

3. Data understanding

There are 2 files: Test and Train. Test file hasn't any info about products and we can't use this file for analysis.

Let's check the number of rows in train datasets, what type of variables are there and whether values are null (info in %).

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 13647309 entries, 0 to 13647308
Data columns (total 48 columns):
#   Column                                Dtype
---  -
0   fecha_dato                            object
1   ncodpers                              int64
2   ind_empleado                          object
3   pais_residencia                       object
4   sexo                                  object
5   age                                    object
6   fecha_alta                            object
7   ind_nuevo                             float64
8   antiguedad                           object
9   indrel                                float64
10  ult_fec_cli_1t                         object
11  indrel_1mes                            object
12  tiprel_1mes                            object
13  indresi                                object
14  indext                                 object
15  conyuemp                               object
16  canal_entrada                          object
17  indfall                                object
18  tipodom                                float64
19  cod_prov                               float64
20  nomprov                                object
21  ind_actividad_cliente                  float64
22  renta                                  float64
23  segmento                               object
24  ind_ahor_fin_ult1                      int64
25  ind_aval_fin_ult1                      int64
26  ind_cco_fin_ult1                       int64
27  ind_cder_fin_ult1                      int64
28  ind_cno_fin_ult1                       int64
29  ind_ctju_fin_ult1                      int64
30  ind_ctma_fin_ult1                      int64
31  ind_ctop_fin_ult1                      int64
32  ind_ctpp_fin_ult1                      int64
33  ind_deco_fin_ult1                      int64
34  ind_deme_fin_ult1                      int64
35  ind_dela_fin_ult1                      int64
36  ind_ecue_fin_ult1                      int64
37  ind_fond_fin_ult1                      int64
38  ind_hip_fin_ult1                       int64
39  ind_plan_fin_ult1                      int64
40  ind_pres_fin_ult1                      int64
41  ind_reca_fin_ult1                      int64
42  ind_tjcr_fin_ult1                      int64
43  ind_valo_fin_ult1                      int64
44  ind_viv_fin_ult1                       int64
45  ind_nomina_ult1                        float64
46  ind_nom_pens_ult1                      float64
47  ind_recibo_ult1                        int64
48  fecha_dato                            float64
49  ncodpers                              float64
50  ind_empleado                          float64
51  pais_residencia                       float64
52  sexo                                  float64
53  age                                    float64
54  fecha_alta                            float64
55  ind_nuevo                             float64
56  antiguedad                           float64
57  indrel                                float64
58  ult_fec_cli_1t                         float64
59  indrel_1mes                            float64
60  tiprel_1mes                            float64
61  indresi                                float64
62  indext                                 float64
63  conyuemp                               float64
64  canal_entrada                          float64
65  indfall                                float64
66  tipodom                                float64
67  cod_prov                               float64
68  nomprov                                float64
69  ind_actividad_cliente                  float64
70  renta                                  float64
71  segmento                               float64
72  ind_ahor_fin_ult1                      float64
73  ind_aval_fin_ult1                      float64
74  ind_cco_fin_ult1                       float64
75  ind_cder_fin_ult1                      float64
76  ind_cno_fin_ult1                       float64
77  ind_ctju_fin_ult1                      float64
78  ind_ctma_fin_ult1                      float64
79  ind_ctop_fin_ult1                      float64
80  ind_ctpp_fin_ult1                      float64
81  ind_deco_fin_ult1                      float64
82  ind_deme_fin_ult1                      float64
83  ind_dela_fin_ult1                      float64
84  ind_ecue_fin_ult1                      float64
85  ind_fond_fin_ult1                      float64
86  ind_hip_fin_ult1                       float64
87  ind_plan_fin_ult1                      float64
88  ind_pres_fin_ult1                      float64
89  ind_reca_fin_ult1                      float64
90  ind_tjcr_fin_ult1                      float64
91  ind_valo_fin_ult1                      float64
92  ind_viv_fin_ult1                       float64
93  ind_nomina_ult1                        float64
94  ind_nom_pens_ult1                      float64
95  ind_recibo_ult1                        float64
96  dtype: float64
```

Train dataset contains info about customers and their products.

Train dataset contains 48 features and 13 647 309 rows. There are no duplicates.

Some of features was defined as object, but it is Numerical Variables: `age`, `antiguedad`.

Some features in opposite were defined as float64, but it is categorical features:

`ind_nuevo`, `indrel`, `tipodom`, `cod_prov`, `ind_actividad_cliente`

In general:

Continuous Variables: `'age'`, `'antiguedad'`, `'renta'`

Categorical Variables: others

There are some features with the same number of missing values, I expect those relate to the same rows. We delete rows with a lot of missing values (0.2% of data).

Null values after deleting rows with a lot of missing values:

```
fecha_dato      0.000000
ncodpers        0.000000
ind_empleado    0.000000
pais_residencia 0.000000
sexo            0.000514
age             0.000000
fecha_alta      0.000000
ind_nuevo       0.000000
antiguedad      0.000000
indrel          0.000000
ult_fec_cli_1t  99.817961
indrel_1mes     0.896115
tiprel_1mes     0.896115
indresi         0.000000
indext          0.000000
conyuemp        99.986725
canal_entrada   1.162973
indfall         0.000000
tipodom         0.000007
cod_prov        0.483547
nomprov         0.483547
ind_actividad_cliente 0.000000
renta           20.313710
segmento        1.186777
ind_ahor_fin_ult1 0.000000
ind_aval_fin_ult1 0.000000
ind_cco_fin_ult1 0.000000
ind_cder_fin_ult1 0.000000
ind_cno_fin_ult1 0.000000
ind_ctju_fin_ult1 0.000000
ind_ctma_fin_ult1 0.000000
ind_ctop_fin_ult1 0.000000
ind_ctpp_fin_ult1 0.000000
ind_deco_fin_ult1 0.000000
ind_deme_fin_ult1 0.000000
ind_dela_fin_ult1 0.000000
ind_ecue_fin_ult1 0.000000
ind_fond_fin_ult1 0.000000
ind_hip_fin_ult1 0.000000
ind_plan_fin_ult1 0.000000
ind_pres_fin_ult1 0.000000
ind_reca_fin_ult1 0.000000
ind_tjcr_fin_ult1 0.000000
ind_valo_fin_ult1 0.000000
ind_viv_fin_ult1 0.000000
ind_nomina_ult1 0.001593
ind_nom_pens_ult1 0.001593
ind_recibo_ult1 0.000000
dtype: float64
```

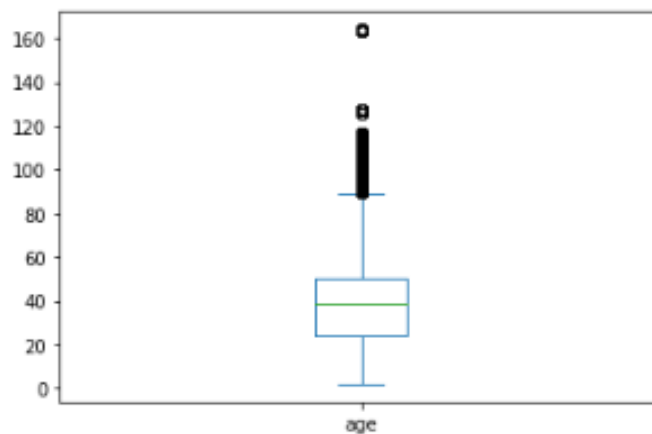
Describe data:

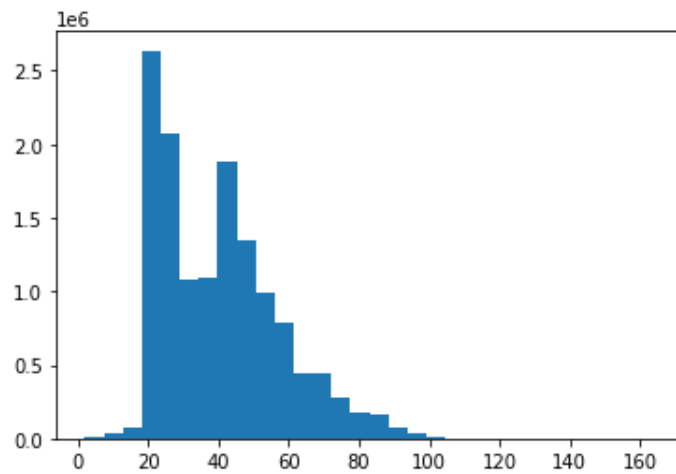
- numeric

	age	antigüedad	renta
count	13619575	13619575	10852934
mean	40	77	134254
std	17	1672	230620
min	2	-999999	1203
25%	24	23	68711
50%	39	50	101850
75%	50	135	155956
max	164	256	28894396

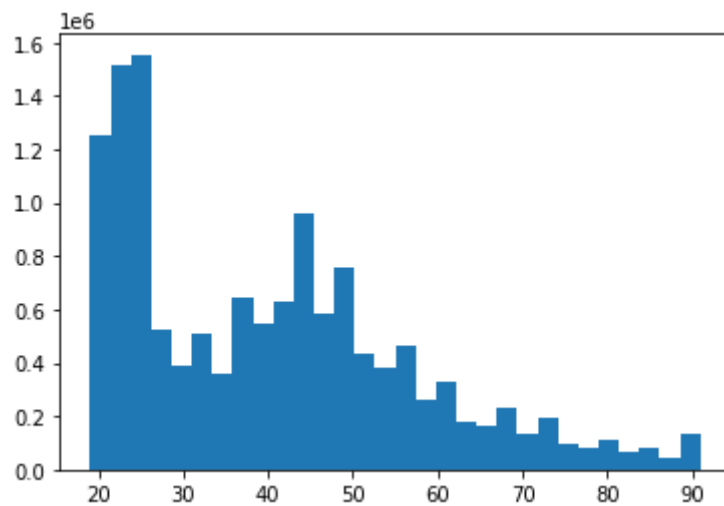
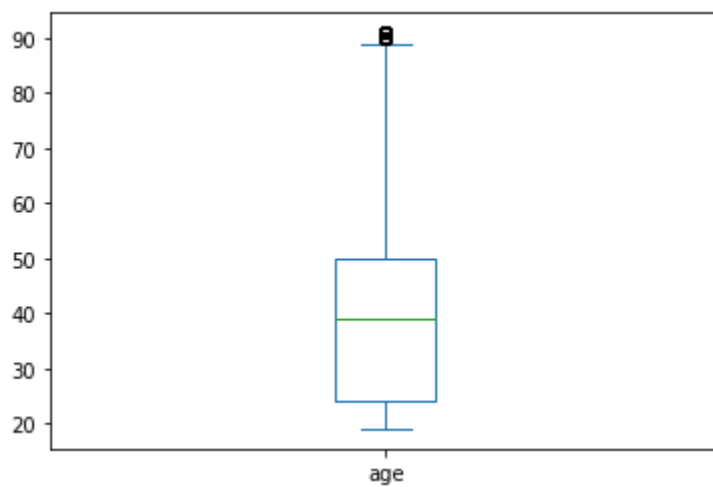
Outliers in numeric data:

The feature 'age' has some rows with customers who are older than 100 years and a few customers who are very young. We think there is a lot of incorrect data. We can see that customers who are older 20 and younger 90 are most. One of the ways to overcome outliers is to unite the youngest and most adult customers into groups.

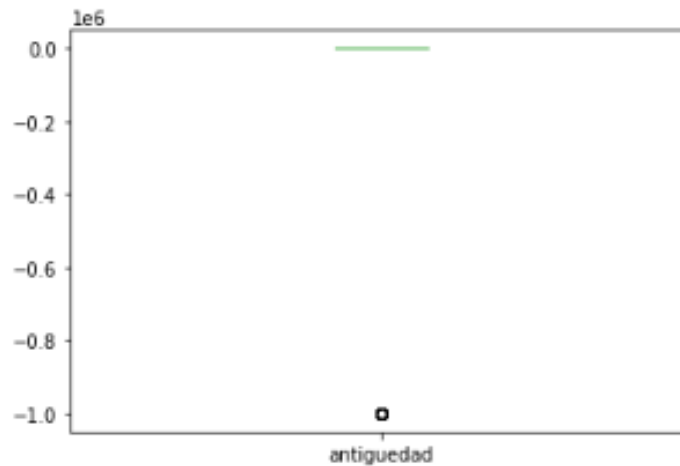




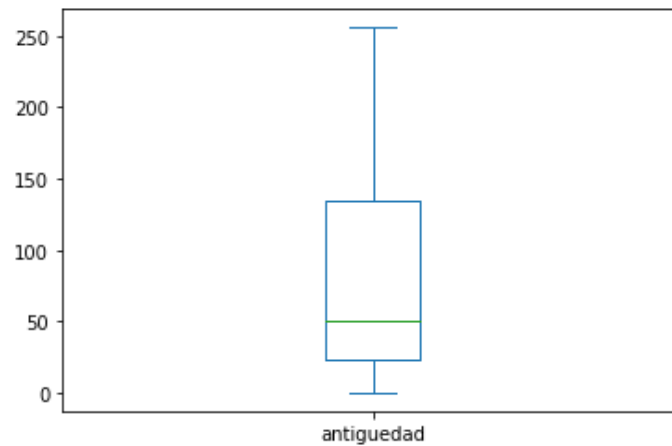
Graphs after corrections:



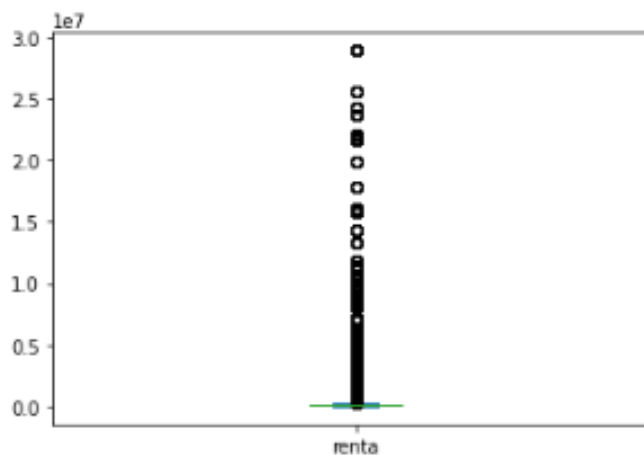
The feature '`antigüedad`' (Customer seniority (in months)) contains 38 rows with value -99999. It makes the data very skewed. We should delete rows with this value, because it is an unknown value:



The box plot feature's '*antiguedad*' after deleting:

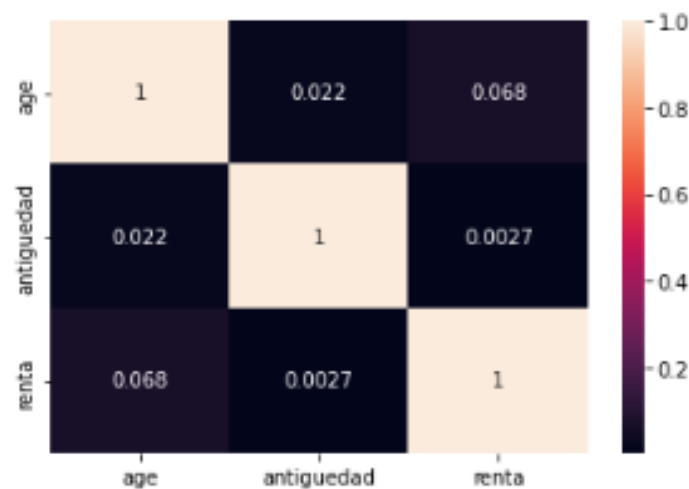


The feature *Renta* is also very shifted, because there is 18,9% data much more than 75% quartile.



Almost 19% of data are the outliers. And 20% of data is null. Delete these rows will be incorrect. It is necessary to carry out work on the replacement of zero values and emissions. For NA values it can be for example mean/median/mode/segmented approach etc. For outliers it can be grouping.

There is no correlation between numerical features:



- **categorical**

1. `ind_empleado` - Employee index. No NA values, 99 % rows have the value N not employee.
2. `pais_residencia` - Customer's Country residence. No NA values. 118 unique values. 99 % rows have the value ES.
3. `sexo` - Customer's sex. A small number NA values (0.0005% or 70 rows). It is necessary to carry out work on the replacement of NA values (the most popular values for example).
4. `fecha_alta` - The date in which the customer became the first holder of a contract in the bank. No NA values.
5. `ind_nuevo` - New customer Index. 1 if the customer registered in the last 6 months. Data type float, should be changed to categorical. No NA values.
6. `indrel` - 1 (First/Primary), 99 (Primary customer during the month but not at the end of the month). No NA values. If you build an ML model, it could be better to change 99 on 0 because it is scaled for ML models.
7. `ult_fec_cli_1t` - Last date as primary customer (if he isn't at the end of the month) and `conyuemp` - Spouse index. (1 if the customer is spouse of an employee). have 99% null values. According to the instructions `conyuemp` feature should contain number 1 if the customer is spouse of an employee. In dataset the feature `conyuemp` contain (N, S, nan) values. I suppose that N=No, S = Si (Yes). The number of clients with value 'S' = 17. *We can delete these features because they contain too small info for analysis.*
8. `indrel_1mes` - Customer type at the beginning of the month and `tiprel_1mes` - Customer relation type at the beginning of the month. There are 0.89% NA values. It is necessary to carry out work on the replacement of NA values.
9. `indresi` - Residence index. No NA values. 99% of customers have the same residence country as the bank country.
10. `indext` - Foreigner index. No NA values. (S (Yes) or N (No) if the customer's birth country is different than the bank country) 0.95 % of rows have value N.

11. `canal_entrada` - channel used by the customer to join. 162 unique values. The most popular is KHE. 1.16% are NA values. We can replace the missing values with the most popular values in general or by region or something else.
12. `indfall` - Deceased index - 0.99 of rows have value N (not). No NA values.
13. `tipodom` - Address type. 1, primary address. No NA values.
14. `cod_prov` (Province code) and `nompров` (Province name) explain the same thing. I suppose delete feature `cod_prov` and change on categorical values feature `nompров`. They have the same number of NA values - 0.48%.
15. `ind_actividad_cliente` - Activity index (1, active customer; 0, inactive customer). No NA values. There are 54% inactive customers.
16. `segmento` - segmentation: 01 - VIP, 02 - Individuals 03 - college graduated. 1.18% NA values. PARTICULARES customers are 58%, UNIVERSITARIO customers are 36%, TOP customers are 4%
17. Other features describe the product and customer's product availability.

Approaches to overcome problems like NA value, outlier etc:

NA values:

- replacing with a mean value where there are not many missing values, this will not affect the result due to the small volume.
- replacing the average value based on the data of another feature (Segmento-Renta).

Outliers:

- Grouping data (all clients with an age of less than 20 years, set the age of 19 years to those from 90 - 91 years)
- Moving from numeric data to categorical data (renta)