Exploratory Data Analysis

Data Analyst:: Cross selling recommendation

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Agenda

Task:

1. Business understanding
2. Data Understanding
3. Data Cleansing and Transformation
4. Exploratory data analysis
5. EDA Recommendation (ppt)

Data Glacier
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Problem Statement:

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

Business understanding

Cross selling involves selling complementary products to existing customers.It is one of the highest effective techniques in the marketing industry.It identifies products that satisfy additional,complimentary needs that are unfulfilled by the original item.Cross selling can alert users to products they didnot previously know you offered,furthur earning their as their confidence as the best retailer to satisfy a particular need.

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  
dtypes: float64(8), int64(23), object(17)
memory usage: 4.9+ GB
```

```
fecha_dato                0.000000
ncodpers                  0.000000
ind_empleado              0.203220
pais_residencia           0.203220
sexo                      0.203732
age                       0.000000
fecha_alta                0.203220
ind_nuevo                 0.203220
antiguedad                0.000000
indrel                    0.203220
ult_fec_cli_1t           99.818330
indrel_1mes               1.097513
tiprel_1mes               1.097513
indresi                   0.203220
indext                    0.203220
conyuemp                 99.986752
canal_entrada             1.363829
indfall                   0.203220
tipodom                   0.203227
cod_prov                  0.685784
nomprov                   0.685784
ind_actividad_cliente     0.203220
renta                    20.475648
segmento                  1.387585
ind_ahor_fin_ult1         0.000000
ind_aval_fin_ult1         0.000000
ind_cco_fin_ult1          0.000000
ind_cder_fin_ult1         0.000000
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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           0.117701
ind_nom_pens_ult1         0.117701
ind_recibo_ult1           0.000000
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

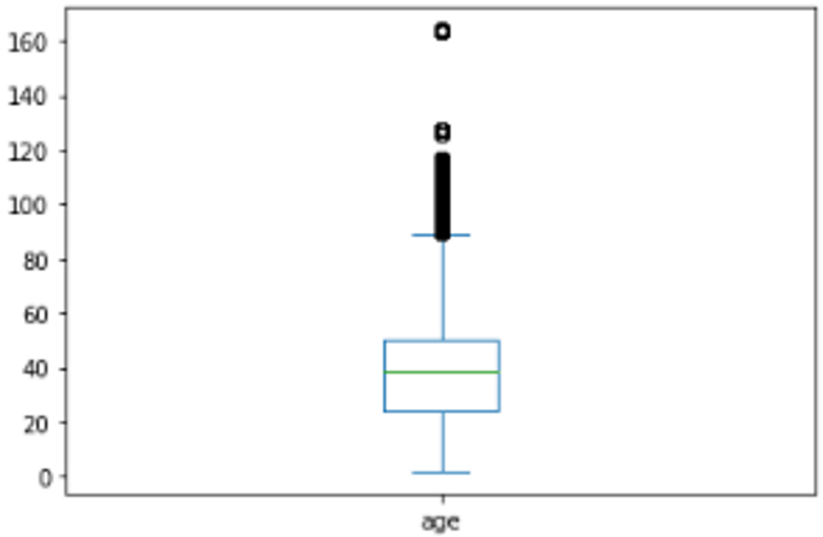
There are some features with the same number of missing values, I expect those relate to the same rows. We delete rows with a lot of missing values (0.2% of data).

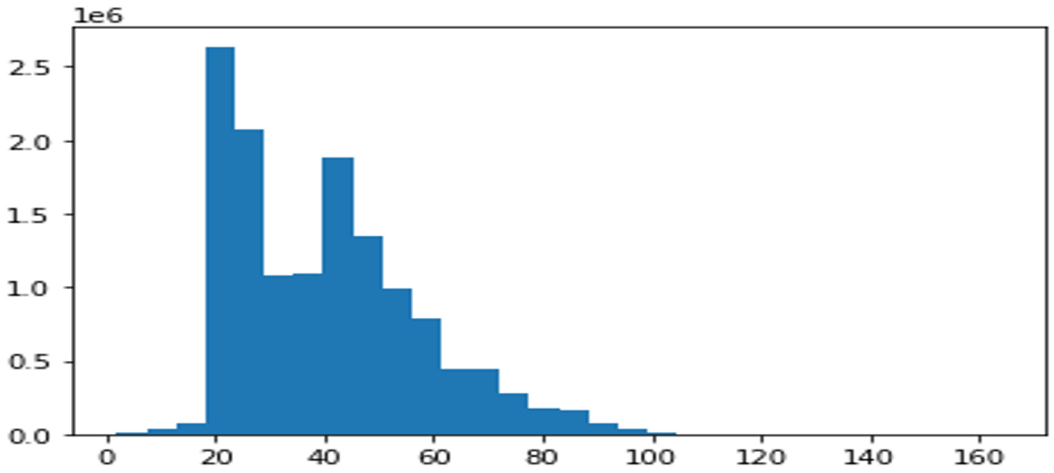
DESCRIBE DATA

	age	antiguedad	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

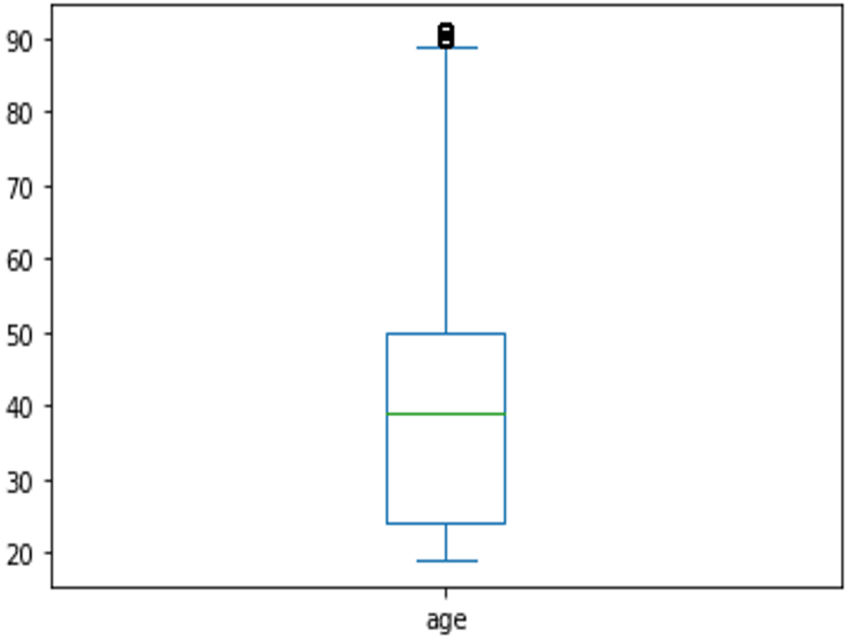
Outliers in numeric data:

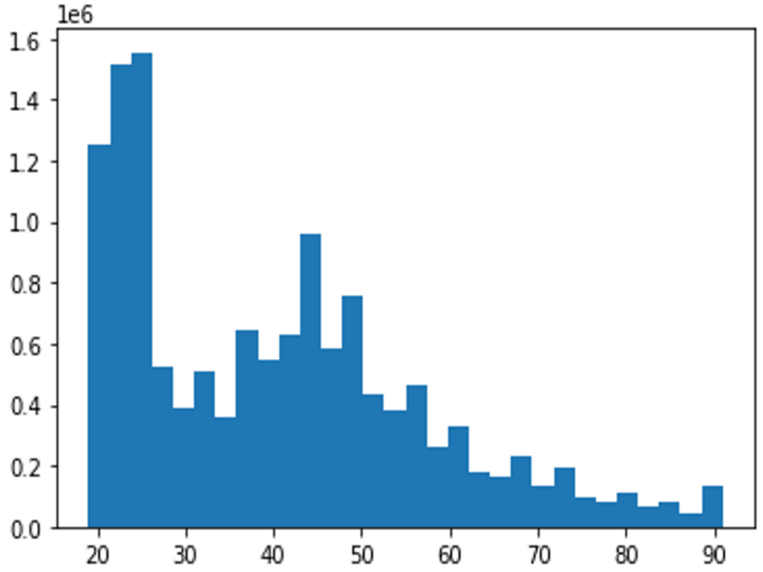
The feature `'age'` has some rows with customers who are older than 100 years and a few customers who are very young. We think there is a lot of incorrect data. We can see that customers who are older 20 and younger 90 are most. One of the ways to overcome outliers is to unite the youngest and most adult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



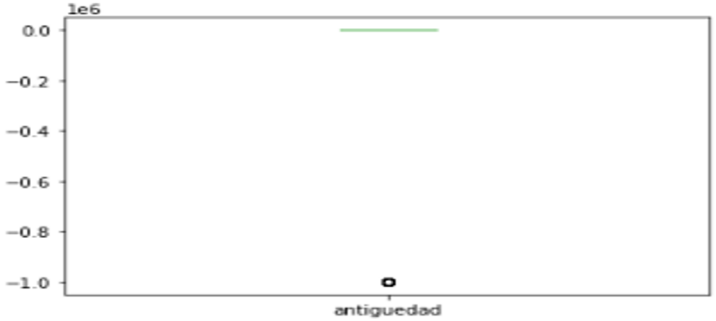


Graphs after corrections:

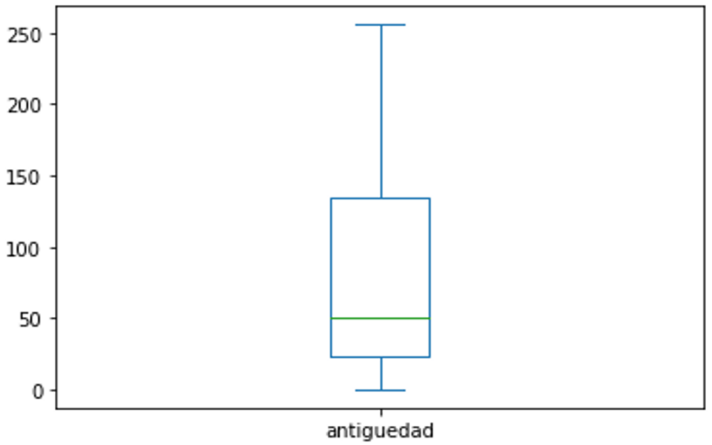




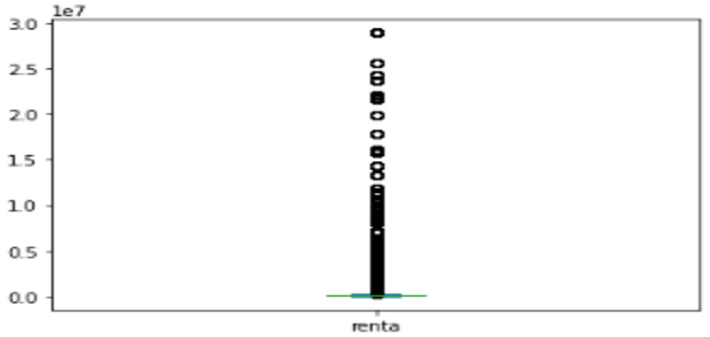
The feature `'antiguedad'` (Customer seniority (in months)) contains 38 rows with value -99999. It makes the data very skewed. We should delete rows with this value, because it is an unknown value:



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



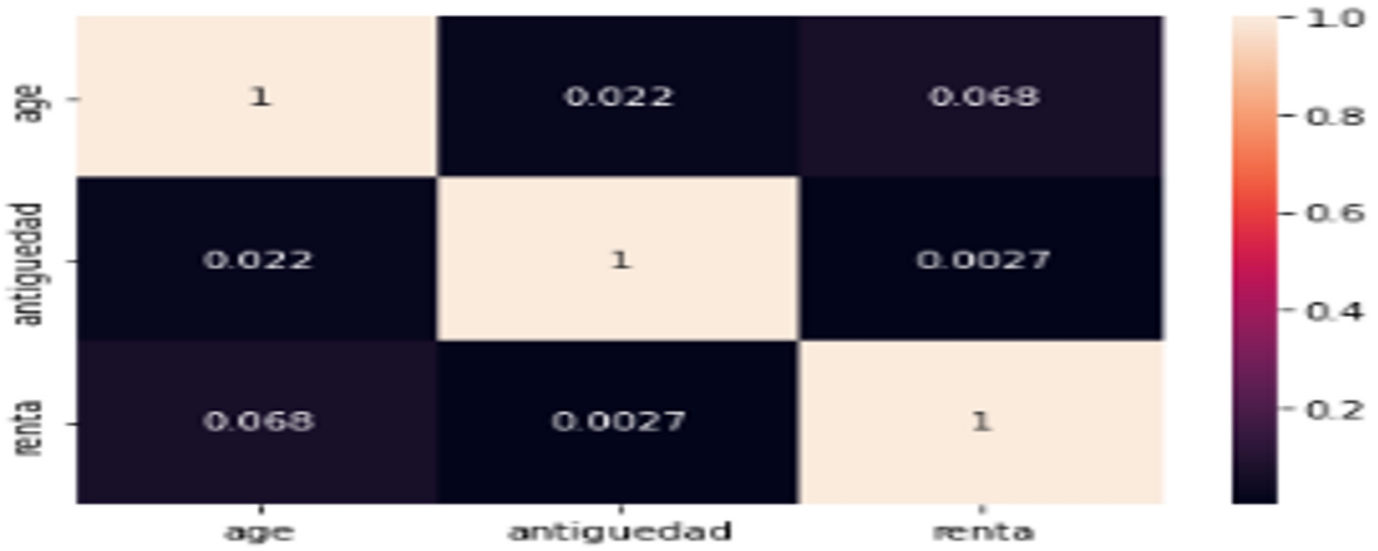
The feature `Renta` is also very shifted, because there is `18,9%` data much more than 75% quartile.



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:



- categori**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).

1. `fecha_alta` - The date in which the customer became the first holder of a contract in the bank. No NA values.
2. `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.
3. `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.
4. `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.*
5. `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.

7) indresi - Residence index. No NA values. 99% of customers have the same residence country as the bank country.

8) 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.

9) 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.

10) indfall - Deceased index - 0.99 of rows have value N (not). No NA values.

11) tipodom - Address type. 1, primary address. No NA values.

12) cod_prov (Province code) and nomprov (Province name) explain the same thing. I suppose delete feature cod_prov and change on categorical values feature nomprov. They have the same number of NA values - 0.48%.

13) ind_actividad_cliente - Activity index (1, active customer; 0, inactive customer). No NA values. There are 54% inactive customers.

14) 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%

15) 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).
- Alternatively, you can set a constant value for NA-marked values. For example, you can put in a special string or numerical value

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)

Data_Cleansing_&_Transformation

link:

https://github.com/KseniyaLem/clean_data_group/blob/main/DATA_CLEANING_WEEK_9.ipynb

Exploratory data analysis

link:

https://github.com/pranav611/week-10-EDA-ON-CROSS-SELLING-RECOMMENSATIONS./blob/main/EDA_ON_CROSS_SELLING_RECOMMENSATIONS.ipynb

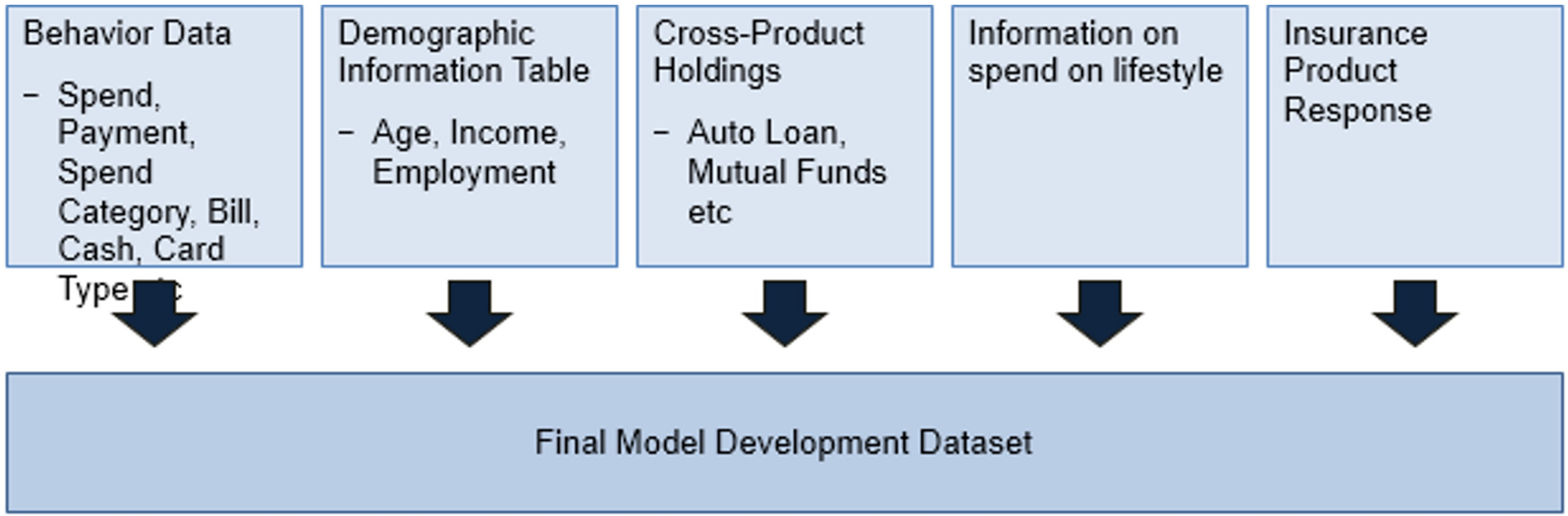
EDA recommendations and proposed model technique

The models provide answers to the following questions

1. What – choice of product
2. Whom – selection of customers
3. When – timing
4. How – contact strategy

Approach	Model	What	Whom	When	How
NEED	Life-Stage	Y	Y	Y	N
	Triggers/RFM	Y	Y	Y	N
PREFERENCES/RESPONSE	Cross-Sell Grid	Y	Y	N	N
	Markov Chain	Y	Y	Y	N
	Market Basket Analysis	Y	Y	N	N
	Recommender Systems - e.g. Collaborative Filtering	Y	Y	N	N
	Segmentation - Classification Tree, Cluster Analysis	Y	Y	N	N
	Logistic Regression Model	Y	Y	N	Y
	Survival Regression Model	Y	Y	Y	N
EXPECTED-REVENUE//PROFITABILTY/CLV	Response and Revenue Optimization	Y	Y	N	Y
	Decision Analysis	Y	Y	N	N
RETURN ON INVESTMENT	Share of Wallet Model	Y	Y	N	N
	Optimization Model	Y	Y	N	Y

2. Segmentation: For customized one- to- one marketing programs as each segment may have different needs and preferences. The Response Model will be developed for the Segment “Affluent Income Low Risk”.



- **Target Variable is Response**

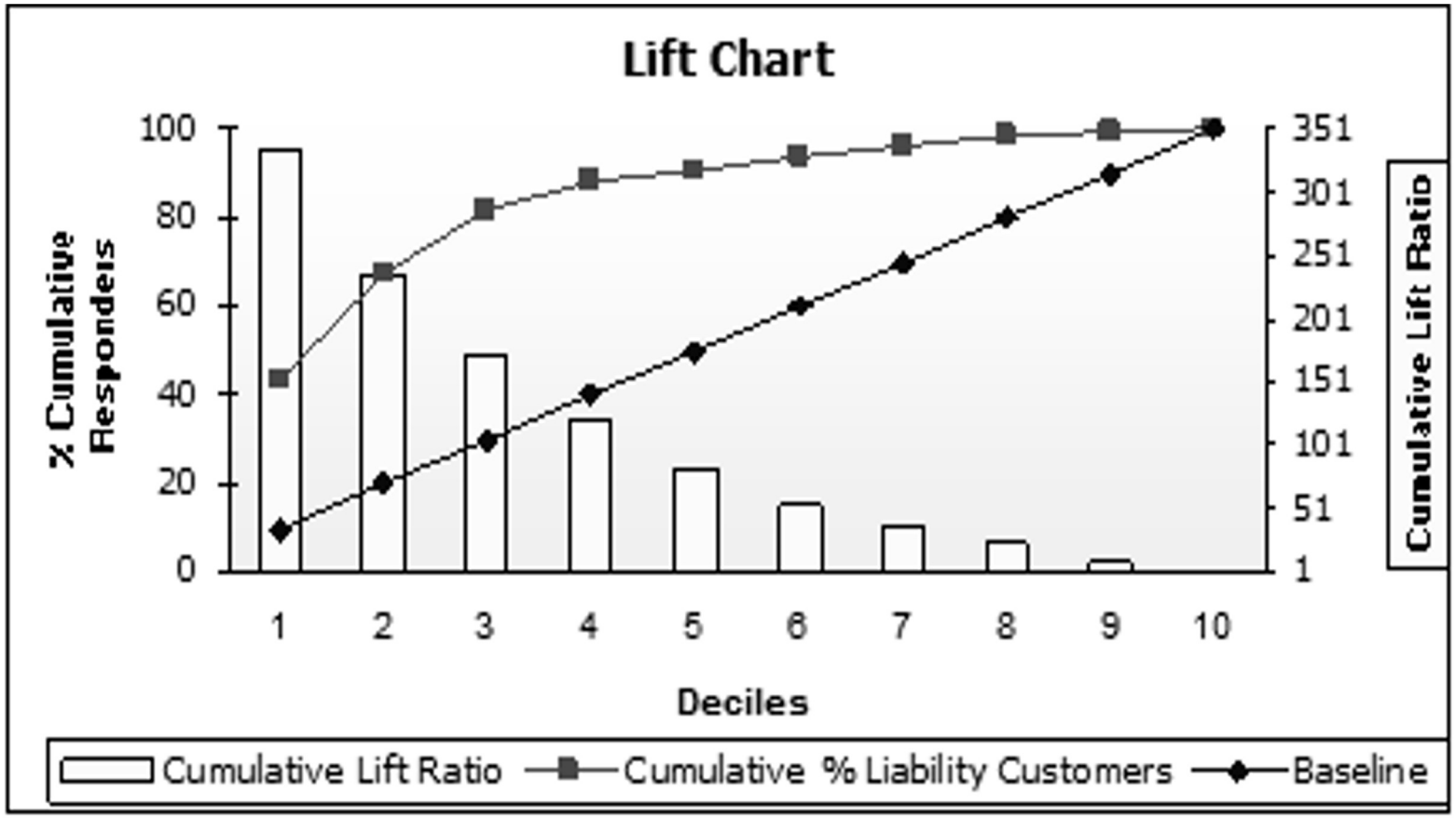
  = 1 if credit card customer has expressed intent to buy an investment product cross-sell offer

  = 0 otherwise

- **Response Rate is 2%**
- Response Rate is No. of Responders divided by customers contacted for the offer.

Response Model: The following table shows the variables description and relationship to cross-sell response / propensity in descending order of importance using Logistic Regression

Variable Description	Relationship with Investment Response
% of times customer has reacted positively when contacted for an offer by the Bank	Positive
Total Credit card Limit	Positive
Ratio of international spend on card to total spend on card	Positive
Is a premium card holder	Positive
Has a travel pack insurance	Positive
Carries a loan	Negative
Average total spend on credit card	Positive
Number of dependents	Negative
Number of years in employment	Negative
Average cash usage on credit card	Negative
Has a credit insurance	Negative



The model captures 80% of the responders in 30% of the customer base resulting in marketing saves of 50%.

In a Business as usual (BAU) scenario, the Bank would target 80% of the customer base to solicit 80% of responders .

Thank You