Mini project BI

Realized by:

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Level: **LA3INFO**

TD: **TD1**

TP: **TP1**

Year: **2020-2021**

Data Description

Dimension of data:

There are 98913 observations (98913 users)

There are 24 Variables

Names of variables, data types and data description

Variable	Type	Description
identifierHash	Num	Anonymous unique id.
type	Chr	The type of entity. This file contains only "user" entities.
country	Chr	User's country (written in french). See also the column "Country Code" if you prefer an ISO identifier.
language	Chr	The user's preferred language (the language of their interface when using the site)
socialNbFollowers	Int	Number of users who follow this user's activity. New accounts are automatically followed by the store's official accounts
socialNbFollows	Int	Number of user account this user follows. New accounts are automatically assigned to follow the official partners.
socialProductsLiked	Int	Number of products this user liked.
productsListed	Int	Number of currently unsold products that this user has uploaded.
productsSold	Int	Number of products this user has sold.
productsPassRate	Num	% of products meeting the product description. (Sold products are reviewed by the store's team before being shipped to the buyer.)
productsBought	Int	Number of products this user bought
gender	Char	user's gender
civilityGenderId	Int	civility as integer

civilityTitle	**Chr**	Civility title
hasAnyApp	**Chr**	user has ever used any of the store's official app
hasAndroidApp	**Chr**	user has ever used the official Android app
hasIosApp	**Chr**	user has ever used the official iOS app
hasProfilePicture	**Chr**	user has a custom profile picture
daysSinceLastLogin	**Int**	Number of days since the last login. All user data were fetchedthe same day. See also "seniority".
seniority senio	**Int**	Number of days since the user registered
seniorityAsMonths	**Num**	see seniority. Here, expressed in months
seniorityAsYears	**Num**	see seniority. Here, expressed in years
countryCode	**Chr**	user's country (ISO-3166-1)

Number of distinct values for each variable

Variable	**Number of distinct values**	**Values description**
type	**1**	User : The type of entity. This file contains only "user" entities
country	**200**	There are 200 name of country
language	**5**	En : English Fr : French De : Deutsche Es : Spanish It : Italian
gender	**2**	F : Female M : Male

civilityTitle	**3**	Mrs : Madam Mr : Mister Miss : Miss
hasAnyApp	**2**	True and false
hasAndroidApp	**2**	True and false
hasIosApp	**2**	True and false
hasProfilePicture	**Chr**	True and false
countryCode	**200**	There are 200 ISO codes of country

Missing values

No missing data

Useless varaibles

There are some useless variables (duplicated variables, variables have no statistics values...)

Identifierhash and type have not statistics values.

civilityGenderId and gender : have the same meaning

country and countryCode : have the same meaning

➔We should to delete the useless columns.

New dimension of data:

There are 98913 observations (98913 users)

There are 20 Variables

Data Exploration

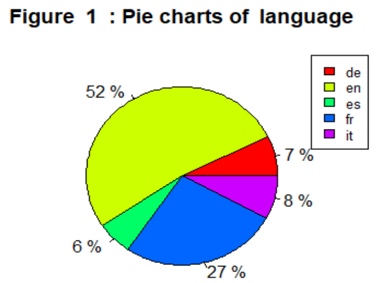
I) Data Exploration (Univariate exploration)

A) The categorical variables

How do you explore categorical data?

We use the pie charts and the barplot

1) Language



- The majority of user preferred the English language 52 % of users preferred it and the second preferred language is French 27% of users preferred it

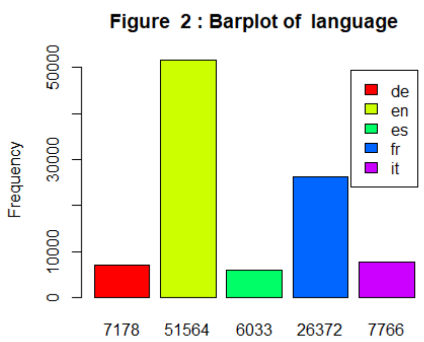
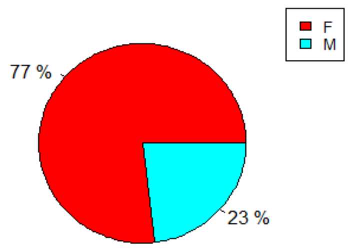


Figure 2 : Barplot of language

- More than 50000 users preferred the English language
- About 30000 users preferred the English language

2) Gender

Figure 3 : Pie charts of gender



- The majority of users are females (77%) and 23% are males

Figure 4 : Barplot of gender

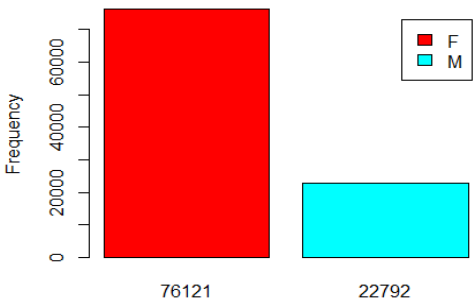
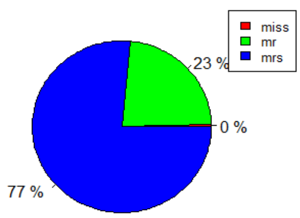


Figure 4 : Barplot of gender

- More than 76000 of users are females
- More than 22000 of users are males

3) civilityTitle

Figure 5 : Pie charts of civilityTitle



- 77% of users are Mrs.
- 23% of users are Mrs.
- About 0% of users are Miss

Figure 6 : Barplot of civilityTitle

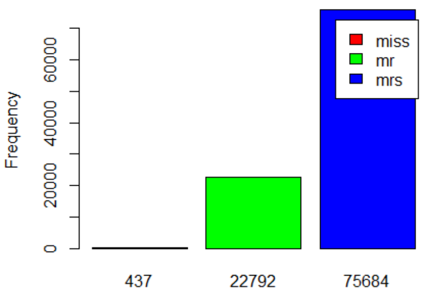
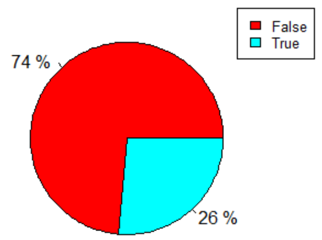


Figure 6 : Barplot of civilityTitle

- More than 75000 of users are Mrs.
- More than 22000 of users are Mrs.
- About 437 of users are Miss (the lower)

4) hasAnyApp

Figure 7 : Pie charts of hasAnyApp



- ➢ 74% of users have not any of the store's official app
- ➢ 26% of users have a store's official app

Figure 8 : Barplot of hasAnyApp

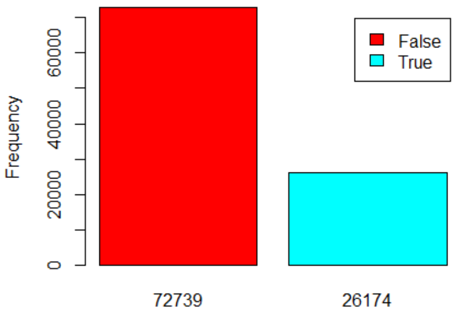
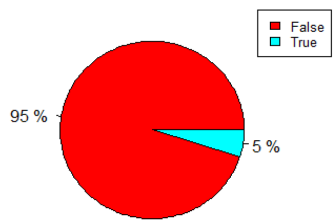


Figure 8 : Barplot of hasAnyApp

- ➢ More than 72000 of users have not any of the store's official app
- ➢ More than 26000 of users have a store's official app

5) hasAndroidApp

Figure 9 : Pie charts of hasAndroidApp



- ➢ 95% of users have not the android app
- ➢ 26% of users have the android app

Figure 10 : Barplot of hasAndroidApp

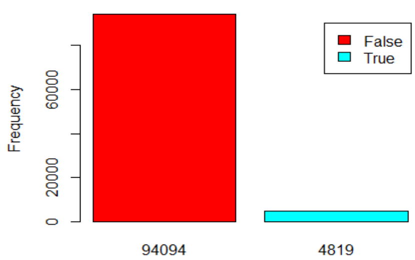
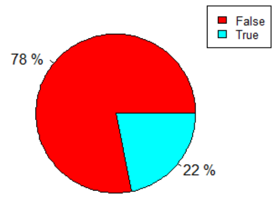


Figure 10 : Barplot of hasAndroidApp

- ➢ More than 94000 of users have not the android app
- ➢ More than 4800 of users have the android app

6) hasIosApp

Figure 11 : Pie charts of hasIosApp



- 78% of users have not the iOS app
- 26% of users have the iOS app

Figure 12 : Barplot of hasIosApp

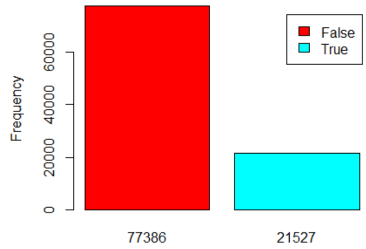
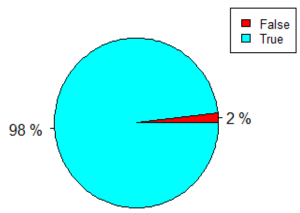


Figure 12 : Barplot of hasIosApp

- More than 77000 of users have not the iOS app
- More than 21000 of users have the iOS app

7) hasProfilePicture

Figure 13 : Pie charts of hasProfilePicture



- 98% of users have not a profile picture
- 2% of users have profile picture

Figure 14 : Barplot of hasProfilePicture

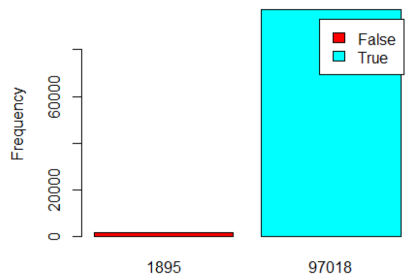


Figure 14 : Barplot of hasProfilePicture

- More than 97000 of users have profile picture
- 1895 of users have profile picture

8) countryCode

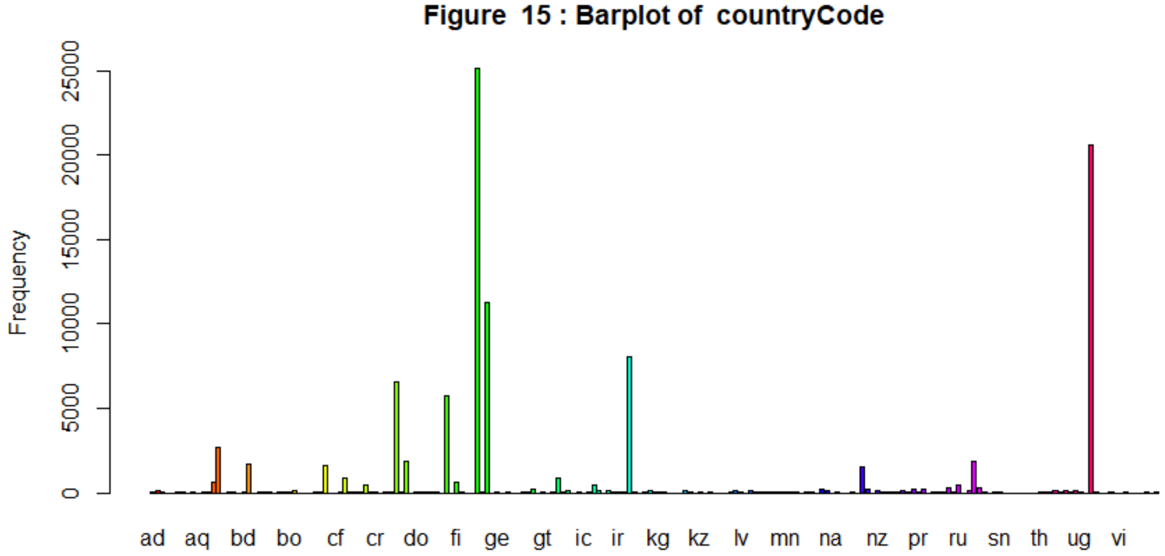


Figure 15 : Barplot of countryCode

- More than 25000 users live France
- More than 20000 of users live US

B) The numeric variables

1) socialnbFollowers

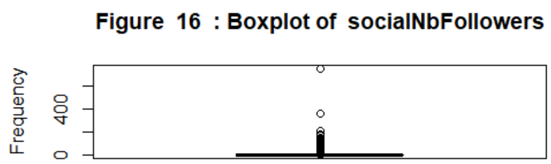


Figure 16 : Boxplot of socialNbFollowers

- **The boxplot is so tight**
- **Presence of some outliers**
- **High density of data between Min and Max**

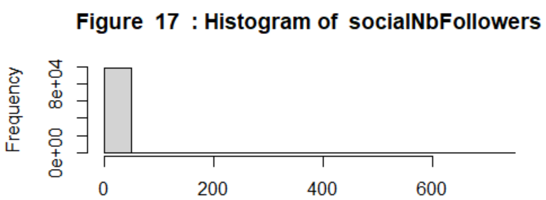


Figure 17 : Histogram of socialNbFollowers

- Uni modal data distribution
- There is one peak of data

2) socialnbFollows

Figure 18 : Boxplot of socialNbFollows

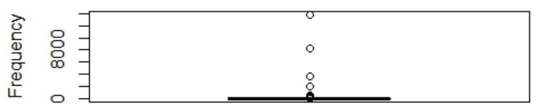


Figure 18 : Boxplot of socialNbFollows

- **The boxplot is so tight**
- **Presence of some outliers**
- **High density of data between Min and Max**

Figure 19 : Histogram of socialNbFollows

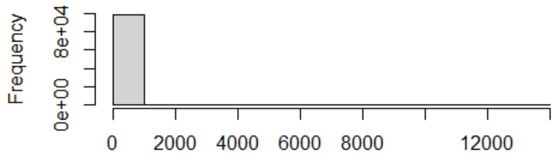


Figure 19 : Histogram of socialNbFollows

- Uni modal data distribution
- There is one peak of data

3) socialProductsLiked

Figure 20 : Boxplot of socialProductsLiked

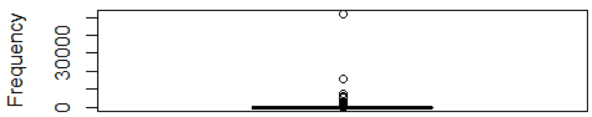


Figure 20 : Boxplot of socialProductsLiked

- **The boxplot is so tight**
- **Presence of some outliers**
- **High density of data between Min and Max**

Figure 21 : Histogram of socialProductsLiked

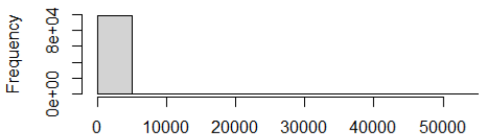


Figure 21 : Histogram of socialProductsLiked

- Uni modal data distribution
- There is one peak of data

4) ProductsListed

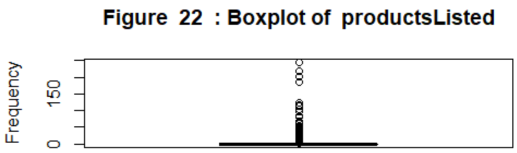


Figure 22 : Boxplot of productsListed

- The boxplot is so tight
- Presence of some outliers
- High density of data between Min and Max

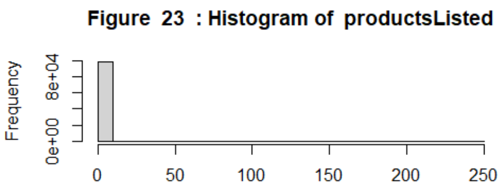


Figure 23 : Histogram of productsListed

- Uni modal data distribution
- There is one peak of data

5) ProductsSold

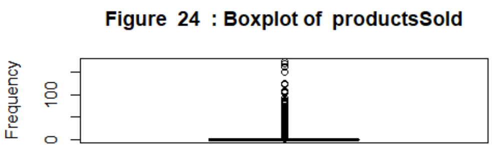


Figure 24 : Boxplot of productsSold

- The boxplot is so tight
- Presence of some outliers
- High density of data between Min and Max

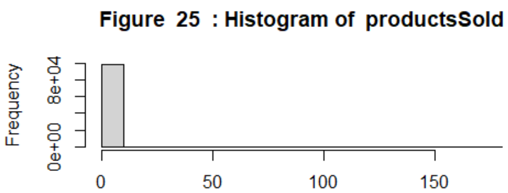


Figure 25 : Histogram of productsSold

- Uni modal data distribution
- There is one peak of data

6)ProductsPassRate

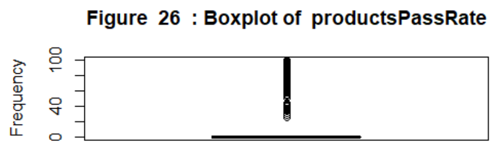


Figure 26 : Boxplot of productsPassRate

- **The boxplot is so tight**
- **Presence of some outliers**
- **High density of data between Min and Max**

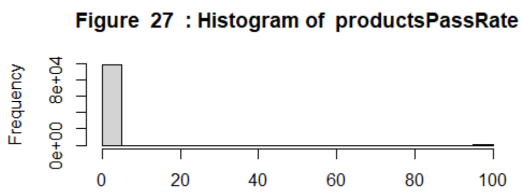


Figure 27 : Histogram of productsPassRate

- Uni modal data distribution
- There is one peak of data

7)ProductsBought

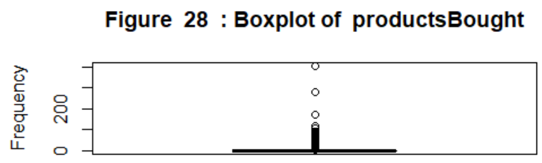


Figure 28 : Boxplot of productsBought

- **The boxplot is so tight**
- **Presence of some outliers**
- **High density of data between Min and Max**

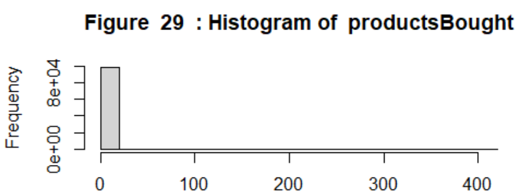


Figure 29 : Histogram of productsBought

- Uni modal data distribution
- There is one peak of data

8)daysSinceLastLogin

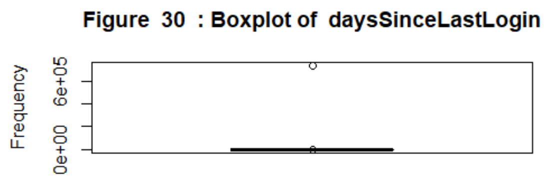


Figure 30 : Boxplot of daysSinceLastLogin

- **The boxplot is so tight**
- **Presence of some outliers**
- **High density of data between Min and Max**

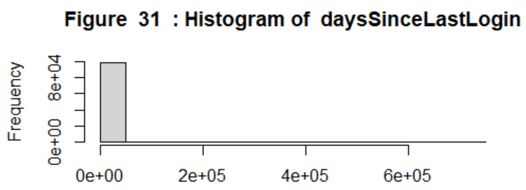


Figure 31 : Histogram of daysSinceLastLogin

- Uni modal data distribution
- There is one peak of data

9)seniority

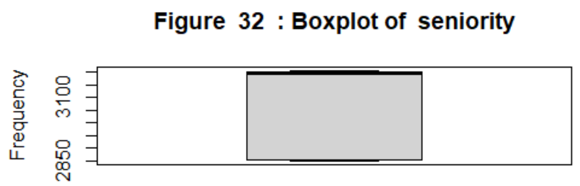


Figure 32 : Boxplot of seniority

- **low density of data between Q1 and Mean**
- **Very higher of density in [min-Q1] and [median-max]**

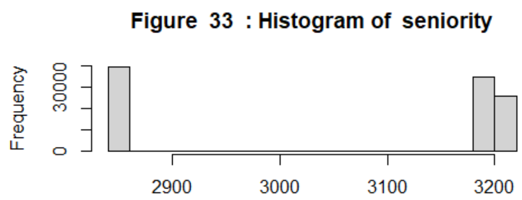


Figure 33 : Histogram of seniority

- Bi modal data distribution
- There is two groups of data well separated

10)seniorityAsMonths

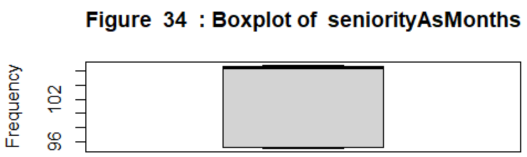


Figure 34 : Boxplot of seniorityAsMonths

- low density of data between Q1 and Mean
- Very higher of density in [min-Q1] and [median-max]

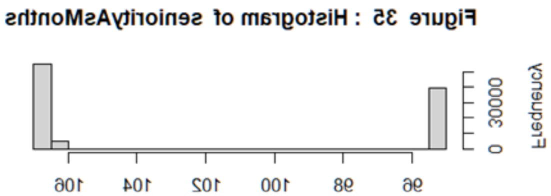


Figure 35 : Histogram of seniorityAsMonths

- Bi modal data distribution
- There is two groups od data well separated

11)seniorityAsYears

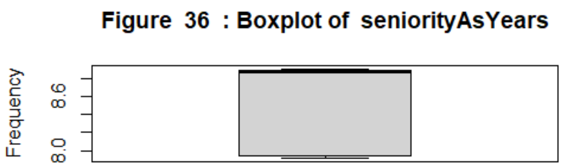


Figure 36 : Boxplot of seniorityAsYears

- low density of data between Q1 and Mean
- Very higher of density in [min-Q1] and [median-max]

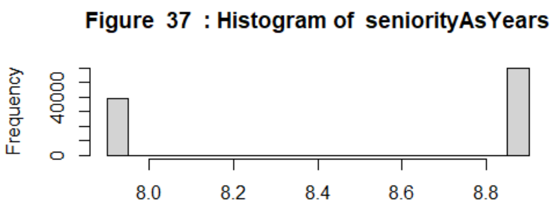


Figure 37 : Histogram of seniorityAsYears

- **Bi modal data distribution**
- **There is two groups of data well separated**
- **The peak is in the end of the histogram**

12)productsWished

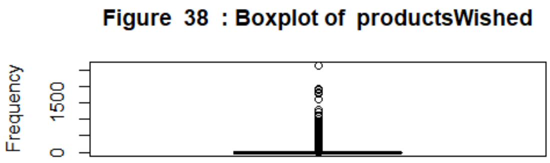


Figure 38 : Boxplot of productsWished

- ➢ The boxplot is so tight
- ➢ Presence of some outliers
- ➢ High density of data between Min and Max

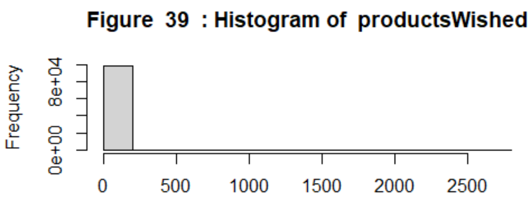


Figure 39 : Histogram of productsWished

- ➢ Uni modal data distribution
- ➢ There is one peak of data

II) Data Exploration (Bivariate exploration)

Correlation of numeric variables (with command cor(data))

1) socialNbFollowers

- **Moderate positive correlation with socialProductsLiked, productsSold and socialNbFollows.**
- **Weak positive correlation with productsListed, productsPassRate and productsWished.**
- **There is independence with the other variables**

2) socialNbFollows

- **Strong positive correlation with socialProductsLiked.**
- **Moderate positive correlation with socialNbFollows.**
- **There is independence with the other variables**

3) socialProductsLiked

- **Strong positive correlation with socialNbFollows.**
- **Moderate positive correlation with socialNbFollowers.**
- **Weak positive correlation with productsWished .**
- **There is independence with the other variables.**

4) productsListed

- **Moderate positive correlation with productsSold**
- **Weak positive correlation with socialNbFollowers and productsPassRate .**
- **There is independence with the other variables.**

5) **productsSold**
  - Moderate positive correlation with socialNbFollowers and productsListed.
  - Weak positive correlation with, productsPassRate.
  - There is independence with the other variables.

6) **productsPassRate**
  - Weak positive correlation with socialNbFollowers and productsSold.
  - There is independence with the other variables.

7) **productsWished**
  - Weak positive correlation with socialNbFollowers, socialProductsLiked and productsBought.
  - There is independence with the other variables.

8) **productsBought**
  - Weak positive correlation with productsWished.
  - There is independence with the other variables.

9) **daysSinceLastLogin**
  - There is independence with all variables.

10) **seniority**
  - Very Strong positive correlation with seniorityAsMonths and seniorityAsYears.
  - There is independence with the other variables.

11) **seniorityAsMonths**
  - Very Strong positive correlation with seniority and seniorityAsYears. There is independence with the other variables

12) **seniorityAsYears**
  - Very Strong positive correlation with seniority and seniorityAsYears.
  - There is independence with the other variables

Conclusion:

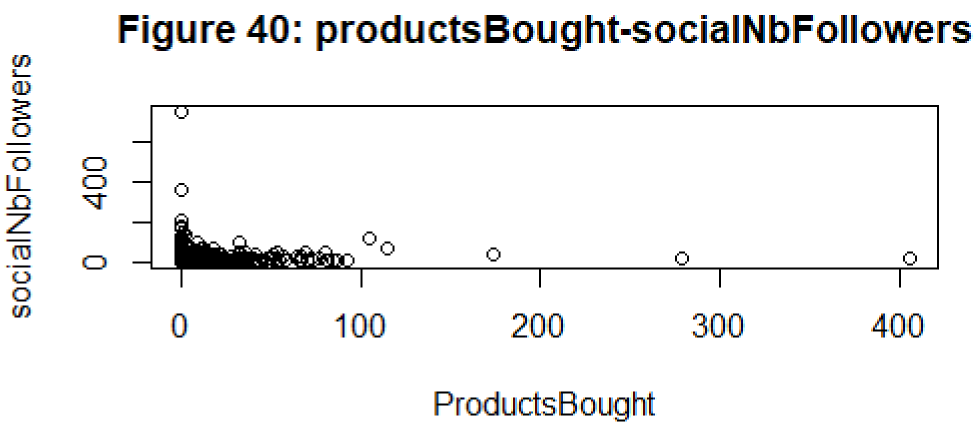
➔We can now considerate seniority, seniorityAsMonths and seniorityAsYears as one column because they have a very strongly positively correlated and they having the same meaning.

➔Now we have 18 variables

Puisque on a pour but de déterminer les personnes qui vont rester dans le store et les personnes qui vont quitter le store on a consentré sur deux variables qui peut nous aider à atteindre notre but à savoir : productsBought & products Sold .
On a étudier les correlations entre productsBought et les autres variables numeriques de meme pour la variable productsSold

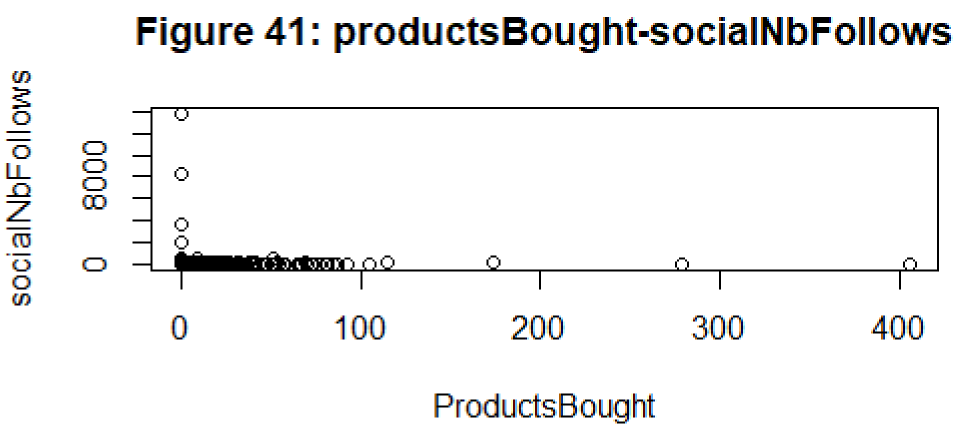
Scatter plots productsBought:

1) productsBought – socialNbFollowers



- **Presence of one group of data between 0 and 100**
- **High density of data**
- **Presence of some outliers**
- **Independent between the 2 variables**

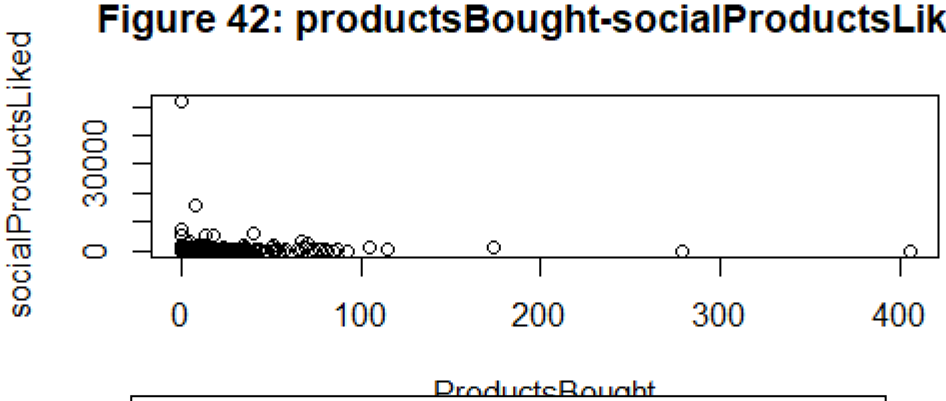
2)productsBought – socialNbFollows



- Presence of one group of data between 0 and 100
- High density of data
- Presence of some outliers
- Independent between the 2 variables

3)productsBought – socialProductsLiked

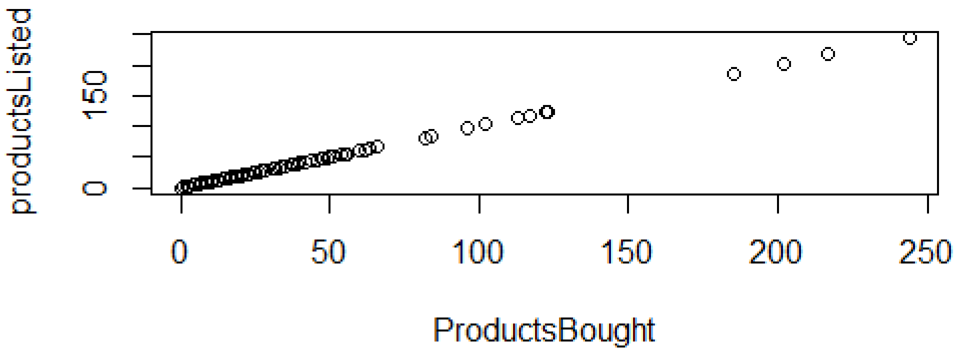
Figure 42: productsBought-socialProductsLiked



- Presence of one group of data between 0 and 100
- High density of data
- Presence of some outliers
- Independent between the 2 variables

4)productsBought – productsListed

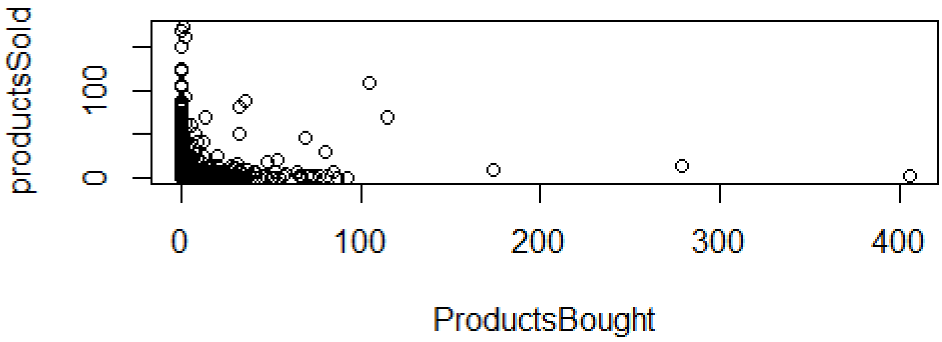
Figure 43: productsBought-productsListed



- Perfect corroelation between the 2 variables
- Discontinious distribution of data
- Presence of some outiers

5)productsBought – productsSold

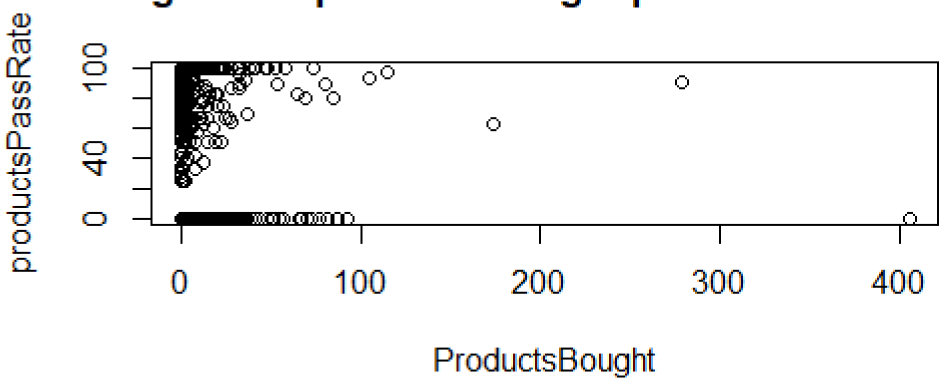
Figure 44: productsBought-productsSold



- **Presence of one group of data between 0 and 100**
- **High density of data**
- **Presence of some outliers**
- **Independent between the 2 variables**

6)productsBought – productsPassRate

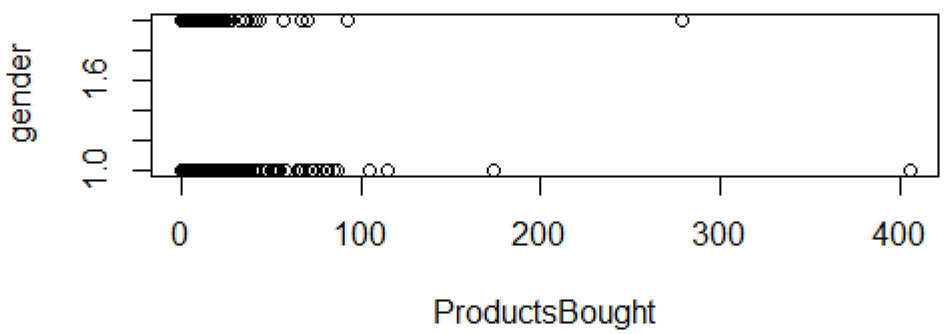
Figure 45: productsBought-productsPassRate



- Presence of 2 groups of data between 0 and 100 well separated
- High density of data in the 2 groups
- Presence of some outliers

7)productsBought – gender

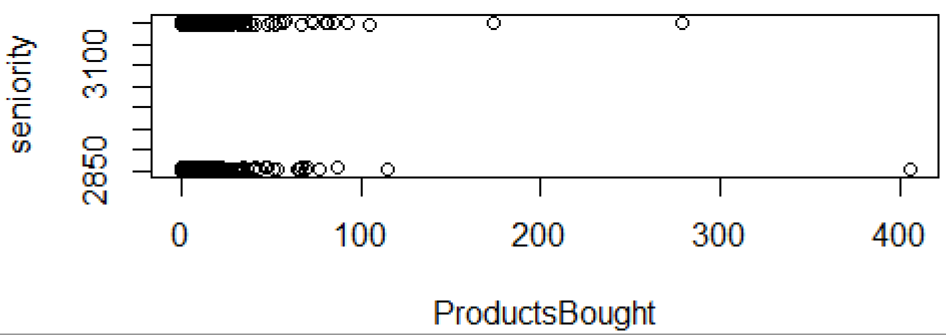
Figure 46: productsBought-gender



- Presence of 2 groups of data between 0 and 100 well separated
- High density of data in the 2 groups
- Presence of some outliers

8)productsBought – seniority

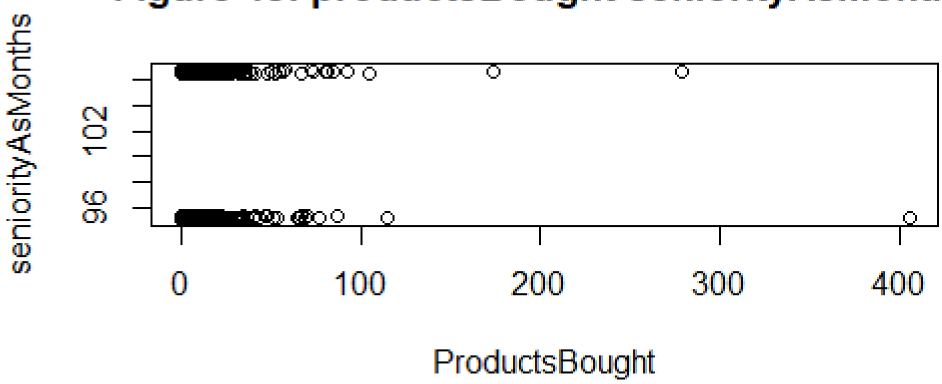
Figure 47: productsBought-seniority



- Presence of 2 groups of data between 0 and 100 well separated
- High density of data in the 2 groups
- Presence of some outliers

9)productsBought – seniorityAsMonths

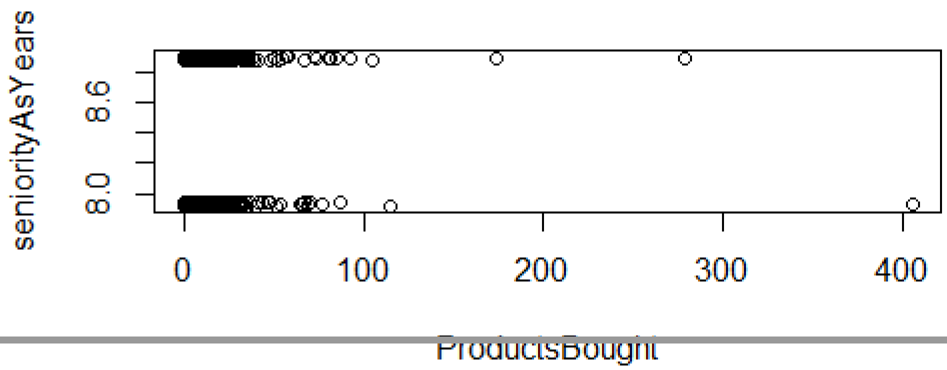
Figure 48: productsBought-seniorityAsMonths



- Presence of 2 groups of data between 0 and 100 well separated
- High density of data in the 2 groups
- Presence of some outliers

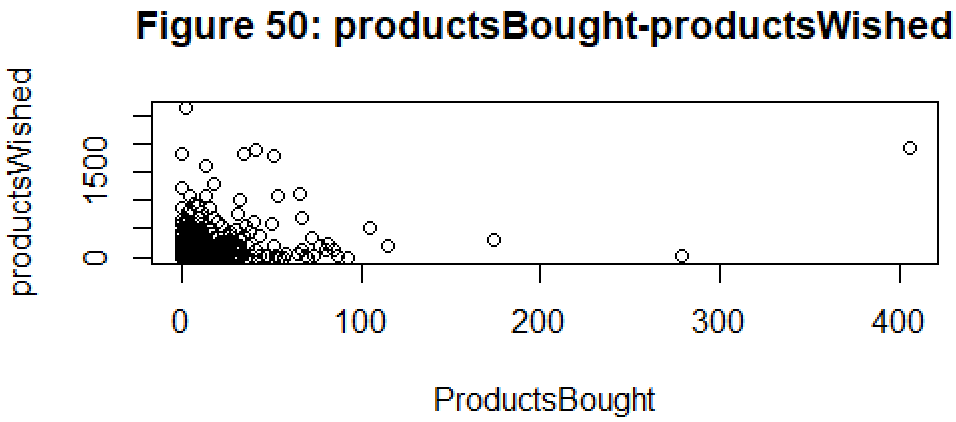
10)productsBought - seniorityAsYears

Figure 49: productsBought-seniorityAsYears



- Presence of 2 groups of data between 0 and 100 well separated
- High density of data in the 2 groups
- Presence of some outliers

11)productsBought - productsWished

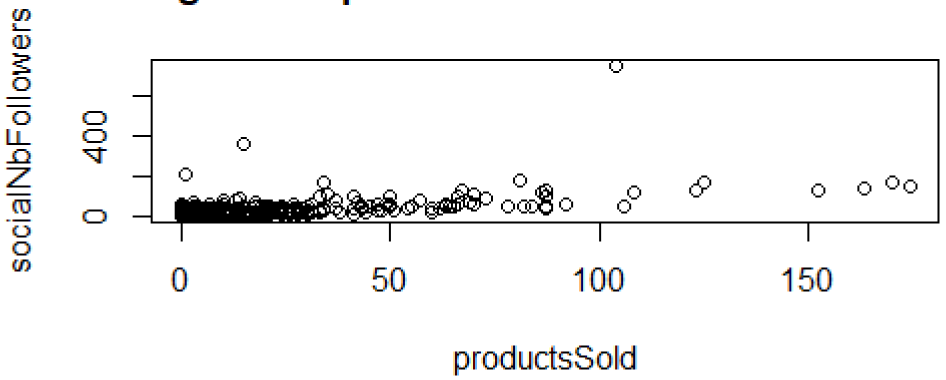


- Presence of one group of data between 0 and 100
- High density of data
- Presence of some outliers
- Independent between the 2 variables

Scatter plots productsSold

1)productsSold– socialNbFollowers

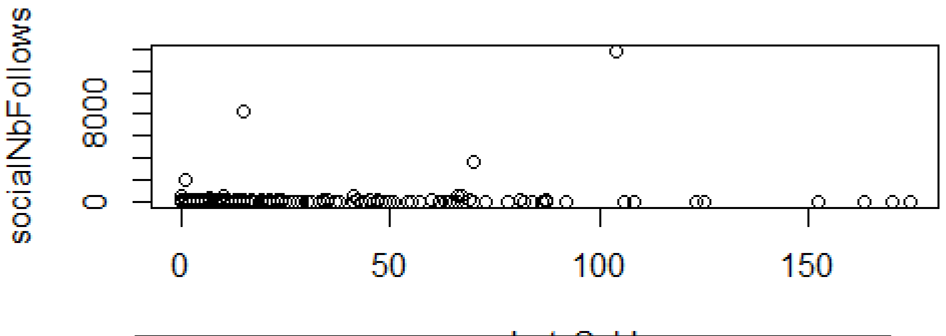
Figure 51: productsSold-socialNbFollowers



- Weak correlation between the 2 variables
- Presence of some outliers
- High density between 0 and 50

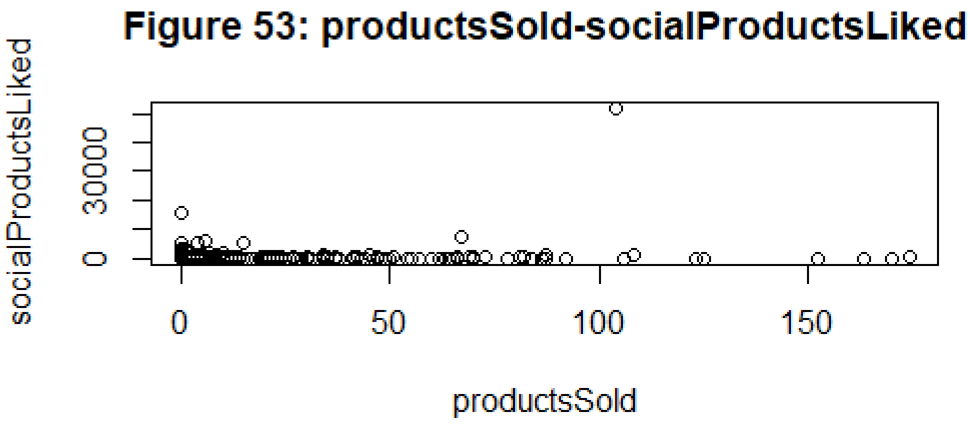
2)productsSold – socialNbFollows

Figure 52: productsSold-socialNbFollows



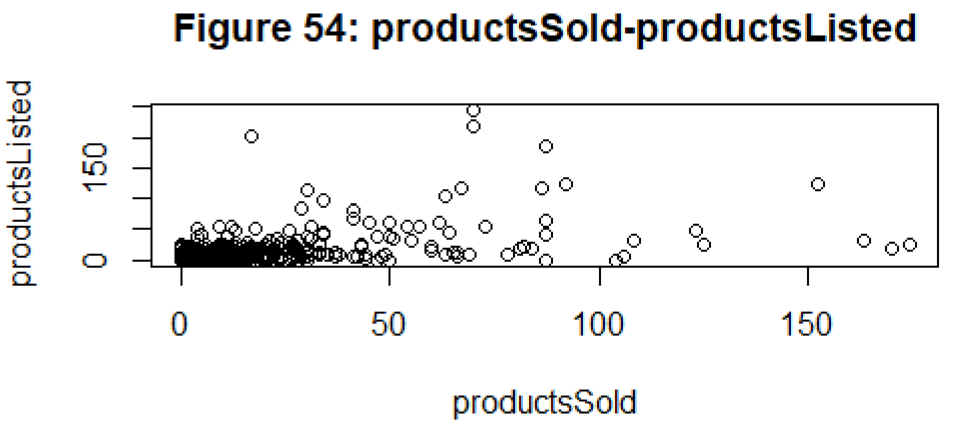
- Independent correlation between the 2 variables
- Presence of some outliers

3)productsSold – socialProductsLiked



> ➢ Independent correlation between the 2 variables
> ➢ Presence of some outliers

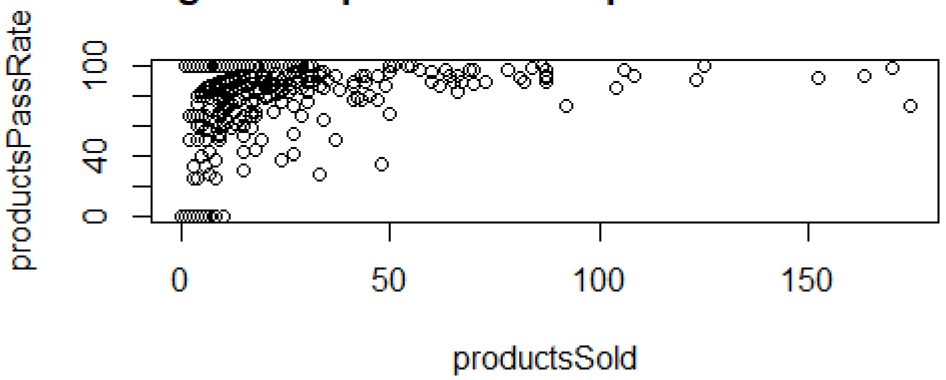
4)productsSold – productsListed



> ➢ Moderate correlation between the 2 variables
> ➢ High density of data between 0 and 50
> ➢ Presence of some outliers

5)productsSold – productsPassRate

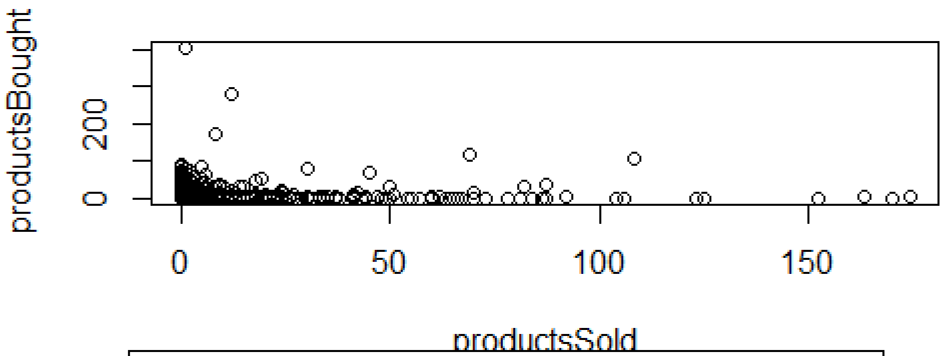
Figure 55: productsSold-productsPassRate



- Presence of two groups of data
- Presence of some outliers
- Weak correlation between the two variables

6)productsSold – productsBought

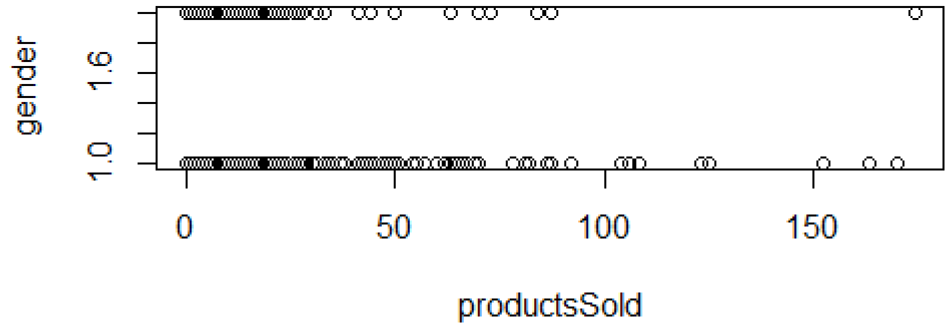
Figure 56: productsSold-productsBought



- Independent
- High density of data
- Presence of some outliers

7)productsSold – gender

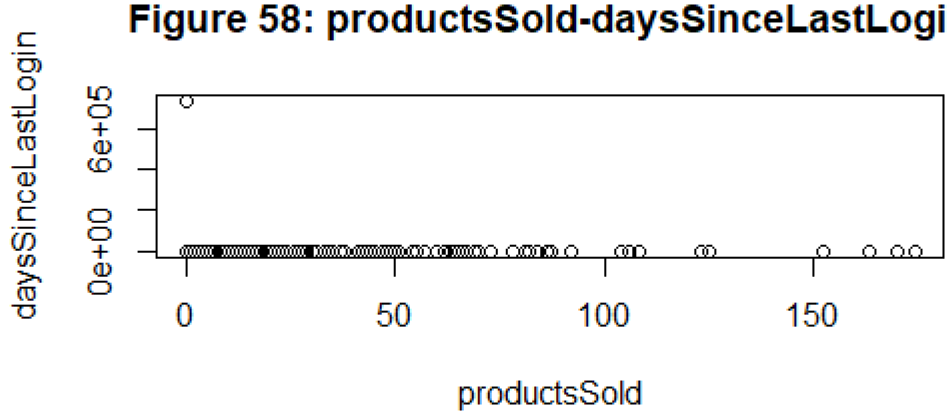
Figure 57: productsSold-gender



- Presence of 2 groups of data between 0 and 70 well separated
- High density of data in the 2 groups
- Presence of some outliers

8)products Sold – daysSinceLastLogin

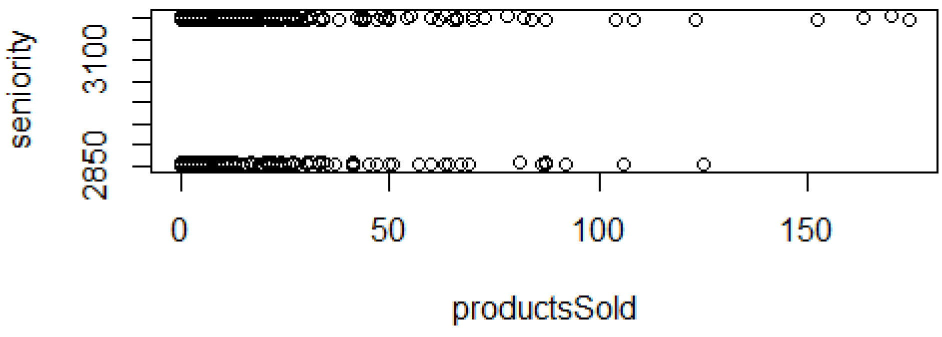
Figure 58: productsSold-daysSinceLastLogin



- High density of data between 0 and 70
- Presence of some outliers

9)productsSold – seniority

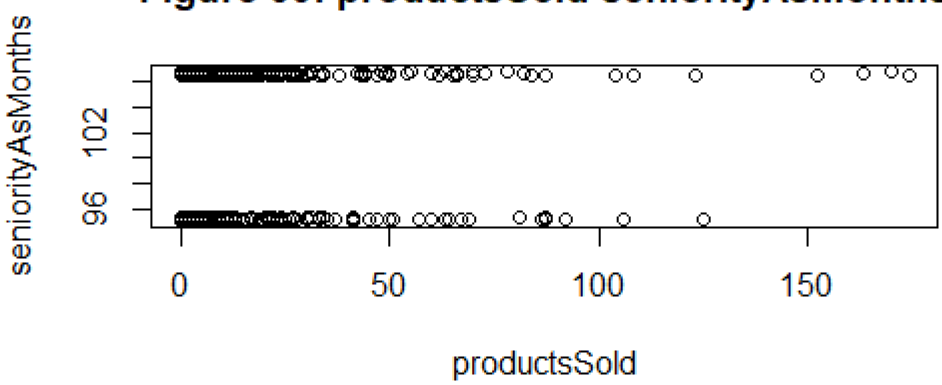
Figure 59: productsSold-seniority



- Presence of 2 groups of data between 0 and 50 well separated
- High density of data in the 2 groups
- Presence of some outliers

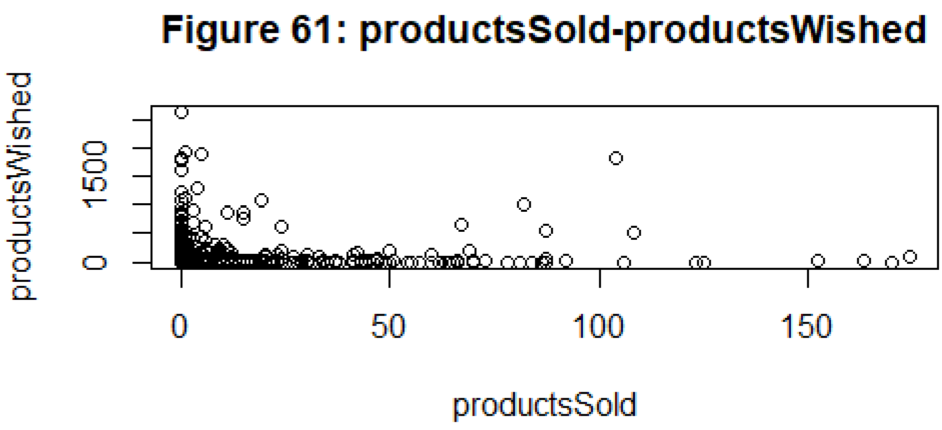
10)productsSold - seniorityAsMonths

Figure 60: productsSold-seniorityAsMonths



- Presence of 2 groups of data between 0 and 70 well separated
- High density of data in the 2 groups
- Presence of some outliers

11)productsSold – productsWished



- Independent
- High density of data
- Presence of some outliers

Data clustering and cluster validation

We have now 18 variables: 2 variables output (productsBought, productsSold) and 16 decisions variables. So:

- **First: we will replace productsBought and productsSold with other column** (leaveStore) **:**
  All users bought or sold a product they take no and others they will take no
- **Second: we will convert all categorical variables to numeric variables because we will be using the k-mean in clustering and this algorithm will only work with numeric variables.**

1-Exploration the result of k-means

```
K-means clustering with 2 clusters of sizes 98903, 10

Cluster means:
  language socialNbFollowers socialNbFollows socialProductsLiked productsListed
1 2.757237          3.432312         8.42572             4.42119     0.09331365
2 2.400000          3.000000         8.00000             0.00000     0.00000000
  productsPassRate productsWished   gender civilityTitle hasAnyApp
1        0.8123849       1.562753 1.230408      2.760755  1.264582
2        0.0000000       0.000000 1.400000      2.600000  1.600000
  hasAndroidApp hasIosApp hasProfilePicture daysSinceLastLogin
1      1.048714  1.217607           1.98084           581.2783
2      1.100000  1.500000           2.00000        737028.0000
  seniorityAsMonths countryCode
1          102.1263    94.71073
2           95.1000   103.70000

Clustering vector:
[98677] 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
[98713] 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
[98749] 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
[98785] 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
[98821] 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
[98857] 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
[98893] 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1

Within cluster sum of squares by cluster:
[1] 8208374205.5      44715.1
 (between_SS / total_SS =  99.8 %)

Available components:

[1] "cluster"      "centers"      "totss"        "withinss"     "tot.withinss"
[6] "betweenss"    "size"         "iter"         "ifault"
```

Centers of clusters

	language	socialNbFollowers	socialNbFollows	socialProductsLiked	productsListed	productsPassRate	productsWished
1	2.757237	3.432312	8.42572	4.42119	0.09331365	0.8123849	1.562753
2	2.400000	3.000000	8.00000	0.00000	0.00000000	0.0000000	0.000000

productsWished	gender	civilityTitle	hasAnyApp	hasAndroidApp	hasIosApp	hasProfilePicture	daysSinceLastLogin	senior
1.562753	1.230408	2.760755	1.264582	1.048714	1.217607	1.98084	581.2783	
0.000000	1.400000	2.600000	1.600000	1.100000	1.500000	2.00000	737028.0000	

civilityTitle	hasAnyApp	hasAndroidApp	hasIosApp	hasProfilePicture	daysSinceLastLogin	seniorityAsMonths	countryCode
2.760755	1.264582	1.048714	1.217607	1.98084	581.2783	102.1263	94.71073
2.600000	1.600000	1.100000	1.500000	2.00000	737028.0000	95.1000	103.70000

Clusters

1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 ·
1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 ·
1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 ·
1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 ·
1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 ·
1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 ·
1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 ·
1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 ·
… · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 ·
1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 ·
1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 ·
1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 ·
1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 ·
1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 ·
1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 ·
1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1 · 1

Size of clusters

First cluster has 98903 users and the second has only 10 users.

➔Clust1 >> Clust2

Totss

Totss = 5431197845194.74 : very big value

withinss of clusters

First clust : 8208374205.53964

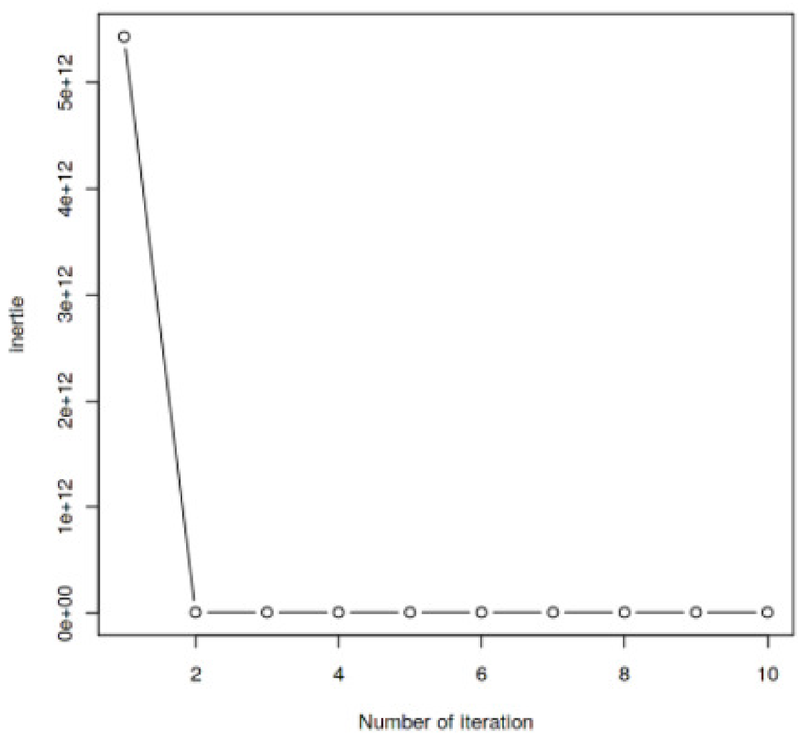
Second clust : 44715.1

tot.withinss

Tot.withinss: 8208418920.63964

2-Evolution of inertie

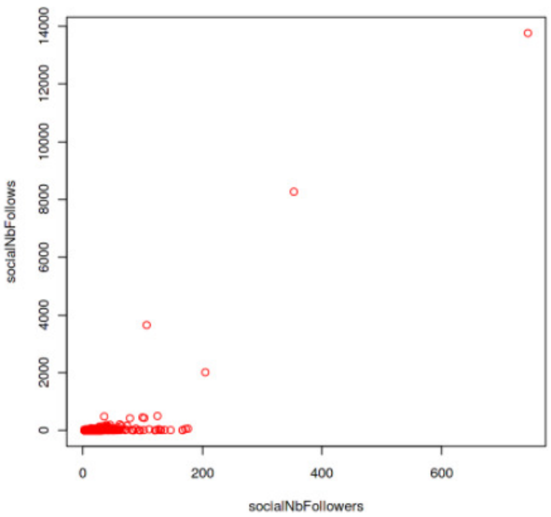
Figure A-1 : Data cluster using k-means



➔In the second time, the value of inertia is reduced and remains constant

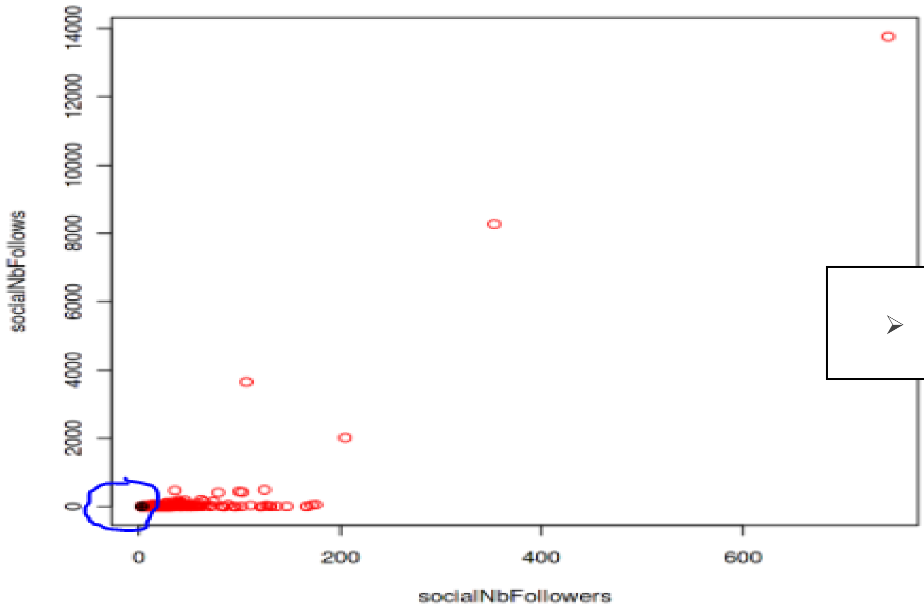
3-Plot of clust

Figure A-2 : Data cluster with k-means



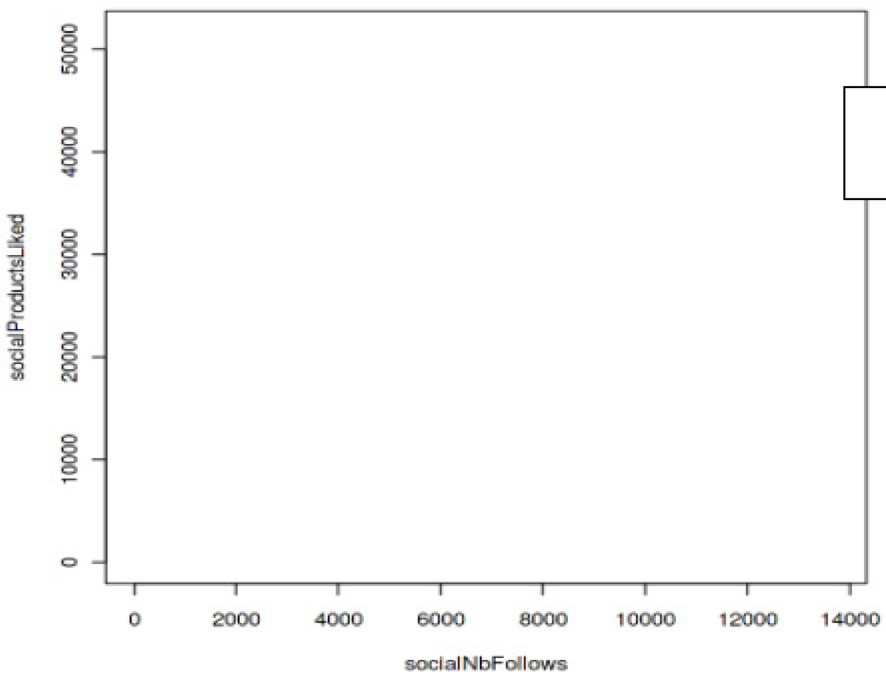
- There are some outliers
- Higher density in [0,200]
- We show only one clust because the other clust has only 10 items very smaller than the first clust

Figure A-3 : Data cluster with k-means



- The black group is very small

Figure A-4 : Data cluster with k-means



- No groups

We thing the clustring of users is not powerful to create 2 cluster of users (leave or not leave the store)

Data classification and validation

We have 18 variables and we replace two columns productsBought and productsSold with leaveStore because all users they buy or sold a product they stay in the store.
leaveStore has 2 class ("no" and "yes")
➔15 decision variables: inputs
➔1 column (leaveStore): output

1) Data classification

Our tree structure:

```
Conditional inference tree with 54 terminal nodes

Response:  leaveStore
Inputs:  language, socialNbFollowers, socialNbFollows, socialProductsLiked, productsLis
ted, productsPassRate, productsWished, gender, civilityTitle, hasAnyApp, hasAndroidApp,
hasIosApp, hasProfilePicture, daysSinceLastLogin, seniorityAsMonths, countryCode
Number of observations:  65942

1) hasProfilePicture == {False}; criterion = 1, statistic = 8071.497
  2) daysSinceLastLogin <= 233; criterion = 1, statistic = 322.369
    3) productsPassRate <= 0; criterion = 1, statistic = 122.698
      4) daysSinceLastLogin <= 17; criterion = 1, statistic = 44.809
        5)*  weights = 183
      4) daysSinceLastLogin > 17
        6) hasAndroidApp == {True}; criterion = 0.979, statistic = 33.732
          7)*  weights = 33
        6) hasAndroidApp == {False}
          8) socialProductsLiked <= 87; criterion = 0.996, statistic = 37.455
            9) productsListed <= 0; criterion = 0.978, statistic = 32.947
              10)*  weights = 196
            9) productsListed > 0
              11)*  weights = 52
          8) socialProductsLiked > 87
            12)*  weights = 23
    3) productsPassRate > 0
      13)*  weights = 229
  2) daysSinceLastLogin > 233
    14) productsPassRate <= 0; criterion = 1, statistic = 66.314
      15) daysSinceLastLogin <= 644; criterion = 1, statistic = 40.509
        16) socialNbFollowers <= 3; criterion = 0.994, statistic = 31.66
          17) socialProductsLiked <= 2; criterion = 0.968, statistic = 9.5
            18)*  weights = 72
          17) socialProductsLiked > 2
            19)*  weights = 7
        16) socialNbFollowers > 3
          20)*  weights = 222
      15) daysSinceLastLogin > 644
        21) socialNbFollows <= 8; criterion = 0.998, statistic = 14.723
          22)*  weights = 196
        21) socialNbFollows > 8
          23)*  weights = 15
    14) productsPassRate > 0
      24)*  weights = 24
1) hasProfilePicture == {True}
  25) socialNbFollowers <= 5; criterion = 1, statistic = 6058.467
    26) socialNbFollowers <= 3; criterion = 1, statistic = 3652.25
      27) socialProductsLiked <= 3; criterion = 1, statistic = 1414.29
```

```
      28) productsWished <= 0; criterion = 1, statistic = 689.095
        29)*  weights = 50861
      28) productsWished > 0
        30) daysSinceLastLogin <= 374; criterion = 1, statistic = 140.349
          31) civilityTitle == {miss, mr}; criterion = 1, statistic = 52.053
            32) gender == {F}; criterion = 0.956, statistic = 24.611
              33)*  weights = 9
            32) gender == {M}
              34)*  weights = 190
          31) civilityTitle == {mrs}
            35) productsListed <= 0; criterion = 1, statistic = 43.994
              36)*  weights = 723
            35) productsListed > 0
              37)*  weights = 15
        30) daysSinceLastLogin > 374
          38) productsWished <= 18; criterion = 1, statistic = 31.18
            39) socialNbFollows <= 8; criterion = 0.985, statistic = 31.328
              40)*  weights = 1563
            39) socialNbFollows > 8
              41)*  weights = 99
          38) productsWished > 18
            42)*  weights = 40
    27) socialProductsLiked > 3
      43) daysSinceLastLogin <= 146; criterion = 1, statistic = 265.529
        44) productsWished <= 0; criterion = 0.999, statistic = 56.525
          45)*  weights = 481
        44) productsWished > 0
          46) daysSinceLastLogin <= 11; criterion = 0.983, statistic = 39.194
            47)*  weights = 69
          46) daysSinceLastLogin > 11
            48)*  weights = 591
      43) daysSinceLastLogin > 146
        49) socialNbFollows <= 8; criterion = 1, statistic = 63.29
          50) daysSinceLastLogin <= 677; criterion = 1, statistic = 47.926
            51)*  weights = 1125
          50) daysSinceLastLogin > 677
            52)*  weights = 442
        49) socialNbFollows > 8
          53) productsWished <= 19; criterion = 1, statistic = 17.649
            54) hasAndroidApp == {True}; criterion = 0.959, statistic = 15.23
              55)*  weights = 19
            54) hasAndroidApp == {False}
              56)*  weights = 111
          53) productsWished > 19
            57)*  weights = 8
  26) socialNbFollowers > 3
    58) daysSinceLastLogin <= 384; criterion = 1, statistic = 1277.87
      59) daysSinceLastLogin <= 70; criterion = 1, statistic = 84.642
        60) productsPassRate <= 0; criterion = 1, statistic = 49.211
          61) productsWished <= 1; criterion = 0.999, statistic = 51.017
            62)*  weights = 361
          61) productsWished > 1
            63)*  weights = 309
        60) productsPassRate > 0
          64)*  weights = 43
      59) daysSinceLastLogin > 70
        65) productsPassRate <= 0; criterion = 1, statistic = 45.162
          66) gender == {M}; criterion = 1, statistic = 47.111
            67)*  weights = 205
          66) gender == {F}
            68) productsWished <= 3; criterion = 0.985, statistic = 41.361
              69)*  weights = 640
            68) productsWished > 3
              70)*  weights = 125
```

```
        65) productsPassRate > 0
          71)*  weights = 20
    58) daysSinceLastLogin > 384
      72) daysSinceLastLogin <= 690; criterion = 1, statistic = 188.943
        73) productsWished <= 0; criterion = 1, statistic = 53.011
          74) socialNbFollowers <= 4; criterion = 1, statistic = 52.513
            75) gender == {M}; criterion = 0.999, statistic = 55.689
              76)*  weights = 284
            75) gender == {F}
              77)*  weights = 838
          74) socialNbFollowers > 4
            78)*  weights = 386
        73) productsWished > 0
          79)*  weights = 255
      72) daysSinceLastLogin > 690
        80) seniorityAsMonths <= 95.23; criterion = 1, statistic = 45.201
          81)*  weights = 1584
        80) seniorityAsMonths > 95.23
          82) daysSinceLastLogin <= 695; criterion = 1, statistic = 50.33
            83)*  weights = 58
          82) daysSinceLastLogin > 695
            84) socialNbFollowers <= 4; criterion = 1, statistic = 46.454
              85) productsWished <= 0; criterion = 1, statistic = 35.155
                86) gender == {M}; criterion = 0.975, statistic = 35.006
                  87)*  weights = 279
                86) gender == {F}
                  88)*  weights = 1094
              85) productsWished > 0
                89)*  weights = 52
            84) socialNbFollowers > 4
              90) daysSinceLastLogin <= 701; criterion = 1, statistic = 37.049
                91)*  weights = 42
              90) daysSinceLastLogin > 701
                92)*  weights = 383
25) socialNbFollowers > 5
  93) daysSinceLastLogin <= 377; criterion = 1, statistic = 265.065
    94) productsPassRate <= 0; criterion = 1, statistic = 95.284
      95) daysSinceLastLogin <= 16; criterion = 0.995, statistic = 56.338
        96)*  weights = 156
      95) daysSinceLastLogin > 16
        97) civilityTitle == {miss, mr}; criterion = 0.966, statistic = 54.219
          98)*  weights = 100
        97) civilityTitle == {mrs}
          99)*  weights = 373
    94) productsPassRate > 0
      100)*  weights = 251
  93) daysSinceLastLogin > 377
    101) productsPassRate <= 0; criterion = 1, statistic = 63.674
      102) civilityTitle == {miss, mr}; criterion = 1, statistic = 66.87
        103)*  weights = 126
      102) civilityTitle == {mrs}
        104) countryCode == {ch, cn, dk, fi, fr, gb, gu, hr, hu, it, la, lb, mc, nl,
nz, pr, ro, sa, se, tw, ua, us}; criterion = 0.992, statistic = 67.857
          105)*  weights = 268
        104) countryCode == {at, au, be, ca, de, ee, es, hk, ie, jp, lt, sg, sk}
          106)*  weights = 93
    101) productsPassRate > 0
      107)*  weights = 19
```

plot(tree)

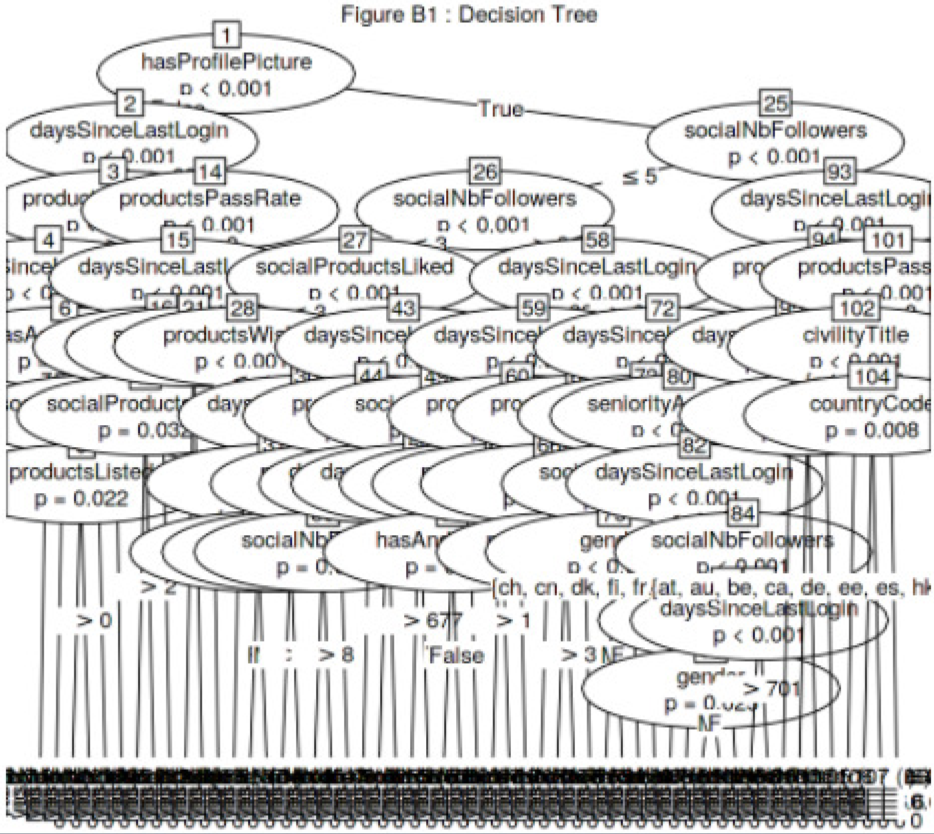


Figure B1 : Decision Tree

There are many nodes we can't read the graphic.
Many decision variable ➔ many nodes

Prédiction

yes yes yes yes yes yes yes yes yes yes yes yes yes yes no yes yes
yes yes yes yes yes yes yes yes yes yes yes yes yes yes yes yes yes
yes yes no yes yes yes yes yes yes yes yes yes yes yes yes yes yes
yes yes yes yes yes yes yes yes yes yes yes yes yes yes yes yes yes
yes yes yes yes yes yes yes yes yes yes yes yes yes yes yes yes yes
yes yes yes yes yes yes yes yes yes yes yes yes yes yes yes yes yes
yes yes yes yes yes yes yes yes yes yes yes yes yes yes yes yes yes
yes yes yes yes yes yes yes yes yes yes yes yes yes yes yes yes yes
yes yes yes yes yes yes yes yes yes yes yes no yes yes yes yes yes
yes yes yes yes yes yes yes yes yes yes yes yes yes yes yes yes yes
yes yes yes yes yes yes yes yes yes yes yes yes yes yes yes yes yes
yes yes yes yes yes yes yes yes yes yes yes yes yes … yes yes yes
yes yes yes no yes no yes yes yes yes yes yes yes yes yes yes yes
yes yes yes yes yes yes yes yes yes yes yes yes yes yes yes yes yes
no yes yes yes yes yes yes yes yes yes yes yes yes yes yes no yes
yes yes yes yes yes yes yes yes yes yes yes yes yes yes yes yes yes
yes yes yes no yes yes yes yes yes yes yes yes yes yes yes yes yes

Prédiction table

```
      prediction
rel      no   yes
  no    817  1550
  yes   273 30331
```

Calculer la précision

```
#calculer la précision de classification
precision=sum(diag(contingence))/sum(contingence)
precision
```

```
0.944708986685269
```

Calculer l'erreur

Erreur = 1-precision =0.0552910133147311

==>Donc on obtient un modèle très fortes puisque la précision plus que 94%