## **Building a Robust Geodemographic Segmentation Model**

#### P12-Churn-Modelling: Lequel des clients est susceptible de quitter la banque?

On a dummify les variables Gender et Geography vu qu'elles sont des variables catégorielles.

## **Apply Backward Elimination (see MLR)**

P-value of Spain was Highest and (>5%), so I am deleting it. We get:

```
Model 2: Logit, using observations 1-10000
Dependent variable: Exited
Standard errors based on Hessian
                                   coefficient std. error
   -3.91097 0.244526 -15.99 1.41e-057 ***

CreditScore -0.000666615 0.000280294 -2.378 0.0174 **

Age 0.0727230 0.00257536 28.24 2.00e-175 ***

Tenure -0.0159766 0.00935423 -1.708 0.0876 **

Balance 2.63733e-06 5.14201e-07 5.129 2.91e-07 ***

NumOfProducts -0.101288 0.0471276 -2.149 0.0316 **

HasCrCard -0.0449303 0.0593378 -0.7572 0.4489

IsActiveMember -1.07519 0.0576828 -18.64 1.53e-077 ***

EstimatedSalary 4.81342e-07 4.73649e-07 1.015
   EstimatedSalary 4.81342e-07 4.73649e-07 1.016 0.3095
Female 0.528343 0.0544870 9.697 3.11e-0
                                   0.528343 0.0544870
0.762937 0.0633614
                                                                                                        3.11e-022 ***
                                                                                  12.04
                                                                                                       2.16e-033 ***
   Germany
Mean dependent var 0.203700 S.D. dependent var 0.402769
McFadden R-squared 0.153137 Adjusted R-squared 0.150961
Log-likelihood -4280.802 Akaike criterion 8583.603
                                                           Akaike criterion
Log-likelihood -4280.802
Schwarz criterion 8662.917
                                                                                                  8583.603
                                                          Hannan-Quinn
                                                                                                  8610.451
Number of cases 'correctly predicted' = 8100 (81.0%)
f(beta'x) at mean of independent vars = 0.135
Likelihood ratio test: Chi-square(10) = 1548.18 [0.0000]
   Actual 0 7665
1 1602
                                     298
                                     435
Excluding the constant, p-value was highest for variable 11 (HasCrCard)
```

P-value of HasCrCard was Highest and (>5%), so I am deleting it. We get:

Model 3: Logit, using observations 1-10000 Dependent variable: Exited Standard errors based on Hessian

		std. error			
		0.240579			**
CreditScore	-0.000664033	0.000280270	-2.369	0.0178	**
Age	0.0727303	0.00257516	28.24	1.73e-175	**
Tenure	-0.0161505	0.00935127	-1.727	0.0842	*
Balance	2.64543e-06	5.14070e-07	5.146	2.66e-07	**
NumOfProducts	-0.101333	0.0471228	-2.150	0.0315	**
IsActiveMember					**
EstimatedSalary	4.81783e-07	4.73661e-07	1.017	0.3091	
Female	0.528489	0.0544853	9.700	3.02e-022	**
Germany					
an dependent var	0.203700	S.D. dependen	t var (	.402769	
Fadden R-squared	0.153080	Adjusted R-sq	uared 0	.151102	
g-likelihood	-4281.088	Akaike criter	ion 8	582.175	
hwarz criterion	8654.279	Hannan-Quinn	ε	606.582	
umber of cases 'c (beta'x) at mean .kelihood ratio t	of independen	t vars = 0.135		ii	
				_	
Predict	ed				
0	1				
Actual 0 7673	290				
1 1599	438				

Excluding the constant, p-value was highest for variable 13 (EstimatedSalary)

#### P-value of EstimatedSalary was Highest and (>5%), so I am deleting it. We get:

<u>Remarque:</u> la (R^2) augmente au fur a mesure, ce qui est prouve que les modèles prédictifs s'améliorent à fur à mesure. Cela signifie qu'on n'a pas retiré à tort une variable.

→ We have decided to stop at this step because all independent variables are significant.

#### Transformer les variables indépendantes.

On remplace la variable Balance par log\_Balance= ln(Balance+1). We get:

```
Model 5: Logit, using observations 1-10000
Dependent variable: Exited
Standard errors based on Hessian
                           coefficient
                                                std. error
   -3.91258

        Mean dependent var
        0.203700
        S.D. dependent var
        0.402769

        McFadden R-squared
        0.152787
        Adjusted R-squared
        0.151006

        Log-likelihood
        -4282.570
        Akaike criterion
        8583.141

        Schwarz criterion
        8648.034
        Hannan-Quinn
        8605.107

Number of cases 'correctly predicted' = 8127 (81.3%)
f(beta'x) at mean of independent vars = 0.135
Likelihood ratio test: Chi-square(8) = 1544.64 [0.0000]
                Predicted
                     0
   Actual 0 7687
                             276
              1 1597
```

On ajoute la variable WealthAccumulation= Balance / Age au modèle précèdent, we get :

```
Model 6: Logit, using observations 1-10000
Dependent variable: Exited
Standard errors based on Hessian

Coefficient std. error z p-value

const -3.82758 0.248202 -15.42 1.18e-053 ***
CreditScore -0.006675560 0.000280329 -2.410 0.0160 **
Age 0.0706681 0.00309455 22.84 2.00e-115 ***
Tenure -0.0159252 0.00934677 -1.704 0.0884 *
NumofProducts -0.0955301 0.0475596 -2.009 0.0446 **
IsactiveMember -1.07339 0.0576722 -18.61 2.57e-077 ***
Female 0.525712 0.0544733 9.651 4.88e-022 ***
Germany 0.746337 0.0651330 11.46 2.13e-030 ***
log_Balance 0.0950938 0.0266187 3.572 0.0004 ***
WealthAccumulati~ -4.33552e-05 3.77862e-05 -1.147 0.2512

Mean dependent var 0.203700 S.D. dependent var 0.402769
McFadden R-squared 0.152918 Adjusted R-squared 0.150940
Log-likelihood -4281.908 Akaike criterion 8583.815
Schwarz criterion 8655.919 Hannan-Quinn 8608.222

Number of cases 'correctly predicted' = 8123 (81.2*)
f(beta'x) at mean of independent vars = 0.135
Likelihood ratio test: Chi-square(9) = 1545.97 [0.0000]

Predicted
0 1
Actual 0 7684 279
1 1598 439

Excluding the constant, p-value was highest for variable 21 (WealthAccumulation)
```

**Remarque :** WeilthAccumulation n'est pas significative et il n'y pas d'amélioration du modèle (la diminution de R^2). Cela est peut-être dû au fait que weilthAccumulation(Balance / Age) est lié a Age et Balance(i.e. existence de colinéarité entre weilthAccumulation, Age, log\_Balance).

## Vérification de multi colinéarité en utilisant VIF.

```
Variance Inflation Factors
Minimum possible value = 1.0
Values > 10.0 may indicate a collinearity problem
                    1.001
     CreditScore
                  1.450
             Age
    NumOfProducts
                    1.152
   IsActiveMember
                    1.011
           Female
         Germany
                    1.271
           Tenure
                    1,001
      Log_Balance
                    5.860
WealthAccumulation 5.722
VIF(j) = 1/(1 - R(j)^2), where R(j) := the multiple correlation coefficient
between variable j and the other independent variables
```

Le VIF de log\_Balance et WealthAccumulation est supérieur aux autres variables, on décide alors de retirer log\_Balance. We get :

```
Model 7: Logit, using observations 1-10000
Dependent variable: Exited
Standard errors based on Hessian
                                        coefficient std. error z p-value
                                      const
   CreditScore
    Age
    Tenure
   Tenure -0.0158045 0.00534123 -1.052 0.0051
NumOfProducts -0.121038 0.0471074 -2.569 0.0102 **
IsActiveMember -1.07881 0.0576645 -18.71 4.23e-078 ***
Female 0.526299 0.0544270 9.670 4.05e-022 ***
Germany 0.808180 0.0629285 12.84 9.44e-038 ***
WealthAccumulati~ 7.07501e-05 1.94600e-05 3.636 0.0003 ***
   NumOfProducts

        Mean dependent var
        0.203700
        S.D. dependent var
        0.402769

        McFadden R-squared
        0.151650
        Adjusted R-squared
        0.149869

        Log-likelihood
        -4288.318
        Akaike criterion
        8594.635

        Schwarz criterion
        8659.528
        Hannan-Quinn
        8616.601

Number of cases 'correctly predicted' = 8121 (81.2%)
f(beta'x) at mean of independent vars = 0.135
Likelihood ratio test: Chi-square(8) = 1533.15 [0.0000]
                   Predicted
                          0
   Actual 0 7685
1 1601
                                    278
```

En enlevant log\_Balance, On obtient que WeilthAccumulation devient très significative et son coefficient est même devenu positif. Revérifions la multi colinéarité:

```
Variance Inflation Factors
Minimum possible value = 1.0
Values > 10.0 may indicate a collinearity problem
      Credit5core
                     1.001
    NumOfProducts
                     1.118
   IsActiveNember
                     1.011
           Female
                     1.003
          Germany
                     1.187
           Tenure
                     1.001
WealthAccumulation
                     1.387
VIF(j) = 1/(1 - R(j)^2), where R(j) is the multiple correlation coefficient
between variable j and the other independent variables
```

Aucun signe de multi colinéarité flagrant.

On décide finalement pour être plus cohérant avec notre étude, nous allons enlever WeilthAccumulation et garder log\_Balance. We get :

```
Model 9: Logit, using observations 1-10000
Dependent variable: Exited
Standard errors based on Hessian
                                              coefficient
                                                                                 std. error
                                                                                                                                                 p-value

        CreditScore
        -0.000674866
        0.000280272
        -2.408

        Age
        0.0726550
        0.00257451
        28.22

        Tenure
        -0.0158791
        0.00934627
        -1.699

        NumOfProducts
        -0.0950198
        0.0475374
        -1.999

        IsActiveMember
        -1.07578
        0.0576458
        -18.66

        Female
        0.526721
        0.0544591
        9.672

        Germany
        0.747595
        0.0650515
        11.49

        log_Balance
        0.0690263
        0.0139592
        4.945

        Mean dependent var
        0.203700
        S.D. dependent var
        0.402769

        McFadden R-squared
        0.152787
        Adjusted R-squared
        0.151006

        Log-likelihood
        -4282.570
        Akaike criterion
        8583.141

        Schwarz criterion
        8648.034
        Hannan-Quinn
        8605.107

Number of cases 'correctly predicted' = 8127 (81.3%)
f(beta'x) at mean of independent vars = 0.135
Likelihood ratio test: Chi-square(8) = 1544.64 [0.0000]
                           Predicted
     Actual 0 7687
                                                  276
                      1 1597
```

# Vérification de multi colinéarité par la matrice de corrélation :

Regardons la matrice de corrélation des variables Age, log\_Balance, WealthAccumulation, log\_WA:

```
Correlation Coefficients, using the observations 1 - 10000
Two-tailed critical values for n = 10000: 5% 0.0196, 1% 0.0258

Age log_Balance WealthAccumula~ log_WA
1.0000 0.0345 -0.2463 -0.0075 Age
1.0000 0.8651 0.9984 log_Balance
1.0000 0.8889 WealthAccumula~
1.0000 log_WA
```

**Astuce :** Plus la valeur absolue des coefficients de la matrice(coeff) se rapproche de 1, plus cela montre la colinéarité entre les variables.

- Si coeff > 0.9 => Très corrélées (Doit retirer une variable)
- Si coeff>0.7 => Très corrélées (recommande de faire qq chose)
- Si 0.3<=coeff<0.5 => corrélation modérée (essayer d'enlever une variable pour voir)
- Si 0<coeff<0.3 => Faible corrélation (on laisse les variables)

#### Par exemple dans notre cas, on a:

- log\_WA et log\_Balance sont très corrélées(on retire une variable).
- WealthAccumulation et log\_Balance sont très corrélées(on retire une variable).
- log\_WA et WealthAccumulation sont très corrélées(on retire une variable).
- log\_WA et Age ne sont pas très corrélées.
- log\_Balance et Age ne sont pas très corrélées.
- WealthAccumulation et Age ne sont pas très corrélées.

# Dans cette section nous avons appris:

- 1. Ce qu'est la segmentation géo-démographique
- 2. Comment construire un VRAI modèle de segmentation
- 3. Comment transformer des variables indépendantes
- 4. Comment créer des variables dérivées (nouvelles VIs)
- L'intuition derrière les colinéarités
- 6. Comment vérifier les colinéarités en utilisant les VIFs
- Comment lire une matrice de corrélation