Analysis

Elodie Kwan and Katia Voltz

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Methodology

In this section we will talk about the methodology that has been used and the different models analysis that has been conducted.

Traning set and Test set

First of all we started by splitting our dataset into 2 sets: **training set** (`German_credit.tr`) and **test set** (`German_credit.te`). We do not forget to take the first variable **OBS.** out as it represents the index number for each observation. These two sets will allow us to train some models on the **training set** and then test the accuracy of the model fit on the **test set**.

Balancing the dataset

Then, we applied the balancing data technique in order to improve the predictions of **Good Credit** and **Bad Credit**, since we have more observations on the **Good Credit**.

The table below reveals the unbalanced problem.

Indeed, we observe that the "Good Credit" (1) response appears **527** times in the training set and "Bad Credit" (0) **223**, two times less. Since there are many more "Good Credit" than "Bad Credit", any model favors the prediction of the "Good Credit". It results a good accuracy but the specificity is low, as well as the balanced accuracy.

Sub-sampling Balancing using sub-sampling consists of taking all the cases in the smallest class (here "Bad Credit") and extract at random the same amount of cases in the largest category (here "Good").

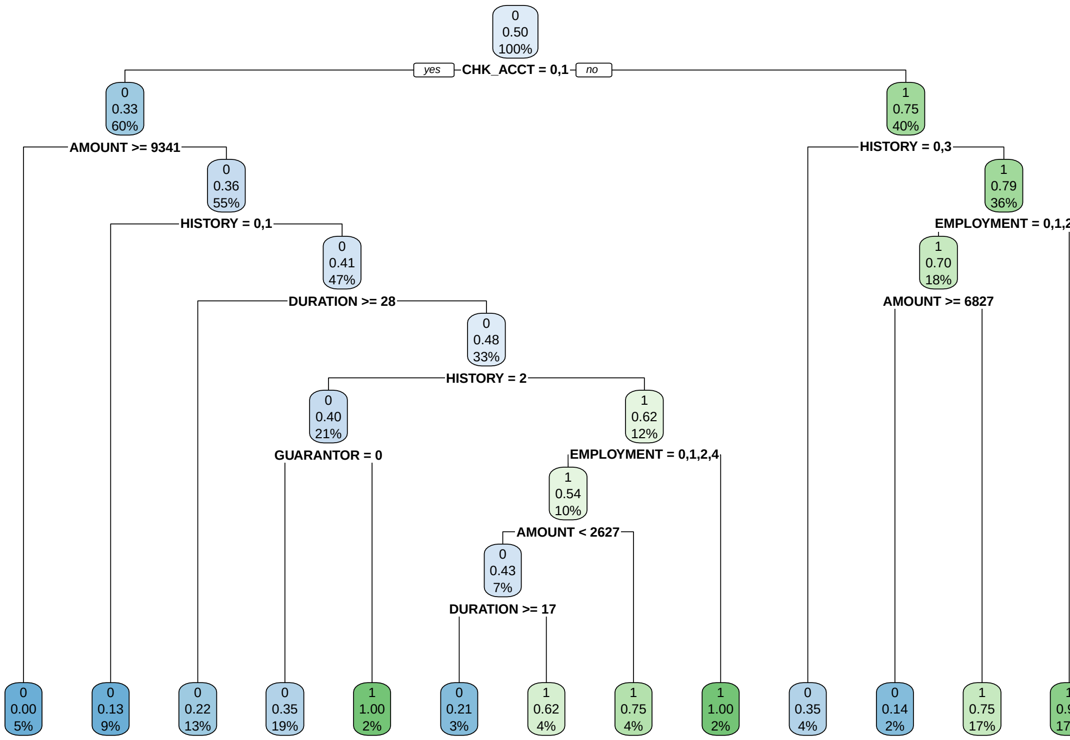
The **training set** is now balanced, we have 223 observations for both "Good Credit" (1) and "Bad Credit" (0). The new balanced training set is called `German_Credit.tr.subs`.

Models Fitting

Once we had our training set and test set, we could fit some models and compare them with together to choose the best model.

1. Classification Tree (Decision Tree) We first started with a decision tree and more specifically we chose the classification tree as we want to classify the applicants. The model was build on our previously balanced training set `German_Credit.tr.subs`. We used the R function `rpart`.

We obtained the following large tree.



We could see that among the 31 explanatory variables, this model uses 6 of them: **CHK_ACCT**, **AMOUNT**, **HISTORY**, **DURATION**, **GUARANTOR** and **EMPLOYMENT**.

Table 1: Confusion Matrix of the Big classification tree

	Bad credit risk	Good credit risk
Bad credit risk	58	70
Good credit risk	19	103

Table 2: Table continues below

Sensitivity	Specificity	Pos Pred Value	Neg Pred Value	Precision
0.7532	0.5954	0.4531	0.8443	0.4531

Table 3: Table continues below

Recall	F1	Prevalence	Detection Rate	Detection Prevalence
0.7532	0.5659	0.308	0.232	0.512

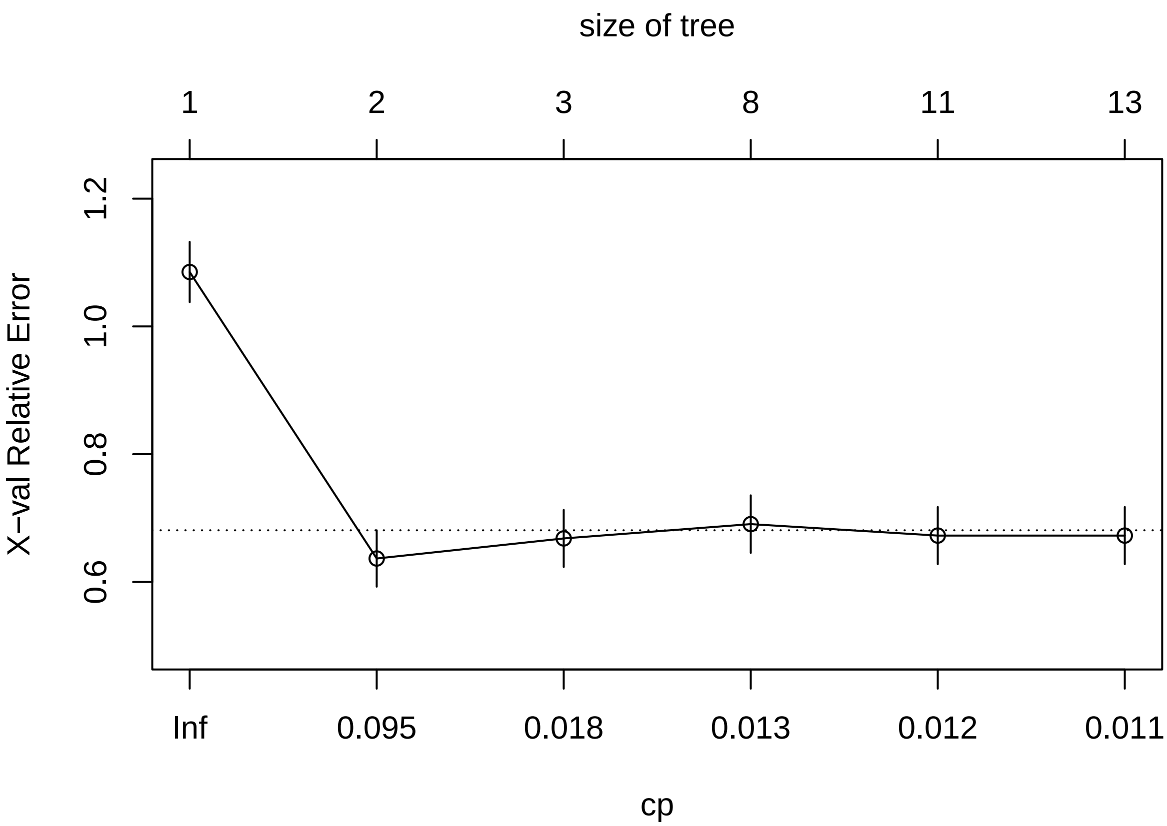
Balanced Accuracy
0.6743

We first have an insight on how well it predict the test set (`German_credit.te`). We recall that 0 means a "Bad Credit" risk and 1 means a "Good Credit" risk. It seems that it has difficulty to predict the "Bad Credit" risk applicants.

As the tree is quite big and we want to know if we can prune it. To do so, we decided to use the `printcp` and `plotcp` commands and choose the best **cp** (complexity parameter) value to prune our tree.

Pruning the tree

```
##
## Classification tree:
## rpart(formula = RESPONSE ~ ., data = German_Credit.tr.subs, method = "class")
##
## Variables actually used in tree construction:
## [1] AMOUNT     CHK_ACCT   DURATION   EMPLOYMENT GUARANTOR  HISTORY
##
## Root node error: 223/446 = 0.5
##
## n= 446
##
##         CP nsplit rel error  xerror     xstd
## 1 0.399103      0   1.00000 1.08520 0.047179
## 2 0.022422      1   0.60090 0.63677 0.044117
## 3 0.014574      2   0.57848 0.66816 0.044668
## 4 0.011958      7   0.48430 0.69058 0.045028
## 5 0.011211     10   0.44843 0.67265 0.044742
## 6 0.010000     12   0.42601 0.67265 0.044742
```

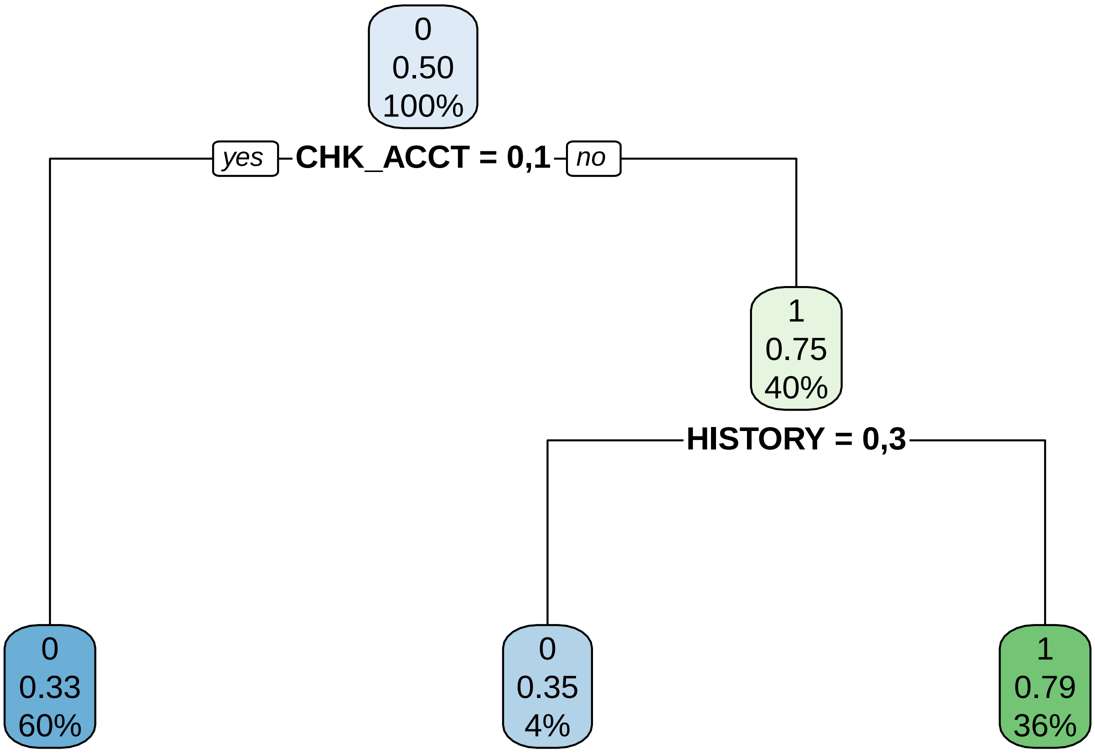


From the list of **cp** (complexity parameter), we would choose the line that has the lowest cross validation error. This can be seen on the column **xerror**. So the best cp would be 0.022422 with one split.

From the graph, we can identify that, according to the 1-SE rule, the tree with 2 and 3 are equivalent. The tree with 3 nodes should be preferred. It appears below the dotted-line.

The value of cp can be chosen arbitrarily between 0.018 and 0.095. So we decided to go with the suggested cp of 0.022 from the summary.

With these value, we obtain a very small tree.



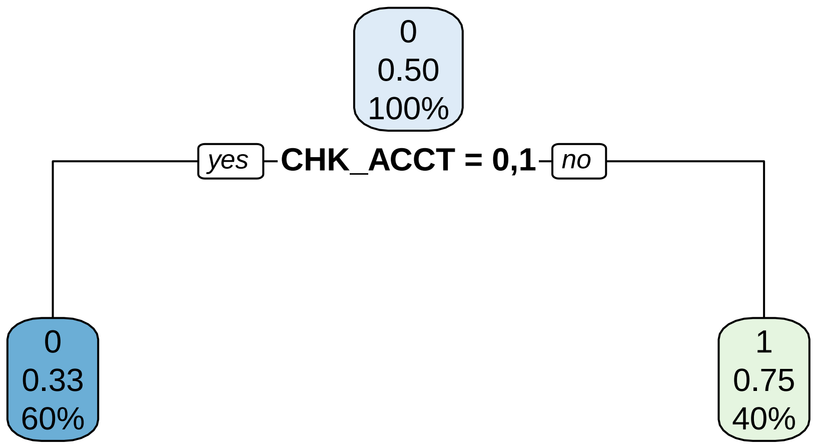
This pruned decision tree with a cp of 0.022 uses the variables **CHK_ACCT** and **HISTORY**.

Using this pruned tree, we can computed the prediction and build a confusion matrix to see the performance of the model.

```
##           Reference
## Prediction  0  1
##          0 63 95
##          1 14 78
```

```
##          Sensitivity          Specificity       Pos Pred Value
##            0.8181818            0.4508671            0.3987342
##       Neg Pred Value            Precision               Recall
##            0.8478261            0.3987342            0.8181818
##                   F1           Prevalence       Detection Rate
##            0.5361702            0.3080000            0.2520000
## Detection Prevalence    Balanced Accuracy
##            0.6320000            0.6345244
```

We also decided to look at what would an automatically pruned using 1-SE rule would give us and whether or not it is better than the pruned tree we made by looking at the cp.



Here, only the variable **CHK_ACCT** is used. As we prune the tree more information are lost.

```
##           Reference
## Prediction  0  1
##          0 61 88
##          1 16 85
```

```
##          Sensitivity          Specificity       Pos Pred Value
##            0.7922078            0.4913295            0.4093960
##       Neg Pred Value            Precision               Recall
##            0.8415842            0.4093960            0.7922078
##                   F1           Prevalence       Detection Rate
##            0.5398230            0.3080000            0.2440000
## Detection Prevalence    Balanced Accuracy
##            0.5960000            0.6417686
```

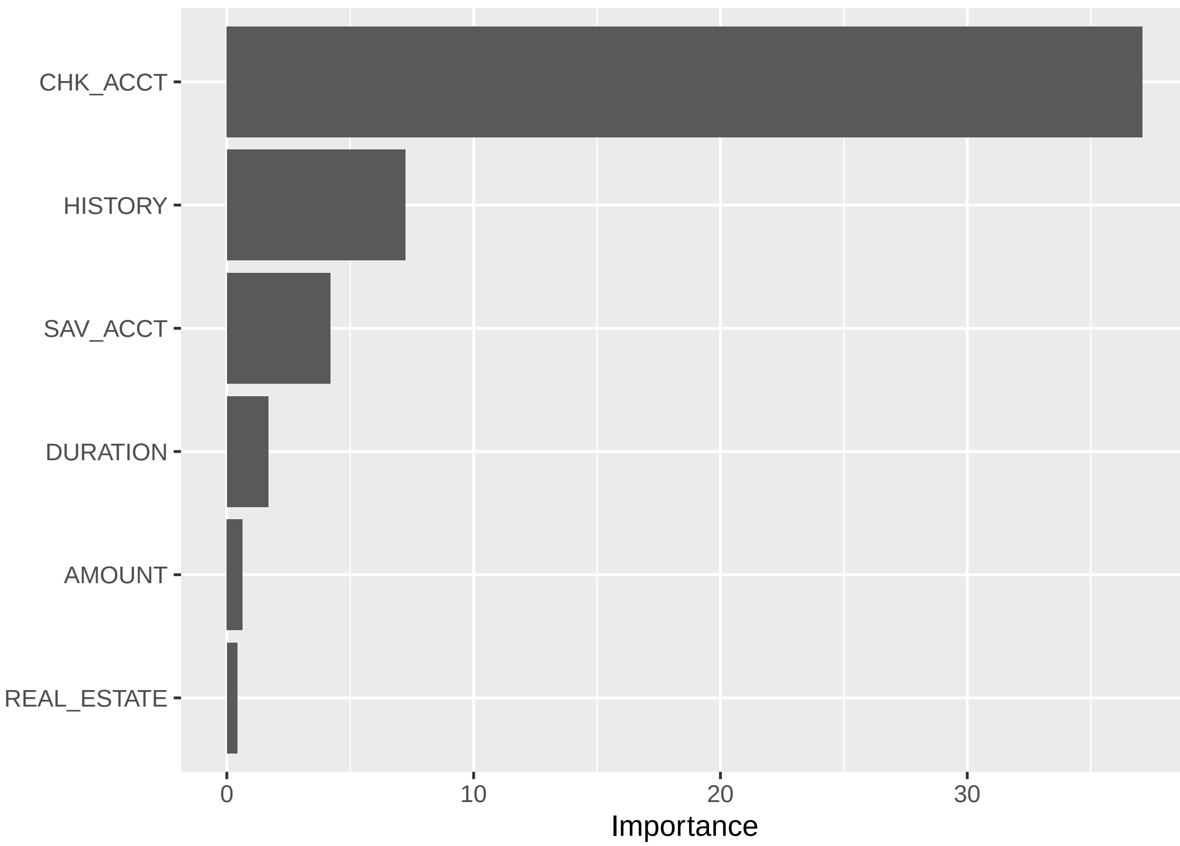
```
varImp(german.ct.prune)
```

Variable importance of the classification tree

```
##                  Overall
## AMOUNT         17.947179
## CHK_ACCT       37.098755
## DURATION       11.073258
## EMPLOYMENT      4.645266
## HISTORY        18.840050
## OTHER_INSTALL   3.216630
## RETRAINING      3.509915
## SAV_ACCT        9.538067
## NEW_CAR         0.000000
## USED_CAR        0.000000
## FURNITURE       0.000000
## RADIO.TV        0.000000
## EDUCATION       0.000000
## INSTALL_RATE    0.000000
## MALE_DIV        0.000000
## MALE_SINGLE     0.000000
## MALE_MAR_or_WID 0.000000
## CO.APPLICANT    0.000000
## GUARANTOR       0.000000
```

```
## PRESENT_RESIDENT  0.000000
## REAL_ESTATE       0.000000
## PROP_UNKN_NONE    0.000000
## AGE               0.000000
## RENT              0.000000
## OWN_RES           0.000000
## NUM_CREDITS       0.000000
## JOB               0.000000
## NUM_DEPENDENTS    0.000000
## TELEPHONE         0.000000
## FOREIGN           0.000000
```

```
vip(german.ct.prune)
```



From this plot, we see that the variables that influences the most are **CHK_ACCT**, **HISTORY**, **SAV_ACCT**, **DURATION**, **AMOUNT** and **REAL_ESTATE**. They are not exactly the same as the one we saw above.

The variable **CHK_ACCT** and **HISTORY** were noticed though.

2. Logistic Regression The next model we performed is a logistic regression.

```
##
## Call:
## glm(formula = RESPONSE ~ ., family = binomial, data = German_Credit.tr.subs)
##
## Deviance Residuals:
##      Min        1Q    Median        3Q       Max
## -2.34578  -0.68043   0.00049   0.65178   2.74937
```

```
##
## Coefficients:
##                     Estimate Std. Error z value Pr(>|z|)
## (Intercept)        1.1911402  1.7958756   0.663 0.507161
## CHK_ACCT1          0.5692882  0.3363406   1.693 0.090533 .
## CHK_ACCT2          0.8404451  0.5339512   1.574 0.115485
## CHK_ACCT3          2.4337691  0.3770606   6.455 1.09e-10 ***
## DURATION          -0.0123731  0.0142153  -0.870 0.384078
## HISTORY1          -1.0734853  0.8514386  -1.261 0.207384
## HISTORY2           0.0865599  0.6747882   0.128 0.897930
## HISTORY3          -0.0598560  0.7410028  -0.081 0.935619
## HISTORY4           1.1072483  0.6576414   1.684 0.092246 .
## NEW_CAR1          -0.4538649  0.5853211  -0.775 0.438096
## USED_CAR1          1.6322817  0.7540134   2.165 0.030404 *
## FURNITURE1         0.0509645  0.6182782   0.082 0.934305
## RADIO.TV1          0.5261147  0.5896893   0.892 0.372291
## EDUCATION1         0.5441469  0.7499724   0.726 0.468111
## RETRAINING1       -0.4293160  0.6787931  -0.632 0.527080
## AMOUNT            -0.0002155  0.0000739  -2.916 0.003550 **
## SAV_ACCT1          0.6181742  0.4475399   1.381 0.167195
## SAV_ACCT2         -0.2531524  0.5541205  -0.457 0.647776
## SAV_ACCT3          0.7292579  0.6813687   1.070 0.284492
## SAV_ACCT4          1.4221687  0.4243610   3.351 0.000804 ***
## EMPLOYMENT1        0.7574673  0.7956778   0.952 0.341108
## EMPLOYMENT2        1.4785839  0.7640267   1.935 0.052959 .
## EMPLOYMENT3        1.9691166  0.7947873   2.478 0.013229 *
## EMPLOYMENT4        1.8560330  0.7511387   2.471 0.013475 *
## INSTALL_RATE      -0.3367533  0.1411404  -2.386 0.017035 *
## MALE_DIV1         -0.5653453  0.5705857  -0.991 0.321775
## MALE_SINGLE1       0.1618525  0.3327207   0.486 0.626647
## MALE_MAR_or_WID1  -0.5551862  0.5312986  -1.045 0.296041
## CO.APPLICANT1     -0.6994379  0.6920599  -1.011 0.312179
## GUARANTOR1         1.7126786  0.6556150   2.612 0.008993 **
## PRESENT_RESIDENT2 -1.1195205  0.4773294  -2.345 0.019008 *
## PRESENT_RESIDENT3 -0.2590309  0.5313455  -0.487 0.625904
## PRESENT_RESIDENT4 -0.9082582  0.4793144  -1.895 0.058104 .
## REAL_ESTATE1      -0.0137202  0.3384983  -0.041 0.967669
## PROP_UNKN_NONE1   -1.4578770  0.6505748  -2.241 0.025032 *
## AGE                0.0167050  0.0141041   1.184 0.236255
## OTHER_INSTALL1    -0.6758552  0.3404321  -1.985 0.047113 *
## RENT1             -1.2066453  0.8244600  -1.464 0.143315
## OWN_RES1          -0.4707135  0.7665544  -0.614 0.539173
## NUM_CREDITS       -0.3634820  0.3011721  -1.207 0.227474
## JOB1              -0.7402802  1.1619781  -0.637 0.524069
## JOB2              -1.2142377  1.1317833  -1.073 0.283337
## JOB3              -1.4358446  1.1604352  -1.237 0.215964
## NUM_DEPENDENTS     0.1270172  0.3832474   0.331 0.740325
## TELEPHONE1         0.6259633  0.3143236   1.991 0.046430 *
## FOREIGN1           1.2496315  0.8543880   1.463 0.143576
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
```

```
##     Null deviance: 618.29  on 445  degrees of freedom
## Residual deviance: 390.97  on 400  degrees of freedom
## AIC: 482.97
##
## Number of Fisher Scoring iterations: 5
```

We see that a lot of variables are not statistically significant for the model so we can think of a model reduction.

Before doing a reduction of the model, we fitted the model and predicted on the test set.

```
##           Reference
## Prediction   0   1
##          0  49  46
##          1  28 127
```

```
##          Sensitivity          Specificity       Pos Pred Value
##            0.6363636            0.7341040            0.5157895
##       Neg Pred Value            Precision               Recall
##            0.8193548            0.5157895            0.6363636
##                   F1           Prevalence       Detection Rate
##            0.5697674            0.3080000            0.1960000
## Detection Prevalence    Balanced Accuracy
##            0.3800000            0.6852338
```

Variable selection and interpretation with step method (AIC criteria) In order to reduce the logistic regression we used a stepwise variable selection. This has been done with the command `step`.

The final reduced model is as follow.

```
summary(mod.logreg.sel)
```

```
##
## Call:
## glm(formula = RESPONSE ~ CHK_ACCT + HISTORY + NEW_CAR + USED_CAR +
##     RETRAINING + AMOUNT + SAV_ACCT + EMPLOYMENT + INSTALL_RATE +
##     GUARANTOR + PRESENT_RESIDENT + PROP_UNKN_NONE + AGE + OTHER_INSTALL +
##     RENT + TELEPHONE + FOREIGN, family = binomial, data = German_Credit.tr.subs)
##
## Deviance Residuals:
##      Min        1Q    Median        3Q       Max
## -2.39343  -0.68768  -0.02628   0.71315   2.60726
##
## Coefficients:
##                    Estimate Std. Error z value Pr(>|z|)
## (Intercept)       -0.6339113  1.1570626  -0.548 0.583786
## CHK_ACCT1          0.5970566  0.3291383   1.814 0.069678 .
## CHK_ACCT2          1.1123874  0.5042812   2.206 0.027392 *
## CHK_ACCT3          2.4109175  0.3597629   6.701 2.06e-11 ***
## HISTORY1          -0.6393459  0.8007632  -0.798 0.424626
## HISTORY2           0.3153810  0.6295178   0.501 0.616379
## HISTORY3           0.0245812  0.7411154   0.033 0.973541
## HISTORY4           1.0638624  0.6476870   1.643 0.100475
## NEW_CAR1          -0.7159178  0.3141611  -2.279 0.022678 *
## USED_CAR1          1.3489217  0.5579072   2.418 0.015614 *
## RETRAINING1       -0.8489518  0.4619050  -1.838 0.066072 .
## AMOUNT            -0.0002631  0.0000595  -4.421 9.81e-06 ***
```

```
## SAV_ACCT1           0.5675624  0.4173990   1.360 0.173906
## SAV_ACCT2          -0.0693577  0.5399345  -0.128 0.897788
## SAV_ACCT3           0.5603771  0.6437202   0.871 0.384011
## SAV_ACCT4           1.3592948  0.4069584   3.340 0.000837 ***
## EMPLOYMENT1         0.5542570  0.6967423   0.795 0.426324
## EMPLOYMENT2         1.2338686  0.6524020   1.891 0.058588 .
## EMPLOYMENT3         1.7999683  0.6887566   2.613 0.008966 **
## EMPLOYMENT4         1.5521376  0.6518729   2.381 0.017264 *
## INSTALL_RATE       -0.3278020  0.1249721  -2.623 0.008716 **
## GUARANTOR1          1.6927223  0.6068573   2.789 0.005282 **
## PRESENT_RESIDENT2 -1.1117822  0.4641005  -2.396 0.016595 *
## PRESENT_RESIDENT3 -0.3408387  0.5041109  -0.676 0.498966
## PRESENT_RESIDENT4 -0.7613632  0.4531619  -1.680 0.092935 .
## PROP_UNKN_NONE1   -1.0532655  0.3848454  -2.737 0.006203 **
## AGE                 0.0181856  0.0128738   1.413 0.157769
## OTHER_INSTALL1    -0.6281982  0.3256821  -1.929 0.053747 .
## RENT1             -0.8736712  0.3412119  -2.560 0.010452 *
## TELEPHONE1          0.5251823  0.2863172   1.834 0.066614 .
## FOREIGN1            1.2896516  0.8049248   1.602 0.109111
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 618.29  on 445  degrees of freedom
## Residual deviance: 403.37  on 415  degrees of freedom
## AIC: 465.37
##
## Number of Fisher Scoring iterations: 5
```

The variables that have been removed are : **FURNITURE**, **RADIO.TV**, **EDUCATION**, **RETRAINING**, **MALE_DIV**, **MALE_SINGLE**, **MALE_MAR_or_WID**, **CO.APPLICANT**, **REAL_ESTATE**, **OWN_RES**, **NUM_CREDITS**, **JOB** and **NUM_DEPENDENTS**

In the end, we get the most significant model:

$$RESPONSE = -0.6339113 + 0.5970566 * CHK_{ACCT1} + 1.1123874 * CHK_{ACCT2} + 2.4109175 * CHK_{ACCT3} - 0.6393459 * HIST$$

$$p = (e^{RESPONSE})/(1 + e^{RESPONSE})$$

It means that :

- The predicted probability of being a good applicant for **CHCK_ACCT3** is higher than for **CHK_ACCT0** (and also higher than for **CHK_ACCT1** and **CHK_ACCT2**).
- The predicted probability of being a good applicant for **HISTORY1** is lower than for **HISTORY0**.
- The predicted probability of being a good applicant for **HISTORY4** is higher than for **HISTORY0** (and also higher than for **HISTORY2** and **HISTORY3**).
- The predicted probability of being a good applicant for **NEW_CAR1** is lower than for **NEW_CAR0**.
- The predicted probability of being a good applicant for **USED_CAR1** is higher than for **USED_CAR0**.
- The predicted probability of being a good applicant for **RETRAINING1** is lower than for **RETRAINING0**.
- **AMOUNT** is negatively associated with **RESPONSE**.

- The predicted probability of being a good applicant for **SAV_ACCT4** is higher than for **SAV_ACCT0** (and also higher than for **SAV_ACCT1** and **SAV_ACCT3**).
- The predicted probability of being a good applicant for **SAV_ACCT2** lower than for **SAV_ACCT0**.
- The predicted probability of being a good applicant for **EMPLOYMENT3** is higher than for **Employment0** (and also higher than for **EMPLOYMENT1**, **EMPLOYMENT2** and **EMPLOYMENT4**).
- **INSTALL_RATE** is negatively associated with **RESPONSE**.
- The predicted probability of being a good applicant for **GUARANTOR1** is higher than for **GUARANTOR0**.
- The predicted probability of being a good applicant for **PRESENT_RESIDENT2** is lower than for **PRESENT_RESIDENT0** (and also lower than **PRESENT_RESIDENT3** and **PRESENT_RESIDENT4**).
- The predicted probability of being a good applicant for **PROP_UNKN_NONE1** is lower than for **PROP_UNKN_NONE0**.
- **AGE** is positively associated with **RESPONSE**.
- The predicted probability of being a good applicant for **OTHER_INSTALL1** is lower than for **OTHER_INSTALL0**.
- The predicted probability of being a good applicant for **RENT1** is lower than for **RENT0**.
- The predicted probability of being a good applicant for **TELEPHONE1** is higher than for **TELEPHONE0**.
- The predicted probability of being a good applicant for **FOREIGN1** is higher than for **FOREIGN0**.

```
##           Reference
## Prediction   0   1
##          0  50  52
##          1  27 121
```

```
##          Sensitivity          Specificity       Pos Pred Value
##            0.6493506            0.6994220            0.4901961
##       Neg Pred Value            Precision               Recall
##            0.8175676            0.4901961            0.6493506
##                   F1           Prevalence       Detection Rate
##            0.5586592            0.3080000            0.2000000
## Detection Prevalence    Balanced Accuracy
##            0.4080000            0.6743863
```

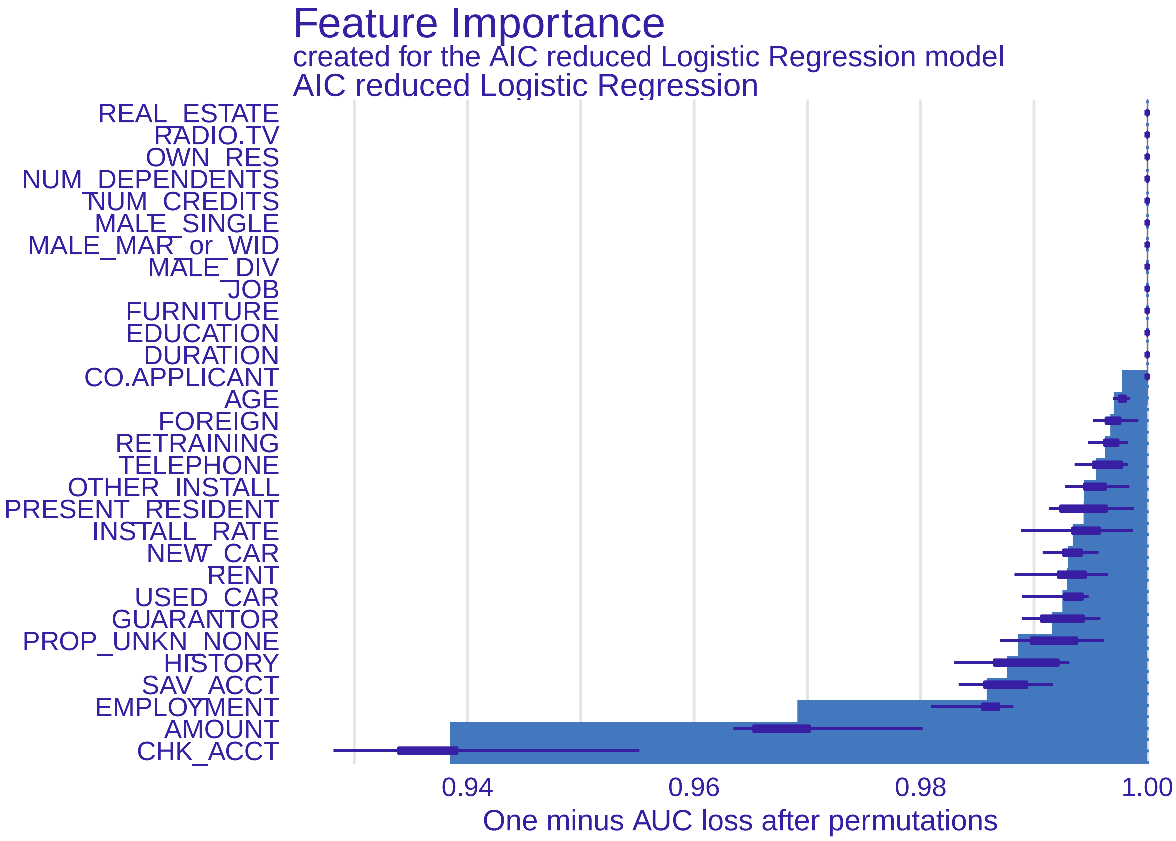
```
x_train <- select(German_Credit.tr.subs, -RESPONSE)
y_train <- pull(German_Credit.tr.subs, RESPONSE)

explainer_logreg <- explain(model = mod.logreg.sel,
                               data = x_train,
                               y = as.numeric(y_train),
                               label = "AIC reduced Logistic Regression")
```

Variable importance for logistic regression

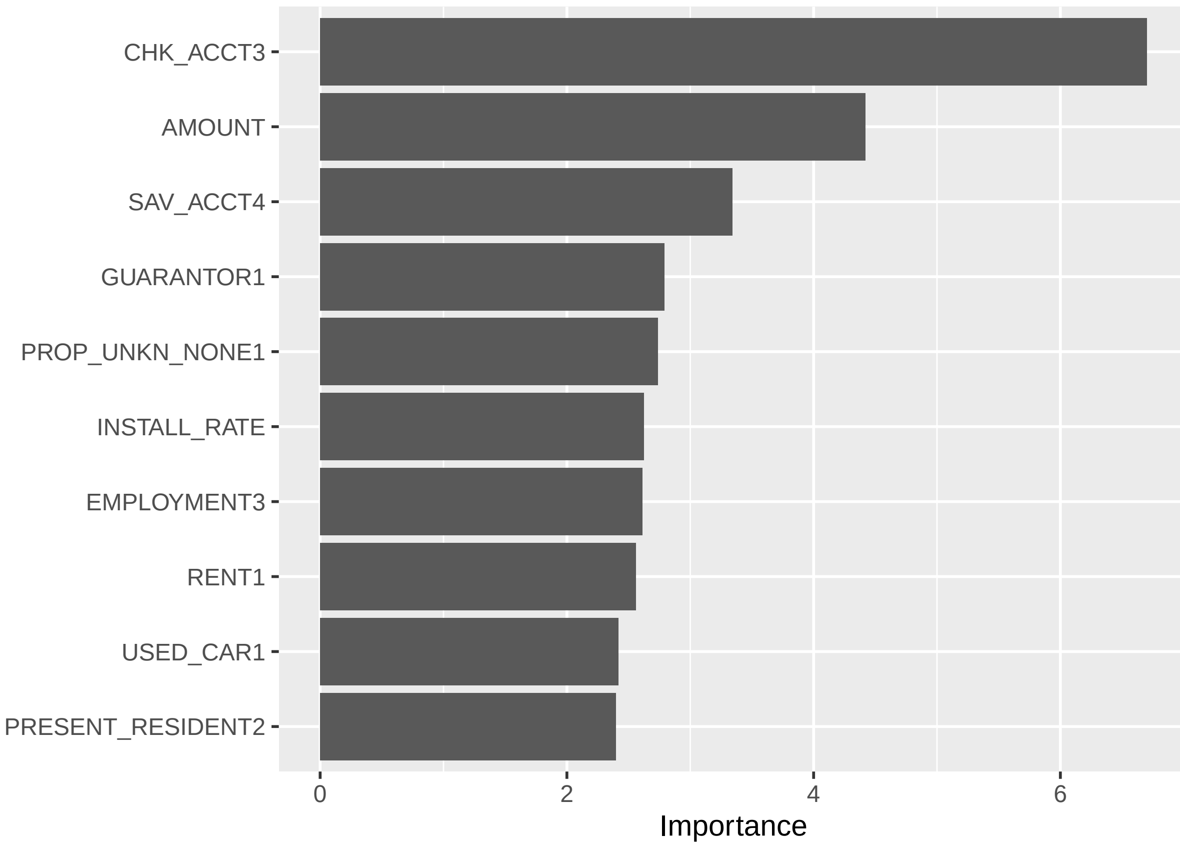
```
## Preparation of a new explainer is initiated
##   -> model label       :  AIC reduced Logistic Regression
##   -> data              :  446  rows  30  cols
##   -> target variable   :  446  values
##   -> predict function  :  yhat.glm  will be used (  default  )
##   -> predicted values  :  No value for predict function target column. (  default  )
##   -> model_info        :  package stats , ver. 4.1.3 , task classification (  default  )
##   -> predicted values  :  numerical, min =  0.007541882 , mean =  0.5 , max =  0.9975191
##   -> residual function :  difference between y and yhat (  default  )
##   -> residuals         :  numerical, min =  0.05702613 , mean =  1 , max =  1.96659
```

```
##   A new explainer has been created!
```

```
importance_logreg  <- calculate_importance(explainer_logreg)
plot(importance_logreg)
```




```
vip(mod.logreg.sel)
```



Listed above are the most important variables for the logarithmic regression we reduced. Here again, the CHK_ACCT variable differentiate itself from the others in term of importance in the model prediction.

3. K-Nearest Neighbor To perform a k-nearest neighbor method, we do not need to balance the data so we will use the unbalanced training set.

We first try to model it using a 2-NN (with Euclidean distance). Note that the model is fitting on the training set and the predictions are computed on the test set.

```
##           Reference
## Prediction   0   1
##          0  21  45
##          1  56 128
```

```
##          Sensitivity          Specificity       Pos Pred Value
##            0.2727273            0.7398844            0.3181818
##       Neg Pred Value            Precision               Recall
##            0.6956522            0.3181818            0.2727273
##                   F1           Prevalence       Detection Rate
##            0.2937063            0.3080000            0.0840000
## Detection Prevalence    Balanced Accuracy
##            0.2640000            0.5063058
```

The table is read as follow :

- We predicted 21 Bad credits and there were indeed 21 observed Bad credits. But the prediction misjudges 45 good credits by predicting bad credits.
- We predicted 128 Good credits as it was in fact a Good credits but 56 where predicted as Good while it was in fact Bad.

The prediction is not perfect. We need to try to improve the prediction by changing K at that point. Therefore, we use K=3.

3.b K-Nearest Neighbor (K=3)

```
##           Reference
## Prediction   0   1
##          0  14  28
##          1  63 145
```

```
##          Sensitivity          Specificity       Pos Pred Value
##            0.1818182            0.8381503            0.3333333
##       Neg Pred Value            Precision               Recall
##            0.6971154            0.3333333            0.1818182
##                   F1           Prevalence       Detection Rate
##            0.2352941            0.3080000            0.0560000
## Detection Prevalence    Balanced Accuracy
##            0.1680000            0.5099842
```

The table is read as follow :

- We predicted 14 Bad credits and they were indeed observed Bad credits. But the prediction misjudges 28 good credits by predicting bad credits.
- We predicted 145 Good credits as it was in fact a Good credits but 6 where predicted as Good while it was in fact Bad.

4. Linear Support Vector Machine The next model is the linear Support Vector Machine.

```
##
## Call:
## svm(formula = RESPONSE ~ ., data = German_Credit.tr.subs, kernel = "linear")
##
##
## Parameters:
##    SVM-Type:  C-classification
##  SVM-Kernel:  linear
##        cost:  1
##
## Number of Support Vectors:  246
```

```
##           Reference
## Prediction   0   1
##          0  50  50
##          1  27 123
```

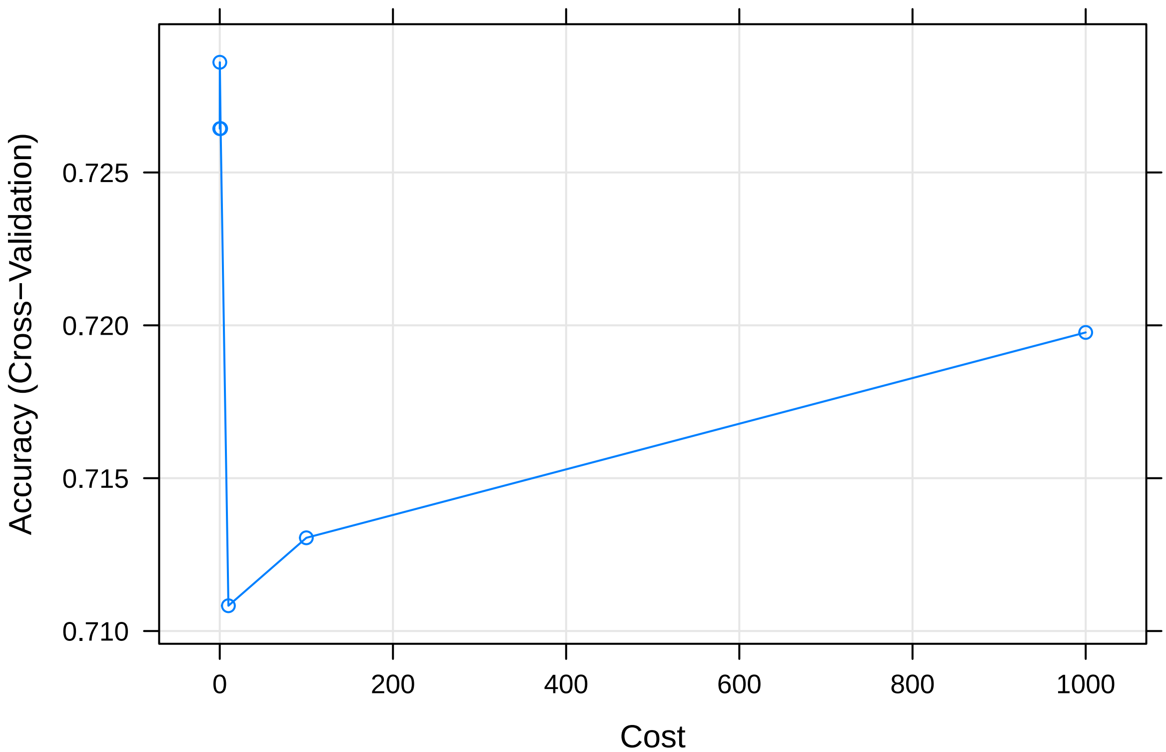
```
##          Sensitivity          Specificity       Pos Pred Value
##            0.6493506            0.7109827            0.5000000
##       Neg Pred Value            Precision               Recall
##            0.8200000            0.5000000            0.6493506
##                   F1           Prevalence       Detection Rate
##            0.5649718            0.3080000            0.2000000
## Detection Prevalence    Balanced Accuracy
##            0.4000000            0.6801667
```

Tunning the hyperparameters of Linear SVM We want to select the good hyperparameters for our linear SVM.

```
## Support Vector Machines with Linear Kernel
##
## 446 samples
##  30 predictor
##   2 classes: '0', '1'
##
## No pre-processing
## Resampling: Cross-Validated (10 fold)
## Summary of sample sizes: 402, 400, 402, 401, 402, 402, ...
## Resampling results:
##
##   Accuracy   Kappa
##   0.7264361  0.4530209
##
## Tuning parameter 'C' was held constant at a value of 1
```

We see that we have a good accuracy (0.72).

```
## Support Vector Machines with Linear Kernel
##
## 446 samples
##  30 predictor
##   2 classes: '0', '1'
##
## No pre-processing
## Resampling: Cross-Validated (10 fold)
## Summary of sample sizes: 402, 400, 402, 401, 402, 402, ...
## Resampling results across tuning parameters:
##
##   C      Accuracy   Kappa
##   1e-02  0.7264339  0.4532044
##   1e-01  0.7286056  0.4575791
##   1e+00  0.7264361  0.4530209
##   1e+01  0.7108278  0.4216992
##   1e+02  0.7130501  0.4261940
##   1e+03  0.7197672  0.4397558
##
## Accuracy was used to select the optimal model using the largest value.
## The final value used for the model was C = 0.1.
```




```
##             Reference
## Prediction   0   1
##            0  49  49
##            1  28 124
```

```
##          Sensitivity          Specificity       Pos Pred Value
##            0.6363636            0.7167630            0.5000000
##       Neg Pred Value            Precision               Recall
##            0.8157895            0.5000000            0.6363636
##                   F1           Prevalence       Detection Rate
##            0.5600000            0.3080000            0.1960000
## Detection Prevalence    Balanced Accuracy
##            0.3920000            0.6765633
```

5. Radial Basis Support Vector Machine We try now with a radial basis kernel (the default).

```
German_credit.rbsvm <- svm(RESPONSE ~ ., data=German_Credit.tr.subs, kernel="radial")
German_credit.rbsvm
```

```
##
## Call:
## svm(formula = RESPONSE ~ ., data = German_Credit.tr.subs, kernel = "radial")
##
##
## Parameters:
##    SVM-Type:  C-classification
##  SVM-Kernel:  radial
##        cost:  1
##
## Number of Support Vectors:  334
```

```r
German_credit.rbsvm.pred <- predict(German_credit.rbsvm,
                                    newdata = German_credit.te)

cm_rbsvm <- confusionMatrix(data=German_credit.rbsvm.pred,
                            reference = German_credit.te$RESPONSE )

cm_rbsvm$table
```

```
##           Reference
## Prediction   0   1
##          0  54  52
##          1  23 121
```

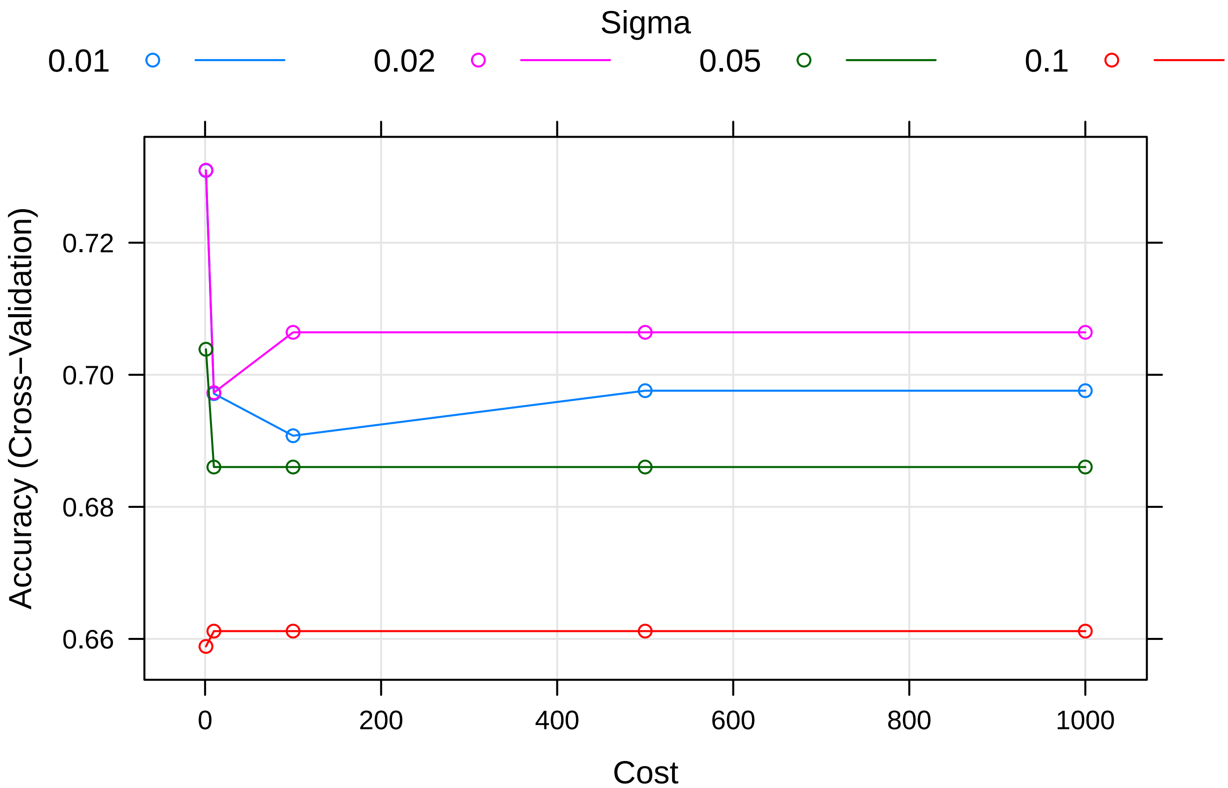
```r
cm_rbsvm$byClass
```

```
##          Sensitivity          Specificity       Pos Pred Value
##            0.7012987            0.6994220            0.5094340
##       Neg Pred Value            Precision               Recall
##            0.8402778            0.5094340            0.7012987
##                   F1           Prevalence       Detection Rate
##            0.5901639            0.3080000            0.2160000
## Detection Prevalence    Balanced Accuracy
##            0.4240000            0.7003603
```

Tunning the hyperparameters of Radial basis SVM

```
## Support Vector Machines with Radial Basis Function Kernel
##
## 446 samples
##  30 predictor
##   2 classes: '0', '1'
##
## No pre-processing
## Resampling: Cross-Validated (10 fold)
## Summary of sample sizes: 402, 400, 402, 401, 402, 402, ...
## Resampling results across tuning parameters:
##
##   sigma  C     Accuracy   Kappa
##   0.01      1  0.7309289  0.4618150
##   0.01     10  0.6971476  0.3942416
##   0.01    100  0.6907708  0.3814209
##   0.01    500  0.6975889  0.3950572
##   0.01   1000  0.6975889  0.3950572
##   0.02      1  0.7309816  0.4620420
##   0.02     10  0.6972925  0.3946754
##   0.02    100  0.7064273  0.4127482
##   0.02    500  0.7064273  0.4127482
##   0.02   1000  0.7064273  0.4127482
##   0.05      1  0.7038647  0.4085756
##   0.05     10  0.6860299  0.3726705
##   0.05    100  0.6860299  0.3726705
##   0.05    500  0.6860299  0.3726705
##   0.05   1000  0.6860299  0.3726705
##   0.10      1  0.6588603  0.3190546
##   0.10     10  0.6611792  0.3234506
```

```
##   0.10    100  0.6611792  0.3234506
##   0.10    500  0.6611792  0.3234506
##   0.10   1000  0.6611792  0.3234506
##
## Accuracy was used to select the optimal model using the largest value.
## The final values used for the model were sigma = 0.02 and C = 1.
```




```
##   sigma C
## 6  0.02 1
```

```
German_credit.rbsvm.tuned <- svm(RESPONSE ~ .,data = German_Credit.tr.subs,
                                 kernel = "radial",
                                 gamma = svm_Radial_Grid$bestTune$sigma,
                                 cost = svm_Radial_Grid$bestTune$C)

German_credit.rbsvm.tuned.pred <- predict(German_credit.rbsvm.tuned,
                                          newdata = German_credit.te)

cm_rbsvm_tuned <- confusionMatrix(data=German_credit.rbsvm.tuned.pred,
                                  reference = German_credit.te$RESPONSE)

cm_rbsvm_tuned$table
```

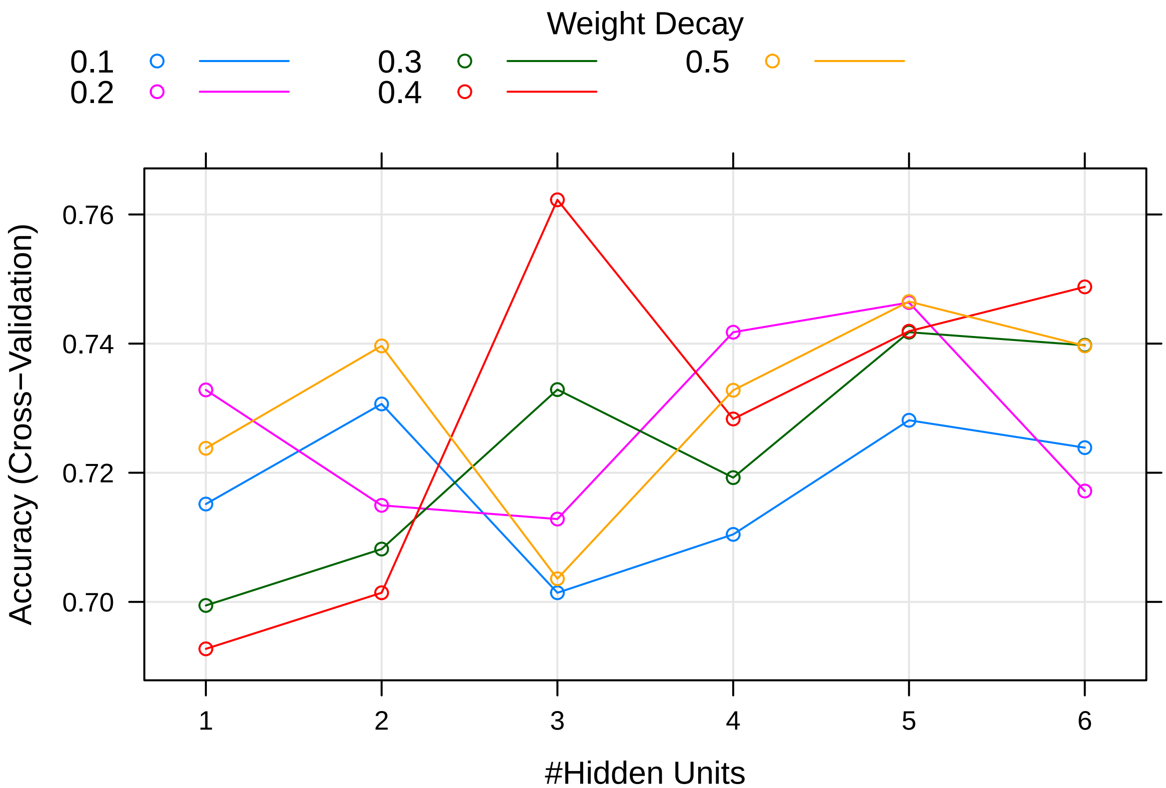
```
##           Reference
## Prediction   0   1
##          0  54  53
##          1  23 120
```

```
cm_rbsvm_tuned$byClass
```

```
##          Sensitivity          Specificity       Pos Pred Value
```

```
##          0.7012987          0.6936416          0.5046729
##     Neg Pred Value          Precision             Recall
##          0.8391608          0.5046729          0.7012987
##                 F1         Prevalence     Detection Rate
##          0.5869565          0.3080000          0.2160000
## Detection Prevalence  Balanced Accuracy
##          0.4280000          0.6974702
```

6. Neural Network - Simple hyperparameter tuning To select the good parameters, we build a search grid and fit the model with each possible value in the grid. This is brute force and time consuming. The best model is selected among all the possible choices.



The best Neural Networks parameters would be to choose 3 hidden layers, with a decay of 0.4.

```
##           Reference
## Prediction   0   1
##          0  52  53
##          1  25 120
```

```
##        Sensitivity        Specificity     Pos Pred Value
##          0.6753247          0.6936416          0.4952381
##     Neg Pred Value          Precision             Recall
##          0.8275862          0.4952381          0.6753247
##                 F1         Prevalence     Detection Rate
##          0.5714286          0.3080000          0.2080000
## Detection Prevalence  Balanced Accuracy
##          0.4200000          0.6844831
```

7. Gradient Boosting The Gradient Boosting model accepts only numerical values so we have some transformation to do on our data in order to use it.

```
## ##### xgb.Booster
## raw: 31.2 Mb
## call:
##   xgb.train(params = xgb_params, data = xgb_train, nrounds = 5000,
##     verbose = 1)
## params (as set within xgb.train):
##   booster = "gbtree", eta = "0.01", max_depth = "8", gamma = "4", subsample = "0.75", colsample_bytre
## xgb.attributes:
##   niter
## callbacks:
##   cb.print.evaluation(period = print_every_n)
## # of features: 46
## niter: 5000
## nfeatures : 46
```

Here we have an accuracy of 68.4%. It is good but there is room for improvement.

```
##           Reference
## Prediction   0   1
##          0  57  59
##          1  20 114
```

```
##          Sensitivity          Specificity       Pos Pred Value
##            0.7402597            0.6589595            0.4913793
##       Neg Pred Value            Precision               Recall
##            0.8507463            0.4913793            0.7402597
##                   F1           Prevalence       Detection Rate
##            0.5906736            0.3080000            0.2280000
## Detection Prevalence    Balanced Accuracy
##            0.4640000            0.6996096
```

Review of statistics

Once all the models were modelized we compared them according to their scores and metrics. Below we summarized all their accuracy into one table.

Table 5: Scores of the models (continued below)

	Big classification tree	Pruned classification tree	Autoprune classification tree	Logistic regression	AIC reduced Logistic regression	Linear support vector machine
Accuracy	0.644	0.564	0.584	0.704	0.684	0.692
Kappa	0.2945	0.2083	0.2251	0.3479	0.32	0.3328
Accuracy lower bound	0.5812	0.5001	0.5202	0.6432	0.6224	0.6307
Accuracy upper bound	0.7033	0.6264	0.6458	0.7599	0.7411	0.7486
Accuracy null	0.692	0.692	0.692	0.692	0.692	0.692
Accuracy P-value	0.9552	1	0.9999	0.369	0.6369	0.5308

	Big classification tree	Pruned classification tree	Autoprune classification tree	Logistic regression	AIC reduced Logistic regression	Linear support vector machine
Mcnemar P-value	1.158e-07	1.822e-14	3.352e-12	0.04813	0.00693	0.01217

	Tuned linear support vector machine	Radial base support vector machine	Tuned radial base support vector machine	Hyperparameter tuned neural network 3 nodes	Gradient Boosting
Accuracy	0.692	0.7	0.696	0.688	0.684
Kappa	0.3283	0.3628	0.3564	0.3352	0.35
Accuracy lower bound	0.6307	0.6391	0.6349	0.6266	0.6224
Accuracy upper bound	0.7486	0.7561	0.7524	0.7449	0.7411
Accuracy null	0.692	0.692	0.692	0.692	0.692
Accuracy P-value	0.5308	0.4219	0.4762	0.5847	0.6369
Mcnemar P-value	0.02265	0.001224	0.0008794	0.002235	1.909e-05

According to these two first tables, the best model would be the "Radial base linear support vector machine" as it has the highest accuracy level of 0.7 and the best kappa value of 0.3628.

The accuracy means that out of total number of observations, the model predicted correctly 70% of them. The Cohen's Kappa Coefficient means that there is 36% of agreement, indicating that the raters agree in their classification for 36% of the cases.

Another table is done to compare the KNN because they were not performed on the balanced dataset.

Table 7: Scores of the KNN models

	2-Nearest neighbor	3-Nearest neighbor
Accuracy	0.596	0.636
Kappa	0.01313	0.02285
AccuracyLower	0.5323	0.573
AccuracyUpper	0.6574	0.6957
AccuracyNull	0.692	0.692
AccuracyPValue	0.9995	0.9752
McnemarPValue	0.3197	0.000365

Overall, we see that the worst model is the 'Autoprune classification tree'. This is understandable because we pruned the model so much that we lost many observations on the way.