Modelling Competition

Regression Models

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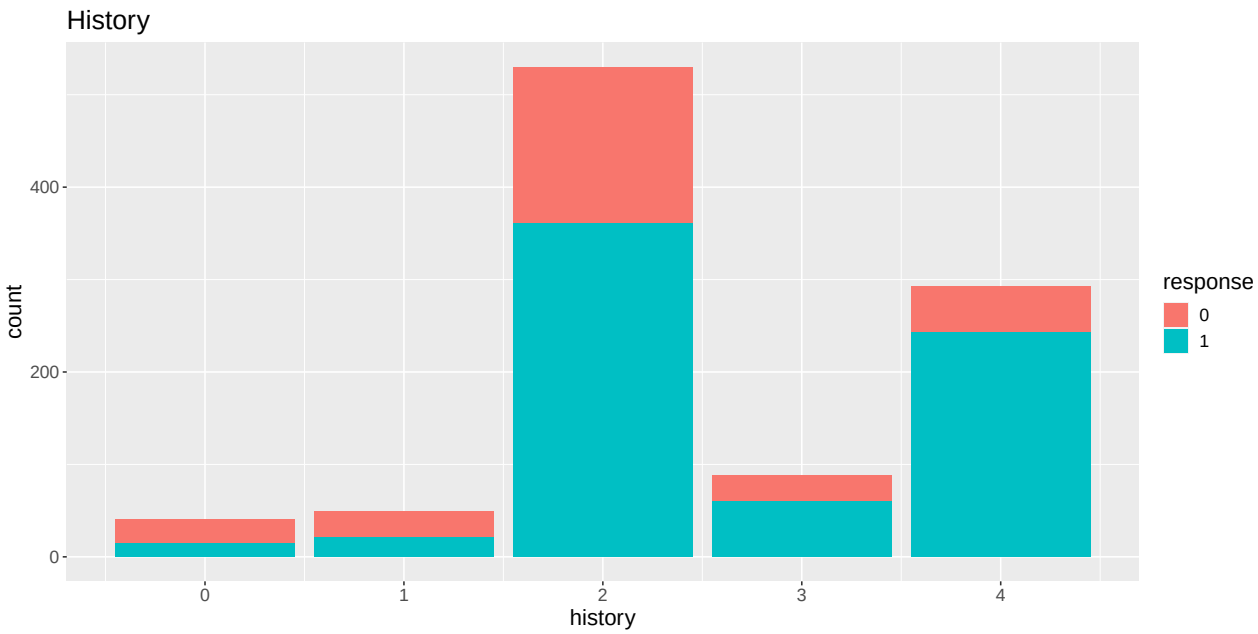
Basic exploratory analysis

Importing and manipulating the data:

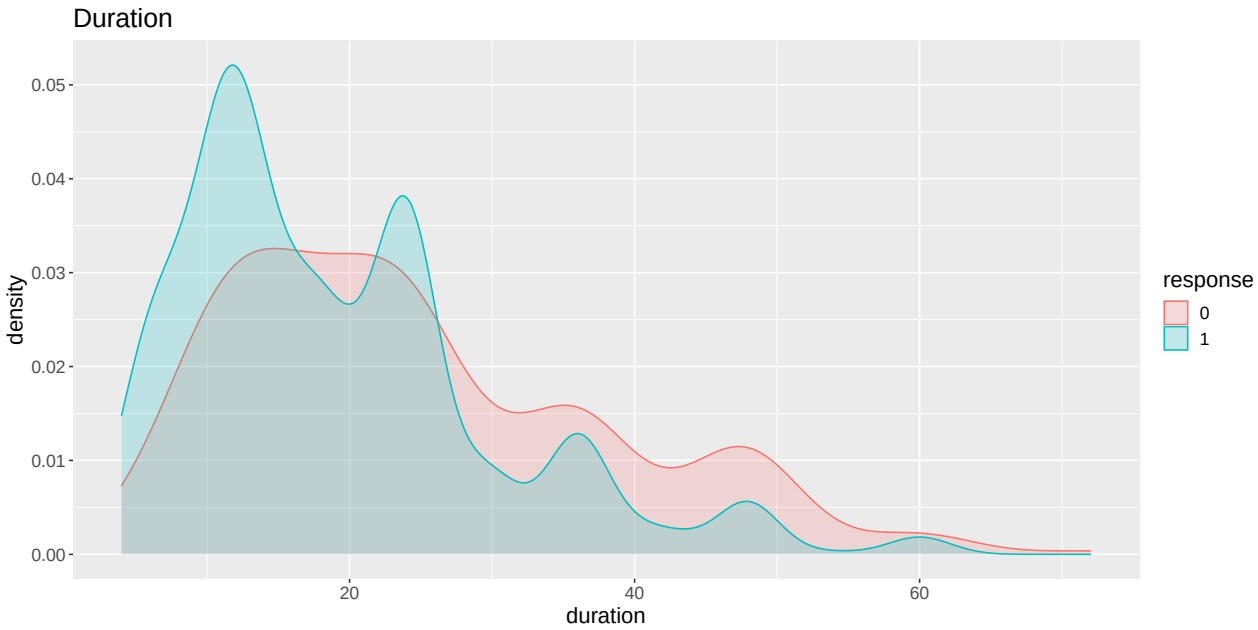
```
# import data
credit <- read.csv('./data/credit.csv')

# change names to lowercase
names(credit) <- tolower(names(credit))

# convert response into a factor
credit$response <- as.factor(credit$response)
```

Visualizing our most important variables



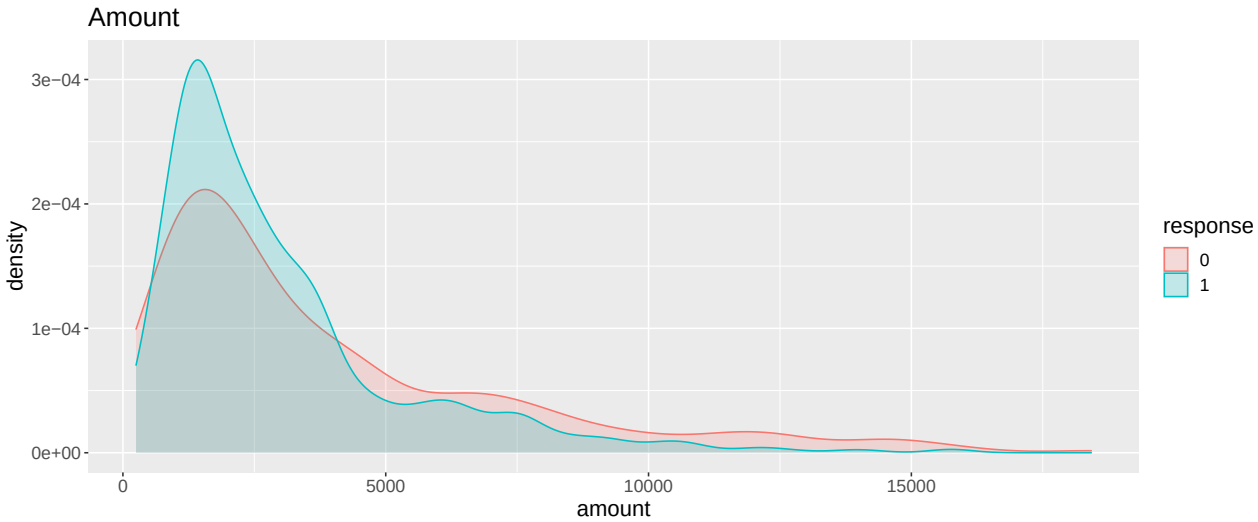
We can see the distribution of clients without good credit is not quite discernible for credit historyWe can see that clients that tend to have good credit history are more likely to have a good credit rating. And we see the higher the amount of credits the client has paid duly, the more likely the client will have good credit rating.

However, delaying paying a past credit doesn't necessarily mean that the client will not have a good credit rating. In fact, the category with the most clients (credit history category 2) has a higher proportion of accounts without good credit rating than the general proportion of clients without good credit rating (30%).



In this plot we can see that clients with good credit rating tend to pay credits sooner on average. Clients without a good credit rating follow a similar trend, where the majority of them will take credits for less time, however, they will also, on average, take longer to pay their credits due.

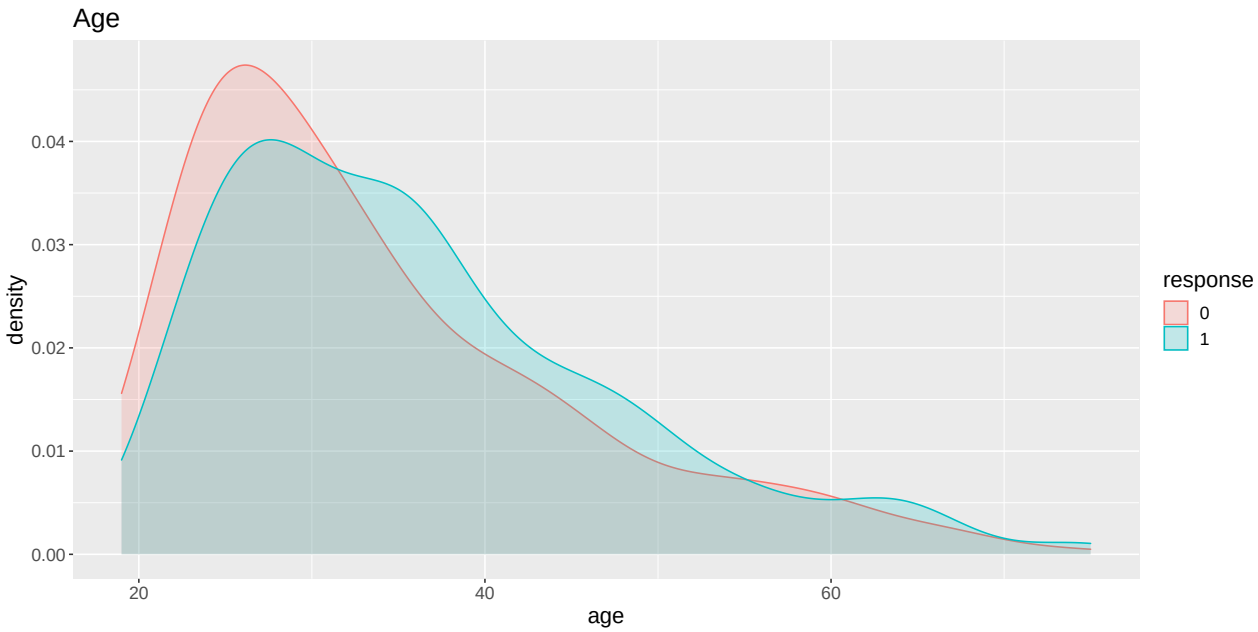
There's about 5 peaks which diminish in size the larger the duration gets, where we see large accumulation of clients which both have and don't have a good credit rating. This highlights that the institution handing out these credits might have fixed timeframes for credit payments which clients are probably offered by default.



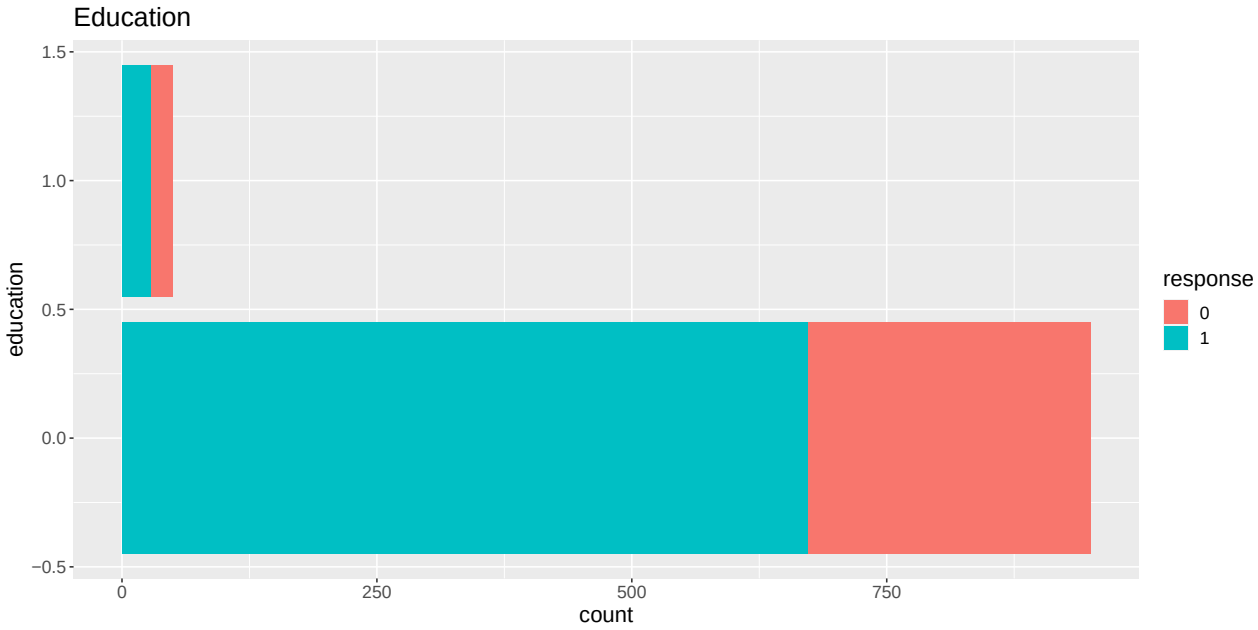
For amounts we notice a trend, where clients with better credit rating also tend to ask for smaller amounts. The plot is strongly right-skewed for both good credit rating rating clients and the opposite.

It seems likely that clients with worse credit rating tend to ask for larger sums which they might, in the future, have more difficulty paying back. Although we might think that the opposite should be true, this ties well with the duration of credits, where clients with worse credit rating tended to ask for longer timeframes to pay their credits due. And it makes sense that larger amounts should take longer to pay (on average).

It also seems likely that a good way to build a good credit rating could be to ask for smaller amounts, which should theoretically be easier to pay.



In the following plot, we can see that the distributions for both groups (clients with and without good credit rating) are very similar, but in general, clients with good credit rating tend to be older than the clients with lesser credit rating. We also notice the plot is significantly right-skewed towards younger ages, perhaps because clients of younger age are incentivized to use financial services and probably might need more credits than those older clients (which tend to have less financial needs as their salaries might be higher).



In the plot we can observe that, for both groups of education level, the proportion of being a good or bad client is very similar.

Testing 1-variable models (with GLM)

We test 1-variable models to assess which variables (by themselves) have the highest predictive power:

Table 1: best models

	vars	accuracy
3	history	0.71375
2	duration	0.70125
10	amount	0.70125
22	age	0.70000
17	co.applicant	0.69625
8	education	0.69500
14	male_div	0.69375
12	employment	0.68875
1	chk_acct	0.68250
21	prop_unkn_none	0.68000

We can see that (individually), the best variables that we obtain are *history*, *duration*, *amount*, *age*, *co.applicant*, *education*, *male_div*, *employment*, *chk_acct* and *prop_unkn_none*.

Logistic regression (generalized linear model)

Basic variable selection

We remove *obs.* given that it's just an index and we remove *real_estate* and *own_res* as they are essentially equivalent to *prop_unkn_none* and *rent*.

We are left with:

```
#>  [1] "chk_acct"         "duration"         "history"          "new_car"
#>  [5] "used_car"         "furniture"        "radio.tv"         "education"
#>  [9] "retraining"       "amount"           "sav_acct"         "employment"
#> [13] "install_rate"     "male_div"         "male_single"      "male_mar_or_wid"
#> [17] "co.applicant"     "guarantor"        "present_resident" "prop_unkn_none"
#> [21] "age"              "other_install"    "rent"             "num_credits"
#> [25] "job"              "num_dependents"   "telephone"        "foreign"
#> [29] "response"
```

Normalizing variables

Given that *amount*, *age* and *duration* are NOT normally distributed, we take their log (we also sum 1 to avoid errors with zeros):

```
credit$amount <- log(credit$amount + 1)
credit$age <- log(credit$age + 1)
credit$duration <- log(credit$duration + 1)
```

Train and test split

We use a randomly selected seed (12) and perform a train and test split with 80% train and 20% test values. We also convert the response variable of each subset of data into a factor.

```
set.seed(12)
spl = caret::createDataPartition(credit$response, p = 0.8, list = FALSE)
Train = credit[spl,]
Test = credit[-spl,]
Train$response <- as.factor(Train$response)
Test$response <- as.factor(Test$response)
```

Functions to aid the modelling and variable selection process

Code for the functions is omitted due to how long they are, to see the code, view Rmd file

Formula creation function

We defined a function to obtain the formula of all models with and without a chosen amount of interactions (2-way, 3-way, etc). The function generates all combinations of variables of a selected size (2 vars, 3 vars, etc) and puts them into a formula neatly, including or excluding their interactions.

Modelling function

We create a function that runs all the models using a chosen dataset, utilizing a list of formulas created by the previously defined function.

Function to testing models with and without interactions

We define a function to perform LRT for models with and without interactions and we check the significance of such interactions. If the p-value displayed in the dataframe is above a certain threshold we deem those interactions less useful.

We also calculate the AIC of each model (with and without interactions) to check if the interaction is not just significant but also improves the model to an extent.

Scoring function

We define a function that will score the models using several different metrics:

- ROC Area under curve (using training set)
- ROC sensitivity
- ROC specificity
- Accuracy from a confusion matrix

Model selection process

Running a model with all the variables

We run a model with all the variables and no interactions, therefore we can roughly see how the model is standing before any significant variable selection.

```
#> Confusion Matrix and Statistics
#>
#>          Reference
#> Prediction   0   1
#>          0  40  24
#>          1  20 116
#>
#>               Accuracy : 0.78
#>                 95% CI : (0.7161, 0.8354)
#>    No Information Rate : 0.7
#>    P-Value [Acc > NIR] : 0.007151
#>
#>                  Kappa : 0.486
#>
#>  Mcnemar's Test P-Value : 0.651077
#>
#>            Sensitivity : 0.6667
#>            Specificity : 0.8286
#>         Pos Pred Value : 0.6250
#>         Neg Pred Value : 0.8529
#>             Prevalence : 0.3000
#>         Detection Rate : 0.2000
#>   Detection Prevalence : 0.3200
#>      Balanced Accuracy : 0.7476
#>
#>       'Positive' Class : 0
#>
```

Using all our variables we reach an accuracy of 0.78, which as a starting point is decent, but this can improve.

Testing models with and without variables to check their significance

Here we perform LRT to check the significance of individual variables. We assess whether the p-value of the test shows significance of each model compared to the one without a specific variable (looping through them):

Table 2: best models

	vars	scores	aic
16	male_mar_or_wid	0.8842872	792.4139
6	furniture	0.8118166	792.4494
19	present_resident	0.5815776	792.6964
9	retraining	0.5454180	792.7583
10	amount	0.5426324	792.7634
17	co.applicant	0.4271850	793.0232
7	radio.tv	0.3475789	793.2750
26	num_dependents	0.3434658	793.2902
8	education	0.2769097	793.5749
25	job	0.2525847	793.7017

This allows us to remove *furniture* and *male_mar_or_wid* which seem to not be signficant given their extremely high p-value, we keep the rest of the variables regardless of their result as they are not as notoriously high as *furniture* and *male_mar_or_wid* and their interactions with other variables might make them useful.

Testing 2-variable models with and without interactions

We create models with all the combinations of 2 variables and then we perform LRT for models with and without interactions between their variables. Then we select models with an LRT p-value under 0.005, in order to keep the most important interactions.

We run the tests:

```
two_var_combs <- test(formulas_with, formulas_without, models_with, models_without)
```

We remove NAs, given that these interactions' product is 0 for all values, the LRT returns a p-value of 1 (meaning there's no difference between the models).

We present the table showing the model formulas and the p-values:

Table 3: best models

	formulas_with	formulas_without	pvals	aic_with	aic_without
212	response~(employment+prop_unkn_none)^2	response~employment+prop_unkn_none	0.0039463	950.6366	956.9450
120	response~(radio.tv+employment)^2	response~radio.tv+employment	0.0034811	956.4306	962.9670
66	response~(history+other_install)^2	response~history+other_install	0.0032266	927.7634	934.4381
33	response~(duration+sav_acct)^2	response~duration+sav_acct	0.0030212	903.7032	910.4979
259	response~(male_single+foreign)^2	response~male_single+foreign	0.0025497	968.1847	975.2893
322	response~(job+foreign)^2	response~job+foreign	0.0008878	969.2991	978.3472
188	response~(amount+telephone)^2	response~amount+telephone	0.0008727	958.6856	967.7654
165	response~(retraining+age)^2	response~retraining+age	0.0007533	967.0877	976.4408
98	response~(used_car+amount)^2	response~used_car+amount	0.0006894	948.6639	958.1815

Testing a model using the best 2-way interactions

We test a model using all the previously ran variables (all the variables in the dataset) but we include the interactions selected as most meaningful:

```
#> Confusion Matrix and Statistics
#>
#>          Reference
#> Prediction   0   1
#>          0  39  19
#>          1  21 121
#>
#>               Accuracy : 0.8
```

```
#>                 95% CI : (0.7378, 0.8531)
#>     No Information Rate : 0.7
#>     P-Value [Acc > NIR] : 0.0009283
#>
#>                  Kappa : 0.5192
#>
#>  Mcnemar's Test P-Value : 0.8743671
#>
#>             Sensitivity : 0.6500
#>             Specificity : 0.8643
#>          Pos Pred Value : 0.6724
#>          Neg Pred Value : 0.8521
#>              Prevalence : 0.3000
#>          Detection Rate : 0.1950
#>    Detection Prevalence : 0.2900
#>       Balanced Accuracy : 0.7571
#>
#>       'Positive' Class : 0
#>
```

Looking at the confusion matrix the model didn't improve much given that we have essentially the same accuracy, but we have higher sensitivity, therefore we continue the process.

Testing 3-variable models with and without interactions

We create models with all the combinations of 3 variables and then we perform LRT for models with and without interactions. Then we select models with an LRT p-value under 0.0005, in order to keep the most important interactions.

We run the tests:

```
three_var_combs <- test(formulas_with, formulas_without, models_with, models_without)
```

We remove NAs, given that these interactions' product is 0 for all values, therefore, the LRT returns a p-value of 1 (meaning there's no difference between the models).

```
three_var_combs <- na.omit(three_var_combs[order(-three_var_combs$pvals),])
best_3_vars <- three_var_combs[three_var_combs$pvals < 0.0005,]
```

We present the table showing the model formulas and the p-values:

Table 4: best models

	formulas_with	formulas_without	pvals	aic_with	aic_without
1132	response~(used_car+amount+num_dependents)^3	response~used_car+amount+num_dependents	0.0004517	947.8746	960.0953
1300	response~(radio.tv+retraining+age)^3	response~radio.tv+retraining+age	0.0003828	955.7608	967.4969
1133	response~(used_car+amount+telephone)^3	response~used_car+amount+telephone	0.0002417	942.4771	956.0685
141	response~(chk_acct+retraining+other_install)^3	response~chk_acct+retraining+other_install	0.0002268	871.4970	885.2273
1082	response~(used_car+education+amount)^3	response~used_car+education+amount	0.0002112	943.4790	956.4047
745	response~(history+male_div+other_install)^3	response~history+male_div+other_install	0.0001857	918.7066	932.8728
439	response~(duration+amount+telephone)^3	response~duration+amount+telephone	0.0000153	920.9474	940.5122

We also see that, as with 2-variable interactions, the fact that an interaction is meaningful also improves the AIC of a model.

Testing a model using the best 3-way and 2-way interactions

We also use all the variables as we did previously, however, we include the interactions selected:

```
#> Confusion Matrix and Statistics
#>
#>          Reference
#> Prediction   0   1
#>          0  38  16
#>          1  22 124
#>
#>                Accuracy : 0.81
#>                  95% CI : (0.7487, 0.8619)
#>     No Information Rate : 0.7
#>     P-Value [Acc > NIR] : 0.0002813
#>
#>                   Kappa : 0.5343
#>
#>  Mcnemar's Test P-Value : 0.4173042
#>
#>             Sensitivity : 0.6333
```

```
#>            Specificity : 0.8857
#>         Pos Pred Value : 0.7037
#>         Neg Pred Value : 0.8493
#>             Prevalence : 0.3000
#>         Detection Rate : 0.1900
#>   Detection Prevalence : 0.2700
#>      Balanced Accuracy : 0.7595
#>
#>       'Positive' Class : 0
#>
```

We see the model improves its accuracy by about 1%, this is an acceptable increase, however, we can keep trying to improve it.

We remove the variables *radio.tv:retraining:age* and *used_car:amount:education* given that they have NA coefficients:

```
#> Confusion Matrix and Statistics
#>
#>          Reference
#> Prediction   0   1
#>          0  40  17
#>          1  20 123
#>
#>                Accuracy : 0.815
#>                  95% CI : (0.7541, 0.8663)
#>     No Information Rate : 0.7
#>     P-Value [Acc > NIR] : 0.0001479
#>
#>                   Kappa : 0.5531
#>
#>  Mcnemar's Test P-Value : 0.7423084
#>
#>            Sensitivity : 0.6667
#>            Specificity : 0.8786
#>         Pos Pred Value : 0.7018
#>         Neg Pred Value : 0.8601
#>             Prevalence : 0.3000
#>         Detection Rate : 0.2000
#>   Detection Prevalence : 0.2850
#>      Balanced Accuracy : 0.7726
#>
#>       'Positive' Class : 0
#>
```

We see our accuracy has increased to about 81.5% after optimizing using stepAIC and removing the variables that have a very high standard error (*used_car:education:amount*, *radio.tv:retraining:age*, *foreign*, *male_single:foreign*, *job:foreign*)

The final model we have chosen for our GLM model section is the model that uses the following formula:

response ~ used_car + radio.tv + chk_acct + history + duration + new_car + retraining + amount + sav_acct + employment + guarantor + prop_unkn_none + age + other_install + rent + telephone + employment:prop_unkn_none + radio.tv:employment + history:other_install + duration:sav_acct + amount:telephone + retraining:age + used_car:amount + chk_acct:retraining:other_install + duration:amount:telephone

Summary of our final GLM

1. Duration: As the exponential of the coeffient for the variable is less than 1, it means that the higher the value of the duration, the higher the probability of being a bad client.
2. History: As the coefficient for the variable history is positive, we can see the odds ratio will be greater than 1. Which means that the more the value of history, the higher the probability of being a good client.
3. Age: The coefficient is positive, so the odds ratio will be greater than 1, which means that the older the client is, the better the client is, and that corresponds to our exploratory analysis.

Generalized additive model penalized splines

We import and manipulate the data, create dummy variables for the categorical variables and we perform a train-test split for 80% train and 20% test.

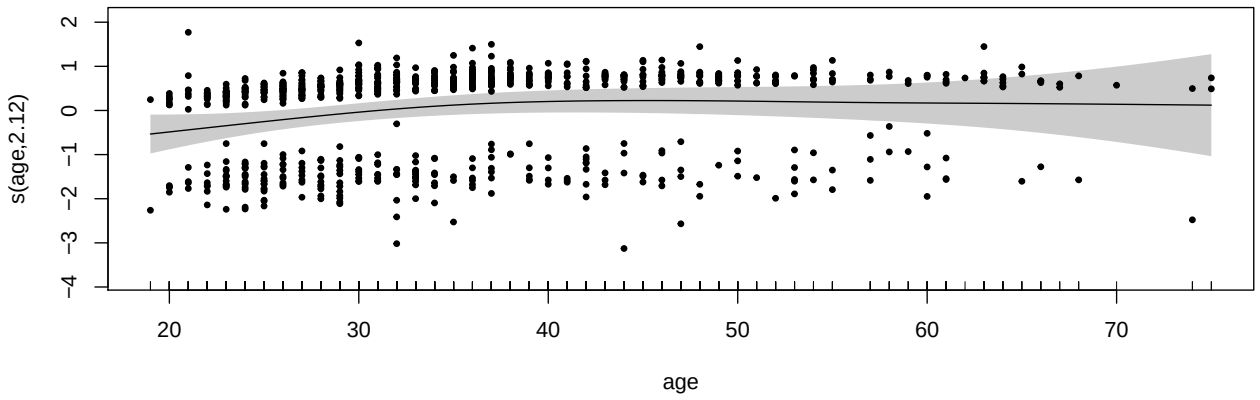
In this part of the work, we will use a generalized additive model (with penalized splines) in order to estimate, and predict a classification for the costumers of the bank. We believe this is a good idea, as by doing this we

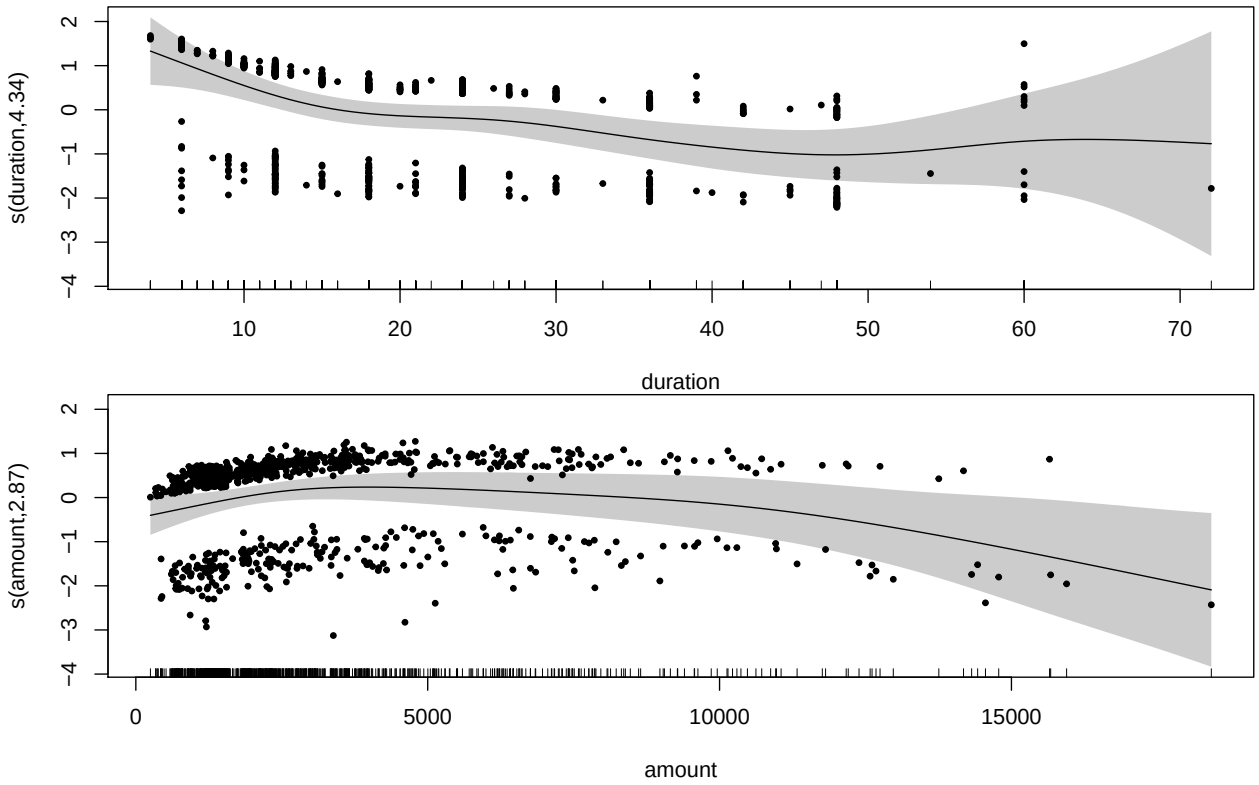
can relaxate the linearity assumption between the response variable and some of our predictors. We first started by fitting a gam model with only three variables (the three continuous) and checked different criteria. As most of our categories are categorical, we first explore a model with the continuous one to check their relevance in the model.

In general, our procedure is based on the following criteria. First, we check the coefficients estimation in the model and see if it is significant (and to what level of confidence it is).

Then we start adding variables and interactions and compare the following: Akaike value (we keep the one with a lower value of akaike, as it penalazes by degrees of freedom), we plot a ROC curve and check the AUC (that is the predictive power that our model has, and we keep on working with the model that has a higher level of AUC: that is, the ROC is closer to the sides of the square of area equal to 1), we build a confusion matrix with both training and testing set and check how many of each of the errors our model produces when predicting and what percentage of errors taking into account all the predictions, and finally we test it with Anova (LRT), using a Chisq test to see if the extra term is significant or we can omit it. We also check the explained deviance of each model. When evaluating the change in all this criteria, we decide if we continue trying with the same model or change it for another one a bit more complex. And so on.

```
fit_gam=logit1 <- gam(response~s(age)+s(duration)+s(amount),family=binomial,select=TRUE,data=creditTrain)
summary(fit_gam)
#>
#> Family: binomial
#> Link function: logit
#>
#> Formula:
#> response ~ s(age) + s(duration) + s(amount)
#>
#> Parametric coefficients:
#>             Estimate Std. Error z value Pr(>|z|)
#> (Intercept)  0.90748    0.08175    11.1   <2e-16 ***
#> ---
#> Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#>
#> Approximate significance of smooth terms:
#>               edf Ref.df Chi.sq  p-value
#> s(age)      2.122      9  8.244   0.0112 *
#> s(duration) 4.342      9 27.488 3.65e-07 ***
#> s(amount)   2.867      9  8.376   0.0219 *
#> ---
#> Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#>
#> R-sq.(adj) =  0.0671   Deviance explained = 6.49%
#> UBRE = 0.16826  Scale est. = 1         n = 800
plot(fit_gam,shade=TRUE,seWithMean=TRUE,pch=19,1,cex=0.55)
```





By looking at the first model, we can tell the both "duration" and "amount" have very small p-values and thus, are significant to a 99,9% confidence level. The three of them do not seem to be linear. We can see very well in the plots that the dots are creating two very differentiate groups. Nevertheless, our three continuous variable model is not being able to capture this effect. We obviously have to check interactions between some continuous variable and some categorical. To do so, we will study the relevance of our categorical variables in a model, and asses each of their relevance to then study possible interactions. This way, our model starts becoming more complex, but also much more accurate.

Second, we run a model with all the variables of the dataset. In the results, we see that variable "age" becomes an irrelevant variable (even when using psplines and hiperparameter tuning for "K"), and subsesive analysis confirms that we can take it out from our models. After losing this variable and using hiperparameter tuning in the other two non linear predictors, we check the categorical variables and we got rid of some more variables that are not useful to explain the credit response. We use only the p-values in order to have a broad or provisional understanding of the variables we for sure want to have in the model. This does not mean (by ane means) that we will forget about the other variables, as we will check their inclusion later on the assigment.

```
fit_gam2<- gam(response~education+chk_acct+history+new_car+used_car+furniture+radio.tv+
               retraining+sav_acct+employment+install_rate+male_div+male_single+male_mar_or_wid+
               co.applicant+guarantor+present_resident+real_estate+prop_unkn_none+other_install+
               rent+own_res+job+num_credits+job+num_dependents+telephone+foreign+s(duration,k=40,bs="ps")+
               s(amount,k=40,bs="ps"),family=binomial,select=TRUE,data=creditTrain)
summary(fit_gam2)
#>
#> Family: binomial
#> Link function: logit
#>
#> Formula:
#> response ~ education + chk_acct + history + new_car + used_car +
#>     furniture + radio.tv + retraining + sav_acct + employment +
#>     install_rate + male_div + male_single + male_mar_or_wid +
#>     co.applicant + guarantor + present_resident + real_estate +
#>     prop_unkn_none + other_install + rent + own_res + job + num_credits +
#>     job + num_dependents + telephone + foreign + s(duration,
#>     k = 40, bs = "ps") + s(amount, k = 40, bs = "ps")
#>
#> Parametric coefficients:
#>                 Estimate Std. Error z value Pr(>|z|)
#> (Intercept)      1.64714    1.19154   1.382 0.166862
#> education1      -0.68195    0.60626  -1.125 0.260656
#> chk_acct1        0.28471    0.25461   1.118 0.263474
#> chk_acct2        0.47130    0.43305   1.088 0.276452
#> chk_acct3        1.74082    0.27663   6.293 3.12e-10 ***
```

```
#> history1          -0.33983    0.66826  -0.509 0.611080
#> history2           0.76789    0.53731   1.429 0.152965
#> history3           1.28754    0.57301   2.247 0.024642 *
#> history4           1.62655    0.53131   3.061 0.002203 **
#> new_car1          -0.47686    0.49122  -0.971 0.331671
#> used_car1          1.43811    0.66237   2.171 0.029919 *
#> furniture1         0.05149    0.52367   0.098 0.921670
#> radio.tv1          0.47016    0.50031   0.940 0.347359
#> retraining1        0.33692    0.56871   0.592 0.553565
#> sav_acct1          0.47283    0.34039   1.389 0.164805
#> sav_acct2          0.99946    0.52944   1.888 0.059057 .
#> sav_acct3          0.82108    0.56378   1.456 0.145291
#> sav_acct4          1.16871    0.32715   3.572 0.000354 ***
#> employment1        0.57958    0.54624   1.061 0.288679
#> employment2        0.68805    0.52990   1.298 0.194132
#> employment3        1.42912    0.56740   2.519 0.011779 *
#> employment4        0.83442    0.52146   1.600 0.109561
#> install_rate2     -0.40445    0.38168  -1.060 0.289292
#> install_rate3     -0.32736    0.42797  -0.765 0.444324
#> install_rate4     -0.78248    0.37256  -2.100 0.035706 *
#> male_div1         -0.49566    0.43873  -1.130 0.258575
#> male_single1       0.45562    0.25363   1.796 0.072429 .
#> male_mar_or_wid1   0.15989    0.37560   0.426 0.670332
#> co.applicant1     -0.66958    0.47702  -1.404 0.160417
#> guarantor1         0.90139    0.48606   1.854 0.063669 .
#> present_resident2 -1.02774    0.36757  -2.796 0.005174 **
#> present_resident3 -0.57658    0.40248  -1.433 0.151987
#> present_resident4 -0.56338    0.35882  -1.570 0.116396
#> real_estate1       0.13709    0.25104   0.546 0.585019
#> prop_unkn_none1   -0.89560    0.48964  -1.829 0.067384 .
#> other_install1    -0.58277    0.25477  -2.287 0.022169 *
#> rent1             -1.35945    0.58733  -2.315 0.020634 *
#> own_res1          -0.69371    0.56218  -1.234 0.217216
#> job1              -1.56745    0.88462  -1.772 0.076413 .
#> job2              -1.65623    0.86530  -1.914 0.055612 .
#> job3              -1.55480    0.87091  -1.785 0.074220 .
#> num_credits2      -0.29339    0.28760  -1.020 0.307671
#> num_credits3      -0.88634    0.65877  -1.345 0.178484
#> num_credits4      -0.28006    1.36178  -0.206 0.837058
#> num_dependents2   -0.29929    0.29617  -1.011 0.312230
#> telephone1         0.40395    0.23903   1.690 0.091036 .
#> foreign1           1.12861    0.70839   1.593 0.111117
#> ---
#> Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#>
#> Approximate significance of smooth terms:
#>               edf Ref.df Chi.sq p-value
#> s(duration)  1.172     29  20.12 5.6e-06 ***
#> s(amount)   26.280     35  40.78  0.0286 *
#> ---
#> Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#>
#> R-sq.(adj) =  0.313   Deviance explained = 32.3%
#> UBRE = 0.012836  Scale est. = 1         n = 800
plot(fit_gam2,shade=TRUE,seWithMean=TRUE,pch=19,1,cex=0.55)
```

We took out the following variables to start trying models: *education*, *used_car*, *furniture*, *radio.tv*, *retraining*, *employment*, *male_div*, *male_mar_or_wid*, *job*, *num_credits*, *num_dependents*, *telephone* and *foreign*.

Now, we can see that there are some varibles that contain some factors that are of special interest in our analysis, while there are others that don´t seem to give us a lot of information. In these cases, we produced dummy variables, transforming catgorical (ordinal) variables into binary ones for each of the levels.For example: the variable "history" accounts for the credit history ("0" for not having taken any credits before, "1" for having paid all credit duly at the bank, "2" for existing credits paid duly till now, "3" for having had a delay in the payback in the past and "4" account for a critical account). There seems to be no significance for the level 1 of the categorical variable, but it is very important to know if the account is critical or not (level 4). In order to capture this effect and make right use of the provided information, we produce a binary variable for each level (for example, a variable will take value "0" if it is not a critical account and "1" if it is a critical account), and so on. Then we test for significance.

After doing this, we try and fit a model only with the levels that looked significant. Once this is done, we start trying interactions, first between continuous variables. When doing this, we see that the interaction between amount and duration is very significant, but we adjust the k parameter to (10,7) because taking a higher k we only slow down the process (increase the computational cost) but our model does not fir better. We take this model as a benchmark. We get with it 24.6% explained deviance, and Akaike value equal to 661.49. When predicting, our Area under the Curve (in the ROC curve) is 0.8104762 and when building our own confusion matrix, we see that 77% of the predictions are right, while 23% are wrong classifications. Please note, that we find in each case, the optimal threshold that optimizes our confusion matrix. As our anove function tells us that an extra interaction is significant (comparing a reduced and full model) then we keep the interaction.

So, from now on, we do this analysis every time: comparing every criteria, and only of they coincide we keep the new term or do not do it. In case the criteria does not tell us a unique answer (for example, with an extra

interaction the prediction gets more accuracy but the AIC gets bigger), we discuss and take into account the meaning of the variables we are treating. And then decide as a team if we keep it, or not.

In order to improve this model (always optimizing the parameters), we start adding interactions between our most significant categorical variables and our continuous variables. In other words, we start checking how our model behaves when we add an interaction between "amount" and "prop_unkn_noun" (meaning that the applicant owns no property). And we do this with all the combinations, until we find the one that best fits our data. Then, we also try adding interactions between categorical variables (first the ones that seem to be very significant to explain our estimation) and then the ones that have a higher p-value.

Once we compared each model doing that, we give another step and start trying with other interactions between categorical variables. To do this, we used the interactions that were more significant in the logistic regression analysis. In other words, we took the interactions that looked significant or interesting in the linear model, and brought them to this gam model to check if they were relevant here too.

At some point, there are some variables we are not including that call our attention. For example, the test told us that the variable "employment" is not significant in any model. As we consider that it should be relevant the current employability situation of the credit consumer, we try and include it as a dummy variable: employed or unemployed. Even when doing this, this variable seems not to be relevant in our estimation.

When we conclude doing all this process, we finally get to two models with gam. One is fit_gam22 and another one called fit_gam27. Let´s discuse the different criteria to chose between one of them. The difference between these two models, is an interaction (that fit_gam27 has and the other one does not have) between "amount" and "history".

```
fit_gam22= gam(response~new_car+used_car+install_rate+foreign+telephone+radio.tv+other_install:history_4+
               guarantor:history_4+ rent+other_install+prop_unkn_none+present_resident_2+guarantor+
               co.applicant+male_single+sav_acct_1+sav_acct_3+sav_acct_4+used_car+history_4+chk_acct_2+
               chk_acct_3+prop_unkn_none:chk_acct_3+prop_unkn_none:history_4+education:own_res+
               co.applicant:chk_acct+ s(duration,k=40,bs="ps",by=rent)+s(amount,k=40,bs="ps",by=used_car)+
               s(amount,k=40,bs="ps",by=telephone) +s(amount,k=40,bs="ps",by=prop_unkn_none)+
               te(amount,age,k=c(10,10),bs=c("ps","ps"),m=2)+te(amount,duration,k=c(10,7),bs=c("ps","ps"),m=2),
               family=binomial,select=TRUE,data=creditTrain)
summary(fit_gam22)
plot(fit_gam22,shade=TRUE,seWithMean=TRUE,pch=19,1,cex=0.55)

fit_gam27= gam(response~new_car+used_car+install_rate+foreign+telephone+radio.tv+other_install:history_4+
               guarantor:history_4+ rent+other_install+prop_unkn_none+present_resident_2+guarantor+
               co.applicant+male_single+sav_acct_1+sav_acct_3+sav_acct_4+used_car+history_4+chk_acct_2+
               chk_acct_3+prop_unkn_none:chk_acct_3+prop_unkn_none:history_4+education:own_res+
               s(amount,k=40,bs="ps",by=history)+co.applicant:chk_acct+s(duration,k=40,bs="ps",by=rent)+
               s(amount,k=40,bs="ps",by=used_car)+s(amount,k=40,bs="ps",by=telephone)+
               s(amount,k=40,bs="ps",by=prop_unkn_none)+te(amount,age,k=c(10,10),bs=c("ps","ps"),m=2)+
               te(amount,duration,k=c(10,7),bs=c("ps","ps"),m=2),family=binomial,select=TRUE,data=creditTrain)
summary(fit_gam27)
plot(fit_gam27,shade=TRUE,seWithMean=TRUE,pch=19,1,cex=0.55)
```

First, we check with the anova function, and we see that the interaction present in fit_gam27 is significant at a confidence level of 99,9%.

```
#> Analysis of Deviance Table
#>
#> Model 1: response ~ new_car + used_car + install_rate + foreign + telephone +
#>     radio.tv + other_install:history_4 + guarantor:history_4 +
#>     rent + other_install + prop_unkn_none + present_resident_2 +
#>     guarantor + co.applicant + male_single + sav_acct_1 + sav_acct_3 +
#>     sav_acct_4 + used_car + history_4 + chk_acct_2 + chk_acct_3 +
#>     prop_unkn_none:chk_acct_3 + prop_unkn_none:history_4 + education:own_res +
#>     co.applicant:chk_acct + s(duration, k = 40, bs = "ps", by = rent) +
#>     s(amount, k = 40, bs = "ps", by = used_car) + s(amount, k = 40,
#>     bs = "ps", by = telephone) + s(amount, k = 40, bs = "ps",
#>     by = prop_unkn_none) + te(amount, age, k = c(10, 10), bs = c("ps",
#>     "ps"), m = 2) + te(amount, duration, k = c(10, 7), bs = c("ps",
#>     "ps"), m = 2)
#> Model 2: response ~ new_car + used_car + install_rate + foreign + telephone +
#>     radio.tv + other_install:history_4 + guarantor:history_4 +
#>     rent + other_install + prop_unkn_none + present_resident_2 +
#>     guarantor + co.applicant + male_single + sav_acct_1 + sav_acct_3 +
#>     sav_acct_4 + used_car + history_4 + chk_acct_2 + chk_acct_3 +
#>     prop_unkn_none:chk_acct_3 + prop_unkn_none:history_4 + education:own_res +
#>     s(amount, k = 40, bs = "ps", by = history) + co.applicant:chk_acct +
#>     s(duration, k = 40, bs = "ps", by = rent) + s(amount, k = 40,
#>     bs = "ps", by = used_car) + s(amount, k = 40, bs = "ps",
#>     by = telephone) + s(amount, k = 40, bs = "ps", by = prop_unkn_none) +
#>     te(amount, age, k = c(10, 10), bs = c("ps", "ps"), m = 2) +
#>     te(amount, duration, k = c(10, 7), bs = c("ps", "ps"), m = 2)
#>   Resid. Df Resid. Dev     Df Deviance  Pr(>Chi)
#> 1    693.44     571.30
#> 2    664.26     491.51 29.188    79.79 1.376e-06 ***
#> ---
#> Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Second, let´s check both Akaike values.

```
#> [1] 765.4875
#> [1] 742.5635
```

As we can see our fit_gam27 has a lower AIC value, which makes it more attractive.

Now, let´s check our ROC curve and the AUC. This is to determine the accuracy of predictions. We will do this, both in our training and testing set.

First, let´s check the ROC for our fit_gam22 (first training set and then in the testing set).

As we can see, our fit_gam22 has an AUC of 0.91 when predicting on our training set, and then an AUC of 0.804 when predicting in our testing set. Let´s now, check these measures for the fit_gam27.

```
#>            [,1]
#> 0 vs. 1 0.9280729
#>            [,1]
#> 0 vs. 1 0.8281548
```

As we can see, the AUC for fit_gam27 when prediciting over the training set is equal to 0.923, and a more realistic AUC of 0.83 when prediciting over the testing set. Between both models, our fit_gam27 has more accuracy power than fit_gam22.

Let´s now build four confusion matrixes for both training and testing set, and fit_gam22 and fit_gam27. With this, we can see the distribution of our errors, not only the error rate.

First, for fit_gam22:

```
#>
#>          0   1
#>   FALSE 153  40
#>   TRUE   87 520
#> [1] 84.125
#> [1] 15.875
#> [1] 0.9285714
#> [1] 0.6375
#>
#>          0   1
#>   FALSE  34  14
#>   TRUE   26 126
#> [1] 80
#> [1] 20
#> [1] 0.9
#> [1] 0.5666667
```

Now, for our fit_gam27:

```
#>
#>          0   1
#>   FALSE 177  38
#>   TRUE   63 522
#> [1] 87.375
#> [1] 12.625
#> [1] 0.9321429
#> [1] 0.7375
#>
#>          0   1
#>   FALSE  36  14
#>   TRUE   24 126
#> [1] 81
#> [1] 19
#> [1] 0.9
#> [1] 0.6
```

As we can see, when predicting over the training set, our fit_gam27 predicts right almost 86.5% of times (either good or bad credit score). In other words, it predicts making mistakes almost 13,5% of the costumers. In this model, our sensitivity is 0.926 and specificity is 0.717. While, our fit_gam22 predicts well almost 85.5% of the cases (that is makes mistakes in predictions almost 14.5% of the cases). Here, our sensitivity is 0.92 and specificity is 0.7.

When looking at the testing set, we get that our fit_gam22 predicts right on 83% of times (while makes mistakes on 17% of the costumers). Its sensitivity is 0.92 and specificity 0.6. In our fit_gam27 we predict 81% of the cases right (19% making mistakes). Our sensitivity is 0.89 and specificity is at 0.62.

All in all, taking into account every consideration, we will use our fit_gam27 to do predict if a future costumer will be good or bad costumer.

Variable Importance

```
#>               new_car              used_car          install_rate
#>           0.000000000          0.000000000         -0.869685455
#>               foreign              telephone              radio.tv
```

```
#>              0.000000000              -0.058026206              0.645424268
#>                     rent             other_install            prop_unkn_none
#>              0.000000000               0.000000000               0.000000000
#>       present_resident_2                 guarantor               co.applicant
#>              0.000000000               0.000000000               0.000000000
#>              male_single                sav_acct_1                sav_acct_3
#>              0.448490129               0.000000000               0.000000000
#>               sav_acct_4                 history_4                 chk_acct_2
#>              1.500239160               1.413031593               0.000000000
#>               chk_acct_3   other_install:history_4      guarantor:history_4
#>              0.000000000               0.000000000               0.000000000
#> prop_unkn_none:chk_acct_3  prop_unkn_none:history_4        education:own_res
#>              0.000000000               0.000000000               1.028640586
#>     co.applicant:chk_acct       s(amount):history0       s(amount):history1
#>              0.000000000               0.000000000               0.000000000
#>       s(amount):history2       s(amount):history3       s(amount):history4
#>              0.000000000               0.000000000               0.306138128
#>        s(duration):rent0        s(duration):rent1      s(amount):used_car0
#>              1.039874201               0.000000000              -0.005261844
#>      s(amount):used_car1     s(amount):telephone0     s(amount):telephone1
#>              0.000000000               0.000000000               1.173471547
#> s(amount):prop_unkn_none0 s(amount):prop_unkn_none1           te(amount,age)
#>             -0.211918974               0.000000000               1.508488928
#>      te(amount,duration)
#>             -0.729349159
```

In order to asses what are the most relevant variables in our model, we will predict 20 points from our testing set, and check the influence af all the terms in each prediction. This way, we can see to what extent each variable contributes to predict a new costumer (either good or bad). We do this in terms of probabilities, so if a variable adds 0.5 of probability toa prediction, it means it does not really add any useful information to that point of prediction. In general, we can see that there are some variables that always (or almost always) take different values to 0.5 in the predictions. This way, we can say that the most important variables in our model to predict whether a costumer will be good or bad, will be: inst_rate (accounts for the % of disposable income), male_single, sav_acct (accounts for the average balance in savings account), duration (duration of the credit in months) and amount (amount of the credit).

Others, that are important, but not as important as the ones previously mentiones are: radio.tv (if the credit is destined to buying a tv or a radio), telephone (the purpose of the credit is to buy a phone), new_car (if the costumer wants to use the credit for a new car), present_residence (amount of years in the present residence), chk_acct (accounts for the checking account status, and _3 is for the one who does not have a checking account).

To sum up, in general a good costumer would be someone who asks a credit for to buy a radio or a tv, or a phone, who has a guarantor, who is single with a high avarage balance in savings account, single and male. For a bad costumer, we could be facing someone who is asking a credit to buy a new car, who rents (residence), who has a high installment rate as % of disposable income, who owns no property, who has not been a resident for more than 2 years and with no achecking account.

Final model

We have chosen a mix of GAM and GLM for our model. We have chosen a final model where we mix both GAM and GLM. We choose based on the following table:

Table 5: best models

gam_result	glm_result	final_choice
1	1	1
1	0	1
0	1	1
0	0	0

And we get the following confusion matrix for it (in sample prediction):

```
#> Confusion Matrix and Statistics
#>
#>          Reference
#> Prediction   0   1
#>          0 137  18
```

```
#>          1 103 542
#>
#>                Accuracy : 0.8488
#>                  95% CI : (0.822, 0.8729)
#>     No Information Rate : 0.7
#>     P-Value [Acc > NIR] : < 2.2e-16
#>
#>                   Kappa : 0.5993
#>
#>  Mcnemar's Test P-Value : 2.234e-14
#>
#>             Sensitivity : 0.5708
#>             Specificity : 0.9679
#>          Pos Pred Value : 0.8839
#>          Neg Pred Value : 0.8403
#>              Prevalence : 0.3000
#>          Detection Rate : 0.1713
#>    Detection Prevalence : 0.1938
#>       Balanced Accuracy : 0.7693
#>
#>        'Positive' Class : 0
#>
```

This returns an accuracy of 84.88%, sensitivity of 57.08% and specificity of 96.79%. This voting composition between both models tends to have a significantly harder time classifying clients without good credit, however, clients with good credit rating are very accurately classified.

And we get the following confusion matrix for it (out of sample prediction):

```
#> Confusion Matrix and Statistics
#>
#>           Reference
#> Prediction   0   1
#>          0  32   3
#>          1  28 137
#>
#>                Accuracy : 0.845
#>                  95% CI : (0.7873, 0.8922)
#>     No Information Rate : 0.7
#>     P-Value [Acc > NIR] : 1.572e-06
#>
#>                   Kappa : 0.5811
#>
#>  Mcnemar's Test P-Value : 1.629e-05
#>
#>             Sensitivity : 0.5333
#>             Specificity : 0.9786
#>          Pos Pred Value : 0.9143
#>          Neg Pred Value : 0.8303
#>              Prevalence : 0.3000
#>          Detection Rate : 0.1600
#>    Detection Prevalence : 0.1750
#>       Balanced Accuracy : 0.7560
#>
#>        'Positive' Class : 0
#>
```

The model has a final accuracy of 84.5% with a sensitivity of 53.33% and specificity of 97.86%. The model strongly predicts clients with a good credit rating and has a hard time predicting clients without a good credit rating.

Reasoning behind our decision

The model chosen prioritizes accuracy at predicting clients with good credit rating. As we do not have a cost function to decide whether assigning a good rating to a client is more important (or not) than a bad rating, we settle for the model with the highest accuracy. Part of the reasoning on prioritizing this subset of clients is that the credits the clients ask for tend to be for relatively low-risk spendings like a used car, radio or tv, and other appliances which do not represent a huge cost for the financial institution in the case of a delay.

Clients without a good rating are also not only significantly less abundant but also much more inconsistent, therefore making it difficult to accurately predict. Alternatively, in case we needed to increase our sensitivity, given that it is, indeed, quite low, we can change our choice table to the following:

Table 6: best models

gam_result	glm_result	final_choice
1	1	1
1	0	0
0	1	0
0	0	0

That way whenever both the GLM and GAM disagree with a rating, we simply decide to assign the bad rating to the client to lower risk for the institution (in case providing credit to bad rating clients was particularly costly or risky, which we don't know).

This model yields a significantly higher sensitivity but an also somewhat lower specificity, and, as a result (as the majority of clients have a good rating), also yields a model with lower accuracy.

These are the results of the (in sample) prediction for the alternative model:

```
#> Confusion Matrix and Statistics
#>
#>          Reference
#> Prediction   0   1
#>          0 197 104
#>          1  43 456
#>
#>               Accuracy : 0.8162
#>                 95% CI : (0.7876, 0.8425)
#>    No Information Rate : 0.7
#>    P-Value [Acc > NIR] : 4.014e-14
#>
#>                  Kappa : 0.5921
#>
#>  Mcnemar's Test P-Value : 7.470e-07
#>
#>             Sensitivity : 0.8208
#>             Specificity : 0.8143
#>          Pos Pred Value : 0.6545
#>          Neg Pred Value : 0.9138
#>              Prevalence : 0.3000
#>          Detection Rate : 0.2462
#>    Detection Prevalence : 0.3762
#>       Balanced Accuracy : 0.8176
#>
#>        'Positive' Class : 0
#>
```

Our in-sample prediction is strong, where we get an accuracy of 81.62% with a significantly more balanced sensitivity and specificity of 82.08% and 81.43% respectively. Our inference from this is that this model could be the model with the lowest risk for the financial institution.

And for the (out of sample) prediction, we get the following result:

```
#> Confusion Matrix and Statistics
#>
#>          Reference
#> Prediction   0   1
#>          0  44  26
#>          1  16 114
#>
#>               Accuracy : 0.79
#>                 95% CI : (0.7269, 0.8443)
#>    No Information Rate : 0.7
#>    P-Value [Acc > NIR] : 0.002725
#>
#>                  Kappa : 0.5227
#>
#>  Mcnemar's Test P-Value : 0.164915
#>
#>             Sensitivity : 0.7333
#>             Specificity : 0.8143
#>          Pos Pred Value : 0.6286
#>          Neg Pred Value : 0.8769
#>              Prevalence : 0.3000
#>          Detection Rate : 0.2200
#>    Detection Prevalence : 0.3500
#>       Balanced Accuracy : 0.7738
#>
#>        'Positive' Class : 0
#>
```

For our out of sample prediction we get an accuracy of 79% but a sensitivity of 73.33% and specificity of 81.43%. Our predictions for good credit rating clients are very consistent but also of significantly less accuracy than our previous model, however, the only reason for this is the fact that more clients have good rating than not (70/30).

If we had a cost function to prioritize one model over the other, we would certainly make use of it in order to determine which model could yield the highest risk-adjusted return for the financial institution. Therefore we must conclude that both are appropriate for the task at hand.