Data Analytics 5 - Default Risk Prediction

Tuomo Kareoja

Version Number	**Changes**	**Date**
0.8	Finished plots and most of the text	11.11.2019
1.0	Finished text and plots	12.11.2019

Problem and Suggested Solution

The Problem: The proportion of customers that we have set the credit limits to are defaulting

What We Can Do: The only leverage we have is the credit limit. Changing the credit limit downward for customers that have a high change of defaulting could create complaints and unlikely to work as the customer might have already taken enough dept to cause them to default and lowering the credit limit would not affect this. An another option would be to check that the credit limit given to customers is low enough from the get-go

Suggested Solution: Build a predictive model that can find the customers to whom we should be giving less credit and find how much should we lower the credit of these customers

The Logic of the Solution

Just finding the customers that are about to default is not enough, because in the end we would like to prevent defaults from happening and even if a customer has a high immediate risk of default we might not have any leverage to change her behavior at this point. Where we would have leverage is in the moment when we are setting the customers credit limit before things escalated.

If we could find the customers where giving them a lower credit limit would prevent their future default by preventing them from taking a loan that too big for them to handle, we would have an option to actually effect the outcome.

To find the customers where a lower credit limit would be appropriate we need go trough the following steps:

1. Clean and process data
2. Build models that predict defaulting
3. Vary the amount of credit given in the data and see how this affects the risk of defaulting
4. Find the credit drops that lower the risk of defaulting most with the lowest drop in credit limit
5. Rank credit limit drops and calculate how much would the percentage of defaulters change and how much credit would need to give up in percentage terms

6. Calculate the percent of defaulters, non-defaulters and customers in general who would be affected

Because the data that we use is so limited we would predict that the results will not be spectacular, but this should be seen more as a proof of concept.

Clean and Process the data

The data that we were given pertains to the immediate risk of defaulting, but we can use this data to simulate a situation where we are setting the customers their credit limits (probably years before the possible default) by just considering the demographic information of the customer.

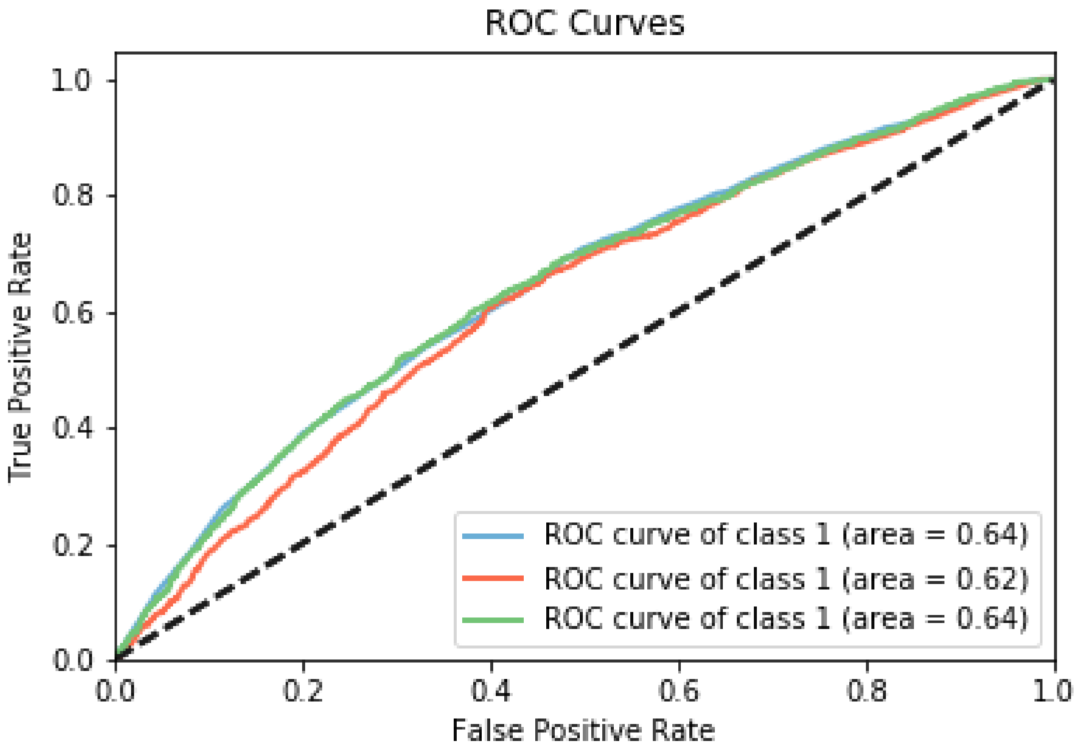
This is the information about the customer that we are left with after dropping columns that do not fit our hypothetical use case:

- sex
- age
- education
- marital status
- credit given
- default

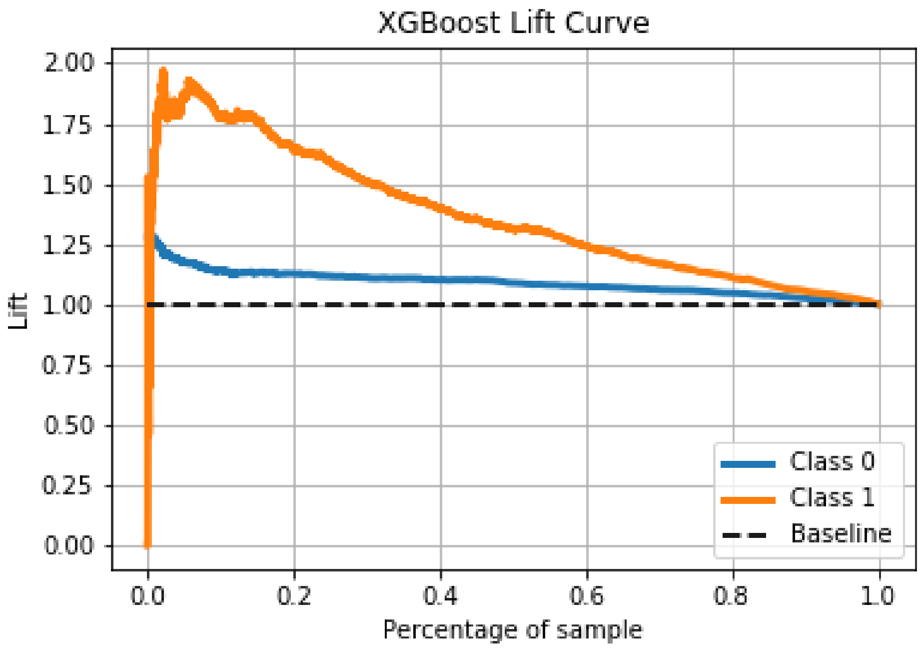
14 customers had education or marital status coded as 0 that we assumed meant missing. These observations were simply dropped, because their number was so small to make no difference and this made rest of the analysis more simple.

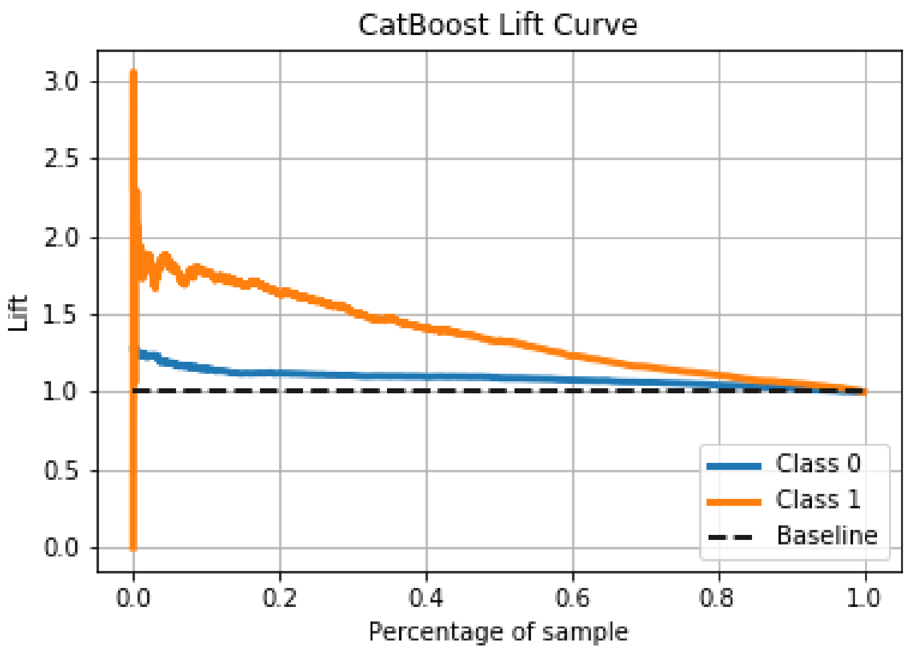
Building Models That Predict Defaulting

We want to find the best model to predict defaulting with the data that we have. For this purpose we tried three models: XGBoost, random forest and CatBoost. Below are the of ROC-curves of the models, unfortunately the models are not labeled in the legend, but blue is XGBoost, red is random forest and green is CatBoost. We see that XGBoost are tied for the best place (AUC=0.64) and that random forest performs significantly worse.



The next statistic to look is lift curve that tells us how much more likely defaulters we would find by using the model and starting with the observations with the highest predicted probability of defaulting versus using a random guess where we would predict defaulting with the base rate of rate of defaulting. As the percent of defaulters is around 20 %, lift of 2 would mean that the model would pick up 40 % of the defaulters and that the random guess would predict defaulting for random 20 % of the customers. The following plots are the lift curves for XGBoost and CatBoost models. Here the lift rate is marked for both classes 0 and 1. We only care about class 1 which means that the customer defaulted. The following plots are the lift curves for XGBoost and CatBoost models. The models perform very similarly except that CatBoost has high variance of lift for the first couple of predictions.





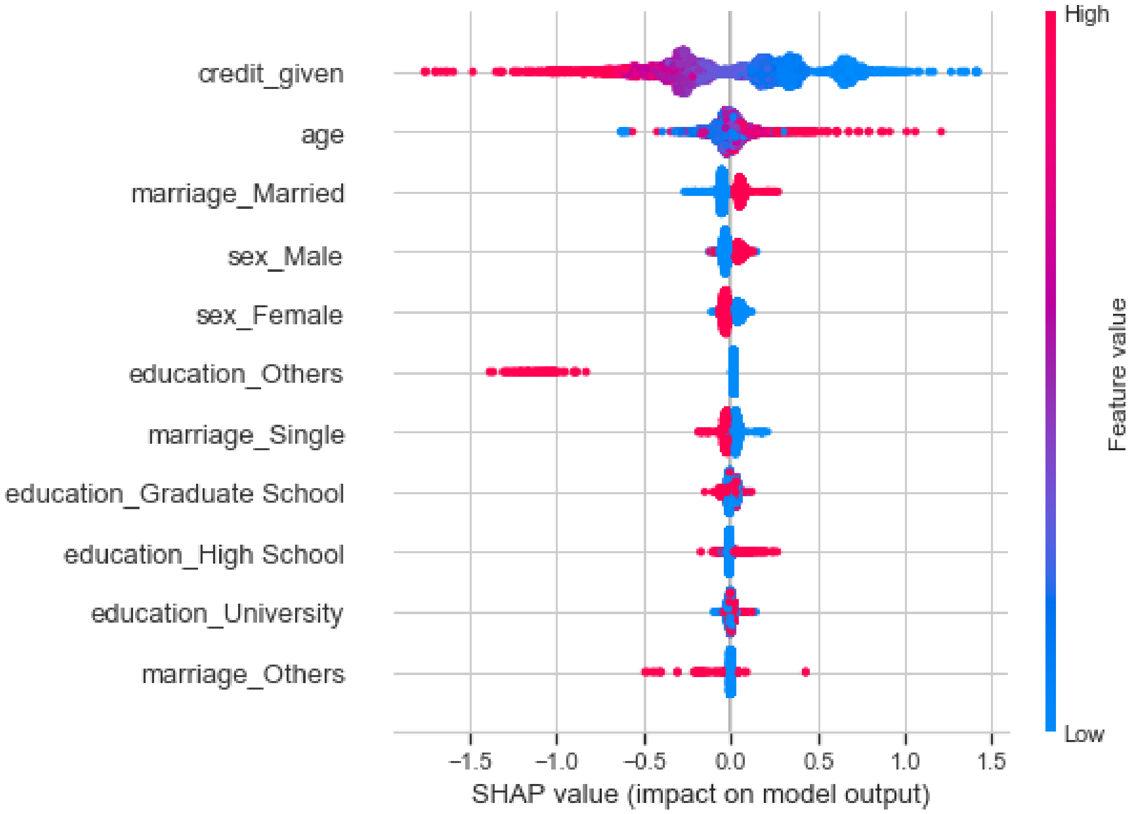
The last metric that we are interested in is how well the predicted probabilities of the models match the real probabilities of defaulting. This means that for customers where we predict a 60 % chance of defaulting we want 60 % of the customers to actually default. We need these to be true as we are are handling these predictions as probabilities to make further steps possible. We can see that all of the models predictions line up quite nicely with actual probabilities. This was initially not case with random forest model that had to tuned separately to have this feature.

Finding the Customers and Credit Drops that Most Lower the Change of Defaulting

Now that we have the models, the next step is to predict for each customer, how big would the drop in the probability of defaulting be if we changed their credit limit by certain percentage. To accomplish this we did the following

- Train models with 80 % of the data
- Use these trained models to predict the base chance of defaulting
- For each customer lower the actual credit limit by different percentages and see how this affects the predicted probability of defaulting

This is procedure was in principle quite simple, but the problem turned out to be that the models didn't have the expected effect of credit limit for most customers. To give an example of this, below are the all the features and their effects in Shapley values for each customer for CatBoost. On the X-axis is the Shapley value that is tells us was the effect of the variable value positive, and increasing the probability of defaulting, or negative and decreasing the probability of defaulting. We can se that for most customers (dots) low credit limit predicts higher probability of defaulting. This obviously does not make sense, but if we consider the variables that we are using there is logical reason for these results.



When the credit limit is decided there are far more background variables taken into account than we have access here. This means that we credit limit contains lots of information about the credit worthiness of the customer that is not accounted by the used demographic variables. So when the models is saying that higher credit rating would lessen the the probability of defaulting, it actually means that higher credit worthiness of the customer would lessen the probability of defaulting.

Even though this is a big problem, there are still few customers where the models would predict drops in defaulting probability with lower credit limit even with this limited data. This means that even with this limited data we are able to capture an effect that we would predict from background knowledge.

Even though the credit though the model would predict that a higher credit limit would prevent defaults, this should not be the case for all customers we would like to find the customer groups that even with the limited amount of demographic data available have a credit limit that seems too high.

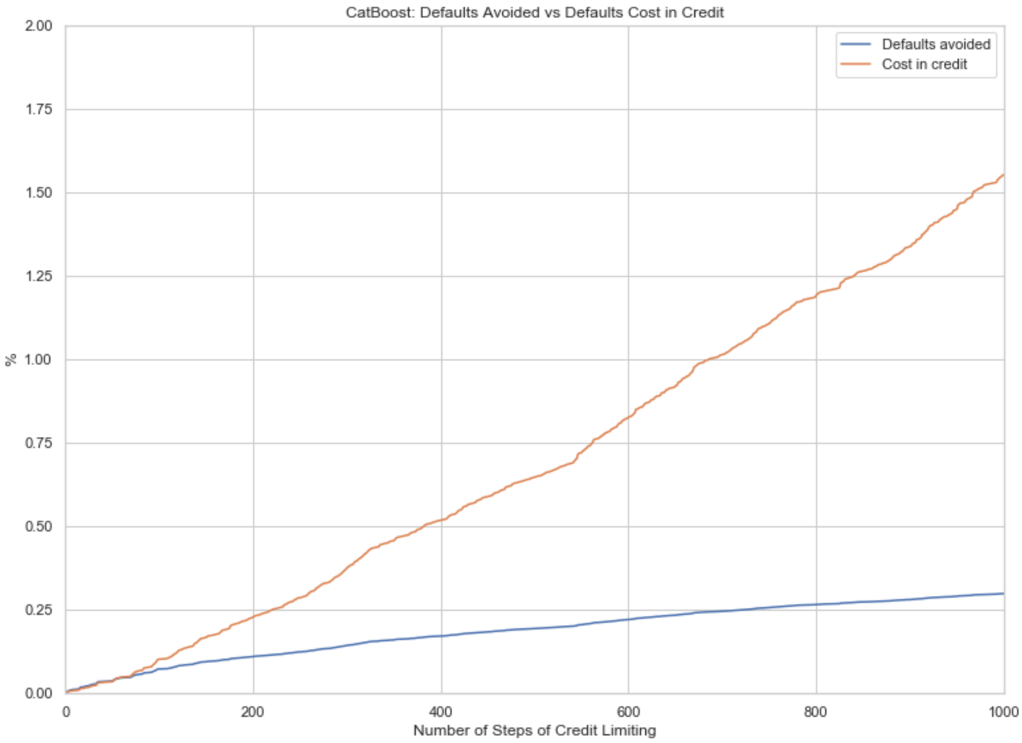
Optimization of the Results

Now that we calculated how the models predict dropping the credit limit affects the defaulting probability for each customer we can move on to picking the optimal customers and credit limit drops to get the maximum effect with smallest changes in the overall credit issued. We did this with the following steps:

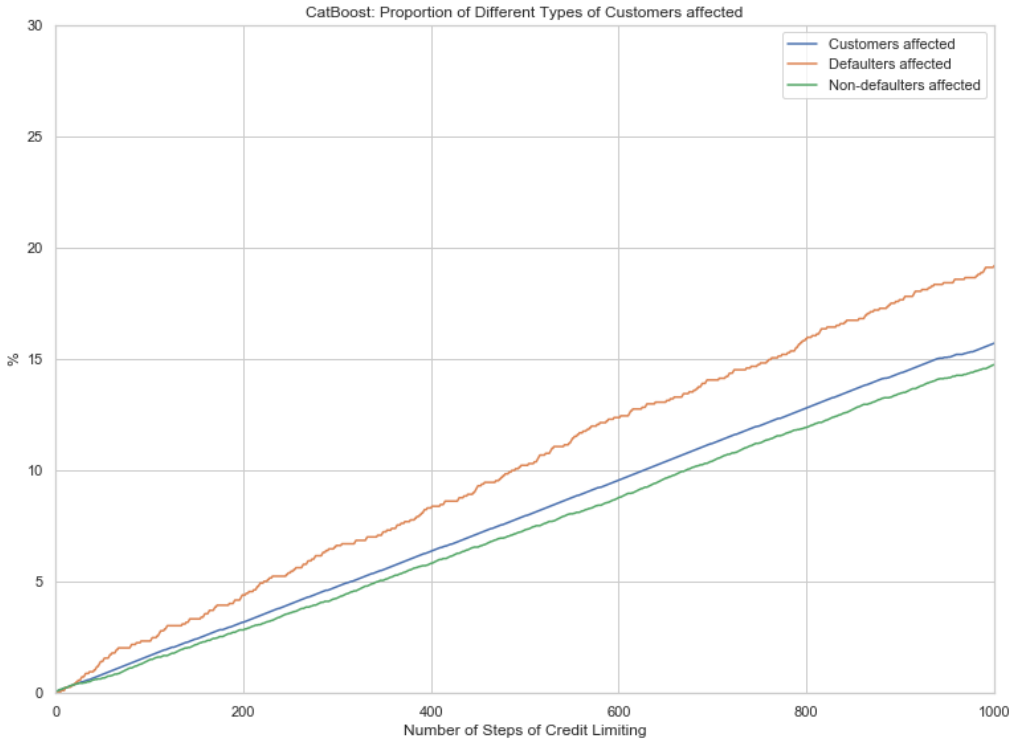
- For each customer and credit limit drop, calculate the absolute loss in credit given divided by the percentage drop in defaulting probability. This gives us a cost for option in dollars per percentage drop
- for each customer find the most cost effective credit drop and calculate the cost of further drops in credit. This has to be done so that on top of considering drops for different customers we have possibilities in credit drop for each customer and these have to be made consecutively
- Put all these different drops in credit in order based on their costs, that is their cost in credit given per percentage drop in defaulting

Only the the results from CatBoost model were considered good. XGBoos model found only around 20 customer (0.4 % of customers in the test data), where lowering the credit limit would also lower the risk of defaulting. Random forest predicted drops in defaulting rate but, these were hovering around zero and seemed more like random occurrences than real effect.

Below is a graph of how the number of steps of credit limiting affect the percentage of defaults and credit given. Steps can be new customers or further drops in the credit for customers where credit was already dropped. We can see that for 1000 steps we would drop percentage of defaulters with 0.3 % percentage points with a corresponding 1.5 % drop in the total credit given.



Here we can see how many percentage of customers would be effected in total and divided to defaulters and non-defaulters. We see that for 1000 credit drops we would affect around 16 % of the customers in test data (800 customers) with significantly higher proportion of these drop hitting customers who actually defaulted.



These results are not spectacular, but demonstrate the logic of the system. With more data come better models and we should be able to prevent more defaults with less drops and affect more of the would be defaulters than non-defaulting customers.

Next Steps

1. **Get Better Data** The method for finding the customers where we should lower the credit limit works in concept, but for actual viability test we would need access to all the same data that are used by our employees to make the decisions about allowed credit limits.

2. **Do a Proper Viability Test** To do a proper of the viability of the concept we would need to have access to the same variables that are used when the credit limit is decided for building the models. Pay special attention in making sure that

the causal link of credit limit and defaulting is tested properly (right direction, statistical tests, etc.)

3. **Small Scale Test of Actual System** The ultimate goal would be to create a system that could warn our employers when they are about to approve a credit limit that is too big and suggest them a suitably lower credit limit that is big enough to have a meaningful effect on the probability of default without denying the customer credit completely