Data-Science report

Table of content

1 Introduction

1.1 Problem

For organisations and management customer satisfaction is offcourse a key measure of success. Unhappy customers will leave your company and unhappy customers don't expli and will suddenly just leave.

In this case we will analyze the Santander bank data and identify which customers are dissatisfied early in the relationshiop. This enables Santander bank to take pro-active steps to improve a customers happiness, before its too late. The dataset contains hundreds of anonymized features to predict if a customer is satisfied or dissatisfied with being a client of the bank.

In addition to this main goal they also want to extract maximu value from the data.

1.2 Goal

The main goal of this case is to predict which custumers will be happy and which will be unhappy early in the relationshio enabling Santander to take proactive steps. In addition we will extract maximum possible value from the data. The valuable insight we'll get from the data will be presented at the end of the report as actionable management insights.

1.3 Management questions

Q1: Which customers are satisfied and which are dissatsfied?
Q2: What are the most important predictors?
Q3: Which valuable insights can we get from the data?

1.4 Points of attention

We will describe a few points of attention to mitigate the risks attached to data-science projects.

1.4.1 Profitability of the Data-Science project

In this case we've kept a lean/agile way of working. That's the reason we started with a fast GBM prediction. To deliver value and a benchmark result as soon as possible. From there on we were focused on keep improving predictions(value optimization) until we've reached our management goal. From there on we focus on the next goals.

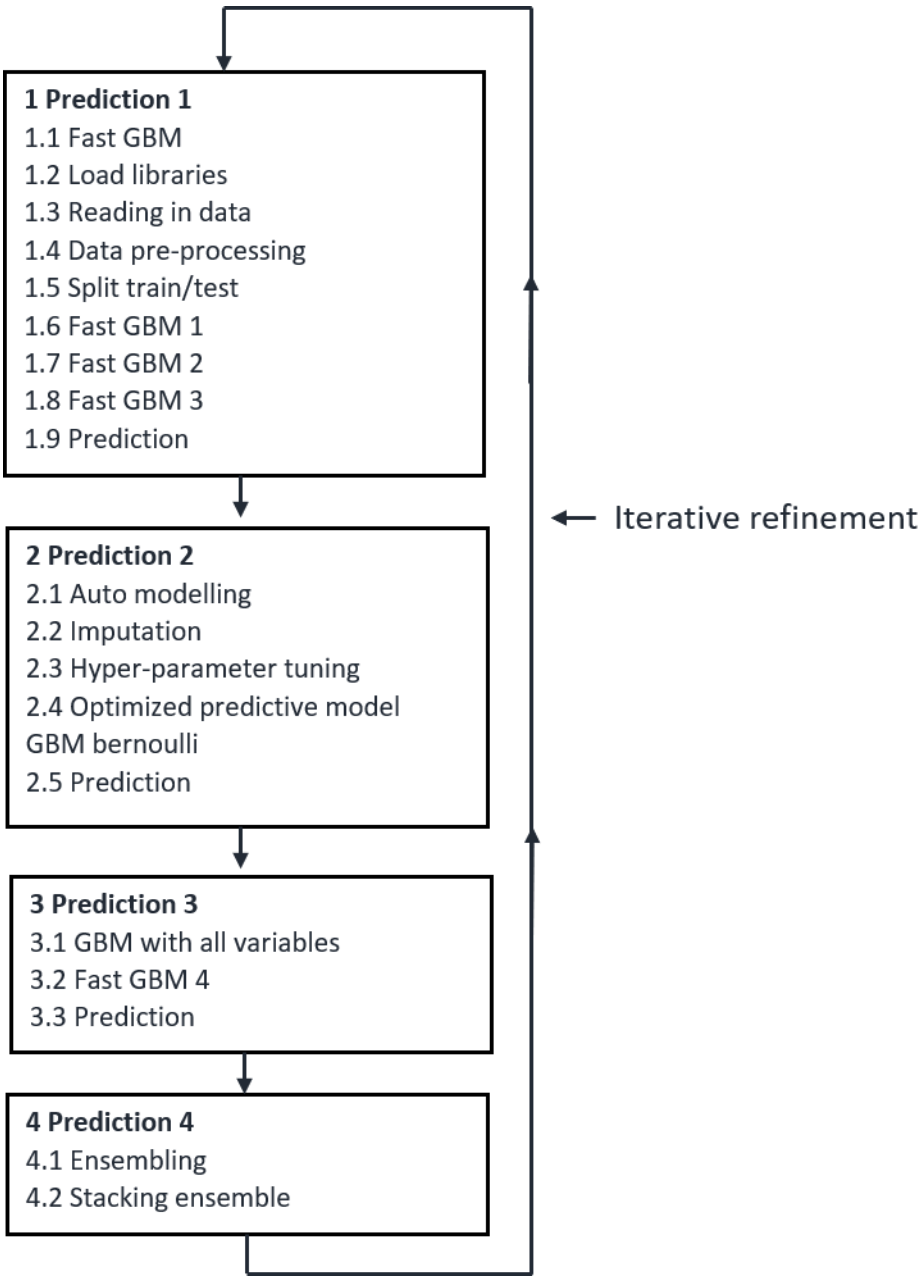
1.4.2 Understanding/Trust of the management

To increase understanding and Trust of the management we'll describe the full process in detail in section 2. (The detailed process description will follow soon).

1.4.3 Data quality

The data was downloaded from Kaggle.com. A very trustworthy source.

2 Procedure


1 Prediction 1
1.1 Fast GBM
1.2 Load libraries
1.3 Reading in data
1.4 Data pre-processing
1.5 Split train/test
1.6 Fast GBM 1
1.7 Fast GBM 2
1.8 Fast GBM 3
1.9 Prediction
2 Prediction 2
2.1 Auto modelling
2.2 Imputation
2.3 Hyper-parameter tuning
2.4 Optimized predictive model
GBM bernoulli
2.5 Prediction
3 Prediction 3
3.1 GBM with all variables
3.2 Fast GBM 4
3.3 Prediction
4 Prediction 4
4.1 Ensembling
4.2 Stacking ensemble
Iterative refinement

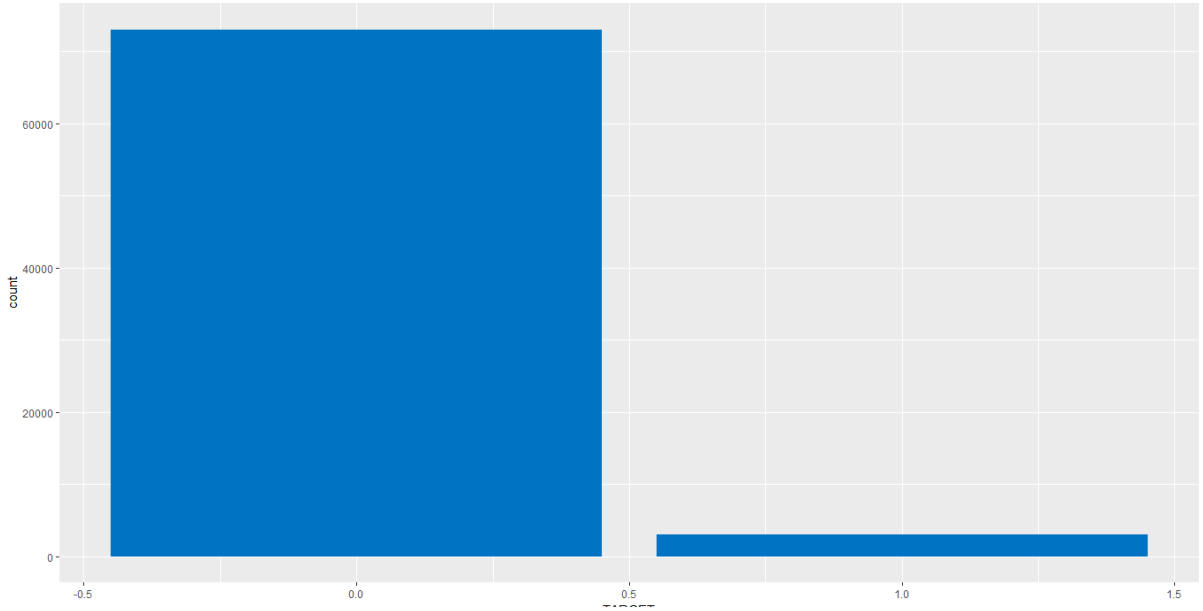
3 Results

3.1 Prediction 1

3.1.1. The dependent variable

The dependent variable consists of 73.012 0 (satisfied) values and 3008 1 (unsatisfied) values. 96% of the customers are satisfied and 4% are unsatisfied. This graphically be seen in figure 1.

Figure 1 – Number of satisfied(1) and unsatisfied(2) customers.



12(Table 2)

Table 2 – The 3 most important variables

*Figure 2 – The 3 most important variables visually***3.11.33 AUC**

The AUC score of the first prediction is `0.8281295.The AUC (Area under the curve) score is an important metric for classification problems. Probably the second most important metric after accuracy.An AUC score of 1 is a perfect test and a score of 0.5 is the lowest score. A general guide for classifying the accuracy of the test;`

```
.90-1 = excellent (A)
.80-.90 = good (B)
.70-.80 = fair (C)
.60-.70 = poor (D)
```

.50-.60 = fail (F)

The AUC score of 0.83 means a good (B class) accurate score.

3.2 Prediction 2 e

3.2.1 Accuracy

The accuracy is 0.96cwhether tustomersatisfiedhis/herexperience08.

3.2.2 AUC

The AUC 0.8signalledan094066.

3.3 Prediction 3

Table 2 – All variables with rel.inf >0

3.2.1 Accuracy

3.3.1 AUC

The AUC is 0.7we'll keep as the578935.

3.4 Prediction 4ved with the models logistic regression, XGboost and Random forest as 3 base models.

3.4.1 Independent model accuracy

The mean accuracy scores are shown in table 1. The XG boost model scores slightly better than the logistic regression, however the score is the same 96% accuracy score that we achieved with the second prediction.

Table 3 – Model accuracy 3 base ensemble models

Accuracy

	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	NA's
glm	0.9605714	0.9607143	0.9607143	0.9606857	0.9607143	0.9607143	0
xgbTree	0.9605714	0.9607143	0.9607143	0.9607143	0.9607143	0.9608571	0
rf	0.9597143	0.9597143	0.9597143	0.9597429	0.9597143	0.9598571	0

3.3.2 Stacking ensemble accuracy

Next we'll do a stacked ensemble. Figure 3 shows the accuracy of the stacked ensemble is 0.96.

```
A gbm ensemble of 2 base models: glm, xgbTree, rf

Ensemble results:
Stochastic Gradient Boosting

7000 samples
   3 predictor
   2 classes: 'No', 'Yes'

No pre-processing
Resampling: Cross-Validated (5 fold, repeated 1 times)
Summary of sample sizes: 5600, 5600, 5600, 5600, 5600
Resampling results across tuning parameters:

  interaction.depth  n.trees  Accuracy   Kappa
  1                   50      0.9624286   0.0000000000
```

4 Conclusion

4.1 General conclusion

Q1: Which customers are satisfied and which are dissatsfied?

The GBM models we've used predicted the satisfaction scores on the test set with 96% accuracy.

Q2: What are the most important predictors?

With the following 3 predictors we were able to predict accuracy in (dis)satisfaction with 96%.

	var	rel.inf
var15	var15	44.84463
saldo_var30	saldo_var30	38.26265
var38	var38	16.89272