Predicting Cross-Sell with Artificial Neural Networks
An Empirical Study of ING's Customer Data

Seminar Thesis

submitted to

Hon.-Prof. Dr. Martin Schmidberger
Gabriela Alves Werb

Goethe University Frankfurt am Main
School of Business and Economics
Chair for E-Commerce

by

Lukas Jürgensmeier
(Mat.-Nr.: 6904281)

in partial fulfillment of the requirements
for the degree of

Master of Science in Business Administration

July 31, 2019

Contents

List of Figures

List of Tables

1 Introduction

The introduction should directly lead to the main topic of the paper. It should not be a historical essay or a deep reaching explanation of the topic, but it should explain concisely what the main questions of the topic are, why they are interesting, and which methods or data will be used. A further goal of the introduction is to define the structure for the paper. This can be achieved by describing the goals, the methods and the main results of the paper. Methods and results do not have to be discussed in detail - this is left to the main part of the paper - but they should be summed up in a short way. The introduction of a paper is often finished by a short "roadmap". This is not necessary, if the aspects mentioned above have been laid out in a satisfactory way before. (Hastie et al. 2017) This is a reference test from the new .tex file 1

2 Introduction from different file

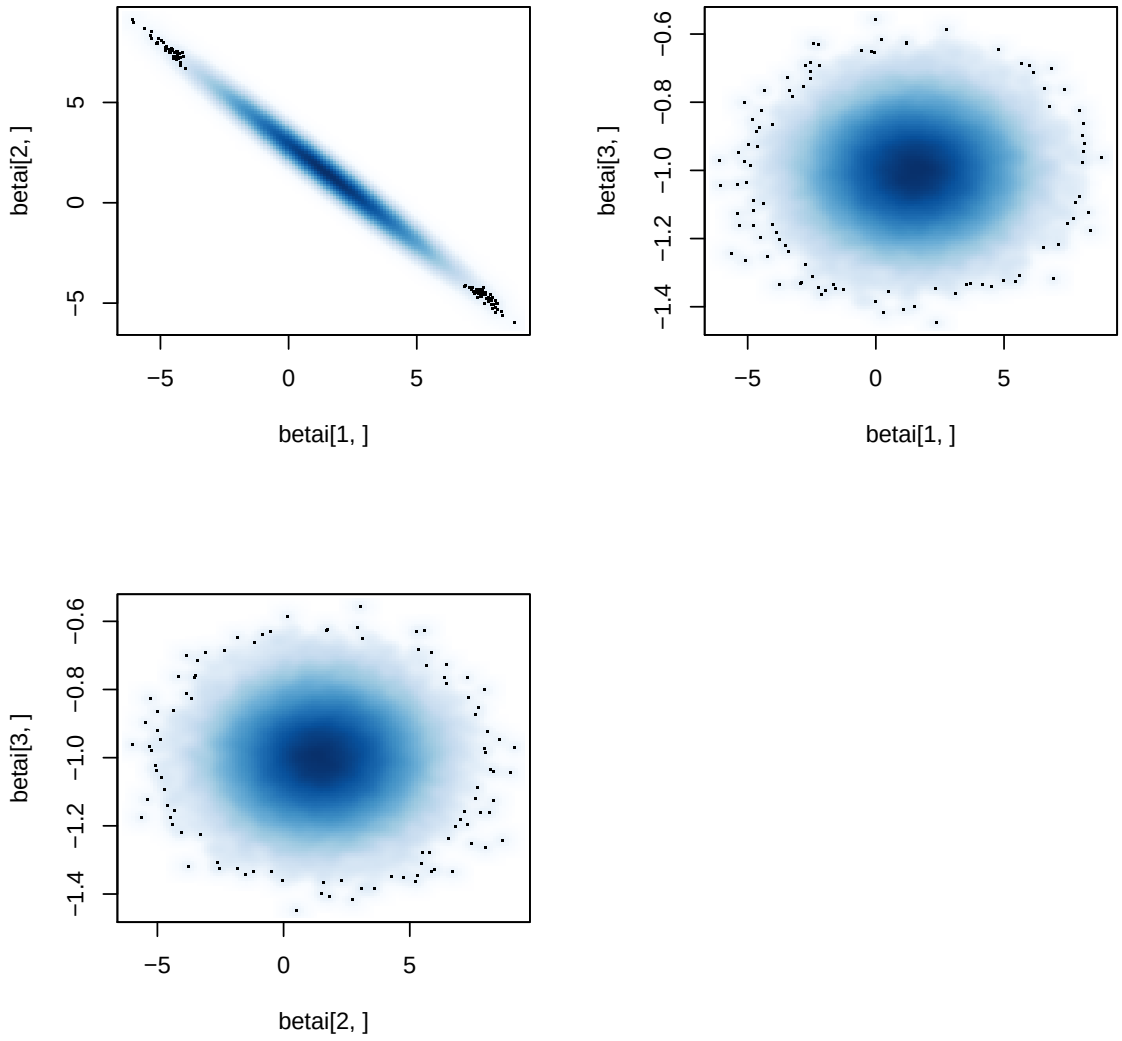
The introduction should directly lead to the main topic of the paper. It should not be a historical essay or a deep reaching explanation of the topic, but it should explain concisely what the main questions of the topic are, why they are interesting, and which methods or data will be used. A further goal of the introduction is to define the structure for the paper. This can be achieved by describing

Figure 1: Mean Bond-Yield-curve (example for a figure)

the goals, the methods and the main results of the paper. Methods and results do not have to be discussed in detail - this is left to the main part of the paper - but they should be summed up in a short way. The introduction of a paper is often finished by a short "roadmap". This is not necessary, if the aspects mentioned above have been laid out in a satisfactory way before. (Hastie et al. 2017)

```
# This script follows this blog post
# https://blogs.rstudio.com/tensorflow/posts/2018-01-11-keras-customer-churn/

# clear workspace
rm(list = ls())

#install packages
#pkgs <- c("keras", "lime", "tidyquant", "rsample", "recipes", "yardstick", "corrr")
#install.packages(pkgs)

# Load libraries
library(keras)
library(lime)
library(tidyquant)
library(rsample)
library(recipes)
library(yardstick)
library(corrr)

```

Figure 2: Example from the CSCC lecture



I have no clue what this figure is all about.

```
20
21 # Install Keras if you have not installed before
22 install_keras(method = "conda")
23
24 # read and check data
25 xsell_data_raw <- read.csv("xsell.csv")
26 glimpse(xsell_data_raw)
27
28 # create new variable tenure
29 xsell_data_raw$tenure <- xsell_data_raw$age - xsell_data_raw$entry_age
30
31 # prune data set
32 # Remove unnecessary data
33 xsell_data_tbl <- xsell_data_raw %>%
34   select(-X) %>% #removes ID
35   drop_na() #%>% # removes all NA's. Bad Solution! Improve! Removes 70% of
         observations
36  # select(xsell, everything())
```

```r
glimpse(xsell_data_tbl)

# Split test/training sets
set.seed(123)
train_test_split <- initial_split(xsell_data_tbl, prop = 0.8)
train_test_split

# Retrieve train and test sets
train_tbl <- training(train_test_split)
test_tbl  <- testing(train_test_split)

# skipped all feature transformations here
# insert if necessary

# # alternative way for dummy coding all non-numeric variables
# non_numeric_var_names <- xsell_data_tbl %>%
#   select_if(negate(is.numeric)) %>%
#   names
#
# xsell_data_tbl <- dummy_cols(xsell_data_tbl, non_numeric_var_names)
#
# # remove non-numeric variables
# xsell_data_tbl <- xsell_data_tbl %>%
#   select(-non_numeric_var_names)
# glimpse(xsell_data_tbl)

# Create recipe
rec_obj <- recipe(xsell ~ ., data = train_tbl) %>%
  #step_discretize(tenure, options = list(cuts = 6)) %>%
  #step_log(TotalCharges) %>%
  step_dummy(all_nominal(), -all_outcomes()) %>%
  step_center(all_predictors(), -all_outcomes()) %>%
  step_scale(all_predictors(), -all_outcomes()) %>%
  prep(data = train_tbl)

# Apply recipe to predictors (all vars excluding xsell)
x_train_tbl <- bake(rec_obj, new_data = train_tbl) %>% select(-xsell)
x_test_tbl  <- bake(rec_obj, new_data = test_tbl) %>% select(-xsell)
glimpse(x_train_tbl)

# define response variables for training and testing sets
y_train_vec <- pull(train_tbl, xsell)
y_test_vec  <- pull(test_tbl, xsell)


# Building our Artificial Neural Network
model_keras <- keras_model_sequential()

model_keras %>%

  # First hidden layer
  layer_dense(
    units              = 16,
    kernel_initializer = "uniform",
    activation         = "relu",
    input_shape        = ncol(x_train_tbl)) %>%

  # Dropout to prevent overfitting
  layer_dropout(rate = 0.1) %>%

  # Second hidden layer
  layer_dense(
    units              = 16,
    kernel_initializer = "uniform",
    activation         = "relu") %>%

  # Dropout to prevent overfitting
  layer_dropout(rate = 0.1) %>%

  # Output layer
```

```
  layer_dense(
    units              = 1,
    kernel_initializer = "uniform",
    activation         = "sigmoid") %>%

  # Compile ANN
  compile(
    optimizer = 'adam',
    loss      = 'binary_crossentropy',
    metrics   = c('accuracy')
  )

keras_model

history <- fit(
  object           = model_keras,
  x                = as.matrix(x_train_tbl),
  y                = y_train_vec,
  batch_size       = 50,
  epochs           = 35,
  validation_split = 0.30
)

# Print a summary of the training history
print(history)

# Plot the training/validation history of our Keras model
plot(history)

# Make predictions
# Predicted Class
yhat_keras_class_vec <- predict_classes(object = model_keras, x = as.matrix(x_test_tbl
    )) %>%
  as.vector()

# Predicted Class Probability
yhat_keras_prob_vec  <- predict_proba(object = model_keras, x = as.matrix(x_test_tbl))
     %>%
  as.vector()

# Evaluate model
# Format test data and predictions for yardstick metrics
estimates_keras_tbl <- tibble(
  truth      = as.factor(y_test_vec), # %>% fct_recode(yes = "1", no = "0"),
  estimate   = as.factor(yhat_keras_class_vec), # %>% fct_recode(yes = "1", no = "0"),
  class_prob = yhat_keras_prob_vec
)

estimates_keras_tbl

# change default positive=0 to positive=1
options(yardstick.event_first = FALSE)

# Confusion Table
estimates_keras_tbl %>% conf_mat(truth, estimate)

# Accuracy
estimates_keras_tbl %>% metrics(truth, estimate)

# AUC
estimates_keras_tbl %>% roc_auc(truth, class_prob)

# Precision
tibble(
  precision = estimates_keras_tbl %>% precision(truth, estimate),
  recall    = estimates_keras_tbl %>% recall(truth, estimate)
)

# F1-Statistic
estimates_keras_tbl %>% f_meas(truth, estimate, beta = 1)
```

```
175
176
177 ######################################################
178 #### Evaluate Feature Importance with LIME #########
179 ######################################################
180
181 # Setup
182 class(model_keras)
183
184 #Setup lime::model_type() function for keras
185 model_type.keras.engine.sequential.Sequential <- function(x, ...) {
186   return("classification")
187   }
188
189
190 # Setup lime::predict_model() function for keras
191 predict_model.keras.engine.sequential.Sequential <- function(x, newdata, type, ...) {
192   pred <- predict_proba(object = x, x = as.matrix(newdata))
193   return(data.frame(Yes = pred, No = 1 - pred))
194   }
195
196
197 # Test our predict_model() function
198 predict_model(x = model_keras, newdata = x_test_tbl, type = 'raw') %>%
199   tibble::as_tibble()
200
201 # Run lime() on training set
202 explainer <- lime::lime(
203   x              = x_train_tbl,
204   model          = model_keras,
205   bin_continuous = FALSE
206 )
207
208 # Run explain() on explainer
209 explanation <- lime::explain(
210   x_test_tbl[1:10, ],
211   explainer    = explainer,
212   n_labels     = 1,
213   n_features   = 4,
214   kernel_width = 0.5
215 )
216
217 # Plot feature importance
218 plot_features(explanation) +
219   labs(title = "LIME Feature Importance Visualization",
220        subtitle = "Hold Out (Test) Set, First 10 Cases Shown")
221
222 plot_explanations(explanation) +
223   labs(title = "LIME Feature Importance Heatmap",
224        subtitle = "Hold Out (Test) Set, First 10 Cases Shown")
225
226 # Feature correlations to xsell
227 corrr_analysis <- x_train_tbl %>%
228   mutate(xsell = y_train_vec) %>%
229   correlate() %>%
230   focus(xsell) %>%
231   rename(feature = rowname) %>%
232   arrange(abs(xsell)) %>%
233   mutate(feature = as_factor(feature))
234
235 corrr_analysis
236
237 # Correlation visualization
238 corrr_analysis %>%
239   ggplot(aes(x = xsell, y = fct_reorder(feature, desc(xsell)))) +
240   geom_point() +
241   # Positive Correlations - Contribute to churn
242   geom_segment(aes(xend = 0, yend = feature),
243                color = palette_light()[[2]],
244                data = corrr_analysis %>% filter(xsell > 0)) +
```

```
  geom_point(color = palette_light()[[2]],
             data = corrr_analysis %>% filter(xsell > 0)) +
  # Negative Correlations - Prevent churn
  geom_segment(aes(xend = 0, yend = feature),
               color = palette_light()[[1]],
               data = corrr_analysis %>% filter(xsell < 0)) +
  geom_point(color = palette_light()[[1]],
             data = corrr_analysis %>% filter(xsell < 0)) +
  # Vertical lines
  geom_vline(xintercept = 0, color = palette_light()[[5]], size = 1, linetype = 2) +
  geom_vline(xintercept = -0.25, color = palette_light()[[5]], size = 1, linetype = 2)
      +
  geom_vline(xintercept = 0.25, color = palette_light()[[5]], size = 1, linetype = 2)
     +
  # Aesthetics
  theme_tq() +
  labs(title = "Cross Sell Correlation Analysis",
       subtitle = paste("Positive Correlations (contribute to xsell),",
                        "Negative Correlations (prevent xsell)"),
       y = "Feature Importance")
```

Listing 1: Tensorflow Model

3 Main part

3.1 Literature overview and citation

The literature overview may be kept short in a bachelor thesis. Bachelor theses whose main purpose is to present and discuss the contents of published articles are exceptions. When referring to articles or other literature, it is essential to mark these as references. This is best

$$f(x) = x^2 \tag{1}$$

$$F(x) = \int_b^a \frac{1}{3}x^3 \tag{2}$$

done in the text itself. When referring to papers, the author and the year of publication should be given, e.g. "Imbens (2002) gives an overview for the GMM-estimator and its empirical likelihood". See for example in (1) for the squared one and (2) for an example of a fancy integral.

If the paper was written by more than two authors, this fact is usually abbreviated as, for example, "Imbens et al. (2002)". If there was more than one publication in the same year, a small letter should be added to the year such as "Imbens (1997a)". When referring to a whole chapter, the chapter should be mentioned, e.g. "Wooldridge (2002), ch. 13".

Direct citations must be enclosed in quotation marks. In this case the year of publication should be added with the author's name, e.g. "Generalized method of moments (GMM) estimation has become an important unifying framework for inference in econometrics in the last 20 years (Imbens (2002), p. 493)". The use of direct citations should be kept to a minimum.

3.2 Theory and methods

When writing an empirical bachelor thesis, the theoretical part should be limited to an amount necessary to understand the empirical part. It is better to limit the theory to the special cases rather than striving for a maximum of generality. Of course, when writing a theoretical paper, or a paper on pure methods, the theoretical part will receive more weight.

However, the presentation should always be structured so that it clearly works out the main points, concentrating on the aspects that are really central to the topic. Detailed proofs should be moved to the appendix.

3.3 Data

When writing an empirical paper, it is necessary to give a concise description of the data set that is being used. This description should include information about the data set provider and the variables used. A descriptive analysis of the data is useful, but it may also be moved to the appendix.

3.4 Empirical Analysis

In the empirical section, the main results should be explained first. If this is not possible, because intermediate steps are required to understand the results, then only intermediate results should be explained that are really essential for this purpose. Tables and figures should be used to present the main results. In addition, the tables and figures have to be discussed in the text. Each table and each figure must have their own title and caption.

It is often useful to investigate the robustness of the results with respect to different aspects. If the results were calculated under the homoskedasticity assumption for example, one should discuss what happens if the assumption is violated. More detailed empirical results should be put into the appendix unless there are important reasons not to do so.

4 Conclusion

The conclusion should contain a summary of the main results and its implications. One can also mention directions for future research.

A R Code

```
1 fib <- function(n) {
2   if (n < 2)
3     n
4   else
5     fib(n - 1) + fib(n - 2)
6 }
7 fib(10)
```

Listing 2: Fibonacci Secquence

```
  fib <- function(n) {
  if (n < 2)
    n
  else
    fib(n - 1) + fib(n - 2)
}
fib(10)
```

See Test Code 2 for the code example.

B Formatting rules

- Letter size 11 to 12pt, line spacing 1 - 1.5 times letter size, margins left/right 2.5cm, bottom 3cm, top 2.5cm.
- Pre-introduction page numbers should be roman, the ones of the main text arabic.
- The table of contents shows chapters and sections.
- The list of figures and tables list all the figures and tables in the paper.
- Every figure and table should have a short title plus description and should be explained in the text.
- The number of pages of the main text should be between 10-15 pages (appendix excluded).

Figure 3: Mean Bond-Yield-curve (example for a figure)

Mean Nelson-Siegel Bond-Yield-curve compared to the realized Bond-Yields.

Table 1: Cointegration of Bond Yields (example for a table)

Rank at least	$\mathscr{L}_{trace}$	5% crit. value	$\mathscr{L}_{max}$	5% crit. value
$r_0 = 0$	299.71	76.07	108.08	34.40
$r_0 = 1$	191.64	53.12	91.00	28.14
$r_0 = 2$	100.64	34.91	65.14	22.00
$r_0 = 3$	35.50	19.96	29.29	15.67
$r_0 = 4$	6.21	9.24	6.21	9.24

The Akaike-Information-criterion suggests a maximal lag length of 14

References

Hastie, T., Tibshirani, R. & Friedman, J. (2017), *The Elements of Statistical Learning: Data Mining, Inference, and Prediction*, Springer Series in Statistics, 2 edn, Springer-Verlag, New York.

Statutory Declaration

I herewith declare that I have completed the present thesis independently, without making use of other than the specified literature and aids. Sentences or parts of sentences quoted literally are marked as quotations; identification of other references with regard to the statement and scope of the work is quoted. The thesis in this form or in any other form has not been submitted to an examination body and has not been published. This thesis has not been used, either in whole or part, for another examination achievement.

Frankfurt am Main, July 31, 2019

. . . . . .

Lukas Jürgensmeier