Rotterdam School of Management
Erasmus University

Part B: Data Analytics

By submitting this assignment, we affirm the following:

1. If we have used AI tools like ChatGPT, Co-Pilot, etc., we only sought guidance or clarification. Any generated content has been fully understood and appropriately modified to align with the assignment.
2. We understand the submitted code and can explain our work if asked.

We declare that we have read, understood, and agree to abide by this honor code.

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Date: 28.11.25

Introduction

The following report has been conducted with the purpose of assisting EuroBank International (EBI) in tackling the rising rates of customer churn it is facing. To address this issue, our team has been assigned to undertake a comprehensive data analytics study with the aim of understanding the drivers of churn and developing an efficient predictive model to identify at-risk customers.

Using a dataset of current customers with known churn rates we conducted data-processing, exploratory analysis and machine learning modelling. Based on these insights, we identified the best performing model to a new set of customers to estimate churn probabilities and we additionally designed a list of actionable recommendations to proactively retain them.

Below our analytical approach, key findings, model performance, and actionable recommendations to help EBI reduce churn, improve customer engagement, and maximize retention value is summarized.

Data Pre-processing

Missing values, Duplicates & Unnecessary Variables

Data processing is essential before eliminating outliers and processing categorical variables. There are no entries that contain: “ ”, “NA”, “NULL”, “-”, “N/A” in the data set. Hence, no iterations were necessary regarding missing values.

Furthermore, there were no duplicate rows identified in the dataset. Additionally, a data-type check confirmed that all the variables were stored in the correct format.
Regarding unnecessary variables, customer ID was removed from the dataset. When researching the underlying causes of customer attrition this variable is not relevant and offers no analytical value. Hence, this variable was taken out of the dataset.

Outlier Analysis

An outlier analysis was conducted on continuous quantitative variables. There are 4 variables that were evaluated to determine whether outliers are present: balance, credit score, estimated salary and age. The data was evaluated through a boxplot and the interquartile range rule.

When observing the boxplot for the ‘Balance’ variable, there were no outliers in the balance data set. The interquartile range analysis indicates the same result. Hence, no iterations were necessary for the ‘Balance’ variable. Based on the boxplot, for the credit score variable, there were a few outliers present in this column. Using the IQR method, there were 16 anomalies identified: 376, 376, 363, 359, 350, 350, 358, 351, 365, 383, 367, 350, 350, 382, 373, 350. To manage the outliers, capping (winsorization) was used. It replaces all the values that are below the 1^{st} percentile with that respective value, and the same applies for values above the 99^{th} percentile. When, observing the boxplot for the estimated salary variable, there were no outliers in the estimated salary data set. This was verified with the IQR method, hence no iterations are necessary. Lastly, based on the boxplot for the age variable there we a few outliers present in the column, however these values are within an acceptable range (63-92).

Categorical variables

There are two categorical variables present in the dataset: gender and country. For gender the male was set to equal 1, and female set to equal 0. One hot encoding was used to process the country variable. This was used to set the category into a separate binary column. There is a separate column for France ("countryFrance"), Germany ("countryGermany"), and Spain ("countrySpain"), which equal 1 when they are from that country and otherwise it is set to 0.

Exploratory data analysis

Churn rate analysis & Heterogeneity

There are various factors that contribute to customer churn rates. An initial analysis of the churn rate indicated 20.36%, without controlling for other variables. To grasp a better understanding of the churning behavior of consumers, various sources of heterogeneity were evaluated. The first heterogeneity that was observed was gender. For males the churn rate of 16.49% was lower than the female churn rate of 24.98%. Another variable to take into account is age. Age brackets were generated to do an analysis per demographic: <25, 25–34, 35–44, 45–54, 55–64, 65+. As seen in the table below, most of the customers in this data set are between 25 to 45. The churning rate is highest for the 45-54 age group, closely followed by the 55-64 age group. These age groups might have higher expectations and financial perspectives, which may result in greater churning behavior.

Age Bracket	Sum	Churn Rate (%)
<25	549	7.47
25–34	3175	8.66
35–44	3378	19.63
45–54	1179	49.87
55–64	485	47.63
65+	234	14.53

Table 1: Churn Rate (%) By Age Group

Lastly, heterogeneity across countries can be evaluated. Germany has the highest churn rate of 32.33%. France and Spain have similar levels of churning, with 16.15% and 16.70% respectively. Hence it could be concluded that Germany is statically different from the other two countries. Germany might have higher banking expectation and specific preferences leading to potential higher churning behavior.

Relationship between tenure and churn

The relationship between the tenure and churn can be further evaluated to grasp a better understanding. Tenure reflects the years a customer has an account with the bank which could represent trust, engagement, and loyalty. Due to these reasons consumers that have a higher tenure might be less likely to churn. Overall, based on the churning rates for the different tenure levels, the rates are not significantly varying (table 2). Hence, the time a customer has been with the bank does not influence the churn rate.

Tenure	Churn Rate (%)
0	22.37
1	22.73
2	19.11
3	20.7
4	19.7
5	20.75
6	19.7
7	17.96
8	19.85

9	22.00
10	20.05

Table 2: Churn Rate (%) By Tenure

Churning Analysis on Financial & Customer Engagement

Additional heterogeneity can be evaluated on certain financial and customer engagement variables. A boxplot analysis of churning and financial factors, such as balance, estimated salary, and credit score, was conducted. Based on the output, the mean estimated salary of individuals that churn is close to the individuals that do not churn. This is also the case for the credit score variable. However, the account balance mean for churning individuals (91093.95) is higher than non-churning individuals (72813.68).

Furthermore, there can be different churning behaviors between customers that have varying levels of customer engagement with the bank. A frequency comparison, using a stacked bar plot, was conducted on churning and various factors, such as the number of bank products owned, whether member is active, and whether member owns a credit card. The chart suggested that there is almost no difference between churning behavior and whether an individual owns a credit card. There was churning variation with the active member status and number of products owned. The stacked bar plot indicated that there is lower churning behavior with active bank members. These members might be more loyal, which reduces the likelihood of churning. Additionally, the customers that own 2 products are least likely to churn. This is followed by the customer owning 1 product from the bank. The individuals that hold 3 products from the bank are more likely to churn than not churn. The few customers that hold 4 products from the bank all churned. Based on these results, customers that hold up to 2 products from the bank are more loyal and less likely to churn.

Model building

Methodology

Our team developed 3 machine learning models to predict customer churn (Yes/ No), a binary classification problem:

- Logistic regression
- Decision tree
- Random forest

To create each model we utilized the cleaned dataset from part C (see Data pre-processing above), removed the age_group column which was created exclusively for part D (see Exploratory data analysis above), converted churn into a factor (Yes / No) by simultaneously setting "Yes" as the positive class and defined an 80% - 20% split between the training and testing data.

To identify the strongest predictors of customer churn, we examined variable importance across the three machine learning models we built. Each model offers a different type of evidence.

Logistic Regression

Logistic regression identifies predictors through statistically significant coefficients. The strongest predictors (statistically significant) were:

Variable	Significant at	Estimate
credit_score	*(0.05)	+0.00065
gender	*** (0.001)	+0.49

age	*** (0.001)	-0.073
balance	*** (0.001)	-0.0000025
active_member	*** (0.001)	+1.11
countryGermany	*** (0.001)	-0.72

Table 3: Statistically significance and estimate for each variable

Decision Tree

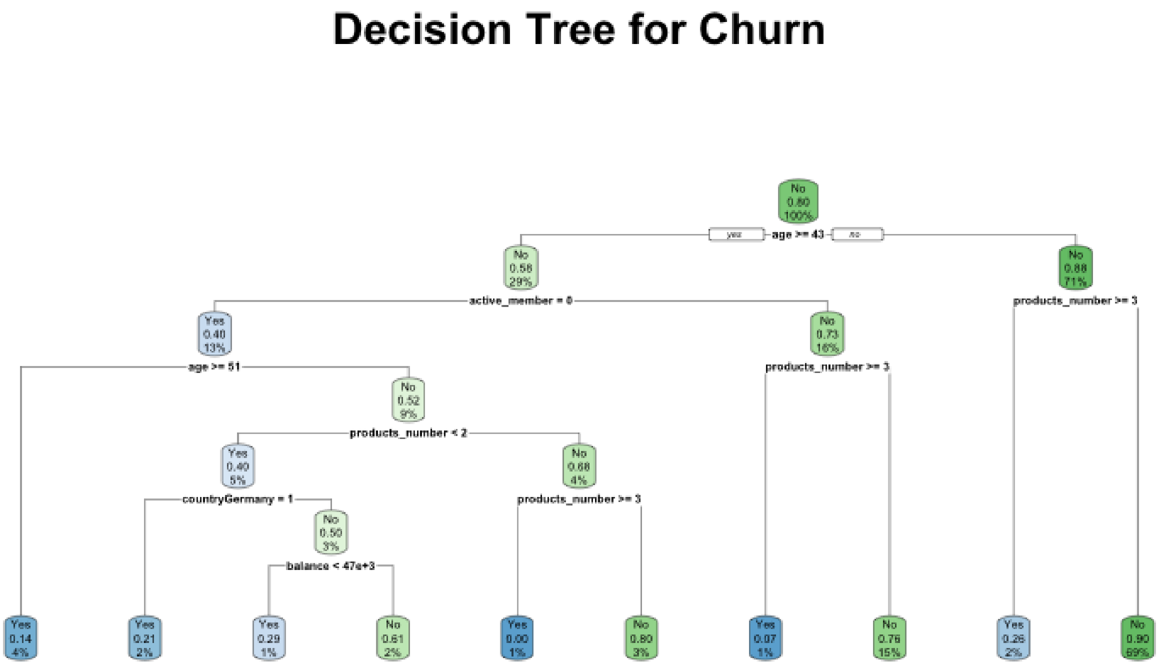

Figure 1: Decision Tree for Churn

The decision tree illustrates that age, active_member and products_number are the strongest predictors of churn since they appear in the earliest tree splits. Moreover, countryGermany and balance are also important but only within specific subgroups of customers.

Random Forest

Random Forest can evaluate the importance of each variable through the MeanDecreaseAccuracy index. This index shows how much the model's prediction accuracy drops when that variable is removed. The higher the value the more important it is for prediction. The most important ones are:

Variable	**MeanDecreaseAccuracy**
age	98.13
products_number	93.78
balance	44.19
active_member	55.86
CountryGermany	24.67

Table 4: MeanDecreaseAccuracy index value for each variable

The other variables are relatively low in value, near zero or negative.
Random Forest can also evaluate the importance of each variable through the MeanDecreaseGini index. This index shows how much a variable helps separate the classes by

reducing impurity in decision trees. The higher the value the more important the variable is for creating pure nodes. The most important ones are:

Variable	MeanDecreaseGini
age	495.06
products_number	289.2
balance	267.67
estimated_salary	264.68
credit_score	250.75
active_member	91.54
countryGermany	52.5

Table 5: MeanDecreaseGini index value for each variable

Important predictors conclusion

Across all three models, the variables that consistently emerge as the strongest predictors of churn are: age, products_number, balance, active_member, countryGermany.
These variables are selected as important because they are either statistically significant in the logistic regression, appear among the primary splitting variables in the decision tree and/ or have high variable importance scores in the random forest.

Evaluation of models

To compare the performance of the 3 models the following metrics were calculated after producing the appropriate confusion matrices:

- Accuracy (proportion of all correct predictions)
- Precision (how many predicted churners churned)
- Sensitivity (how many churners were correctly identified)
- Specificity (how many non-churners were correctly identified)

<u>Logistic Regression - Confusion matrix</u>

	Actual Yes	Actual No
Predicted Yes	294 (TP)	1385 (FP)
Predicted No	72 (FN)	48 (TN)

Table 6: Logistic Regression - Confusion matrix

<u>Decision Tree - Confusion matrix</u>

	Actual Yes	Actual No
Predicted Yes	144 (TP)	39 (FP)
Predicted No	222 (FN)	1394 (TN)

Table 7: Decision Tree - Confusion matrix

<u>Random Forest- Confusion matrix</u>

	Actual Yes	Actual No
Predicted Yes	163 (TP)	53 (FP)
Predicted No	203 (FN)	1380 (TN)

Table 8: Random Forest- Confusion matrix

Metrics comparison matrix

Model	Accuracy	Precision	Sensitivity (recall)	Specificity
Logistic regression	0.19	0.1751	0.803	0.033
Decision tree	0.855	0.786	0.393	0.972
Random forest	0.857	0.754	0.445	0.963

Table 9: Metrics comparison matrix

The logistic regression has a very low accuracy and specificity (see definitions above). On the other hand, it has a high recall meaning it flags most churners but this is because it predicts "Yes" for everyone (high FP). Also, precision is poor which means most predicted churners do not churn.

The decision tree has a significantly higher accuracy and specificity which means non-churners are identified correctly most of the time. Precision is also high, so when it says "Yes" it's usually right. However, recall is lower than the previous model.

Finally, the random forest has the highest accuracy, near equal specificity and precision to the decision tree. However, it has a better recall than the tree. This indicates that overall, it has the best trade-off between identifying churners and not producing false results.

In addition, each model was assessed using the AUC, which hints to how well each model separates churners and non-churners across all probabilities. As depicted in the table below, the random forest model scored the best.

Model	AUC (test set)
Logistic regression	0.749
Decision tree	0.75
Random forest	0.852

Table 10: AUC values for each model

In order to ensure a robust evaluation of the 3 models a 5-fold cross-validation was performed on the full dataset. Thus, it is ensured that multiple data points are used for both training and testing, since a single test split can lead to bias in performance estimates. Specifically:

- the data is split in 5 equal subsets (folds)
- 4 folds are used for training
- 1 fold is used for testing
- each fold is used once for validation
- process is repeated 5 times, testing each fold
- average performance across the 5 folds provides robust results

This way, overfitting and underfitting issues are also detected effectively.

Cross-validation was performed using **ROC** as the optimisation metric for each model:

Model	ROC	Sensitivity	Specificity
Logistic Regression	0.764	0.21	0.962
Decision Tree	0.76	0.443	0.965
Random Forest	0.855	0.473	0.963

Table 11: ROC, Sensitivity, Specificity values based on 5-fold cross validation

Once again, the random forest model scored the highest ROC and sensitivity, while having a high specificity.

Model evaluation conclusion

Random forest is the optimal model since it achieves the strongest combination of metrics:

- highest AUC (discriminates between churns and non-churns the best)
- highest cross-validation ROC (consistently the best across all folds)
- high precision, accuracy, specificity
- uses bootstrap and bagging which is preferable to decision trees (high variance models, if a variable is changed the resulting tree is different)
- OOB error estimate is 13.57% (generalization is sufficient)

Recommendations

The exploratory data analysis results and model insights revealed several customer characteristics that consistently emerged as strong predictors of churn. These factors include age, number of products, balance, country of residence (especially Germany) and an active membership status. Based on these findings, the following actionable recommendations are proposed:

1. *Target high-risk customer segments*

Rationale: The analysis revealed that customers from the aged groups of 45-54 and 55-64 have the highest churn rates (between 48-50%). These values are considerably higher than in the younger customer segment. Moreover, the models reinforced these result by showcasing age as on of the strongest predictors by consistently ranking first across logistic regression, decision tree and random forest models.

The possible reasons for these statistics might be the more complex financial needs, higher expectations for service quality, more stable incomes and assets among these age groups, making them more attractive for competing banks. Moreover, these age groups could have a higher sensitivity to dissatisfaction or poor customer experience, making them more likely to churn.

In order to combat this and increase customer retention, the following actions are proposed:

- Developing a targeted loyalty programme for customers aged 45+ that would highlight greater financial needs such as mortgage optimization, retirement-support products and personalized financial planning.
- Implementing proactive check-ins for these age segments.
- Providing dedicated support and advisors for high-value customers in these age brackets to reduce perceived dissatisfaction in the service gaps.

By focusing on these high-risk and high-value customers, the bank can address churn where it is most concentrated and financially impactful.

2. *Increase engagement among inactive customers*

Rationale: Another aspect discovered that influences the churn rate significantly is the activity of the members. The exploratory analysis shows that inactive members churn more frequently than active ones, indicating that engagement is a key signal of loyalty. This pattern is reinforced by the models, the active_member attribute being a significant predictor in logistic regression, appeared in the early split of the decision tree and ranking among the more important variables in the random forest model.

Inactive customers could be more prone to churning due to having a weaker relationship with the bank, having less familiarity with available products or services. Moreover, inactive customers might not perceive the value in remaining with the bank and are more susceptible to offers from competing banks.

Targeted interventions could influence directly engagement, so the bank can conduct the following actions to reduce the churning levels:

- Implementing activation campaigns to encourage use of mobile banking, online services and financial tools among customers who show low engagement.
- Offering personalized prompts or reminders, such as product recommendations, financial tips or unused banking features to increase customer relationship
- Rewarding engagement behaviors by offering small incentives for different actions and services.

In conclusion, by increasing the engagement among inactive customers, the bank can strengthen customer relationship, reduce churn risk and create long-term customer loyalty.

3. Country specific intervention

Rationale: The country-level heterogeneity reveals that Germany has a significantly higher churn rate (around 32%), more than double than other countries such as France and Spain. The logistic and random forest models also highlight that countryGermany is a significant churn predictor, suggesting that the drivers of churn in Germany differ from those in other countries.

This could suggest a structural or service-level problem affecting German customers specifically. This could be related to pricing, product fit, customer service expectations or competitive pressure.

The following actions are recommended:

- Conducting a targeted customer experience diagnostic for the German market to identify specific pain points
- Adapting the marketing, communication styles and product bundles to better reflect German customer preferences
- Offering localized retention incentives, such as fee reductions or region-specific promotions.

Overall, by addressing this country-specific discrepancy, the bank could significantly reduce overall churn.

Targeting Strategy to Maximise Expected Profit

In order to retain the specific customers from the ebi_exp_customers.csv dataset, the bank would like to target this segment with specific measures such as telemarketing. To determine the highest value customers, the best predictive model tested was chosen. In this case, the random forest model was used to estimate churn probabilities for each customer. Furthermore, an expected profit calculation was applied to determine whether contacting a customer creates a positive economic return.

The expected profit formula is:

$$\text{Expected Profit} = V \cdot P(\text{churn}) - C$$

Where:

- V= economic value of retaining a customer
- C = €1= cost of contacting
- P(churn)= predicted churn probability

A customer should be targeted if:

$$V \cdot P(\text{churn}) - 1 > 0$$

Two scenarios were evaluated:

Scenario 1: Retention Value = 5€

The profitability condition becomes:

$$5 \cdot P(\text{churn}) - 1 > 0 \Rightarrow P(\text{churn}) > 0.20$$

Results: 981 customers have $P(\text{churn}) > 0.20$. A list of customer ids will be provided in the Appendix.

The customers should be targeted when the expected benefit of retention exceeds the cost. In the case of retention value of 5€, the customers with a churn risk above 20% should be considered. This would ensure the bank focuses its resources on customers where intervention would result in a meaningful financial return.

Scenario 2: Retention Value = 10€

The profitability condition becomes:

$$10 \cdot P(\text{churn}) - 1 > 0 \Rightarrow P(\text{churn}) > 0.10$$

Results: 1000 customers have $P(\text{churn}) > 0.10$. A list of customer ids will be provided in the Appendix.

This includes all 977 high-risk customers from the previous scenario plus 23 additional customers with moderate churn risk (between 10% and 20%), resulting in all the customers in the dataset in our case. Because the value of retaining a customer is higher, the bank can profitably target a broader audience, including medium-risk customers. The expanded target list increases the total expected profit.

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Appendix

Appendix Part A: Data Pre-processing

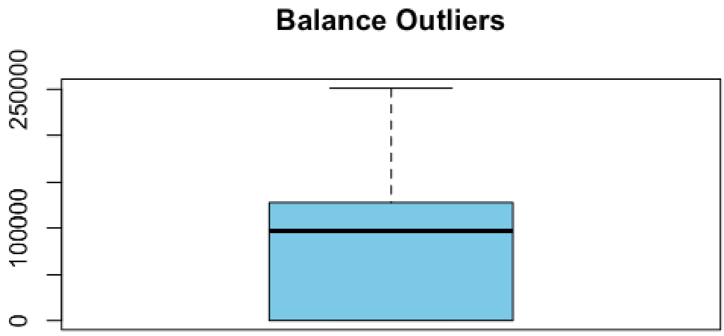

Figure A.1: Balance Outliers

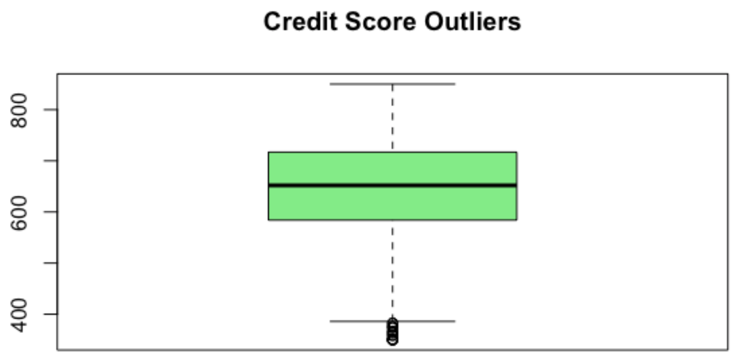

Figure A.2: Credit Score Outliers

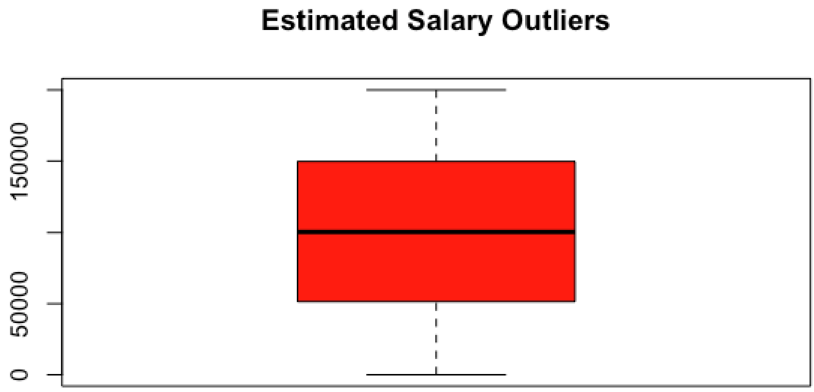

Figure A.3: Estimated Salary Outliers

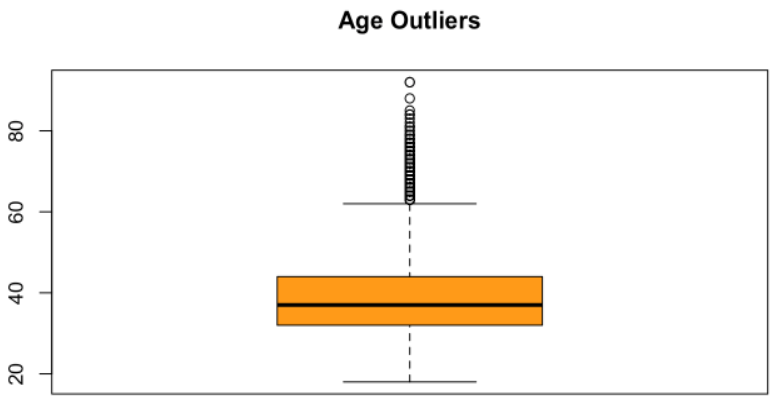

Figure A.4: Age Outliers

Appendix Part B: Exploratory Data Analysis

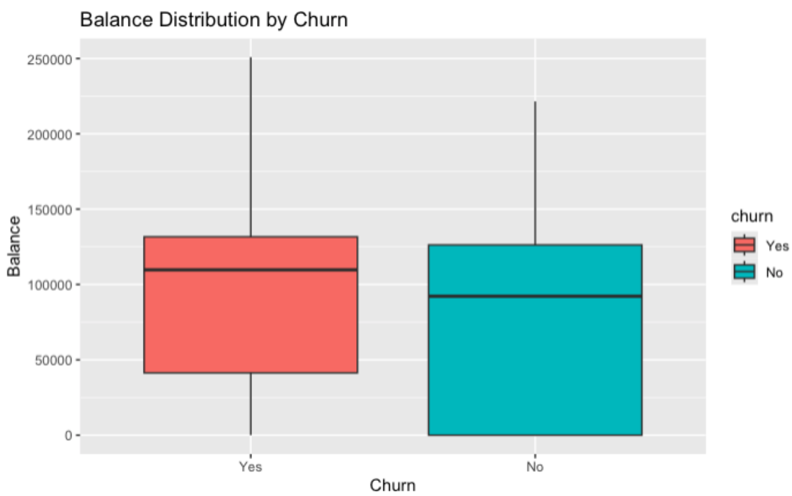

Figure B.1: Balance by Churning Behaviour

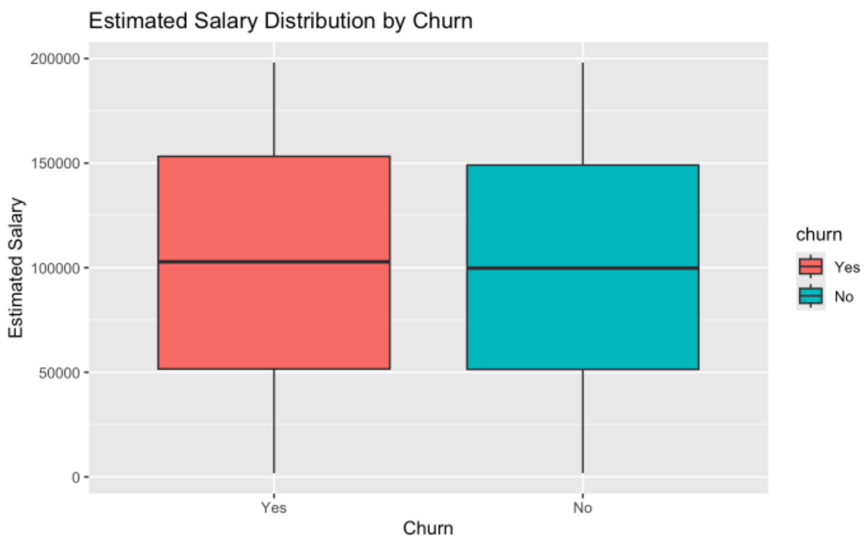

Figure B.2: Balance by Churning Behaviour

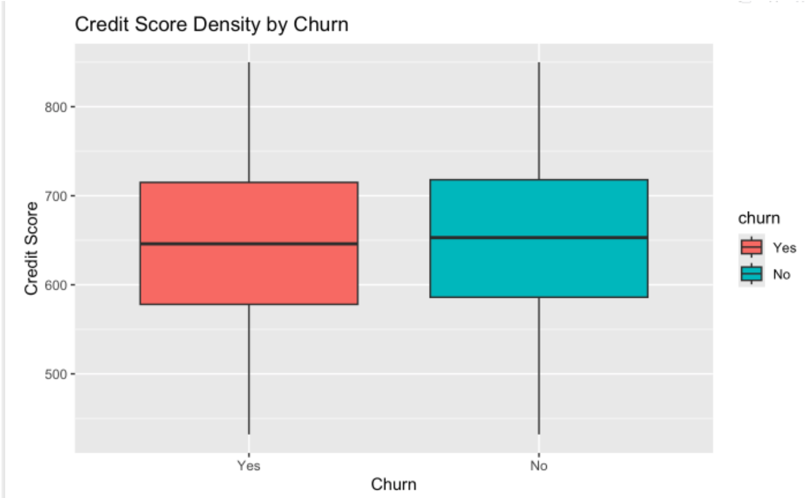

Figure B.3: Credit Score by Churning Behaviour

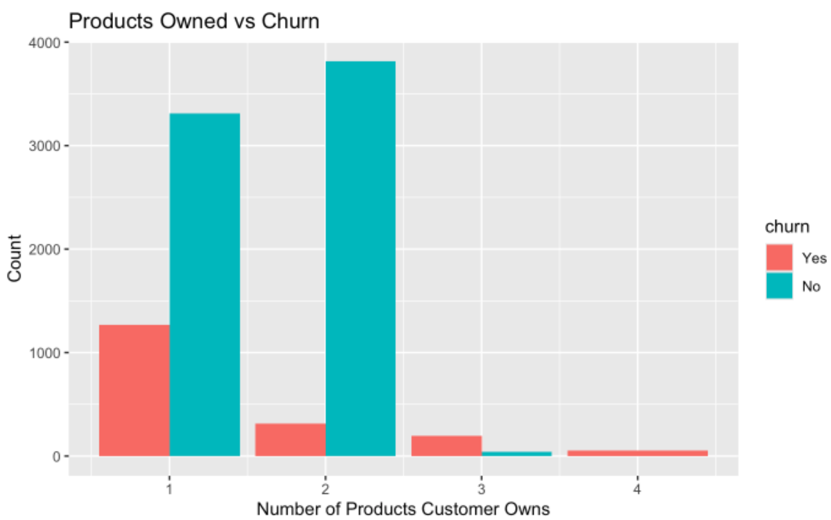

Figure B.4: Products Owned by Customer by Churning Behaviour

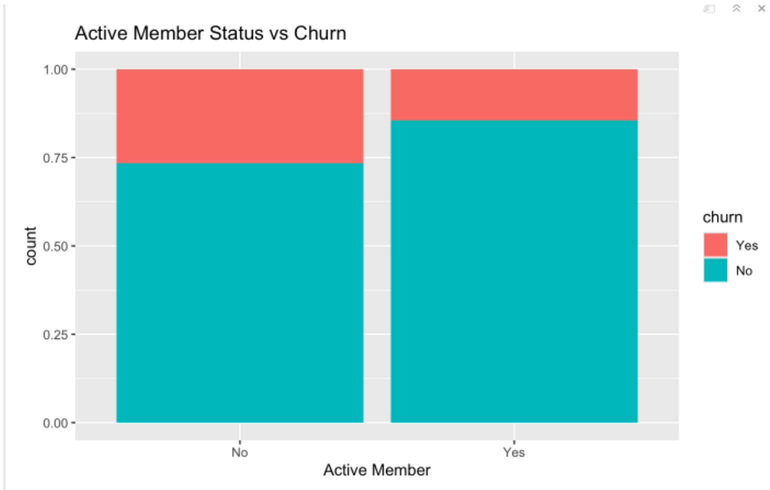

Figure B.5: Active Member Status by Churning Behaviour

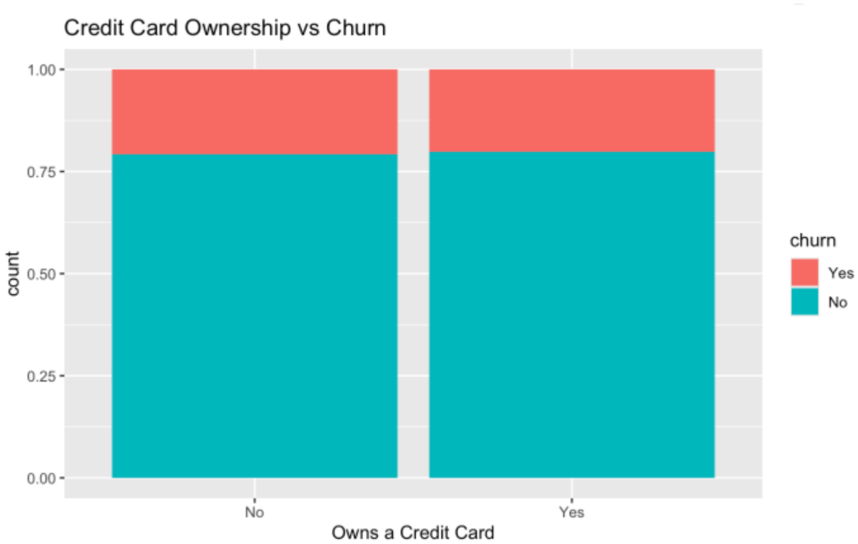

Figure B.6: Credit Card Ownership by Churning Behaviour

Appendix Part C: Model building

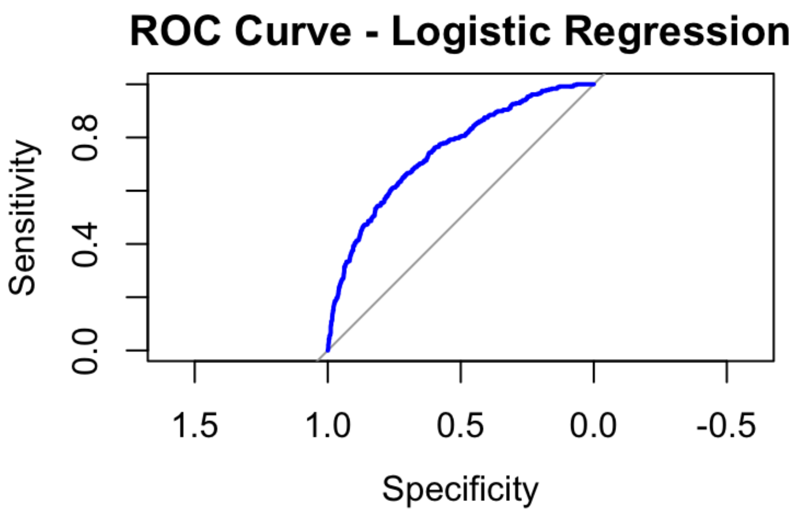

Figure C.1: ROC Curve for Logistic Regression

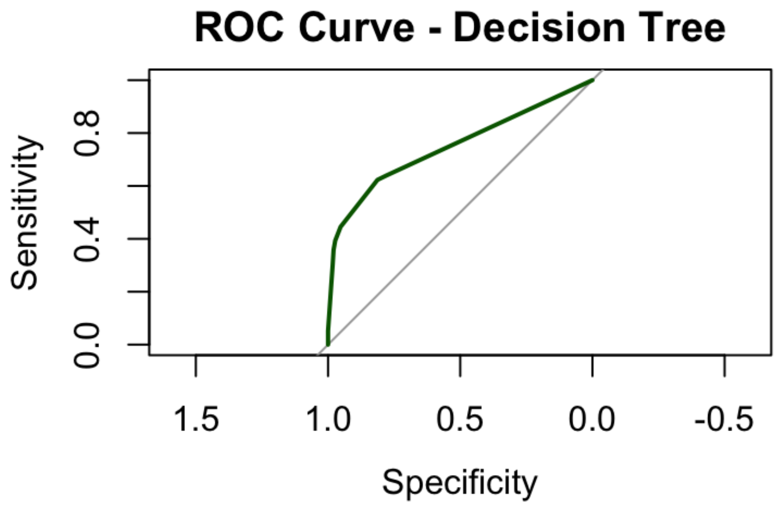

Figure C.2: ROC Curve for Decision Tree

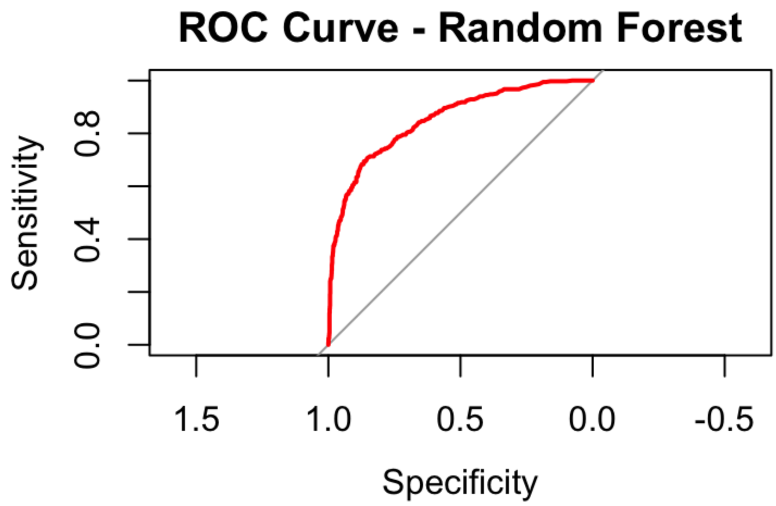

Figure C.3: ROC Curve for Random Forest

Appendix D: Recommendations

Targeted customers list when Retention Value = 5€

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