**MEF UNIVERSITY** 

# ALTERNATIVE CREDIT SCORING MODEL FOR THIN FILE CUSTOMERS

**Capstone Project** 

İstem Akca Korkmaz

İSTANBUL, 2019

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Asst. Prof. Duygu TAŞ KÜTEN

İSTANBUL, 2019

## **MEF UNIVERSITY**

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..../.../2019 Asst. Prof. Duygu TAŞ KÜTEN

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Director of Big Data Analytics Program

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## **EXECUTIVE SUMMARY**

#### ALTERNATIVE CREDIT SCORING MODEL FOR THIN FILE CUSTOMERS

İstem Akca Korkmaz

Advisor: Asst. Prof. Duygu TAŞ KÜTEN

AUGUST, 2019, 21 pages

Credit scoring is a widely used tool for banks, financial institutions or corporations. Traditional credit score models are calculated from past financial history of users, and this may lead to exclude some people who have limited financial history from the credit system. Alternative credit scoring allows sector players to access to a larger portion of these customers. The credit scoring industry has expanded with an "all data is credit data" approach that combines traditional credit scoring systems with new data points.

In this study, we aim to build an alternative credit scoring model for customers who have limited financial historical data (thin file) by using alternative data points for a national bank in Turkey. Some of the alternative data points and variables have been gathered from one of the bank's products: the authorized card for Turkish national league football tickets (Passolig). Using alternative data points combining with demographical and geographical information, we perform a comparison between the machine-learning approaches. We use logistic regression approach as a base model and perform a comparison between tree-based approaches: decision tree, random forest and XGBoost to select the most effective modelling approach.

**Key Words**: Alternative Credit Scoring, Thin File Customers, Binary Classification Techniques, Logistic Regression, Tree Based Algorithms

## ÖZET

### KREDİ GEÇMİŞİ AZ OLAN KİŞİLERE YÖNELİK ALTERNATİF KREDİ PUANLAMA MODELLERİ

#### İstem Akca Korkmaz

### Tez Danışmanı: Asst. Prof. Duygu TAŞ KÜTEN

## AĞUSTOS, 2019, 21 sayfa

Kredi puanlama yöntemleri bankalar, finansal kurumlar ve şirketler tarafından yaygın olarak kullanılır. Geleneksel kredi puanlama yöntemleri, finansal kullanıcıların geçmiş verilerine dayanarak hesaplanır ve bu durum, finansal geçmişi sınırlı olan kişilerin kredi sisteminin dışında kalmasına yol açabilir. Alternatif kredi puanlama yöntemleri, sektör oyuncularının bu kişilerin büyük bir kısmına erişmesine olanak sağlar. Geleneksel kredi puanlama yöntemlerini yeni alternatif veri kaynaklarıyla birleştiren kredi puanlama sektörü, "tüm veriler kredi verisidir" yaklaşımıyla genişlemektedir.

Bu çalışmada, Türkiye'deki bir ulusal bankanın kredi geçmişi az olan müşterilerine, alternatif veriler kullanarak bir kredi puanlama modeli oluşturmak amaçlanmaktadır. Alternatif veri kaynağı olarak bankanın ürünlerinden biri olan Türkiye ulusal futbol ligi yetkili kartı Passolig verileri kullanılmıştır. Demografik ve coğrafi verilerle birleştirilen bu alternatif veri farklı makine öğrenimi yaklaşımlarıyla modellenerek karşılaştırılmıştır. Lojistik regresyon yaklaşımı temel model olarak alınmış ve karar ağacı, rasgele orman ve XGBoost gibi ağaç tabanlı yaklaşımlarla karşılaştırılarak en etkili modelleme yaklaşımına ulaşılmaya çalışılmıştır.

Anahtar Kelimeler: Alternatif Kredi Puanlaması, Kredi Geçmişi Az Olan Müşteriler, İkili Sınıflandırma, Lojistik Regresyon, Ağaç Tabanlı Algoritmalar

## TABLE OF CONTENTS

Academic Honesty Pledgevi
EXECUTIVE SUMMARYvii
ÖZETviii
TABLE OF CONTENTSix
1. INTRODUCTION
2. LITERATURE REVIEW
2.1. Alternative Data
2.2. Modeling
3. PROJECT DEFINITION
3.1. Project Objectives7
3.2. Project Scope
4. EXPLORATORY DATA ANALYSIS
4.1. Data Summary
4.2. Pre-processing and Exploratory Analysis10
5. METHODOLOGY
5.1. Logistic Regression12
5.2. Tree-Based Models
6. CONCLUSIONS
6.1. Comparison of Evaluation Results of Models15
6.2. Conclusions16
APPENDIX A17
APPENDIX B
REFERENCES

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## **1. INTRODUCTION**

Credit scoring is a widely used tool for banks, financial institutions or corporations that open a credit account for the customer while selling a product. The risk of nonpayment has led to lenders use a systematic credit scoring, so that make reliable decisions about whom to offer credit. Credit scores are not only used for lending decisions, many employers review credit reports when determining whom to hire, or when deciding whether to promote an existing employee (Hurley and Adebayo, 2016).

Traditional credit score models are calculated from past financial history of users. This traditional approach may lead to exclude some people who have limited or no financial history from the credit system (Pedro et al., 2015). Traditional credit scoring models do not cover a significant proportion of consumers globally, especially among those with thin or no files like millennials, members of Gen Z, refugees and immigrants (Stafferöd Westerlund, 2019).

Using traditional credit score models does not create a problem for only non-banked or thin file customers; it also results in a large amount of missed opportunity for banking sector and financial institutions. In the global economic conditions, with rates on the rise, banking sector seeks new strategies for the shifting lending landscape.

Alternative credit scoring allows sector players to lend more responsibly and help more qualified customers, with more accurate and expanding access to a larger portion of the global economy.

## **2. LITERATURE REVIEW**

In this section, we present a review of the literature on alternative credit scoring and machine learning applications. In Section 2.1, we summarize some studies that represents the use of alternative data sources for credit scoring models. Section 2.2, we present the review of papers that use different machine learning models for credit scoring.

#### 2.1. Alternative Data

Hurley and Adebayo (2016) discuss the current and future place of big data applications for credit scoring. The credit scoring industry has expanded with an "all data is credit data" approach that combines traditional credit scoring systems with new data points mined from consumers' offline and online footprints. The study presents an overview of techniques and methodologies that big data credit scoring likely use to design, test, and deploy machine-learning tools to assess creditworthiness. Scroll down pace of a loan applicant while scanning online terms and conditions or geographic location can be indicators of a high-risk borrower. These non-traditional data points can be used for alternative credit scoring models.

Pedro et al. (2015) present an approach to build a model of financial risk assessment from mobile phone usage detail records gathered from telecommunication companies. Every time a mobile phone is used, the communication event is logged into telecommunication companies' database as a CDR (Call Detail Record) entry. CDRs contain information about the details of the communication event: caller ID and dialed number, time and date of the call or SMS, duration and so on. BTS (Base Transceiver Station) connects mobile devices within a telecommunications network through set of cell towers and allows to get and receive signals. Records from BTS which provide geographical location in latitude and longitude of the communication events are also logged into the database. Pedro et al. (2015) combine these data points and apply supervised machine learning methods to build a new credit scoring model named "MobiScore". This approach allows authors to create an alternative credit scoring model for thin file customers in a Latin America country who cannot take part in the credit system because of the lack of past financial records.

Schoen et al. (2013) present a comprehensive review on models using social media data as a rich source of data for individuals. Researchers use the social media data for various prediction models such as stock market movement predictions, forecasts for movie box-

office revenues, prediction of election outcomes and so on. The repository of accumulated data on social media (such as education status, the number of followers, work history, shares, activities, whom they are friends with) provides a lot of information about individuals without financial background. Wei et al. (2015) presents that there are advantages to collect information from an individual's network rather than only individualized data. Consumers have the above average chance of interaction with people who have similar creditworthiness, and thus network-based scoring can help lenders to reduce misjudgments about customers who have limited personal financial history.

There exists an adequate and expanding amount of literature on alternative credit scoring models and alternative data points. In the big data era, possibilities for alternative data sources is numberless; that's why; it is possible to determine alternative data points based on the specific business needs and the accessibility of the data. In this study, we use detailed data points of the customers who have the authorized card for Turkish national league football tickets (Passolig) whereas have thin financial history in the bank's database.

#### 2.2. Modeling

Abdou et al. (2011) present a review of different statistical methods applied in building credit scoring models. Regression analysis, support vector machines, discriminant analysis, decision trees, logistic regression, neural networks, k-nearest neighbors are widely used examples for credit scoring models. Among these, it is not possible to talk about an approach that works best and always works well.

Munkhdalai et al. (2019) compare the results of several machine learning approaches, and FICO credit scoring system which is a human expert-based model for credit scoring. The authors also comprehensively review the most recent studies in credit scoring to determine the machine algorithms for using their comparative study. They encounter that most of the studies compare their recommended methods with logistic regression approach, based on the review of documentation. Louzada et al. (2016) represent a broad and also systematic review on studies related with theoretical and practical approaches on binary classification methods for credit scoring over the years. In this paper, the authors classify the methods used in certain aspects by covering researching studies made between the years 1992 and 2015; including 187 papers. As illustrated in Figure 1, the logistic regression is one of the most used binary classification techniques among all during the considered time

period, on the comparison studies. One of the main reasons of using logistic regression widely for credit scoring models is interpretability. Logistic regression models are easy to interpret for knowledge extraction from the components of the model (Munkhdalai et al., 2019). If there is a rejection decision based on a credit scoring model, banks need to provide the reasons of rejection to the certain regulatory parties. Logistic regression models are transparent in terms of providing the functional relationship of the variables. (Dong et al., 2010)

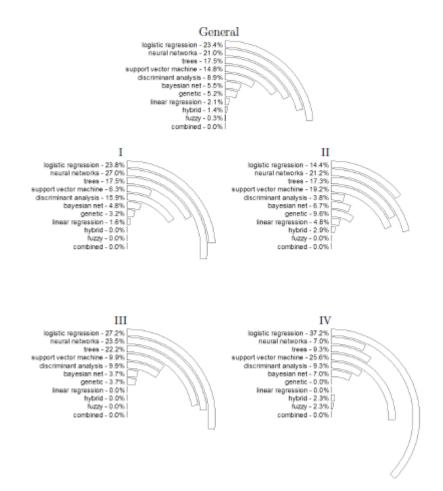


Figure 1: Circular bar plots concerning the techniques used in the paper's comparison studies. Reprinted from "Classification methods applied to credit scoring: Systematic review and overall comparison," by F. Louzada, A. Ara, and G. B. Fernandes, 2016, Surveys in Operations Research and Management Science, 21(2), 117-134.

Mues et al. (2004) propose to use of decision diagrams based on the decision tree models in credit scoring to develop easily understandable and applicable models in daily practice. Decision tree models represent non-parametric statistical methods that provide high

flexibility without assumption on data distribution (Jiang, 2009). Galindo and Tamayo (2000) address decision tree models as an example for the transparent models that can be conveniently interpretable by the local decision maker. Moreover, the set of attributes to be used for credit scoring models may contain missing values for some individuals. For example, the bank transaction information may be unavailable for a new bank customer. Missing value imputation approach can be chosen under these conditions; however, the real-time imputation will require additional computational power and time. Considering the credit allocation decisions need to be made instantly, decision tree-based methods which are not overly sensitive to the loss values can offer an effective solution. Jiang (2009) considers the advantage of decision trees as the background knowledge for the users is less required. As shown in Figure 1, decision tree algorithms are the third most used binary classification techniques in general, stated specifications of the decision tree-based models can seem to be the reasons for this.

On the other hand, Bastos (2007) and Zhang et al. (2008) claim that decision tree models have limitations on the stability of classification accuracy. Small variations on a variable may lead large changes in classification results. For instance, considering two features that have similar classification power on a dataset, if there is a small change in one of them, decision tree algorithm may split a node by using the other feature rather than the previous one. This tendency of the decision trees may create an entirely different split and tree structure than the classification based on the former feature (Bastos, 2007). Munkhdalai et al. (2019) and Louzada et al. (2016) summarize ensemble methods used for improving the performance of credit scoring models. Ensemble methods combines several decision trees to reach the better classification performance than a single decision tree. Bagging and boosting are two of most popular ensemble methods. The main idea of the ensemble methods is to use set of a weak learners to create a one strong learner using the same learning algorithm. Bagging method chooses each weak learner model independently, learns in parallel and combines the results by averaging the responses of the weak learners. On the other hand, boosting method chooses the weak learner models sequentially by taking into account the previous ones' success. Random Forest is an algorithm that uses bagging method based on decision trees, and XGBoost is an algorithm that can apply boosting technique on both linear model solver and tree learning algorithms.

Our primary goal in this study is to build an alternative credit scoring model using real consumer data and to provide machine-learning approaches that can serve as a baseline. Therefore, we use logistic regression approach as a base model and perform a comparison between tree-based approaches: decision tree, random forest and XGBoost to select the most effective modelling approach for our alternative data and features.

## **3. PROJECT DEFINITION**

#### **3.1. Project Objectives**

This project aims to build alternative credit scoring model for customers who have limited financial historical data (thin file) by using alternative data points for a national bank in Turkey that currently uses only traditional scoring approach.

The breakdown of project objectives are as follows:

- Using alternative data points combining with demographical and geographical information,
- Building several binary classification algorithms with alternative data,
- Evaluating the best performing model.

With the alternative scoring model, the bank can expand the credit penetration in the national market and reach the customers who have limited financial historical data (thin file).

#### 3.2. Project Scope

In this project, some of the alternative data points and variables have been gathered from one of the bank's products: the authorized card for Turkish national league football tickets (Passolig). The card is mainly used to buy combined or single tickets for Turkish national football league, where monetary transactions can also be performed by the users. We have combined several spending data points from the authorized card, and demographic and geographical data. Additionally, we have added the past credit status data of the customers, who have the card, into dataset.

We consider this business problem as a binary classification problem where the target variable is credit status. We apply logistic regression, decision trees, random forest and XGBoost algorithms based on these past different data points, in order to calculate an alternative credit score for the future customer.

## 4. EXPLORATORY DATA ANALYSIS

#### 4.1. Data Summary

In this project, we used a dataset shared by the bank including 142 variables and 40,370 unique customer records who both has a Passolig card and already got loan from the bank (See Appendix A). The variables contain different kinds of data types and various information that we have combined in following headings:

Variable Category	No of Variables
Bank Acquisition	4
Bank Service Transaction	ns 5
Card - Shop	24
Card - Top up	6
Card - Transaction	12
Card - Withdrawal	6
Credit	20
Date	13
Demographical	21
Geographical	6
ID	2
Passolig - Football Ticket	s 20
Telecom Invoice	3
TOTAL	142

Table 1: Summary of Variables

- Bank acquisition and bank service transactions: Bank acquisition variables indicate the channel and product information of the customers. Bank service transaction variables provides information about the activities like password inquiry or payment of visa fee for the card.
- Card: This group of variables indicates shopping, transaction, withdrawal and top up activities such as top up TL to Passolig debit card or shopping transaction made with Passolig card excluding transactions related with national football league.
- Credit: Credit variables include data for credit status, application amount, interest rates and late payment credits. We have defined "credit status" as the target variable which is classified into this heading.

- Date: Date variables give information about the time at which the credit or card application is started and the beginning of legal proceedings.
- Demographical: These variables include age, gender, the place of birth, marital and educational status, the address and e-mail information.
- Geographical: These variables include specific late payment ratios by county and district calculated based on the past data in the bank's database.
- Passolig: The variables related with Passolig give information about tickets purchased. In addition, there are variables indicates the class of the tickets bought such as VIP, combined and so on.
- Telecom Invoice: These variables include late payment or legal proceedings for telecom invoices that are ordered as automatic payment by the user.

Credit status is our target variable and named as "KREDI\_HESAP\_DURUM" in the dataset. Distribution of the certain credit status types in the dataset can be found as below:

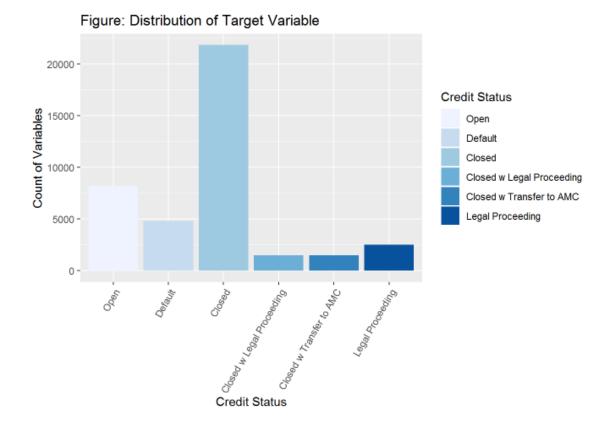


Figure 2: Distribution of Target Variable

"Closed" and "Open" status show that loans that are paid and closed, and still have installments, respectively. "Default" status implies loans that have late payments in the maturity terms. "Closed w Legal Proceeding" and "Legal Proceeding" status reveal the loans closed with legal proceedings or have an ongoing legal process. "Closed w Transfer to AMC" status shows the loans that are transferred to asset management companies because of the late payments. Categories rather than "Closed" and "Open" show the loans that have the problem in the installments. In the pre-processing stage, we thus have to manipulate these four categories into one category as "Default" and the remaining two categories combined as "Good" for binary classification models.

#### 4.2. Pre-processing and Exploratory Analysis

During the pre-processing phase, we have excluded 15 out of 20 variables from "Credit" category since these variables indicate the results of the credit status and may cause multicollinearity for our models. Remaining variables in "Credit" category includes numerical variables like the day of the week or the hour of the day of the loan application. These variables may contribute to regression model as categorical indicators. Additionally, we have excluded the variables in "ID" and "Date" categories. "ID" category has distinct ID features which would be no contribution to the classification models. There are other separate columns rather than variables in "Date" category that show information about the duration of the membership or duration from last shopping date and so on. Thus, there is no need to make feature engineering on "Date" category to create new variables. There are 6 more variables that are excluded from the dataset that we have examined through visualizations and indicate no correlation with the target variable or same values for all rows.

After excluding certain variables, we have analyzed the ratio of missing variables for each remaining feature. 70 variables out of remaining 108 have missing values in different ratios.

NA % Range	No of Variables
>90	10
70-89	30
40-69	19
10-39	5
<10	6

Table.2: Summary Table of Ratio of Missing Variables

When we investigate missing values for each variable, 64 variables out of 70 variables show shopping, transaction, withdrawal and top up activities. Thus, missing values for these variables indicate that there is no transaction for this specific customer. Missing value ratios for these variables are between 90% and 10%. We have imputed missing values with zero for these 64 features, because all of them are numerical values and we would like to investigate their contribution to model in the modeling stage.

Remaining 6 variables indicates NPL values which shows specific late payment ratios by county and district calculated based on the past data in the bank's database. These ratios can be strong indicators for regression model, and thus we have considered to impute missing values with mean/median imputation approach. We have calculated mean and median values for each column and replaced missing variables with both mean and median. We have compared mean imputed, median imputed and original distribution of variables through data visualizations (See Appendix B). We have not come across with significant differences on distributions. On the other hand, median value for "Ilce NPL – Tasit" variable is calculated as zero which means that if we impute missing variables for this feature with median value, default probability for missing values would be 0. This may mislead our algorithms for calculating default probability. Therefore, we have move forward to model building with mean imputed variables.

We have grouped our target variable into two categories as "Good" and "Default". Additionally, we have grouped some categorical variables by setting range like age or the application hour of the day, and created two different datasets with grouped and non-grouped categorical variables. Since all categorical variables should be converted into binary variables for regression model, we would like to decrease the number of variables so that we can save time on computing. However, this can create a certain risk on accuracy or classification effectiveness of the model, thus, we have created two different versions and compared the results of the models for both versions to find the most efficient and accurate model for credit scoring.

## **5. METHODOLOGY**

#### 5.1. Logistic Regression

Logistic regression builds a model based on the estimation of linear combination between the explanatory variables and the binary response variable, and transforms log-odds to probability with logistic function (Munkhdalai et al., 2019). Variation of the explanatory variables affect the classification performance of a regression model; thus, we evaluate regression models for the determination of optimal parameters. One of the measurement criteria for model selection with optimal parameters is AIC value. AIC is a relative measure of model parsimony and estimates information loss with respect to different models. As AIC value indicates the relative information loss among the variation of the variables, the model with a lower AIC value is healthier.

To build a successful credit scoring model, a classifier needs to be understandable, accurate and fast (Liu, 2002). Considering ease of interpretability of the model, we seek for a model as simple as possible with a combination of reliable accuracy rate and calculation speed. Therefore, we compare the AIC score of the different variations of regression models as well as their accuracy rate via confusion matrices and ROC curves.

We build two different logistic regression models as our initial models with two different datasets that we have created during the pre-processing phase: dataset with non-grouped categorical variables (Model 1) and dataset with grouped categorical variables (Model 2). We try many iterations with two base models by feature selection based on *p*-values of each independent variables. We summarize accuracy and AUC values of model iterations with comparative AIC scores in Table 3.

Model Iteration	AIC	Accuracy %	AUC %
Model 1.a	42,926	75.58%	69.10%
Model 2.a	42,932	75.50%	68.60%
Model 1.b	42,923	75.57%	69.10%
Model 2.b	42,930	75.49%	68.60%
Model 1.c	42,919	75.52%	68.70%
Model 2.c	42,912	75.51%	68.50%

Table 3: Evaluation Metrics of Logistic Regression Iterations

Model 1.a and Model 2.a corresponds to the initial model that is trained with all variables. According to the summary of the results of Model 1.a and Model 2.a, there are some variables that are strongly correlated with other variables. We thus have excluded these variables and built a revised model: Model 1.b and Model 2.b. Then, we have investigated *p*-values and selected the variables that have *p*-values very close to 1 and exclude them from the model. We have created a new model based this selection, that are Model 1.c and Model 2.c.

We compare the evaluation metrics of each model. While evaluating a model performance, accurate approach would interpret the combination of certain metrics and evaluate the tradeoff between them (Liu, 2002). Although accuracy score and AUC value are slightly lower than the rest of the models, Model 1.c and Model 2.c seem as healthier models in terms of AIC value. We consider this difference on accuracy and AUC value is acceptable. When we compare Model 1.c and Model 2.c, accuracy and AUC values are almost similar. Therefore, we consider to move forward with Model 2.c because of its better performance in calculation time. Also, we apply different algorithms to grouped dataset in order to compare the model performances, accordingly.

#### 5.2. Tree-Based Models

Decision tree models basically creates classification models by creating a set of ifthen determination conditions in tree-based structures. Decision tree algorithms can be used for both regression and classification problems. CART (Classification and Regression Tree) method uses Gini index for classification criterion, for our binary classification problem we use CART method (Louzada et al., 2016).

We use the grouped dataset for training of the model and use "rpart" package to build a classification tree. We have built our first model with the default parameters of the package and investigated the results. Our initial tree model gives 74.36 % accuracy rate. Then, we try iterations with the model by changing "minsplit" value which corresponds to the minimum number of observations should exist in a node for a split to be attempted. Default value for this parameter is given as 30 in the "rpart" package. We set the value as 10 in order to create a more detailed tree and, inherently to obtain more accurate classification. As it is known, CP value represents complexity parameter and is used to control the size of the tree. If the cost of adding a variable from the current node is higher than CP value, then decision tree structure stops growing. Default CP parameter value is 0.01, however we prefer to create a bigger tree and set value as 0.001. With the parameter tuning, our decision tree classification model gives accuracy rate as 76.15%. It's possible to make more iterations via parameter tuning; however, this may create the risk of overfitting and increase in computing time.

Random Forest algorithms use a set of decision trees created from subset data that are randomly selected from the train dataset. Building a random forest classifier for our credit scoring model, we use "randomforest" package in R. We build the initial model with default parameters and investigate the results. However, the calculation time of the random forest model is quite high. As we aim to create an alternative model with speed, it is not preferred to apply parameter tuning for random forest algorithm since it would increase the number of trees. The accuracy rate of the initial random forest model is 75.93%.

XGBoost algorithm is an ensemble boosting method that optimizes the size of the tree and objective function with regularization parameters. We create initial boosting model with default parameters, and we then investigate the results by iterations with parameter tuning. XGBoost algorithm is quite flexible and fast, that we can test various iterations in a short amount of calculation time. Nevertheless, in this study, we aim to compare different algorithms for the alternative credit scoring model, and thus we have set parameters of XGBoost algorithm similar to decision tree model. Final XGBoost model gives 76.10% of accuracy rate.

## 6. CONCLUSIONS

#### 6.1. Comparison of Evaluation Results of Models

Models on credit scoring problems predict "Default" and "Good" credit status as binary variables based on the past data. It is widely agreed that accuracy score is a simple and direct measurement of the binary classification performance. Nevertheless, accuracy score may not be sufficient as standalone for evaluation of the model. Interpretability, simplicity and velocity of the model are other practical benchmarks of the credit scoring models.

Furthermore, a lending institution should assess the risk of misclassification errors in terms of loss and opportunity cost. Confusion matrix may serve this purpose for estimating the risk. Confusion matrix provides a comparison table for actual and predicted class labels as illustrated:

Ta	able : : C	onfusion r	natrix.
		Λ	Λ
		{1}	{0}
D	{1}	ŤΡ́	ÈŃ
D	{0}	FP	TN

Table 4: Confusion Matrix

If a customer's status is predicted as "Good" while the actual status is "Default; it will create a commercial risk for the lending institution. This type of error is named "Type II Error" or "False Positive Rate (FPR)". In other case, if a customer is classified as "Default" status while the actual status is "Good", this will cause opportunity loss for the lending institution. The latter error is named "Type I Error" or "False Negative Rate (FNR)". Thus, evaluation criteria for credit scoring models should be combined with multiple benchmarks so that the financial risk would be assessed. Therefore, we use accuracy rate, Type I error, Type 2 error and the computation time to compare our models.

	Logistic Regression	Decision Tree	Random Forest	XGBoost
Accuracy %	75.51%	76.15%	75.93%	76.10%
Type I Error (FNR)	1.54%	2.04%	2.41%	3.22%
Type II Error (FPR)	22.97%	21.81%	21.71%	20.77%
Calculation Time	26.62 sec	29.20 sec	14.48 min	40.16 sec

Table.5: Summary of Evaluation Metrics of the Models

The primary finding on comparison of accuracy scores is that all models have marginally close rates. XGBoost algorithm shows the best performance in terms of Type II error among all models. The computation time of the random forest algorithm is quite long, and thus it is not suggested to apply random forest algorithm in the bank's alternative scoring implementation. Although the decision tree performance seems sufficient; due to the possible risk about the limitations on the stability of classification accuracy, it is cautious to monitor how it will perform with future data points. In the light of this study, our suggestion is to use XGBoost, logistic regression and decision tree models for the bank's alternative scoring implementation by comparing the results together with future data points.

#### 6.2. Conclusions

It is a necessity that credit scoring models become more efficient, accurate, and more inclusive for the people like have thin financial history, in rapidly changing world. Innovative models based on alternative data sources and machine learning applications creates opportunities for new customers as well as creates efficiency for the financial institutions on risk management.

It is easier to create alternative models with reasonable amount of time and resources thanks to the enhancement of machine learning applications and growing transactional data. As alternative credit scoring models advance, their capacity to precisely assess the risk will increase thanks to the learning loop created by data science and sector players. This enable more customers to reach financial credit and create growth for financial lending sector.

## APPENDIX A

Image: Control Program       Numerical       Application Due         0       REPUT ID       Numerical       Application Due         0       REPUT ID       Numerical       Application Due         0       NUMERIA       Application Due       Numerical         0       NUMERIA       Application Due       Numerical         0       NUMERIA       Application Due       Numerical         0       NUMERIA       Application Due       Numerical         0       NUMERIA       Application Due       Numerical         0       NUMERIA       Data       Print Due of Application State Controm Storker Contract         0       NAM       Caregorical       Print Due of Application Due       State Control Control Contract         10       NAM       Caregorical       Print Due of Application Due of State Opplication Control Control Control Control Control Control Control Takes Opplication State Control Control Takes Opplication Due to Control Control Control Control Control Control Control Control Control Control Control Takes Opplication Due to Control Control Control Takes Opplication Due to Control Control Control Control Control Control Takes Opplication Due to Control Control Control Takes Opplication Due to Control Control Control Takes Opplication Due to Control Control Control Takes Opplication Due to Control Control Control Control Control Control Control Control Due Control Co	#	Columns	Data Type	Explanation
2       MAPPENDER       AppEndance Date         3       REDU_HERN_LPURUM       Carageord Situation of the cells         4       DONEMA       Numerical       Carageord Situation of the cells         6       MISTERI, CLAMA_TARIH       Date       First Signatum Date of Action Proceed Confit Contant         6       MASTERI, CLAMA_TARIH       Date       First Signatum Date of Action Proceed Confit         7       ACAT_TIME       Carageord Signatum Consolity Confit       First Signatum Date of Action Proceed Confit         10       TACMA       Carageord Signatum Consolity Contant Strategord Contant       First Signatum Consolity Contant Strategord Contant         11       TACMA       Carageord Signatum Consolity Contant Strategord Contant Strategord Contant       First Signatum Consolity Contant Strategord Contant Strategord Contant         12       KANT_TARIH       Numerical Contant Consolity Signatum Contant Strategord Contant Strategor				
I       DORMA       Numerical Custor       Application Date an Yuenk Media         6       MUSTRU, OLMA, TARIH       Date       First Signature Date of Customer Sorvice Contract         7       CARD, JMMOSS, DATE       Date       Lash Print Date of Active Passolg Card         8       RERT, TARIOSS, DATE       Date       Lash Print Date of Active Passolg Card         8       RERT, TARIOSS, DATE       Date       Lash Print Date of Active Passolg Card         8       RERT, TARIOSS, DATE       Date       First Application Date Socies Signature of Contorers Socies Contract         8       RANT, TARIH       Date       First Application Date Socies Signature of Contorers Socies Contract         8       MAX, SHOP, AMOUNT       Numerical       Control Date Signature Of Card Shopping (cacl. Single & Combined Foodall Tickes)         9       MAX, SHOP, AMOUNT       Numerical       Datation from DAte Card Shopping (cacl. Single & Combined Foodall Tickes)         9       MAX, SHOP, AMOUNT       Numerical       Datation from DAte Card Datas Shopping (cacl. Single & Combined Foodall Tickes)         9       MAX, ONSHOP, AMOUNT       Numerical       Datation from Date Card Datas Shopping (cacl. Single & Combined Foodall Tickes)         20       NN, ONSHOP, AMOUNT       Numerical       Datation from Date Card Data Sh				
j       King Ku, Chang	3		Categorical	
6       MSTERLOAM_TARTH       Date       First Spanner Date of Castoma Server Connect         8       IRST_TAMOSS_DATE       Date       Last Pern Dae of Ache Passoig Card         8       IRST_TAMOSS_DATE       Date       Last Pern Dae of Ache Passoig Card         10       TAKAM       Categoria       Food Team Norme of Rassoig Card         10       TAKAM       Categoria       Food Team Norme of Castoma Foreice Contract         11       TAKAM       Date Castoma Team Of Passoig Card         12       KAYT_TARHI       Date       Food Sagata         13       RIP_CONTONT       Numerical       Cand Date Castoma Sagata       Candinata Food Sagata         13       RIP_CONTONT       Numerical       Maximum Annum Of Date Cast Shappig Cast. Shapp & Contral Sactoma Teachon         14       RIPAT_SANOUNT       Numerical       Maximum Annum Of Date Card Shappig Cast. Shapp & Contral Sactoma Teachon         15       RIPAT_SANOUNT       Numerical       Cannot Date Stopping Date Cost Shapp & Contral Sactoma Teachon         16       RIPAT_SANOUNT       Numerical       Cannot Date Stopping Date Cost Shapp & Contral Sactoma Teachon         17       RIPAT_SANOUNT       Numerical       Cannot Date Cast Date Cast Date Cast Date Castoma Sactoma Teachon </td <td>4</td> <td>DONEM</td> <td>Numerical</td> <td>Application Date as "Year&amp;Month"</td>	4	DONEM	Numerical	Application Date as "Year&Month"
Image: Sec: Sec: Sec: Sec: Sec: Sec: Sec: Se	5	CUST_ID	Numerical	Customer ID Number
skill       Date       Lark Prim Date of Active Passoft Cord         iv       KART_TARIN       Caragorical       Poorbal Tams Name of Passoig Cad         iv       TAKM       Caragorical       Poorbal Tams Name of Passoig Cad         iv       RANT_TARIN       Due       First Application Date before Signature of Coloners Service Contract         iv       SHOP_COLONT       Numerical       Count of Dabit Cad Shopping (ccd. Single & Combined Foorbal Takets)         iv       SHOP_COLONT       Numerical       Numerical       Count of Dabit Cad Shopping (ccd. Single & Combined Foorbal Takets)         iv       SHOP_COLONT       Numerical       Duatism from Dabit Can Dabit Cad Shopping (ccd. Single & Combined Foorbal Takets)         iv       Dastor Shop P.AMOUNT       Numerical       Duatism from Dabit Can Dabit Cad Diase Date (ccd. Single & Combined Foorball Takets)         iv       Dastor Shop P.AMOUNT       Numerical       Numerical       Numerical       Numerical         iv       MAX, ONSHOP_AMOUNT       Numerical       Numerical       Numerical       Numerical       Numerical         iv       Numerical       Numerical       Numerical       Numerical       Numerical       Numerical         iv       Numerical       Numical			Date	First Signature Date of Customer Service Contract
9       KART_TUPI       Caregorial       Points         10       TAKIM       Caregorial       Forobal Tama Nuce of Passolig Cad         11       TEAM, ID       Caregorial       Forobal Tama Nuce of Passolig Cad         12       KAYT_TARH       Dae       First Application Date More Signature of Customer Service Contract         13       MAX_SHOP_AMOUNT       Numerical       Matimum Anound Tobic Cad Stopping (excl. Single & Combined Forobal Tickes)         14       MAX_SHOP_AMOUNT       Numerical       Mamium Anound Tobic Cad Stopping Cads. Single & Combined Forobal Tickes)         16       NATS, SHOP_AMOUNT       Numerical       Mamium Anound Tobic Cad Stopping Cads. Single & Combined Forobal Tickes)         17       INST, SHOP_AMOUNT       Numerical       Mamium Anound of Debic Cad Otains Stopping (excl. Single & Combined Forobal Tickes)         10       NAK, ONSHOP_AMOUNT       Numerical       Mamium Anound of Debic Cad Otains Stopping (excl. Single & Combined Forobal Tickes)         11       NINC, ONSHOP_AMOUNT       Numerical       Mamium Anound of Debic Cad Otains Stopping (excl. Single & Combined Forobal Tickes)         12       NAC, ONSHOP_AMOUNT       Numerical       Maximum Anound of Debic Cad Cash Withdrawal         13       NAC, ONSHOP_AMOUNT       Numerical       Maximum Anound Debic Cad				-
10       FRAM, D       Caregorial Foodhal Tam D Plassoing Cadl         11       FRAM, D       Caregorial Foodhal Tam D Of Passoing Cadl Same Contoner Service Contract         12       KANT_TARIH       Dae       FFA Application Date befors Signature of Cantomer Service Contract         13       SHOP_COUNT       Numerical Control Fobb Cadl Shopping Cacl. Single & Combinel Foodhal Teckes)         14       MAS, SHOP_AMOUNT       Numerical Cand Onine Shopping (ext. Single & Combinel Foodhal Teckes)         10       NNS.NEOP_AMOUNT       Numerical Numerical Cand Onine Shopping (ext. Single & Combinel Foodhal Teckes)         11       Numerical Numeri				-
11     Extra Tr.ArtH     Dae     First Application Dave before Signame of Custome Service Contract       13     BKUP, COUNT     Numerical     Maxima manuari Debit Card Shopping (excl. Single & Combined Foothal Teckes)       14     MAX, SHOP, AMOUNT     Numerical     Maxima manuari Debit Card Shopping (excl. Single & Combined Foothal Teckes)       15     MAX, SHOP, AMOUNT     Numerical     Numerical Numerical Numerical Numerical Card Shopping (excl. Single & Combined Foothal Teckes)       16     RAST, SHOP, DANS     Numerical     Numerical Num			-	
Instruct       Date       First Application Date before Signature of Customer Service Contract         IS SHOP, COUNT       Numerical       Count of Debit Call Shopping (excl. Single & Combined Foodal Teckes)         IS MUS, SHOP, AMOUNT       Numerical       Numerical       Numerical         IS MUS, SHOP, AMOUNT       Numerical       Numerical       Numerical         IS MUS, SHOP, CANDINT       Numerical       Numerical       Numerical         IS REST, SHOP, DAVIS       Numerical       Numerical       Numerical         IS NUM, SHOP, AMOUNT       Numerical       Numerical       Numerical       Numerical         IS NUM, OSHOP, AMOUNT       Numerical       Numerical       Numerical       Numerical       Numerical         IS NUM, OSHOP, AMOUNT       Numerical			-	-
15       SIOP_COUNT       Numerical       Count of Debit Cast Shopping (cast. Single & Combined Foothall Teckets)         15       MMX_SINP_AMOUNT       Numerical       Minimun Annount of Debit Cast Shopping (cast. Single & Combined Foothall Teckets)         16       FIRST_SIND_DAYS       Numerical       Daration from Debit Cast Shopping (cast. Single & Combined Foothall Teckets)         17       FIRST_SIND_DAYS       Numerical       Daration from Debit Cast Obset Shopping (cast. Single & Combined Foothall Teckets)         18       IAST_SIND_AMOUNT       Numerical       Daration from Last Shopping (cast. Single & Combined Foothall Teckets)         19       INMX_ONSHOP_AMOUNT       Numerical       Minimun Annount of Debit Cast Ohnes Shopping Bact (cast. Single & Combined Foothall Teckets)         21       AVG_ONSHOP_AMOUNT       Numerical       Minimun Annount of Debit Cast Ohnes Shopping Bact (cast. Single & Combined Foothall Teckets)         22       AVG_ONSHOP_AMOUNT       Numerical       Maniton Annount of Debit Cast Ohnes Shopping Bact (cast. Single & Combined Foothall Teckets)         23       MAX_ONSHOP_AMOUNT       Numerical       Maniton Annount of Debit Cast Cash Windraval         24       MAX_ONS_MOUNT       Numerical       Maniton Annount of Debit Cast Cash Windraval         24       MAX_ONS_MOUNT       Numerical       Maniton Annount of Debit Cas				
Int       Max. SHOP_AMOUNT       Numerical       Maximum Annound or Debic Card Shopping (excl. Single & Combined Foothall Teckets)         IS       MIX.SHOP_AMOUNT       Numerical       Average Annound of Debic Card Shopping (excl. Single & Combined Foothall Teckets)         IS       AST, SHOP_DAYS       Numerical       Duration from Debic Card Shopping (excl. Single & Combined Foothall Teckets)         IS       AST, SHOP_DAYS       Numerical       Duration from Debic Stopping (excl. Single & Combined Foothall Teckets)         IS       MAX, ONSIOP_AMOUNT       Numerical       Maximum Annound O Debic Card Online Shopping (excl. Single & Combined Foothall Teckets)         IMM, COSSIOP_AMOUNT       Numerical       Maximum Annound O Debic Card Online Shopping (excl. Single & Combined Foothall Teckets)         IMM, COSSIOP_AMOUNT       Numerical       Numerical       Card Is Debic Card Cable Stopping (excl. Single & Combined Foothall Teckets)         IMM, COS, MANDUNT       Numerical       Numerical       Card Is Debic Card Cable Windrawal         IMM, COS, ANDUNT       Numerical       Numerical       Card Is Debic Card Cable Windrawal         IMM, COS, ANDUNT       Numerical       Numerical       Numerical       Numerical         IMM, SM, ANDUNT       Numerical       Card Is Debi Card Cable Windrawal       Card Is Debic Card Cable Stopping       Numer				
15   Minimum Anovani of Debit Card Stopping (coxt. Single & Combined Football Teckes)     16   AVG, SHOP, AMOUNT   Numerical     17   FIRST_SHOP_DAYS   Numerical     18   LAST_SHOP_ANOVINT   Numerical     19   OSINOP_COUNT   Numerical     10   NUMAX_OSINOP_AMOUNT   Numerical     11   MAX_OSINOP_AMOUNT   Numerical     12   MAX_OSINOP_AMOUNT   Numerical     13   MIST_OSINOP_AMOUNT   Numerical     14   Numerical   Mariann Anovan of Debit Card Online Stopping leads (card) Single & Combined Football Teckes)     13   MAX_OSINOP_AMOUNT   Numerical     14   Numerical   Numerical   Numerical     15   MIX_ON_AMOUNT   Numerical   Numerical     16   MAX_ON_NAMOUNT   Numerical   Numerical     17   Numerical   Naiman Anovan of Debit Card Cash Widnaval     17   Numerical   Naiman Anovan of Debit Card Cash Widnaval     18   NAX_ON_NAMOUNT   Numerical   Numerical     19   NAX_ND_AMOUNT   Numerical   Numerical     10   NAX_ND_AMOUNT   Numerical   Numerical     10   NAX_ND_AMOUNT   Numerical   Numerical     10   NAX_ND_AMOUNT		_		
17       FIRST_SHOP_DAYS       Numerical       Duration from Datis Carl Issue Date (co.L. Single & Combined Football Tickets)         18       IAST_SHOP_DAYS       Numerical       Outor of Debt Card Shopping Conline (cock. Single & Combined Football Tickets)         19       MAX_OSNIOP_AMOUNT       Numerical       Numerical       Notion Tool Shopping Cock. Single & Combined Football Tickets)         21       MAX_OSNIOP_AMOUNT       Numerical       Numerical       Numerical       Numerical         21       MAX_OSNIOP_DAYS       Numerical       Numerical       Numerical       Numerical         21       MAX_OSNIOP_DAYS       Numerical       Numerical       Numerical       Numerical       Numerical         23       MAX_ONNIOP_DAYS       Numerical			Numerical	
Is       Daration from Last Stopping Date to Credit Issue Date (cxl. Single & Combined Football Tickets)         19       ONSHOP_AMOUNT       Numerical       Maximum Annount of Dabit Card Online Shopping (cxl. Single & Combined Football Tickets)         11       MIN, ONSHOP_AMOUNT       Numerical       Average Annount of Dabit Card Online Shopping (cxl. Single & Combined Football Tickets)         12       MAY, ONSHOP_DAYS       Numerical       Average Annount of Dabit Card Online Shopping Date (cxl. Single & Combined Football Tickets)         15       WD, COUNT       Numerical       Daration from Last Online Shopping Date (cxl. Single & Combined Football Tickets)         16       MAX, WD, AMOUNT       Numerical       Daration from Last Online Shopping Date (cxl. Single & Combined Football Tickets)         16       MAX, WD, AMOUNT       Numerical       Daration from Last Cash Windrawal         17       MN, WD, AMOUNT       Numerical       Average Annount of Dabit Card Cash Windrawal         18       MAX, INS, AMOUNT       Numerical       Daration from Last Cash Windrawal         19       INS, COUNT       Numerical       Maximum Annount of Dabit Card Cash Top up         10       NAX, INS, AMOUNT       Numerical       Count of Dabit Card Cash Top up         10       Start, INS, DAYS       Numerical       Count of Dabit Car	16	AVG_SHOP_AMOUNT	Numerical	Average Amount of Debit Card Shopping (excl. Single & Combined Football Tickets)
19       SNRIOP_COUNT       Numerical       Count of Debit Card Shopping - Online (sext Single & Combined Foothall Tickes)         21       MAX, ONSHOP_AMOUNT       Numerical       Minimu Amount of Debit Card Online Shopping (sext. Single & Combined Foothall Tickes)         21       AVG, ONSHOP_DANS       Numerical       Daration from Debit Card Issue Date 1s to Date Shopping Date (sext. Single & Combined Foothall Tickes)         25       FIRST_ONSHOP_DANS       Numerical       Daration from Debit Card Issue Date 1s to Date (sext. Single & Combined Foothall Tickes)         26       MAX, ONS, AMOUNT       Numerical       Out of Debit Card Cash Withdrawal         27       MON, WD, AMOUNT       Numerical       Minimum Amount of Debit Card Cash Withdrawal         28       AVG, UD, AMOUNT       Numerical       Daration from Debit Card Cash Withdrawal         29       FIRST_WD_DANS       Numerical       Daration from Last Cach Sin Top up         20       MAX, INS, AMOUNT       Numerical       Daration from Last Cach Sin Top up         21       MAX, INS, AMOUNT       Numerical       Daration from Debit Card Cach Top up         21       SINST_COUNT       Numerical       Cash Top up         21       MAX, INS, AMOUNT       Numerical       Cash Top up         21       SI	17	FIRST_SHOP_DAYS	Numerical	Duration from Debit Card Issue Date to 1st Shopping Date (excl. Single & Combined Football Tickets)
Jo       Max, ONSHOP_AMOUNT       Numerical       Maximum Anomut of Debit Card Online Shopping (cscl. Single & Combined Foothal Tickets)         JI, MK, ONSHOP_AMOUNT       Numerical       Average Anount of Debit Card Online Shopping (cscl. Single & Combined Foothal Tickets)         JE, MK, ONSHOP_DAYS       Numerical       Duration from David Card Isaue Boopping Date (cscl. Single & Combined Foothal Tickets)         JE, MKZ, ONSHOP_DAYS       Numerical       Duration from Last Online Shopping Date (cscl. Single & Combined Foothal Tickets)         JE, WLZ, ONSHOP_DAYS       Numerical       Outer of Debit Card Cash Withdrawal         JE, MKZ, WD, AMOUNT       Numerical       Maximum Anount of Debit Card Cash Withdrawal         JE, MKZ, WD, AMOUNT       Numerical       Average Anount of Debit Card Cash Withdrawal         JE, MKZ, WD, AMOUNT       Numerical       Duration from Last Cash Withdrawal         JE, MKZ, NNS, AMOUNT       Numerical       Duration from Last Cash Withdrawal         JE, MKZ, JNS, AMOUNT       Numerical       Maximum Anount of Debit Card Cash Top up         JE, MKZ, JNS, AMOUNT       Numerical       Average Anount of Debit Card Cash Top up         JE, MKZ, JNS, AMOUNT       Numerical       Average Anount of Debit Card Cash Top up         JE, MKZ, JNS, AMOUNT       Numerical       Average Anount of Debit Card Cash Top up			Numerical	Duration from Last Shopping Date to Credit Issue Date (excl. Single & Combined Football Tickets)
1       MIN, ONSHOP_AMOUNT       Numerical       Minima Amount of Debit Card Onise Shopping (excl. Single & Combined Football Tickets)         2       AVG, ONSHOP_ANS       Numerical       Daration from Debit Card Issue Date to 1st Onine Shopping Date (excl. Single & Combined Football Tickets)         3       HERT_ONSHOP_DAYS       Numerical       Daration from Debit Card Issue Date to Lotd Issue Date (excl. Single & Combined Football Tickets)         4       MAX_UPA_AMOUNT       Numerical       Count of Debit Card Cash Withdrawal         7       MIN_ND_AMOUNT       Numerical       Minimum Amount of Debit Card Cash Withdrawal         29       HEST_VD_DAYS       Numerical       Daration from Debit Card Issue Date to 1st Cash Withdrawal         30       LAST_VD_DAYS       Numerical       Daration from Debit Card Cash Withdrawal         31       NS_COUNT       Numerical       Daration from Debit Card Issue Date to 1st Cash Withdrawal         31       MAX_INS_AMOUNT       Numerical       Maintan Amount of Debit Card Cash Top up         34       AVG_UNS_AMOUNT       Numerical       Count of Debit Card Cash Top up         34       AVG_INS_AMOUNT       Numerical       Count of Debit Card Cash Top up         35       IPAS_TINS_AMOUNT       Numerical       Count of Stappring transactions - Debit Card				
12       Averge Annount of Debit Card Oaline Shopping fewel Single & Combined Foothal Tickets)         12       FIRST, ONSHOP, DAYS       Numerical       Duration from Last Oaline Shopping Date to Lst Oaline Shopping Date (set. Single & Combined Footbal Tickets)         14       LAST, ONSHOP, DAYS       Numerical       Count of Debit Card Cash Withdrawal         26       MAX, WD, AMOUNT       Numerical       Maximum Annount of Debit Card Cash Withdrawal         27       MIN, WD, AMOUNT       Numerical       Maximum Annount of Debit Card Cash Withdrawal         28       AVG, WD, AMOUNT       Numerical       Datation from Last Cash Withdrawal         29       REST, WD, DAYS       Numerical       Datation from Last Cash Withdrawal         31       IAST, WD, DAYS       Numerical       Caunt of Debit Card Cash Top up         34       MAX, INS, AMOUNT       Numerical       Maximum Annount of Debit Card Cash Top up         34       VAG, ISS, AMOUNT       Numerical       Duration from Last Cash Top up         34       VAG, ISS, AMOUNT       Numerical       Count of password transactions - Debit Card         35       FIRST, NS, DAYS       Numerical       Count of password transactions - Debit Card Cash Top up         34       VAG, ISS, RAMOUNT       Numerical       Cou				
12   FIRST_ONSHOP_DAYS   Numerical     12   ILAST_ONSHOP_DAYS   Numerical     12   MAX_DNADUNT   Numerical     13   MAX_MO_AMOUNT   Numerical     14   Namerical   Cash Wihdrawal     15   WG, WD_AMOUNT   Numerical     16   MAX_MO_AMOUNT   Numerical     17   MIN_WD_AMOUNT   Numerical     16   MAX_MO_AMOUNT   Numerical     17   Numerical   Minimum Amount of Debit Cash Wihdrawal     18   Norg WD_AMOUNT   Numerical     19   IAST_WD_DAYS   Numerical     10   IAST_WD_DAYS   Numerical     11   Nac, NS, AMOUNT   Numerical     11   Nac, NS, AMOUNT   Numerical     12   IAST_NS, AMOUNT   Numerical     13   MAX, INS, AMOUNT   Numerical     14   AVG, INS, AMOUNT   Numerical     15   IEST, INS, DAYS   Numerical     16   IAST_NS, DAYS   Numerical     17   Numerical   Count of pastron from Last Cash Top up     16   ICCARACARA, COUNT   Numerical     17   Numerical   Count of stopping transactions - Debit Card     18   ICCARACARA, COUNT   Numerical				
14       LAST_ONSHOP_DAYS       Numerical       Detration from Last Online Shopping Date to Credit Lsue Date (seeL Single & Combined Football Tackets)         26       MAX_WD_AMOUNT       Numerical       Maximum Amount of Debit Card Cash Withdrawal         27       MIN_WD_AMOUNT       Numerical       Maximum Amount of Debit Card Cash Withdrawal         28       AVG_WD_AMOUNT       Numerical       Duration from Last Cash Withdrawal       Cash Withdrawal         29       PIST_WD_DAYS       Numerical       Duration from Last Cash Withdrawal       Cash Withdrawal         31       INS_COUNT       Numerical       Duration from Last Cash Withdrawal       Cash Withdrawal         32       MAX_INS_AMOUNT       Numerical       Maximum Amount of Debit Card Cash Top up         34       AVG_INS_AMOUNT       Numerical       Duration from Last Cash Top up         37       ILAST_INS_AMOUNT       Numerical       Count of spending transactions - Debit Card (cash Single & Combined Football Tickets)         39       ILAST_INS_REA_COUNT       Numerical       Count of spending transactions - Debit Card (cash Single & Combined Football Tickets)         40       IC_SARRERIS_COUNT       Numerical       Count of spending transactions - Cardit Card (cast Single & Combined Football Tickets)         41       IC_SARRE				
15   WOLCOUNT   Numerical   Maximum Amount of Debi Card Cash Windrawal     26   MAX.WD.AMOUNT   Numerical   Minimum Amount of Debi Card Cash Windrawal     27   MIN, WD. AMOUNT   Numerical   Minimum Amount of Debi Card Cash Windrawal     28   AVG, WD. AMOUNT   Numerical   Duration from Last Cash Windrawal     29   IRRST, WD. DAYS   Numerical   Cont of Debi Card Cash Top up     30   LAST, WD. DAYS   Numerical   Cont of Debi Card Cash Top up     31   MAX, INS, AMOUNT   Numerical   Minimum Amount of Debi Card Cash Top up     32   MAX, INS, AMOUNT   Numerical   Maximum Amount of Debi Card Cash Top up     34   AVG, INS, AMOUNT   Numerical   Duration from Last Cash Top up     35   FIRST, INS, DAYS   Numerical   Count of payemout framework in a bebi Card Cash Top up     36   LAST, INS, DAYS   Numerical   Count of payemout framework in a bebi Card Sub Top up     37   DC, SIRRE, COUNT   Numerical   Count of payemout framework in a bebi Card Sub Top up     38   DC, CARSCAAA, COUNT   Numerical   Count of payeming transactions - Debi Card (secl. Single & Combined Football Tickets)     40   CC, ALISVERIS, COUNT   Numerical   Count of payeming transactions - Credit Card (secl. Single & Combined Football Tickets)     41				
16   MAX_WD_AMOUNT   Numerical   Maximum Amount of Debit Card Cash Withdrawal     28   AVG_WD_AMOUNT   Numerical   Average Amount of Debit Card Cash Withdrawal     28   RINT_WD_DAYS   Numerical   Duration from Debit Card Cash Withdrawal     29   IRST_WD_DAYS   Numerical   Duration from Debit Card Cash Top up     31   INS_COUNT   Numerical   Maximum Amount of Debit Card Cash Top up     33   MIN_INS_AMOUNT   Numerical   Minimum Amount of Debit Card Cash Top up     34   AVG_INS_AMOUNT   Numerical   Average Amount of Debit Card Cash Top up     35   FIRST_INS_DAYS   Numerical   Duration from Debit Card Cash Top up     36   ILAST_INS_DAYS   Numerical   Count of password transactions - Debit Card     37   DC_SIRRE_COUNT   Numerical   Count of password transactions - Debit Card     38   DC_ALSVERIS_COUNT   Numerical   Count of shopping transactions - Debit Card (cacl. Single & Combined Football Tickets)     40   DC_ALSVERIS_COUNT   Numerical   Count of shopping transactions - Cedit Card (cacl. Single & Combined Football Tickets)     41   DCTNR_CAMA_COUNT   Numerical   Count of shopping transactions - Cedit Card (cacl. Single & Combined Football Tickets)     42   CC_ALISVERIS_COUNT   Numerical   Count of shopping transactions - Cedit Card (cacl				
17   MN.WD.AMOUNT   Numerical   Minium Amount of Debit Card Cash Withdrawal     28   AVG. WD.AMOUNT   Numerical   Duration from Debit Card Cash Withdrawal     30   LST_WD.DAYS   Numerical   Duration from Debit Card Cash Withdrawal     31   INS_COUNT   Numerical   Count of Debit Card Cash Top up     32   MAX_INS_AMOUNT   Numerical   Minium Amount of Debit Card Cash Top up     34   AVG_INS_AMOUNT   Numerical   Minium Amount of Debit Card Cash Top up     35   FIRST_INS_DAYS   Numerical   Duration from Last Cash Top up     36   LST_JNS_DAYS   Numerical   Duration from Last Cash Top up     37   DC_SREE_COUNT   Numerical   Count of password transactions - Debit Card     38   DC_SAGRU_COUNT   Numerical   Count of spondping transactions - Debit Card     39   DC_LARCAMA_COUNT   Numerical   Count of spondping transactions - Debit Card     40   DCALSTERIS_COUNT   Numerical   Count of forohoping transactions - Credit Card     41   DCTN_COUNT   Numerical   Count of forohoping transactions - Credit Card     42   CC_ALSTERIS_COUNT   Numerical   Count of forohoping transactions - Credit Card     43   CC_TON_COUNT   Numerical   Count of forohoping transactions - Credit Card		_		
28   AVG_VD_AMOUNT   Numerical   Average Annount of Debit Card Cash Windrawal     39   IRST_WD_DAYS   Numerical   Duration from Last Cash Vindrawal to Credit Issue Date     30   IAST_WD_DAYS   Numerical   Count of Debit Card Cash Top up     31   INS_COUNT   Numerical   Mainimum Annount of Debit Card Cash Top up     32   MAX_INS_AMOUNT   Numerical   Mainimum Annount of Debit Card Cash Top up     33   MIN_INS_AMOUNT   Numerical   Average Annount of Debit Card Cash Top up     34   AVG_INS_AMOUNT   Numerical   Duration from Debit Card Cash Top up     35   FIRST_INS_DAYS   Numerical   Duration from Dask Card Top up to Credit Issue Date     36   LAST_INS_DAYS   Numerical   Count of password transactions - Debit Card     37   DC_SIFRE_COUNT   Numerical   Count of shopping transactions - Debit Card (secl. Single & Combined Football Tickets)     40   DC_ALISVERIS_COUNT   Numerical   Count of shopping transactions - Debit Card (secl. Single & Combined Football Tickets)     41   DCT_PACAMA_COUNT   Numerical   Count of shopping transactions - Credit Card (secl. Single & Combined Football Tickets)     42   CC_ALISVERIS_COUNT   Numerical   Count of shopping transactions - Credit Card (secl. Single & Combined Football Tickets)     43   SC_PARCAMA_COUNT   Numeri				
19   LAST_WD_DAYS   Numerical   Duration from Last Cash Withdrawa to Credit Issue Date     31   INS_COUNT   Numerical   Maximum Annount of Debit Card Cash Top up     33   MIN_INS_AMOUNT   Numerical   Maximum Annount of Debit Card Cash Top up     34   AVG_INS_AMOUNT   Numerical   Arreage Annount of Debit Card Cash Top up     35   FIRST_INS_DAYS   Numerical   Duration from Debit Card Cash Top up     36   LAST_INS_DAYS   Numerical   Duration from Last Cash Top up to Card Issue Date     37   DC_SIREF_COUNT   Numerical   Count of password transactions - Debit Card     38   DC_SORGU_COUNT   Numerical   Count of shopping transactions - Debit Card (excl. Single & Combined Football Tickets)     40   DC_ALISVERIS_COUNT   Numerical   Count of shopping transactions - Cardit Card (excl. Single & Combined Football Tickets)     41   DCTNN_COUNT   Numerical   Count of transactions - Cardit Card (excl. Single & Combined Football Tickets)     42   CC_FAIZ_COUNT   Numerical   Count of transactions - Cardit Card (excl. Single & Combined Football Tickets)     43   AMOUNT_PAID_SELF   Numerical   Count of transactions - Cardit Card (excl. Single & Combined Football Tickets)     44   CC_FAIZ_COUNT   Numerical   Numerical   Count of transactions - Cardit Card (excl. Single & Combined Football Tickets) <td>28</td> <td>AVG_WD_AMOUNT</td> <td></td> <td></td>	28	AVG_WD_AMOUNT		
31   INS_COUNT   Numerical   Count of Debit Card Cash Top up     32   MAX_INS_AMOUNT   Numerical   Maximum Amount of Debit Card Cash Top up     34   AVG_INS_AMOUNT   Numerical   Marinum Amount of Debit Card Cash Top up     34   AVG_INS_AMOUNT   Numerical   Duration from Debit Carl Sush Top up     36   LAST_INS_DAYS   Numerical   Duration from Debit Carl Suse Date 1st Cash Top up     37   DC_SIFRE_COUNT   Numerical   Count of passwort transactions - Debit Card     38   DC_ALNEXPERS_COUNT   Numerical   Count of spending transactions - Debit Card (excl. Single & Combined Football Tickets)     40   DC_ALSVERIS_COUNT   Numerical   Count of spending transactions - Debit Card (excl. Single & Combined Football Tickets)     41   DCTN. COUNT   Numerical   Count of spending transactions - Cardi Card (excl. Single & Combined Football Tickets)     42   CC_ALSVERIS_COUNT   Numerical   Count of spending transactions - Cardi Card (excl. Single & Combined Football Tickets)     43   STN_LINSTAL_TYPE   Boolan   Installment transactions on orter's - Cardi Card (excl. Single & Combined Football Tickets)     44   CC_FAIZ_COUNT   Numerical   Count of single football tickets bought for user by user     45   SNSTAL_CNT   Numerical   Count of single football tickets bought for user by user <td< td=""><td>29</td><td>FIRST_WD_DAYS</td><td>Numerical</td><td>Duration from Debit Card Issue Date to 1st Cash Withdrawal</td></td<>	29	FIRST_WD_DAYS	Numerical	Duration from Debit Card Issue Date to 1st Cash Withdrawal
12     MAX_INS_AMOUNT     Numerical     Maximum Anount of Debit Card Cash Top up       33     MIN_INS_AMOUNT     Numerical     Manimum Anount of Debit Card Cash Top up       34     AVG_INS_AMOUNT     Numerical     Duration from Debit Card Cash Top up       35     FIRST_INS_DAYS     Numerical     Duration from Debit Card Issue Date to 1st Cash Top up       36     LAST_INS_DAYS     Numerical     Duration from Last Cash Top up     Cash Top up       37     DC_SIFRE_COUNT     Numerical     Count of password transactions - Debit Card     Cash Top up     Cash Top up       39     DC_ALISVERE_COUNT     Numerical     Count of shopping transactions - Debit Card (excl. Single & Combined Football Tickets)       41     DCTXN_COUNT     Numerical     Count of shopping transactions - Credit Card (excl. Single & Combined Football Tickets)       42     CC_ALACACAA_COUNT     Numerical     Count of shopping transactions - Credit Card (excl. Single & Combined Football Tickets)       43     CC_FARZ_COUNT     Numerical     Numerical     Count of top shopping transactions - Credit Card (excl. Single & Combined Football Tickets)       44     CC_FARZ_COUNT     Numerical     Numerical     Numerical     Numerical       45     CTALAR_CAMA_COUNT     Numerical	30	LAST_WD_DAYS	Numerical	Duration from Last Cash Withdrawal to Credit Issue Date
33     MNL_TNS_AMOUNT     Numerical     Minimum Amount of Debit Card Cash Top up       34     AVG_INS_AMOUNT     Numerical     Duration from Debit Card Cash Top up       35     FIRST_INS_DAYS     Numerical     Duration from Debit Card Issue Date to 1s Cash Top up       36     LAST_INS_DAYS     Numerical     Duration from Last Cash Top up to Credit Issue Date to 1s Cash Card       37     DC_SIFRE_COUNT     Numerical     Count of apawris - Debit Card     Card       39     DC_HARCAMA_COUNT     Numerical     Count of apawris - Debit Card (excl. Single & Combined Football Tickets)       40     DC_ALISVERIS_COUNT     Numerical     Count of top partinascitons - Debit Card (excl. Single & Combined Football Tickets)       41     DCTN_COUNT     Numerical     Count of spending transactions - Credit Card (excl. Single & Combined Football Tickets)       42     CC_HARZCAUL_TYPE     Bookan     Installment transactions or netrest - Credit Card (excl. Single & Combined Football Tickets)       43     KMOUNT_PAID_SELF     Numerical     Numerical     Numerical       44     MOUNT_PAID_SELF     Numerical     Average price of single football tickets bought for user by user       45     TNN_INSTALL_TYPE     Bookan     Installment transactions on ord? (', Nd) (excl. Single & Combined Football		_		
34   Average Amount of Debt Card Lash Top up     35   FIRST_INS_DAYS   Numerical     36   FIRST_INS_DAYS   Numerical     37   DC_SIFRE_COUNT   Numerical     38   DC_SIFRE_COUNT   Numerical     39   DC_HARCAMA_COUNT   Numerical     40   DC_ALSVERIS_COUNT   Numerical     41   DCT_ALSVERIS_COUNT   Numerical     42   CC_ALISVERIS_COUNT   Numerical     43   CC_ALISVERIS_COUNT   Numerical     44   DCT_ANCOUNT   Numerical     45   TAN_INSTALL_TYPE   Count of spending transactions - Debt Card (excl. Single & Combined Football Tickets)     46   CC_ALISVERIS_COUNT   Numerical   Count of transactions on interest - Credit Card (excl. Single & Combined Football Tickets)     47   CC_HAZ_COUNT   Numerical   Count of transactions on interest - Credit Card (excl. Single & Combined Football Tickets)     48   AMOUNT_PAID_SELF   Numerical   Count of single football tickets bought for user by user     50   AMOUNT_PAID_SELF   Numerical   Average price of single football tickets bought for user by user     51   BOUGHT_GVN_TOTAL   Numerical   Average price of single football tickets bought for user by user     52   AMOUNT_PAID_SPQ_OTHERS   Numerical   Count of single football				
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78       TOTAL_MNS.RIPC_AMOUNT       Numerical				
7       107L_AVG_SHOP_ANDLYN       Numerical				
80       TOTAL_CPLST_SHOP_DAYS       Numerial       Numerial       Numerial       Numerial         81       TOTAL_CALSYERS/COUNT       Numerial       Count of shopping transactions - bobb Cald (incl. Single & Combined Football Teckes)         81       TOTAL_CALSYERS/COUNT       Numerial       Count of shopping transactions - bobb Cald (incl. Single & Combined Football Teckes)         81       TOTAL_CCALSYERS/COUNT       Numerial       Count of shopping transactions - Cedit Cald (incl. Single & Combined Football Teckes)         81       TOTAL_CCALSCALVENT       Numerial       Count of specing transactions - Cedit Cald (incl. Single & Combined Football Teckes)         81       TOTAL_CCALSCALVENT       Numerial       Count of specing transactions - Cedit Cald (incl. Single & Combined Football Teckes)         81       TOTAL_CCALSCALVENT       Numerial       Control of Specing transactions - Cedit Cald (incl. Single & Combined Football Teckes)         81       TOTAL_CCALSCALVENT       Numerial       Control of Specing transactions - Cedit Cald (incl. Single & Combined Football Teckes)         81       TOTAL_CCALSCALVENT       Numerial       Application Chemel         82       VASAL_TAKIH       Numerial       Application Chemel         83       Total Specification Affect Cedit       Application Affect Cedit         84	78	TOTAL_MIN_SHOP_AMOUNT	Numerical	Minimum Amount of Debit Card Shopping (incl. Single & Combined Football Tickets)
81       707AL_ACS_SHOP_DAYS       Numecia Count of shopping Date to Credit Issue Ear Carbake Fordum Fordum Trekes)         83       707AL_DC_JARNERAN_COUNT       Numecia Count of shopping transactions - Debt Card (incl. Single & Combined Fordum Trekes)         84       707AL_CC_JARNECAMA_COUNT       Numecia Count of spanding transactions - Debt Card (incl. Single & Combined Fordum Trekes)         85       707AL_CC_JARNECAMA_COUNT       Numecia Count of spanding transactions - Cardit Card (incl. Single & Combined Fordum Trekes)         86       707AL_CC_JARZ_COUNT       Numecia Count of spanding transactions in coll (acl. Single & Combined Fordum Trekes)         87       707AL_CT_SARS_COUNT       Numecia Count of spanding transactions in coll (acl. Single & Combined Fordum Trekes)         88       707AL_TSARS_COUNT       Numecia Count of spanding transactions in coll (acl. Single & Combined Fordum Trekes)         80       707AL_CT_SARS_COUNT       Numecia Combine of spanding transactions in coll (acl. Single & Combined Fordum Trekes)         81       707AL_TSARS_COUNT       Numecia Combine of spanding transactions in coll (acl. Single & Combined Fordum Trekes)         82       707AL_TSARS_COUNT       Numecia Combine of spanding transactions in coll (acl. Single & Combined Fordum Trekes)         83       707AL_TSARS_COUNT       Numecia Combine of spanding transactions in coll (acl. Single & Combined Fordum Trekes)         84       707AL_TS	79	TOTAL_AVG_SHOP_AMOUNT	Numerical	Average Amount of Debit Card Shopping (incl. Single & Combined Football Tickets)
Sil       TOTAL_DC_ALSVERS.COUNT       Numerial         Sil       TOTAL_DCARCAM_COUNT       Numerial         Sil       TOTAL_DCAN_COUNT       Numerial         Sil       TOTAL_CLARCAM_COUNT       Numerial         Sil       TOTAL_CCALSVERS.COUNT       Numerial         Sil       TOTAL_CCALSVERS.COUNT       Numerial         Sil       TOTAL_CCALSVERS.COUNT       Numerial         Sil       Numerial       Count of spaning manascinos. Cedit Cland (incl. Single & Combined Foothall Tickes)         Sil       TOTAL_CCAN_NOLT       Numerial       Count of numeriascinos (incl. Single & Combined Foothall Tickes)         Sil       TOTAL_CCAN_NOLT       Numerial       Count of numerics- Cedit Cland (incl. Single & Combined Foothall Tickes)         Sil       TOTAL_CCAN_NOLT       Numerial       Count of numerics and incl. Single & Combined Foothall Tickes)         Sil       TOTAL_CCAN_NOLT       Numerial       Count of numerics and incl. Single & Combined Foothall Tickes)         Sil       TOTAL_CCAN_NOLT       Numerial       Count of numerics and incl. Single & Combined Foothall Tickes)         Sil       TOTAL_CCAN_NOLT       Numerial       Count of numerics and incl. Single & Combined Foothall Tickes)         Sil       TOTAL_CCAN_NOLT	80	TOTAL_FIRST_SHOP_DAYS	Numerical	Duration from Debit Card Issue Date to 1st Shopping Date (incl. Single & Combined Football Tickets)
Si DTAL_DC.HARCAMA_COUN       Numerical Count of spacing maccions - Debit Card (ncl. Single & Combined Foodal Tickes)         Si DTAL_CC.ALSVERS_COUN       Numerical Count of spacing marcacions - Coefit Card (incl. Single & Combined Foodal Tickes)         Si DTAL_CC.ALSVERS_COUNT       Numerical Count of spacing marcacions - Coefit Card (incl. Single & Combined Foodal Tickes)         Si DTAL_CC.FAZ_COUNT       Numerical Count of spacing marcacions - Coefit Card (incl. Single & Combined Foodal Tickes)         Si DTAL_CT.FAZ_COUNT       Numerical Count of transactions or not? (V1, N0) (incl. Single & Combined Foodal Tickes)         Si DTAL_TCN.NOUNT       Numerical Count of transactions - Coefit Card (incl. Single & Combined Foodal Tickes)         Si BXVITTTAR       Numerical Count of transactions - Coefit Card (incl. Single & Combined Foodal Tickes)         Si BXVITTTAR       Numerical Count of transactions - Coefit Card (incl. Single & Combined Foodal Tickes)         Si BXVITTTAR       Numerical Count of transactions or not? (V1, N0) (incl. Single & Combined Foodal Tickes)         Si BXVITTTAR       Numerical Count of transactions - Coefit Card (incl. Single & Combined Foodal Tickes)         Si BXVITTTAR       Numerical Count of transactions or not? (V1, N0)         Si BXVITTTAR       Numerical Count of transactions or not? (V1, N0)         Si BXVITTTAR       Numerical Count of transactions or not? (V1, N0)         Si BXVITTTAR       Numerical Count of transactions coefit (V1, N0)	81	TOTAL_LAST_SHOP_DAYS	Numerical	Duration from Last Shopping Date to Credit Issue Date (incl. Single & Combined Football Tickets)
Si DTAL_DC_HARCAACOUN       Numerial Count of spacing macacinos - Debit Card (incl. Single & Combined Foodbal Tickes)         Si TOTAL_CC_ALSVERS_COUNT       Numerial       Count of spacing macacinos - Cordi Card (incl. Single & Combined Foodbal Tickes)         Si TOTAL_CC_HARCAMCOUNT       Numerial       Count of spacing macacinos - Cordi Card (incl. Single & Combined Foodbal Tickes)         Si TOTAL_STAL_CNT       Numerial       Count of spacing macacinos - Cordi Card (incl. Single & Combined Foodbal Tickes)         Si TOTAL_STAL_CNT       Numerial       Count of standardismactinos - Cordi Card (incl. Single & Combined Foodbal Tickes)         Si TOTAL_STAL_CNT       Numerial       Count of transactions or not? ('1, NO) (incl. Single & Combined Foodbal Tickes)         Si TOTAL_STAL_NONT       Numerial       Count of transactions or not? ('1, NO) (incl. Single & Combined Foodbal Tickes)         Si TOTAL_TRANDRIM_TUTAR       Numerial       Count of transactions or not? ('1, NO) (incl. Single & Combined Foodbal Tickes)         Si TOTAL_TRANDRIM_TUTAR       Numerial       Numerial       Numerial         Numerial       Numerial       Numerial       Numerial         Numerial       Numerial       Numerial       Numerial         Numerial       Numerial       Numerial       Numerial         Numerial       Numerial       Numerial       Numerial	82	TOTAL_DC_ALISVERIS_COUNT	Numerical	Count of shopping transactions - Debit Card (incl. Single & Combined Football Tickets)
sk       DTAL_NCTNN_COUNT       Numerical Count of shorping transactions - Code Card (icel. Single & Combined Football Teckets)         sk       DTAL_AC_LARVERLS_COUNT       Numerical Count of shorping transactions - Code Card (icel. Single & Combined Football Teckets)         sk       DTAL_INSTAL_TUNT       Numerical Count of transactions or nord? (C1, ND) (icel. Single & Combined Football Teckets)         sk       DTAL_SCTNN_COUNT       Numerical Count of transactions or nord? (C1, ND) (icel. Single & Combined Football Teckets)         sk       DTAL_CTNN_CUNT       Numerical Count of transactions or nord? (C1, ND) (icel. Single & Combined Football Teckets)         sk       DTAL_ACTNN_CUNT       Numerical Count of transactions or nord? (C1, ND) (icel. Single & Combined Football Teckets)         sk       DTAL_ACTNN_CUNT       Numerical Count of transactions or nord? (C1, ND) (icel. Single & Combined Football Teckets)         sk       Numerical Count of transactions or nord? (C1, ND) (icel. Single & Combined Football Teckets)         sk       Numerical Count of transactions or nord? (C1, ND) (icel. Single & Combined Football Teckets)         sk       Numerical Count of transactions or nord? (C1, ND)         sk       Numerical Count of transactions or nord? (C1, ND)         sk       Numerical Count of transactions or nord? (C1, ND)         sk       Numerical Count of transactions or nord? (C1, ND)         sk	83	TOTAL_DC_HARCAMA_COUNT	Numerical	Count of spending transactions - Debit Card (incl. Single & Combined Football Tickets)
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## **APPENDIX B**

Figure App B.1: Distributions "Mahalle NPL" with Mean & Median imputed values

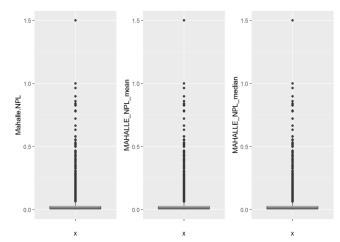


Figure App B.2: Distributions "Ilce NPL" with Mean & Median imputed values

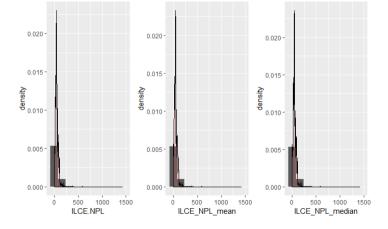
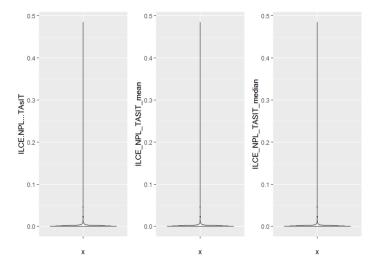


Figure App B.3: Distributions "İlce NPL - Tasıt" with Mean & Median imputed values



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