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Research Article

Using the Hybrid Model for Credit Scoring (Case Study: Credit Clients of Microloans, Bank RefahKargaran of Zanjan, Iran)

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Abstract

In any country, commercial banks lay the groundwork for economic growth by collecting national resources and capitals and allocating them to different economic sectors. Optimal allocation of resources is especially important in achieving this goal. Banks with an effective and dynamic system of customer assessment can efficiently allocate their resources to customers regardless of their geographic area. Following a linear programming optimization approach, this research employs the Utilities Additives DIS criminates (UTADIS) model for credit scoring of bank customers. The advantages of the proposed technique are high flexibility, mutual interaction with decision makers, and the ability to update under various macroeconomic conditions. The chosen environment is a branch of Bank RefahKargaran, one of the popular banks in Iran. According to the experimental results, the proposed technique demonstrates high effectiveness. Also, the results indicate that the initial credit score and age of the applicants are the most influential factors for credit scoring of customers.

Keywords: Credit scoring; Clustering; Data mining; UTADIS.

1. Introduction

Debt collection makes up a large part of banks' required funds. Failure to collect debts results in a massive loss of assets and equity. Therefore, banks try a variety of methods to better assess credit applicants in order to reduce credit risk and non-repayment risk. Today, expert estimates and forecasts of applicants' credit score and the future of their economic activities form the basis for their lending decisions. One of the main problems with this method is the prolonged lending process, which aims to select borrowers with the ability to repay and asses the necessary collaterals; this increases the cost of lending both for the recipient of the loan and for the bank itself. Also in the present situation, assessor's or bank's preferences will have a significant effect on this process, which, along with the lack of a single approach based on scientific principles, can cause dissatisfaction in customers and provide grounds for corruption. Thus, using a method that can help to understand better the factors affecting non-repayment of loans can provide a more accurate assessment of risks of new credit applications, which can reduce the duration of the loan approval process and lead to lower collateral pledge by creditworthy borrowers, which opens up lending opportunities.

Therefore, reviewing and managing credit risk (the risk of default on debt) is essential. Management of financial institutions has never been an easy task and, in recent years, has been faced with many problems in the revolves around borrowing. In addition, financial institutions must ensure their customers' ability to repay in order to gain more profit. In other words, they must have low credit risk. Lack of risk management and risk reduction can lead to irreparable damages. Today, credit granting has become more critical than ever due to economic pressures caused by the increasing demand for various forms of credit, along with widespread business competition and the efforts of banks and other financial institutions to reduce the percentage of defaulting customers. However, banks have always faced challenges in choosing the right indicators in assessing credit applicants, and traditional methods of making lending decisions based on personal judgments, as is the case in Iran, are no longer capable of distinguishing between good and bad borrowers. Massive amounts of bank claims are a testament to this notion. Thus, given the importance of risk, the primary challenge facing financial institutions is assessing the possibility of default and non-repayment by applicants and ensuring that those selected have the ability to repay. This is made possible by using a comprehensive model with the right criteria.

Machine learning, a field of artificial intelligence, has been successfully employed in several areas such as portfolio selection (Faezy Razi & Shadloo, 2017), customer segmentation (Parvaneh et al., 2012), and customer relationship management (Kazemi & Babaei, 2011). It has also been used to address the problem mentioned above, which is the credit scoring of customers. Various studies in the literature propose machine learning based methods for credit scoring (Bequé

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& Lessmann, 2017; He et al., 2018; Luo et al., 2017; Xia et al., 2018). Also, Jones et al. (2015) present an empirical comparison of different machine learning based credit rating techniques.

Following a linear programming optimization approach, this paper attempts to use appropriate criteria and assess different models of customer credit scoring to propose a model that can properly rank credit applicants and reduce the credit risk of bank customers. To this end, the UTilités Additives DIS criminantes (UTADIS) model is used for credit scoring of bank customers, and to the best of our knowledge, it is the first time that UTADIS has been used for this purpose. The advantages of the proposed technique are high flexibility, mutual interaction with decision makers, and the ability to update under various macroeconomic conditions.

The focus of this study is on microloans, and the chosen environment is the Zanjan branch of Bank RefahKargaran. According to the experimental results, the proposed technique is more effective compared to the baselines. Also, the results indicate that the initial credit score and age of the applicants are the most influential factors in this process, while the least influential factors are collateral value and loan amount.

The remainder of this paper is structured as follows: Section 2 reviews the literature; Section 3 presents the methodology of this paper and provides the results; Section 4 concludes this work.

2. Review of the Literature

Doumpos and Zopounidis (2002b) used a multi-criteria hierarchical discrimination approach for credit risk assessment. They compared three clustering techniques, i.e. UTADIS, ELECTRE, and Rough Sets, and found that UTADIS was the most effective model for classification and discrimination of applicants. Otten and Bams (2002) used the UTADIS technique to classify 506 funds from five European mutual fund countries. In a literature review on multi-criteria financial decision making, Zopounidis and Doumpos (2002) compared several portfolio selection techniques, including PROMETHEE, ELECTRE, UTA, UTADIS, and MHDIS.

Spathis et al. (2003) used UTADIS to create an auditor's opinion model. The model was explained using financial ratios and non-financial information such as lawsuits. A set of 20 variables served as the initial set, of which eight financial ratios (i.e. sales to total assets; net profit to sales; receivable to sales; net profit to fixed assets; net profit to total assets; current assets to current liabilities; working capital to total assets; and working profit to total assets), financial distress (measured by Altman z-score), and lawsuits were found to be significant predictors of auditor's opinion.

Gaganis et al. (2008) examined and compared four classification techniques, namely discriminant analysis, log it analysis, UTADIS, and nearest neighbors in the development of classification models that could assist auditors during the examination of Asian commercial banks. The models were tested in a sample of 527 unqualified financial statements and 52 ones that received a qualified opinion over the period 2002-2004. The results showed that the developed auditing models could discriminate between financial statements that should receive qualified opinions from those that should receive unqualified ones with satisfactory accuracy. The highest classification accuracy is achieved by UTADIS, followed by logit analysis, nearestneighbours, and discriminant analysis.

Abdou (2009) investigated the ability of genetic programming in the analysis of credit scoring models in Egyptian public sector banks. They also compared genetic programming with probit analysis and weight of evidence in their ability to predict the creditworthiness of borrowers. Dong et al. (2010) proposed a logistic regression with random coefficients for building credit scorecards. They used a German credit data set to evaluate the performance of this algorithm. The empirical results indicated that the proposed model could improve the prediction accuracy of the logistic regression with fixed coefficients without sacrificing its desirable features.Zheng et al. (2011) proposed a two-step method for portfolio selection problems. First, the reference set is identified using ELECTRE TRI, and then firms are classified using the UTADIS technique. As a result, appropriate indicators, weights, and cut-off points are specified.

Louzada et al. (2012)analysed the credit scoring performance of a naive logistic regression model and a logistic regression with state-dependent sample selection model in a simulation study. The idea was to analyse the impact of disproportional samples on credit scoring models. Simulation results revealed that there is no significant difference in predictive capacity between these models. Vukovic et al. (2012) used case-based reasoning (CBR) model that uses preference theory functions for credit scoring. The results showed that the proposed approach could outperform the traditional k-nearest neighbour (k-NN) model in some cases.

The use of group decision-making models in credit scoring has also been investigated in many studies. Danenas and Garsva (2015) used particle swarm optimization (PSO) for the optimal selection of linear support vector machines (SVM) classifier for credit scoring. Esmaelian et al. (2017) applied a hybrid model with PSO and genetic algorithm to nominal and ordinal datasets. They used a polynomial function instead of linear division and labelled the UTADIS model as P-UTADIS. The results on a dataset were compared with other techniques, with P-UTADIS showing high efficiency. Doumpos and Figueira (2019) used a hybrid model for credit rating with ELECTRE TRI-C and UTADIS. They tested a sample of European firms rated by three major rating agencies. The strengths of this model were fuzzy outranking relations, flexibility, multiple characteristic profiles for each class, internal credit ratings, and appropriate conditions for DM veto rights.

Mousavi and Gholipour (2009) used the Delphi method to rank a set of credit scoring criteria. The required information was collected from experts and bankers using a questionnaire. The results supported the relevant economic and financial theories, indicating that the factors affecting the credit risk of banks' legal customers are not equal in weight and some factors are better predictors of credit risk.
Alborzi et al. (2012) used a genetic algorithm in the optimization of decision trees for credit scoring. They showed that using the proposed model in building decision trees leads to higher classification accuracy compared to other algorithms they examined. However, the complexity of the proposed model was higher than the other algorithms.
Armeshi (2011) examined a set of financial and demographic variables that affect credit risk. The necessary data were extracted from Saman Bank's records. Logistic regression was used to evaluate the data. After estimating the model, results showed that variables such as credit applicants' gender, income, residence, marital status, age, and occupation affected credit risk, while income was negatively related to credit risk. Also, loan size and repayment period were not significantly related to credit risk in the studied sample.
In a case study, Kamali (2011) investigated the factors affecting the credit score of customers to provide a model for ranking them using logit, probit, and neural networks. The qualitative and financial information of a sample of 349 customers who received facilities from different branches of Sina Bank in Iran was examined over the period 2007-2009. After examining the credit history of each sample, 19 explanatory variables were identified and examined. Eight variables were found to be effective in discrimination of creditworthy and non-creditworthy applicants.

3. Methodology

The present research is an applied, developmental research that uses descriptive data and data mining. It must be noted that mixed methods research is used to allow for better analysis and to provide more effective solutions.

3.1. Process

The process is described below.

- Step 1: Literature review. In this step, the literature is extensively reviewed. Definitions of data mining, theories, approaches, techniques, and models are discussed.
- Step 2: Developing the theoretical framework. Based on the literature review, the conceptual model of credit scoring is proposed.
- Step 3: Collecting information from experts. Variables of the research are extracted from the literature and naturalized.
- Step 4: Extracting of the conceptual model and finalizing the indicators.
- Step 5: Data management and removal of the outliers.
- Step 6: Initial customer clustering and removal of non-significant features, and clustering under best possible conditions.
- Step 7: Constructing the UTADIS model using the concept of utility and post-optimality analysis.
- Step 8: Calculating weights and specifying cut-off points for different classes of customers.

Required data are collected from the database of Refah Bank of Zanjan Province and are analyzed in Clementine 18.0 and MATLAB. The simulator consists of training and testing processes, and in the training process, all the parameters necessary for machine learning are customizable (Figure 1). Some of these parameters are the learning rate, final error for terminating training, number of neurons in input and hidden layers, and the number of layers.

3.2. Database

The database of Refah Bank in Zanjan Province is used to train the model using a number of techniques. After consulting several experts within the field, 19 input fields (i.e., indicators) were chosen among the available ones in the database. Table 1 illustrates these 19 input fields which are as follows: applicant's age, gender, marital status, education, and occupation, loan duration, collateral type, collateral value, average balance for the past six months, loan size, work history in the current job, credit history, credit score, nominal capacity matching obligations, ownership of the workplace, and reputation and public image.
The statistical population includes customers with loans ranging from four to 100 million Tomans. The sample used in this research includes 1,000 bank customers whose repayment status is available. This sample is quite large and has a decent variety of customers, and thus, the obtained results can be generalized for other groups as well.
The output of this database is the creditworthiness parameters of the loan applicant. Since the inputs of machine learning techniques are defined as numbers, texts are converted into numerical values according to their number based on the code that is defined for each phrase.
This process should be repeated for other text inputs as well. The output is also converted to 0 or 1 based on the creditworthiness of the applicant. Seventy percent of the data collected from databases are used for machine learning techniques, and the remaining 30 percent is used for testing.

3.3. Data pre-processing and identification of outliers

Using the Data Audit node, a preview of the data, as illustrated in Figure 1, is obtained, and outliers and extreme values are, by default, identified as observations with a three and five standard deviation from mean respectively.

Using the Distribution function, the distribution of creditworthy and non-creditworthy applicants in all the fields can be observed, which is indicated in Figure 2. For example, in the Job field, there is a severe imbalance in the fourth job category. Therefore, this field is expected to removed from the dataset. Only those records that do not contain essential and statistically significant information are removed. The significance of the data is determined using histograms.

One hundred clustering models are created using the Auto Cluster node. These models include K-Means, two-step, have an essential role in clustering and machine learning techniques.

The Anomaly Index chart is used to identify outliers (Figure 3). In this chart, ten outliers are identified. Records with an anomaly index greater than 1.5 are and Kohonen clustering techniques. These models are then ranked using the Silhouette index, and the best model is selected. The results show that the K-Means with five clusters is the best model.

Table 1
Model’s input fields (Zimmermann, 2001)

Credit Capacity	**Financial**	**Guarantee**	**Asset - Debt**	Type of collateral the customer can provide
				Nominal capacity matching credit obligations
				Average balance for the past six months
				Direct obligations to the bank
			Net Assets	Total value of movable and immovable assets
		Cash Flow	**Cost - Income**	Average monthly income
	Personal	**Ability**	**Mental Ability**	Age
				Gender
				Reputation and public image
				Activity (main job)
			Motivation	Field of study
				Credit score
				Repayment quality
				How obligations to the bank are fulfilled
				Number of deferred days during the total repayment period
				Number of returned checks that have been restituted (due to insufficient balance)
				Amount of deferred debt
		Business Behaviour	**Economic Mindset**	Ownership of the workplace
				Residential status (homeowner or renting)
				Type of contract (leasing, partnership, unilateral contract)
				Facility amount (in a millionrials)
				Interest rate
				Loan repayment term
				Number of instalments
			Compliance with Social and Economic Standards	Duration of activity in the bank (i.e., contact with the bank)
				Work experience in the current job
				The relationship between occupation and education
				Recognition based on the duration of activity

Table 2
Coding for data entry

Average balance
1 = less than 50 m rials
2 = 50 to 100 m rials
3 = 100 to 300 m rials
4 = more than 300 m rials

Work experience in the current job
1 = less than 5 yrs.
2 = 5-10 yrs.
3 = 10-20 yrs.
4 = more than 20 yrs.

Duration of activity in the bank
1 = less than 2 yrs.
2 = 2-5 yrs.
3 = 5-10 yrs.
4 = more than 10 yrs.

Age
1 = less than 30 yrs.
2 = 30-45 yrs.
3 = 46-60 yrs.
4 = more than 60 yrs.

Creditworthiness
1 = creditworthy
0 = non-creditworthy

Ownership of workplace
1 = owned
2 = rented

Marital status
1 = single
2 = married

Gender
1 = male
2 = female

Nominal capacity matching obligations
1 = nominal capacity not matching the required loan amount
2 = maximum capacity matching previous obligations without any additional capacity
3 = capacity perfectly matching the requested loan amount and previous obligations
4 = capacity exceeding the requested loan amount and previous obligations

Collateral
1 = deposit
2 = bills of exchange
3 = real assets
4 = other

Loan term
1 = less than 5 yrs.
2 = 5-10 yrs.
3 = 10-15 yrs.
4 = more than 15 yrs.

Credit score
1 = less than 55
2 = 55-70
3 = 70-85
4 = more than 85

Loan amount
1 = less than 100 m rials
2 = 100-500 m rials
3 = more than 500 m rials

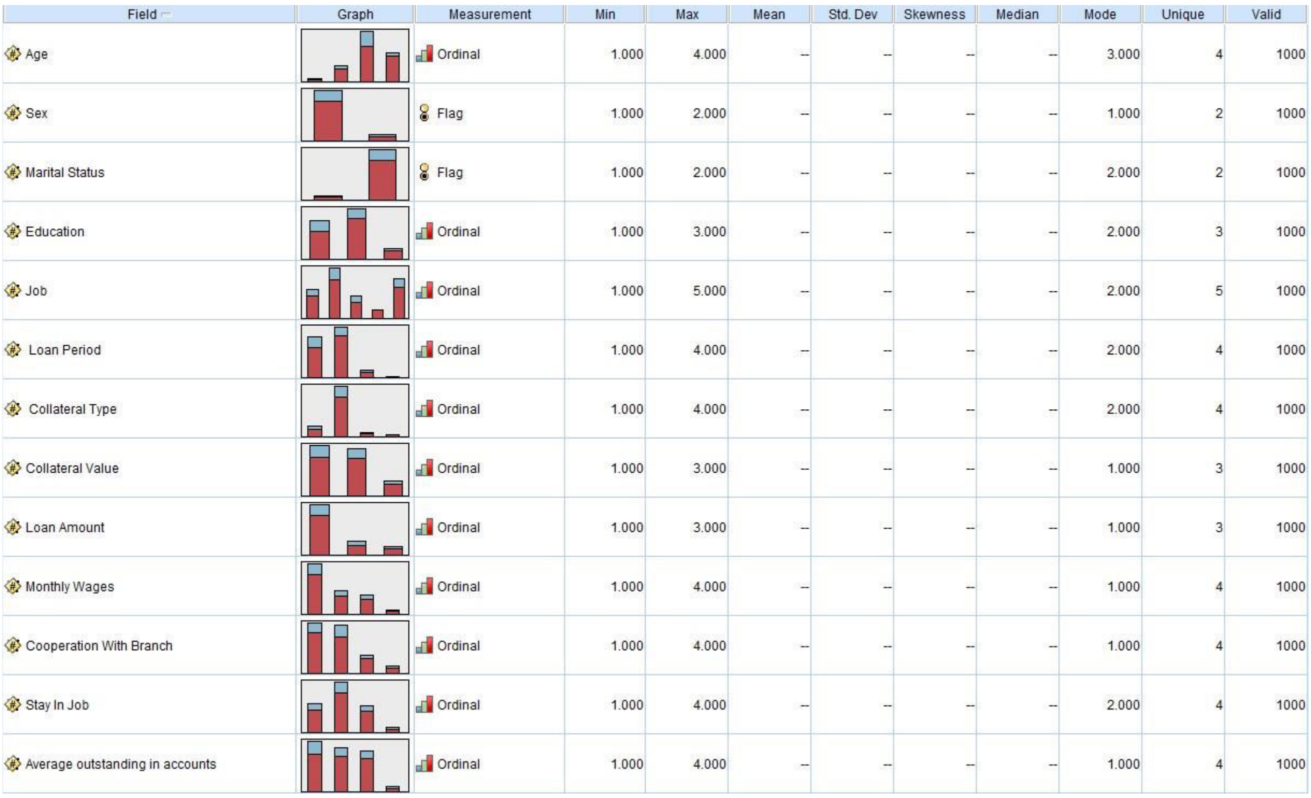
Collateral value
1 = less than 100 m rials
2 = 100-500 m rials
3 = more than 500 m rials

Education
1 = high school diploma
2 = Bachelor's degree
3 = Master's degree or higher

Monthly income
1 = less than 20 m rials
2 = 20-50 m rials
3 = 50-100 m rials
4 = more than 100 m rials

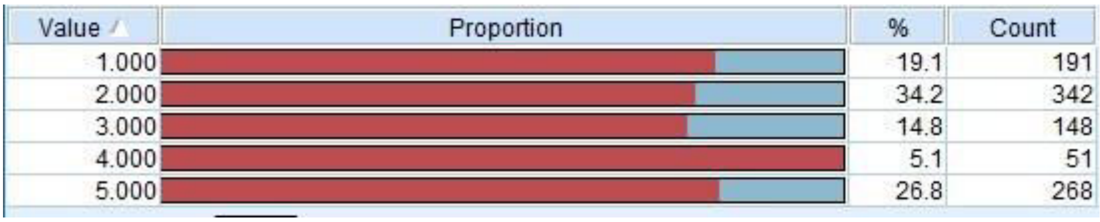
Job
1 = contract employee
2 = official employee
3 = engineer
4 = doctor, lawyer, judge
5 = entrepreneur, freelancer

Reputation and public image
1 = poor reputation
2 = not very reputable
3 = approved by the minority
4 = approved by the majority
5 = very reputable



Field	Graph	Measurement	Min	Max	Mean	Std. Dev	Skewness	Median	Mode	Unique	Valid
Age		Ordinal	1.000	4.000	–	–	–	–	3.000	4	1000
Sex		Flag	1.000	2.000	–	–	–	–	1.000	2	1000
Marital Status		Flag	1.000	2.000	–	–	–	–	2.000	2	1000
Education		Ordinal	1.000	3.000	–	–	–	–	2.000	3	1000
Job		Ordinal	1.000	5.000	–	–	–	–	2.000	5	1000
Loan Period		Ordinal	1.000	4.000	–	–	–	–	2.000	4	1000
Collateral Type		Ordinal	1.000	4.000	–	–	–	–	2.000	4	1000
Collateral Value		Ordinal	1.000	3.000	–	–	–	–	1.000	3	1000
Loan Amount		Ordinal	1.000	3.000	–	–	–	–	1.000	3	1000
Monthly Wages		Ordinal	1.000	4.000	–	–	–	–	1.000	4	1000
Cooperation With Branch		Ordinal	1.000	4.000	–	–	–	–	1.000	4	1000
Stay In Job		Ordinal	1.000	4.000	–	–	–	–	2.000	4	1000
Average outstanding in accounts		Ordinal	1.000	4.000	–	–	–	–	1.000	4	1000

Fig. 1.A preview of data entry.



Value	Proportion	%	Count
1.000		19.1	191
2.000		34.2	342
3.000		14.8	148
4.000		5.1	51
5.000		26.8	268

Fig. 2.Distribution of credit capacity for one indicator.

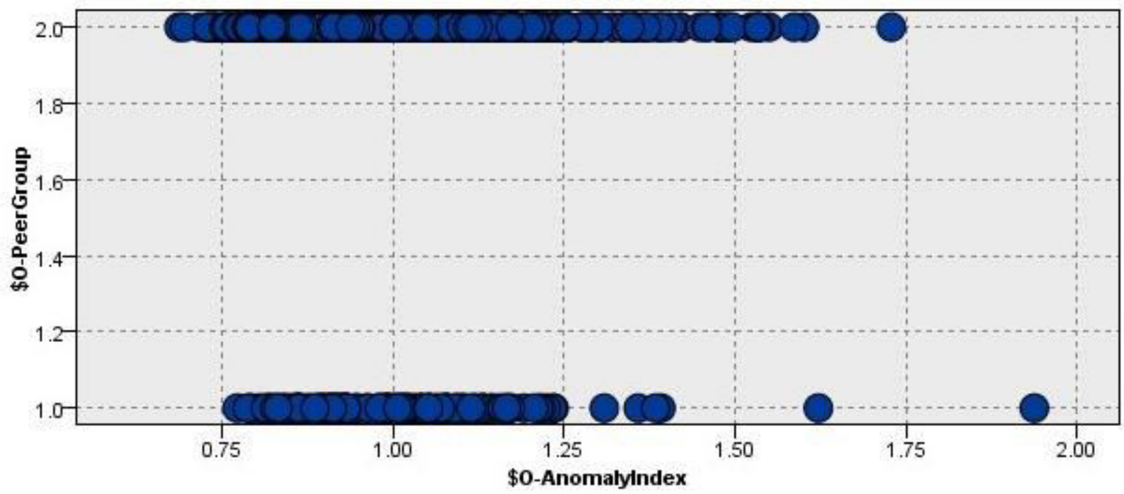


Fig. 3.Automatic identification of outliers by the software.

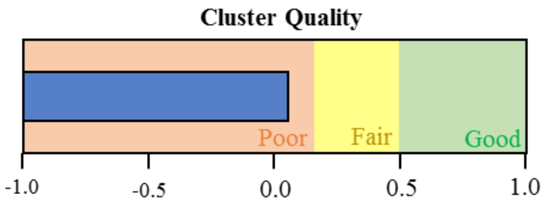


Fig. 4. Evaluating clustering quality using the K-Means technique.

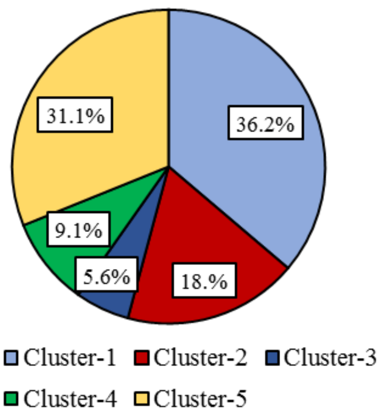


Fig. 5.Dispersion and distribution of data in five clusters using the K-Means technique.

Figure 4 shows the Silhouette index of the K-Means model for five clusters, before the removal of non-significant indicators. As this chart shows, clustering quality is rather weak,and it is essential to remove non-significant indicators from the model to make it more accurate.

Figure 5 shows the characteristics of the clusters. The smallest cluster contains 5.6 percent (i.e., 56) and the largest cluster contains 36.2 percent (i.e., 362) of the records. Thus, the ratio of the size of the largest cluster to the size of the smallest cluster is 6.46.

Figure 6 shows the relative importance of the indicators within the model. As shown in this figure, the first six indicators are more important than the others.

To increase the accuracy of the clustering model, we try to work with a limited number of variables that best explain the behavior of customers. Therefore, eight indicators with the most significant effects are selected which is obtained by re-running the model. These eight indicators are shown in Figure 7, which are loan amount, collateral value, loan term, monthly income, age, collateral type, work experience, and initial credit score. Also, Figure 8 indicates the K-Means clustering quality for these eight indicators, where the number of clusters is five.

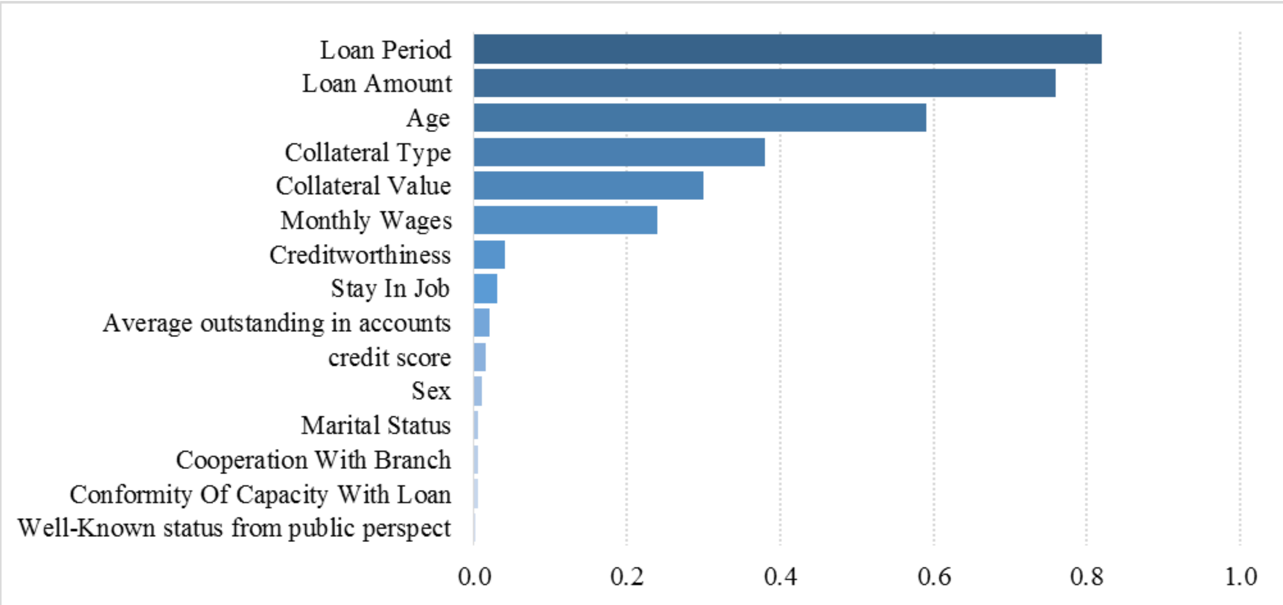


Fig. 6.Diagram of the importance of indicators in K-Means clustering technique.

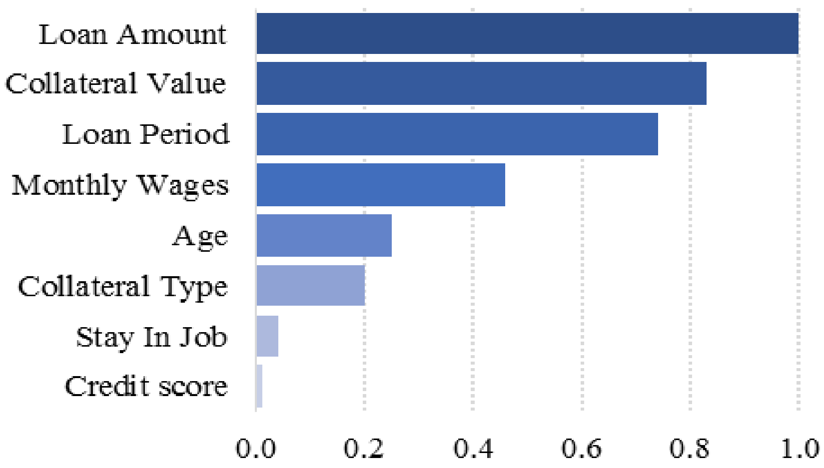


Fig. 7. Diagram of the importance of indicators in K-Means clustering technique after removing non-significant indicators.

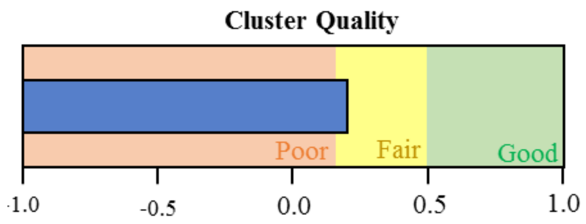


Fig. 8. Evaluation of clustering quality in the K-Means technique after removing non-significant indicators.

Figure 9 shows the improvement of the K-Means clustering model after removing non-significant indicators as well as the state of the central parameters of the model, including mode.

Table 3 shows the importance of the variables information of each cluster. Classification is based on cluster size. As can be seen, customer age has an unusual distribution in cluster formation, and it is one of the most important indicators in the output of the final model. After initial data refinement and data management, initial clustering is performed to identify key customer indicators. As for the main clustering with the goal of discovering a customer model, the target variable, i.e. creditworthiness, is excluded from calculations and only accompanies the model as an important variable in the Auto Cluster node. However, in all the machine learning techniques for credit scoring that are run as follows, the Creditworthiness field is introduced as the Target field.

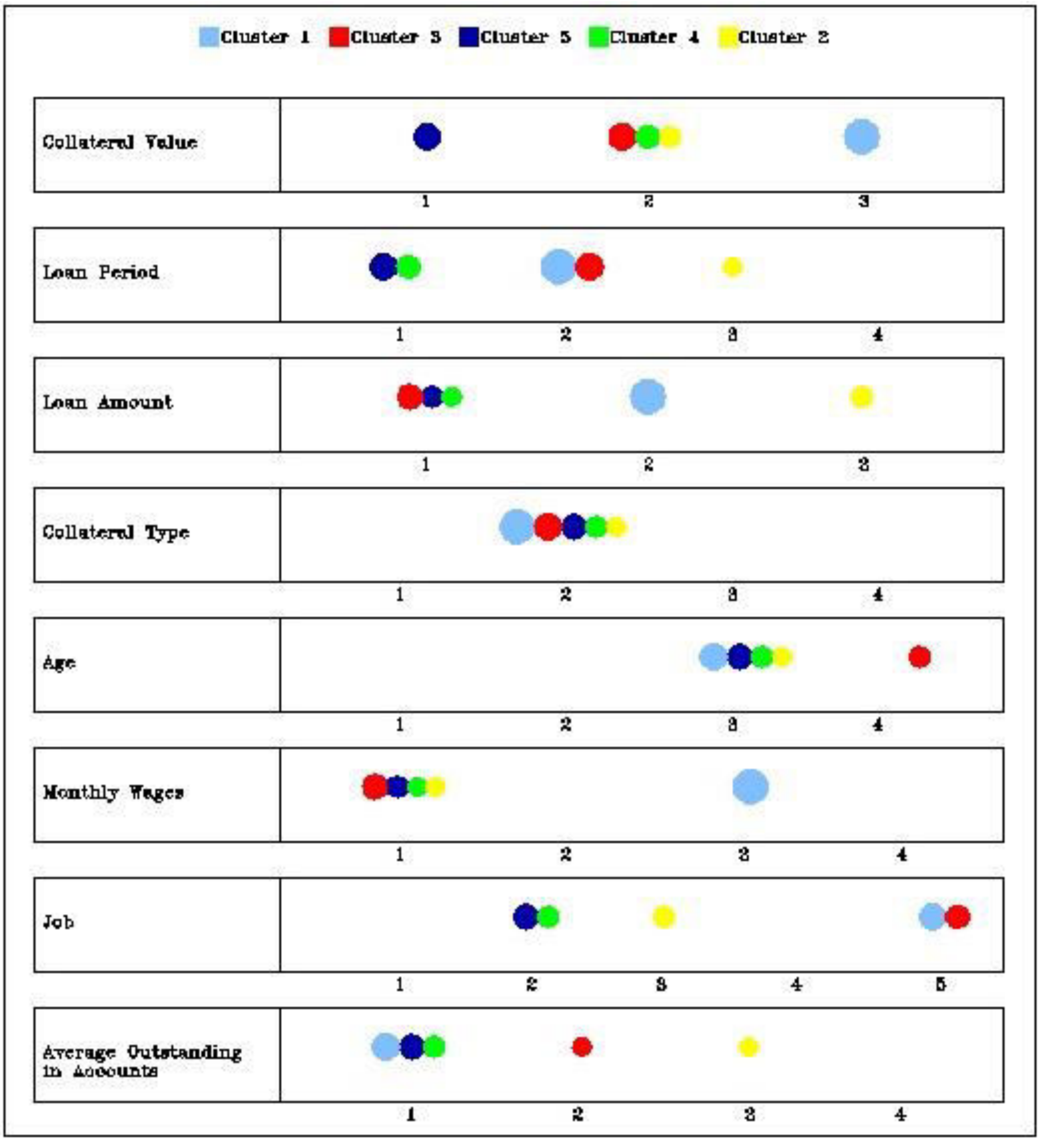


Fig. 9. Comparison of clusters and dispersion of cluster centers in one diagram.

Table 3
Important indicators for each cluster

Input (Predictor) Importance
1.0 0.8 0.6 0.4 0.2 0.0

Cluster	cluster-1	cluster-3	cluster-5	cluster-4	cluster-2
Label					
Size	37.8% (378)	18.8% (188)	17.7% (177)	13.2% (132)	12.5% (125)
Inputs	Collateral Value 3	Collateral Value 2	Collateral Value 1	Loan Period 1	Loan Period 3
	Loan Amount 2	Age 4	Loan Period 1	Collateral Value 2	Loan Amount 3
	Monthly Wages 3	Loan Period 2	Loan Amount 1	Age 3	Collateral Type 2 (46.4%)
	Loan Period 2	Loan Amount 1	Age 3	Loan Amount 2	Job 3 (36.8%)
	Age 3	Job 5 (60.1%)	Job 2 (31.1%)	Job 2 (40.9%)	Collateral Value 2
	Job 5 (44.4%)	Monthly Wages 2	Monthly Wages 2	Monthly Wages 1	Monthly Wages 1
	Collateral Type 2 (83.1%)	Collateral Type 2 (83.5%)	Collateral Type 2 (81.4%)	Average outstanding in accounts	Average outstanding in accounts
	Average outstanding in accounts	Average outstanding in accounts	Average outstanding in accounts	Collateral Type 2 (84.1%)	Age 3

3.4. UTA model

UTA (UTilités Additives) is an ordinal regression model that has been developed as a response to ranking problems. The objective of the model is to optimally infer additive utility functions so that these functions are as consistent as possible with the global decision maker's preferences. The input of the model is a reference set of alternatives that have been ranked based on the decision maker's preferences. If the utility function of the UTA model ranks the reference set as close as possible to the ranking of the decision maker, the consistency between the model and the decision maker's preference system is confirmed(Figueira et al., 2005).

3.5. UTADIS model

UTADIS (UTilités Additives DIS criminantes) is a variant of the UTA model that has been developed as a response to clustering problems. In this model, the decision maker clusters a set of reference alternatives in groups with a specific order of preference, and utility functions are estimated so that the model's results are as consistent as possible with the decision maker's clustering (Figueira et al., 2005). In studies by Doumpos and Zopounidis (2002a)and Pendaraki et al. (2005), the UTADIS model has been found to be one of the most efficient MCDM models. This model is described in detail in the following section.

3.5.1. A Review of the UTADIS Methodology

A criteria aggregation model is created, whereby the alternatives are classified into two groups with a predefined order.

$$c_1 \succ c_2 \succ \ldots \succ c$$

where C_1 is the most preferred group and C_2 is the least preferred group.

3.5.2. Additive value model

The criteria aggregation model is assumed to be an additive value function. This model provides an indicator of the final or overall performance of each alternative with a set of criteria. The objective of the model is that alternatives placed in the C_1cluster gain the highest score in this indicator, with other alternatives gaining a lower score as we move from C_1 to C_q. The additive function has the following form:

$$U(g) = \sum_{i=1}^{n} p_i u_i(g_i) \tag{1}$$

where $g = (g_1, g_2, ..., g_n)$ is the vector of evaluation criteria.p_i is a non-negative constraint that denotes the weight or importance of the criterion g_i.

Marginal utility functions are monotonic functions that are defined for the criteria with the following conditions:

$$\begin{cases} ui(g_{i*}) = 0 \\ ui(g_i*) = 1 \end{cases} \tag{2}$$

where$g_{i^*}$and$g_i^*$are the most and least preferred values for i-th criterion respectively. These values are calculated as follows:

- For additive value criteria (an increase in the value of the criteria increases the utility of the alternative):

$$\begin{aligned} g_{i*} &= \min\{g_{ji}\} \quad \forall X_i \in A \\ g_i* &= \max\{g_{ji}\} \quad \forall X_i \in A \end{aligned} \tag{3}$$

- For decreasing value criteria (an increase in the value of the criteria decreases the utility of the alternative):

$$\begin{aligned} g_i* &= \min\{g_{ji}\} \quad \forall X_i \in A \\ g_{i*} &= \max\{g_{ji}\} \quad \forall X_i \in A \end{aligned} \tag{4}$$

The marginal utility function of the criteriong_{i^*} is shown in Figure 10.

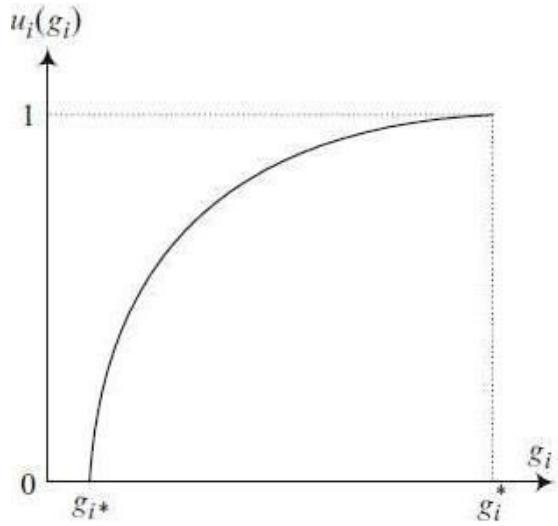


Fig. 10. Marginal utility function for the i-th criteria.

Given the marginal utility of each criterion, the global utility of the alternative X_i, which is calculated by equation (1), indicates the overall performance of that alternative relative to the set of criteria. The global utility of each alternative takes a value between 0 and 1 and is a measure used for classification of alternatives.

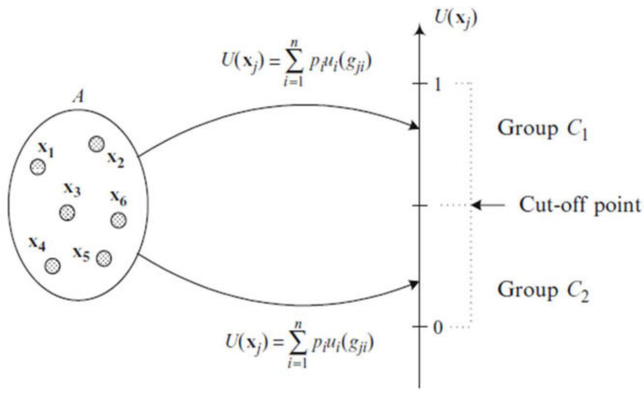


Fig. 11. Classification of alternatives in a simple two-cluster model.

Figure 11 shows the classification of alternatives in a simple two-cluster model. Classification is performed by comparing the global utility of each alternative with the predefined utility threshold U in the interval [0,1]. Therefore, alternatives with a higher utility than this threshold are placed in the group C_1 and those with a lower utility than the threshold are placed in C_2.

In the global mode where alternatives are placed in q different groups, classification is done as follows:

$$\begin{cases} U(X_i) \le u_i \Rightarrow X_i \in C_1 \\ u_2 \le U(X_i) \le u_1 \Rightarrow X_i \in C_2 \\ \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \\ U(X_j) \le u_{q-1} \Rightarrow X_j \in C_q \end{cases} \tag{5}$$

where U_k is the utility threshold that discriminates C_k from C_{k+1}. In the following, the general UTADIS model for multiobjective linear programming is demonstrated.

$$\min \sum_{k=1}^{q} \left[\frac{\sum_{\forall x_j c_k} (\sigma_j^+ - \sigma_j^-)}{m_k} \right] \tag{6}$$

$$\text{S.T:}$$
$$U(g_i) - u_1 + \sigma_j^+ \geq \delta_1, \quad \forall x_i \in c_1 \tag{7}$$

$$U(g_i) - u_k + \sigma_j^+ \geq \delta_1, \quad \forall x_j \in c_k (k = 2,3,\dots,q-1) \tag{8}$$

$$u(g_j) - u_{k-1} - \sigma_j^- \leq -\delta_2, \forall x_j \in C_k (k = 2,3,\dots,q-1) \tag{9}$$

$$u(g_j) - u_q - 1 - \sigma_j^- \leq -\delta_2, \forall x_j \in c_q \tag{10}$$

$$u(g^*) = 1$$
$$u(g_*) = 0 \tag{11}$$

$$u_k - u_{k+1} \geq S, \quad k = 1,2,\dots,q-1 \tag{12}$$

$$u_i(g_i) \text{ increasing Functions}$$

$$\sigma_j^+, \sigma_j^- \geq 0 \qquad j = 1,2,\dots,m \tag{13}$$

The detailed UTADIS model for multiobjective linear programming is as follows:

$$\min \sum_{k=1}^{q} \left[\frac{\sum_{\forall x_j \in C_k} (\sigma_j^+ + \sigma_j^-)}{m_k} \right] \tag{14}$$

$$\text{S.T:}$$
$$\sum_{i=1}^{n} \left(\sum_{t=1}^{r_{ji-1}} w_{it} + \frac{g_{ji} - g_i^{r_{ji}}}{g_i^{r_{ji}+1} - g_i^{r_{ji}}} w_{i,r_{ji}} \right) - U_1 + \sigma_j^+ \geq \delta_1, \forall x_j \in C_1 \tag{15}$$

$$\sum_{i=1}^{n} \left(\sum_{t=1}^{r_{ji-1}} w_{it} + \frac{g_{ji} - g_i^{r_{ji}}}{g_i^{r_{ji}+1} - g_i^{r_{ji}}} w_{i,r_{ji}} \right) - U_k + \sigma_j^+ \geq \delta_1, \forall x_j \in \{C_2, \dots, C_{q-1}\} \tag{16}$$

$$\sum_{i=1}^{n} \left(\sum_{t=1}^{r_{ji-1}} w_{it} + \frac{g_{ji} - g_i^{r_{ji}}}{g_i^{r_{ji}+1} - g_i^{r_{ji}}} w_{i,r_{ji}} \right) - U_{k-1} - \sigma_j^- \leq \delta_2, \forall x_j \in \{C_2, \dots, C_{q-1}\} \tag{17}$$

$$\sum_{i=1}^{n} \left(\sum_{t=1}^{r_{ji-1}} w_{it} + \frac{g_{ji} - g_i^{r_{ji}}}{g_i^{r_{ji}+1} - g_i^{r_{ji}}} w_{i,r_{ji}} \right) - U_{q-1} - \sigma_j^- \leq -\delta_2, \forall x_j \in C_q \tag{18}$$

$$\sum_{i=1}^{n} \sum_{t=1}^{a_i-1} w_{it} = 1 \tag{19}$$

$$U_k - U_{k-1} \geq S, \qquad 1 \leq k \leq q-1 \tag{20}$$
$$w_{it}, \sigma_j^+, \sigma_j^- \geq 0$$

Inthis model:

- k: number of classes of the reference set
- m_k: Number of members in each class of the reference set
- U_{g_i}: Global utility of the i-th alternative
- σ: Error due to incorrect classification
- δ_i: An auxiliary variable for converting bounded constraints into normalization constraint
- C_i: Threshold for each class

To calculated weights and thresholds of the model for creditworthy, non-creditworthy, and low-risk customers, ten samples are randomly selected from the Test group of the SVM output, and the model was coded in the Excel software in terms of the number of classes, estimated utility values, and the number of variables. These codes are provided in the attachments. The number of errors decreases as the number of subintervals increase, which may lead to so-called overfitting.

The optimal number of subintervals can be obtained through trial and error, and codes related to four to ten subintervals are provided in the attachments.

The proposed linear programming model can be solved using the Solver tool in Excel. The outputs of the model (weight of indicators) are m_{ij} and u_i values (thresholds) for the utility of a new customer with respect to the reference set.

Post-Optimality of the Model. Given that the primary goal is to minimize errors, a solution of the optimal model can lead to many weights having a value of zero. To solve this problem, the model is implemented as many times as the number of indicators and Us by setting the coefficients of W_{ij} to 1, maximizing the objective function, and controlling the sum of the weights of indicators. The optimal solution in the sample implementation of ten models is provided in Table 4.

Table 4
Optimal solution in the sample implementation of ten models

	W_j	Ranking
Age	0.234953	2
Job	0.078900	4
Collateral Value	0.045276	8
Loan Amount	0.045146	9
Monthly Income	0.280769	5
Average Balance	0.048943	7
Credit Score	0.280679	1
Nominal capacity matching obligations	0.138653	3
Reputation and Public Image	0.138653	3

The proposed technique of this paper has been compared with nine machine learning based state-of-the-art techniques which are CART, C5, ANN, ANN1, ANN2, ANN3, RL, KNN, and BN. The results of this coparison is illustrated in Table 5.

Table 5
Effectiveness comparison of the proposed technique with nine machine learning based state-of-the-art techniques

			Accuracy								
	Train	**Test**	**Train**	**Test**	**Different**	**Recall=TPR**	**Precision**	**Specificity**	**F-Measure**	**AUC**	**Gini**
CART	578	237	82.57%	79%	4%	0.250	0.004	0.209	0.008	0.633	0.265
C 5	599	216	79.86%	72%	8%	0.656	0.170	0.184	0.270	0.644	0.287
ANN	571	234	81.57%	78%	4%	1.000	0.004	0.217	0.008	0.954	0.187
ANN 1	570	235	81.43%	78.33%	3%	0.500	0.021	0.207	0.041	0.653	0.307
ANN 2	583	233	83.29%	77.67%	6%	0.625	0.021	0.212	0.041	0.62	0.241
ANN 3	580	230	82.86%	76.67%	6%	0.632	0.051	0.206	0.094	0.615	0.231
R L	578	231	82.57%	77%	6%	0.625	0.043	0.208	0.080	0.636	0.272
KNN	580	231	82.86%	77%	6%	0.750	0.026	0.216	0.049	0.544	0.088
B N	600	211	85.71%	70.31%	15%	0.721	0.135	0.210	0.227	0.596	0.191
Proposed	699	223	99.86%	74.33%	26%	0.714	0.085	0.210	0.152	0.583	0.166

4. Conclusion and Recommendations

Financial institutions and banks incur considerable losses from non-creditworthy customers. These are customers who breach their loan contracts and can push some financial institutions toward bankruptcy. On the other hand, retaining creditworthy customers by granting facilities keeps money in that institution and results in good progress. A model that can accurately predict customer behavior can be beneficial for banks, financial institutions, and service providers. The present research uses UTADIS to predict the future behavior of customers. The results show that the most influential factors in this process are the initial credit score and age of the applicants, while the least influential factors are collateral value and loan amount. Considering the wide variety of factors that affect credit risk, the study of other factors that may increase the possibility of defaulting on debts and evaluating their impact can be the subject of further research. Also, the use of other models such as neural network models and Adaptive Neuro-Fuzzy Inference System (ANFIS) for credit scoring can be further explored.

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