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Class Labeling of Bank Credit's Customers Using AHP and SAW for Credit Scoring with Data Mining Algorithms

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Abstract—**One of the most important parts in credit scoring is determining the class of customers to run the Data Mining Classification algorithms. The purpose of this research is allocating the Labels of Credit customers with using of AHP and SAW methods. Here, in the first step, each customer is labeled by AHP and SAW and then the data mining algorithms are run. In this way, via this method the acquired results of data mining algorithms can be improved. The presented steps have been studied in an Iranian Bank as empirical study.**

Index Terms—**Data mining, credit scoring, classification, labeling, SAW, AHP.**

I. Introduction

Data mining techniques have been applied to solve classification problems for a variety of applications, including credit scoring, bankruptcy prediction, insurance underwriting, and management fraud detection. These techniques automatically induce prediction models, called classifiers, based on historical data about previously solved problem cases. The classifiers can then be applied to recommend solutions to new problem cases. By unearthing the patterns or knowledge from the data itself, data mining methods obviate the need for eliciting knowledge from a human expert. In addition, Credit Scoring is one of the mentioned problems which can be solved via Data mining methods. The main objective of credit scoring systems is to classify samples into affinity groups. Generally, credit scoring problems are related to classification by statistical methods. Investigating more sophisticated classifiers to match the characteristics of the samples is crucial in providing results that meet the needs of particular credit scoring applications. Techniques for developing classifiers have evolved from simple parametric to nonparametric statistical methods [1]. Credit scoring models help to decide whether to grant credit to new applicants using customer's characteristics such as age, income and martial status [2]. Other efforts are leading to the investigation of nonparametric statistical methods for credit scoring applications. A research compared several Bayesian network classifiers with statistical and other artificial intelligence techniques for classifying customers [3]. The credit scoring accuracy of five neural network models has be investigated , and reported that the nonparametric and hybrid design architectures are very useful in developing effective credit scoring systems[4].Neural network (NN), Bayesian network (BN), and Support vector machine (SVM) have been shown to perform well in credit prediction [5] Another study presents a hybrid mining approach in the design of an effective credit scoring model, based on clustering and neural network techniques[2]. Another study applied neuro-fuzzy models to analyze consumer loan applications and compared the advantages of neuro-fuzzy systems over traditional statistical techniques in credit-risk evaluation [6]. A genetic fuzzy and a neuro-fuzzy classifier for credit scoring has been applied in another research [7]. Data mining classifiers have been developed in several application domains, such as bankruptcy prediction [8], financial performance prediction [9], bond rating analysis [10], credit evaluation [11],credit risk assessment [12].In the area of SAW, another study is using , simple average weight (SAW),''Technique for Order Preference by Similarity to an Ideal Solution'' (TOPSIS) and ''VlseKriterijumska Optimizacija I Kompromisno Resenje'' (VIKOR), which are based on an aggregating function and provide a comparison analysis of the above-three methods[13].About the studies around AHP ,A paper proposed an integrated AHP–DEA methodology to evaluate bridge risks of hundreds or thousands of bridge structures, [14].The other study proposes a new data envelopment analysis (DEA) method for priority determination in the AHP and extends it to the group AHP situation and uses the simple additive weighting (SAW) method for aggregation of the best local priorities without the need of normalization[15].

Determining the customers' classes by experts is done based on several criteria and each criterion has different special importance degree in comparison with others and AHP technique is used to weight the criteria. The SAW technique is ranking the choices according to the sum of non-scale weighty values. Ranking is not the aim of this paper but according to the resulted spectrum values, the choices can be labeled with three classes. Then Data Mining algorithm is done on the data.

The scope of the current paper however is limited to the evaluation of the considered Bank[1]. Section 2and 3 of this paper present a survey of the literature related to the Data Mining and Credit Scoring and SAW and AHP. Section 4 provides an empirical study in mentioned Bank, while Section 5 discusses the relative benefits and the managerial implications of the proposed methodology as the conclusion.
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II. Data Mining and Credit Scoring

Data Mining (DM) is an iterative process within which progress is defined by discovery, either through automatic or manual methods. Data mining is the process that uses Statistical, Mathematical, Artificial Intelligence and

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[1] Since the information of considered bank are confidential, The Authors have not been authorized to present The name of considered Band.

Machine-Learning techniques to extract and identify useful information and subsequently gain knowledge from large databases. Data mining is the process of extracting or detecting hidden patterns or information from large databases. With comprehensive customer data, data mining technology can provide business intelligence to generate new opportunities. DM is most useful in an exploratory analysis scenario in which there are no predetermined notions about what will constitute an ''interesting'' outcome. Data mining techniques, therefore, can help to accomplish such a goal by extracting or detecting hidden customer characteristics and behaviors from large databases. The generative aspect of data mining consists of the building of a model from data. Each data mining technique can perform one or more of the following types of data modeling: (1) Association; (2) Classification; (3) Clustering; (4) Forecasting; (5) Regression; (6) Sequence discovery; (7) Visualization. Here are some examples of some widely used data mining algorithms:(1) Association rule;(2) Decision tree;(3) Genetic algorithm;(4) Neural networks;(5) K-Nearest neighbor; (6) Linear/logistic regression[16]. Association aims to establishing relationships between items which exist together in a given record. Common tools for association modeling are statistics and Apriori algorithms. Classification is one of the most common learning models in data mining. Common tools used for classification are neural networks, decision trees and if then-else rules. Clustering is the task of segmenting a heterogeneous population into a number of more homogenous clusters. Common tools for clustering include neural networks and discrimination analysis. Forecasting estimates the future value based on a record's patterns. It deals with continuously valued outcomes .Common tools for forecasting include neural networks and survival analysis, Regression is a kind of statistical estimation technique used to map each data object to a real value provide prediction value. Common tools for regression include linear regression and logistic regression. Sequence discovery is the identification of associations or patterns over time .Common tools for sequence discovery are statistics and set theory. Visualization refers to the presentation of data so that users can view complex patterns. It is used in conjunction with other data mining models to provide a clearer understanding of the discovered patterns or relationships. Examples of visualization model are 3D graphs, ''Hygraphs" and ''SeeNet" [17]. A major benefit of using a data mining technique is that it bypasses the knowledge acquisition bottleneck. By unearthing the patterns or knowledge from the data itself, data mining methods obviate the need for eliciting knowledge from a human expert...The field of data mining has its origins in statistics and machine learning. Several data mining methods are available for classification problems, including statistical techniques such as naive Bayes, discriminant analysis, and logistic regression, and machine learning techniques such as decision tree/rule induction and neural network. [18]. One of the applications of Data Mining is Credit scoring. In a credit scoring model, analysts usually used their historical experience with debtors to derive a quantitative model for the segregation of acceptable and unacceptable credit applications. Using a credit scoring system, a credit application is self-operating processed and consistently all credit decisions are made. The scoring system is based on the addition or subtraction of a statistically extracted number of points relating to the applicant's score given to the predictor variables, such as time on a job or the number of credit sources used. As a result, it can be said that credit scoring enables advancers to assess the credit worthiness quickly. Also, provides moderate scale to adjust the accepted quality by the lenders, and of course provides statistical techniques which enable lenders to measure it. Moreover, credit scoring give a chance to the advancers to improve the customer services process to avoid any estimated future decline. By using a statistically extracted cut-off credit score, an analyst can of course separate the acceptable from the unacceptable credit applicants [19].

Classification is concerned with the categorization of records in a data set, typically achieved by applying a set of Classification Rules (CRs), also sometimes referred to as prediction rules. A classification rule has the general form A--> C, where A, the antecedent, is the union of some set of attribute values of the records involved: The consequent, C, is the label of a class to which records can be assigned. Classification rules are typically derived from examination of a training set of records that have been previously annotated with appropriate class labels. Many techniques exist to generate CRs from a given training set including techniques based on decision trees, Bayesian networks, and Support Vector Machines [20].

III. SAW AND AHP METHOD

A. AHP Method

The AHP is a method developed to support multi-criteria decision making. It involves decomposing a complex MCDM problem into a hierarchy, assessing the relative importance of decision criteria, comparing decision alternatives with respect to each criterion, and determining an overall priority for each decision alternative and an overall ranking for the decision alternatives. The hierarchy is constructed in such a way that the overall decision goal is at the top level, decision criteria (and sub-criteria if any) are in the middle level(*s*), and decision alternatives at the bottom. The AHP method provides a structured framework for setting priorities on each level of the hierarchy using pairwise comparisons that are quantified using 1–9 scales. Let $C1, \ldots, Cm$ be m decision criteria and $W = (w1, \ldots, wm)^t$ be their normalized relative importance weight vector, which is to be determined by using pairwise comparisons and satisfies the normalization condition $\sum_{j=1}^{m} wj = 1$ with $wj \geq 0$ for $j = 1, \ldots, m$. The pairwise comparisons between the m decision criteria can be conducted by asking the decision maker (DM) or expert questions such as which criterion is more important with regards to the decision goal and by what scale (1–9). The answers to these questions form an m × m pairwise comparison matrix which is defined as follows:

$$A = (aij)mm = \begin{bmatrix} a11 & \cdots & a1m \\ \vdots & \ddots & \vdots \\ am1 & \cdots & amm \end{bmatrix}$$

If the pairwise comparison matrix $A = (aij)\ m \times m$ satisfies $a_{ij} = a_{ik}a_{kj}$ for any $i,j,k = 1, \ldots, m$, then A is said to be perfectly consistent; otherwise it is said to be inconsistent. Form the pairwise comparison matrix A, the weight vector W can be determined by solving the following characteristic equation:

$$AW = \lambda_{\max} W;$$

where $\lambda_{\max}$ is the maximum eigenvalue of A. Such a method for determining the weight vector of a pairwise comparison matrix is referred to as the principal right eigenvector method (*EM*) .Since the DM may be unable to provide perfectly consistent pairwise comparisons, it is demanded that the pairwise comparison matrix A should have an acceptable consistency, which can be checked by the following consistency ratio (*CR*):

$$CR = \frac{(\lambda_{\max} - 1)/(n-1)}{RI}$$

where *RI* is a random inconsistency index, whose value varies with the order of pairwise comparison matrix. If $CR \leq 0.1$, the pairwise comparison matrix is thought to have an acceptable consistency; otherwise, it need to be revised. Decision alternatives can be compared pairwisely with respect to each decision criterion in the same way.

B. SAW Method

After the weights of decision criteria and the weights of decision alternatives with respect to each criterion are obtained by using pairwise comparison matrices, the overall weight (or called priority) of each decision alternative with respect to the decision goal can be generated by using the following simple additive weighting (*SAW*) method :

$$W_{Ai} = \sum_{j=1}^{m} w_{ij} w_j \quad , \quad i = 1, .., n$$

where $w_j (j = 1, . . . , m)$ are the weights of decision criteria, $w_{ij} (i = 1, . . . , n)$ are the weights of decision alternatives with respect to Criterion j, and $W_{Ai} (i=1,..,n)$ are the overall weights of decision alternatives. Based upon the overall weights of decision alternatives, decision can be made and the alternatives can be ranked or prioritized. The best decision alternative will be the one with the biggest overall weight with respect to the decision goal [14].

IV. EMPIRICAL STUDY

In this paper which has been run in an Iranian bank, the main purpose is to identify the credit label of customers with the use of SAW and AHP techniques before implementing data mining algorithms. The labeling task which is categorizing the customers in three levels based on their credit degree, is run according to three effective variables in customers' credit scoring that these variables have been specified by the bank experts.

The database fields which are customers attributes include: Activity time, The number of employees, The age of managing director, The education level of managing director, The years of cooperation with the bank, The Type of Collateral, The amount of loan, The current ratio, The debit ratio, The period of the collection of claims, The activity area, The profit Ratio or the rate of return.

The empirical study has done in 6 steps as shown in Fig 1.

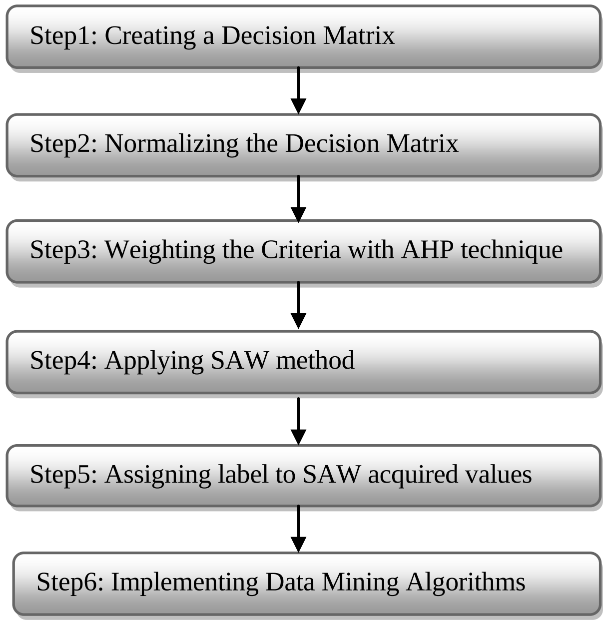

Fig. 1. The steps of empirical study

Step1: Studying the decision matrix criteria by the bank experts, the effectiveness of three main criteria on the bank credit degree of customers has been specified and the judgment about the credit degree of customers is depends on them. So for each of 120 customers, these three criteria have been extracted from the bank customers of database systems which is shown in table 1.This table is same as the decision matrix for the Simple Additive Weighting(SAW).

TABLE I: DECISION MATRIX FOR LABELING TO CUSTOMERS

	Days of Delay	Number of payments with Delay	The amount of payments with Delay
Customer1	a11	a12	a13
Customer2	a21	a22	a23
…	…	…	…
Customer120	a1201	a1202	a1203

Step2: Thus the values of decision matrix are not normalized, they will be normalized with linear normalization method. The formula $n_{ij}=1-(a_{ij}/\max a_{ij})$ has been used for normalizing, according to the negative sign of all criteria. Table 2 shows the normalization.

TABLE II: NORMALIZED DECISION MATRIX

	Days of Delay	Number of payments with Delay	The amount of payments with Delay
Customer1	0.334	0.455	0.202
Customer2	0.612	0.328	0.426
…	…	…	…
Customer120	0.541	0.32	0.187

Step3:Since the importance degree of these criteria from the bank customers' view is not the same, the AHP technique has been used to determine the weight of each of them according to experts opinions and the comparison between the criteria, the weight of each criterion as vector W= (0.364 , 0.113 , 0.523)

Step4: Now, with the decision making matrix and a weight vector, the SAW model has been used. Normalized matrix in the previous step will be multiply in the criteria weights which has been resulted from AHP method and the A^* vector is obtained with the values between 0 and 1. Therefore $A^*=(A^*1=0.23, A^*2=0.512\ldots A^*120=0.387)$. According to these values, the customers can be ranked based on the credit degree.

Step5: In this step, to assign a specific label to each customer, with considering the credit degree from the A^* vector, the following spectrums (Table3) from the bank experts have been determined.

TABLE III: DETERMINING THE CLASS LABEL BASE ON A*VECTOR

Class label	Credit Degree(A*vector values)
Good	0-0.399
Medium	0.4-0.699
Bad	0.7-1

Step6: Finally, The data mining algorithms can be applied which is done by Clementine software. The results of accuracy of different algorithms are shown in Table 4.

TABLE IV: THE ACCURACY OF OBTAINED RESULTS OF DATA MINING ALGORITHMS

Algorithm	CART	C5	CHAID	Logistic -R
Accuracy	67.03%	70.42%	56.63%	54.57%
Algorithm	BayesNet	NN	SVM	Discriminant
Accuracy	62.17%	63.34%	73.14%	52.93%

V. CONCLUSION

In this paper with the use of SAW and AHP techniques, the classes to database records have been assigned and then the Data Mining algorithms have been run .Accurate Labeling to the records is a crucial issue in Data Mining process, otherwise the Data Mining process has no integrity and the obtained result is not secure. In this paper, labeling to each record in terms of determining credit level of customers, based on some important criteria from the experts' view as the effective criteria in credit scoring of customers, has been done. In next step, some Data Mining algorithms on the bank database has been run that the results show the Support Vector Machine (SVM) has the higher accuracy in comparison with the other algorithms. This research for classifying problems like credit scoring, can be applied and specifying each record class is done according to experts' opinions and the situation of some criteria with the different importance degree should be considered here.Thus, SAW technique in such situations before Data Mining process ,can be effective.

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