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Multiple Criteria Decision Making based Credit Risk Prediction using Optimal Cut-off Point Approach

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Abstract

Credit risk assessment is an important task for banks and financial institutions as the loan defaulters and market competition has been increased. In the competitive market, data mining proved to be an efficient technique for predicting credit risks accurately. But in practice, the data mining classifiers use the default cut off value of 0.5 to predict the binary outcomes. If the group size is not equal in datasets, then the cut-off point of 0.5 is not suitable. For imbalance multiple criteria classification problems, it is essential to determine the optimal probability cut-off point. In this paper, a different approach, MCDM (Multiple Criteria Decision Making) based optimal probability cut-off point is proposed for predicting credit risk using hybrid data mining methods. The proposed approach is more advantageous than the usual approach because it determines the optimal cut-off point with improved correct classifications and it also considers MCDM methods for choosing the optimal cut-off point which is very effective in decision making process among multiple criteria.

Keywords- Credit Risk, Data Mining, K-Means clustering, Logistic Regression Classifier, Multiple Criteria Decision Making, Probability cut-off point.

1. Introduction

Credit Risk refers to the loss occurred to the financial institutions due to borrower’s failure to repay the debt. Intelligent credit risk prediction model is important for any financial institutions to understand the thorough knowledge of customers and their credit risk. Data mining techniques plays a major role in predicting the credit risk customers accurately and also the classification techniques of data mining bring advantages to credit risk prediction [1]. Classification algorithms when combined with clustering approach gives improved performance compared to single classification models [2]. But most of the classifiers in data mining use 0.5 as default cut-off point for predicting binary results. If the group sizes of the datasets are not equal in size, then the 0.5 default probability cut-off point is not suitable. In this case,selecting the optimal cut-off point is very important for predicting the binary outcomes accurately. Best cut-off point selection for classifiers is considerably difficult as this is involved with multiple criteria and the previous literatures mentioned that classifiers performances may differ with different performance measure in financial risk prediction [3]. Optimal cut-off point selection can be considered as a multiple criteria decision making problem and it is very effective in decision making process among multiple criteria [4].

The main objective of this paper is to determine the optimal probability cut-off point based on MCDM technique because the group size of the datasets is not always equal and it is better to evaluate the classifier performance based on multiple criteria and another objective is to predict the credit risks by combining clustering and classification approach with the selected probability cut-off point to make more accurate prediction.

In this paper, Firstly, the right number of clusters is identified based on knee point based method and applied to K-Means clustering approach. Secondly the relabeled cluster samples are applied to Logistic Regression classifier and the important performance measures are evaluated for their classifying performances with different choices of probability cut-off point. Thirdly, MCDM - AHP and TOPSIS approaches are used to find the optimal probability cut-off point and Finally, Efficient credit risk prediction is made with the determined optimal cut-off point.

The rest of this paper is organized as follows: Section 2 briefly reviews the literature, Section 3 describes the evaluation approach and the experimental process of the proposed work, Section 4 discusses the experimental results observed in credit risk prediction and Section 5 concludes the entire work

2. Literature Review

The imbalance in classes' imposes a great challenge in developing accurate classification methods [5]. So, best cut-off point selection reduces the overall error rate of credit risk prediction with data mining classifiers [6]. Logistic regression classifier was selected for the study as its falls within top three classifiers in finding undetected fraud cases [4]. Logistic Regression model with random effects improves the quality of credit risk prediction [7]. Moreover, supervised learning methods are the commonly used technique for credit risk fraud detection systems [8].Also the classification algorithms can predict withgreater accuracy than other traditional approaches [9]. The five important performance measures used in this study are selected from the literatures. Overall Accuracy is a commonly used metric to measure the performance in classification [10]. It is the percentage of correctly classified cases. The higher TP rate can help the companies to reduce the credit losses [11]. True

Positive rate is the correctly classified abnormal cases i.e., bad credit risks. True Negative rate is the correctly classified normal cases i.e., good credit risks. Area under ROC is the suitable metric for unknown conditions [12]. F-Measure is a suggested performance measure as they reveal true positives [13].

For Pre-processing, K-Means clustering algorithm is used to divide the dataset into homogeneous clusters with different degrees of risk. Without identifying the value of K it is very difficult to get the clustering model correctly [14]. Therefore, Knee point based K-Means clustering method is used in this study to detect the right number of clusters [16].

Many Top MCDM methods have been proposed in the literatures for ranking the classifiers in credit risk prediction and these methods have different fundamental assumptions, analysis and decision rules to solve the decision making process. MCDM method VIKOR was applied for business performance evaluation [17]. These methods produce consistent rankings when applied to credit risk datasets. But none of the previous literatures uses MCDM approach for determining the optimal cut-off point.

In this paper, different approach is implemented to determine the optimal probability cut-off value for data mining classifiers using AHP (Analytic Hierarchy Process) and TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) MCDM approaches. These approaches are suggested to find the ranking among cut-off point with multiple criteria and it shows high performance in predicting the credit risks accurately.

3. Proposed Work

This paper proposes different stages to determine the optimal cut-off point of classifiers for credit risk prediction. The first three parts of this section describes the overview of the evaluation approach of credit risk prediction and the remaining parts describe the experimental process.

3.1 Knee Point Based K-Means Clustering

K-Means is one of the popular and simplest clustering algorithm. But many data mining software packages, requires the number of clusters (say K) to be specified before it is applied to the K-Means algorithm [15]. So, in this study to identify the right number of clusters (K) knee point based technique is applied [16] to achieve the best clustering result.

The steps to compute the knee point based K-Means Clustering

1) For a given dataset, the average sum of squared errors for different values of clusters using K-Means algorithm is determined and plotted as a curve against the number of clusters. The average sum of squared errors is an objective measure in K-Means to represent the mean of a cluster and the points in the cluster [18].
2) The change in the curve is identified as knee-point which is the right number of clusters (K) for the given dataset.

3) Initialize K=knee-point value is the number of clusters.
4) Determine the centroid coordinate or cluster center.
5) Calculate the Euclidean distance for all objects based on cluster center.
6) Group the objects based on minimum Euclidean distance from step 5.
7) Repeat step 5 and step 6 until the objects do not move into groups.

1.1 Logistic Regression Classifier

Logistic Regression is a popular classification method that is widely used in many data mining applications [19]. It could build a model with binary outcome from a set of independent variables [20] where the response is either success or failure. In case of credit risk prediction, the success is the presence of bad credits. The form of the logistic regression model to predict a logit transformation for the effect of independent variables is in the form of binary response and it is represented as

$$logit(pr(Y = 1|X)) = b_0 + b_1X_1 + b_2X_2 + b_3X_3 + \cdots . + b_kX_k \qquad (1)$$

wherepr is the probability of success of the attributes of interest(X). The logit transformation is defined as the odds of success and it is shown in the following equations.

$$\log\_odds = \frac{p}{1-p} \qquad (2)$$

and

$$logit(pr(Y = 1|X)) = ln\left(\frac{p}{1-p}\right) \qquad (3)$$

The model assumes that log_odds ratio is linearly related to X.

The principle of maximum likelihood is used to estimate the parameters in logistic regression. The maximum likelihood ratio helps to find the statistical importance of independent variables on the dependent variables [21].

1.2 MCDM Methods

MCDM is a technique to evaluate, assess and ranking alternatives for diverse applications. The Analytic Hierarchy Process MCDM method was used to allocate the weights [22].TOPSIS method helps to select the best alternative for fixed number of criteria [23].

1.2.1 Analytic Hierarchy Process (AHP)

The AHP method calculates the weight for each criterion based on pairwise comparison of the criteria. The greater the weight, the more important is the particular criteria [24].

The steps to compute the vector of criteria weights are shown as below:

1) A pairwise comparison matrix M is determined. The intensity of importance between two criteria is measured by Saaty [25] scale of relative importance. scale 1 represents m^{th} criteria and n^{th} criteria are equally important, scale 3

represents m^{th} criteria is slightly more important than n^{th} criteria, scale 5 represents m^{th} criteria is more important than n^{th} criteria, scale 7 represents m^{th} criteria is strongly more important than n^{th} criteria and scale 9 represents m^{th} criteria is extremely more important than n^{th} criteria [19]. Each entry in the matrix denotes the importance of m^{th} criteria relative to n^{th} criteria.

i. If an m^{th} criterion is more important than n^{th} criteria, then the entry in the matrix is greater than 1.
ii. If an m^{th} criterion is less important than n^{th} criteria, then the entry in the matrix is less than 1.
iii. If it is equally important then it is equal to 1.

2) Once matrix M is built, a normalized pairwise comparison matrix is determined. It is computed by dividing each entry in matrix M by the sum of the entries in column.
3) Finally W_i is computed by taking the row averages from the normalized pairwise comparison matrix.

1.2.2 TOPSIS

The TOPSIS approach was introduced by Hwang (1981) and it was used to rank the best alternatives for decision making. This approach is to find the best alternative that is closest to the ideal solution and extreme from the negative ideal solution.
To compute the best alternative, TOPSIS approach includes the following steps:

1. Form a normalized decision matrix N_{ij} i.e., score of criteria i with respect to alternative j (X_{ij}) divided by square root of sum of square of X_{ij}.
2. Form a weighted normalized decision matrix WN_{ij} which is the weight of criteria $W_i$by AHP process multiplied by N_{ij}. Determine the maximum of ideal and minimum of ideal solutions from WN_{ij}

- Ideal solution A*=Max(WN_{ij})
- Extreme Ideal solution A'= Min(WN_{ij})

3. Find the separation from ideal solution I_i^* which is the sum of square of $WN_j^* - WN_{ij}$ to the power of 0.5.
4. Find the separation from negative ideal solution I_i' which is the sum of square of $WN_j' - WN_{ij}$ to the power of 0.5.
5. Determine the closeness to the ideal solution CI_i^*which is I_i' divided by sum of I_i' and I_i^* .
6. Greater the score CI_i^* is the best alternative.

1.3 Experimental Process

The different stages of the proposed approach for credit risk prediction are depicted inFig. 1 and discussed in these sub-sections.

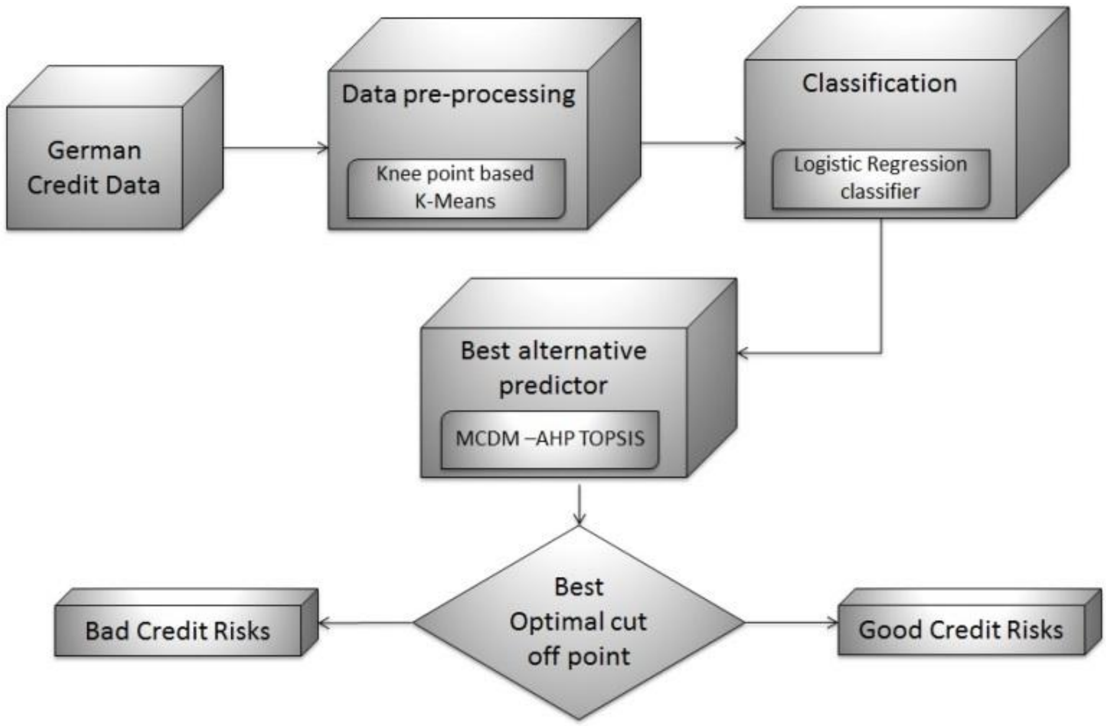

Fig.1 System Architecture of MCDM based optimal probability cut-off point approach

1.3.1 Dataset Selection and Pre-Processing

German Credit data set is used for the experiment from the UCI machine learning repository [27]. The German credit dataset contains 1000 instances with 20 predictor attributes and 1 class attribute. The class variable specifies good or bad cases. 700 instances are good cases and 300 instances are bad cases.

For pre-processing, K-Means clustering algorithm is used to divide the dataset into different degrees of risks. The right value of K is identified by knee point detection [16]. Using the value of K by knee-point, the K-Means algorithm is applied to divide the dataset into different homogeneous cluster groups.

1.3.2 Classification

The identified homogeneous clusters from previous step are relabeled into different degrees of risk say very high, high, medium, low and very low. Using these clusters as input, Logistic regression data mining classification algorithm is applied for different choices of probability cut-off point to determine the important performance measures such as overall accuracy, TP rate, TN rate, F-Measure and Area under ROC for classification.

1.3.3 Best Alternative Predictor

In this step, the top MCDM methods such as AHP and TOPSIS are used to find the optimal cut-off point for classifier. The AHP method is used to calculate the weights of each criterion which is needed by TOPSIS method. Using performance measures evaluated in previous step are considered as criteria and different choices of probability cut-off point as alternatives; the TOPSIS method finds the optimal cut-off point.

1.3.4 Prediction

The determined optimal cut-off point from the previous step is used to predict the credit risk data with correct classification of bad and good credit risks. Bad credit risks indicate the abnormal cases and Good credit risks indicate the normal cases present in the credit risk dataset.

4. Experimental Results

In this section, the efficiency and effectiveness of the proposed approach are determined using German credit dataset from UCI machine learning repository. The experiment is conducted according to the proposed approachin four evaluation stages and implemented using WEKA 3.7, a data mining software [26] and Microsoft Excel 2010.

To classify the dataset into different degrees of risks, simple K-Means clustering algorithm is implemented in WEKA and the right value of K is identified by knee point detection [16].Using simple K-Means clustering algorithm of WEKA, the average sum of squared errors for different number of clusters are plotted against the different number of clusters say 1 to 12 to find the knee-point and is shown in the following Fig. 2

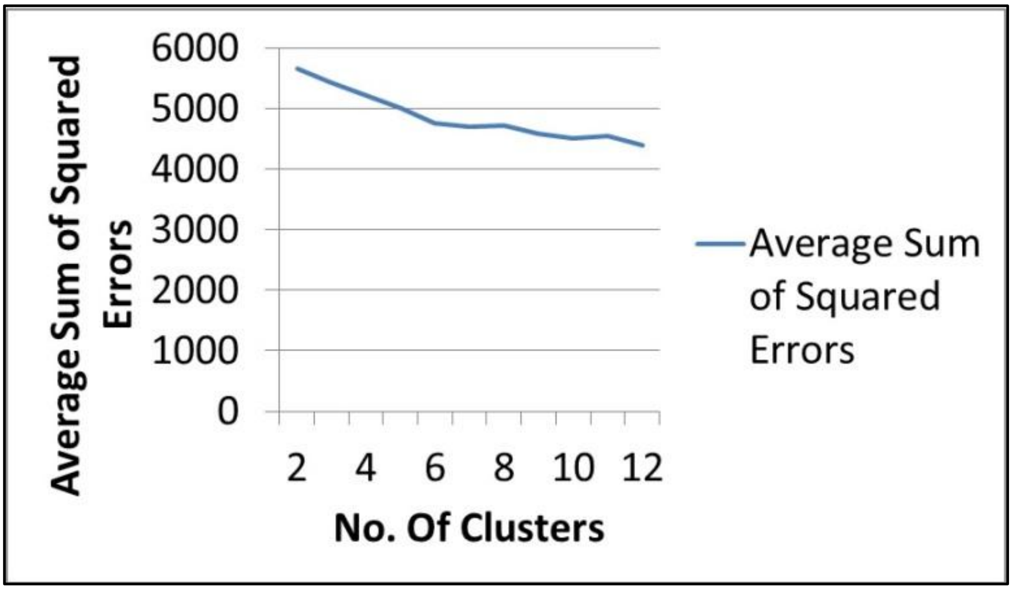

Fig. 2Knee Point Detection to Find the Number of Clusters based on Average Sum of Squared Errors

From the figure, there are five clusters identified at knee point for German credit dataset and applied to simple K-Means clustering algorithm of WEKA 3.7 package to divide the entire dataset into different degree of risks based on the characteristics of the clusters and it is shown in Table I.

Table I. Different Degrees of Risk

Degrees of Risk	Characteristics	Cluster Number
Very high	Seeks high amount for used car with 3.1% income commitment for installment and <0 checking balance and free housing	Cluster 1
High	Seeks for new car with 3.0% income commitment for installment and <0 checking balance with rented housing property	Cluster 4
Medium	Seeks for radio/tv with 3.2% income commitment for installment and <0 checking balance and own life insurance	Cluster 3
Low	Seeks for new car with 2.7% income commitment for installment and <0 checking balance with own housing and real estate property	Cluster 0
Very low	Seeks for radio/tv with 2.7% income commitment for installment and 0 to 200 DM checking balance and own a house	Cluster 2

Identified homogeneous clusters were relabelled with the different degree of risks and Logistic Regression classifier of WEKA package was applied with different arbitrary choices of probability cut-off points to determine five important performance measures such as overall accuracy, True Positive Rate, True Negative Rate, F-Measure, Area under ROC using 10 fold cross validation and the results are listed in Table II.

Table II. Logistic Regression Classifier Performances for Different Probability Cut-Off Point

Probability Cut-Off Point	Overall Accuracy	TP Rate	TN Rate	F-Measure	Area under ROC
0.1	0.621	0.917	0.494	0.592	0.839
0.2	0.719	0.81	0.68	0.634	0.839
0.3	0.778	0.71	0.807	0.657	0.839
0.4	0.788	0.623	0.859	0.638	0.839
0.5	0.8	0.567	0.9	0.63	0.839
0.6	0.808	0.513	0.934	0.616	0.839
0.7	0.795	0.433	0.95	0.559	0.839
0.8	0.789	0.353	0.976	0.501	0.839
0.9	0.767	0.247	0.99	0.388	0.839
0.99	0.704	0.013	1	0.026	0.839

Once the logistic regression classifier is evaluated, the decision has to be taken to select the cut-off point for predicting good or bad credit risks. Using performance measures as multiple criteria and probability cut-off point as alternatives, the MCDM TOPSIS approach finds the best alternative (best cut-off point) that is closest to the ideal solution and extreme from the negative ideal solution. The weights needed to compute the weighted normalised decision matrix are computed by analytic hierarchy process (AHP) which is normalized in the interval 0 to 1 so that the sum of all weights is equal to 1 and it is depicted in Table III.

Table III. Weights by AHP Method

Overall Accuracy	TP rate	TN Rate	F- Measure	Area Under ROC
0.5028	0.2603	0.0348	0.1344	0.0677

The best alternative i.e., optimal cut-off point is the one that has greatest closeness to ideal solution and are depicted in TableIV.

Table IV. Evaluation of Optimal Cut-Off Point

Probability cut-Off Point	Closeness to Ideal Solution by TOPSIS
0.1	0.77
0.2	0.84
0.3	0.79
0.4	0.71
0.5	0.66
0.6	0.62
0.7	0.54
0.8	0.46
0.9	0.35
0.99	0.12

The result from TABLE IV indicates that the selected optimal cut-off point maximizes the TP rate i.e., correctly classified abnormal cases when compared to default cut-off point and it is shown in Fig. 3.

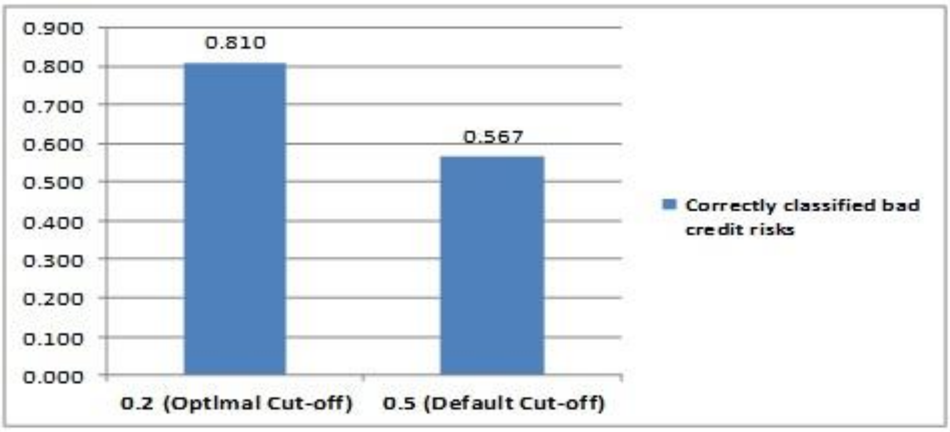

Fig. 3Default Cut-Off Vs Optimal Cut-Off

The MCDM based optimal probability cut-off point approach is more advantageous than the traditional approach because it considers multiple criteria for choosing the optimal cut-off point which leads to accurate prediction. The optimal cut-off point i.e., 0.2 from Table IV which has greatest closeness to ideal solution indicates that the high value of 0.81% correctly classified bad credit risks at 0.2 cut-off value is suitable for accurate credit risks prediction when compared to the default cut-off value of 0.5 with 0.567% correctly classified bad credit risks.

5. Conclusion

This paper presented an efficient approach with 0.81 % correct classification of bad credit risks at 0.2 cut-off value as compared to default cut-off (0.5) value of 0.567%. The outcome of this analysis shows that the proposed approach is more advantageous than the traditional approach because it determines the optimal cut-off point with improved correct classifications using MCDM AHP-TOPSIS approach which is very effective in decision making process among multiple criteria. As a future work, the selected optimal cut-off point will be implemented for other important classifiers and in pre-processing and clustering stage a fuzzy logic and genetic algorithm will be used for optimization to increase the accuracy of the classifier performances and to provide a better solution for credit risk prediction.

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