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Credit scoring and rejected instances reassigning through evolutionary computation techniques

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Abstract

The credit industry is concerned with many problems of interest to the computation community. This study presents a work involving two interesting credit analysis problems and resolves them by applying two techniques, neural networks (NNs) and genetic algorithms (GAs), within the field of evolutionary computation. The first problem is constructing NN-based credit scoring model, which classifies applicants as accepted (good) or rejected (bad) credits. The second one is better understanding the rejected credits, and trying to reassign them to the preferable accepted class by using the GA-based inverse classification technique. Each of these problems influences on the decisions relating to the credit admission evaluation, which significantly affects risk and profitability of creditors. From the computational results, NNs have emerged as a computational tool that is well-matched to the problem of credit classification. Using the GA-based inverse classification, creditors can suggest the conditional acceptance, and further explain the conditions to rejected applicants. In addition, applicants can evaluate the option of minimum modifications to their attributes.

Keywords: Credit scoring; Classification; Inverse classification; Neural networks; Genetic algorithms

1. Introduction

With the rapid growth in credit industry, credit scoring models have been extensively used for the credit admission evaluation. The credit scoring models are developed to categorize applicants as either accepted (good) or rejected (bad) credits with respect to their characteristics such as age, income and marital condition. Creditors accept the application provided that it is expected to repay the financial obligation, and vice versa. Creditors can construct the classification rules based on the data of the previous accepted and rejected applicants. With sizable loan portfolios, even a slight improvement in credit scoring accuracy can reduce the creditors' risk and translate considerably into future savings. From the Brill (1998) study, the benefits of credit scoring include cost reduction in credit analysis, faster credit evaluation, closer monitoring of existing accounts and improvement in cash flow and collections.

Linear discriminant model (Reichert, Cho, & Wagner, 1983) is one of the first credit scoring models, and it is commonly used today. Linear discriminant analysis (LDA) for credit scoring has been challenged due to the categorical nature of the credit data and the truth that the covariance matrices of the accepted and rejected classes are likely to be unequal (West, 2000). Practitioners and researchers have also applied statistical techniques to develop more sophisticated models for credit scoring, which involve logistic regression analysis (LRA) (Henley, 1995), k nearest neighbor (KNN) (Henley & Hand, 1996) and decision tree (Davis, Edelman, & Gammerman, 1992).

Classification is a commonly encountered decision making tasks in business. Categorizing an object into a predefined group or class based on a number of observed attributes related to that object is a typical classification problem (Zhang, 2000). In addition to credit scoring and corporate distress prediction, neural networks (NNs) have been successfully applied to a variety of real world classification tasks in industry, business and science. A number of performance comparisons between neural and conventional classifiers have been made by many studies (Curram & Mingers, 1994; Markham & Ragsdale, 1995). Conventional statistical classification procedures such as LDA and LRA are constructed on the Bayesian decision theory. In these classification techniques, an underlying probability model must be assumed in order to calculate

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the posterior probability upon which the classification decision is made.

In credit industry, NN has recently been claimed to be an accurate tool for credit analysis (Desai, Crook, & Overstreet, 1996; Malhotra & Malhotra, 2002; West, 2000). Desai et al. (1996) have explored the ability of NN and traditional statistical techniques such as LDA and LRA, in constructing credit scoring models. Their results indicated that NN shows promise if the performance measure is percentage of bad loans accurately classified. However, if the performance measure is percentage of good and bad loans accurately classified, LRA is as good as NN. The percentage of bad loans correctly classified is an important performance measure for credit scoring models since the cost of granting a loan to a defaulter is much larger than that of rejecting a good applicant (Desai et al., 1996).

West (2000) has investigated the accuracy of quantitative models commonly used by the credit industry. The results indicated that NN can improve the credit scoring accuracy. West also suggested that LRA is a good alternative to NN. Additionally, LDA, KNN, and classification and regression tree (CART) did not produce encouraging results.

In the field of corporate failure analysis, which is also an important classification problem in business, NNs were also reported to be successful. Coats and Fant (1993) have utilized both LDA and NN to classify firms obtained from COMPUSTAT as either viable or distress. Coats and Fant concluded that NN is more accurate than LDA, remarkably for predicting the distressed companies. Salchenberger, Cinar, and Lash (1992) reported that NN performs as well as or better than the LRA in the prediction of the financial health of savings and loans. From the computational results made by Tam and Kiang (1992), NN is most accurate in bank failure prediction, followed by LDA, LRA, KNN and decision trees.

From the extensive survey of NN applications in business (Vellido, Lisboa, & Vaughan, 1999), it indicates that NN shows promise in various areas where nonlinear relationships are believed to exist within the datasets, and traditional statistical approaches are deficient. In credit prediction, the nonlinear features of NNs make them a potential alternative to traditional parametric (e.g. LDA and LRA) and nonparametric (e.g. KNN and decision tree) methods. However, NN is commonly considered as a black-box technique without logic or rule-based explanations for the input–output approximation. A main shortage of applying NN for credit scoring is the difficulty in explaining the underlying principle for the decision to rejected applications (West, 2000).

In order to investigate the possibility of translating a rejected decision into the accepted class for applicants, creditors can suggest modifications to the adjustable attributes with minimum modification cost. This approach lessens to a degree the deficiency of applying NN for credit scoring in explaining the rationale for the decision to rejected applications. Creditors can suggest the conditional acceptance, and further explain the conditions to rejected applications. On the other hand, applicants can evaluate the option of minimum modifications to their attributes. Some of the factors are adjustable, and they may change currently or in the near future.

This study focuses on two interesting credit analysis problems and resolves them by applying two techniques, NNs and GAs, within the field of evolutionary computation. The first problem is constructing the NN-based credit scoring model. The second one is better understanding the rejected credits, and trying to reassign them to the preferable accepted class by using the GA-based inverse classification technique. The rest of paper is organized as follows. Section 2 presents the formulation of inverse classification. Section 3 introduces the NN-based credit scoring and GA-based inverse classification technique. The computational results of the illustrative example are given in Section 4. Finally, Section 5 makes a conclusion to this study.

2. Formulation of inverse classification

The credit scoring issue of rejected instance analysis addressed in this paper is a particular *inverse classification* problem defined by Mannino and Koushik (2000). The inverse classification problem determines the minimum cost alternative by which a reference instance $A = \{a_1, a_2, \ldots, a_n\}$, currently categorized in class C_i, $i \in \{1, 2, \ldots, m\}$, can have its attribute values adjusted such that it is categorized in a different class C_j, $i \neq j \in \{1, 2, \ldots, m\}$. The process of classifying an instance A is a mapping from the set of attribute values $\{a_1, a_2, \ldots, a_n\}$ and classification model M to exactly one of m classes: $classify\ (A, M) \rightarrow C_i$, $i \in \{1, 2, \ldots, m\}$. Let $X = \{x_1, x_2, \ldots, x_n\}$ denote an adjusted instance of A after one or more attribute values have been manipulated, and $TC(A, X)$ denote the total cost of attribute adjustments. Mathematically, the inverse classification problem can be formulated as follows

$$\text{Minimize} \quad TC(A, X) \tag{1a}$$

$$\text{Subject to}: classify\ (X, M) \rightarrow C_j \tag{1b}$$

The growing application of classifiers in credit scoring system suggests that creditors can significantly benefit from this inverse classification formulation. It lessens to a degree the deficiency of applying NN for credit scoring in explaining the rationale of rejected applications. A number of factors including account longevity, credit history, employment category, assets owned, years residence, amount of loan, etc. are used by creditors in arriving the credit scoring. Some of the factors are adjustable, and they may change currently or in the near future. In order to investigate the possibility of translating rejected credits into the accepted class, which is preferable to applicants, creditors can perform the minimum possible modifications