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The human-like intelligence with bio-inspired computing approach for credit ratings prediction

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ABSTRACT

Corporate credit rating analysis is a topic of considerable academic concern, and statistical and machine learning techniques for establishing credit ratings have been extensively studied. Recently developed hybrid models that combine different machine learning techniques have shown promising results. This research proposes a novel classification model based on bio-inspired computing mechanism to combine the artificial bee colony (ABC) approach and support vector machine (SVM) technique to enhance the credit ratings and credit rating changes prediction. Experiments are based on a ten-year real-world dataset taken from the Compustat credit rating database. Three additional financial datasets from the UCI datasets are also used to access the robust and convergence performance. The experimental outcomes indicate the proposed model provides improved prediction accuracy than other traditional statistical or soft-computing approaches, suggesting that the proposed approach is well-designed to potential credit rating or changes predicting.

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1. Introduction

The mechanism to measure the credit of the company or security, based on its assets quality, liabilities, debt, payment, and overall business performance is called credit rating. The credit rating also aims to analyze the gap between the ideal and real return on outstanding financial obligations [26]. Issuers seek ratings for several reasons. First, use ratings as a basis for improving the marketability or pricing of their financial obligations. Second, a high rating will reduce a firm's cost of capital. Third, ratings may increase a firm's credit with counterparties and debtors. Finally, investors favor firms with good ratings. In addition, some investors are needed to only hold investment grade debt securities. Hence, it can offer useful information and provide the reference for investors to make the investment decision through the fair enough measure. Many institutional investors can only have willingness to keep the securities with well-ranked investment grade. Therefore, ratings organize important information in financial public markets.

The failure of a public corporation can saddle its shareholders and debtors with significant losses, but these losses could potentially be minimized through the development of an accurate method of predicting potential failures [12,18]. A firm's credit rating score provides easily obtained and understood information which can be useful in forecasting corporate failure [1]. While nine firms are recognized by the Securities and Exchange Commission (SEC) for registration as Nationally Recognized Statistical Ratings Organizations (NRSROs). Recently, the grade rating is administrated and managed by three famous firms – S&P, Moody's, and Fitch, and the remaining six firms playing a much smaller role in financial markets. S&P is the oldest of the Big Three credit rating agencies and provides both short-dated and long-dated credit ratings. Beaver [5], Altman [2], and Ohlson [29] all developed models for forecast failure based on a firm's financial reports. This paper, by contrast, focuses on determining the factors that influence credit ratings.

The research of credit rating prediction is a popular issue about the financial status for the companies from the specific financial ratios. In 1960s, there were many conventional statistic approaches applied into the credit rating researches, including univariate analysis [5], discriminant analysis [2], multiple regression [28], logistic regression [27], and probit analysis [39]. More recently, a number of studies adopted machine learning and soft computing approaches to enhance the perdition accuracy of rating changes issues. West [36] investigated credit scoring accuracy using an artificial neural network (ANN) model with a radial basis function, benchmarked against several traditional methods, including

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traditional statistical methods, decision tree classification, and k nearest neighbor clustering. Results demonstrated that the ANN model can be a suitable solution for use in credit rating issues. In addition, logistic regression was proven to be the best performance accuracy among other traditional statistical approaches. After that, the support vector machine (SVM) method [34], is one kind of artificial neural networks, it has widely applied into classification problems. Huang et al. [19] adopted SVM to investigate credit rating analysis for financial markets in the United States and Taiwan, with results showing that SVM outperformed the back-propagation neural network (BPNN), LR, and multiple discriminant analysis (MDA) methods. Lee [25] integrated a grid-search technique with SVM to develop a classification model and results showed that SVM outperformed the MDA method. Huang [17] implemented SVM classifier to predict credit ratings and compared the results with logistic regressions and Bayesian networks. The results showed that the SVM classification model produces more accurate predictions than traditional techniques. Kim and Ahn [24] developed multi-class support vector machines (MSVMs) to forecast real-world bond ratings. Their proposed model outperformed other traditional AI techniques. Recently, Zhong et al. [38] found SVM performed well in terms of prediction accuracy and output distribution for real corporate credit rating data in comparison with three other learning algorithms, including back-propagation (BP), extreme learning machine (ELM), and incremental ELM (I-ELM). Although AI approach has many advantages, there are many researches figured out it cannot be satisfied with expectations because real world data are often unevenly distributed among several classes and it is hard to handle the sequential features of credit ratings issues [30,32]. This paper therefore applies a combined artificial bee colony (ABC) algorithm and SVM classification model to process a dataset consisting of ten years of credit rating data for 556 firms from the Compustat database.

The streucture of this study is described in the follows. Section 2 surveys related literatures about classification methods and bio-inspired computing. In Section 3, the research methodology is presented. Then, the prediction performance for the dataset of the 556 Compustat firms, along with three popular financial UCI datasets in Section 4. In Section 5, this study is draw the contributions and future researches.

2. The related researches

2.1. SVM

Nowadays, the artificial intelligent and soft computing provide new guidelines and in-depth analysis of the general characteristics and properties of the model to establish the implementation, learning, and fitting procedures [11]. Many new artificial intelligent and soft computing methods generalized idea of parameter estimation, and SVM attracted particular interest to achieve this goal. SVM first by Vapnik [33] introduced a new artificial intelligent approach. It is calculated with computational learning theory of structural risk minimization (SRM) principle. Hearst et al. [13] noted that the SVM algorithm is very simple mathematical analysis, because it has the ability to apply linear concept and solution in nonlinear correlation input space with height-dimensional feature space. With this point of view, SVM is a combination of theory-driven advantage, easier than traditional statistical methods to analyze the data and also more robust and data-driven to classify than other machine learning methods [34].

In SVM, it use the mapping function Φ(x) to enhance the ability of input vector x to provide linear separability for highly dimensional feature space issues. We design N is $(x_i, y(x_i))$ and it represents the relationship with input and output node, where $i=1,\ldots, N$. Then, SVM adopts the following concept to classify the x and y, x_i will be belonged to Class 1 if $y(x_i)=1$, otherwise, x_i will be belonged to Class 2 if $y(x_i)=-1$. The linear function is formulated in the highly dimensional feature space via below equation

$$y = f(x) = w^T\varphi(x) + b \tag{1}$$

where w is a weight value, b is a bias value, and $y(x_i)f(x_i) > 0$ for $i=1,\ldots,N$.

In addition, the SVM is also designed to solve the classification issues for non-linearly separable in the feature space, the following equations can be used to achieve the optimization classification in the separating hyperplane.

$$\text{Minimize} \quad R_{svm}(w,\xi) = \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{N}\zeta_i \tag{2}$$

$$\text{Subject to } y(x_i)(w^T\varphi(x)+b) \geq 1-\zeta_i$$

$$\text{For } \zeta_i \geq 0,\ i = 1, 2, \ldots, N \tag{3}$$

where R_{svm} is the risk function to find the minimization of the regularized risk, C is designed as the tradeoff parameter to tune the maximizing margin and minimizing classification error. In addition, ζ_i is the variable for non-negative slack of x_i. Thus, the classification decision function becomes:

$$f(x) = sign\left(\sum_{i=1}^{N} L_i y_i K(x_i, x_j) + b\right) \tag{4}$$

where L_i are Lagrange multipliers and $K(X_i,X_j)=\Phi(X_i)\cdot\Phi(X_j)$ is a symmetric positive definite kernel function [35].

2.2. Artificial bee colony (ABC)

The artificial bee colony (ABC) algorithm was stimulated from the honey bees for their intelligent foraging behavior, and has been widely applied into solving many types of numerical optimization problems [4]. Artificial bees search the global minimizer while looking for suitable food sources in the possible search space. In this ecosystem, the artificial bees will searched for the suitable and advantage food sources near their colony [21]. In addition, there are three roles of artificial bees: employed, onlooker, and scout bees, their detail descriptions are discussed in the follows.

The aims of employed bees are designed to associate with the possible food sources; the aims of onlooker bees are designed to observe the dancing of the employed bees and then decide the suitable food source; the aims of scout bees are designed to look for new food sources by randomly choosing. ABC is one kind of the optimization methodologies and the food source is designed to indicate one possible solution even local or global optimization. In the previous optimization studies, the quality is always replaced by the “fitness”. When the ABC algorithm begins, a random initial population distribution (i.e., the location of a food source). After initialization, the population reuse, search and reconnaissance processing cycles of employed, onlooker, and scout bees. Then, the ABC algorithm generated another source location in its memory, and found a new food source location by the employed bee.

Provide a new source of nectar is higher than that of a bee before the memory location of the new source, and forget the old. Otherwise, a bee remembered that its memory of the location. When searching process is done, employed bees will communicate the dance crowd source of location information with onlooker bees. Each onlooker bee will assess all the information about the possible nectars and then select one best food source has a maximum number of nectar. Similar to the employed bee, the onlooker bee generates the modified her memory of the source location and checks its nectar amount. Provide a new source of the nectar content is higher than the old, bee will forget the old one and memory the new location. The abandoned sources are determined and new sources are randomly produced by the artificial scouts to replace

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