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Credit risk assessment and decision making by a fusion approach

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ABSTRACT

The sub-prime mortgage crisis of 2007 and the global financial tsunami of 2008 have undermined worldwide economic stability. Consequently, the timely analysis of credit risk has become more essential than ever before. The performance of early risk warning mechanisms may vary according to the criteria used and the underlying environment. This study establishes numerous criteria to assess the performance of classifiers and introduces a multiple criteria decision making method to determine suitable warning mechanisms. After undergoing these evaluations, the enhanced decision support model (EDSM), which incorporates the relevance vector machine with decision tree, is proposed. A decision tree is employed to overcome the opaque nature of the relevance vector machine; it yields knowledge as logical statements and aids in the interpretability of the forecasting results. The advantages of the EDSM involve overcoming the timeliness problem, fostering faster credit financing decisions, diminishing possible mistakes and reducing the credit analysis cost. This study also examines the feasibility of corporate transparency and the information disclosure (TD) criterion during an upturn in the economy, and finds that this procedure presents a suitable policy-relevant direction for regulators to design future measurements. Finally, this study shows that the EDSM is a promising way for investors, creditors, bankers and regulators to analyze credit rating domains.

1. Introduction

Assessing corporate financial failure or distress has become an active research topic over the past three decades, attracting wide attention in the fields of finance, accounting, and auditing. The global credit crisis, preceded by the sub-prime mortgage crisis in the United States (US), impacted negatively the economic steadiness of many developed countries [37]. A well-developed early warning mechanism is much more important and undoubtedly holds greater public attention when the global economic environment turns into a depression. Because banks play the role monetary intermediary in the financial market, a precise evaluation of financial risk can help them effectively discriminate target customers, set appropriate charges, and foster efficiency in their credit funding. In addition, banks working under a superior early warning model achiever competitiveness over their opponents. Even a slight amelioration in predicting the chance of default could bring lenders substantial additional profits [8].

Following the globalization trend of economic markets, Taiwan in 2002 deregulated its banking industry by permitting the further build-up of private banks and encouraging the establishment of holding companies. These policies unfortunately created a more severe circumstance when uncensored and reckless monetary lending resulted in a higher number of loans cannot be collected. Due to a sharp decline in the Taiwan stock market in the last decade, the proportion of non-collected loans has increased significantly. Thus, a proper evaluation of the credit worthiness of banks is vital for stakeholders, investors, regulators, depositors, and decision makers in such a volatile economic environment.

A credit rating procedure is an independent measurement that aims to find out how an object is capable and willing to meet its payable obligations and is specifically based on a complicated analysis of all risk factors of the measured object [24]. It is conducted by rating agencies such as Standard and Poor's (S&P), Moody's, Fitch Ratings, and Taiwan Rating Corporation (TRC). Capital market participants (e.g., bond issuers, debt issuers, and governmental officers) utilize credit ratings as a measure of a corporation's risk. They provide a means of determining the risk premium and marketability of bonds, allowing corporations issuing debt to estimate the likely return that investors require [24]. It is the same with banks that allot internal credit ratings to evaluate the credit worthiness of their borrowers [23]. With such sophisticated examinations, investors are willing to lend money to corporate borrowers that are better off financially [50]. Indeed, the asymmetric information between borrowers and lenders can be eliminated by this monitoring procedure.

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The external ratings have been suitable constructed in the early 1990s and then the financial intermediary increasing relying on internal ratings in the late 1990s [61]. Based on numerous financial and non-financial criteria, the internal credit ratings can be generated for specific corporate borrower. From the financial intermediary perspective, the ratings represent the basis for loan approval, pricing, monitoring, and loan loss provisioning [23]. Altman [1] proposed that prior researches have laid much emphasis on the financial criteria for predicting borrower insolvency, but the role of non-financial criteria still not defined.

The well-established structure of corporate governance (CG) can serve as an effective mechanism to eliminate the opportunistic behaviors of management, to increase the corporation's reporting quality and accountancy, and to improve the corporation's value and reputation [30,16,7]. The organization for economic co-operation and development (OECD) has indicated that corporate transparency and information disclosure (TD) are the core features of CG and are viewed as an extremely essential factor in the quality of CG. Additionally, TD can be utilized to reduce agency cost by increasing the monitoring of management's actions, limiting top-level managers' improper investing decisions, and enhancing the integrity of the financial market [40,2].

Credit ratings are high-priced to acquire, because rating agencies invest an extensive amount of resources into executing the credit rating procedure [57]. Thus, large efforts are made in order to mimic the credit rating process of the rating agencies through statistical [27,6,47,17,21] and machine learning approaches [26,12,53,52,48,13,65]. The difficulty in constructing such mechanisms lies in the subjectivity of the credit rating procedure, as the complicated relations among the financial features are hard to measure. Such a complex procedure makes it hard to discriminate rating classes through statistical approaches. However, machine learning approaches can be utilized for modeling such complicated relations.

The relevance vector machine proposed by Tipping [59] is an emerging kernel-based machine learning technique and performs a satisfactory job in numerous research domains. The difference between support vector machine and relevance vector machines is that the relevance vector machine incorporates probabilistic output through a Bayesian inference [42]. Moreover, the inherent parameters of relevance vector machine to establish the decision function is lesser than support vector machine. Thus, it may allow better prediction estimates for small datasets with high dimensionality [34].

Numerous studies have proposed that the performance of classifiers in credit risk forecasting may differ when applied to different criteria (e.g., accuracy, sensitivity and specificity) and under different environments. In other words, no specific classifier could achieve the best performance for all measurements. Determining how to provide reasonable and comprehensive measurements and recommend a suitable classifier are active areas of research in risk management [46]. Rokach [49] suggested that the aforementioned problem can be viewed as a multiple criteria decision-making (MCDM) problem, and that the MCDM approach can be utilized to systematically determine the appropriate classifier. After going through each evaluation procedure, the enhanced decision support model (EDSM), which incorporates the relevance vector machine and decision tree, was applied. However, the superior performance of kernel-based classifiers has a serious drawback, namely the lack of interpretability, which impedes its practical application. Interpretation has been one of the widely discussed topics, in both the fields of philosophy and artificial intelligence [5]. Therefore, several methods have been introduced for knowledge acquisition in relation to kernel-based classifiers. The knowledge acquisition methods can be divided into two mainstreams: pedagogical structure and de-compositional structure. The pedagogical structure treats the kernel-based classifiers as a black box, and extracts rules that describe the relationship between the model's inputs and outputs [4,58,38]. The de-compositional structure utilizes a rule-based learner with the relevance vectors. For each of the relevance vectors, the original class labels are replaced with the class labels predicted by the relevance vector machine. Consequently, a rule-based learner is executed to extract the informative rules from the kernel-based classifier. Barakat and Diederich [4] suggested that the rules derived from the de-compositional structure have a high degree of accuracy, comprehensibility and fidelity. The most common method of developing expressive and human readable representations of knowledge is the use of if-then production rules [32]; thus, the decision tree is utilized to extract the knowledge from the relevance vector machine. This study further examines the feasibility of corporate transparency and the information disclosure (TD) criterion during the period of ex-ante and ex-post the financial tsunami. The findings can present a suitable policy-relevant direction for regulators to design future measurements.

The remainder of this study is structured as follows: the following section illustrates the proposed EDSM model, Section 3 presents the numerical example and experimental results, and Section 4 provides conclusions.

2. The enhanced decision support model (EDSM)

The flowchart of the enhanced decision support model (EDSM) for forecasting credit rating status is illustrated in Fig. 1. The EDSM can be divided into four parts: data preprocessing, model establishment and cross-validation, statistical test and final ranking determination through the MCDM approach, and knowledge acquisition. Data preprocessing includes data cleaning and feature selection. The former is used to avoid confusion in the mining results, which would lessen the reliability of the model (e.g., outlier elimination, missing value deletion, etc.) and the latter is executed to alleviate the computational cost and increase the performance of data analysis. In this study, the feature selection was performed by the correlation-based feature selection method (CBFS) [25]. CBFS is an uncomplicated filter algorithm that arranges feature subsets according to a correlation-based heuristic evaluation function. The intention of the evaluation function involves subsets that contain features which are highly correlated with the class and uncorrelated with each other [25]. Useless or irrelevant features should be omitted because they have a low correlation with the class, and the redundant features should be filtered out as they will be highly correlated with one or more of the remaining features. The evaluation function is expressed in Eq. (1).

$$CBFS_s = k\bar{r}_{cf} / \sqrt{k + k(k-1)\bar{r}_{ff}} \tag{1}$$

where $CBFS_s$ denotes the score value of an attribute subset s containing k attributes, $\bar{r}_{cf}$ denotes the average attribute to class relation, and $\bar{r}_{ff}$ denotes the average attribute to the correlation [67]. The CBFS is performed with a heuristic algorithm to determine the most representative features from the original datasets. The forward selection, backward selection and 'best first' are three common strategies. The 'best first' strategy was adopted in this study. The selected features were then divided into two subsets: the training subset and the testing subset. The training subset is used to determine an appropriate model, and the testing subset is employed to examine the performance of well-trained models. The relevance vector machine is a basic classifier of EDSM; a detailed illustration of the approach can be found in Appendix A. Cross-validation (CV) is utilized to solve the over-fitting problem when the classification tasks are performed. In k-fold CV, we divide the training data into subsets of equal size. Then, one subset is