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Business failure prediction using hybrid^2 case-based reasoning (H^2CBR)

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A B S T R A C T

We have investigated business failure prediction (BFP) by a combination of decision-aid, statistical, and artificial intelligence techniques. The goal is to construct a hybrid forecasting method for BFP by combining various outranking preference functions with case-based reasoning (CBR), whose heart is the *k*-nearest neighbor (*k*-NN) algorithm, and to empirically test the predictive performance of its modules. The hybrid^2 CBR (H^2CBR) forecasting method was constructed by integrating six hybrid CBR modules. These hybrid CBR modules were built up by combining and modifying six outranking preference functions with the algorithm of *k*-NN inside CBR. A trial-and-error iterative process was employed to identify the optimal hybrid CBR module of the H^2CBR forecasting system. The prediction of the optimal module is the final output of the H^2CBR forecasting method. We have compared the predictive performance of the six hybrid CBR modules in BFP of Chinese listed companies. In this empirical study, the classical CBR algorithm based on the Euclidean metric, and the two classical statistical methods of logistic regression (Logit) and multivariate discriminant analysis (MDA) were used as baseline models for comparison. Feature subsets were selected with the stepwise method of MDA. The predictive performance of the H^2CBR system is promising; the most preferred hybrid CBR for short-term BFP of Chinese listed companies is based on the ranking-order preference function.

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1. Introduction

Business failure prediction (BFP) is a useful tool to assure the financial health of companies. Statistical methods have been employed to predict business failures since the 1960s. Discriminant analysis (DA) [1,2] and logistic regression (Logit) [3,4] are the main methods in this area; nowadays they are regarded as baseline models. An advantage of statistical methods is that there are many software packages available, such as SPSS and SAS. With the development of artificial intelligence, intelligent methods have been introduced to predict business failure; although these methods are time-consuming, they can produce more accurate predictions than statistical methods on the whole. Decision trees [5], neural networks [6–9], case-based reasoning (CBR) [10–14], support vector machines [15–22], multi-classifier combinations [23–27], and decision-aiding techniques [28] have been employed for business failure prediction. Since the 1990s, data mining has become a popular technique derived from artificial intelligence, database, and statistics to discover hidden patterns in huge business data sets [29,30]. Data mining has also been employed to predict business failure [23,31] by finding hidden patterns which can distinguish failing companies from healthy ones.

Case-based reasoning, a methodology for problem solving, can also be viewed as a classification method in data mining [32–37]. There are three main reasons why CBR is interesting for BFP:

- First, the predictive result of a CBR system can be explained by the cases used to make the prediction [12,14,38]. Moreover, studying these cases can aid the recovery of a company that was predicted to fail. BFP is different from classical pattern recognition problems, such as face and voice recognition. Its objective is not just to provide a classification of a company's financial state. The people concerned need more information on how the classification was reached. This information can be provided by the CBR methodology, since the prediction was generated by integrating similar historical cases. Whether those similar companies eventually recovered from financial distress or/and how those companies ended up are surely of interest, as well. This can also be retrieved by a CBR forecasting system if the corresponding information has been stored in the case library.
- Second, CBR is a non-parametric method which does not make any data distribution assumptions [14]. Some statistical methods, for example, MDA, Logit, and two-step clustering, assume normal distribution of the data. Although these methods can produce acceptable, even excellent, predictive performance in various

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applications, the theoretical foundation of the results would be weak.
- Third, the problem of BFP does not involve huge data sets. In the CBR algorithm, the similarity between a target case and each historical case must be computed. This would incur a large computational cost if the database were huge. However, Kumar and Ravi's [39] review shows that the volume of business case data is relatively small, and consequently the computational problem of CBR is not serious. For example, there are no more than 2000 companies listed in the Shanghai Stock Exchange and Shenzhen Stock Exchange. Since the data for BFP are limited and feature selection methods can provide reduced data representations, the relatively simple and time-consuming CBR method can do a good job.

Earlier applications of CBR in BFP mainly used similarity measures derived from the Euclidean metric in the context of k-nearest neighbor (k-NN) [10–12]; one exception [40] used an inductive approach. Since the k-NN algorithm was developed in the statistical area and the basic principles of CBR were developed in cognitive science, CBR can be regarded as a hybrid intelligent-statistical technique. Research on BFP in the last decade has attempted to combine the advantages of intelligent and statistical techniques. Recently, our team [38,41,42] has attempted to integrate decision-aiding techniques with intelligent and statistical techniques to implement BFP. This means that we attempt to incorporate decision-aiding techniques into CBR with k-NN as its heart. This is a data-oriented method like those used in data mining or pattern recognition. The outranking approach is a major family of decision-aiding techniques. The concepts of CBR with k-NN are similar to those of outranking relations (OR); they both derive from the concept of distance and difference between a pair of objects. Thus, Li et al. [41] presented the idea of using outranking relations for calculating similarity measures in CBR to predict business failure, and provided evidence from cross-validation. The outranking relations they used were based on the preference function in ELECTRE III. Slowinski and Stefanowski [43,44] also made an early attempt to apply outranking relations to define different similarity functions for data features. However, there is a lack of research on how and why to combine outranking approaches with CBR to form a hybrid method. The preference function of ELECTRE III is based on evidence supporting the assertion that two objects are similar and evidence vetoing that assertion. There have been no discussions on the effects of evidence supporting and vetoing the assertion, either. Thus, it is valuable to study whether classification methods can be constructed on the basis of evidence supporting or vetoing an assertion independently. It is also necessary to consider whether the use of evidence vetoing the assertion that two objects are similar can improve the predictive performance of the hybrid CBR system in BFP. Thus, Li and Sun [42] presented research and provided empirical evidence that a hybrid CBR method based on evidence supporting and vetoing an assertion can produce better cross-validation performance by avoiding over-fitting than a hybrid CBR system which is constructed only on evidence supporting an assertion. Meanwhile, Li and Sun [38] attempted to use ranking-order information among cases in CBR and to apply the hybrid CBR method in BFP. Since CBR did not perform very well in its early applications [10,40] in the area of BFP, it is valuable to study how to obtain better performance from CBR forecasting systems.

Indeed, there are other preference functions in outranking approaches besides those used by Li et al. [41] and Li and Sun [38,42]. However, there has been no comparative research on the performance of hybrid CBR systems with various outranking preference functions. Since there may be different optimal preference function for different data in BFP, we believe that it is valuable to construct a hybrid CBR forecasting system which takes advantage of all the available preference functions in outranking approaches, such as ELECTRE, PROMETHEE, and ORESTE. Thus, six hybrid CBR mechanisms based on six preference functions are employed as basic hybrid modules. They are integrated by a trial-and-error approach to generate a hybrid^2 CBR (H^2CBR) forecasting method. The optimal hybrid CBR module for a specific application is selected by the trial-and-error approach.

The contribution of this research is the construction of a H^2CBR forecasting method using hybrid CBR modules employing various outranking preference functions, and an empirical comparison of the performance of the six hybrid CBR modules. The H^2CBR forecasting system is constructed by integrating the outranking approach to decision-making, the intelligent technique of CBR, and the statistical technique of k-NN. The next section gives a brief description of the background. Section 3 presents the construction of the H^2CBR forecasting method. Section 4 describes the design of the empirical study, its results, and analysis. Section 5 makes conclusions and remarks.

2. Outranking approaches and case-based reasoning (CBR)

2.1. Outranking approaches

Outranking approaches are named ELECTRE, PROMETHEE, ORESTE, and others [45,46]. ELECTRE was firstly developed in the mid-1960s [47]. ELECTRE methods are founded on the concepts of concordance and discordance by using thresholds of indifference and preference. Besides the extension of ELECTRE by Roy [48–51], Mousseau and Dias [52,53], PROMETHEE and ORESTE were also developed on the basic concept of outranking relations. PROMETHEE was first described by Brans and Vincke [54] and further developed by Mareschal [55,56], Mareschal and Brans [57], and Brans [58]. PROMETHEE introduced different preference functions and net preference flow as an aggregating function. ORESTE was proposed and extended by Roubens [59] and Pastijin and Leysen [60]. ORESTE uses ranking order information. PROMETHEE and ORESTE extend the notion of preference function, allowing other types of preference functions to be utilized than the true, quasi, and pseudo criteria of the ELECTRE methods. The starting point of such outranking approaches is an evaluation table, in which all alternatives are evaluated on various criteria. Outranking relations are set up from pairwise comparison of evaluations. The aim is to determine whether or not there exists a preference between each pair of alternatives. Preference functions from outranking approaches translate difference between evaluations of each pair of alternatives on each criterion into a preference degree ranging from 0 to 1. Six specific preference functions have been proposed; five are linear or stepwise linear and one has a Gaussian shape.

2.2. Case-based reasoning (CBR)

CBR focuses on how people generate solutions for new situations based on their past experiences [61–65]. The advantages of CBR include [66,67]:

- An explicit domain knowledge model is not required, so the knowledge elicitation bottleneck is avoided.
- The identification of significant features of various application areas is the main task in implementing a CBR system, which is easy to do.
- Large volumes of historical cases can be efficiently stored and managed by database techniques.
- A CBR system can learn new cases to improve its performance. As a result, knowledge learning becomes easier.

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