Failure Prediction in Commercial Banks with a Hybrid Prediction Model

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Abstract In this paper, a new prediction model which was combined by trait recognition and SVM is examined through the use of accounting data measured 1 year prior to the commercial bank failure. To identify the features of problem banks and predict them as early as possible seems to be crucial for the stability of financial systems. Failure prediction models help to identify causes of failure, and thus lead to make a better understanding of bank operation. The contribution of six variable categories: profit, liquidity, loan risk, interest rate risk, capital and size are examined. The empirical data are collected from the Federal Deposit Insurance Corporation. Nine different comparing models, logistic regression method, C-SVM, Bayesian Network and so on were employed to justify the advantages of the hybrid method. In addition, the new method outperformed nine prediction models in overall accuracy. It was also shown

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that ROA, liquidity assets and short-term gaps are sound predictors for bank failure prediction.

Keywords Early warning · Commercial bank · Failure · Hybrid · Trait recognition · SVMs

1 Introduction

August 2007, Bear Stearns, which is the top fifth investment bank in America, announced that two funds under its supervision went insolvent. This signified that the serious subprime crisis had spread in America and wrapped around the globe rapidly. A bust housing market in the U.S. led to massive losses on mortgage-related securities, which were magnified by massive amounts of leverage in derivatives tied to those securities. Commercial banks and other financial institutes were subjected to loan losses due to the rupture of fund chain. When a bank is unable to meet its obligations to depositors and others, it will go into bankruptcy.

As a result, these losses have forced regulators to seize a growing number of banks and other financial institutions in America and other countries around the world, leading to a freeze-up in credit markets and a global recession. Therefore, it becomes critically important to forecast bank failure for policy makers and bank risk managers. In order to forecast bank failure precisely, it is necessary to grasp the most determining factors which lead to bank failure and establish effective models to predict bank failure.

The elements which lead to bank failure are sophisticated. Generally speaking, they include external factors and internal operation problems. Economic recessions have negative effects on bank systems. However, the direct reason for bank failures depends on their operation condition.

Existing research demonstrate that historical data from accounting sheets have the ability to predict future operating condition of banks [1,2]. It is far-reaching to establish an effective early warning model for commercial banks. Firstly, it is propitious to allocate resources for central banks. The timely detection of troubled banks can help reduce the cost of regulation and supervision. Secondly, it can make full use of historical data. The attributes variables mainly come from the accounting sheets of the banks, based on which bank failure can be forecasted. Thirdly, it can provide an evaluation standard to supervisory board to judge whether banks are given the proper rating.

With the development of computer technology, intelligent models are widely applied in the area of bank failure prediction. This paper has two problems to deal with. One is to examine if the performance of the trait recognition method is efficient in different data sets. According to the test result, a new method is proposed to predict commercial bank failure. Another one is to identify what the crucial factors are under the new background.

The main contributions of this paper are twofold. Firstly, we propose a hybrid method and compare its result with nine algorithms using accounting data of U.S. commercial banks under the subprime mortgage crisis background. Secondly, try to analyze and select the most important predictors using F-Score algorithm.

The remaining of the paper is organized as follows. The next section reviews current literature on how to establish the early warning system for bank failure prediction. In the third section, we will introduce the whole construction process of hybrid method. After that, in the forth section, empirical study and results will be presented. In the last section, the conclusions are presented.

2 Literature Review on Risk Supervision and Prediction for Banks

In the research field of bank risk supervision, there are large number of papers focus on credit risk, market risk or operational risk [3–13]. Due to a new round of economy deteriorating, especially, bank failure prediction has become research focus again [1,3]. Two aspects of questions are involved in bank failure prediction. One is how to select proper predictors. The other is which algorithms should be utilized. This review is followed by an introduction of the two questions.

In many applications of risk prediction, data are commonly presented as high-dimensional feature vectors. Therefore, the selection of predict factors is useful and have crucial impact on the results of prediction. The methods of feature selection can be categorized into three groups. Filter methods are independent of the classifiers [14]. Wrapper methods evaluate their fitness based on classification accuracy [15]. And embedded method incorporate feature selection in the classifier objective function [16,17].

The use of accounting information for failure prediction has a long history because of its public availability [19]. Jin [1] identified low capital and risky assets as major reasons for bank failure. Then, the accounting variables like loan loss provisioning, balance sheet strength, and loan quality and mix are chosen as proxy of important factors. Brunnermeier [20] has concluded that the rise in popularity of securitized products ultimately led to a flood of cheap credit quality. The cheap credit and loan lending standard resulted in the housing frenzy that laid the foundations for the crisis. Lanine [19] considered that bank failures are mainly caused by deteriorating liquidity of the banks, but deteriorating profit and low levels of capital adequacy are also important predictors.

In the light of second question, studies have proven that data mining is effectively used for knowledge discovery and decision making [21]. Data mining techniques are also broadly used for prediction of financial distress recently [22]. The most hotly used techniques recently in financial distress prediction are support vector machines (SVMs), proposed by Vapnik and his cooperators in 1990s [23], and firstly applied into the area of financial distress prediction after 2005. In addition, some another methods are commonly used, including artificial neural network [24,25], decision tree [26], AHP-based model [27], trait recognition [19,28], and hybrid models [29]. Some intelligent models do not have explanation of the results like artificial neural network, decision tree. This character limits to support decision making.

A non-parametric method named trait recognition was firstly introduced into the research of bank failure prediction by Kolari [28]. Ref. [28] sampled 1950 American commercial banks during 1984 and 1985. The accuracy in both original split sample and holdout split sample is more than 95 %. The relative work [19] on trait recognition

investigated the 582 failed banks dating from 1988 to 2004 in Russia. The accuracy of their modified trait recognition model is 85.1 % in holdout split sample. The main conclusions are summarized in Table 1.

Although the trait recognition technique has some advantages, it also has some deficiencies. The process of selecting good or bad feature is arbitrary, which will lead to missing the important information during the selection process. Besides, the robustness of the trait recognition model need further testing in different period data samples. The linear SVM may overcome the shortcoming of the trait recognition. It is able to give a specific weight to every input variable. Therefore, the contribution of each input variable is clear. Meanwhile the encoding technique in trait recognition takes the correlation between two or three variables into consideration. In this paper, a hybrid model of trait recognition and liner kernel SVM is proposed to overcome their shortcomings.

3 Hybrid of Trait Recognition (TR) and Support Vector Machines (SVMs)

To overcome the deficiencies in existing trait recognition models, we combine information encoding technique that is used in trait recognition with the SVMs model reasonably. For more details on TR, you can refer to the literature by Kolari et al. [28]. The motivation to establish a hybrid prediction model is to combine the advantages of both TR and SVMs. The advantages of the TR technique are that it imposes no priori assumptions on the variables. TR emphasizes the interactions among the independent variables and can give useful knowledge on attribute union.

In the next section, we will introduce the whole process of constructing the new hybrid prediction model, see Fig. 1. First of all, try to select the proper accounting factors as comprehensive as possible. The liquidity of the bank is usually used to measure the bank health.

Under the new era of global financial crises, liquidity of the bank and quality of assets should be examined by quantitative models, including whether or not they have anticipative correlation with commercial bank failure. The accounting factors we chose contain 12 attributes which belong to six categories. We proxy bank profit capability with the following variables: profit margin, ROA, ROE. The loan quality particularly loan loss provision is crucial in determining the health of a bank [1]. In addition, we choose two additional attributes to proxy loan risk: loan exposure and loan funding. The liquidity is also deemed as one of most important accounting attributes of bank. In this category, we choose liquidity asset and cash asset ratio. Further, this study considers capital, interest rate risk and size to portray the condition of the commercial bank from various angles, see Table 2.

3.1 Step1. Attribute Selection and Quantitative Transformation

The first step is to construct a binary string according to financial ratios of each bank. Based on sample data, the distribution of these ratios can be plotted. Then for each ratio, two breakpoints are established to segment the distribution of observation into three segments: (1) High segment purely consisting of non-failed banks is denoted

Table 1 Summary of the main conclusions of relative work on trait recognition

Model	Sample		Data source	Indicator	Accuracy	
	1984	1985			1984	1985
James, Caputo and Wagner 1996	Failed bank: 126	Failed bank: 123	FDIC(federal deposit insurance of corporation)	Profit, size, growth, liquidity, loan risk, taxes, interest rate risk, loan mix, capital	Original split sample: 96.6 %	Original split sample: 98.6 %
	Nonfailed bank: 878	Nonfailed bank: 862				
Gleb and Vennet 2006	Failed bank: 582 from 1988-2004	Nonfailed bank: 2910	CBR(central bank of Russia)	Profitability, liquidity risk, capital adequacy,	Original split sample: 91.6 % Hold out sample: 85.1 %	Holdout split sample: 95 %

Fig. 1 The whole process of the hybrid prediction method

Table 2 Accounting ratio for each commercial bank

Category	Accounting ratio	Remarks	Abbreviation
Profit	Profit margin	Net interest income/Total assets	PM
	ROA	Net income after taxes/Total assets	ROA
	ROE	Net income after taxes/Total equity	ROE
Liquidity	Liquid asset	Total securities/Total assets	LA
	Cash asset ratio	Cash and due from depository institutions /Total asset	CAR
Loan risk	Loan exposure	Net loans and leases/Total assets	LE
	Loan funding	Net loans and leases/Total deposits	LF
	Provision rate	Provision for possible loan losses/Total assets	PR
Capital	Capital growth	(Total equity(t)–Total equity(t–1))/Total equity	CG
	Capital ratio	Total equity/Total assets	CR
Interest rate risk	Short-term gap	(Assets adjustable 1 day – 1 year – liabilities adjustable 1 day to 1 year)/ Total assets	STG
Size	Asset	Total assets	ASS

as “H” and coded as “00”; (2) The mixture of failed and non-failed banks is denoted as “M” and coded as “01”; (3) Low segment purely consisting of failed banks is denoted as “L” and coded as “11”. Generally, the observation M is described by the binary code $M_1M_2\dots M_l$, l is the length of the string. When the cutoff points are chosen, we allow 10 % failed banks existing among the non-failed banks in the high section. In a similar way, 10 % non-failed banks are allowed to exist among the failed banks in the low section. However, either higher or lower value of some attributes represents the failed banks or healthy bank. Therefore, we dropped these attributes.

Table 3 The matrix of traits for a bank

p	q	r	PQR	p	q	r	PQR
1	1	1	000	2	3	3	000
2	2	2	000	2	4	4	011
3	3	3	000	3	4	4	001
4	4	4	111	1	2	3	000
1	2	2	000	1	2	4	001
1	3	3	000	1	3	4	001
1	4	4	011	2	3	4	001

Table 4 Top ten scoring attributes combination

Rank	Attributes combination	Rank	Attributes combination
1	ROA and CG	6	ROA and STG
2	ROA and LA and CG	7	ROA and LE and CG
3	ROA and LA	8	ROE and PM and CG
4	ROA and CG and STG	9	ROA and CG and CR
5	ROA and LA and STG	10	ROA and LA and LE

3.2 Step2. Establish the Matrix of Traits

To extract the distinctive feature that represent the common pattern of different groups of observations, the string of binary code should be transferred into a matrix of trait. Each trait is comprised of an array with six integers: $T = p, q, r, P, Q, R$. The symbols p, q, r represents the positions in the binary string from left to right. P, Q, R give the values of the binary code at the position p, q and r . Take the binary string “0001” for example; the matrix of traits for this bank is as follows (Tables 3, 4):

3.3 Step3. Select Proper Trait and Train them into SVM Model

After carrying out step1 and step2 described above, a series of trait which reflect the operating conditions 1 year prior to bank failure are received. However, not all traits are useful to predict the bank failure. Some of them may contain repetitive or noisy information. Therefore, we need to select features from large amounts of traits. By utilizing F-Score [14], it can give an explicit score to each attribute and rank them in descending order. The larger the attribute score is, the better the prediction outcome is.

The support vector machine proposed by Vapnik [23] is one of the most popular algorithms in machine learning research. The main idea of this algorithm is that it maps the input vector x into a high-dimensional feature space Z through some nonlinear mapping, chosen a priori.

Given a training set $T = \{(x_1, y_1), \dots, (x_l, y_l)\} \in (R^n \times \gamma)^l$, $x_i \in R^n$, $y_i \in \gamma = (1, -1)$, $i = 1, \dots, l$; Select proper penalty coefficient C , $C > 0$. A convex quadratic programming problem is constructed as function (3.1).

$$\begin{aligned} \min_{\alpha} \quad & \frac{1}{2} \sum_{i=1}^l \sum_{j=1}^l y_i y_j (x_i \cdot x_j) \alpha_i \alpha_j - \sum_j \alpha_j \\ \text{s.t.} \quad & \sum_{i=1}^l y_i \alpha_i = 0 \\ & 0 \leq \alpha_i \leq C, \quad i = 1, \dots, l \end{aligned} \quad (3.1)$$

The parameter $\alpha^* = (\alpha_1^*, \alpha_2^*, \dots, \alpha_l^*)^T$ can be solved. Then calculate the b^* as function (3.2),

$$b^* = y_i - \sum_{i=1}^l y_i \alpha_i^* (x_i \cdot y_j) \quad (3.2)$$

Finally, construct the optimal separating hyper plane $(\omega^* \cdot x) + b^* = 0$, and the decision function $f(x)$ can be presented as function (3.3).

$$f(x) = \text{sgn}(g(x)) \quad (3.3)$$

where

$$g(x) = \sum_{i=1}^l y_i \alpha_i^* (x_i \cdot x) + b^* \quad (3.4)$$

The new proposed method has three advantages. Firstly, it will not miss any useful information. Secondly, it can give a clear result whether a bank belongs to the failed group or the non-failed group. And third, it can consider the correlations among two or three attributes during the encoding process.

In the third part, we will employ nine different algorithms to examine the effect of hybrid method using four model performance measures respectively.

4 Experiment and Results

The data is collected from the Federal Deposit Insurance Corporation (FDIC), including both failed and non-failed commercial banks. The total number of failed bank is 158. And we select the same number of non-failed bank corresponding to the failed bank. Every bank is described by eight financial ratios, including ROA, ROE, Profit margin (PM), Liquidity assets (LA), Loan exposure (LE), Capital growth (CG), Short term gap (STG), Capital ratio (CR). These financial ratios cover six aspects of financial conditions, including profit, liquidity, growth, loan risk, interest rate risk and capital.

For each bank in training sample, there are 816 traits reflecting the information among any two or three financial ratios. We utilize F-Score method to give a score to each attribute. The top ten highest score attributes or attributes union are listed in Table 5. In the top ten scoring attributes union, ROA is the most important accounting

Table 5 Result comparison between different algorithms

Algorithm	Overall accuracy	Rank	precision	Rank	True positive rate	Rank	True negative rate	Rank
Bayesian network	0.9177	4	0.9240	7	0.9125	7	0.9230	6
Naïve Bayes	0.9240	2	0.9303	5	0.9187	5	0.9294	4
RBFNetwork	0.8892	8	0.9493	2	0.8474	10	0.9424	3
J48	0.8987	6	0.9620	1	0.8539	9	0.9565	1
ADTree	0.8829	9	0.7658	9	1.0000	1	0.8102	9
LADTree	0.8797	10	0.7594	10	1.0000	1	0.8061	10
NBTree	0.9240	3	0.9303	6	0.9187	6	0.9294	5
Logistic	0.8984	7	0.8747	8	0.9191	4	0.8688	8
C-SVM	0.9177	5	0.9492	3	0.8984	8	0.9463	2
Hybrid of TR and SVM	0.9385	1	0.9430	4	0.9427	3	0.9146	7

attribute which represents profit ability of commercial bank. Further, ROA combined with CG, LA and STG are better predictors than other attributes union.

In order to verify the predict power of the hybrid model further, we compare its performance with nine other prediction models. They are Bayesian Network, Naïve Bayes, RBF Network, J48, ADTree, LADTree, NBTree, logistic model and SVMs. The input attributes are accounting variables selected in Sect. 3 the first part. Moreover, the result for each algorithm is based on ten-fold cross validation.

Accuracy and error rate are important measures of classification algorithms in financial risk prediction [30]. This paper utilizes overall accuracy, precision, true positive rate and true negative rate, see function (4.1)–(4.4). Accuracy measures the overall correctly classified instance.

$$\text{Overall accuracy} = \frac{TN + TP}{TN + FP + TP + FN} \quad (4.1)$$

where TP, TN, FP, and FN represent true positive, true negative, false positive, and false negative, respectively.

Precision is the number of classified positive or failed instances that actually are positive instances.

$$\text{Precision} = \frac{TP}{TP + FP} \quad (4.2)$$

True positive rate is the number of correctly classified positive or failed instances. TP rate measures how well a classifier can recognize failed instance. It is also called sensitivity.

$$\text{True positive rate/sensitivity} = \frac{TP}{TP + FN} \quad (4.3)$$

True negative rate is the number of correctly classified negative or normal instances. TN rate measures how well a classifier can recognize normal instance. It is also called specificity.

$$\text{True negative rate/specificity} = \frac{TN}{TN + FP} \quad (4.4)$$

From the ten-fold cross validation results, the hybrid method ranks the first in overall accuracy, the third in precision and TP rate and the fourth in Precision.

5 Conclusions and the Future Work

The hybrid method is an important one to predict commercial bank failure. It can make full use of information represented by financial data. The empirical results conclude that it outperforms the other nine algorithms in overall accuracy by ten-fold cross validation.

Among the traits, ROA is the most important accounting attribute which represents profit ability of commercial bank. Further, ROA combined with CG, LA and STG are better predictors than other attribute combination.

The hybrid method proposed in this paper still has some deficiencies. For example, the result of the method has a strong relationship with the training sample and the selection of cutoff point is arbitrary to some degree, which are worthy of further research.

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