CLUSTER-BASED CLASSIFICATION METHODS FOR PREDICTING BANK FAILURE

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Early warning models are established procedures for classifying banks into groups, typically failed and non-failed, in order to timely and accurately identify problem banks so as to warn interested parties of potential failure. Financial state of banks may change from time to time and the underlying dynamic that change may be useful in predicting whether a bank will fail or remain viable. In this paper, we exploit the information in financial dynamics of banks to improve failure prediction. We adopt a cluster-based classification framework in which banks are grouped into clusters and attached to each cluster is a neural network predictor. Using data obtained from Federal Insurance Deposit Corporation (FDIC), we find two basic failure patterns, *brittle and gradual*, and show that cluster-based classification methods improve by between 2 to 11% over non-cluster-based techniques.

Keywords: Cluster-based-classification; bank failure prediction; brittle failure; gradual failure.

1. Introduction

Bank failure is an unfortunate global phenomenon. Unlike other profit-maximising entities which are regarded as failed when their liabilities outweigh their assets (*i.e.* a negative net worth position), making it impossible for them to honour their financial obligations when due, a broader view of failure is usually adopted for banks because of the impact of bank failures on the economy. In a broader sense, a bank is deemed to have failed if it is liquidated, merged with a healthy bank, purchased and acquired under central government supervision or rescued with state financial support [1].

To reduce the incidence of bank failure, several interest groups (e.g. supervisors and regulators) use early warning systems (EWS) as a tool to monitor bank condition and performance for a timely identification of failing banks. EWS models employed in bank failure predictions are commonly based on statistical methods such as logit models and more recently, machine learning techniques such as neural networks.

The financial state of banks may change from time to time as they reposition their portfolios and lending strategies in response to a dynamic operating environment. The financial dynamic underlying that change may be useful in predicting whether a bank will fail or remain viable. In this paper, we exploit the information in financial dynamics of banks to improve failure prediction, using the equity to asset ratio as basis of dynamics.

We adopt a cluster-based classification framework in which banks are grouped into clusters and attached to each cluster is a neural network predictor. The rest of the paper is organised as follows: in section 2, we give the background to the study and related work. In section 3 cluster-based classification for bank failure is presented. In section 4, we present our experiments and results with discussion. The paper ends in section 5 with conclusion and future work.

2. Background and Related Work

The underlying idea of failure prediction models has not changed since the seminal work of Altman [2], who proposed that financial structures differ among firms, with firms with certain financial structures being more probable to fail within a time period than firms with opposite characteristics. Bank failure models broadly fall into three main categories namely, statistical-based, artificial intelligence (AI) oriented, and hybrid models. Statistical models are typically parametric in nature as they depend on distributional assumptions for the explanatory variables. AI models are predominately non-parametric and include neural networks and evolutionary algorithms [3,4].

Statistical models include multivariate analyses and survival time/hazard models. Multivariate analyses use a number of predictive variables to predict a dependent variable (e.g. failed or non-failed), a probabilistic estimate of future events and are commonly based on logistic regression [5]. Duration models look into the probable time of failure of a bank, given that it has survived to a certain time [6]. A recent review of bank failure prediction models can be found in Kumar [7]. From the early 90s, many studies began to apply artificial neural networks, an AI technique, to bank failure prediction having found that multilayer perceptron neural networks offered better predictive accuracy than some of the other predictors.

Cluster-based classification [8] is a recent approach to solving multi-class classification problems. It provides an improvement over non-cluster classification methods with a higher accuracy between 1 and 2% having being reported [8], and has been applied to domains including feature selection [9] and credit scoring [10].

Alam [11] proposed a fuzzy clustering approach and Peresetsky [12] incorporated preliminary expert clustering to construct the probability of default model. Glennon [13] developed a Markov model of bank failure, estimating the transition probabilities with a view to capturing the dynamic process leading to financial distress on an aggregate level. In our own study, we investigate the transition patterns of banks on an individual basis.

3. Cluster-Based Classification for Bank Failure Prediction

3.1. *The Framework*

Our cluster-based classification framework is shown in Figure 1. A clustering algorithm is firstly used to partition the data into separate clusters. After establishing separate clusters, a variable selection is conducted on each of the clusters and each cluster is trained using different neural network classifiers.

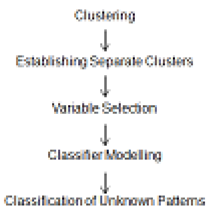

Fig. 1. The Framework for Cluster-Based Classification

Example illustration of architectures of cluster-based classification framework can be found in [8–10].

3.2. *Estimating Bank Dynamics*

Following Glennon [13], we define the transition states based on the capital levels identified in the FDIC Improvement Act of 1991, which defines five financial states in terms of book equity, namely, well capitalized, adequately capitalized, undercapitalized, significantly undercapitalized, and critically undercapitalised. As with Glennon [13], we include an insolvency state. The failure state in which the bank is closed by primary supervisor is the only terminal state used in this work. We have a total of seven financial states as shown in Table 1).

States	Label/Zone	Criteria
0	Failure	Closed by Primary Supervisor
1	Insolvent (Book-Value)	Equity/Assets < 0
2	Critically Undercapitalized	$0 <$ Equity/Assets $< 2\%$
3	Significantly Undercapitalized	$2\% <$ Equity/Assets $< 3\%$
4	Undercapitalized	$3\% <$ Equity/Assets $< 4\%$
5	Adequately Capitalized	$4\% <$ Equity/Assets $< 5\%$
6	Well Capitalized	$5\% <$ Equity/Assets

4. Experiments

We implemented our cluster-based classification algorithm as outlined in section 3 using two common clustering algorithms namely, k-means [14] and Farthest-first [15]. We applied a correlation-based feature selection [16] (CFS) algorithm to each of the clusters based on a set of 100 variables that have been used in various bank failure prediction models. CFS is a fast feature selection algorithm that identifies feature subsets based on the individual predictive ability of each variable and the degree of redundancy between them, preferring feature that are highly correlated with the class with low intercorrelation. A Multilayer perceptron neural network classifier was utilised for each cluster using a 10-fold cross-validation.

4.1. *Data*

The data were based on FDIC data of U.S. commercial banks that failed between first quarter 1988 and first quarter 2003. As common in other studies, only well established commercial banks were considered by excluding banks that were less than 5 years old at the time of failure (known as *de novo* banks) as *de novo* banks have different characteristics and failure patterns than well established banks [17]. We matched each of the failed banks with non-failed commercial banks (age $>$ 5years) a year ahead of failure on the basis of asset size and geographical location. In all, there were 326 failed banks and 324 non-failed banks, after excluding banks with incomplete data, yielding a total of 650 banks in all. For each of the bank in the dataset, we derived the transition states based on equity-to-asset ratio as described in section 3.2. In total for all the 650 banks studies we had 21,435 transition states.

4.2. *Results*

We conducted 3 experiments each for the two clustering algorithms (comprising 2 to 4 cluster models) and one non-clustering experiment, yielding a total of 7 experiments. We limited the number of clusters to four because of the size of our data. The results are shown in Figure 2. In the 2 and 3-cluster models, the two clustering algorithms recorded an improvement of between 1.6% and 11.4% over the non-clustering model. In the 4-cluster models, the farthest-first algorithm out-performed the non-clustering model in all of the clusters with accuracy between 4% and 9% above the non-clustering model whereas k-means underperformed the non-clustering model in 2 out of the 4 clusters.

A significant aspect of our cluster-based classification framework is that different feature sets can be used in different clusters. As shown in the third panel of Figure 2, the feature selected varied from model to model with the non-clustering model selecting 28 features. The number of features selected by the other models was smaller ranging from 1 to 21 with liquidity and capital related variables being the most common variables that cut across the models. These variables are in line with those commonly reported in bank failure prediction studies [5,12,18]. The number of banks in each cluster is reported in the last panel of the table.

Number of of clusters	Classification accuracy (%)		Number of features selected		Number of banks in cluster	
1 (all dataset)	83.85		28		650	
	k-means	farthest-first	k-means	farthest-first	k-means	farthest-first
cluster0	91.97	95.22	7	8	249	272
cluster1	86.03	85.45	17	21	401	378
cluster0	88.46	86.67	16	20	130	105
cluster1	94.33	93.06	2	6	194	216
cluster2	87.73	90.27	10	14	326	329
cluster0	77.89	92.86	4	1	95	14
cluster1	75.91	87.88	19	21	137	99
cluster2	95.45	92.31	1	6	176	208
cluster3	94.63	90.27	5	14	242	329

Fig. 2. Summary of results

The transitions yielded two main patterns which we refer to as *brittle* and *gradual*. Banks with *brittle* failure pattern were well/adequately capitalised banks with no change in transition until in the last year of failure. Examples of the transition patterns of failed banks exhibiting *brittle* failures are as shown in Figure 3.

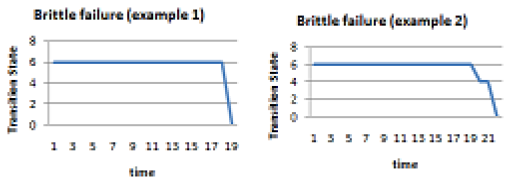

Fig. 3. Examples of *brittle* failure transition patterns

Banks with *gradual* failure transition pattern had fluctuations in their transitions prior to failure. Banks exhibiting gradual failure can further be grouped into two patterns.

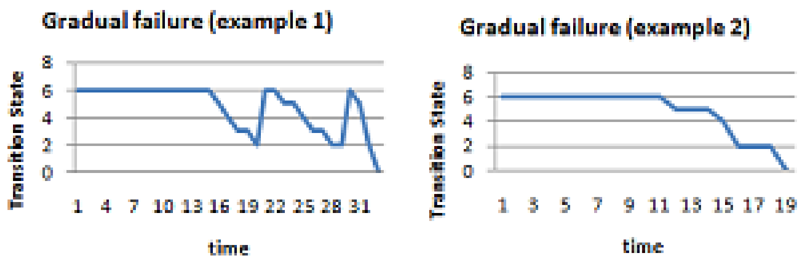

Fig. 4. Examples of gradual failure transition patterns

Those that were initially well/adequately capitalised but lapsed into an undercapitalised state only to recover to a well-capitalised state prior to failure and those that did not show any indications of recovering from the undercapitalised or insolvency state prior to failure. Once the transition state of the bank began deterioration to an undercapitalised state, the bank did not recover but gradually declined to failure. The examples of *gradual failure* patterns are shown in Figure 4.

5. Conclusion and Future Work

In this paper, we implemented cluster-based classification methods for predicting bank failure in which we used a different number of clustering techniques coupled to a neural network classifier. Our empirical results show an improvement of classification accuracy over non-cluster based model. It is worth noting that doing clustering independently of classification may not be optimal, ideally one would like to perform the clustering with respect to the classification task. An area of future work lies in developing an approach that optimally integrates clustering and classification stages in the cluster-based classification framework.

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