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Identification of failing banks using Clustering with self-organising neural networks

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Abstract
This paper presents experimental results of cluster analysis using self organising neural networks for identifying failing banks. The paper first describes major reasons and likelihoods of bank failures. Then it demonstrates an application of a self-organising neural network and presents results of the study. Findings of the paper demonstrate that a self-organising neural network is a powerful tool for identifying potentially failing banks. Finally, the paper discusses some of the limitations of cluster analysis related to understanding of the exact meaning of each cluster.

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Keywords: Cluster analysis, Self-organising neural network, Kohonen layer

1 Introduction

In 2008, a series of bank failures triggered a financial crisis. By any historical standard, this crisis was the worst since the Great Depression of the 1930s. The immediate cause of the crisis was the bursting of the United States housing bubble. This, in turn, caused the values of securities tied to real estate pricing to nose-dive, damaging financial institutions worldwide. Bank insolvencies and lack of credits reduced the investor confidence and, as a result, the stock market plummeted. In 2009, the global economy contracted by 1.1%, while in advanced countries, the contraction reached 3.4%. After intervention by central banks and governments of an unprecedented scale, the global economy began to recover. However, the global financial system remains at risk.

The danger of cascading failures of major banks would be reduced significantly if we could identify banks with potential problems before they face solvency and liquidity crises. There are many reasons for bank failures. These include high risk-taking, interest rate volatility, poor management practices, inadequate accounting standards, and increased competition from non-depository institutions. Since the crisis, bank regulators have been increasingly concerned with reducing the size of deposit insurance liabilities. It has even been suggested that the best regulatory policy is to close banks before they become undercapitalised. Therefore, identifying potentially failing banks as early as possible is essential for avoiding another major financial crisis.

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Over the last thirty years many tools have been developed to identify problem banks. While early models mostly relied on statistical techniques (Abrams & Huang, 1987; Booth et al., 1989; Espahbodi, 1991), most recent developments are based on fuzzy logic and neural networks (Zhang et al., 1999; Alam et.al., 2000; Ozkan-Gunay & Ozkan, 2007). Most of these models use a dichotomous classification – bankruptcy versus non-bankruptcy. In real world, however, banks are ranked in terms of their *likelihood* of bankruptcy. What regulators really need is an early warning system that can "flag" potentially failing banks. Once such banks are identified, different preventive programs tailored to each bank's specific needs can be put in place, thereby avoiding a major banking failure.

In this paper, we "flag" potentially failing banks using cluster analysis.

2 Cluster Analysis

Cluster analysis is an exploratory data analysis technique that divides different objects into groups, called *clusters*, in such a way that the degree of association between two objects is maximised if they belong to the same cluster and minimised otherwise.

The term "cluster analysis" was first introduced over 70 years ago by Robert Tryon (1939). Since then, cluster analysis has been successfully applied in many fields including medicine, archeology, astronomy, etc. In clustering, there are no predefined classes – objects are grouped together only on the basis of their similarity. For this reason, clustering is often referred to as unsupervised classification. There is no distinction between independent and dependent variables, and when clusters are found the user needs to interpret their meaning.

We can identify three major methods used in cluster analysis. These are based on statistics, fuzzy logic and neural networks. In this case study, we will apply a self-organising neural network.

In this paper, we "flag" potentially failing banks using cluster analysis.

3 Bank Rating System

Our goal is to cluster banks using their financial data. The data can be obtained from annual reports of the Federal Deposit Insurance Corporation (FDIC). The FDIC is an independent agency created by the Congress of the United States. It insures deposits, examines and supervises financial institutions, and manages receiverships. To assess the overall financial state of a bank, regulators use the CAMELS (*C*apital adequacy, *A*sset, *M*anagement, *E*arnings, *L*iquidity, and *S*ensitivity to market risk) rating system. The CAMELS ratings have been applied to 8,500 banks in the U.S. It was also used by the United States government in selecting banks for the capitalisation program of 2008.

For our case study, we select 100 banks and obtain their financial data from the FDIC annual report for the last year. We adapt the following five ratings based on the CAMELS system:

1. NITA – *N*et *I*ncome divided by *T*otal *A*ssets. NITA represents return on assets. Failing banks have very low or even negative values of NITA.
2. NLLAA – *N*et *L*oan *L*osses divided by *A*djusted *A*ssets. Adjusted assets are calculated by subtracting the total loans from the total assets. Failing banks usually have higher NLLAA values than healthy banks.
3. NPLTA – *N*on-*P*erforming *L*oans divided by *T*otal *A*ssets. Non-performing loans consist of loans that have past their due dates by 90 days and non-accrual loans. Failing banks usually have higher values of NPLTA than healthy banks.

4. NLLTL – *N*et *L*oan *L*osses divided by *T*otal *L*oans. Failing banks have higher loan losses as they often make loans to high-risk borrowers. Thus, failing banks usually have higher values of NLLTL than healthy banks.
5. NLLPLLNI – Sum of *N*et *L*oan *L*osses and *P*rovision for *L*oan *L*osses divided by *N*et *I*ncome. The higher the NLLPLLNI value, the poorer the bank performance.

Preliminary investigations of the statistical data can reveal that a number of banks may experience some financial difficulties. Clustering should help us to identify groups of banks with similar problems.

4 Self-Organising Map

Figure 1 shows a self-organising map (SOM) with a 5-by-5 array of 25 neurons in the Kohonen layer. Note that neurons in the Kohonen layer are arranged in a hexagonal pattern.

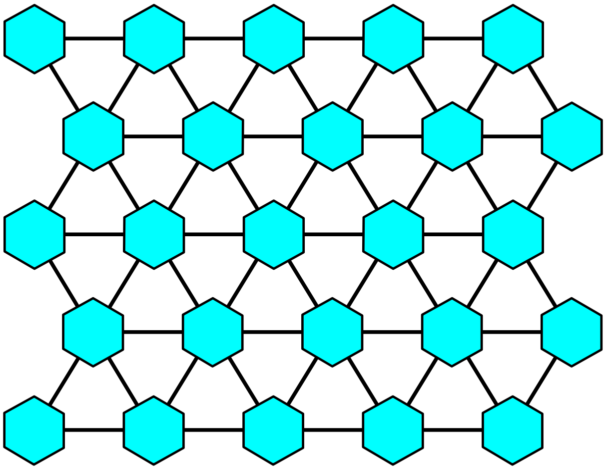
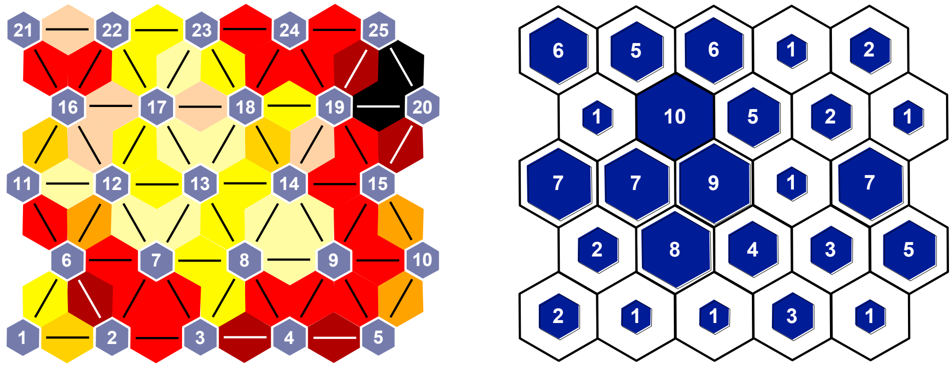


Figure 1: The SOM structure

The input data are normalised to be between 0 and 1. The network is trained for 10,000 iterations with a learning rate of 0.1. After training is complete, the SOM forms a semantic map where similar input vectors are mapped close together while dissimilar apart. In other words, similar input vectors tend to excite either the same neuron or neurons closely located to each other in the Kohonen layer. This SOM property can be visualised using the weight distance matrix, also known as the *U-matrix*. Figure 2 shows the U-matrix and the SOM sample hit plot for the bank financial data. In the U-matrix, the hexagons represent the neurons in the Kohonen layer. The colours in the regions between neighbouring neurons indicate the distances between them – the darker the colour the greater the distance. The SOM sample hit plot reveals how many input vectors are attracted by each neuron of the Kohonen layer.

Typically, a SOM identifies fewer clusters than the number of neurons in the Kohonen layer, and thus several input vectors attracted by close neighbouring neurons may, in fact, represent the same cluster. For instance, in Figure 2(*a*), we can observe that distances between neurons 3 – 8, 7 – 8, 7 – 12, 7 – 13, 8 – 9, 8 – 13, 8 – 14, 9 – 14, 11 – 12, 12 – 13, 12 – 16, 12 – 17, 13 – 14, 13 – 17, 13 – 18, 14 – 19, 16 – 17, 17 – 18, 17 – 22, 17 – 23, 18 – 19, 18 – 23, 21 – 22 and 22 – 23 are relatively short (the colours in the regions between neighbouring neurons are lighter, so the distances are shorter).

Thus, we can reasonably assume that neurons 3, 7, 8, 9, 11, 12, 13, 14, 16, 17, 18, 19, 21, 22 and 23 form a single cluster. At the same time, we should also notice that the distance between neurons 3 and 7 is much greater than the distances between neurons 3 and 8, and 7 and 8. Therefore, it might be useful to examine what makes the input vectors associated with neuron 3 so different from these attracted by neuron 7. Table 1 shows results of clustering. Interpreting the meaning of each cluster is often a difficult task. Unlike classification where the number of classes is decided beforehand, in SOM-based clustering the number of clusters is unknown, and assigning a label or interpretation to each cluster requires some prior knowledge and domain expertise.



(a) (b)

Figure 2: The 5-by 5 SOM after training: (*a*) the U-matrix; (*b*) the sample hit plot

For a start, we need a way to compare different clusters. As we discussed in Case Study 6, the centre of a cluster often reveals features that separate one cluster from another. Therefore, determining the average member of a cluster should enable us to interpret the meaning of the entire cluster. In Table 1, the last column "Financial profile of the cluster" contains mean, median and standard deviation (STD) values of the CAMELS ratings utilised in this study. Using these values an expert can identify groups of banks that exhibit similar patterns of behaviour or experience similar problems.

Let us begin out analysis by identifying problem banks with negative returns on their assets. As can be seen in Table 1, three clusters, E, F and G, have negative values of NITA. For example, banks included in Cluster E have mean net losses of 0.06% of their total assets. On the other hand, healthy banks usually report a positive return on their assets. Thus, banks included in Cluster A, which has the highest value of NITA, could be considered healthy.

highest mean value, followed by Cluster E. Note that although banks in Cluster E are problem banks, their NLLAA values are at least 12 times lower than these of Cluster D (a 3.63% mean against 44.48%). This could be a clear indication that the three banks associated with Cluster D experience severe difficulties with their loans (even though they still have a positive return on their assets). Banks in Clusters A, B and C show negative NLLAA values, which is normal for healthy banks.

The value of NPLTA is highest for Cluster B, followed by the problem banks in Clusters E, F and G. This may indicate that the bank in Cluster B (Cluster B is a solitary cluster) experiences difficulties in recovering its loans. In fact, the situation with this particular bank could be even worse than with the problem banks associated with Clusters E, F and G.

Finally, the values of NLLTL and NLLPLLNI are highest for the two banks in Cluster H, followed by the problem banks. Because higher values of NLLTL indicate higher loan losses, we may find that banks in Cluster H are involved in providing loans to high-risk borrowers. High risk-taking also contributed to the poor performance of these banks, reflected by the high NLLPLLNI values.

An important part of cluster analysis is to identify outliers, objects that do not naturally fall into any larger cluster. As can be seen in Table 1, there are three banks that are viewed as solitary clusters – Cluster B, Cluster F and Cluster G. These banks are outliers, and each of them has a unique financial profile. While conventional clustering algorithms, such as K-means clustering, do not handle outliers well, a SOM can easily identify them.

It is difficult, however, to determine the number of clusters in a multidimensional data set. In fact, when a clustering algorithm attempts to create larger clusters, outliers are often forced into these clusters. This may result not only in poorer clustering but, even worse, in failing to distinguish unique objects.

As an example, let us cluster the same set of banks using a 2-by-2 SOM. The SOM is trained for 1,000 iterations. Figure 3 shows the U-matrix and the SOM sample hit plot. Obviously, now we have only four clusters. Further investigation reveals that based on their average values, banks associated with neurons 1, 2 and 3 can be classified as healthy, while 13 banks attracted by neuron 4 as failing. Two failing banks and two banks with unusually high values of NLLPLLNI, previously identified by the 5-by-5 SOM, are now absorbed by the "healthy" cluster.

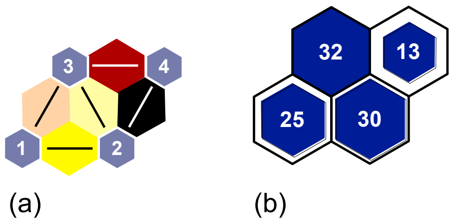


Figure 3: The 2-by 2 SOM after training: (*a*) the U-matrix; (*b*) the sample hit plot

5 SOM Testing

In order to test a neural network, including a SOM, we need a test set. From the FDIC Annual Report we can obtain a list of failed banks, and collect appropriate financial statement data. Several studies of bank failures suggest that failed banks could be detected between six and 12 months before the call date, and in some cases as early as four years before a bank fails (Alam et al., 2000; Eichengreen, 2002). Although solvency and liquidity are the most important predictors of failure close to the call date, asset quality, earnings and management practices become increasingly significant as the time before failure increases. To test the SOM performance, we select 10 banks that failed last year, and collect their one-year-prior financial statement data. Table 2 contains mean, median and standard deviation (STD) values of their CAMELS ratings. Now we can apply 10 input vectors to see the SOM response.

As expected, in the 2-by-2 SOM, all 10 input vectors are attracted by neuron 4. In the 5-by-5 SOM, the situation is more complicated. Six input vectors are attracted by neuron 5, two by neuron 10, one by neuron 20 and two by neuron 24. Thus, in both cases, failing banks are clustered correctly.

Finally, a word of caution. Although a SOM is a powerful clustering tool, the exact meaning of each cluster is not always clear, and a domain expert is usually needed to interpret the results. Also a SOM is a neural network, and any neural network is only as good as the data that goes into it. In this case study, we have used only five financial variables. However, to identify problem banks well in advance of their failure, we might need many more variables that hold additional information about bank performance (researchers in the industry use up 29 financial variables based on the CAMELS rating system).

A good example of challenges associated with clustering is given in Berry & Linoff (2004). A large bank decided to increase its market share in home equity loans. It gathered data on 5,000 customers who had home equity loans and 5,000 customers who did not have them. The data included appraised value of a house, amount of credit available, amount of credit granted, customer age, marital status, number of children and household income. The data was then used to train a SOM. It identified five clusters. One of the clusters was particularly interesting. It contained customers who took home equity loans. These customers were in their forties, married with children in their late teens. The bank assumed that they were taking loans to pay college tuition fees for their children. Thus, the bank organised a marketing campaign to offer home equity loans as a means to pay for college education. However, results of the campaign were disappointing.

Further investigation revealed that the problem was in the interpretation of the clusters identified by the SOM. Consequently, the bank decided to include more information about its customers such as type of accounts, deposit system, credit card system, etc. After retraining the SOM, it was discovered that customers who took home equity loans in addition to being in their forties with college-age children often also had business accounts. So, the bank concluded that when children left home to go to college, parents took out home equity loans to start new businesses. The bank organised a new marketing campaign targeting this group of potential customers, and this time the campaign was successful.

6 Conclusions

A very large number of bank failures in 2008 triggered a financial crisis. Although unprecedented intervention of central banks and governments helped economies to recover, the global financial systems remains at risk. As a result, identifying failing banks as early as possible is essential. This paper has clearly demonstrated a great potential of a self-organising neural network as a tool for performing this task. The results show that self-organising maps can successfully carry out bank clustering tasks and identify banks that require immediate attention from the regulatory bodies.

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Cluster	Size	Neuron number	Financial profile of the cluster														
			NITA			NLLAA			NPLTA			NLLTL			NLLPLLNI		
			Mean	Median	SD	Mean	Median	SD	Mean	Median	SD	Mean	Median	SD	Mean	Median	SD
A	4	1,6	0.0369	0.0369	0.0043	−0.1793	−0.1340	0.2516	0.0125	0.0100	0.0055	0.0050	0.0057	0.0036	0.2839	0.2839	0.0164
B	1	2	0.0121	0.0121	0	−0.4954	−0.4954	0	0.0323	0.0323	0	0.0006	0.0006	0	1.1522	1.1522	0
C	75	3,7,8,9, 11,12,13, 14,16,17, 18,19,21, 22,23	0.0101	0.0094	0.0097	−0.0899	−0.0701	0.1646	0.0153	0.0144	0.0102	0.0143	0.0121	0.0093	0.8399	0.6973	0.7252
D	3	4	0.0066	0.0041	0.0064	0.4448	0.4528	0.0672	0.0190	0.0185	0.0058	0.0133	0.0145	0.0068	0.1894	0.1676	0.1617
E	13	5,10,15	−0.0006	−0.0010	0.0044	0.0363	0.0357	0.0257	0.0205	0.0166	0.0144	0.0388	0.0376	0.0108	8.0965	7.1786	3.9200
F	1	20	−0.0092	−0.0092	0	0.0089	0.0089	0	0.0215	0.0215	0	0.0055	0.0055	0	9.4091	9.4091	0
G	1	24	−0.0060	−0.0060	0	0.0199	0.0199	0	0.0198	0.0198	0	0.0662	0.0662	0	0.3612	0.3612	0
H	2	25	0.0014	0.0015	0.0019	0.0225	0.0225	0.0048	0.0164	0.0164	0.0029	0.0740	0.0740	0.0052	10.9785	10.9785	1.2720

Table 1: Clustering results of the 5-by-5 SOM

NITA			NLLAA			NPLTA			NLLTL			NLLPLLNI		
Mean	Median	SD	Mean	Median	SD	Mean	Median	SD	Mean	Median	SD	Mean	Median	SD
−0.0625	−0.0616	0.0085	0.0642	0.0610	0.0234	0.0261	0.0273	0.0065	0.0341	0.0339	0.0092	7.3467	6.9641	3.8461

Table 2: Financial profile of the failing banks