Common Characteristics in Takeover Targets: A Self Organising Map Approach

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Abstract

In this paper the use of Kohonen's Self Organising Map as a tool for financial analysis is explored in the context take over target identification. A Self Organising Map (SOM) is a dimension reducing transform that maps an high dimension information set to a two dimensional grid that is amenable to visualisation. This dimension reduction step is a key component of all financial analysis tasks. The potential of this method is investigated in the context of the problem of takeover target identification. The consensus finding in the literature on take over target identification is that the models developed perform no better than chance. Use of SOM analysis on two samples from different time periods charts temporal instability in the information sets of sufficient magnitude to breach the stationarity assumptions of standard statistical modelling methods.

Keywords: Self Organising Map, Financial Analysis, Takeover

Introduction

At an abstract level financial analysis can be viewed as a two stage process; firstly mapping a high dimensional information set into a lower dimensional set, then partitioning the lower dimensional set on the basis of some attribute of the companies being studied. Once the low dimensional set has been partitioned any company can be classified by passing its information through the mapping function to obtain its position relative to the partition in the lower dimensional set.

The bankruptcy prediction literature is a well known formal application of this approach. In Altman (1968) five financial ratios and an indicator of solvency are used as the information set for each company. The mapping from this five dimensional space to a one dimensional space is accomplished via a linear equation derived by applying the Linear Discriminate Analysis statistical technique. The partition of the resulting one dimensional set is based on the selection of a cut off value which minimises the number of misclassifications of solvency in the set of firms used in the estimation of the discriminate function.

This can be contrasted with the less formal judgemental approach used by analysts in the production of buy / sell recommendations. Financial information for the company of interest and a number of comparable companies is collected. Summary financial measures derived from the full information of the company and its peers are then used by the analyst to generate recommendations. The selection of the summary financial measures is analogous to the dimension reduction step and the analyst's decision rules leading to a recommendation are equivalent to the partitioning step.

The financial analysis task examined in this study is the identification of takeover targets. If it is possible to predict takeovers with accuracy greater than chance, it is possible to generate abnormal returns from holding a portfolio of the predicted targets, an objective that has proved difficult to achieve[1]. In the words of Barnes (1999), *if the stock market is a casino, then anyone who can predict takeover targets*

[1] Harris et al (1982) found a predictive model with high explanatory power, which was unable to accurately discriminate between target and non target firms. Palepu (1986) provided evidence that the predictive ability of the logit model he constructed was no better than a chance selection of target and non target firms.

will surely break the bank. Ideally there will be a stable functional relationship between a set of explanatory variables and the probability of becoming a takeover target. When the explanatory variables found to be significant explanitors are consistent with a well reasoned economic explanation of takeover activity, it is also reasonable to assume that they will remain significant over time. Inter-temporal consistency in the structure of firms information sets, stationarity, is a necessary condition for meaningful predictive accuracy.

A number of explanations of the drivers of takeover activity have been proposed. Jensen and Meckling (1976) posit that agency problems occur when decision making and risk bearing are separated between management and stakeholders[2], leading to management inefficiencies. Manne (1965) and Fama (1980) theorised that a mechanism existed which ensured that management acted in the interests of the vast number of small non-controlling shareholders[3]. They suggest that a market for corporate control exists in which alternative management teams compete for the rights to control corporate assets. The threat of acquisition aligns management objectives with those of stakeholders as managers will be terminated in the event of an acquisition to rectify inefficient management of the firm's assets. Jensen and Ruback (1983), suggest that both capital gains and increased dividends are available to an acquirer who can eliminate the inefficiencies created by target management, with the attractiveness of the firm for takeover increasing with the level of inefficiency.

Jensen (1986) looks at the agency costs of free cash flow, another from of management inefficiency. In this case, free cash flow refers to cash flows in excess of positive NPV investment opportunities and normal levels of financial slack. The agency cost of free cash flow is the negative NPV value that arises from investing in these negative NPV projects rather than returning funds to investors. Jensen (1986) suggests that the market value of the firm is discounted by the expected agency costs of free cash flow, he argues that these costs can be eliminated either by issuing debt to fund an acquisition of stock, or through merger or acquisition with/of a growing firm which has positive NPV investments that require the use of these excess funds. Smith

2 Stakeholders are generally considered to be both stock and bond holders of a corporation.

3 We take the interests of shareholders to be in the maximization of the present value of the firm.

and Kim (1994) combine the financial pecking order argument of Myers and Majluf (1984) with the free cash flow argument of Jensen (1986) to create an another motivational hypothesis. Myers and Majluf (1984) indicate that slack poor firms forgo profitable investment opportunities because of informational asymmetries. Jensen (1986) argues that firms will undertake negative NPV projects rather than returning funds to investors. Smith and Kim (1994) suggest that a combination of these firms, the slack poor and the slack rich firm, will be an optimal solution to the two respective resource allocation problems resulting in a market value for the combined entity which exceeds the sum of the individual values of the firms. This is one form of financial synergy that can arise in merger situations.

Jensen (1986) also suggests that an optimal capital structure exists, where the marginal benefits and marginal costs of debt are equal. At this point, the cost of capital for a firm is minimised, which suggests that increases in leverage will only be viable for those firm's which suffer from free cash flow excesses, and not for those which have an already high level of debt. Lewellen (1971) proposes that in certain situations, *financial efficiencies* may be realised even if no operational efficiencies are realised. Relying on a simple Miller and Modigliani (1964) model, this proposes that increases in a firm's leverage to reasonable levels, in the absence of corporate taxes, will increase the value of the equity share of the company through realisation of a lower cost of capital. Lewellen (1971) agues that a merger of two firms, where either of the firm's has not utilised its borrowing capacity, will result in a financial gain. This financial gain will represent a valuation gain above that of the sum of the equity values of the individual firms, but requires that the firms are unable to achieve this result without merger or acquisition. This is another form of financial synergy, which results from a combination of characteristics of the target and biding firms.

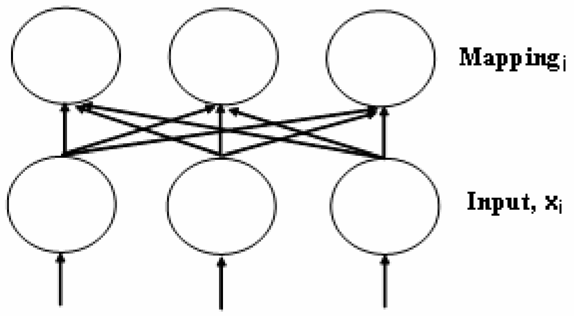
These theories provide a theoretical base for the selection of variables to explain takeover activity. They lead us to propose a number of hypotheses, which lead to the nine explanatory variables used as inputs to the SOM's constructed in each of the two time periods analysed.

Self Organising Maps

SOMs are a form of neural network which attempt to cluster data using an unsupervised learning algorithm proposed by Kohonen (1982). In an unsupervised learning environment it is not necessary to associate an output with an input data vector. It is not necessary to know the output value for an input vector for a SOM to be constructed. The SOM projects the input data vectors into a low-dimensional space. Typically, the projection is onto a two-dimensional grid structure, allowing a visual representation of the high-dimensional input data.

A SOM is a neural network consisting of two layers; an input layer and the mapping layer (see Figure 1). The input layer has as many nodes as there are input variables. The two layers are fully connected and each of the nodes in the hidden layer has an associated weight vector, with one weight for each connection with the input layer.

Figure 1: Simple Structure of a SOM



The aim of a SOM is to group like input data vectors together on the mapping layer, the method is constructed to be topology preserving, so items which are close in the input space are close in the mapping space. During training data vectors are presented to the SOM through the input layer one at a time. The mapping node whose vector of incoming connection weights most closely resembles the components of the input data vector is assigned the input vector. This node has the values of its weight vector adjusted to move them towards the values of the input data vector, and the mapping layer nodes in the neighbourhood of the assigned node have their weight vectors updated to reflect the input data vector. As more input data is passed through the network, the weights of the mapping layer nodes will self-organise. By the end of the training process, regions on the mapping layer will represent regions in the higher dimensional input space. When the network has been trained, clusters in the output layer can be used to gain understanding of the relationships in the underlying data.

The general training algorithm for the SOM is as follows:

1. Initialise the weights between the input nodes and the mapping nodes to random values on the unit interval.
2. Present an input vector x*:* $x_0, x_1, \ldots, x_{n-1}$.
3. Calculate the Euclidian distance between the input vector and the weight vector for each mapping layer node j

   $$d_j = \sum_{i=1}^{n-1} (x_i - w_{ij})^2 \qquad (1)$$

4. Select the mapping node $j*$ that has the minimum value of d_j .
5. Update the weight vector for mapping node $j*$ and its neighbouring mapping nodes as follows:

   $$w(t+1)_{ij} = w(t)_{ij} + \eta h(t)(x_i - w_{ij}) \qquad (2)$$

   where η is the learning rate of the map, and h defines a neighbourhood function. The neighbourhood size and the learning rate decline during training, in order to fine tune the developing SOM.
6. Repeat steps (2)-(5) until the change in weights is less than a convergence criterion value.

In summary, SOMs are equivalent to a non linear, non-parametric regression that produces a topological, low-dimensional representation of data, which allows visualization of patterns and clustering in the data.

Method

Definition of Variables for Takeover Identification

The most commonly accepted motivational for takeovers is the *inefficient management hypothesis*. Also known as the disciplinary motivation for takeovers. The suggestion of the hypothesis is that inefficiently managed firms will be acquired by more efficiently managed firms:

H_1: Inefficient management will lead to an increased likelihood of acquisition.

The following variables are suggested by this hypothesis:

1. ROA (EBIT/Total Assets – Outside Equity Interests)
2. ROE (NPAT/Shareholders Equity – Outside Equity Interests)

A number of different effects of undervaluation on acquisition likelihood have been proposed. The competing explanations suggest a consistent impact of undervaluation on acquisition likelihood:

H_2: Undervaluation of a firm will lead to an increased likelihood of acquisition.

The following variable is suggested by this hypothesis:

3. Market to book ratio (Market Value of Securities/Net Assets)

The *growth resource mismatch hypothesis* is the fourth hypothesis. Note, however, that the variables used to examine this hypothesis separately capture growth and resource availability:

H_4: Firms which possess low growth / high resource combinations or high growth / low resource combinations will have an increased likelihood of acquisition.

The following variables are suggested by this hypothesis:

4. Capital Expenditure/Total Assets
5. Current Ratio (Current Assets/Current Liabilities)

The *dividend payout hypothesis* suggests that firms which payout less of their earnings are doing so to maintain enough financial slack to exploit future growth opportunities as they arise:

H_5: High payout ratios will lead to a decreased likelihood of acquisition.

The following variable is suggested by this hypothesis:

6. Dividend Payout Ratio

Rectification of capital structure problems is an obvious motivation for takeovers, although there has been some argument as to the impact of low or high leverage on acquisition likelihood. This paper proposes a hypothesis known as the *inefficient financial structure hypothesis*:

H_6: High leverage will lead to a decreased likelihood of acquisition.

The following variables are suggested by this hypothesis:

7. Net Gearing (Short Term Debt + Long Term Debt)/Shareholders Equity
8. Long Term Debt/Total Assets

Size will have an impact on acquisition likelihood; it seems plausible that smaller firms will have a greater likelihood of acquisition, as larger firms generally will have fewer bidding firms with the resources to acquire them.

H_8: The size of a firm will be negatively related to the likelihood of acquisition.

The following variables are suggested by this hypothesis:

9. Ln (Total Assets)

It is standard practice in the development of neural networks and SOM's to normalise the input data to be distributed with zero mean and standard deviation of one. The calculation of industry relative variables is an alternative normalisation method.

Data

The data required to operationalise the variables defined is derived from the financial statements for Australian listed companies and balance sheet date price information. The financial statement information was sourced from the AspectHuntley data base, which includes annual financial statement data for all ASX listed companies between 1995 and 2005. The database includes industry classifications for all firms, facilitating the construction of industry relative ratios. Lists of takeover bids and their respective success were obtained from the Connect4 database. This information makes possible the calculation of variables for relative merger activity between industries. Also, stock prices for the relevant reporting dates of all companies were sourced from the AspectHuntley online database, the SIRCA Core Price Data Set, and Yahoo! Finance.

Sampling Schema

The sampling procedure was constructed to mimic the problem faced by a practitioner attempting to predict takeover targets into the future. The first sample that is used to estimate the model is based on financial data for the 2001 and 2002 financial years for firms that became takeover targets target between Jan 2003 to Dec 2004. The financial data for the non target firms included in the model estimations were also from the 2001 and 2002 financial years. The lag in the dates allows for the release of financial information and also allows for the release of financial statements for firms whose balance dates fall after the 30th June. A second sample is used to assess the stability of the model this sample includes the financial data for the 2003 and 2004 financial years, which is used in conjunction with target and non target firms for the period Jan 2005 to Dec 2006. This sampling methodology allows for an evaluation of the functional stability of the estimated models.

In the estimation of the models, we use a technique known as *state based sampling*. All target firms along with an equal number of randomly selected non target firms for the same period are used in the estimation of each model. Allison (2006) suggests that using state based sampling, in cases where the dependent variable states are unequally distributed in the population, minimises the standard error of estimated parameters. Targets for the estimation sample are paired with a random sample of non target firms for the sample period, where financial data is measured over an identical period. This approach differs from matched pair samples where targets are matched to non targets on the basis of variables such as industry and/or size.

Industry Relative Ratios

Platt and Platt (1990) advocate the use of industry relative variables to increase the predictive accuracy in bankruptcy prediction models, as these variables enable the model to take into account variability across industries and through time. This argument is based on two main contentions. Firstly average financial ratios are inconsistent across industries, as they reflect the relative efficiencies of production commonly employed in those industries. The second is that average financial ratios are inconsistent throughout time, as performance will also vary with economic conditions and other factors. They argue that we cannot analyse firms from different industries or different time periods without some form of industry adjustment. This study will use both raw and industry adjusted financial ratios to determine the contribution of industry adjustment to model stability.

This results in two different model specifications in each time period – one based on raw financial ratios for the year prior to the sample period (raw model), and one based on industry adjusted financial ratios for the year prior to the sample period (adjusted model. Most researchers use industry relative ratios calculated by scaling the firms' financial ratio by the industry average, see equation four. Under this procedure all ratios are standardised to one, with industry relative ratios above one indicating out performance of the industry and those below indicating underperformance of the industry for the ratio. Problems are encountered when the industry average has a negative value. In this case, those firms which under perform the industry average are given industry relative ratios which are greater than one, as a large negative number will be divided by a smaller negative number. Additionally, those firms which outperform the negative industry average ratio but still retain a negative financial ratio will have a ratio less than one. This ambiguity in the calculation of industry relative ratios has implications for models which include variables where negative industry averages are possible. This problem may explain the inability of researchers to accurately predict target and non target firms with models which utilise industry adjustments, and may have caused the Barnes (1999) model to predict no takeover targets at all.

$$Industry\ Relative\ Ratio = \frac{x}{I} \quad [4]$$

$$where\ x = individual\ firm\ financial\ ratio$$

$$I = industry\ average\ financial\ ratio$$

An alternative methodology, suggested by the variable scaling procedures common in Neural Network modelling, was implemented to account for negative industry averages. Equation five uses the difference between the individual firm's ratio and the industry average ratio, which is divided by the absolute value of the industry average ratio. This standardises all ratios to zero rather than one, and also corrects problems relating to the sign of the industry relative ratio. Underperformance of the industry results in an industry relative ratio which is less than zero, out performance obviously results in a ratio which is greater than zero. This approach was used for the models based on industry relative variables. Industry segments are based on the ASX 24 industry classification (now replaced by S&P's GICS).

$$Industry\ Relative\ Ratio = \frac{x - I}{|I|} \quad [5]$$

Results

Self Organising Maps are constructed for the four sets of data used in this study. A map for 2003 and 2005 takeovers using a z normalisation over the whole data set for each variable; and one for each of 2003 and 2005 takeovers using an industry relative normalisation of the variables. The maps constructed consist of 49 nodes arranged in a 7 by 7 grid. The maps are trained using the Kohonen library in R. The node weights are initialised to small random values. In the training of the map the observations are randomised and presented to the algorithm 500 times. A trained map consists of the variable weights for each node of the output layer and a distance minimising node assignment for each data vector used in the training of the map. A visual representation of each of these outputs can be constructed and used as tool for exploratory data analysis.

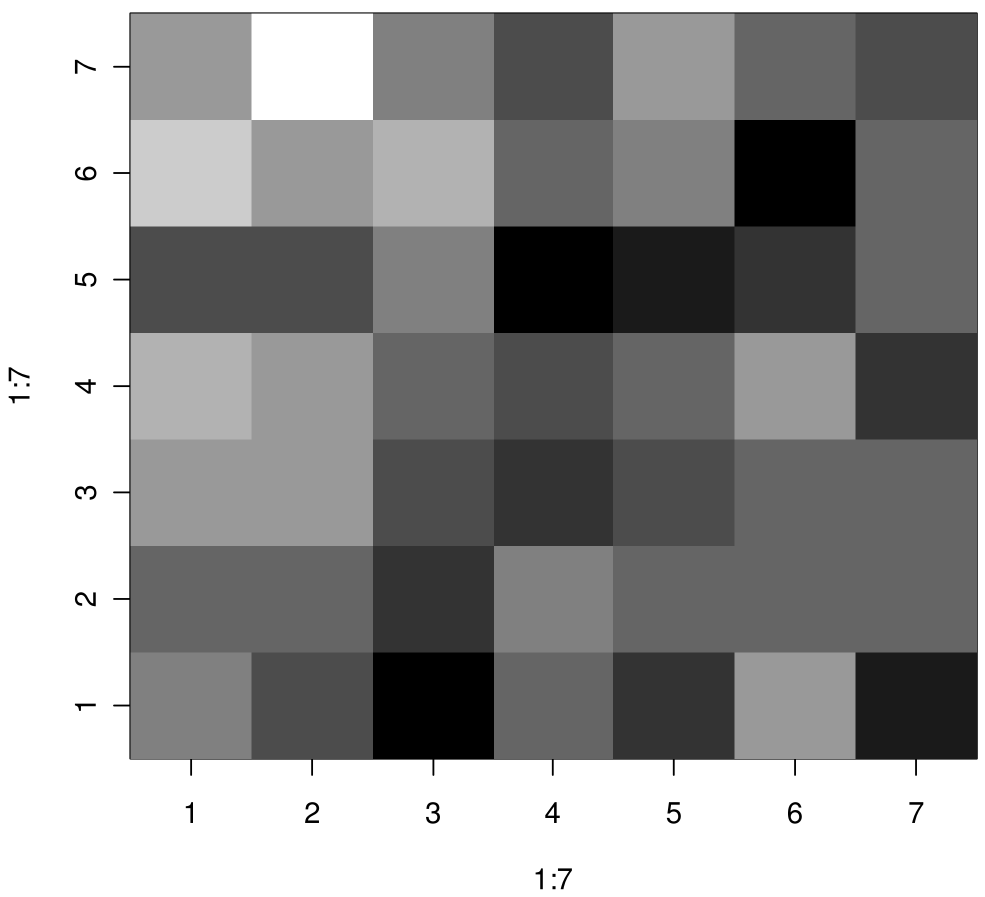
The map presented in Figure 1 is known as a feature map. It is constructed from the node assignments of the training data. A score matrix for the map grid is constructed by adding one to the cell which corresponds to the node in the map that the observation is assigned to when the observation which is a target and subtracting one when the observation is not a target, an example of a score matrix is presented in Table 1. The score matrix is in effect the result of a simple voting mechanism for the nodes, a node that has more targets than non targets mapped to it will have a positive tally, nodes with more non targets than targets will have a negative tally. The feature map is a grid graph of the score matrix using a gray scale to represent the tallies, the node with the highest number of associated targets is plotted in white and the node with the largest number of non targets is plotted in black.

Table 1 - Score Matrix 2003 Takeovers using z normalized data

	[,1]	[,2]	[,3]	[,4]	[,5]	[,6]	[,7]
[1,]	1	0	2	3	-1	4	2
[2,]	-1	0	2	2	-1	2	6
[3,]	-4	-2	-1	0	1	3	1
[4,]	0	1	-2	-1	-5	0	-1
[5,]	-2	0	-1	0	-3	1	2
[6,]	2	0	0	2	-2	-4	0
[7,]	-3	0	0	-2	0	0	-1

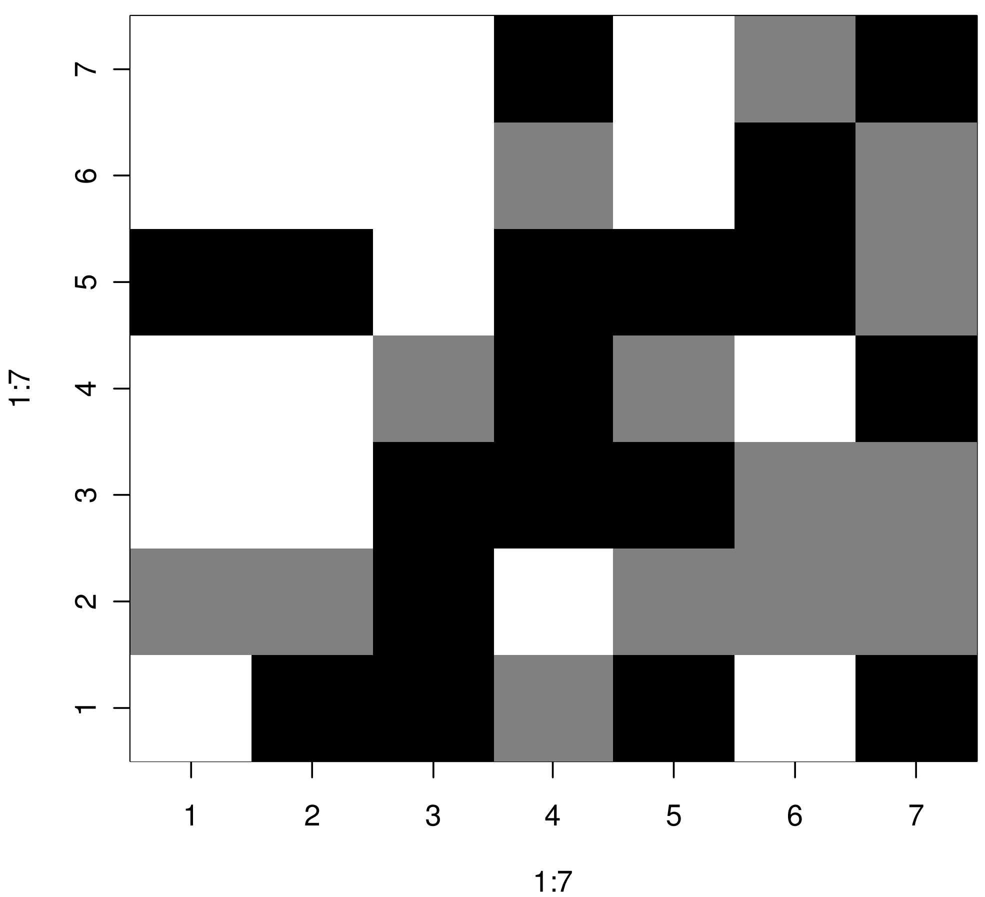
The grid graph in Figure 1 uses eleven shades of gray, the range of the tally values, to visualise the score matrix. Note that the graph plots the (1,1) cell of the score matrix in the bottom left corner, columns in the matrix are transposed to rows in the graph. The lighter the element in the grid the greater the number of target companies associated with the node represented by that element.

Figure 1: Feature Map of 2003 Takeovers – z Normalisation of Variables



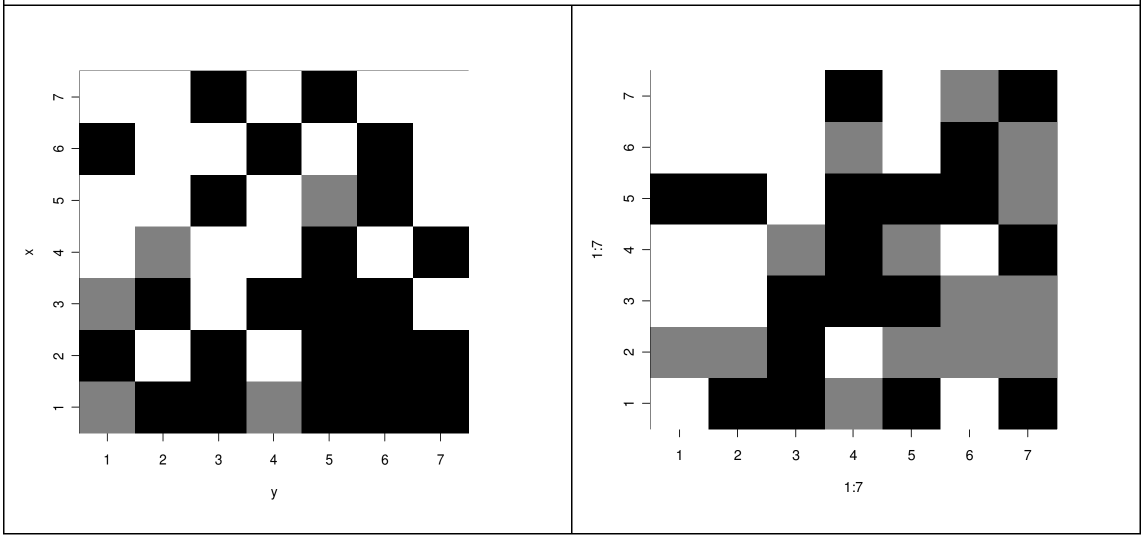
While Figure 1 presents all of the information on the strength of association of each node in the map based on simple voting, it is difficult to delimit clusters of activity at this level of detail. The information in Figure 1 can be simplified by defining a cluster matrix that corresponds to the score matrix. Each cell in the cluster matrix has a value of -1, 0 or 1; -1 for cells with more non takeovers, zero of ties and 1 for cells with more takeovers. When this matrix is plotted as a grid graph, a cluster map, groupings of target and none target companies are easily identified. The cluster map for takeovers in 2003 is presented in Figure 2. Grid elements that are white represent votes won by target firms, elements in black represent votes won by non target firms and grey elements represent ties.

Figure 2: Cluster Map of 2003 Takeovers – z Normalisation of Variables



In terms of an analysis task involving a categorical recommendation, the ideal cluster map would contain a clean partition of the graph elements into a distinct region for each class. In the case of takeover target identification the ideal map would contain only white and black elements, grouped into separable regions. The cluster map in Figure 2 is not in this ideal form. There are two main clusters of target firms in the top left corner of the map, and four other isolated target elements which account for 34% of the map elements. The non take over and tied elements account for the remaining 66% of map elements. The fragmented nature of the target elements in the map indicate that a reliable rule for class assignment will be hard to discover using the current information set, a result that is born out in the lack of predictive accuracy reported in the target prediction literature.

Figure 3: Temporal Stability of Z Normalised Cluster Maps, 2003 and 2005 Takeovers



Stationarity of the relationships in the input data is a necessary condition for the development of a successful classification model. Testing for stationarity is well understood in time series context, testing for the stationarity of the joint distributions that underlie higher dimensional data sets is a small sample context is less well understood. Analysis can use a comparison of sequence of cluster maps to make a qualitative assessment of the stationarity of set of relationships within a data set. If the relationships are stable the structure of the cluster map will be retained over a sequence of maps. A substantial change in the structure of the map is an indicator of a change in the relationships within the data set. Figure 3 shows the cluster maps for the z normalised data for 2005 on the left and 2003 on the right. The plots show a substantial change, the 2005 map displays a much higher degree of fragmentation in the target nodes, it also has fewer tied elements, with 90% of the elements mapping to a specific state.

The information set used to derive the cluster map in Figure 2 uses a z normalisation of the raw data. As noted above an alternate normalisation can be achieved by calculating industry relative values for the input variables. Authors such as Platt and Platt (1990) argue that the use of industry relative normalisation can lead to improved modelling outcomes. This claim can be evaluated by comparing the cluster map derived from an industry normalised data set with the cluster map derived from a z normalisation of the data set.

Figure 4 – Industry Relative and Z Normalised Cluster Maps, 2003 Takeovers

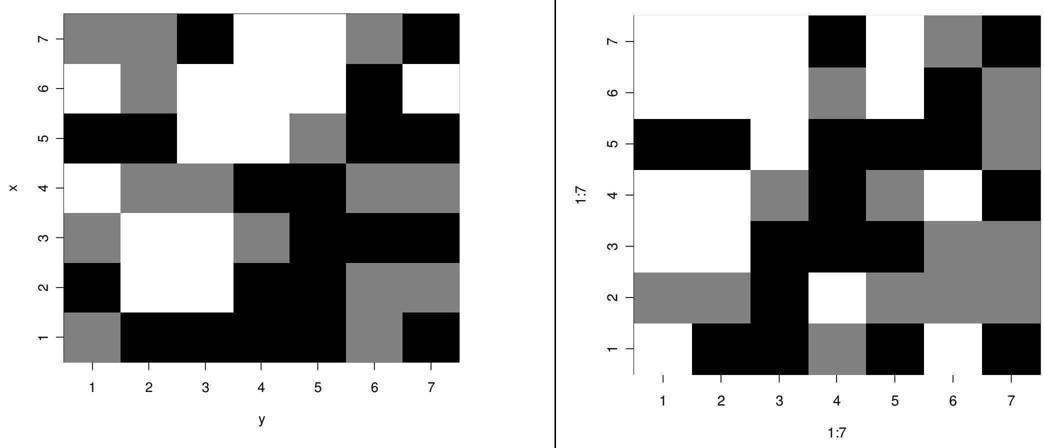


Figure 4 shows the industry relative cluster map on the left, with the z normalised cluster map on the right. The industry relative cluster map displays less fragmentation and well defined clustering in comparison to the z normalised data. While the clusters of targets are well defined there are two non contiguous main clusters evident, suggesting that the classification rules required in the industry relative case will be more complex than a simple cut off value applied to values mapped to the unit interval.

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