Volume : 3 | Issue : 2 | Feb 2014 • ISSN No 2277 - 8160

Research Paper ECONOMICS

Bankruptcy Prediction Models: A Bet on Artificial Neural Networks

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ABSTRACT

The proper prediction of future bankruptcy of an organization is vital to all its stakeholders, from its owners/ shareholders to employees, passing of course through their creditors. This paper presents a quantitative approach using the discriminant analysis, analysis logit and a multilayer perceptron networks applied to economic data of one hundred forty-three companies to generate the models bankruptcy prediction. The results demonstrate that artificial neural networks provide analysis and predictions significantly superior than the statistical classical methods, resulting in an ideal tool for the financial management

KEYWORDS : Prediction. Bankruptcy. Discriminant Analysis. Logit Analysis. Artificial Neural Networks.

Introduction

In these times of constant changes and faced a growing competitiveness in the business field, the ability to adapt to the environment is becoming a determining factor in the success of organizations. Companies have to be more flexible and agile, with the ability to innovate and to be able to react quickly to changes in the market and the competition.

Artificial Intelligence (AI) and its techniques are gaining ever more importance in the theory of decision field and particularly in what refers to the business financial aspects.

This work is a comparative study of three qualifiers and predictive techniques applied to the analysis of the solvency of enterprises, determining the factors influencing this phenomenon, and then applying the obtained model to the prediction. Two of them are technical statistics traditionally used, discriminant analysis (DA) and logit analysis (LA) and the third is a multilayer perceptron network (MLP), an AI technique. The work is performed with the SPSS 20 Neural Networks computer program.

Artificial Neural Networks in the decision-making of the company

Artificial neural networks (ANN) emulates the biological systems in a simplified way (Bischof et al., 1992). Information processors, which would be the equivalent to biological neurons, interconnected among themselves and structured in levels of layers made up of many elements. There is an entry level, which introduces the data to the network, and an output level that provides the response to the input data, and one or more levels that process the data. They learn the relationship between the input and output data, therefore, everything you need to train an ANN with is a dataset containing the input/output relationship.

In reality, the ANN are internally multivariate mathematical models that use iterative procedures processes to minimize error functions. Artificial neurons, as well as biological ones, are defined to be in state of activation at all times, which can be expressed by a numeric value corresponding to the formula:

$$a = \sum_{i=1}^{n} w_i x_i$$

being x_i the value of from each previous neuron activation layer, and w_i the weight assigned to that value. A transfer or output function transforms this value into an output signal that travels through the connections to other neurons of the subsequent levels, eliminating the linearity of the network and limiting values within a certain range.

Signals sent to a neuron from several others are modified according to the weight of the connection, w_i, and are combined to reach the destination according to a rule of propagation that produces the total input. A special type of ANN is the network *feedpropagation*, in which the data flow comes from the input level and spreads to the hidden layer, and finally to the output layer. Learning occurs in the stage of training and weights will remain constant, during the operation of the network, when it applies to another set of different data to predict new results.

For the creation of a model, two stages should be established: the design and training of the network with predictability, and the validation of results.

Originally the neural network does not have any type of stored useful knowledge. To allow a neural network to run a task, it is necessary to train it. The training is done by example patterns. There are two types of learning: supervised and unsupervised learning. If the network uses supervised learning we must provide pairs of input/output patterns and the neural network learns to associate them. In statistical terminology, it is equivalent to models in which there are vectors of independent and dependent variables. If the training is not supervised, we must only provide input data to the network so that the essential characteristic features can be extracted. These unsupervised neural networks are related to statistical models such as the analysis of clusters or multidimensional scales (Serrano-Cinca, 1997).

There are a variety of neural networks and associated architectures. Some of the most important applied to solving real problems are: the multi-layer perceptron, radial basis function or self-organized Kohonen maps.

Research, methodology and data

The database has been extracted from the study carried out by Serrano-Cinca (1996), based on the application of the artificial neural networks named self-organized maps (SOFM). It gathers accounting data corresponding to 129 companies in the time period between 1975 and 1985, in which 65 are classified as bankrupt companies and 64 as solvent companies.

Similar empirical studies used the same data base applying other types of neural networks, as the Rahimian et al. (1993), Wilson and Sharda (1994), or Odom and Sharda (1990), which allows us to compare results.

In our case we have also included a second data base of 14 companies collaborating with this study, and which intend to predict their classification as solvents or bankrupt. These companies are our test sample.

Sample of 129 companies is randomly divided into two groups, but equally for the three methods to ensure comparability of results: training sample and validation sample.

The dependent variable is a dichotomous nominal variable that we call solvency, whose values are 1 in a solvent company and 0 in a company in bankruptcy.

The independent variables or predictors that help to explain the behavior of the solvency variable appear in Table No 1, and are the same ratios selected by Altman (1968) in his study to calculate the Z score because we assumes that the technique applied to the information stored in these ratios is the key factor that determines the success of the company classification and the prediction of critical situations.

Table No 1. Independent variables

R01	Working capital/total assets
R02	Retained earnings/total assets
R03	Earnings before interest and tax/total assets
R04	Market value of equity/total debt
R05	Sales/total assets

Analysis of the results

The discriminant function, obtained as linear combination of the explanatory variables, allow classifying individuals in the sample into groups defined by the dependent variable through the establishment of a cut-off point for scores calculated from the corresponding function.

Based on coefficients of canonical discriminant functions, the AD model corresponds to the equation:

$$f = -0{,}703 + 2{,}188 \times R02 + 6{,}039 \times R03$$

The application of this model gives us the classification presented at Table No 2. As we can see, 86.8% of the initial 129 companies have been correctly classified. In it appears that 51 out of the 65 original companies in bankruptcy have rated well, or in other words, 14 companies rated wrong, which gives a percentage of hits for the bankruptcy of 78.5%. However, only 3 errors have been detected in the case of the 64 original pre-classified companies, giving a percentage of hits to the solvency of 95.3%.

With regards to unbundled cases, our test sample, the DA model shows us that there are 10 bankrupt companies and only 4 solvent companies. Given that the forecast for the soundness of the method used is very high, we can bet with some degree of confidence on the good economic health of these companies. But not one could argue with equal assurance the bankruptcy of 10 other companies, because with a 21.5% chance you can have crept any false bankruptcy.

Table No 2. Classification DA results

		Solvency	Predicted group		Total
			00	1.00	
Original	Count	00	51	14	65
		1.00	3	61	64
		Unbundled cases	10	4	14
	%	00	78.5	21.5	100.0
		1.00	4.7	95.3	100.0
		Unbundled cases	71.4	28.6	100.0

The LA model allows us to determine the probability that a company is solvent or not, using the estimated coefficients for each explanatory variable included in the model that reflects the influence of each of them in the analyzed phenomenon.

According to this, we get a final model with two independent variables, which are showing significance in the explanation of the dependent variable as justified by their respective coefficients in table No 3:

Table No 3. Equation's LA variables

		B	E.T.	Wald	GL	GIS	Exp (B)
Step 2	R02	12,873	2,964	18,867	1	000	389587,489
	R03	26,691	6,599	16,358	1	000	390610178178,835
	Constant	-4,702	990	22,562	1	000	009

As seen in Table No 3, the independent variable that has a bigger effect on the dependent variable solvency is R03, followed by the ratio R02, which have in addition a very high and positive sign coefficients, which indicates that when the independent variable increases by one unit, the logarithm of the odds of probability as a solvent company increases in the value of the respective coefficient.

It is clear then that the measure of operating efficiency, apart from taxes and leverage factors is an important determinant of the solvency of a company. Similarly, these coefficients recognize the benefits of exploitation as important to long-term viability, as well as the importance of measuring the profitability of a company from their age and their purchasing power.

The LA estimated model gets a rate of 92.3% hits for bankruptcy cases and 92.2 % for the solvency ones, which gives a global rate of 92.2 % as shown in Table No 4.

Table No 4. LA model classification

	Observed		Predicted		
		SOLVENCY		Percentage correct	
		0	1.0		
Step 2	SOLVENCY	0	60	5	92.3
		1	5	59	92.2
	Global percentage				92.2
The cut-off is , 500					

For the construction of the MLP, we chose a single hidden layer and functions of hyperbolic tangent activation in the hidden layer and SOFTMAX in the output layer, training mini batch with gradient descent optimization algorithm.

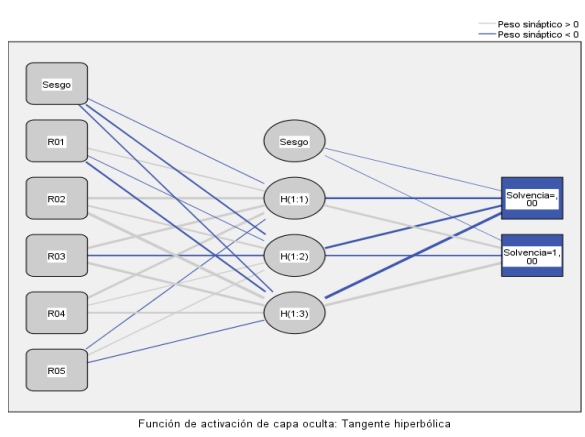

Fig. No 1: MLP feedforward

The MLP model works almost as well predicting the companies that are bankrupt as those that are not as shown in the Table No 5.

Table No 5. MLP classification

Sample	Observed	Predicted		
		00	1.00	Correct Percentage
Training	00	38	0	100.0 %
	1.00	1	35	97.2 %
	Global percentage	52,7 %	47.3 %	98.6 %
Test	00	23	4	85.2 %
	1.00	4	24	85.7 %
	Global percentage	49.1 %	50.9 %	85.5 %
Dependent variable: solvency				

Conclusions

We have analyzed the characteristics of three methods applied to the classification and prediction of the solvency or bankruptcy of a group of companies: DA, LA, and MLP

The models obtained have a high predictive capacity, which in the case of the DA is greater in the case of solvency, 95.3% and lower for bankruptcy, 78.5%, while in the LA it is the 92.3% for solvency and 92.2% for bankruptcy. Regarding the MLP model, there are a significant difference compared to the DA model, having a better prediction in cases of bankruptcy, 92.6%, and 85.4% in the case of solvency. However, the three methods have made exactly the same prediction for the companies of our test sample. In terms of the variables that most discriminate and therefore better classify two separate groups, solvent companies or insolvent companies, the three methods have agreed to the election of the ratios *R02* = retained earnings divided by total assets and *R03* = operating profit divided by total assets. Thus, any decisions in regards to issues such as investment in the company, loans, etc. should be linked to these ratios, which are related to liquidity and self-financing. The higher the retained earnings and operating profit compared to the total assets of the company, the better prospects for the future.

Finally, with regards to the management and interpretation of the models, it has been demonstrated that using artificial neural networks can be a useful technique of decision making. In fact, programs like the 20 SPSS Neural Networks which include artificial intelligence techniques to provide better decision tools are increasingly used in the industry.

Due to its empirical data, the results of these studies, although positive and interesting, are not conclusive and almost all of them invite us to continue conducting more empirical studies to identify in which problems and under what conditions neural networks can be a more efficient solution than the models commonly used.

REFERENCES

Altman, E. (1968) Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy. The Journal of Finance, 23(4), 589-609. | Bischof, H. et al. (1992). Multispectral classification of Landsat images using neural networks. IEEE Transactions on Geoscience and Remote Sensing, 30, 482-489. | Odom, M. & Sharda, R, (1990) A neural networks model for bankruptcy prediction. Proceedings of the IEEE International Conference on Neural Network, 2,163–168. | Rahimian, E.; Singh, S.; Thammachote, T. y Virmani, R. (1993). Bankruptcy Prediction by Neural Network. Neural Networks in Finance and Investing. Chicago: Ed Trippi y Turban. Probus Publishing Company. | Serrano-Cinca, C. (1996) Self organizing neural networks for financial diagnosis. Decision Support Systems, 17(3), 227-238. | Serrano-Cinca, C. (1997). Feedforward Neural Networks in the Classification of Financial Information. European Journal of Finance, 3(3), 183-202. | Wilson, R. L., & Sharda, R. (1994). Bankruptcy prediction using neural networks. Decision support systems, 11(5), 545-557. |