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Comment

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The paper stresses the role of neural networks in classification problems where groups to be classified are linearly nonseparable. This discussion may begin by clarifying such a statement, distinguishing between those nonlinear relationships which require the use of neural networks and those which do not. Such distinction, along with a more cautious assessment of the existing literature on the subject, leads to questioning whether such literature is offering a balanced view of the prospects of neural networks in bankruptcy prediction and what may be the potential of those studies to improve our knowledge of processes leading to bankruptcy.

Neural networks and nonlinear relationships

Quadratic discriminant analysis and other conventional techniques may also solve classification problems involving linearly nonseparable groups. The strength of neural methodologies lies in the ability to solve a specific kind of linearly nonseparable classification problem requiring the use of more than one boundary for separating groups.

A typical example is known as the 'exclusive OR' (XOR) (Rumelhart *et al.*, 1986) which involves, in its simplest form, two groups of cases, e.g. groups *A* and *B*, and two explanatory variables, e.g. x_1 and x_2. When both x_1 and x_2 are either large or small then the group is *B*. When the same variables trend in opposite directions, then the group is *A*.

Whereas, in theory, two independent variables are sufficient to separate the two groups *A* and *B*, conventional classifiers such as linear or quadratic discriminant analysis are ineffective since a single boundary, either linear or nonlinear, is inadequate. In contrast, neural methodologies may solve the XOR problem because each node or intermediate function in a neural network is a partial classifier and contributes one boundary to the overall classification. The 'output' nodes of a neural network then utilize these boundaries for building an arbitrary complex frontier.

The XOR classification problem is of paramount importance in pattern recognition and the success of neural networks in such a task domain stems from its ability to solve it. Using neural networks in classification task domains where there is no plausible reason to expect XOR interactions reduces its potential utility when compared with conventional statistical methodologies and substantially increases the risk of overfitting (Hill *et al.*, 1994).

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Moreover, in pattern recognition as in other experimental sciences, samples of required size can be generated artificially. Not so in the social sciences, where samples are in general small and case data cannot be simulated. This gravitates against trying to fit complex relationships between dependent and independent variables as the risk of overfitting increases and the reliability of hold-out sample test is eroded when samples are small.

Thus the important question is whether neural networks may be too powerful an instrument when used for modelling relatively simple relationships using samples of limited size, as is the case in bankruptcy prediction studies.

Literature review: recent trends

To date, most of the authors exploring this subject seem to overlook the above question. They mostly focus on performance, simply comparing the classification results of a neural network approach with those of traditional tools such as linear discriminant analysis (LDA) or logit methodologies. Studies such as Salchenberger *et al.* (1992), Tam and Kiang (1992), Sharda and Wilson (1993), Coats and Fant (1993) and Rahimian *et al.* (1993), report an increase in the rate of correct classification of firms, banks or savings and loans associations as failed and non-failed using neural networks.

Such comparative studies often do not use best practice in their statistical modelling (Chatfield, 1993) and samples are selected on a matched basis leading to the likelihood of bias in any hold-out tests. Most importantly, their neural network models are grossly over-fitted for the number of observations. The most extreme case is Tam and Kiang (1992) who use 19 highly collinear input variables with 10 nodes (190 coefficients fitted) and only 118 cases in model fitting. Numbers of coefficients derived compare with only 4 or 5 in the case of conventional Z-score models (e.g. Altman, 1968; Taffler, 1983).

It is important to single out for comparison a recent study by Altman *et al.* (1994). Drawing on deep knowledge and understanding of the task environment and previous work, as well as the comparative methodologies, these authors find little or no difference in classification performance between neural networks conventional techniques.

Altman *et al.* (1994) derive their models from groups of failed and non-failed companies, each of 400 small and medium size Italian firms, by far the largest sample to date in the literature. In addition, unlike other studies outlined above, Altman *et al.* is a real-world application not a methodological 'test-bed'. Their best neural network which has nine independent variables and, significantly, only five intermediate nodes (45 coefficients estimated) performs no better than the equivalent 11-variable linear discriminant model in classifying the held-out cases.

Altman *et al.*, in particular, point to the problems for the financial analyst posed by illogical network behaviour,[1] as well as stressing the trap of overfitting. In addition, they notice that the derived coefficients are not readily

[1] Changes in the output variable are not monotonically related to small perturbations in input variables considered one at the time. This phenomenon is consistent with the existence of a degree of overfitting and sample bias in the derived model.

interpretable as with discriminant or logit analysis. They conclude (p. 507), conventional discriminant analysis '... proves to be a very effective tool that has the significant advantage for the financial analyst of making the underlying economic and financial model transparent and easy to interpret'. Altman *et al.* also describe how their discriminant models are used in practice by around 30 of the member banks of the *Centrale de Bilanci* in Turin and it is not clear how opaque neural networks could similarly be applied in practice.

The paper by Altman *et al.* adds to the conviction that improvements in performance of predictive models obtained by using powerful, prone to overfitting methodologies, may be meaningless and even misleading when such use is not rooted in theory.

Neural networks and knowledge of bankruptcy processes

Prior to reverting to neural network methodologies, authors should ask whether there is any theoretical reason to support the relevance of XOR-like interactions in explaining how firms go bankrupt. Is it reasonable, for instance, that firms are sound when liquidity and profitability are either large or small whereas firms are in trouble when such features are in opposite directions?

The paper being discussed here is a carefully undertaken empirical study where sensitive issues such as overfitting are treated with due caution. In this, it is clearly a 'second generation' piece of research, resembling recent studies such as Altman *et al.* (1994) rather than the other papers referred to above. However, our knowledge is not advanced by crude comparison of empirical tools alone. Indeed, studies using neural network approaches have yet to add to our understanding of processes leading to bankruptcy.

We hope that, in the near future, a third generation of papers will emerge, where authors explain why do they use neural networks, i.e. why are complex interactions between independent variables expected in their specific task domain. In scientific method, the goal is a better understanding of the issues of concern to the researcher (Tomkins and Groves, 1983: 362; Chua, 1986: 608). The analytical tool used is not of intrinsic interest itself but only a means for elucidating the underlying phenomena. Results of studies failing to apportion a theoretical support to their choice of neural network methodologies will ultimately be regarded as irrelevant.

References

Altman, E. (1968) Financial ratios, discriminant analysis and the prediction of corporate bankruptcy, *Journal of Finance*, **23**(4), 589–609.

Altman, M.G. and Varetto, F. (1994) Corporate distress diagnosis: comparisons using linear discriminant analysis and neural networks (the Italian experience), *Journal of Banking and Finance*, **18**(3), 505–29.

Chatfield, C. (1993) Neural networks: forecasting breakthrough or passing fad? *International Journal of Forecasting*, **9**(1), 1–3.

Chua, W. (1986) Radical developments in accounting thought, *The Accounting Review*, **61**(4), 601–32.

Coats, P. and Fant, F. (1993) Recognising financial distress patterns using a neural network tool, *Financial Management*, **22**(3), 142–65.

Hill, T., Marquez, L., O'Connor, M. and Remus, W. (1994) Artificial neural network models for forecasting and decision making, *International Journal of Forecasting*, **10**(1), 5–15.

Rahimian, E., Singh, S., Thammachote, T. and Virmani, R. (1993) Bankruptcy prediction by neural network. In R. Trippi and E. Turban (eds), *Neural Networks in Finance and Investing*. Chicago: Probus, pp. 159–71.

Rumelhart, D., Hinton, G. and Williams, R. (1986) Learning internal representations by error propagation, *Parallel Distributed Processing*, **1**. The MIT Press.

Salchenberger, L., Cinar, E. and Lash, N. (1992) Neural networks: a new tool for predicting thrift failures, *Decision Sciences*, **23**(4), 899–916.

Sharda, R. and Wilson, R. (1993) Performance comparison issues in neural network experiments for classification problems. In E. Nunamaker and R. Sprague (eds) *Organisational Systems and Technology: Proceedings of the 26 Hawaii International Conference on System Sciences (IV)*. IEEE Computer Society Press, pp. 649–57.

Taffler, R. (1983) The assessment of company solvency and performance using a statistical model, *Accounting and Business Research*, **13**(52), 295–307.

Tam, K. and Kiang, M. (1992) Managerial applications of neural networks: the case of bank failure predictions, *Management Sciences*, **38**(7), 926–47.

Tomkins, C. and Groves, R. (1983) The everyday accountant and researching his reality, *Accounting Organisations and Society*, **8**(4), 361–74.