Industrial applications of neural networks, F. Fogelman, P. Gallinari, eds (World Scientific, 1996)

NEURAL-NETWORK-AIDED PORTFOLIO MANAGEMENT

H. STOPPIGLIA*,**, Y. IDAN**, G. DREYFUS**
** Informatique CDC - Groupe Caisse des Dépôts*
Direction Technique, RDT
113 rue Jean-Marin Naudin
92220 BAGNEUX

*** Ecole Supérieure de Physique et de Chimie Industrielles*
Laboratoire d'Electronique
10, rue Vauquelin
75005 PARIS

The paper presents the design of an automated system assessing the risk of long-term investments. Although the problem is a relatively standard classification problem, it has specific features, especially as far as input selection is concerned. We show that the combination of "neural" and "standard" statistical methods allows us to obtain results similar to those obtained by a heuristic choice of descriptors, but in a more rigorous, principled and reliable fashion. The system is in actual routine use within a large French financial group.

1. Introduction

We describe a neural-network-based aid to the financial analysis of companies, which is in current use for portfolio management with a view to long-term investments, within the Groupe Caisse des Dépôts. The system rates companies into three classes, based on financial ratios. The choice of the relevant inputs, which is a crucial step in the design of a neural network, has been performed in two different ways: heuristically, based on a statistical analysis of the financial data, and through an automatic input selection technique. Interestingly, both methods lead to similar results.

2. Analysis of the available data

Before buying or selling stock of a given company, the portfolio manager performs a financial analysis of the company in order to assess its profitability[1]. The assessment is based on a set of fifteen financial ratios (e.g. working capital/fixed assets, profit after taxes and interest/net worth, etc.) per year from accounting documents (balance sheet and income statement), spanning the past three years (hence a total of 45 ratios). The neural system must rate each company as a A company (a company which is a safe investment), a B company (a company which may be a risky investment at present, but whose evolution should be watched), and a C company (a company which is definitely a risky investment).

The data base comprises 398 companies, with 172 A companies, 172 B companies, and 54 C companies. A preliminary analysis, and discussions with the expert, led to the conclusion that the latter's decision was based essentially on the ratios of the past year, and, even more specifically, on 7 of them. We also looked for significant differences of the mean value and of the standard deviation for the three classes, and found such differences in these 7 ratios.

The distribution of examples was also investigated by principal component analysis. Figure 1 shows the distribution of examples in the plane of the first two eigenvalues, with 45 ratios (Figure 1a) and with 7 ratios (Figure 1b). It is clear that the separation is simpler when the patterns are described by 7 ratios than when they are described by 45 ratios

Whatever the number of ratios, classes A and C are linearly separable; conversely, the separation of class B from classes A and C always requires a non-linear separation, for which neural networks are attractive candidates.

3. **Classification by neural networks**

The first step of the design of the portfolio management aid was a comparison of two sets of descriptors (7 ratios and 45 ratios) and four classification methods :
- pairwise linear separation by 3 independent neurons, without hidden layer,
- pairwise nonlinear separation by 3 separate neural networks with one hidden layer each,
- global nonlinear separation by a neural network with one hidden layer, with 1-out-of-N output encoding (hence 3 output neurons),
- global nonlinear separation by a neural network with one hidden layer, with Softmax outputs[2].

Table 1 shows the percentage of correct classification obtained with these methods. It should be noted that no confusion between classes A and C was found: the only errors are confusions between A and B or between B and C. The results are averages over 100 different partitions of the database into a training set (80 % of the base) and a test set (20 % of the base). For pairwise nonlinear separation of classes A and C from class B, the best results were obtained with 4 hidden neurons (37 weights) in each network when 7 ratios were used; when 45 ratios were used, the best results were obtained with 2 hidden neurons (95 weights) for the separation of A from B, and 3 hidden neurons (139 weights) for the separation of B from C; the decrease of the number of inputs leads to a decrease of the number of weights, hence to a smaller risk of overtraining. The best results are obtained with pairwise nonlinear separators, which have the smallest number of weights.

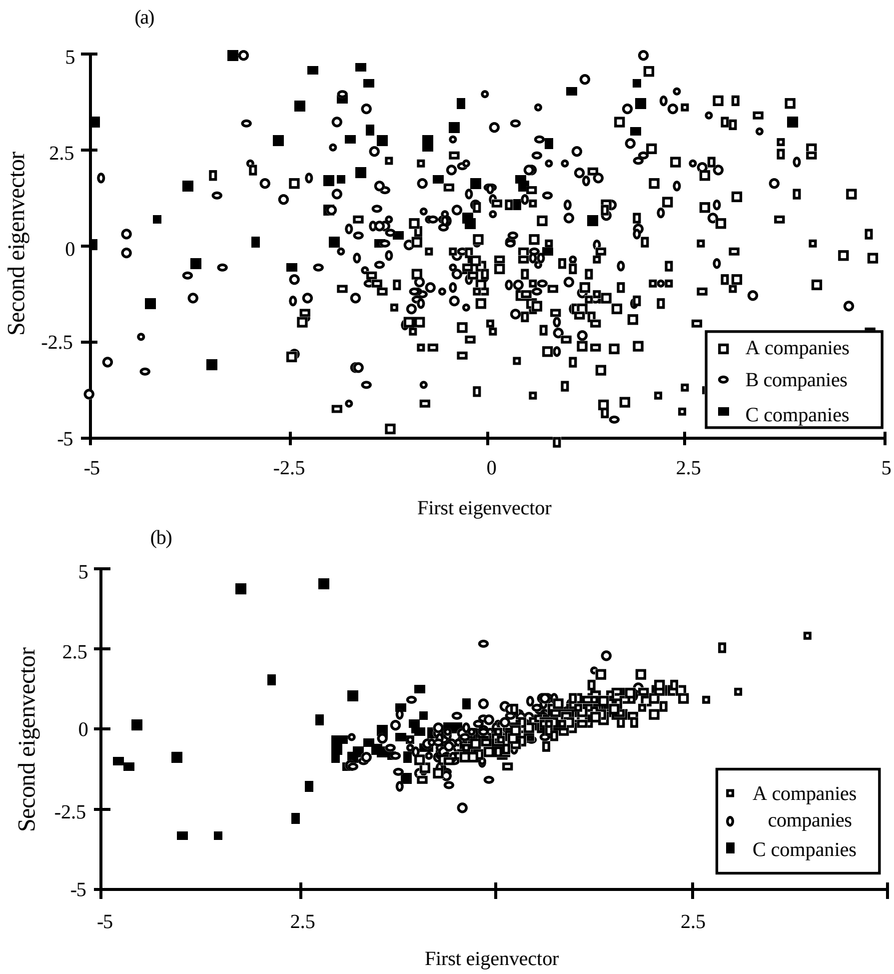

Figure 1 Principal component analysis :
projection on the plane of the first two eigenvectors; (a) 45 ratios - (b) 7 ratios.

Table 1
Average classification rate for the various networks tested.
() : Standard deviation

	45	ratios	7	ratios
	Training	Test	Training	Test
Pairwise linear separation	85.4 % (3.4 %)	80.7 % (3.5 %)	78,5 % (1,8 %)	80,8 % (3,9 %)
Pairwise nonlinear separation	89.5 % (4.5 %)	82.4 % (3.7 %)	87,5 % (3.5 %)	**86.1 % (3.3 %)**
Global nonlinear separation	89.2 % (4.7 %)	79.1 % (3.8 %)	84.2 % (4.4 %)	82.6 % (3.3 %)
Global nonlinear separation with Softmax	91,4 % (6,1 %)	80,2 % (3,5 %)	83,9 % (3,1 %)	83,9 % (3,7 %)

3. **Polynomial classification with automatic input selection**

One of the open problems with neural networks is that of input selection. Since the output of the neural network is not linear with respect to the weights, the input selection methods, which were extensively developed in connection with linear modeling, cannot be taken advantage of. In contrast to neural networks, polynomials (which are not parsimonious since the number of weights grows exponentially with the degree of the polynomial) are linear with respect to the weights. Therefore, in order to substantiate the heuristic result obtained above, namely, that 7 ratios were sufficient, we used polynomial classifiers, for which automatic input selection can be performed. Since pairwise separation gave the best results with neural networks, we investigated pairwise polynomial separators only.

The first step of input selection is the ranking of the inputs in order of decreasing contribution to the output. This is performed in the following way : assume that the output y is a linear combination of the inputs x_i (which are monomials constructed from the n ratios r_1, r_2, r_n); if there are N examples, then an N-vector $\boldsymbol{x}_i$ can be associated to each input i, and an N-vector $\boldsymbol{y}$ can be associated to the output. The input i which has the maximum contribution to the output is such that

$$\cos^2(\boldsymbol{x_i}, \boldsymbol{y}) = \max_j \left[\cos^2(\boldsymbol{x_j}, \boldsymbol{y})\right] \;.$$

Once this input has been selected, all other inputs, and the output, are orthogonalized with respect to the first input. In order to select the second most important input, the same procedure is repeated in the space (of dimension n-1) orthogonal to the first selected input; the remaining inputs and the outputs are orthogonalized with respect to the subspace defined by the first two inputs, and the procedure is repeated until all inputs (or a number of them which is deemed sufficient) are thus ranked.

Starting from the description by 45 ratios, polynomials of degree 3 gave rise to approximately 17,000 monomials. The best results were obtained with 2 inputs and a linear output for the separation of C from A (as mentioned above, these classes are linearly separable), with 40 inputs (monomials up to third degree) for the separation of B and A, and with 30 inputs (also monomials up to third degree) for the separation of C from B. Interestingly, all 7 ratios selected heuristically appear within monomials in the very first selected inputs. One of the advantages of pairwise classification is clearly apparent here: one may use different ratios for different pairwise separation, thus optimizing the parsimony of the classifier.

Instead of using polynomials, i.e. linear combinations of monomials, one may think of using linear combinations of ratio combinations other than monomials, such as sums, products, or ratios of ratios... Finally, it is also possible to use both monomials and the latter combinations. However, the improvement on polynomial classifiers is not significant. The results are summarized in Table 2.

Table 2 Classification with automatic input selection
() : Standard deviation

	Training set	Test set
Polynomials (up to 3rd degree)	90,9 % (2,5 %)	**86,9 % (3,4 %)**
Combinations	91,3 % (2,1 %)	86,7 % (3,2 %)
Polynomials and combinations	91,6 % (2,6 %)	**87,0 % (3,2 %)**

Although the system is in routine use at present, there is still room for many improvements; statistical tests for the selection of inputs[3] are being investigated.

4. **Conclusion**

By using a pragmatic blend of heuristics and statistics, reliable results have been obtained. A set of three neural networks with one hidden layer, performing pairwise class separation, allows the correct classification of over 86 % of the companies considered by the portfolio manager, without serious classification errors.

To date, most tools for the financial rating of companies are based on discriminant analysis[4]. The present method outperformed discriminant analysis, on the same data set, by approximately 5 %.

The system is in current use: every month, the portfolio manager is provided with the ratings of the neural system, with a special emphasis on the companies whose rating changed. Similar applications, in somewhat different fields of financial analysis, are being developed within the Caisse des Dépôts.

Acknowledgments

The authors would like to express their thanks to Léon Personnaz for helpful discussions on model selection.

References

1. E.I. Altman, Corporate Financial Distress and Bankruptcy. (Wiley, 1993).
2 J.S. Bridle, in Neurocomputing, Algorithms, Architectures and Applications, eds. F. Fogelman and J. Hérault (Springer, New York, 1990).
3 See for instance: D. Urbani, P. Roussel-Ragot, L. Personnaz, G. Dreyfus, in Neural Networks for Signal Processing IV (IEEE, 1994).
4 R.M. Miller, Computer-Aided Financial Analysis. (Addison-Wesley, 1991).