TRADITIONAL METHODS IN BANKRUPTCY FORECAST

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REZUMAT. În această lucrare, se prezintă o bază teoretică a metodelor tradiţionale utilizate pentru înţelegerea rolului de reţele neuronale artificiale (RNA) în predicţia de faliment. Rezultă o revizuire cuprinzătoare de aplicaţii reţele neuronale în acest domeniu. Metoda de validare încrucişată este utilizată pentru a examina variaţia între-eşantion de reţele neuronale pentru predicţia faliment. Bazat pe un eşantion corespunzător de firme, constatările indică faptul că reţelele neuronale sunt semnificativ mai bune in predicţie, precum şi estimarea ratei de clasificare. În plus, reţelele neuronale sunt robuste la variaţiile de eşantionare, în performanţă clasificărilor globale.

Cuvinte-cheie: inteligenta artificiala; Reţele neuronale, Predicţii faliment; Clasificare

ABSTRACT. In this paper, we present a theoretical base of the traditional methods used for understanding the role of artificial neural networks (ANNs) in bankruptcy prediction. We give a comprehensive review of neural network applications in this area. The method of crossvalidation is used to examine the between-sample variation of neural networks for bankruptcy prediction. Based on a matched sample of firms, our findings indicate that neural networks are signicantly better in prediction as well as classification rate estimation. In addition, neural networks are robust to sampling variations in overall classication performance.

Key-words: Artificial intelligence; Neural networks; Bankruptcy prediction; Classification

1. INTRODUCTION

Forecasting has been called both an art and a science. It is an ability to recognize patterns through a logica land analytical approach. With today's forecasting techniques, managers are able to understant the future better than managers of past eras.

Prediction of bankruptcy has long been an important topic and has been studied extensively in the accounting and finance literature.

In using neural networks, the entire available data set is usually randomly divided into a trening (in-sample) set and a test (out-of-sample) set. The training set is used for neural network model building and the test set is used to evaluate the predictive capability of the model.

1. Beaver model

The studies regarding the behavior of financial rates at the bankrupt companies are datet back almost seventy years. However one of the initiators is considered Beaver. He studied based on univariate analysis, the financial situation of a sample of 79 non-bankrupt firms.

Beaver was supported in his study on the concept of cash flow.

- The larger the reservoir, the lower the probability of bankruptcy.
- The higher the workflow, the lower the probability of bankruptcy.
- The greater the flow of operational costs, the greater the probability of bankruptcy.
- The greater the amount of debt, the greater the probability of bankruptcy.

Based on these ideas, the average value of five financial rates differ significantly from bankrupt companies group to non - bankrupt companies group.

Financial variables used by Beaver

Selection of financial rates was based on three criterias:

- Their popularity in the literature
- Performance rates in previous studies
- Adherence to the concept of cash flow

After analyzing the performance of rates, it was proved that the debt coverage rate with cash - flow is the the best predictor.

The main advantages of the study are:

- to provide a high predictability based on a relatively simple model.
- to provide a theoretical point of discussion on the results of the study.

Table 1

Financial rates	**Prediction**
1. Cash-flow / Total assets	Non-bankrupt> bankrupt
2. Net Profit / Total assets	Non-bankrupt> bankrupt
3. Total debt / Total assets	Non-bankrupt> bankrupt
4. Working capital / Total assets	Non-bankrupt> bankrupt
5. Current liquidity	Non-bankrupt> bankrupt

2. Băileşteanu model

Strating from traditional studies it is considered that the states which precede the appearance bankruptcy are:
- Failure of paying current obligations.
- Lack of financial resources to repay loans.
- Late collection of high-value products delivered.
- Recording of losses.

Without specifying how the choice of variables, are proposed:

$$G1,\ \text{General liquidity} = \frac{\text{current assets}}{\text{current liabilities}}$$

$$G2,\ \text{Solvency} = \frac{\text{Net profit + depreciation}}{\text{Credit refunded + interest rate}}$$

$$G3,\ \text{Client rotation} = \frac{\text{Turnover}}{\text{Customer}}$$

$$G4,\ \text{Cost-effectiveness} = \frac{\text{profit}}{\text{cost}} \times 100$$

The function is:

B = 0,444 G1 + 0,909 G2 + 0,0526 G3 + 0,0333 G4 + 1,414

B has a maximum value equal to 4 and a minimum value equal to -1,4.

The value function recorded is considered:
- B <0,5 - imminent bankruptcy
- 0,5 <B <1,1 - limited area;
- 1,1 <B <2,0 - intermediate zone;
- B> 2,0 - favorable area;

3. The Z score

Construction of Z score for the Romanian economy is based on a sample of 276 companies belonging to 12 sectors of national economy; enterprises were chosen on a random basis, without knowing their names, only the numeric codes that express the branch code (the first two digits) and enterprise code in the branch (the nest three digits).

The analysis took into account the period 1994-1998 and initial used a number of 20 economic and financial indicators.

Financial rates adopted in the approach of establishing the financial profile was classified into five groups, each covering a interest of a particular group of analyze users:
- Activity rate
- Liquidity rate
- Leverage rate
- Rentability rate
- Other financial and economic information

The activity indicators retain a particular interest for business partners and management. The recovery period of receivables or the payment of debt represent a very interesting information for those who provide / purchase products to / from this branch. Also, the rotation of stocks or total assets is a key parameter for evaluating the quality and ability of management.

The liquidity rates show the ability of firms to deal with payments due. They are mainly used by short-term sponsors.

Rentability rates are mainly seen by capital providers (other than shareholders) because this rates highlight the dependence of capital attracted or borrowed, the adequacy of cash flow at the borrowed level etc.

The rentability rates has as mainly users the shareholders, but in equal measure and management. In developed countries, the financial rentability rates depends, in many cases, on the maintaining or changing of management.

The "other information" group retain specific financial indicators determined by the national economy (financial blockage problem, the situation of recording part of the depreciation off-balance, etc.) and financial rates useful to others (example "dividend rate" is interesting for the minor investors).

After selecting the indicators which achieved the best discrimination there were retained four financial variables: revenue rentability rate, coverage rate of liabilities with cash flow, leverage of the assets and the payment period of obligations.

XI - Net profit / income;
X2 = Cash-Flow/Active

X3 = Liabilities / Assets
X4 = (Liabilities / Turnover) x 360

In the two groups in previous assumptions there is a function score A which represents the best discrimination.

$$A = c + ajXj + a_2X_2 + .. \;\; \boldsymbol{a;X_2} + \ldots + \boldsymbol{a_nX_{,,}}$$

where
a, - weight coefficients;
c - constant, and X,, financial variables. It results the follows values of weight coefficients a,-.

$a_1 =$ 6,3718
$a_2 =$ 5,3932
$a_3 =$ -5,1427
$a_4 =$ -0,0105

In addition, it is considered a constant c – 5,676.

In summary the score function is:

A = 5,676 + 6,3718 XI + 5,3932 X2 - 5,1427 X3 - 0,0105 X4

And the appreciation is based on the following classification

Risk assessment in the model A

A < 0	- failure / failure
0 > A < 2,05	- the uncertainty
A > 2,05	- non-bankruptcy

Bankruptcy 0,0 > Z > 2,05 favorable situation

4. CONCLUSIONS

The application of neural networks has been reported in many recent studies of bankruptcy prediction. However, the mechanism of neural networks in predicting bankruptcy or in general classification is not well understood. Without a clear understanding of how neural networks operate, it will be di•cult to reap full potentials of this technique. This paper attempts to bridge the gap between the theoretical development and the real world applications of ANNs.

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