A neural network model to forecast and describe bond ratings

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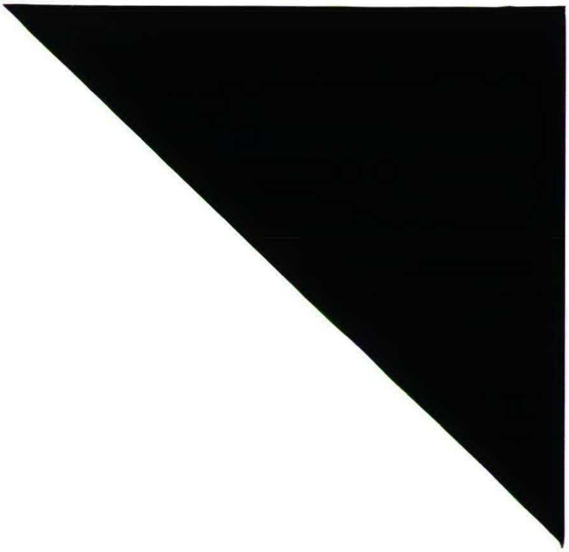

A neural network model to forecast and describe bond ratings

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This is a brief introduction to the research project conducted by Bart Kamp at Tilburg University, Department of Accounting & Auditing. The reader needs to have some general knowledge about financial accounting is assumed. No advance knowledge of neural networks is assumed. The description of neural networks in this paper will be general. More technical details are presented in the appendix, but these are not necessary to comprehend the paper.

Contents:

1. Introduction and summary

This paper presents a number of research items from a research project on the function of financial statements in assessing the solvency of a company. This function is discussed in Part I of this paper. Here, the operationalization of solvency is discussed. This is achieved by using bond ratings as a proxy for solvency. Subsequently, several statistical methods are described of models simulating bond ratings. At the end of Part I, neural networks are introduced as possible outperformers of conventional statistical models.

In Part II is a description given of how bond ratings can be simulated by neural networks. A number of methodological problems are discussed, and tentative results of developed neural networks are presented.

Part I Background of the problem

1.1 Introduction

In the literature on this subject, the interpretation of financial statements is not well-defined. Although the objective of financial statements seems clear, providing insight into the equity and profit of the firm, in practice the analysis of financial statements lacks structural methods. This may be due to an inability to define an all-purpose concept of profit and the uncertain future.
But even if different concepts of profit are recognized, there is no single theory which explains in which case each concept is applicable. The applicable concept of profit may be not only dependent on the firm, but also on the type of user of the financial statement.
These dependencies are largely unknown.

However, financial statements are widely used. Research shows that financial analysts for instance regard financial statements as very important.
The analysis of financial statements is supported by a large number of ratios. The choice and interpretation of these ratios is based on the judgment of the analyst. With experience, the analyst might be able to recognise trends or problem areas.

However, in many cases the specific purpose of the financial analysis is rather vague. Investment brokers often conclude their analysis with a Buy, Hold or Sell recommendation. This is a rather broad area of analysis and, therefore, hard to operationalize for further study.
Therefore, the bond rating was chosen as object for further study. The objective of bond rating analysis is straightforward: will the analyzed firm be able to pay interest and redemption on the maturity date of the issued bond? In other words, this is an assessment of the solvency of the firm.
The result of this analysis is presented in an easy to understand form: a rating which can range from AAA (very reliable) to D (in default).

In this study, an attempt was made to gain insight of the use of financial statements by bond rating agencies. If more is known about the real needs of (this category of) users, recommendations for improving financial accounting can be more objective-related.

1.2 Bond ratings

Bond ratings are prepared by bond rating agencies. The most well-known bond rating agencies are US-based. In this investigation, only these agencies were considered. Although bond rating agencies are private enterprises, their function is a semi-government. The two major agencies are the Moody's Corporation and Standard & Poor's. Other well known agencies are Fitch and Duff & Phelps.
Moody's and S&P rate the majority of all bonds outstanding. This is done on the request of the issuing company or on their own initiative. Municipal bonds issued by (local) public services as well as corporate issues are rated. In this study, the rating of corporate (industrial) debt are investigated.

Bond ratings are presented in the form of a letter combination. The highest rating is AAA (S&P) or Aaa (Moody's). The ratings descend through AA, A, BBB, BB etc. (Aa, A, Baa, Ba for Moody's) to D, the rating for issues in default.
The meaning of the ratings of both S&P and Moody's are equivalent. In practice, a major division is made at ratings of BBB (Baa). Ratings of BBB (Baa) and higher are considered 'investment grade', which means that these issues are relatively safe. Ratings below BBB (Baa) are considered speculative issues (junk bonds).

The bond rating agencies likewise regard this point as the major distinction. Positive elements in their analysis will raise the rating above BBB (Baa), negative elements will decrease the rating below this level.

The definition of bond ratings implies that a rating is applied to a specific bond issue, not to the entire company. In practice, this distinction may be not that relevant. If a rating is applied strictly to a specific issue, one may expect that the rating will tend to move to one of the extremes when it approaches maturity. If a loan matures within one month, the uncertainty about a possible default will be very low, so that the rating would be AAA or D, but not a middle rating. In practice however, this movement does not exist. In general, redemption of a bond is realised through the issue of a new bond (or another form of financing). The success of this new issue depends on the financial health of the company (in the broadest sense). Thus, since the financing by bonds is a continuous process, the rating of a specific bond equals a rating that can be applied to the entire company.
In general, if a company has issued several bonds, they all will have (almost) the same rating. Some differences may occur between different issues, but these are due to differences in indenture (see Indenture).

The bond rating agencies are reluctant to present a detailed description of their analysis procedures. This is because bond ratings are to a large extent based on judgments. These judgments might be hard to explain using only sound and logical arguments. The agencies argue that if they have to explain the analysis in detail, they will have to stick to 'hard' figures. The resulting lack of 'soft' information and judgment will diminish the quality of the rating.

1.3 The role of bond ratings on financial markets

Bond ratings are regarded as reliable and unbiased estimates of solvency.
Since demanded return on loans vary with the level of risk incurred, interest yields relate strongly to bond ratings. Thus, the bond rating influences the interest costs of the firm.

Bond rating agencies stress that the ratings are not a recommendation to buy, hold, or sell. A rating is only an indication of the default risk. It is up to the investor to decide whether a certain bond matches his risk preferences.
In this fashion, bond ratings play a role in the access to the financial market. Most insurance companies and saving banks are statutory or legally restricted to invest their funds in investment-grade bonds. Because of this restriction, the issue of higher-risk bonds is more difficult.

Several investment models for bond trading include the bond rating as a variable. One of the underlying hypotheses is that since the interest risk is a more significant part of the total risk for high-rated bonds than for low-rated bonds (which contain an additional default risk), high-rated bonds will react more strongly to interest changes than low-rated bonds.

These points indicate that bond ratings play an important role on the bond market.

1.4 The bond-rating process

When a company plans a bond issue, an application form for a rating can be sent to one of the bond-rating agencies. After acceptance, the agency holds what could be termed a type of audit. A team of analysts prepares reports on the company. The main sources of information are:
-financial statements of the previous years
-issue contracts
-market-development information
-discussion with the board of directors

Based on this information, forecasts are prepared regarding the cash-flow capacity and estimated profits.
Although bond-rating agencies regard themselves as outsiders to the company, they may receive more information than the general public. Several authors have previously pointed out the internal company forecasts that are presented to the bond rating-analysts.
The agencies claim that the real contents of the forecast are not as important as the fact that the company does have a forecast. Having forecasts indicates that the company is aware of those future events that may influence the health of the company.
Other non-public information is also presented to the analysts, for example, the VAR of Dutch banks.

Analysis by bond rating analysts is directed at 5 areas:
-Liquidity
-Profitability
-Indenture (the legal structure of the issue and the rights of creditors)
-Asset protection (value of the assets if sold at default)
-Quality of the management

Liquidity and profitability

Liquidity (cash generating power) and profitability are objects of financial analysis. Several handbooks regarding the analysis of financial statements are currently available. However, these books focus on the meaning of the distinctive elements of the financial statements, such as definitions of goodwill, deferred taxes, etc. .
The use of these figures is always described in terms of ratio analysis. Several common ratios are discussed, such as the leverage ratio (equity/debt), the coverage ratio (interest and other fixed costs/net profit or cash flow) and current ratio. Surprisingly, no alternative approaches to financial statement analysis other than ratio analysis were found in the process of this investigation. Apparently, there are no methods or conceptual frameworks for dealing with non-quantitative information in financial statements.

Financial analysis as it is described in literature does not answer such questions as:

-How do financial statements relate to other sources of information regarding solvency? Dutch law states that financial statements should inform about solvency (and liquidity) *as far as the nature of financial statements makes this possible*. The reserve regarding the nature of financial statement may point to the lack of explicit future-oriented information. However, taking into account the perceived relevance of financial statements by analysts, this lack does not prohibit the use of financial statements. Apparently, relevant information is included in an implicit manor. In the current investigation an attempt was made to identify these possibilities and constraints of the use of financial statements.

-Which ratios does one need in order to assess the solvency? In the literature, some authors have criticized the theoretical foundation of common ratios.

-How can different methods of accounting be dealt with? Most methods are based on the assumption of 'going concern'. If your analysis is directed at testing this assumption (i.e., solvency = 'will the concern continue to 'go'?'), will this assumption cause bias?

-How can one best decide between profit oriented ratios and cash flow oriented ratios? Some authors regard cash flow as more relevant than profit, but there is little relevant theory about the use of the statement of funds.

-How can ratios be interpreted?
Ratios are not integrated to any kind of overall assessment model. For each ratio, the analyst has to use his judgment in appraising the level of the calculated ratio. Some authors point out that ratio analysis is only a first tool for indicating potential problem areas. Whether additional information is available for exploring potential problem areas in

more detail is, however, not discussed.

Rating agencies state that the stability of relevant ratios is more important than the actual level. Rating agencies dislike surprises. They expect the management of the issuer firmto inform them in a timely manner of negative developments in market conditions. Unexpected bad news will result in a stronger downgrading than anticipated bad news.

Indenture

The contracts of bond issues contain restrictions or constraints and legal claims to protect the bond holders.
Research has revealed that 90% of all indenture provisions found in practice can be categorised into one of four groups:

-lien restriction: the firm is restricted in issuing additional secured debt.
-sale-and-lease-back restriction: this prohibits the increase of leverage by sale and lease back contracts.
-debt restriction: the leverage is restricted to a maximum (measured by a defined ratio)
-dividend restriction: this restricts the pay-out of dividends to certain limits. Otherwise wealth can be transferred from bond holders to shareholders.

The degree to which indenture is included in the issue is a trade-off. If severe constraints are implemented, the firm will not be able to accept some worthy opportunities because indenture provisions will prohibit this. For example, Chrysler almost collapsed because it was not allowed to raise extra secured debt in order to finance reorganisation. On the other hand, extensive indenture provisions will raise the level of the bond rating, which will result in lower interest costs.

Some authors stress the importance of indenture provisions in bond-rating models. This can be regarded as doubtful. First, investigations have revealed that 40% of all issues do not have any indenture provisions described above. Second, a bond rating is, theoretically at least, given to a specific issue, not to the entire company. Many companies have several issues outstanding. In general, the bond ratings of the issues of the same company have the same bond rating. Only minor differences may appear, for example an added + or -. In the literature, these differences are directed at differences in indenture. Apparently, the influence of indenture may be rather modest.

Asset protection

If a company is not able to meet its obligations, the assets will be sold to raise cash for the creditors, as a last resort. The amounts presented on the balance sheet are, however, no indication of the realisable revenues in such circumstances. If default is not expected, the balance sheet contains the costs of the assets (whether based on historical cost or current cost) to be deferred to future periods. Thus, these amounts are not related to the receivable revenue in the event of immediate sale of the asset.

For some assets, a forced sale will have a stronger impact on the realisable price than for others. Highly industry-specific machines may be hard to sell, while fast-moving inventory items may be easy to sell. This kind of liquidity is not always assessable from the financial statements. A description of the assets in the notes to the financial statements may reveal this to some extent.

Asset protection only plays a role at the moment the company does, in fact, collapse. If the company has good prospects, asset protection is not important. Therefore, the rating agencies state that asset protection is of limited relevance.

Quality of management

Quality of management is assessed by reviewing the history of the firm, the ability of the management to make forecasts and other management skills. The analysts also review the recruitment and outplacement of management. A high rate of change in managers may indicate instability in the firm's policies.

To illustrate the distribution of bond ratings, the appendix presents the S&P ratings of a number of well-known companies.

1.5 Simulation of bond ratings

In the last three decades, attempts have been made to explain and predict bond ratings by statistical means.
One of the purposes is to predict changes of bond ratings. The ability to anticipate on these expected changes could be an advantage when the trading in bonds.
Another purpose is more scientifically oriented. Simulation could help in describing the process of financial analysis and in lifting the lid of the black box called 'judgment'.

1.5.1 The purpose of bond-rating simulation

The purpose of simulating bond ratings in this study is to gain more insight into the relevance of financial statement figures in relation to solvency.
When possible, also variables which are not in the financial statements but may be suitable for inclusion in the annual accounts will be included. If these data prove to be relevant, inclusion of these figures in the financial statements could be recommended.

Some consideration should be given to the fact that bond ratings are subjective opinions about solvency. A more direct method of obtaining an assessment of solvency could be observing actual default.
Several studies have been made to the prediction of default. The most famous study resulted in the Altman Z-score model. This model is limited in that it calculates only two possibilities: the company will default of it will not default (within a specific time-horizon). Bond ratings offer a more diverse scale of financial health.

1.5.2 Statistical tools

Several analytical tools of simulation can be used. The main tools are regression analysis and multiple discriminant analysis.
These tools are non-model tools, which means that no assumptions of the underlying model is required. Input variables are simply fitted to the corresponding output. The results of these models are moderate.

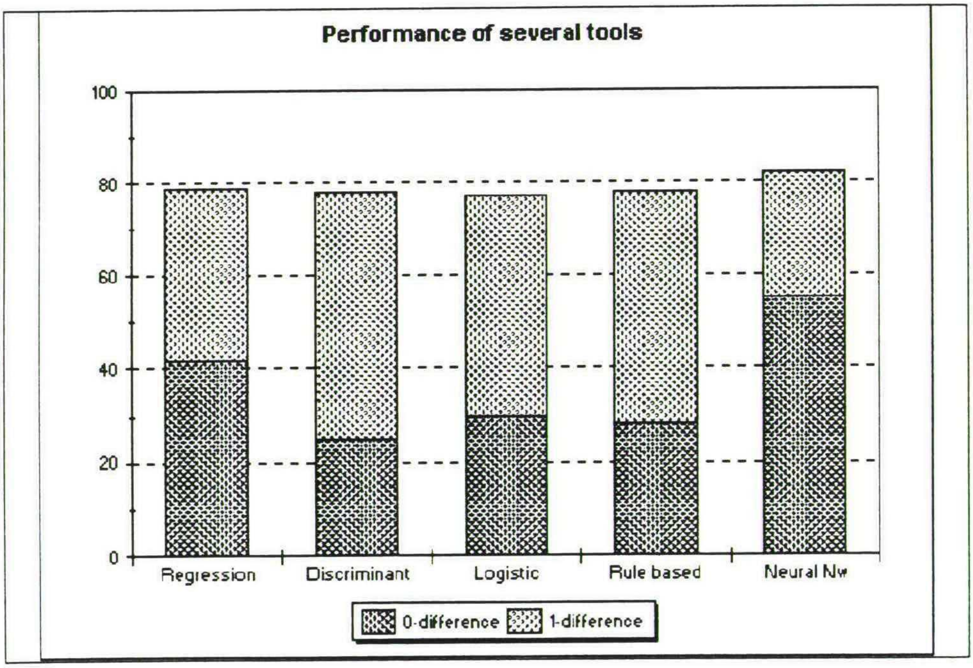
Another category is that of expert systems. These models are based on rules obtained by observing and interview of 'experts'. In the case of bond ratings, this means that the bond rating analysts is asked how they reache to a rating. Then this method is described in logical rules and programmed into a computer.
A major drawback of expert systems is that experts are not always capable of explaining their decisions. Many decisions are made based on judgment and experience.
In the literature, there were some references to expert systems on the area of credit rating by banks. This credit rating is related to the bond rating process but only to a limited extent. The bank decision is an accept/not accept problem and the methods may differ from bank to bank. There is no generally accepted standard for this kind of solvency rating.
Since rating agencies stress the importance of judgment and the fact that a rating is a compromise decision of several analysts, application of expert systems would not appear to be very appropriate.

Since 1990 several new forms of Artificial Intelligence raised quickly in development, such as machine learning and neural networks.

Part II Neural networks

2.1 Reasons for using neural networks

Neural networks are a type of statistical tool. Neural networks are able to recognise non-linear patterns in data. Examples of inputs with the corresponding outputs are presented to the network. By making slight adjustments to its model each time an example is presented, the neural network fits its model to any pattern in the data. This process of continuous adjusting of its model is called 'learning': at the start, the network is not able to recognise the relations between inputs and outputs, but each time a new example is presented, it learns a bit how inputs relate to outputs. (for more technical details, see the appendix.)
Similar to regression and multiple discriminant analysis, neural networks require do not require assumptions about the underlying model.
(To prevent misunderstanding: neural networks are *software* products and do not need special kinds of computers. Computer networks such as LAN or otherwise connected computers have nothing to do with neural networks.)



Several studies have explored the performances of neural networks in bond-rating classification. Jun Woo Kim made a comparison of the performance of neural networks, regression-, discriminant-, logistic analysis and rule based systems. The predictive power of these tools are presented in the chart.

2.1.1 Reasons for building a new bond-rating neural network

The literature on developed models does not specify the details of the neural network architecture. Therefore, one cannot study the significance of the used input variables, or make adjustments to customize the model for further study.

Second, the numbers of patterns used are limited and often the patterns are restricted to investment grade bond ratings (= ratings higher than average). If more patterns are used, the model may be improved.

Another problem is the type of variables used in these neural networks. A neural network model developed by Dutta included variables such as "projected next 5 year revenue growth rate" and "subjective prospect of company".
Due to their subjective nature, these variables may be biased by the researcher since the researcher may be aware of the actual ratings. This would invalidate the model, since the input would already implicitely contain the corresponding output. In other words, such a model has no predictive power. If a prediction has to be made for a bond rating of an unknown company, except for the financial statements, the model cannot be used since the value of the input variable "subjective prospect of company" is unknown. If this variable would be known, the solvency is known, even without using the model.

To extend the model to all bond ratings, and using other financial statement input variables, I am preparing neural network models myself.

Another reason for using neural networks is that, although the image of neural networks is complex, their use is rather easy. At a conference on neural networks at the Technical University in Delft, the statement "Neural networks, statistics for amateurs" was defended. With neural networks the user does not have to bother (in fact: *cannot* bother) with autocorrelation, t-statistics and other considerations crucial in the application of regression analysis. This may be an advantage, but, of course, there are disadvantages (see section 2.3). In the future, neural networks might be applied in several areas of business science, including auditing. For example, some companies use neural networks for the detection of fraud. In such cases, the auditor has to be convinced of the reliability of this internal control tool. This research may be a first step in making neural networks more familiar in the auditing profession.

2.2 Building a neural network

In order to achieve sufficient capacity for learning, the neural network requires a lot of examples. The more examples it is given, the better it can recognise general patterns.
Neural networks described in literature use approximately 150 to 250 examples. These examples include only investment grade ratings or ratings of B and higher.
In order to make the domain of the model more complete, all rating categories are used and the number of examples was increased. Currently, approximately 600 examples have been collected, although for some of the examples the number of variables per example is yet rather small. There is a database with an extended set of variables for 300 examples.

The choice of variables included in the model is based on publications of the bond rating agencies and theoretical relations between financial statements and solvency. Examples of possible variables are:
-equity to debt
-interest to cash flow
-total balance
-dividend payout ratio

Using dummy variables makes possible the use of variables such as business industry. Using more than one year's figures, it is possible to calculate additional variables regarding average values and the stability measures of used ratios.

2.3 General problems in building neural networks

Although neural networks can make models of classification problems, they have some serious shortcomings.
The most remarkable shortcoming is that a neural network does not reveal its "internal representation" (i.e. the structure of its solution of the problem). Observing the neural network, it is very difficult/impossible to explain how the neural network made its classification. In regression models, one can see through the regression formula, in which manner a variable influences the output. In theory, a neural network model can be written as a formula, but this formula is extremely complex. All of the variables are put together and then redistributed in a complex manner. Thus, there is no clear-cut relation between input and output. Currently, the internal representation of neural networks is a black box.
This problem is inherent in the use of this sort of tools. Since 'easy' linear models such as regression are not appropriate, one may chose a non-linear model such as neural networks. But in that case it is obvious that the resulting model is harder to understand than a simple model.

Due to this black box, it is not possible to enter information about the relations the user already knows. For example, there are rules of thumb stating that AA-rated companies have some minimal level of certain ratios, or that in a specific industry ratings higher than AA are rare. This kind of information cannot be implemented in a neural network. The network has to find this out by itself.
Neural networks are therefore fundamentally different from expert systems. (Expert systems are sets of consistent logical rules, derived from human experts).

Also the way in which neural networks learn is largely unknown. Although the calculations performed in each neuron and the calculation of the weight adjustment is known, the dynamics are hard to predict. How a neural network converges to an optimal setting of the weights is not clear. Thus, it is hard to say which variables are important. Using regression analysis, one can select the relevant variables based on assumptions of the distribution of certain elements (for example, a normal distribution of the residuals). Since neural networks are nonlinear, these assumptions are not valid, so these advanced statistics cannot be used.

These shortcomings imply that there are no general rules for constructing a neural network. One should try several different architectures on a trial and error basis. In discussion with colleague-neural network engineers, I obtained several rules of thumb for some problem areas.

This results in a remarkable paradox. It is possible to construct a model of a difficult problem which performs well, but you do not know how it operates. Thus, it is much easier to make a prediction using neural networks than to describe the process of prediction.

On the other hand, this problem is only an extreme on a scale which is also applicable for other methods, for example regression analysis. The regression coefficient is also a rather complex formula. It is hard to understand at first sight why this formula minimizes the squared residuals ("BLUE", Best Linear Unbiased Estimator). The acceptance of regression is more a matter of tradition than full understanding of its characteristics by most users.

There seems to be some development in assessing a better insight into the role of the several variables, but this is still in a experimental stage.

2.4 Results up to now

As many ratings as possible ratings were selected from Standard & Poor's Bond Guide November 1993. The bond guide contains additional information like several key ratios for most companies. More than 600 companies were eligible for inclusion in the model. The key ratios are:
-fixed charge coverage 1990, 1991, 1992
-cash & equivalents
-current assets
-current liabilities
-long term debt
-capitalization
-total debt to capital

From the total set of patterns, approximately 50 patterns are set aside for testing purposes. The remaining patterns are used for training. Thus, the number of training patterns is far larger than earlier (neural network) models. The number and nature of the variables is, however, restricted to the figures given in the bond guide. For example, ratios regarding cash flow and the sort of industry are not used in this model. Neither are corrections made for differing accounting methods.

After several trainings using different architectures and learning paradigms the best models predict 60% to 65% of the test set correctly. Only 5% to 8% of the test set had an error of more than one rating category (i.e., a prediction of BBB while the actual rating is B). (Each model took 10 to 20 minutes training time.) This almost outperforms the conventional models. A direct comparison is not possible since the range of ratings in the conventional models are restricted to investment grade ratings.

Models that should predict whether a company has an investment grade rating or a speculative rating predict more than 90% correctly. Taking into account the limited set of variables, this is a remarkable result.

Other data are downloaded from Datastream, resulting in a total of 45 possible variables. A rule of thumb says that one needs some variables with high correlations with the output, and some variables with small correlations. Like other statistics, variables should not be correlated with each other (multicollinearity).
The four variables with the highest correlation (in absolute terms) with the quantified bond rating are:

-average fixed charge coverage (logarithm)	-0.70
-cash flow/total debt	-0.59
-average net profit	-0.57
-total debt to capital	0.54

Finding these variables as the highest correlated variables is supported by the literature on financial statement analysis. The signs of the correlations are also in line with the theory.

Using these variables, the neural network can predict 60% correctly. Leaving the average interest coverage out, the performance decreases to 56%. (This small decrease may be due to the moderate collinearity with the other variables).

Adding the next four highest correlated variables (equity, current liabilities, current assets and total return) resulted in a 58% performance.
It can be noted that most figures presented in the Bond Guide are positioned in the upper region of correlated variables.

Using only the four least-correlated variables (debtors' days, creditors' days, stock days and the stability of capital leverage) resulted in a 30% performance.

2.5 Directions for further research

The performance of the neural networks are slightly better than conventional models. Their predictions are at least as good as the conventional models, but use fewer variables. Performance may be improved by a better selection of variables and network design. One of the possibilities is to explore the potentials of the Altman Z-score as a variable. Likewise, other variables used in earlier models have not yet been included.
Industry-indicating variables may be relevant and it may be possible to develop industry-specific models. For example, there are large sub-sets of oil companies and gas & electric distributors in the total pattern-set.

Likewise, models restricted to investment grade/speculative grade classification may be interesting, since this is the major distinction between "good" and "doubtful" companies.

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Appendix: Well-known companies with their Standard & Poor's bond rating at April 1994.

General Electric	AAA
Kellogg	AAA
Chesebrough-Pond's	AAA
Exxon	AAA
Shell	AAA
Boeing	AA
Mobil	AA
Procter & Gamble	AA
Mc Donald's	AA
Dow Jones	AA
Heinz	AA
Coca Cola	AA
Walt Disney	AA-
Merrill Lynch	A+
Gilette	A+
Colgate-Palmolive	A+
PepsiCo	A
Xerox	A
Texas Instruments	A
Philip Morris	A
IBM	A
Dow Chemical	A
Ford	A
American Express	A
Digital Equipment	A-
Lockheed	A-
Reebok	A-
Kodak	A-
Polaroid	BBB+
Hertz	BBB+
Mc Donnell Douglas	BBB
Union Carbide	BBB
Chrysler	BBB
Black & Decker	BBB-
Mattel	BBB-
Chiquita	BB
Delta Airlines	BB
Unisys	BB-
Playtex	B+
Trump Plaza	B
Seven Up	B-
Memorex	C

Technical details of the bond-rating neural network model

The total pattern set contains 254 patterns of bond ratings with corresponding financial statement figures and ratios. The bond ratings are selected from the Standard & Poor's Bond Guide, April 1994. From this total set 54 patterns were set aside for testing purposes (test set). The remaining patterns were used for training.

Output definition

The bond ratings in the pattern set vary from AAA to CCC. In practice, bond ratings are refined by added + and - signs (for example: AA+, AA and AA-). As in other bond rating models, this refinement was neglected, so AA+, AA and AA- were considered as AA. This results in seven possible ratings.
These seven outputs can be quantified using one of several methods. The most straightforward form is assigning the value 1 to AAA and 7 to CCC. This has some theoretical disadvantages.
Using this definition, AAA (1) is twice as good as AA (2), or AA is three times as good as B (6). This fictive relation is not supported by the real descriptions of the meaning of the distintive ratings. Secondly, this definition neglects the importance of the distinction between investment grade (BBB and above) and speculative grade (lower than BBB): in this definition the distance between BBB and BB is equal to the distance between other ratings. In practice, the distance between investment grade and speculative grade is more significant than the distances between other ratings. This can be solved by creating an extra space between BBB and BB (4,6) but it would remain arbitrary. Thirdly, the range from 1 to 7 is rather broad; the relative difference between 3 and 4 is small. This might cause problems of exact distinction in the neural network.

A general method of output definition for classification purposes is a "binary" definition. The values of 1 to 7 are translated to 0 to 6 and rewritten in binary figures:

```
0= 000
1= 001
2= 010
3= 011
4= 100
5= 101
6= 110
```

These binary figures are split into three columns, with each column serving as an output variable. This method maximizes the relative differences in variable values. A variable is either 0 or 1, but not a value in between. However, the ordinal characteristic of the bond ratings are lost. For example, the output column on the right oscillates from 0 to 1 for each next rating level. This method of output definition is more suited to non-ordinal classification problems.

In the following scheme the two methods were combined:

```
0= 000000
1= 000001
2= 000011
3= 000111
4= 001111
5= 011111
6= 111111
```

This scheme results in 6 output variables. This output definition has ordinal characteristics without there being equal differences between the several outputs. The disadvantage is that it requires a higher number of output variables which makes the model more complex.

Choosing input variables

One of the main problems with neural networks is how to choose which variables to include in the model. There are no analytical methods for finding the appropriate explanatory variables.
A high correlation with the output may be important, but is not sufficient. The four variables with the highest correlation, correlate moderately in relation to each other, which is assumed to be less desirable.

Number of neurons

The neural network package called Brainmaker has the option of adding neurons during training. If performance does not increase over a specified number of epochs, an extra neuron is automatically added. A neural network with one hidden layer was trained, starting with 3 hidden neurons with the neuron adding feature switched on. Each time a neuron was added, the network was saved to disk after ten epochs. (Saving just before the addition is not possible since this addition is not announced. Saving the network shortly after the adding results in inferior networks, since the weights of the new neuron will still be quite random).
After reaching a model of 35 hidden neurons, the training was stopped and each saved network was tested using the test set.
The performance of the models with 12 to 30 was almost equal. The 35 neuron model performed worse. Therefore, the number of hidden neurons should be around 12, since a higher number increases the complexity of the model without increasing the performance.

Number of hidden layers

Experimenting with different numbers of hidden layers, with and without jumping connections, showed no significant increase in performance in comparison with one hidden layer.

Activation function

Experimenting with tangent-hyperbolic functions instead of the sigmoid function showed no increase in performance. In the literature, a linear function in the output layer is recommended but this did not increase the performance.

Scaling of input

Input values are not scaled between the minimums and maximums of the total pattern set since the input contains some very extreme values. Therefore, the scaling edges are set in such a way that approximately 95% of the patterns fit into the scaling range.
If an input falls outside this range, the scaling may be restricted to the scaling max or min, or exceed these values (in NN-terms: [1,-1] versus <1,-1>). Restriction to the scaling range did not increase the performance.

Learning parameters

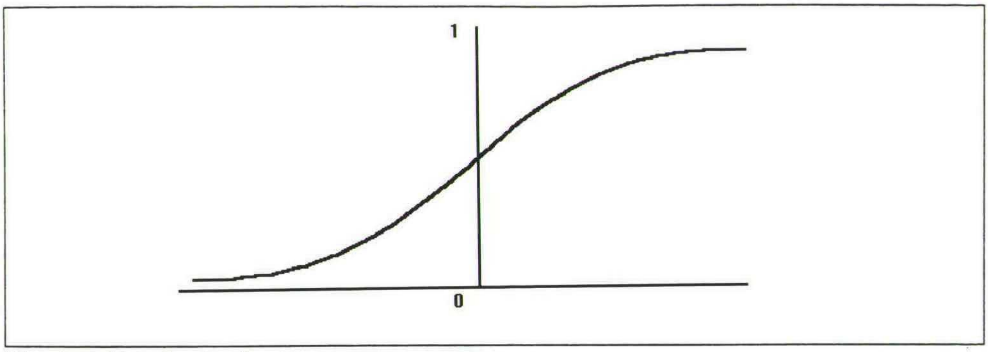
All trainings were performed using backpropagation. Several settings of learning rate and momentum were used. Batch weight update methods were also used. Batch updates mean that the weights are updated only at the end of each epoch, instead of at each event. The errors of all events of an epoch are summarized. Thus, the weight update is based on the average error of the total epoch.

Measuring performance

After the learning process, the saved network is applied to the test set. For each pattern in the test set, the prediction of the model is compared to the actual rating of the corresponding pattern. If rounding of the predicted rating results in the same value as the actual rating, the prediction is considered "correct", otherwise it is considered "false".

Results

When experimenting with several architectures, learning algorithms and inputs, the performance often converged to 60% correct classification of the test set. The mean squared error at the 6 outputs model was the highest for the "middle range"output neurons: 0.116 and 0.149.
Surprisingly, the straightforward output definition of one output varying from 0 to 6 did not perform significantly worse than the theoretically better 6-fold "binary" output definition.
The number of hidden neurons could be reduced to 6 with approximately the same performance.



The sigmoid activation function

Appendix: Basics of Neural Networks

Neural network algorithms are widely usable statistical tools. In many cases, they perform better than regression analysis, particularly with:
-Ill-conditioned and colinear data
-Noisy data
-Small quantities of data
-Data with an underlying structure which is nonlinear or chaotic.

Neural networks train on sets of examples (inputs with corresponding outputs) and by themselves learn any pattern in the data. No a priori model or constraint is required. When trained, neural networks are able to predict outputs for input patterns that have not been confronted, previously.

Neural networks got their name because of their resemblance to the communication system of brain cells.

There are several neural network software systems for PC available, at Tilburg University there is a system called Brainmaker for PC use. Other systems are Neuro Shell, Four Thoughts, Explore Net, Dynamind and Knowledge Seeker.

Below is a short explanation of neural network technical matters.

The most straightforward neural network is the 3-layer backpropagation neural network. Where necessary the items will be illustrated with examples of the bond-rating neural network presented in this paper.
The 3-layer backpropagation neural network consists of three layers: an input layer, a hidden layer and an output layer.

Each layer consists of several neurons. (A neuron is a small calculation entity, see section on Processes in the neurons.)
Every neuron has a connection to each neuron of the next layer. All neurons in the input layer are connected to all neurons in the hidden layer, and all neurons in the hidden layer are connected to all neurons in the output layer.

The number of neurons in the input layer is recommended to the number of input categories. If the input variables chosen are the ratio Equity to debt, the total balance amount and the interest coverage, there will be three categories of input, and therefor 3 neurons will be needed in the input layer.

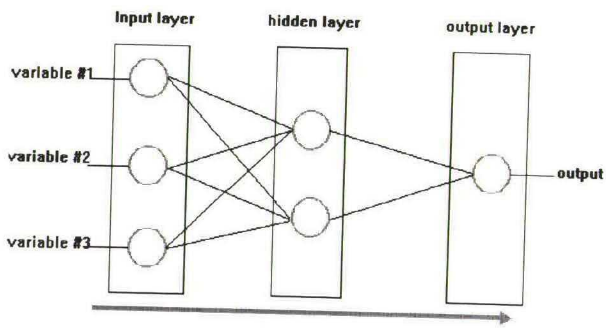
The bond ratings have to be quantified for the output. There are several ways of doing this, the simple form will be used by assigning a 10 to AAA and a 1 to D, with proportional values for the ratings in between.
As there is only one output category, only one neuron is needed in the output layer.

The choice of the number of neurons in the hidden layer is less straightforward. There is a recommended calculation which consists of taking the square root of the number of input and output categories and adding a few. Too few hidden neurons will cause a complete failure to train at all, too many neurons will create a "grandmother" which memorizes everything but does not recognize new (unseen) patterns.

Processes in the neurons

In the input layer neurons, the values of the input variables are standardised to values between 0 and 1. Prior to the learning process, the minima and maxima in the total pattern set are calculated for input variables which are used to transform these variables to values between 0 and 1.

> Example:
> If the lowest Equity to debt ratio occurring in the patterns is 0.1 and the highest ratio is 5, then the 0.1 is reduced to 0 and the 5 to 1, and every other input value is proportionally reduced between 0 and 1. (This is the simplest form of standardisation, more complex forms are available)



After this standardisation has taken place an activation function is applied to the neuron input.
There are several kinds of activation function available. The common form is a type of S-curved function: little increase at low input values, moderate increase at medium inputs, and again little increase for large inputs.
This S-shape has the advantage that the difference for small changes of medium input values is more significant than for small changes at the extremes. This prohibits dominating effects of large input signals. A commonly used activation function is the sigmoid function:

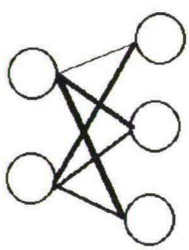
neuron output = 1/(1 + exp(-input)),

but other functions such as tangent hyperbolic or even linear functions can also be used.

This output of the input neuron is propagated to each neuron of the hidden layer. However, each connection has its own weight. This weight is the fraction of the neuron output that is propagated to the next layer. A weight can vary between -1 and 1.
(Note: each neuron has an input and an output, regardless of whether it is an input-layer neuron, hidden-layer neuron or output-layer neuron)

Example:
the output of input neuron #2 amounts to 0.8 ;
the connection weight of input neuron #2 to hidden neuron #1 is 0.3
the connection weight of input neuron #2 to hidden neuron #4 is -0.5

therefore:



Different connection weights presented as varying thickness of lines

the hidden neuron #1 receives 0.24 from input neuron #
the hidden neuron #4 receives -0.4 from input neuron #2

In this fashion, each hidden neuron receives its input from the former layer (the input layer).
In the hidden neurons, all inputs are aggregated and processed by the activation function. The hidden neurons propagate their output to the output layer, in the same fashion as described above.

The neuron(s) in the output layer (in the bond-rating example, there is only one output neuron) calculate the neural network output in the same fashion as the hidden neurons. In the example here, this output is the estimated bond rating (in quantitative form), given the presented pattern of input.

Error-Backpropagation

During training, the network adjusts the weights of each connection in order to minimize the difference between the prediction of the neural network and the actual output value. Each pattern is presentedto the neural network sequentially and processed as described above. When all patterns are presented (one cycle, an "epoch"), the presentation is repeated. Training requires several epochs.

Using a complex mathematical definition, the error (the difference between the actual neuron output and the supposed output) is calculated for each neuron.
For each epoch, the total sum of squared errors is calculated. Its average is called R-squared and it measures how well the neural network is operating. The objective is to minimize R-squared.

After each epoch, the connection weights are adjusted in the direction of the assumed optimal value. (The initial weights values are randomly set.)

weight(new)= weight (old) + L.(difference (weight (old) vs. supposed optimum))

As can be seen in the formula, the adjustment is limited to a fraction L (between 0 and 1) of the difference of the actual weight and the supposed optimum.
L is called the learning rate. The learning rate determines the magnitude of the weight adjustments. A high learning rate may result in a fast learning process, but the adjustments may be too wild to reach the optimum. The neural network keeps swinging around the optimum.
This is like a bowled surface with bulbs and niches in it. On the surface is a little ball that you want to move to the lowest point in the middle of the bowled surface . The learning rate resembles the force used to push the ball to the middle. If you do not push hard enough, the ball will not move or will stop in a niche or bulb. If you push too hard, the ball will cross the middle and contimue to roll, away from the middle.

Another factor is added to the weight adjustments:

weight(new)= weight (old) + L.(diff.) + M.(change weight (old))

M is called the momentum (between 0 and 1). The momentum determines the extent to which the former adjustment influence the new adjustment.

Small adjustments in opposite directions are thus overruled by general trends in adjustments.
In the ball example, the momentum resembles the weight of the ball. If a light ball encounters a bulb, this bulb could make the ball roll back. If the ball is heavy, the ball will override the resistance of the bulb dissipating its moving energy and will maintain its direction.

The learning rate and momentum are general parameters to be set by the user. The setting of these parameters is more art than science. For very noisy data a low L and a high M are recommended. For the bond-rating network, an L of 0.01 and an M of 0.5 were used .

When to stop the training process

In general, the neural network continues to adjust the connection weights to minimize the average error. At a certain level however, the neural network recognises not only the general trend in the data, but also the non-systematic noise in the data. This results in a neural network that memorizes the data, but cannot predict new sets of data.
This can be solved by adding a test set. A set of patterns are set aside. The neural network trains on the remaining patterns. After each epoch, the neural network is also applied to the test set. (that is, the neural network uses the current connection weights to predict the patterns in the test set). Since the neural network has not seen the test set before (the neural network has not trained on it) this may be a good indicator of the ability of the neural network to generalize.
As long as the average error in the test set continues to decline, it is worthwhile to contimue the training. Eventually, the neural network will become overtrained by learning the specific noise in the training set. At this level, the average error in the test set will increase. Further training is not worthwhile since the neural network will not perform better on new, unseen patterns.
However, this is only valid as long as the test set is representative of the total set of patterns. If the performance on the training set is worse than on the test set, there may be a coincidental good fit. The use of a large test set diminishes this risk. However, when using a large test set, fewer patterns are available for training. One has to trade off these problems.

Using a trained neural network

When the optimal connection weights are reached, the neural network is ready for use. If new data patterns are presented to the neural network it will predict the corresponding output.

> Example:
> You want to predict the bond rating of a company which does not yet have a rating.
> You enter the appropriate values for the input variables:
> Equity to debt ratio: 1.2
> total balance: 630.000.000
> interest coverage: 3.1

Subsequently, the neural network can be applied to this pattern (no further training takes place, the neurons are only used with their optimal connection weights). The neural network will produce an output, say 6.1534 . This is the quantified bond rating. Looking this 6.1534 up in the bond rating table reveals that this output is corresponding with BB (quantified as 6). So this company has the most resemblance with BB-rated companies.

Analyzing a neural network

In practice, the first time a neural network is trained, the results will be rather moderate. The network has to be redesigned with regard to the number of layers, neurons, and variables. Unfortunately, there are no well-defined methods for choosing a specific design. The most important choice is which variables to use. However, there are almost no clues which indicates which variable is relevant. Because of the nonlinearity, standard statistical keys are not applicable. For example, when using regresssion analysis, and assuming that in a linear model the residuals of a regression line are normally distributed, one can test whether the variable is significant or that a significant variable has been omitted (autocorrelation).The "line" through the data of a neural network is highly nonlinear. Therefore, the residuals are not normally distributed.

The variables may be chosen on the basis of a high correlation with the output and a low correlation with other variables (multicollinearity). However, some practioners have found that also low-correlated variables can improve the performance.
Adding or excluding variables requires a new training of the network, since the number of input neurons changes. This may result in a very different set of connection weights, making it difficult to compare the new model to the old one.

The makers of Neuro Shell2 assumed that relevance may be indicated by the sum of the weights of the outgoing connections from the input neurons. If a neuron has only low-value weights (in absolute terms), then this variable may not be relevant. New research revealed, however, that this assumption was not valid.

Sensitivity analysis may contribute to finding the relevant variables, but caution should be excercised. Varying one variable and leaving all other variables constant may indicate how the output changes due to the input changes. However, due to the nonlinearity, the sensitivity regarding a specific variable may be very dependent on the level of the other (constant) variables. If other values are chosen for the other variables, the sensitivity may differ significantly.

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