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Theory and Methodology

# Qualitative company performance evaluation: Linear discriminant analysis and neural network models

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**Abstract**

In this paper, we present a classification model to evaluate the performance of companies on the basis of qualitative criteria, such as organizational and managerial variables. The classification model evaluates the eligibility of the company to receive state subsidies for the development of high tech products. We furthermore created a similar model using the backpropagation learning algorithm and compare its classification performance against the linear model. We also focus on the robustness of the two approaches with respect to uncertain information. This research shows that backpropagation neural networks are not superior to LDA-models (Linear Discriminant Analysis), except when they are given highly uncertain information. 

*Keywords:* Artificial intelligence; Gradient methods; Multivariate statistics; Networks

## 1. Introduction

In this paper, we present a classification model that was designed to classify the performance of companies on the basis of managerial and organizational criteria. The tool is used to determine to what extent a company is eligible for state subsidies. This approach contrasts with the more traditional way to classify companies on the basis of financial criteria. This information may, however, not always be available or the company may have to be evaluated using other criteria.

The main contributions of the paper are the following:
- Qualitative criteria, such as internal coordination and the organization of the innovation process, are important factors for the overall performance of companies.
- The backpropagation neural network models and linear discriminant models have comparable classification performance.
- Backpropagation neural networks are more robust with respect to high volumes of uncertain information.

The paper is organized as follows. We first justify the approach of performance evaluation on the basis of managerial and organizational criteria rather than pure financial ones. We consequently

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present the sample used to construct the models and discuss the preprocessing of the data and we present and interpret the linear discriminant model. We then introduce the neural network model based on the backpropagation algorithm (BPA). We conclude by evaluating the robustness of the classification power of both approaches.

## 2. Managerial efficiency

Management research is more and more studying the characteristics of the firm, and how they contribute to explain the performance of the firm in a competitive environment. The literature underlined various variables affecting the economic performance of the firm. Different theoretical backgrounds, such as microeconomics, strategic management and the organizational or financial theories, were used to define those performance determinants. Microeconomics provides a useful basic theoretical framework which relates the influences of market structure with the firm's performance. Hansen and Wernerfelt (1989) propose an economic model of the firm's performance including several sets of explanatory performance variables such as industry indicators, factors relating the firm to its competitors and finally firm variables. In Cameron (1986) and Goodman and Pennings Associates (1977) an organizational model is proposed including environmental variables as well as individual and organizational ones contributing to an efficient organizational climate. We can mention the effects of not only corporate strategy and management efficiency variables on the level of firm's performance, but also of financial ratios and other determinants of the firm's position in terms of risk and vulnerability. Moreover, we can point out that most of the studies included only one particular dimension (e.g. strategy, finance, etc.).

However, a number of studies have tried to take into account this multidimensionality (see Hansen and Wernerfelt, 1989; Miller, 1986; Hambrick et al., 1982; Lentz, 1981). All of these studies report that the explanatory power of performance indicators increases considerably when the model incorporates indicators from various dimensions such as the financial, organizational and managerial domain. For example, in Hansen and Wernerfelt (1989), the authors obtained a higher explanatory power when combining both economical and organizational factors into their model. The necessity to include more than one dimension in the performance evaluation was also proposed in Bughin and Jacques (1994), where the authors state that not only pure financial or other economical factors account for good company results, but also "the ability of the firm to obey to some key managerial principles" (Bughin and Jacques, 1994). An efficient and innovative management in R&D, communication skills (Nonaka and Yamanouchi, 1989), managerial and organizational excellence (Burgelman, 1985) were also found to be very influencing. The importance of innovation was also described in Cohen and Levin (1989) and extended by Stuart and Abetti (1987) and Roure and Keeley (1990) to include factors such as organization, strategy and general management.

For our purposes, the literature overview, as described above, has allowed to compose a multidimensional questionnaire resulting in eight variable groups (Jacques et al., 1992): characteristics of innovation (product quality and competitive advantages), market driving forces, marketing and R&D departments efficiency, synergy factors between these departments, internal communication factors, managerial and organizational factors, financial constraints and innovation protection (patent, etc.). We also chose groups of variables which were identified to have a significant influence on performance (Jacques et al., 1994). The second group of eight variables is: firm's primary and secondary characteristics (size, age, etc.), economic environment (market conditions, conjuncture, etc.), organizational structure, strategy, information systems, management style and characteristics, financial factors and components and quality of the strategic planning process.

## 3. Sample creation and data preprocessing

To measure the independent variables, we created a questionnaire containing 72 questions. 138

Walloon companies were visited and during a direct interview, the company's manager answered to the questions. The technological sectors from which the sample was constructed are: biotechnology, telecommunication, computer information systems, electromechanics, chemistry, food and transformation (raw material, construction, etc.)

As was shown in Bughin and Jacques (1994), the performance and overall behavior of companies has to be studied differently for large companies and small and medium sized ones. We therefore split the sample into two parts and, of course, classification models were created for either category.

In order to reduce the number of variables we have performed a factor analysis (with orthogonal rotation) on each of the two samples which allows to discover linearly related variables and regrouping them into a compound factor. The results of the factor analysis can be summarized as follows:

- For the sample of the large companies, the original set of 72 variables was reduced to 23, where still 96% of the variance was explained.
- For the small and medium sized companies, the factor analysis resulted in 21 factors, explaining 78% of the variance.

The newly obtained factors could be grouped into three different categories which are shown in Table 1.

The next step was to assess the performance of the company which was to be explained by the managerial and organizational factors. To this purpose, we have collected the relevant information from a CD-ROM holding balance sheets data published by the National Bank of Belgium (BNB) and consequently, we computed for each company its performance as evaluated by means of financial ratios. Among the available ratios, five ratios were retained because of their relevance for our research, namely the two liquidity ratios (current ratio and acid test), two solvability ratios, debt ratio (current liabilities and long term debt by assets) and times interest earned and one profitability ratio (return on total assets). We then asked an expert to classify the companies as either performance or not.

In summary, for each company we have a vector having 23 (21) values for the 23 (21) vari-

Table 1
Some of the factors which are linearly dependent

| | | |
|---|---|---|
| Innovation process | Internal cordination | $F_1$ |
| | Introduction of new products | $F_2$ |
| | Characteristics of innovation | $F_3$ |
| | Innovation performance | $F_4$ |
| | Protection of innovation | $F_5$ |
| | Organization of the innovation process | $F_6$ |
| | Finance innovation | $F_7$ |
| | Rival environment of innovation | $F_8$ |
| General management | Rival position of the company | $F_9$ |
| | Size of the company | $F_{10}$ |
| | Structure of the company | $F_{11}$ |
| | Management of the company | $F_{12}$ |
| | Stability of the company | $F_{13}$ |
| | Importance of the secondary and tertiary markets | $F_{14}$ |
| | Coordination and environment | $F_{15}$ |
| Management and innovation | Activity field of the enterprise | $F_{16}$ |
| | Information and planification | $F_{17}$ |
| | Innovation environment and market strategy | $F_{18}$ |
| | Company environment | $F_{19}$ |
| | Strategic aspects of the company | $F_{20}$ |

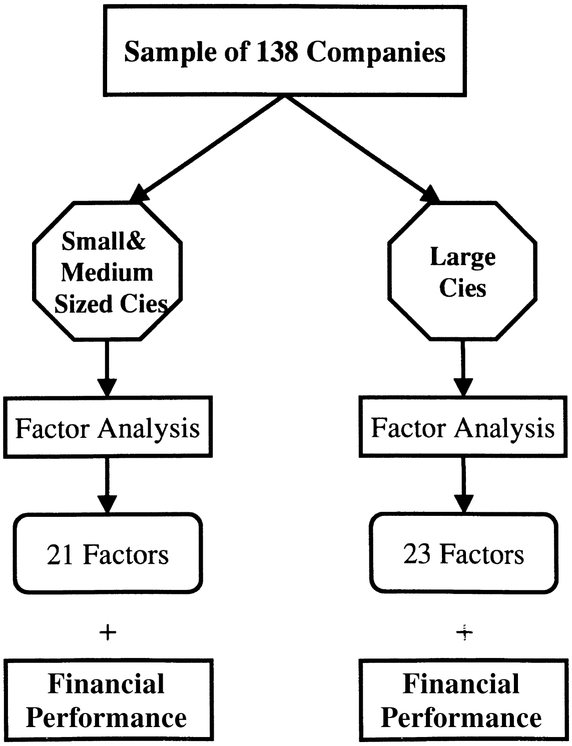


Fig. 1. The sample preprocessing phase.

ables plus a 1 or 0, indicating respectively the performance or nonperformance of the company. Fig. 1 gives an overview of the sample analysis and preprocessing phase.

## 4. The Linear Discriminant Analysis (LDA) model

In this paragraph, we present the LDA-model and the corresponding classification results. As explained above, we need to construct a model for the large companies and one for the small and medium sized ones. These two groups and the data corresponding to the respective factors were analyzed by means of a discriminant analysis to obtain a linear model. This model is a linear combination of organizational and managerial factors that separate in the best way the two groups.

The equation for the medium and small companies is

$$x = 0.12 + 0.436F_1 - 0.469F_{17} - 0.817F_{15}.$$

The equation of the big companies is

$$x = 3.4 - 0.177F_9 + 0.439F_{17} - 0.607F_{18} - 0.735F_6.$$

The critical cutting score value is $-2.1$, implying that when $x \leqslant -2.1$ the performance of the company is considered as good. When $x \leqslant 0.2$, it is considered as moderately good and when $x > 0.2$, it is rated as bad. Table 2 summarizes the classification results. These equations have classification levels comparable to the financial ratio classification (see Ooghe and Van Wymeersch (1990) for an extensive discussion) of 67% for the small and medium companies and of 69% for the large ones.

Without discussing in detail each of the factors, we can elaborate a little on the first factor, representing the coordination within the company. This factor takes into account the degree to which coordination takes place at different organizational levels such as project groups, departments, team members of a project group. The rationale behind this factor is that internal coordination and intensive communication inside an organization allows to better outline common strategic objec-

Table 2
Results of the LDA

| | | SM | L |
|---|---|---|---|
| $F_1$ | Internal coordination | 0.436 | – |
| $F_9$ | Rival position | – | −0.177 |
| $F_{17}$ | Innovation environment and market strategy | −0.469 | 0.439 |
| $F_{18}$ | Company environment | – | −0.607 |
| $F_{15}$ | Coordination and environment | −0.817 | – |
| $F_6$ | Organization of the innovation process | – | −0.735 |

tives, synchronize development efforts and resolve conflicts before they reach an uncontrollable level. [1]

## 5. The backpropagation neural network model

Neural networks are more and more used in different research areas and are widely praised for their flexibility and computational power. In order to find out how such tools compare against the more traditional statistical tools, such as LDA, we have used the same data to create a neural network that had to make the same classification.

In this section, we briefly present the equations used in the BPA and we refer to standard textbooks for a more detailed discussion (see Rumelhart and Mc Clelland (1988) and Hertz et al. (1991) and a very good introductory text is Aleksander (1991)). We only mention here that the main reason why the BPA was chosen is that for each firm in our sample, we knew in advance what its performance was (cfr. Infra). It is therefore reasonable to exploit this information by using a supervised learning algorithm of which the BPA is its best known example.

### 5.1. The backpropagation algorithm

The following equations allow to compute the output of any node (hidden or output):

$$A_{pj} = \sum_{i=1}^{m} W_{ji} O_{pi} - U_j, \tag{1}$$

$$O_{pj} = f_j(A_{pj}) = \frac{1}{1 + e^{-A_{pj}}}, \tag{2}$$

where $A_{pj}$ is the activation for input pattern $p$ presented to node $j$, $W_{ji}$ is the weight of the connections between nodes $i$ and $j$, $O_{pi}$ is the input $p$ presented to node $i$ and $U_j$ is the threshold of node $j$. $O_{pj}$ is then the output of node $j$. Being able to calculate the output for the network, we can now easily calculate the error and consequently the necessary weight changes for the output and hidden nodes.

– The delta rule that allows to calculate the changes for any weight is:

$$\Delta_p W_{ji} = \beta \delta_{pj} O_{pi}, \tag{3}$$

where $O_{pi}$ is the value of the $i$th incoming connection and $\beta$ is the learning rate. This learning rate determines by how much the computed error will be used to modify the weights of the connections between the neurons. A low $\beta$ will imply a longer time to learn but when the value of $\beta$ is set too high, the network may never learn as it will easily 'overshoot' the solution(s). The error $\delta_{pj}$ needs to be calculated separately for the hidden and the output nodes.

– For the output nodes, the error can be computed in the following way:

$$\delta_{pj} = (t_{pj} - O_{pj}) f'(A_{pj}), \tag{4}$$

where the term $(t_{pj} - O_{pj})$ computes the difference between the expected and actual output of the network. This error is then multiplied by the first derivative of the transfer function. This allows to sanction nodes that generate an uncertain output (an activation value close to 0) because there the first derivate will be high and consequently the weight change will be larger. The inverse is true for nodes that generate large activation values.

– For the hidden nodes, the error can be computed in the following way:

$$\delta_{pj} = \left( \sum_{k=1}^{n} \delta_{pk} W_{kj} \right) f'(A_{pj}), \tag{5}$$

where $\delta_{pk}$ represents the error of the connected neurons of the above layer which are propagated throughout the network. $W_{kj}$ is the weight of the connetions between neurons $k$ and $j$. For exactly the same reasons, the first derivative of the transfer function is included.

[1] The full study can be obtained upon request to the authors.

### 5.2. Structure of the model

Due to the division of the sample in two parts, two distinct models are constructed: one for the large companies and one for the small and medium sized ones. As the factor analysis reduced the number of variables, the neural network models only needed 23 and 21 input nodes for respectively the large companies neural network (LCNN) and the medium and small companies neural network (SMNN). The output of the neural network gives the company's performance represented by a single binary value (where 1 represents good performance and 0 bad performance). The choice of the number of hidden layers depends on the complexity of the relation between the input and the output. However, this complexity is not known a priori. Furthermore, increasing the number of hidden nodes (or layer) increases more than proportionally the CPU-time. For instance, each new node at the first hidden layer increases the number of weights to compute with respectively 21 and 23.

For our application, the two neural networks each have two hidden layers with respectively 31 and 15 nodes. The learning rate is modified during learning: starting at 0.5, it is decreased incrementally. The training set for LCNN comprises 91 companies, where 15 had a bad performance evaluation and 76 a good one. Only 50 of these data were used for training and 41 were used for testing. For the MSNN, the network was trained on 44 companies, 12 having a good performance and 32 a bad one. Of these 44 companies, only 30 were used for training.

Table 3
Classification results of the four models

| | | |
|---|---|---|
| Large companies discriminant analysis | LCDA | 67% |
| Large companies neural network | LCNN | 70% |
| Small and medium companies discriminant analysis | SMDA | 69% |
| Small and medium companies neural network | SMNN | 100% |

#### 5.2.1. Training and test

As was said previously, the difference between the output and the target value in function of the number of iterations is the error which is propagated back into the network. The training of the neural network, which is nothing but the iterative modification of the different weights in order to reduce the error, stops when the error is smaller

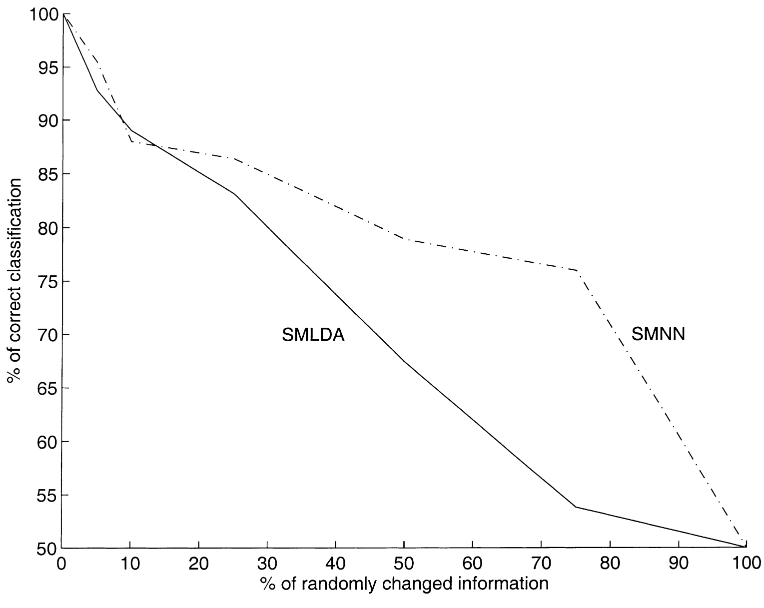


Fig. 2. Classification with randomly changed information: Small and medium sized companies.

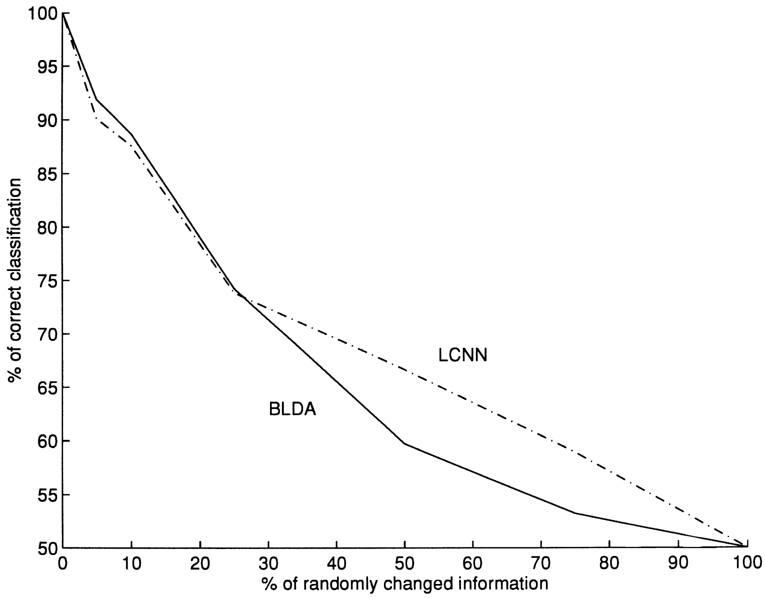


Fig. 3. Classification with randomly changed information: Large companies.

that a user defined constant. Once the net has sufficiently converged to a solution, the weights are fixed and the next stage in the development process can be executed.

This next step, before the final use of the model, is to establish whether the model can accurately classify those companies which have not been used for training. As given in Table 3, the LCNN classifies correctly in 70% of the cases and the MSNN has 100% good classifications.

## 6. Robustness evaluation

A widely proclaimed advantage of neural networks is that they can deal with incomplete information and still make a valid and reliable abstraction. In comparing LDA-models with BPNN, we therefore have to verify to what extent BPNN are superior to LDA in this respect. The fact that we want to compare these two techniques, immediately constrains the kind of robustness test we can perform. LDA-models need information for each of the variables in the equation in order to compute an output value. BPNN would then automatically be considered superior.

We therefore chose a second strategy which consisted of modifying arbitrarily the input values. The rationale behind this strategy is the following. As explained previously, the classification is done on the basis of managerial and organizational (rather than financial) information which must be obtained by interviewing people. We can never be sure that the provided answers accurately reflect the real situation. It is therefore not unrealistic to suppose that some of the answers are highly uncertain with respect to their information content. [2]

For all of the models, we incrementally increased the percentage of uncertain information up to 100% and computed the performance evaluation for each company in the overall sample. We reused the whole sample because we can consider each new input vector as a new company which to a greater or lesser extent resembles the companies used for training.

We can make the following observations from Fig. 2:

[2] We emphasize however that we do not claim that missing data and uncertain data are equivalent.

– As expected the classification performance of both the SMLDA and SMNN-model degrades.
– Up to 10% of arbitrarily changed information, SMLDA and SMNN do equally well in classifying.
– When the amount of uncertain information exceeds 10%, the classification performance of the SMLDA degrades faster than its NN counterpart.
– When all the information is changed at random, the classification falls back for both techniques to 50%.

Similar conclusions can be drawn from Fig. 3 with this difference that the BLDA-model performs as well as the LCNN-model for randomly modified information up to 25%.

## 7. Conclusion

The main results of this paper are twofold. The first is that organizational and highly qualitative factors play an important role in stimulating the innovation process within the organization. Our model suggests that success cannot be exclusively be measured in financial terms, and that as far as promoting innovative activity is concerned, pure organizational and managerial elements are important determinants for the (innovative) success of the company. A second result of this paper shows that the BPA- and LDA-models are equivalent in classifying companies and that BPA-models are more robust with respect to high volumes of uncertain information.

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