Neural Networks In Action :"An Engine For The Marketing Information System"

Efficiency of NN Decisions vs. human being in selection of new prospects

Harri Tuominen
Leonia Bank plc
Kenneth Halin
Marknadsanalys Finland Ltd
Hannu Jaakkola
Tampere University of Technology

1. Abstract

The rapid changes in the business environment require more efficient production of up-to-date and relevant information. This is possible through judicious application of information technology. The bulk of available information is growing steadily, and thus requires ever faster processing. Information that is relevant for decision-making must be sifted from the great mass.

Business operations in fragmented and turbulent markets require competitive products and services, competitive pricing and good management information systems; the latter are a prerequisite for cost-efficient allocation of resources for services and, particularly, selling.

This paper describes an empirical approach, a model of a Neural Segmentation Process. This paper gives an overview of the efficiency of MLP[1] trained by Back-propagation decisions vs. humans in the selection of new prospects, and an overview of the reference model, its application in the target organisation (the Bank) and experiences of the utilisation of the new segmentation system as part of the whole Marketing Information System.

As a consequence of changes in the operational environment and in the competitive situation, companies have to manage in an ever more complex and faster changing market environment.

When the amount of available information increases, sales and marketing functions must separate the relevant information from a great bulk of existing data. To develop the operations of a business, on both the strategic and operational level, a fast and flexible feedback system to support the management of marketing activities is mandatory, and this requires powerful tools. An improved marketing information system is a strategic, competitive tool for businesses. Using information technology, the markets can be divided into two different databases: time-consuming customer groups

[1] Multi-Layer Perceptron

demanding person-to-person contacts, having a great profit potential, and groups with numerous customers and a small profit potential.

The subject of this study is how even faster to generate significant data for the Database Marketing System (DBMS) and the Marketing Decision Support System (MDSS) using neural network applications. Information systems used in marketing to individuals were beyond the scope of this study. More exact presentation of the frame model of a marketing information system and its application and implementation is given in an earlier study by one of us [1,8,9].

The aim of this study was to establish whether there is a model and a method that can be used for efficient categorisation and segmentation of corporate customers for sales and marketing purposes. The decisions made by the model are compared with corresponding ones made by humans. This project has yielded a construction that for the purposes of this study seems to work with a significantly better cost efficiency than traditional, manual classification. The result of the categorisation process is a mathematically derived estimate of the funds saved in the customer categorisation and segmentation processes of the Bank, and in the use of the results of the categorisation.

2. Background of The Study

This study was divided into three partial studies, the aim of which are, and have been, to improve the efficiency of decision making and operations in sales and marketing, at all stages of the sales and marketing processes. The third stage of the entire study, now to be presented, and the model and construction for customer categorisation created within the study, have been adopted and incorporated into the infrastructure of the Bank.

In earlier studies, a structure for support for decision-making in the sales and marketing operations of the Bank was created (MDSS, Marketing Decision Support System) [1,2,3,4,5]. In the second stage of the study, the Bank switched to new technology and adopted a new *modus operandi* [Business Process Re-engineering], utilising the implementation model created in the study, and the study's results on the propagation of diffusion processes (KHLS, Know How Level Score) [6,7.8,9]. When the use of the marketing information system had become established routine, it was possible to continue the study, this time focusing on the improvement of information and on a more efficient customer categorisation as part of the Marketing Decision Support System (HTKH, High Technology Knowledge Highway)

The progress of the research projects can be described as follows:

Table 1 Roadmap for the three phases of the research projects

Phase of Business Process re-engineering and Modeling Information Systems	***Phase of Implementation and use***	***Phase of Improvement of Marketing Decision Support System***

Phase 3: A NEURAL NETWORK BASED APPLICATION – " ENGINE FOR THE MARKETING INFORMATION SYSTEM"

1. Efficiency of MLP Decisions vs. human being in selection of new prospects
2. Mathematical model behind the construction of the decisions of new potential prospects
3. IT Construction of the Neural Network Decision Support System

Phase 2: An Empirical Approach to the Information Technology Development Process: The Marketing Decision Support System and its implementation and use in strategic management and operational work: Harri Tuominen (1996)
TAMPERE UNIVERSITY OF TECHNOLOGY
Department of Information Technology

Phase 1: Markkinoinnin tietojärjestelmän kehysmalli Frame Model of a Marketing Information System; Tuominen Harri (1993) Tampere University of Technology. Tampere: TTKK (1993)

3. Focus of the study: *Efficiency of NN Decisions vs. human decisions in the selection of prospects*

This paper deals with the selection of a method to be used as a model for customer categorisation for the purposes of sales and marketing, and the application of the selected method, and the results of this application. This study compares the decisions made by humans and the model regarding their exactness and the efficiency of the process, and evaluates whether the use of the model is beneficial to the Bank.

The aim of the study was to create a model for the categorisation of corporations, providing the Bank with a better general view over its present customer and prospective customer base, and thus enable it better to allocate the sales and marketing efforts to both existing corporate customers and to new potential. The categorisation must be dynamic[2] and easy to be applied when situations change in corporations and/or their environment. The categorisation must be faster and more efficient than the present one,

In part, the goal of this study is to establish how well it is possible to define variables that define the bank potential, profitability, loyalty and risk. Another partial goal of this study is to make the approved variables available to the Bank as supplemental information and part of the market potential information database, as one source of information for the data systems of sales and marketing, e.g. when selecting prospective customers.

4. Categorisation and information content of the sources of information

The source data for enterprises included the database of the Bank on approx. 450 000 enterprises[3] and corporations, and information on the category, risk, financial situation and payment behaviour of all Finnish enterprises, acquired from external commercial sources. By content, this information could be divided into four categories. For the purposes of this study, four quality categories were defined as follows: vertical classification: by quality and extent of information per enterprise; horizontal classification: by information source Table 2.

For the purpose of the creation of a model, and in regard of the goals of the study, it is essential to group the available information into two sets: internally available information, and information to be acquired from external sources. It is then possible to construct a model of the enterprises, and to describe them in terms of the external information. The aim for the classification of the information sources was to find a group of enterprises, whose information was as complete as possible in all sources. The categories of information sources, and the amount of available information, expressed verbally, are shown in Table 2.

Table 2 Source of Information and classification

[2] In this context, dynamic means that the model can be taught and a new model created to correspond with any changes in the environment and/or the target organisation in such a manner that the construction is utilised, and the application, the databases and the process remain unchanged.

[3] In this context, small firms and self-employed are also regarded as enterprises.

The information of the Bank expressing commercial success	Information expressing commercial success by financial information	Information on the behaviour of the enterprise from the point of view of payment records and risk assessment	General basic information on the enterprise
Abundant information from all product segments	Complete financial information	Complete information on payment behaviour and risk	Complete information
Limited information on some product segments	Limited financial information	Complete information on payment behaviour and risk	Complete information
Scarce information on some product segments	No financial information	Complete information on payment behaviour and risk	Complete information
No information	No information	No information	Incomplete information

4.1 Information content of the sources of information

According to Table 2, part of the material provides adequate information from all sources, thus making it possible to construct a model. At the other end of the scale are the enterprises, the information on which is purely external, and subject to acquisition from public sources.

Finnish enterprises are mainly small, and official financial information is available on a very small portion of the total number of enterprises. Information on payment behaviour is available on 130 000 enterprises, and during 1998 some 200 000 pieces of information on changes in sales and employee data were updated by Statistics Finland. These updates mainly concern 1996 figures. The target population for our model construction included 215 000 enterprises.

The enterprises are distributed per sales volume and available financial information as follows:

1. The distribution of active enterprises according to sales:
    1. less than MFIM 5 73%
    2. MFIM 5-10 11%
    3. MFIM 10-50 11%
    4. MFIM 50-100 2%
    5. MFIM 100+ 3%

2. For 1997, financial information is available on 22 500 enterprises. The corresponding number for 1996 was 17 300. The number of enterprises with available financial information:
    1. 1991 3271
    2. 1992 4121
    3. 1193 8674
    4. 1994 9887
    5. 1995 11498
    6. 1996 13322
    7. 1997 17300
    8. 1998 22550 (11/98)

The most important source of information was the database of the Bank; at the beginning of the study it contained 117 columns of information on the sales per product, risk classification and profitability as customer of the Bank.

4.2 Grounds for the selection of sources of information

The sources of information were selected with a view to the desire to create a model based on complete internal and detailed external information. On the basis of this material, it was possible to test the classification model and the construction in the projected operational environment. As the aim of the work was the creation of a model for the classification of customer prospects, the model was to include information that, regardless of the volume of the customer's business with the Bank, yielded sufficient information for the implementation of the model. This is information that can be acquired from public and commercial sources. In this case, information was acquired from Suomen Asiakastieto Oy (Finska) (www.asiakastieto.fi), and from Statistics Finland (www.stat.fi).

5 New segmenting classification for enterprises

Technically, the segmentation of enterprises is performed on the basis of industry, sales, personnel or other variable. This type of classification yields information on the situation and needs of the enterprise from the point of view of a seller. By adding the customer information of the seller's organisation to the segmentation variables, the segmentation, for the part of the seller's existing customers, can be significantly better specified. Segmentation for the purposes of prospecting and marketing activities often lack information on customer behaviour, making it necessary to rely solely on external information. The selection is performed from a great amount of target companies. Performed manually, this is a time-consuming and often cost-inefficient.

In an industry, where risk management is a central area of know-how and essential for the continued profitability of a company, it is quite essential to be able to pick the companies offering the best probable long-term prospects from the seller's point of view as subjects for prospecting and marketing operations. Two companies, that on the face of it seem nearly identical, may prove very different from the Bank's point of view.

Before commencing any sales or marketing activities, the Bank always has to assess, i.e. classify, the desirability of a company. If this classification is performed technically as described above, half of the selected sample will, by virtue of the normal distribution curve, prove less than interesting. This type of selection is a squandering of resources that may manifest as unnecessary marketing costs, costs for two-way contacting (seller->customer, customer->seller), personnel costs, material costs, and losses of prospects and existing customers due to the time and human resources required by the process. The selection of customers and the classification of prospects also require human resources.

It is interesting to see whether it is possible to make the process of classification and segmentation of customers more efficient through the application of external information when this is supplemented by internal information. Is it possible to create a model, through the application of which we can increase the cost efficiency of the process, and the accuracy of marketing activities.

5.1 Description of Segmenting Variables

Variables

As prospective dependent variables, and to be added to the Bank's own database of marketing potential, DW[4], those most significant for the purpose of this study were selected. The formulae and information content in the database of the prospective variables are described below. The prospective dependent variables are:

1. The bank potential (PPO) is the annual sum total of the banking fees and the marginal revenue paid by the enterprise to all its bankers
2. The profitability potential (prpot) is the total revenues in relation to the amount of banking services rendered and the risk of the Bank.
3. Loyalty (loy) is the relation between the actual revenues and the bank potential. Loyalty expresses the Bank's share of the total banking revenues paid by the enterprise.
4. The risk (R1 – R5) is a measure of the risk classification of the enterprise, derived either through the financial information or through the information on its payment behaviour.

Bank potential

The bank potential is the calculated total fees and revenues paid by the enterprise to all its bankers. The bank potential is a bank-specific classification factor, defined by the creditors, cash in hand and at bank, bank receivables, and the volumes of payment

[4] DataWarehouse

traffic, risk management and investments. The letters A, B, C and D are used as symbols for the classification factors.

The variable for profitability

The potential profitability of a customer is defined by the relation between the total revenues to the financial services products. The financial services products computationally bind the capital of the Bank in relation to the risk of the enterprises. The lower the credit rating and the security position of the enterprise, and the higher any other risk factor, the higher the marginal return required on the capital bound by financial services. The potential profitability of a customer is defined here by the total revenues paid by the customer.

The variable for loyalty

From the Bank's point of view, the larger the share of the total banking expenditure of the customer paid to the Bank, the more loyal the customer. Such revenues include revenues for payment traffic, cash management and investment services, and other fees besides revenues for financial services. In practice, this equals the relation between the total paid to the Bank by the enterprise in relation to the banking potential, i.e. the market share of the total available revenues. A special problem encountered when assessing loyalty issues is the group of large companies using several banks and for whom the use of just one bank organisation would be unthinkable. As far as this study is concerned the problem is irrelevant, as big companies and corporations are closely analysed and examined by the customer management in other contexts. Regarding classification, small and mid-size companies are the central target group of this study. Another problem relating to the determination of loyalty is the absence of information on the life cycle in the material that explains the variable.

The variables for risk

This study utilised available internal information, and risk classification data from external sources, based upon financial information and information upon the payment behaviour of companies.

6 Selection and pre-processing of research material

The basic material was subject to a selection process and pre-processing. The goal was to define the variables that best explain bank potential, profitability, loyalty and risk. Using these variables, models will be constructed for the estimation of the classification factors that will enable us to make more efficient selections of target groups for sales and marketing operations.

6.1 The regressors and how these are selected

The basic material included almost all Finnish enterprises. First the enterprises were divided into three groups: **1)** those that are not customers of the Bank; **2)** those that are passive customers of the Bank, i.e. lack transaction data from the most recent year; and **3)** those that are active customers of the Bank. The information content in these three groups varied greatly. There was a lot of information available on the active customers of the Bank; on transaction volumes and revenues, and external financial and industry information from the trade register. On enterprises that are not customers of the Bank, trade register data and credit information only are available as a rule.

The available information provides us with the possibility to build models at three levels:

(a) The model of complete information (Bank, Finska, and Statistics Finland, and financial information), using which 10 000 - 20 000 enterprises can be classified.
(b) Information available internally at the Bank and from Finska and Statistics Finland, altogether some 60 000 enterprises.
(c) Using a combination of information from Finska and Statistics Finland, and financial information, it is possible to classify 20 000 - 25 000 enterprises.
(d) Using a combination of information from Finska and Statistics Finland, it is possible to classify almost all active enterprises, some 140 000 in all.

The grouping also functions as an inverted indicator of the quality of the model. The best model that can be constructed involves the maximum number of regressors. The model (A) is a representative of this category. Correspondingly, when using external variables that appear in the data on almost every enterprise, we arrive at a more loosely constructed model.

As the aim of this study was to create a company classification system that would priorise present customers and primarily find new corporate prospects, the final classification utilised only external information. Using external variables, models were constructed that yield estimates for bank potential, profitability potential and loyalty.

The model used in this study was of type (d). Models for enterprise categories (a), (b) and (c) are a goal to be implemented in the foreseeable future.

6.2 The selected external regressors and the dependent variables

The external information utilised for modelling

Postal code	regional variable
Industry code	
Number of personnel	
Personnel class	determined through number of personnel

Company form	
Date of first entry in the trade register	for calculation of the age of the enterprise
Turnover	from the financial information
Own capital	from the financial information
Paid-up own capital	from the financial information
Date of risk classification	the time at which the credit rating was established
Model of risk classification	grounds for assessment of risk class
Risk classification, most recent	present credit rating code
Risk classification, second recent	previous credit rating code
Risk classification, third	previous credit rating code

Dependent variables

There are three dependent variables: ***Bank potential*, *Profitability potential, and Loyalty potential.*** Of these three, the bank potential is defined for part of the Bank's customers, and kept up to date at various offices of the Bank. The profitability potential is estimated when it cannot be calculated directly from the information on the enterprise. It was decided to express the risk using purchased external risk classification data. Profitability was defined using the following formula:

$$\text{Profitability} = \text{Customer revenues from beginning of year}$$

and loyalty using this formula:

$$\text{Loyalty} = \frac{\text{Customer revenues from beginning of year}}{\text{Bank potential}}$$

The variables to be included in the model were selected according to the following principle: If the material contains three variables, A, B and C, we first construct MODEL(A), MODEL(B) and MODEL(C), and then we measure the power of each model. If MODEL(C) is the best one, we then build MODEL(CA) and MODEL(CB), and then again measure the power of each new model. We then continue, adding variables to the best model found so far, until the power of the model does not appreciably improve.

6.3 Pre-processing of variables

All fields of the database and the acquired external data were statistically analysed, and the range, distribution, nominal number and number of lacking data of each variable noted. When the analysis led to a statistically speaking abnormally distributed result, the reasons were investigated, corrective measures were taken, or the above information was rejected as a regressor.

6.3.1 The importance of pre-processing

Special attention was paid to the variables entered into the model. Problems like missing data, outliers and multicollinearity were expected to make the construction of the model difficult, and even cause the model to work in a faulty manner When using statistical and mathematical methods, the basic prerequisites for a multivariable analysis are: normality of variables, homoscedasticity of regressors and dependent variables, linearity, and the elimination of correlated errors) [10].

The pre-processing of variables is a very important part of the modelling project. The aim of this stage is to facilitate the teaching of the model by reducing noise and inconsistent data without losing any important information.

Usual pre-processing procedures include a reduction of the number of dependent variables, normalisation of the data and a variety of transforms with a view to increase the power of the variables [11].

6.3.2 Pre-processing of variables in the HTKH model

In this project we have replaced missing values (not of dummy variables) with the median, as the average, due to the extremely large difference between large and small companies, often is too high and does not represent a medium company well.

Variables on the nominal scale, postal code, industry code and company form, were processed by forming new dummy variables with values in the set {-1, 1}, where –1 means that the enterprise does not have this property. ($OY_{Yritys(i)} = -1$ means that enterprise no. *i* is not a limited company), and, correspondingly, 1 means that the enterprise has this property. ($KY_{Yritys(i)} = 1$ means that enterprise no. *i* is a limited company).

The risk classes were coded with the digits 1-5, of which 1 designates the highest and 5 the lowest risk category.

Numerical variables (turnover, personnel and shareholders' equity) were entered into the model after the following pre-processing:

$$Variable(i)_{SIG} = \tanh\left(c * \frac{\left(Variable(i) - \overline{Variable}\right)}{s_{Variable}} \right)$$, where

$$\overline{Variable} = \frac{\sum_{i=1}^{n} Variable(i)}{n}$$, i.e. the average of the variable *Variable,* and

$$s_{Variable} = \sqrt{\frac{n * \sum_{i=1}^{n} Variable(i)^2 - \left(\sum_{i=1}^{n} Variable(i)\right)^2}{n*(n-1)}}$$, i.e. the standard deviation of the variable *Variable,* where *n* is the number of observations.

In the figure above, $\frac{Variable(i) - \overline{Variable}}{s_{Variable}}$ normalises the variable. This normalisation is often called Zscore normalisation. However, this does not solve the problem of excessively large (or small) variable values, and this is why the *tanh(x)* transform is used in the model to make the value of variables fall within the interval [-1, 1]. The constant *c* is used to adjust the distance between outliers and the average.

7 Choice of model

The following is a brief presentation of the algorithms that were tested in the classification study; the MLP method, selected on the basis of the results, is described at a slightly greater length. Each algorithm was tested with material selected in four different ways. The correct and incorrect classifications yielded by the algorithms were compiled into a ranking list that determined the final choice of model.

7.1 Algorithms

Several algorithms were tested in the search for the best model. The computer runs were made using the Unica Technologies program PRW (Pattern Recognition Workbench), version 2.1. The particular strength of this program is its ability to automate the parametrisation of the algorithms [12], thus eliminating the need for tedious manual iteration.

All five algorithms were tested using the PRW software: linear regression analysis (Lin), logistic regression analysis (Log), MLP with back propagation (MLP), Radial Basis Functions (RBF) and K Nearest Neighbour (KNN).

7.1.1 Linear regression analysis (Lin)

This method is often used as a reference method when investigating the power of another algorithm to explain a phenomenon. The resulting variable y can be described through the entered information $x_1, x_2, ..., x_n$ using the following formula:

$$y = w_0 + w_1 x_1 + w_2 x_2 + ... + w_n x_n$$

where $w_i, i \in [1,2,...,n]$ are independent parameters. If the linear dependence is not perfect, we get

$$y = w_0 + w_1 x_1 + w_2 x_2 + ... + w_n x_n + error \text{ .}$$

The task of the algorithm is thus to minimize the *Error* term. This is done using the least sum of squares method.

7.1.2 Logistic regression analysis (Log)

The logistic regression analysis is based upon the assumption that the relation between the input variables and the desired target variable can be expressed using a logarithmic function [13]:

$$y = \frac{1}{\left(1 + e^{-(w_0 + w_1 x_1 + w_2 x_2 + ... + w_n x_n)}\right)}$$

The logistic regression analysis is an iterative algorithm, in which the initial situation is first generated, and then values are assigned for the weights. After this, the values of the weights are varied, the objective being the minimisation of the error made by the model. The error made by the model is calculated using the cross-entropy cost function:

$$E_k = d_k \cdot \ln\left(\frac{1}{y_k}\right) + (1 - d_k) + \ln\left(\frac{1}{1 + y_k}\right)$$, where

E_k is the error from the k:th example pattern

y_k is the output produced with the input vector of the k:th example pattern (x_k)

d_k is the desired output for the k:th example pattern.

The cross - entrophy error for the whole training set is

$E = \mathop{}_{k=1}^{n} E_k$.

7.1.3 The MLP network with Back Propagation (MLP)

The MLP is a neural network, consisting of an input layer, one or more hidden layers and an output layer [14]. There may be several neurons in the output layer; one was enough for our purpose, because we modelled only a single dependent variable on a ratio scale in each model. We noticed that one hidden layer was enough to produce a sufficient accuracy.

In the figure below (Fig. 1), the variables in the output layer are called $x_0, x_1, x_2, ..., x_n$, where x_0 is the input of the threshold value of the activation function, usually a constant, 1. The weight coefficients of the connections between the input layer and the hidden layer are called $w_{i,j}$, where *i, j* designates the connection between input variable i and neuron j in the hidden layer Correspondingly, the weight coefficients of the connections between the hidden layer and the output layer are called W_j, and W_0 is here the threshold value of the activation function of the input layer.

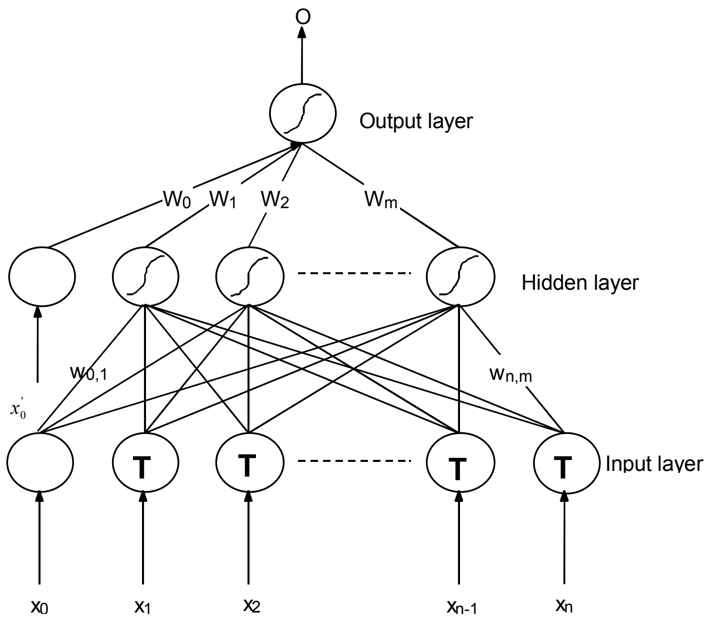

Figure 1 MLP and Back Propagation (MLP)

T in the input layer indicates the pre-processing of the variable. In the hidden layer, the *tanh* function is used as the activation function; it is of a sigmoid shape and its values are in the interval [-1, 1].

The input value to neuron j in the hidden layer is calculated using the formula $p_j = \sum_{i=0}^{n} w_{i,j} x_i$, and the corresponding output value

$$P_j = \tanh(p_j) = \tanh\left(\sum_{i=0}^{n} w_{ij} x_i\right).$$

The input value to the neuron of the output layer is

$$o = W_0 x_0' + \sum_{j=1}^{m} W_j P_j = W_0 x_0' + \tanh\left(\sum_{i=0}^{n} w_{ij} x_i\right)$$ and the output value

$$O = \tanh(o) = \tanh\left(W_0 x_0' + \tanh\left(\sum_{i=0}^{n} w_{ij} x_i\right)\right).$$

Before the calculation of the weight coefficients of the connections between the input layer and the hidden layer, and, correspondingly, between the hidden layer and the output layer, the error function

$$E\left[\overline{W}\right] = \tfrac{1}{2}\sum_{l=1}^{k}\left(C^{l} - O^{l}\right)^{2}$$

was minimised in relation to the connection vector $\overline{W}$ between the hidden layer and the output layer. In the formula for the error function *k* is the number of data sets in the development sample, and C^{l} is the correct answer of data set number *l*. The weight coefficients W_j are obtained using the "gradient descent" method

$$\Delta W_j = -\eta\frac{\partial E}{\partial W_j} = -\eta\tfrac{1}{2}\sum_{l=1}^{k}\left(C^{l} - \tanh\left(W_0 x_0^{'} + \tanh\left(\sum_{i=1}^{n} w_{ij} x_i^{l}\right)\right)\right),$$

where η is the coefficient used for adjusting the learning rate.

The weights of the earlier layers can be calculated in a corresponding manner, through repeated application of the chain rule

$$\frac{\partial E}{\partial w_{ij}} = \frac{\partial E}{\partial V_j}\frac{\partial V_j}{\partial w_{ij}}.$$

Stop conditions determine when the MLP algorithm will terminate training. In this project were the stop conditions a maximum number of epochs of training or when the RMS fell below a target value.

7.1.4 Radial Basis Functions (RBF)

The radial basis function network is a network consisting of one hidden layer and on output layer; the activation functions of the neurons in the hidden layer are of a specific radial basis function type [13].

The radial basis function describes the relation between the input and the desired output as a weighted sum of basis functions.

$$y = \sum_{i=1}^{N} w_i\, e^{\left(-\frac{1}{2\sigma_i^2 h}(X - Mean_i)^T (X - Mean_i)\right)}$$

where

N is the number of basis functions
X is the input vector
$Mean_i$ is the centre point of basis function number *i*.
σ_i is the centre point of basis function number *i*
h is the equalisation parameter

The RBF can be taught using the iterative gradient descent method used with the BP algorithm.

7.1.5 K Nearest Neighbours (KNN)

For the purpose of teaching the KNN network, all input-output pairs are stored in a database. When the new pattern is classified, the answer is based upon the K closest teaching patterns in the database.

The KNN does not require much time for the teaching process; time is required only for the pre-processing of variables and for the storing of data. The algorithm does require a lot of RAM, as the entire teaching material is stored there. Classification is slow, as the distances between the new pattern and all the teaching patterns have to be calculated.

The measure of distance used defines the meaning of ”closest neighbour”. The most common measure is the Euclidean:

$$Dist(X,Y) = \sqrt{\sum_{i=1}^{D} (x_i - y_i)^2}$$

where

$Dist(X,Y)$ is the distance between two D-dimensional vectors.

7.2 Tests

The tests were performed by feeding variables to the software as follows: **1)** without pre-processing (Ex1); the PRW performed the pre-processing; **2)** the pre-processed variables were fed (Ex2), while the pre-processing function of the software was disabled. **3)** Min-max pre-processing (Ex3) and **4)** pre-processing performed by the sigmoidal function (Ex4) were also tested.

The results were assessed in three ways: The greatest portion of correctly classified enterprises (EntCorr), the greatest portion of correctly classified enterprises (Corr2), with just two alternatives (Good/Bad) to choose from, and the portion of entirely incorrectly classified enterprises (EntIncorr).

An enterprise in entirely incorrectly classified, when the model yields a classification that is not a neighbour of the correct classification (see the table below).

	D	**C**	**B**	**A**
D			X	X
C				X
B	X			
A	X	X		

The teaching process was discontinued, when the RMS (Root Mean Square) fell below the target value, or when a desired number of iterations was performed.

The RMS is calculated using this formula:

$RMS = \sqrt{\sum_{i=1}^{n} (d_i - y_i)^2}$, where *n* is the number of observations, d_i is target value number *i* and y_i is the corresponding estimate.

Table 3 The power of the various models when modelling the bank potential.

Model	EntCorr	Corr2	EntIncorr
Ex1Lin	74.7 %	93.5 %	2.8 %
Ex1Log	65.1 %	91.0 %	6.2 %
Ex1MLP	76.8 %	93.7 %	2.4 %
Ex1RBF	73.9 %	91.7 %	8.1 %
Ex1KNN	77.9 %	93.4 %	2.7 %
Ex2Lin	76.0 %	93.6 %	2.6 %
Ex2Log	59.6 %	84.3 %	12.7 %
Ex2MLP	75.8 %	93.4 %	2.7 %
Ex2RBF	67.7 %	89.5 %	6.4 %
Ex2KNN	77.8 %	93.4 %	3.1 %
Ex3Lin	73.3 %	92.8 %	3.1 %
Ex3Log	55.0 %	84.9 %	15.4 %
Ex3MLP	73.4 %	93.0 %	3.0 %
Ex3RBF	64.8 %	86.3 %	10.4 %
Ex3KNN	74.4 %	92.5 %	3.6 %
Ex4Lin	76.7 %	93.7 %	2.3 %
Ex4Log	72.1 %	93.4 %	3.1 %
Ex4MLP	76.6 %	93.8 %	2.2 %
Ex4RBF	68.5 %	92.3 %	4.6 %
Ex4KNN	76.9 %	93.8 %	2.7 %

Table 4 Ranking lists

Model	EntCorr	Corr2	EntIncorr	Sum
Ex4MLP	6	2	1	9
Ex4KNN	3	1	5	9
Ex1MLP	4	3	3	10
Ex4Lin	5	4	2	11
Ex1KNN	1	7	6	14
Ex2Lin	7	5	4	16
Ex2KNN	2	8	10	20
Ex1Lin	9	6	8	23
Ex2MLP	8	9	7	24
Ex3MLP	12	11	9	32
Ex4Log	14	10	11	35
Ex3KNN	10	13	13	36
Ex3Lin	13	12	12	37
Ex4RBF	15	14	14	43
Ex1RBF	11	15	17	43
Ex1Log	17	16	15	48
Ex2RBF	16	17	16	49
Ex3RBF	18	18	18	54
Ex2Log	19	20	19	58
Ex3Log	20	19	20	59

The differences between the various alternatives were, with a few exceptions, very small. *MLP, Lin* and *KNN* topped the ranking list; the latter partly due to the fact that the results were weighted to the largest class (PPO = D), and the errors were greater in the smaller (but most important) classes A, B and C. This was the reason to not choose KNN as the production algorithm.

By virtue of the ranking list and the goals of the construction, the MLP was selected as the primary tool. The majority of Finnish enterprises are small (turnover below FIM 5 million in 73% of all cases). It is thus presumed that a sufficient accuracy and as little error as possible are important factors for the reason that the largest target group (PPO D) then can be divided into subgroups of approximately the same size as classes A, B and C without any deterioration of the result of the classification performed by the model.

8 Efficiency of Neural Network decisions vs. human decisions in the selection of new prospects.

The ability and efficiency of the model was assessed using a test arranged for this purpose - the test involved a situation in which people who make assessments of prospects in the course of their work performed the classification using almost the same information as the network. When implementing the classification using traditional methods, the information available for the classification process or for the implementation of the DM campaign is usually approximately equal to the one used here.

8.1 Sample

A total of 400 enterprises were selected through random sampling in such a manner that all four bank potential groups, A, B, C and D, were equally represented. The Bank's material included 23 000 enterprises, whose bank potential was defined. The material was divided into four parts by bank potential, and 100 enterprises were randomly drawn from each group, using the random number generator of the SPSS software. These samples were then combined into one material, and the variables that the model uses in its decision-making process were added, with the one exception that the name and industry of the enterprise were in plain text, just as in the process implemented by humans.

This material was sent to three sales offices - Helsinki, Tampere and Oulu - for assessment. The aim was to assign a grade from one to four to bank potential, profitability and loyalty. A grade of one indicates that the enterprise has little of the property in question, four that it has a lot. The assessors saw their classifications together with the original data. The strategy of choosing four groups of equal size and bank potential was used, because it was then possible to assess the real classification instead of making pure guesses. If the test material had been drawn randomly from the entire material, guessing D would have yielded a better result than random guessing.

In a corresponding manner, the real numbers returned by the network were divided by quartiles into four groups of equal size per classifiable property, but in such a manner that the network did not have access to the previous classification - something the human could draw on in the test situation.

8.2 Results

The results were examined only for the enterprises for which nearly all data from Finska and Statistics Finland were available. The test sample included 234 such enterprises. As part of the enterprises remained unclassified by the humans, we wanted to make sure that the prerequisites for correct classification existed. It was thus possible to classify, on correct grounds, a ”no data” as an incorrect answer. If the database of the Bank contained the information ”no data”, the ”no data” was classified as a correct answer.

Potential of Bank Profit (PPO)

Table 5 PPO Classification in Helsinki

Pankkipotentiaali, oikea * Pankkipotentiaali Helsinki Crosstabulation

			Pankkipotentiaali Helsinki					
			0	1	2	3	4	Total
Pankkipotentiaali, oikea	1	Count	32	18	2			52
		% of Total	13,7%	7,7%	,9%			22,2%
	2	Count	14	25	17	6	3	65
		% of Total	6,0%	10,7%	7,3%	2,6%	1,3%	27,8%
	3	Count	3	16	31	10	4	64
		% of Total	1,3%	6,8%	13,2%	4,3%	1,7%	27,4%
	4	Count	1	6	13	21	12	53
		% of Total	,4%	2,6%	5,6%	9,0%	5,1%	22,6%
Total		Count	50	65	63	37	19	234
		% of Total	21,4%	27,8%	26,9%	15,8%	8,1%	100,0%

Helsinki had left 21.4% of the material unassessed. There were 57 entirely correct answers (24.4%), which may be compared with the 25% yielded by random guessing. If the material is divided into two groups, the one containing the non-potential classes 0, 1 and 2, and the other the potential classes 3 and 4, the success rate of Helsinki was 66.2%. A gross mistake, where the classification differed from the correct one by two units, occurred in 17.9% of the cases.

Table 6 PPO Classification in Oulu

Pankkipotentiaali, oikea * Pankkipotentiaali Oulu Crosstabulation

			Pankkipotentiaali Oulu					
			0	1	2	3	4	Total
Pankkipotentiaali, oikea	1	Count	8	36	6	2		52
		% of Total	3,4%	15,4%	2,6%	,9%		22,2%
	2	Count	3	16	18	20	8	65
		% of Total	1,3%	6,8%	7,7%	8,5%	3,4%	27,8%
	3	Count	2	3	14	21	24	64
		% of Total	,9%	1,3%	6,0%	9,0%	10,3%	27,4%
	4	Count	1	2	6	8	36	53
		% of Total	,4%	,9%	2,6%	3,4%	15,4%	22,6%
Total		Count	14	57	44	51	68	234
		% of Total	6,0%	24,4%	18,8%	21,8%	29,1%	100,0%

The percentage of not classified enterprises was very much lower than in Helsinki, 6%, which improves the overall result in Oulu. There were 111 (= 47.4%) entirely correct observations, which, compared with 25%, is an excellent result. The division into non-potentials/potentials produced 75.2 correct classifications. Of all observations in Oulu, only 10.3% were entirely incorrect.

Table 7 PPO Classification in Tampere

Pankkipotentiaali, oikea * Pankkipotentiaali Tampere Crosstabulation

			Pankkipotentiaali Tampere					
			0	1	2	3	4	Total
Pankkipotentiaali, oikea	1	Count	23	29				52
		% of Total	9,8%	12,4%				22,2%
	2	Count	9	40	13	2	1	65
		% of Total	3,8%	17,1%	5,6%	,9%	,4%	27,8%
	3	Count	2	30	23	5	4	64
		% of Total	,9%	12,8%	9,8%	2,1%	1,7%	27,4%
	4	Count		10	17	12	14	53
		% of Total		4,3%	7,3%	5,1%	6,0%	22,6%
Total		Count	34	109	53	19	19	234
		% of Total	14,5%	46,6%	22,6%	8,1%	8,1%	100,0%

At Tampere, 61 enterprises were entirely correctly classified (=26.1%), while 14.5% remained not classified; a result that was much worse than that of Oulu, and just slightly better than that of Helsinki. With the binary distribution, 63.7% of the classifications were correct, while the frequency of gross mistakes was 25.6%.

Table 8 PPO Classification of MLP

Pankkipotentiaali, oikea * Estimoitu pankkipotentiaali Crosstabulation

			Estimoitu pankkipotentiaali				
			1	2	3	4	Total
Pankkipotentiaali, oikea	1	Count	41	11			52
		% of Total	17,5%	4,7%			22,2%
	2	Count	19	36	7	3	65
		% of Total	8,1%	15,4%	3,0%	1,3%	27,8%
	3	Count	4	19	24	17	64
		% of Total	1,7%	8,1%	10,3%	7,3%	27,4%
	4	Count	3	6	13	31	53
		% of Total	1,3%	2,6%	5,6%	13,2%	22,6%
Total		Count	67	72	44	51	234
		% of Total	28,6%	30,8%	18,8%	21,8%	100,0%

The results obtained by the network were also compared with the average results of the three sales offices. The network yielded 132 entirely correct classifications (= 56.4%), the percentages for the sales offices and chance were 32.6% and 25%. For the binary distribution, the network yielded 82.1% correct answers, compared with the 68.4% and 50% of the sales offices and chance, respectively. The network made gross mistakes only in 6.9% of the cases, the figures for the sales offices and chance being 17.9% and 37.5%, respectively.

It is to be observed, that the enterprises, regarding which every model returned an incorrect answer, all belonged to group A or group B. There were no cases to the contrary, i.e. enterprises in groups A and B were never classified as C or D. Another thing to be noted was that the sales offices were better at classifying enterprises located within their own district than others, which makes one surmise that these classifications were not based entirely on the data available during the test.

Table 9 Summary of PPO Classifications

	Helsinki	Oulu	Tampere	Sales offices	Chance	Network
Entirely correct	24.4	47.4	26.1	32.6	25.0	56.4
Pot./not pot.	66.2	75.2	63.7	68.4	50.0	82.1
Gross mistakes	17.9	10.3	25.6	17.9	37.5	6.9

Profitability

In this context, a profitable enterprise is one that earns the Bank lots of revenue. Enterprises are ranked by volume. It is thus possible to compare the bank potential with the real profitability of the enterprise.

First, the correlation between the classification yielded by the answers and the value calculated on the basis of the data in the database of the Bank, was calculated.

Table 10 Correlations of Profitability Classifications

Correlations

		Kannattavuus oikea luokka	Kannattavuus Helsinki	Kannattavuus Oulu	Kannattavuus Tampere	Kannattavuus verkko
Pearson Correlation	Kannattavuus oikea luokka	1.000	.133*	.094	.202**	.269**
	Kannattavuus Helsinki	.133*	1.000	.514**	.688**	.661**
	Kannattavuus Oulu	.094	.514**	1.000	.514**	.509**
	Kannattavuus Tampere	.202**	.688**	.514**	1.000	.740**
	Kannattavuus verkko	.269**	.661**	.509**	.740**	1.000

*. Correlation is significant at the 0.05 level (2-tailed).

**. Correlation is significant at the 0.01 level (2-tailed).

The above table shows that the results of the network and Tampere correlate positively with the real profitability at the 0.01 significance level, and that of Helsinki correlates positively at the 0.05 level. The results of Oulu also correlates positively, but not quite at the 0.05 level. The network's correlation figures are the best.

As stated above under Bank potential, the sample does not represent the Finnish population of enterprises; far too many have a high bank potential. As bank potential correlates with profitability, the sample is biased also with regard to profitability, i.e. the sample contains a greater number of enterprises that are profitable from the Bank's point of view than an unbiased sample would. The distribution of the assessments of the sales offices was closer to the normal distribution, which seems to explain the low correlation of the results of the sales offices.

In the next paragraph, both the profitability calculated on the basis of the information in the database and the assessments were divided into for equally large groups, after which a cross-tabulation was performed. For ten enterprises it was not possible to calculate their profitability or the data was missing.

As could be surmised on the basis of the correlation table, the results of all sales offices were very similar and conservative: The amount of entirely correct classifications was 22.2% in Helsinki, 20.1% in Oulu, 29.5% in Tampere, the average being 23.9%. Here, the result of the network was 41.9%. For the division into non-potential/potential, the results were: Helsinki 55.1%, Oulu 35.5%, Tampere 59.0%, sales offices on an average 49.9% and the network 63.7%. The amount of gross misclassifications was 26.1% in Helsinki, 20.9% in Oulu, 23.1% in Tampere, the average for the sales offices being 23.4%, and the result of the network 23.0%.

It proved much harder to measure potential profitability than to assess bank potential. The distribution of the sales offices was as follows:

Group 1	6.3%
Group 2	45.5%
Group 3	31.1%
Group 4	17.1%

The network seemed to make much more accurate classifications than the sales offices, counting only correctly classified enterprises. The results were more even, when examining the number of gross mistakes. This is probably explained by the table above, showing that humans have a tendency to avoid extreme values, and to think along the lines of the normal distribution.

Table 11 Summary of Profitability Classifications

	Helsinki	Oulu	Tampere	Sales offices	Chance	Network
Entirely correct	22.2	20.1	29.5	23.9	25.0	41.9
Pot./not pot.	55.1	35.5	59.0	49.9	50.0	63.7
Gross mistakes	26.1	20.9	23.1	23.4	37.5	23.0

As the material in the sample was biased regarding profitability, the function of the network is examined using a larger material. This sample included more than 43 000 enterprises. In table n, the estimate of the network and the profitability calculated on the basis of the Bank's database are cross-tabulated. In this material, the correlation between the estimate of the network and the actual profitability is as high as 47%.

Table 12 Profitability Classification of MLP

Kannattavuus oikea luokka * Kannattavuus verkko Crosstabulation

			Kannattavuus verkko				
			1	2	3	4	Total
Kannattavuus oikea luokka	1	Count	12974	8085	2038	381	23478
		% of Total	30.0%	18.7%	4.7%	.9%	54.3%
	2	Count	4199	3946	1715	418	10278
		% of Total	9.7%	9.1%	4.0%	1.0%	23.8%
	3	Count	1729	1959	1428	583	5699
		% of Total	4.0%	4.5%	3.3%	1.3%	13.2%
	4	Count	580	831	1165	1243	3819
		% of Total	1.3%	1.9%	2.7%	2.9%	8.8%
Total		Count	19482	14821	6346	2625	43274
		% of Total	45.0%	34.2%	14.7%	6.1%	100.0%

(a) P(Correct class 3 or 4 | Estimate = 1) = 0.12
(b) P(Correct class 3 or 4 | Estimate = 2) = 0.19
(c) P(Correct class 3 or 4 | Estimate = 3) = 0.41
(d) P(Correct class 3 or 4 | Estimate = 4) = 0.70

from which we see that, relatively speaking, there are almost six times as many profitable enterprises in group (d) as in group (a). It is also true that, in absolute terms, there is a greater total number of profitable enterprises in groups (a) and (b) than in groups (c) and (d). When examining the assessment yielded by the network as **potential profitability**, one could entertain the positive thought that the enterprises whose estimate is 3 or 4, but at the time being are not profitable, can be moved to the category of profitable ones, as they show the same pattern as profitable enterprises do.

Loyalty

Loyalty proved to be the variable that was the hardest to assess. Loyalty was defined as follows:

$$\text{Loyalty} = \frac{\text{Customer revenues from beginning of year}}{\text{Bank potential}}$$

Table 13 Correlations of Loyalty, Profitability and PPO

Correlations

		Pankkipotentiaali, oikea	Lojaalisuus oikea	Kannattavuus oikea luokka
Pearson Correlation	Pankkipotentiaali, oikea	1.000	-.057	.209**
	Lojaalisuus oikea	-.057	1.000	.843**
	Kannattavuus oikea luokka	.209**	.843**	1.000

**. Correlation is significant at the 0.01 level (2-tailed).

which shows that loyalty, in the sample, does not correlate at all with bank potential, but correlates on the 0.01 level with profitability. This means that, regarding loyalty, the sample is not as strongly biased as regarding profitability.

Table 14 Coefficients of Correlations between human estimates and MLP

Correlations

		Lojaalisuus oikea	Lojaalisuus Helsinki	Lojaalisuus Oulu	Lojaalisuus Tampere	Lojaalisuus verkko
Pearson Correlation	Lojaalisuus oikea	1.000	-.052	.001	.043	.213**
	Lojaalisuus Helsinki	-.052	1.000	.146*	-.024	.161*
	Lojaalisuus Oulu	.001	.146*	1.000	-.055	-.121
	Lojaalisuus Tampere	.043	-.024	-.055	1.000	.064
	Lojaalisuus verkko	.213**	.161*	-.121	.064	1.000

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

The assessments regarding this dependent variable were strongly conflicting, and it seems that the assessments of the sales offices do not correlate at all with the loyalty figures calculated on the basis of the Bank’s database. The estimate of the network correlates with the actual loyalty on the 0.01 level.

It is also interesting to note the fact that the assessments provided by the sales offices are in conflict with each other.

The portions of entirely correctly classified enterprises were: Helsinki 21.8%, Oulu 20.9%, Tampere 21.4%, sales offices average 21.4%, and the network 30.3%, only the network yielded an assessment that was better than one arrived at by chance. For the binary non-potential / potential groups the figures were: Helsinki 50.9%, Oulu 51.3%, Tampere 50%, sales offices average 50.7%, and the network 60.3%. Gross mistakes, the random result being 37.5%: Helsinki 35.5%, Oulu 29.9%, Tampere 32.5%, sales offices average 32.6%. Here, the result of the network was 28.2%.

When assessing loyalty as well as profitability, the sales offices used the normal distribution, while loyalty in reality was evenly distributed among the various classes.

No assessment	4.3%
Class 1	28.2%
Class 2	18.4%
Class 3	23.5%
Class 4	25.6%

Table 15 Summary of Loyalty

	Helsinki	Oulu	Tampere	Sales offices	Chance	Network
Entirely correct	21.8	20.9	21.4	21.4	25.0	30.3
Pot./not pot.	50.9	51.3	50.0	50.7	50.0	60.3
Gross mistakes	37.5	29.9	32.5	32.6	37.5	28.2

As was the case regarding profitability, we also here examine the performance of the network using a larger sample; we use the 43 000 enterprises discussed above. The correlation coefficient between estimate and reality is small, $r^2 = 0.183$. The table below is similar to that in the section on profitability:

Table 16 Loyalty Classification of MLP

Lojaalisuus oikea * Lojaalisuus verkko Crosstabulation

			Lojaalisuus verkko				
			1	2	3	4	Total
Lojaalisuus oikea	1	Count	8801	7500	4694	1799	22794
		% of Total	20.3%	17.3%	10.8%	4.2%	52.7%
	2	Count	3194	3222	2676	1169	10261
		% of Total	7.4%	7.4%	6.2%	2.7%	23.7%
	3	Count	1601	1731	1642	1052	6026
		% of Total	3.7%	4.0%	3.8%	2.4%	13.9%
	4	Count	762	1089	1254	1088	4193
		% of Total	1.8%	2.5%	2.9%	2.5%	9.7%
Total		Count	14358	13542	10266	5108	43274
		% of Total	33.2%	31.3%	23.7%	11.8%	100.0%

Probabilities:

(a) P(Loyalty is 3 or 4 | Estimate = 1) = 0.16
(b) P(Loyalty is 3 or 4 | Estimate = 2) = 0.21
(c) P(Loyalty is 3 or 4 | Estimate = 3) = 0.28
(d) P(Loyalty is 3 or 4 | Estimate = 4) = 0.42

Here the lift is much smaller than the corresponding one in the case of profitability: the probability for group (d) is just 2.6 times that of group (a).

9 Summary and conclusions

In this summary we would like to emphasise that this is a tool designed to streamline business operation. The final decisions on the applicability of the results of this study must be taken by humans. The aim was to facilitate the classification of a large mass of so-called ”unknown” enterprises with a view to making it easier to compile target groups for sales and marketing operations.

This study and the classification tests clearly show that it is difficult for humans to make fast, rational decisions based solely on external information variables - in this case on information from Finska and Statistics Finland. In this context, the bank potential was the easiest property to classify, as the size of the enterprise, here described by the number of employees and annual turnover, partly explain the PPO variable. The size of the enterprise alone did not seem to be a sufficient indicator of the bank potential, as both the sales offices and the neural network were able to provide assessments that were much better than the estimates based solely upon workforce and turnover.

In this test, the neural network was able to yield better classification results than the participating sales offices did on an average. The neural network modelled for this study was much faster than the human workforce. Using the neural network, it was possible to classify the material used in this study (more than 200 000 enterprises) in relation to three segmenting classification criteria (Bank potential, Profitability and Loyalty) in just one day. In this test, a human classified the target group of 234 enterprises in 1.5 workdays. The classification of all enterprises in the entire database would at this rate take approx. five working year. Given more time and access to knowledge of local conditions, it is probable that the estimates provided by humans would be significantly more accurate, particularly regarding the bank potential.

The list on bank potential, compiled by the sales network of the Bank, at present covers one third of the Bank's active customers. Besides on the financial information on the enterprises, the assessments are based on the knowledge the account persons have on the situation of each enterprise They have got this information in the course of their work with the Bank's customers. This information can be made accessible to the classification system only by processing memoranda stored in electronic format.

Due to the positive results yielded by the selected model, it was decided to divide the bank potential Class D and the profitability potential into ten sub-classes (D10-D1 and K10-K1, respectively). In this manner, the network has access to target groups, classified by risk, and of manageable size, that can be used for sales and marketing purposes. In this classification, index 10 designates the most, and index 1 the least attractive target group. In this manner the Bank can avoid unnecessary investment in marketing activities, utilise its resources in a rational manner and free its personnel from the tedious and often frustrating initial definition and classification of potential target groups - all in line with the aim of this study.

By dividing each of the three variables in four classes as shown above, and adding the five risk classes provided by Finska, we arrive at 4 x 4 x 4 x 5 = 320 segments that can be used in the definition of target groups for marketing activities. Calculated in this fashion, one target group would include, on an average, 625 enterprises without any occlusive or prioritising classification. The exclusion of loyalty from the example above would yield 80 segments, each with 2500 enterprises.

A critical assessment of the results of the study seems to show that the model for defining target groups for prospecting performs even better than expected. Regarding profitability, the results are better than those yielded by humans, but it seems that this variable could be even better utilised through models, whose information content is a, b and c, as defined in Section 6.1.

The classification of loyalty was not published, but stored in the Banks database on marketing potential. The added value of this classification was regarded slight and uncertain. The variables selected did not explain the target classification to a sufficient extent. It was decided to let the modelling of loyalty be a subject of future research and modelling in the context of an investigation into customer management (CRM) for the part of customers, whose business is of vital importance to the bank, and regarding whom a sufficient amount of information on customer conduct and on the life cycle of the customer relationship is available.

It seems that the main goal of this study - a more effective classification process and utilisation of consequential effects - was reached. In a simultaneous classification process involving the four groups (1=little, 4=much) of bank potential and profitability potential, the neural network made three times as many entirely correct decision than humans. This implies that the target group selected by the network is that much better from the viewpoint of sales and marketing operations. The ratio of entirely wrong classifications, network vs. human, was 1.5:7. The different success ratios imply that marketing activities focusing on one thousand enterprises selected by the neural network have the same effect as corresponding activities focusing on three thousand enterprises selected by humans. An addition of the benefits of lower classification costs, the smaller amount of marketing material required, and the lesser amount of contacting required, shows that the use of the model saves a great deal of money, not counting the other benefits proposed in the hypothesis.

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