A COMPARATIVE ANALYSIS OF ARTIFICIAL NEURAL NETWORKS TOPOLOGIES IN DEFAULT FORECASTING

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Abstract: *Artificial neural networks are widely used in many classification tasks. One of them can be the classification of potential debtors into healthy and unsound due to their ability to pay back the debt in contractual time due to the ex-post financial information (financial ratios). Though the entry data may vary, depending on the applied approach, data limitations or the choice of ratios selection, it is the topology of the neural networks that has the biggest input on the outcome.*
The objective of the paper is to investigate the use of different artificial neural networks (NN) structures in the process of classification of banks' potential clients. Topologies and architectures of neural network are presented through literature review and an experimental case study implementing compares the results of a supervised learning multi-layer perceptron feed-forward neural network (MLP-FF) with the one based on back-propagation (denoted as MLP-BP). The paper uses a cross-national sample of 300 companies applying for credit to an international bank operating in Poland. Results of those different methods are juxtaposed, and their performance compared to present which architectures are more efficient than others in debtors' classification process.

Key words: *credit risk, default, neural networks*

JEL codes: *C45, C53, G33, G21*

1. Introduction

Banks have always been considered institutions of public trust as one of their operations is to manage individual people's deposits. This trust is strongly affected by the perception of performance characteristics and attributes of banks. However, that trust has also been significantly violated owing to the global financial crisis which started in the USA in 2007 and which led to many bankruptcies and it did not matter that it originated in a specific market of mortgage and collateral deals, still, it affected the whole banking sector.

Due to an increased number of bankruptcies noted among companies, banks pay more attention to credit risk management and evaluation of potential debtor's default. In a bank, credit risk, which in a subsequently is a part of economic risk, operational risk, banking risk and financial risk, is one of the main risks which can disrupt bank's operations and eventually decide about its survival. It can be defined as *a possibility of loss arising from the failure of a counterparty to make a contractual payment which means that the creditor will not receive contractual payment in agreed time* (Jajuga, 2004).

The intensification of business operations results in an intensification of negative occurrences such as the loss of liquidity, delays in payments or insolvency. A continuing trend of globalisation, crises transmission and cross-country corporate connections finds credit risk in the focus of attention. In fact, also financial advisory institutions like Basel Committee on Banking Supervision acknowledge the importance of risk management in such documents as Basel III which specifically focuses on strengthening regulations and risk management and supervision. It also confirms and expends the grounds of Basel II referring to credit risk and sophisticated models (within internal rating-based approach – IRB) to calculate capital charges and to manage credit risk. Unfortunately, Basel III does not clearly define methods of credit risk assessment and focuses still on statistical models, which in the past proved to be ineffective. Nowadays, risk analysis in financial markets is one of the most important factors and new methods must be very flexible and adaptive to changing realities of market economy.

The growing competition between banks sometimes leads to extremes. Banks competing for the client lower their requirements (or margin) and loose focus concerning their safety. Finally, the victorious hunt for the customer might be the reason for bank's failure. Nevertheless, the final decision, whether to grant funding or reject the application, always depends upon the creditor (bank) and it is the bank that is responsible for the potential loss or bankruptcy.

There are many different methods implemented in the credit risk management: experts' systems, scoring methods, discriminant analysis, logistic regression, logit and probit models, cluster analysis, tailor-made internal models etc. as well as so-called methods of the new approach which can be divided into:

1. defaults models which:
   - focus on establishing probability of default of the other contractual party,
   - establish rating;
2. marking to market models which describe the possible loss in case of bankruptcy and a current value of loans.

Unfortunately, it is believed that none of the existing methods of risk management in banks provides satisfactory results. Some even claim that VaR methodology, which is so popular, is inadequate when applied to credit risk (Savic et al., 2014). Moreover, analysists often need to choose between accuracy, efficiency and simplicity of chosen methods.

However, the implementation of various tools should provide banks with an opportunity to quickly identify and preselect companies that are in financial distress. This preselection should be followed by a more thorough analysis. It must be stressed that a correct preselection is both, cost- and time-effective, however, the advances in information technology have already significantly lowered the costs. Moreover, the selection must be always followed by a monitoring system, through the whole period of the loan. The same methods which are used for the initial screening can be used for monitoring to spot the deteriorating standing of the debtors in time to take efficient actions to protect bank's funding.

Therefore, referring to all the above, new approaches are constantly being developed and implemented. Neural networks are believed to be able to offer a powerful alternative to linear models for forecasting, classification, and risk assessment in finance. The neural network became so popular due to their adaptive nature and the fact that they are not forced to implement a forced prechosen function but can flexibly adapt to an economic task. This is due to their built-in capacity to adapt the synaptic weights to changes in the surrounding environment relatively quickly. However, in case of neural networks, it is not only the exact type but the structure which is vital. The structure of networks (complex to a bigger or lesser extent) is a crucial determinant of the way the information is transferred. All the merits aside, there still remain several concerns. One of these concerns refers to a challenge which occurs when we try to decipher what links are used in a particular neural network.

The objective of the paper is to present the difference between a topology of the net and its architecture, elements and algorithms and to deliver an answer of which (if any) algorithm implemented within a chosen architecture and topology of neural network regularly gains an advantage over other types – which is more efficient. The study can be classified in applied studies group and the research strategy is descriptive.

2. Literature review

Neural networks in the scope of credit risk are broadly analysed. Atiya (2001) presents an empirical approach, basing on the relationship of default and the characteristics of a firm learnt from the financial data. The conclusions indicate the superiority of neural networks over other techniques and the need for improvements in training methods, architecture selection, or input. Baesens et al. (2003) investigated neural networks' contribution in helping the credit-risk managers in explaining why a particular applicant is classified as either bad or good. They conclude that neural network rule extraction and decision trees are effective and powerful management tools, allowing the construction of advanced and user-friendly decision-support systems for credit-risk evaluation.

Also, in work of Pacelli and Azzollini (2011) it is stated that neural networks are particularly suited to analyse and interpret complex and often obscure phenomena and processes.

Lee et al. (2002) point out that the decision of network's topology, importance of potential input variables and the long training process has often long been criticized and hence limited its application in handling credit scoring problems. Still, other research proves that despite the weaknesses, neural networks show good performance when data are noisy or incorrect (Angelini et al., 2007; Tollo, 2006).

Zhang et al. (2004) presented a very interesting comparative analysis of the forecasting accuracy of univariate and multivariate linear models that incorporate fundamental accounting variables with the forecast accuracy of neural network models. This research proved that accuracy of neural network is better than the accuracy of linear models.

The computational experiments in Tsai (2000) on five data sets obtained from publicly available sources indicate that the basic Probabilistic Neural Network (PNN) with variables chosen by the ad hoc approach outperforms the Probabilistic Neural Network using variables selected by two benchmark methods, back-propagation neural network and stepwise linear discriminant analysis.

Also, there are many hybrid approaches. For instance, in Papatla et al. (2002) where the choice models and neural network were tested it resulted in a conclusion that hybrid models may capture aspects of predictive accuracy that neither standalone model is capable of on their own.

The latest application of neural networks also includes the use of neural networks for big data analysis – deep learning which application can be found in, for instance Najafabadi et al. (2015) where authors claim that Deep Learning has an advantage over traditional machine learning and other engineering algorithms when it comes to massive data input. However, some researchers indicate that deep learning with massive input is not always advisable as in case of some problems multi-layer network seems to provide better performance than state-of-the-art deep networks (Kasun et al. 2013) and that the number of features or dimensions should rather be reduced than enhanced.

The numerous examples of other research literature on neural networks and other techniques were presented in Wójcicka-Wójtowicz (2018).

3. Neural networks: architecture, topology, dynamics

In credit risk assessment the most-commonly used tools are discriminant analysis and logistic regression. Neural networks add an alternative, particularly in situations when the connections between variables (dependent and independent) are not straightforward.

Artificial neural networks are defined as "[…] *a massively parallel distributed processor made up of simple processing units that has a natural propensity for storing experiential knowledge and making it available for use*." (Haykin, 2011).

There are several architectures which can be implemented when training the network. The architecture is generally identified by two characteristics: topology and dynamics. The kind of dynamics bases on the direction in which the information flows in the network. The networks where the information goes only one-way (from the input to output) are called static. The structures where the movement is permissible in both directions are called dynamic. It is due to the character of those networks where the feedback is crucial and must be included.

In turn topology has more subgroups which are as follows: supervised learning, unsupervised learning, reinforced learning and semi-supervised learning.

The supervised learning process is a dependent one and a part of the training data acts as a teacher (supervisor) to the algorithm to determine the model. The network must be taught to generalize the final output by learning the essential aspects of the input-output relation. Each example is a pair consisting of an input object and a desired output value which is considered to be correct. A supervised learning algorithm analyzes the training data and produces an inferred function, which can be used for mapping new examples. The output can be categorical (like true/false or 0/1/2) or continuous (like 1,2,3, and so on). While learning the algorithm iteratively makes predictions on the training data and is corrected if necessary. The adjustment is made when the network compares the produced output with the target one. If there is a discrepancy, the error signal is created, and consequently learning is improved. Learning stops when the algorithm achieves an acceptable level of performance. This topology is mainly used in classification tasks (for categorical response values) and regression (for continuous-response values).

The unsupervised learning has the input data without any targeted output. This topology is typically used to identify clusters, reduce dimensions and for data-mining. As there is no desired output the network must self-organize.

In reinforced learning a constant feedback is given to the network to modify the weights. That topology is especially useful in case of tasks where the final result is a product of a sequence of actions.

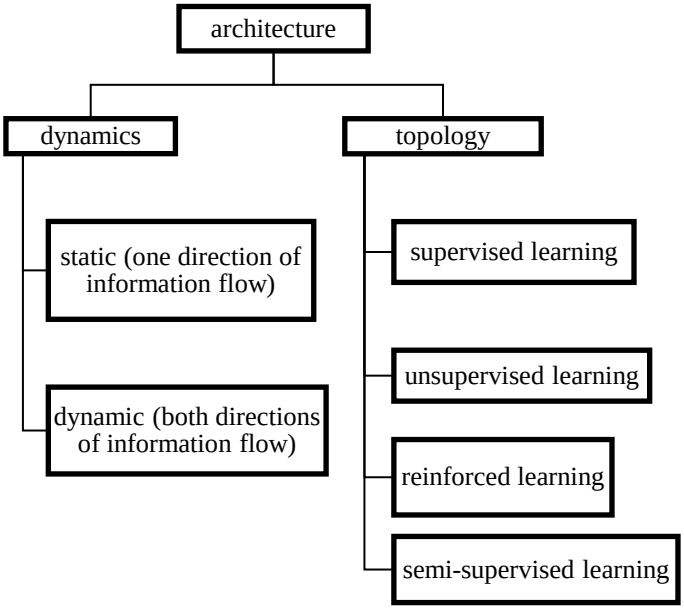
In the literature we can also find examples of semi-supervised learning which is a link between supervised and unsupervised learning and is mostly used to discover and learn the structure in the input variables, as well as to make best guess predictions for the unlabeled data.

The architecture and its divisions are presented in figure 1.

All topologies and more generally speaking, architectures, have some basic elements in common. These are:

- nods – known also as processing elements,
- layers (input, hidden, output) - each layer consists of nodes which are interconnected with the adjacent nodes,
- activation function
- transfer function
- output function.

Fig. 1 Characteristics of neural network architectures



Source: Own elaboration based on Pacelli and Azzollini (2011).

Each network can implement various functions, e.g. Linear, Tanh, Logistic sigmoid, Hyperbolic tangent, Exponential, Sine, Softmax, Gaussian etc. The neural networks can also be divided into feed-forward which means no loops are allowed – connections between the units do not form a cycle and a perceptron (neuron) has no backward link to the neurons in the previous layer as the input to one of the neurons of that layer. The opposite are recurrent neural networks where feedback loops occur. Very often also the backpropagation algorithm which uses gradient descent is implemented in training deep neural networks. Given an artificial neural network and an error function, the method calculates the gradient of the error function with respect to the neural network's weights. It repeatedly applies the chain rule through all of the possible paths in the network. The backpropagation algorithm can refer to feed-forward computation, back propagation to the output or hidden and weight updates. Backpropagation algorithms aside, there are also other used such genetic algorithms, evolutionary algorithm, simulating annealing algorithm, particle swarm optimization algorithm, and so on (Zhang et al., 2007).

The most common architectures (used for instance in Statistica Artificial Neural Networks – SANN) are: Linear, Single-layer Perceptron, Multi-layer Perceptron, Radial Basis Function, Generalized Regression Neural Network, Clustering Network, Principal Components Network, Probabilistic Neural Network, Fuzzy Adaptive Resonance, Learning Vector Quantization etc.

Generally, the most common topology used in credit risk decision-making process is the supervised learning (either feed-forward or accompanied by backpropagation). The division of debtors into a minimum of two groups with a given output (sound, unsound; healthy, unhealthy; good, bad etc.) is the initial input and networks learns that pattern. After the learning process the network can be fed new data and produce a target output. However, in case of big databases which are incomplete referring to proper prior classification or the classification is not also the unsupervised learning can be executed.

4. Results of the experiment

As it was presented above the topology of neural networks which fits credit classification tasks the best is the supervised learning. Therefore, the research was run as an experiment which compares the results of a supervised learning multi-layer perceptron feed-forward neural network (MLP-FF) with the one based on back-propagation (denoted as MLP-BP).

In MLP the data is provided in the neurons of input layer, the neurons in this first layer propagate the weighted data and randomly selected bias through the hidden layers. The MLP can be trained by a backpropagation algorithm Data is forwarded layer by layer until the activation process at the output layer occurs. In each layer, a weight is calculated for each possible connection. Then, a transfer function, which determines the output value for each neuron, is applied. In the research, there are several transfer functions

possible. The MLP network is trained with error correction learning, which means that the desired response for the system must be known.

The paper uses a cross-national sample of 300 companies applying for credit to an international bank operating in Poland. The structure of the sample reflects the structure of the general population of companies. The input is a balanced sample of good and bad debtors. The data covers a period of 2010 – 2016. It refers to companies from various sectors (inter alia construction, pharmaceutical, media etc.). These sectors cover a wide variety of companies. The sample contains financial statements of companies. Independent variables are the financial ratios. The dependent variable was identified as a "good" or "bad" company. The implemented tool is STATISTICA Neural Networks (SANN).

Preliminary, data set was divided into two groups in a following manner:

- learning group (75%),
- validation group (25%).

The experiment was run for each industry individually and also separately for the total sample. Results of quality in validation group for chosen algorithm – the best networks divided into (FF) and (BP) algorithm are shown in table 1.

Tab. 1 Quality of validation group for MLP-FF and MLP-BP in chosen industries

algorithm / industry	construction	pharmaceutical	media	total sample
MLP-FF	85.67%	88.67%	84.33%	82.33%
MLP-BP	87.33%	89.00%	82.33%	81.33%

Source: Own calculations.

The results in validation group are generally lower than in learning group, however, they are due to the specific character of the neural network more reliable. Therefore, we can assume that they are satisfactory (more than 80%). Pharmaceutical sector – probably due to its homogeneous character – achieved more levelled results. It can be observed that both MLP-FF and MLP-BP twice indicate better results than the other algorithm. Therefore, we cannot point which one is undoubtedly better than the competitive algorithm. That is not a big surprise as it is mostly the topology (in this case supervised learning) and architecture (MLP) that influences the result the most, despite the exact algorithm.

5. Conclusions

In order to improve the whole credit risk management system, there is a need to automate the initial credit decision-making process. The methods used so far all seem to be lacking in some aspects. Discriminant analysis is believed to be lacking due to a grey zone (inconclusive zone), logit and probit are supposed to be inefficient when it comes to complex problems, experts' systems are too subjective and vulnerable etc. Also, VaR methods which are so popular, are supposed to be inadequate when applied to credit risk.

Neural networks represent a certain alternative. As a group of machine learning and artificial intelligence methods used for modeling complex target functions, they can be successfully used in the classification task (also called neural network scoring or discriminant methods). Despite their drawbacks (lack of information on specific connections in hidden layers) they still provide useful and reliable information which the analysist can use in an initial stage of accepting or rejecting the application. Frequently, a network model is better in terms of overall explanatory power than a linear model. Artificial neural networks are also advantageous to statistical models for risk evaluation. According to some researchers, artificial neural networks are among the most effective learning methods currently known.

The paper presents and explains the difference between the architecture and topology, which sometimes are confused. Through a description of kinds and characteristics (elements, functions, etc.) of neural networks it also emphasizes which topology is most favorable in case of credit risk classification task (debtors analysis). Also, a literature review shows how important neural networks became in the past years and how much trust is put in possible implementations and their abilities to natural adaptation to changing economic environment. This is their flexibility which is greatly appreciated by the researchers and analysists.

The carried-out experiment compared one topology (supervised learning) of a Multi-layer perceptron in the form of pure feed-forward neural network on one hand and on the another with the implementation of a back-propagation algorithm.

The experiment proved that MLP-BP did slightly better than MLP-FF, however the differences in quality of the networks are very small (less than 2 percent) in validation group. The difference was even smaller in learning group, however, results of validation set are more reliable as these are the results achieved on the new set of data. Moreover, basing on these results we can expect the network to do similarly well on a new data input in the future.

Therefore, basing on this and previous research (Wójcicka-Wójtowicz, 2017) it can be concluded that in case of credit risk classification task (supervised learning topology) it is just the architecture and not the chosen algorithm that influence the quality of the results.

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