Methods of Artificial Intelligence for Prediction and Prevention Crisis Situations in Banking Systems

JERZY BALICKI, PIOTR PRZYBYŁEK, MARCIN ZADROGA, MARCIN ZAKIDALSKI
Faculty of Electronics, Telecommunications and Informatics
Gdańsk University of Technology
G.Narutowicza 11/12 St., 81-230 Gdańsk
POLAND
balicki@eti.pg.gda.pl, piotr.przybylek@gmail.com, marcin.zadroga@gmail.com, mzakidalski@gmail.com

Abstract: - In this paper, a support vector machine has been studied due to prediction of bank crisis. To prevent outcomes of crisis situations, artificial neural networks have been characterized as applied to stock market investments, as well as to test the credibility of the bank's customers. Finally, some numerical experiments have been presented.

Key-Words: - prediction, support vector machine, genetic algorithm, banking system

1 Introduction

Initial work on the forecasting system banking crisis emerged in the mid-nineties of the twentieth century, when Frankel and Rose developed a forecasting model using some indicators in relation to the emerging currency markets [10]. These variables can be divided into four categories.

The first category includes indicators of foreign markets, such as integrated indicators of interest rates and output growth. The second group includes national macroeconomic indicators, such as sudden changes in the rate of production, or the criteria for drastic changes in monetary and fiscal sense. In contrast, external variables, such as indicators of price revaluation, the state of the current account deficit and debt level can be in the third category. The fourth class of variables describes the determinants of a debt structure [10].

Kaminsky and Reinhart extended above model arguing that the causes of the crisis in the banking sector impinge on the causes of balance of payments crisis [14]. Analysis of the crisis in many countries has shown that on the basis of earlier signals of problems in the banking sector, it can provide balance of payments crisis. Since the liberalization of the financial usually precedes banking crises, it is easier to provide them with appropriate statistical methods.

Demirguc-Kunt and Detragiache developed a multi-valued logic model to predict banking crises [9]. The proposed approach is based on available data and assessment of the likelihood of a banking crisis. Moreover, it has a clear interpretation based on sample statistics. The monitoring system can be tailored to the preferences of decision makers. It may be useful for initial forecasts to save on the costs of monitoring.

Hanschel and Monnin presented a different approach to warning models of banking and financial crises [12]. This approach is based on the regression. They defined the crisis vulnerability index (called the stress index), which is designated for the banking sector in Switzerland. Also they discussed its role in the context of macroeconomic imbalances, which can serve as early warning signs for possible crisis in the banking sector for developed countries.

Davis and Karim compared early warning systems for banking crises [8]. Also worthy of mention is the SAFE [18].

This paper proposes a method of support vectors applied to estimate the risk of the whole banking sector. In contrast, artificial neural networks have been characterized as applied to stock market investments as well as to test the credibility of the bank's customers. Further interesting innovation described in this class implemented systems over the past few years.

2 Forecasting systems of banking crises

The development of the modern economy significantly affects efficient banking sector. It is worth mentioning that the banking crises in Ireland,

ISBN: 978-960-474-379-7

Spain and Portugal could undermine the stability of the financial sector in the euro zone.

The stability of banks is a key factor in maintaining wider financial stability. Banking network is unstable and trouble or bankruptcy of one bank can trigger a domino effect. Moreover, it can plunge the entire banking sector in the country or in the wider area. The result of the financial crisis can be serious problems associated with banking institutions to maintain the financial flow of the sector, as well as the loss of customer confidence in the banks. It may result in an avalanche payment of funds from bank deposits.

Therefore, corrective action relating to the operation of banks is not only to grant direct financial assistance, but also for predicting the crisis in the banking sector, bank capital adequacy test, or the introduction of innovations that reduce operating costs of the bank.

A stress test usually refers to the designation of the bank's capital relative to its assets (deposits and loans). If this ratio is too low, then the bank is unlikely to survive the financial crisis.

The progress of information technology enables the modernization of banking systems. It is worth noting that the severity of the bank's web offer is important criterion for choosing a financial institution. Effective web banking affects the development of electronic commerce, which indicates a highly competitive economy of the state. It is estimated that e- banking is a term five years the main sector in banking, as well as e-commerce in traditional trade [11].

3 SVM for banking systems

The methods used to measure and estimate the risk of debt securities are generally based on statistics or machine learning techniques [2]. Apart from assessing the rating of particular debt instrument (e.g. a specific batch of bonds), we can also evaluate rating of a bank as a whole.

Using statistical methods, we can expect accurate predictions for approximately two thirds of cases [3]. The most serious limitation of statistical approach turns out to be sensitiveness to the dependent variables and assumption of multivariate normality of the probability distribution for many input variables [4].

The inference of expert system is performed by classifying new cases of input data for the class to which it was assigned the most similar case from the training set [5].

Back-propagation artificial neural networks with sigmoidal or radial activation functions belong to the basic and most popular machine learning methods used for the evaluation of debt instruments and whole companies.

However, in recent years, banks have started to use also alternative methods. Support Vector Machine - SVM is getting widely acknowledged as a tool to assess risk [22]. Empirical studies show that SVM are characterized by a slightly better performance than artificial networks in estimating the risk of corporate debt securities. The aim of SVM is to create a hyperplane separating considered classes (eg. rating of debt securities with possible classes: *A*, *B* or *C*).

The SVM proposed by Vapnik focused initially on the classification of linearly separable input points, which could be assigned to one of two classes. However, the present method allows the classification of input points to nonlinearly separable sets.

The simplest version of SVM is *Linear Support Vector Machine* LSVM (Fig1). Training set consists of vectors which describe characteristics of considered object (e.g. revenue, equity, long term debt in case of assessing a company). There is assigned a class of value 1 or -1 for each input vector.

Two sets of points are linearly separable if a hyperplane can be defined in such a way that points belonging to one class are separated from points belonging to second class. Points from two dimensional space can be separated using line. Points from three dimensional space can be separated by plane etc. There exists a solid statistical foundation to determine whether the separating hyperplane can be defined for a given set of points.

The main aim of LSVM is not only separating points of two classes (which is achievable using simple perceptron), but separating with greatest possible margin. The problem here is to find the coefficients of hyperplane which separates two classes with maximum margin.

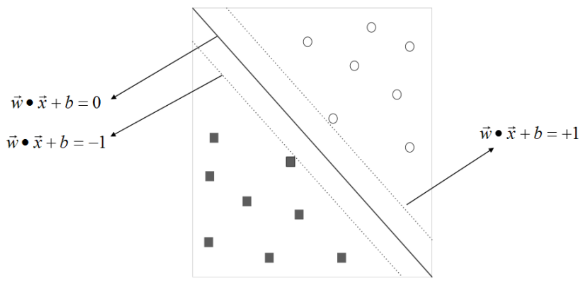

Fig.1. Separating two classes with maximum margin

ISBN: 978-960-474-379-7

The problem of finding weights for optimal hyperplane can be transformed to a problem of minimisation the half of square of norm of weight vector *w* [1]. Then, the problem can be presented in dual form (where the vector of weights is presented as a linear combination of input points).

Above optimization problem can be solved using Lagrange multipliers α, where different coefficients are assigned to each input vector. Generally, most input vectors are assigned 0. Input vectors with non-zero value become support vectors. In order to use LSVM for non-linearly separable sets, there was introduced a mapping of input space into high - dimensional feature space, where the sets are very likely to be linearly separable.

Support Vector Machine is becoming more popular in a wide range of banking areas, because it is characterized by much better prediction ability in comparison to traditional statistical approach (like linear regression, multiple regression) or artificial neural network.

Shouwei, Mingliang and Jianmin applied SVM and another methods for estimation of systemic risk of whole bank sector in China [19]. Assessing probability of financial crash of a bank, the researchers took into consideration not only the economic indicators of given bank (like ROE, ROI etc.), but also macroeconomic indicators (like GDP rate of growth) and indicators which reflected the inter-banking operations.

There were chosen 17 indicators for 36 banks in China. Data was divided into training set (19 cases) and testing set (17 cases). The researchers used SVM method with kernel function which allows to indirectly map input space into high dimensional feature space.

Kernel function defines only inner products between vectors from feature space. This is called 'kernel trick', because it allows operating in feature space without explicit mapping of input vectors into feature space. Thanks to that approach the sets non-linearly separable can become linearly separable in a high dimensional feature space. There are many types of kernel function. In this case study, a radial basis function was used. A function *f* that is the result of leveraging SVM method, assigns given input vector to one of two classes (1 or -1), as follows:

$$f(x) = sign(\sum_{i=1}^{M} \alpha_i y_i K\,(x, x_i) + b) \quad (1)$$

where:
x - the vector of new case which should be assigned to one of the output classes (-1 or 1),
M – number of points from training set (19 in this case, because of 19 test cases),
α_i - weight associated with xi test case,
y_i – class assigned to xi test case (either 1 or -1),
b – the bias (the value of shift of inner product between weight $\boldsymbol{w}$ vector from primal form of problem and vector $\boldsymbol{x}$)

SVM method can be tuned by optimizing its parameters (e.g. the value of minimum possible margin to separate points of two classes). The parameter tuning can be performed using different techniques like: Grid Search, Particle Swarm Optimization or genetic algorithms. Results of effectiveness for each of these methods are presented in Table 1. Grid Search turned out to return the best parameters which resulted in best effectiveness of SVM

Table 1. The effectiveness of selected artificial intelligence methods to determine the parameters of the method SVM [19]

	Grid Search	*Algorytm genetyczny*	*Particle Swarm Optimization*
Training set	100%	100%	100%
Exam set	94.12%	88.24%	88.24%

In order to compare the accuracy of SVM in terms of banking crash the researchers used 3 another AI methods:
- back-propagation artificial neural network;
- multiple discriminant analysis (MDA);
- logistic regression.

Artificial neural network was trained using different activation functions and different number of neurons in hidden layer in order to achieve best prediction capability for given testing set. The comparison results are presented in Table 2.

Table 2. Comparison of methods to estimate banking risk [19]

	SVM	ANN with backpropagation	MDA	Logistic Regression
Training set	100%	100%	94,74%	100%
Exam set	94.12 %	84.62%	76.47%	76.47%

SVM outperforms other AI methods for given testing set. McNemar test (small sample set) proved that SVM is characterized by better prediction efficiency than neural network (significance level 0.1) and latter AI techniques (significance level 0.05).

ISBN: 978-960-474-379-7

The results of empirical studies show the great accuracy and prediction effectiveness of SVM method. It outperforms other widely used AI methods (ANN, MDA or Logistic Regression) giving statistically better results. We can conclude that SVM is a very promising method for supporting key decisions in banking industry.

4 Artificial neural networks to support the stock market investment

Artificial neural networks ANNs can support prediction usually for an economic forecast [6]. It uses the ability of the network to generalize and extract knowledge from the input data in the learning process [7]. This is done without explicitly defining the relationship between the input and output variables.

Furthermore, ANNs can be applied for classification and recognition. An assignment of objects is described by the input parameters to the appropriate class.

ANNs in data analysis look for links between the data and conclusions. The network, due to the ability to generalize helps automate the process of inference and extract data important links between them. ANNs is capable for NP-hard problem optimization, such as the traveling salesman problem that is solved by a recursive Hopfield neural network.

Among the tasks related to financial activities, for which it was able to use support based on artificial neural networks is analysis of the creditworthiness of bank customers (risks prediction associated with granting a mortgage loan could be also supported by ANN).

Project management as well as some building bidding strategies are crucial developments of ANNs. Moreover, neural networks can improve forecasting index values and directions of trends in the marketplace. Similarly, ANNs can support determination of risk classes by financial instruments. The other subjects are detection of regularities in the evolution of the price of financial instruments and forecasting bankruptcies and corporate insolvencies.

The efficiency of network forecasting depends on the decisions taken by the analyst at the stage of its architecture. The results of networks with different architectures for the same input data can vary significantly from each other. There are several approaches to the problem of how to design ANN for financial purposes. When considering stock market movements' prediction, the use of the variables of both technical as well as fundamental analysis for this kind of prediction is very widely used.

In this kind of approach, analyst responsible for creating ANN, not only selects appropriate structure for the network itself, but also often run experiments with the different approaches regarding input data pre-processing (as well as output data interpretation).

Worth mentioning is also how researchers handle the issue of getting data, and testing theirs ANNs. Generally, two approaches emerged. One focuses on performing experiments in artificial (virtual) markets. Second one is focused directly on the real data from financial markets. First approach is interesting because it is often connected with modelling complex economics relationships to mimic the behaviour of real market.

Researches indicate that ANNs intelligent models often outperforms classical models, it might be easily seen especially in short-term predictions. Taking into account how situation rapidly changes on market, and how stock markets reacts in response to many complex factors – could be easily seen that there is always a room for improvement and tweaking in the ANNs training algorithms, structures, data processing.

5 ANNs to assess creditworthiness

Among the traditional methods of assessing creditworthiness the oldest approach is to conduct a detailed interview with the client. Results obtained from such screening depend largely on the technical knowledge, experience and integrity of the expert interviewer. Due to such constraints methods of artificial intelligence (with emphasize on the artificial neural networks) are becoming extensively used in this field. Credit risk assessment systems using artificial neural networks are in production use in banks in the United States, Germany and the United Kingdom.

Artificial neural networks are not the only ones to be utilized in such systems. Among other techniques used in this area are e.g. discriminatory models, logit models and k-nearest neighbours technique.

Discriminatory models are used for determining the linear combination of the characteristics for selected objects that allows one to divide objects into classes corresponding to the probability of future repaying of the credit.

Logit models are based on the transformation of the probabilities of particular events to the real values. In further steps linear regression models are applied to the results of those transformations.

In a method called *k-nearest neighbours* a potential client is marked as eligible/ineligible for credit depending on the class which is predominant among *k* other classified representatives of the analysed set which are in the closest neighbourhood of the analysed point [13]. *Genetic algorithms* and *decision trees* are applied to the assessment of the creditworthiness as well.

Artificial intelligence techniques are also used for the selection of clients who are very likely to stop paying their liabilities in the nearest future [15].

Obtaining training data for the creditworthiness assessment is difficult, because information concerning credit credibility is confidential (this confidentiality is usually regulated by local secrecy acts).

There are two solutions to this problem in the literature [16,17]:

- usage of available benchmark data describing creditworthiness, e.g. German Credit Data from Statlog dataset ;
- acquisition of data samples from the real-life cases. Such data must belong to the subset of customers of a particular financial institution. In some cases size of data is limited e.g., Nazari used the sample of 90 cases [17].

The typical input data attributes for the assessment of personal loans consists of: age, marital status, number/kind of real estate properties owned by the customer, monthly income, the fact of owning private business, details of client's other personal commitments, number of children and the period of employment by the current employer [20].

While examining the creditworthiness of companies, banks use financial indicators calculated on the basis of the last balance sheet of the company [21].

Analysed case studies were based on very different architectures of neural networks: multilayer perceptron with radial activation function, the unidirectional network with linear activation function. Finally, the combination of two neural networks was used among which the first one calculated the preliminary value of creditworthiness. In the analysed case studies performance of artificial neural networks was comparable to the performance of traditional econometric methods. The obtained results - due to limited samples size - should be considered as an evidence for the potentially high prognostic value of neural networks in the this field rather than convincing proof of such situation.

In case of loan decisions the decisive body has to deal with incomplete information. What might be even more important is the fact that the stored data undergoes continuous changes (e.g. customer is being assigned new liability). Neural networks – as a self-adopting tools – perform extremely well in such ambiguous situations.

The neural networks do not have to be the only tool for assessing creditworthiness. They might be used as a preliminary assessment tool. In further steps of credit process some more traditional actions might be taken. Anyway, the benefit of credit decision automatisation might be significant as the bigger number of banks offers loans via Internet.

Baesens *et al* presented interesting approach to assessing creditworthiness. Instead of using the artificial neural network as a black box he decided to extract fuzzy rules from trained neural network [1]. Such a reversal of the sequence of operations allowed him to construct a new tool for assessing creditworthiness based on rules learned by neural network. These extracted rules might serve as an input for the creditworthiness specialists in financial institutions.

6 Conclusion

This paper proposes a method of support vector applied to estimate the risk of the banking sector. Moreover, the application of artificial neural networks to stock market investments, as well as to test the credibility of potential borrowers.

An interesting direction for further research is to develop a method of vectors bearing to verify the domestic banking sector, as well as the implementation of artificial neural networks to verify the credibility of potential borrowers GPU.

References:

[1] Baesens B., Setiono R., Mues C., Vanthien J.: *Using neural network rule extraction and decision tables for credit-risk evaluation*. Management Science, Vol. 49, No. 3, March 2003, pp. 312–320.

[2] Balicki J., Balicka H., Masiejczyk J., Zacniewski A.: *Multi-criterion Decision Making in Distributed Systems by Quantum Evolutionary Algorithms*. Proceedings of The 2th European Conference on Computer Science, Puerto de la Cruz, Spain, November 30 – December 2, 2010, WSEAS Press, pp. 328-333

[3] Balicki J., *Multi-criterion Decision Making by Artificial Intelligence Techniques*. Proc. on the 8th Int. Con. on Artificial Intelligence,

Knowledge Engineering and Data Bases, February 2009, Cambridge, pp. 319-324.

[4] Balicki J.: *Multi-criterion Tabu Programming for Pareto-optimal Task Assignment in Distributed Computer Systems, in: Mastorakis N.E., at el. "*New Aspects of Computers*", Crete 2008, WSEAS Press, pp. 142-152*

[5] Balicki J.: *An Adaptive Quantum-based Multi-objective Evolutionary Algorithm for Efficient Task Assignment in Distributed Systems,* Proc. of *The WSEAS Int. Conf. on Computers, July22-26, 2009, Rodos Island, Greece*, WSEAS Press, pp. 417-422

[6] Brown C.: *Technical Analysis for the Trading Professional, Second Edition: Strategies and Techniques for Today's Turbulent Global Financial Markets*. The McGrawHill Companies, New York 2011.

[7] Chaveesuk R., Srivaree-Ratana C., Smith A.E.: *Alternative neural network approaches to corporate bond rating*. Journal of Engineering Valuation and Cost Analysis, vol. 2, 1999, ss. 117-131.

[8] Davis E. P., Karim D.: *Comparing early warning systems for banking crises*. Journal of Financial Stability, vol. 4, no. 2, 2008, pp. 89–120.

[9] Demirguc-Kunt A., Detragiache E.: *Monitoring banking sector fragility: a multivariate logit approach*. World Bank Economic Review, vol. 14, no. 2, 2000, pp. 287–307.

[10] Frankel J. A., Rose A. K.: *Currency crashes in emerging markets: an empirical treatment.* Journal of International Economics, vol. 41, no. 3-4, pp. 351–366, 1996.

[11] Golicic S. L., et al.: *The impact of e-commerce on supply chain relationships.* Int. Journal of Physical Distribution, vol. 32, 2002, pp. 851–871.

[12] Hanschel E., Monnin P.: *Measuring and forecasting stress in the banking sector: evidence from Switzerland*. Investigating the Relationship between the Financial and Real Economy, BIS Papers, no. 22, 2005, pp. 431-449.

[13] Henley W.E., Hand D.J.: *A k-nearest-neighbour classifier for assessing consumer credit risk*, The Statistician, Volume 45, Issue 1 (1996), pp. 75 – 95.

[14] Kaminsky G. L., Reinhart C. M.: *Thetwin crises: the causes of banking and balance-of-payments problems*. American Economic Review, vol. 89, no. 3, pp. 473–500, 1999

[15] Majer I.: *Application scoring: logit model approach and the divergence method compared,* Department of Applied Econometrics, Working Paper, No. 10-06, 2006.

[16] Mylonakis J., Diacogiannis G.: *Evaluating the likelihood of using linear discriminant analysis as a commercial bank card owners credit scoring model*. International Business Research, Vol. 3, No. 2, 2010.

[17] Nazari M., Alidadi M.: *Measuring credit risk of bank customers using artificial neural network*. Journal of Management Research, vol. 5, No. 2, 2013.

[18] Oet M., Eiben R., Bianco T., Gramlich D., Ong S., Wang J.: *SAFE: an early warning system for systemic banking risk*. *Proceedings of the 24th Australasian Finance and Banking Conference*, SSRN, 2011.

[19] Shouwei L., Mingliang W., Jianmin H.: *Prediction of Banking Systemic Risk Based on Support Vector Machine*. Mathematical Problems in Engineering, Vol. 2013, April 2013, p. 3

[20] Srivastava R. P.: *Automating judgmental decisions using neural networks: a model for processing business loan applications*, Proceedings of the 1992 ACM annual conference on Communications, pp. 351-357

[21] Yobas M.B., Crook J.N., Ross P.: *Credit scoring using neural and evolutionary techniques.* IMA Journal of Mathematics Applied in Business and Industry, Vol. 11, 2000, pp. 111-125.

[22] Zan H. et al.: *Credit rating analysis with support vector machines and neural networks: a market comparative study*. Decision Support Systems, vol. 37, 2004, ss. 543–558.