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An evaluation of Iranian Banking System Credit Risk: Neural network and Logistic Regression Approach

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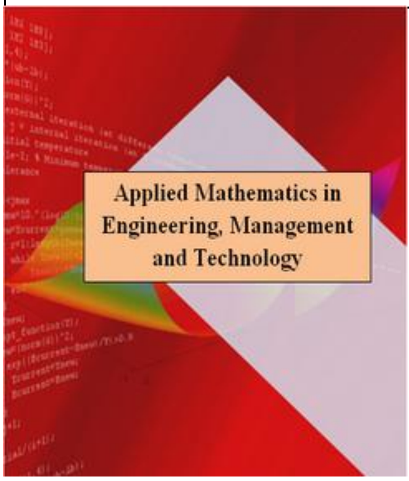


Abstract

One of the most important problems that usually banks and financial institutions encounter is the credit risk or unfulfillment of obligations by applicant of the credit facilities in all over the world .The noticeable figure of outstanding claims bank show its importance and consideration. Therefore, various efforts have been done for presenting an efficient model in order to more accurate evaluating and ranking of applicants" credit facilities. In this essay, we have tried to investigate and review the efficiency of the logistic regression models and neural network for ranking of the applicants of the Meli Bank.
The population of this research are all legal customers (corporate applicants) whom they have utilized the facilities of Meli Bank of Esfahan province during the 2013-2014 years, and so by using of random sampling, 400 files have been selected for data gathering.
In this research, we have used logistic regression model, multi-layers perceptron neural networks and seven 5 variables concluding qualitative and independent financial variables in which they have a meaningful effect on credit risk and resolution between two groups of applicants, and we processed the final model by using them.
We compared the results of logistic regression to neural networks models in order to evaluate their efficiency. Reviewing of the results shows that because of incorporating of complexity of
Nonlinear relations between performing measures and measuring of customers credit risk
Using of neural networks models has had more accurate and reliable results.

Key Words: neural network, logistic regression Credit risk, legal customer

1) Introduction

Service receiver validity regarding repaying facility principle and interest should be determined for granting financial services. Recently, the number of banks as well as private banks and financial institutions increase and also it is possible to determine facilities rate based on client validity. Therefore, banks could design their credit portfolio considering diversity principle for client ranking system and credit risk assessment. Credit risk management regards as one of the most important issues whish should be considered by credit managers and policymakers. Credit rank systems are very essential for mentioned risk control and management.
Accepting and rejecting client credit application could be determined by assessment techniques and validation models. In assessment techniques, analysts assess clients based on their previous and present records and information and also some issues such as reputation and reliability, repayment ability, characteristic and pledges. Regarding these methods, final decision has been made by bank managers and experts involved in credit sector. This affair results in increasing the error rate in making decision about client credit risk and consequently increasing bank credit risk.

2) Literature review

Florez-Lopezz (2015) conducted a research named"Enhancing accuracy and interpretability of ensemble strategies in credit risk assessment. A correlated-adjusted decision forest proposal" The results showed that Empirical results suggest CADF is an encouraging solution for credit risk problems, being able to compete in accuracy with much complex proposals while producing a rule-based structure directly useful for managerial decisions.
Nurul Kabir and his coworkers (2015) Comparative credit risk in Islamic and conventional bank" Islamic and conventional bank shows that calculate the accounting informationbased Z-score and nonperforming loan (NPL) ratio for the purpose ofcomparison. they results show that Islamic banks have significantly lower credit risk than conventional banks as based on DD. In contrast, and as expected, Islamic banks display much higher credit risk using the Z-score and NPL ratio. These findings suggest that the measure chosen plays a significant role in assessing the actual credit risk of Islamic banks.
Bakht and Elter (2014) "assessment model of credit risk Jordan commercial banks: neural network approach" Jordan bank credit risk assessment shows that there is no perfect model for program assessment and regarding ranking rate, LR is more efficient than RBF. Variables such as company type, loan amount, gender, age and interest rate have been used in this study.
Lopez Iturriaga (2014) conducted a research named "Bankruptcy visualization and prediction using neural networks: A study of U.S. commercial banks" Bankruptcy visualization and prediction using neural networks shows that that failed banks are more concentrated in real estate loans and have more provisions. Their situation is partially due to risky expansion, which results in less equity and interest income. After drawing the profile of distressed banks, we develop a model to detect failures and a tool to assess bank risk in the short, medium and long term using bankruptcies that occurred from May 2012 to December 2013 in U.S. banks. The model can detect 96.15% of the failures in this period and outperforms traditional models of bankruptcy prediction.
Shomara and Shebalkofe (2013) "neural network, modeling and simulation application for Russian banks operation assessment", Russian bank credit risk assessment shows that automatically designed neutral network has the capacity of assessing Russian bank operation .Variables such as dept to stockholders (D/E), deposit rate and stockholders total interest have been used in this research.
Recently, Blanco et al. (2013) used the multilayer perceptron neural network (MLP) to develop a specific microfinance credit scoring model. They compared the performance of the MLP model against three statistical techniques: linear discriminant analysis, quadratic discriminant analysis, and logistic regression. The MLP model achieved higher accuracy with lower misclassification cost. The findings confirmed the superiority of the MLP over the parametric statistical techniques.
Poyanfar and Phalahpoor (2013) conducted a research named "estimating banks clients credit rate regarding support vector machine minimum squares approach based on genetic algorithm". Displaying UCI for assessing credit risk of services applicants (Ga-LSSVM) applying support vector machine minimum squares approach is the main purpose of this study. For this purpose, Germany bank data collection has been used in the machine learning data-base. Besides, results of the present model have been compared with Ga-LSSVM statistical model of Logit ranking precision and effectiveness as well as support vector machine optimizing approaches. Ga-LSSVM research findings show that the examined models have desirable performance regarding credit risk assessment of services applicants.
Showrozy and his coworkers (2012) conducted a research named "credit risk assessment of Export Bank entity clients based on artificial neural network, Logit and comparing both of them". Variables such as financial ratios and credit information obtained from sample companies balance sheet and profit (loss) statement have been used in this research. Results show that these two models have the same efficiency for credit risk assessment of bank entity clients.
Ebrahimi and Daryabar (2012) studied the factors influencing on the credit risk, risk prediction, credit ranking of bank clients using data envelopment analysis method, logistic regression, and neural network. The results showed that neural network model was more efficient in predicting credit risk of real clients and credit rating. Iran Supreme Banking Institute compared the efficiency of credit risk in linear probability, logistic and artificial neural networks models to predict credit risk of bank clients. The results showed that artificial neural network and logistic models had better prediction accuracy, respectively.
Mansoori and Azar (2012) assessed the credit risk of bank clients using multilayer perceptron neural networks. They showed that neural networks and logistic regression had the same potentiality, but neural network models were more potential in estimating the credit capacity of clients.
Pasilly (2011) conducted a research named "artificial neural network method in managing credit risk" and examined Italy bank credit risk. Variables used in this research including stockholder income and financial

circulation and so on. Results show that Multi Layers Perceptron (MLP) neural network is more desirable than other methods in managing Italy banks risk.
In their study, Jagric et al (2011) emphasized that a bank's main challenge is to build up new credit risk models with higher predictive accuracy. They stressed on using ANNs to construct a credit scoring model because of its ability to capture non-linearity in financial data. They developed a credit decision model using learning vector quantization (LVQ) neural network for retail loans and logistic regression model for benchmarking. A real life dataset from Slovenian banks was used. The results showed that LVQ model outperformed the logistic model and achieved higher accuracy results in the validation set.
Ghorsy (2011) categorized Mellat bank entity client credit in her research. Modeling of Mellat bank clients credit risk assessment and validation by Probit and Logit regression method and neural network model is the main purpose of this study. For this purpose, qualitative and financial data on random sample about 200 clients has been studied. Studying clients credit cases, 11 variables such as qualitative and financial variables have been identified and also GMDH has been determined by which the model has been processed.
Shirin Bakhsh (2011) with using Logit regression method, conducted a research named “factors influencing the banks credit services default” regarding credit risk assessment of Iran Export Development Bank.
In this study, the random sample has been selected among 330 entity clients (265 clients with bad bank account and 65 clients with good bank account) who received services in 2008. Based on statistical index and financial and economical theories and among 13 selected financial ratios as effective variables on default possibility, 7 variables like companies credit risk have been determined in the meaningful level of 5%LR model. After examining this model, meaningful total regression has been processed by final statistics. Results show that variables including the ratio of cash flow to total debt, the ratio of assets circulation and the ratio of current account to cash account have a reverse effect on credit risk, but the ratio of free cash flow, the ratio of total debt and the ratio of current debt to added value have a direct effect on credit risk.
Yeldize and Akook (2010) In a research named “Turkey banks bankruptcy applying Neuro-Fuzzy network”, studied Turkey bank. Independent variables in 6 financial ratios including capital ratios, qualitative assets, cash ratios, profitability ratios, revenue structure, activity ratios and cost. Results show that the accuracy of the model is 91%.
Khashman (2010) employed neural networks to credit risk evaluation using the German dataset. Three neural network models with nine learning schemes were developed and then the different implementation outcomes were compared. The experimental results showed that one of the learning schemes achieved high performance with an overall accuracy rate of 83.6%. Similarly, Angelini et al (2008) developed two neural networks credit scoring models using Italian data from small businesses. The overall performance assured that neural networks can be applied successfully in credit risk assessment.
San and Chang (2010) In a research named “comprehensive analysis of risk affairs effect on bank performance: evidences from Asian developing countries”, have compared the relationship between Thailand bank markets and their operational and credit risks with the performance of sample bank branches in which Data Envelopment Analysis (DEA) non-parametric method and Stochastic Frontier Analysis (SFA) parametric method have been used. Results show that there is a meaningful relationship between risk affairs and band performance.
Chive and Chen (2009) in a research named “Taiwan banks performance analysis: combination of external and internal risks”, have compared the relationship between bank markets and their operational and credit risks with the performance of banks. They estimated bank risk and performance based on SFA DEA methods. It is found that there is a meaningful relationship between these two components.
roodposhty and his coworkers (2009) Applying Altman and Falmer models, predicted companies’ bankruptcy. The results obtained show that there is a significant difference between results of these two models and Altman model is more conservative than Falmer model.
Pasiras (2008) considering bank risk determinative indexes and variables such as defaulted loans ratio as DEA variable, performed a research named “Greek commercial banks technical performance estimation: international performance and credit risk effect” and built up a meaningful relationship between banking industry performance and risk.
Angelini et al. (2008) pointed out that ANNs have emerged effectively in credit scoring because of their ability to model non-linear relationship between a set of inputs and a set of outputs. They viewed ANNs as black boxes because it is impossible to extort any symbolic information from their internal configurations.
In their research, Loong Huwang and his coworkers (2008) validated hybrid technical modeling. It involves combination of genetic algorithm and support vector machine for both selecting options and optimization of

validation model parameters. They also compared support vector machine technique, neural network classification, genetic programming and found that the results obtained are all the same. But experimental results show that support vector machine is more effective than current technical data analysis. Regarding special characteristics of the mentioned method in data collection of exploratory assessment and census method, a certain theory has not been developed in the present research. Therefore, answering research questions is the main purpose of this study.
Gao et al. (2006) used feed forward neural network with a structured tuning particle swarm algorithm to optimize the structure and weights for the network simultaneously. The training algorithm improved data handling efficiency and generalization ability of the neural network. The results showed that the fitting classification model has reduced the creditor's risk and thereby provides a promising alternative for credit analysis system. Additionally, Malhorta and Malhorta (2003) used a collective dataset of twelve credit unions to evaluate the ability of ANNs in classifying loan applications into "good" or "bad". The effectiveness of the ANNs model in screening loan applications was compared with multiple discriminant analysis (MDA) models. They found that neural network models outperformed the discriminant analysis model in identifying potential loan defaulters.
Witkowska et al. (2004) used multilayer perceptron and RBF networks to classify customers into "good" or "bad" credit risk. They stressed that ANNs are useful tools for supporting decision-making in financial institutions.
West (2000) examined the potential of five neural network architectures in credit scoring accuracy and benchmarked the results with traditional statistical methods: linear discriminant analysis and logistic regression, and other non-parametric methods: decision trees, kernel density estimation, and nearest neighbor. The results showed that neural networks credit models were able to improve credit scoring accuracy from 0.5 to 3%.
Almer and Profski (1998) applied perceptron multi-layer neural network model with Altman variables. The results indicated that perceptron model had a more productive power than credit scoring model.
Desai et al. (1997) compared linear differential analysis neural network to logistic regression. They suggested that neural network works better than linear differential analysis and had a relatively similar performance compared with logistic regression, considering the classification of loan applicants of good and bad credit.

3) Research questions

Main question

Which model (logistic regression or neural network) is more efficient and precious for client credit ranking?

Other questions

What are the obtained results of client credit ranking based on logistic regression model?
What are the obtained results of client credit ranking based on neural network model?
By comparing the obtained results, how we can distinguish between these two models performance?

4) Research method

4- 1 General method

The purpose of this research is based on practical principles.
In this research, descriptive method and inferential method have been used for validation regarding neural network and logistic regression, respectively. Therefore, the former could not be generalized but the latter could be generalized based on test statistical results. In research conclusion, we use inferential question- answer method. Besides, Expose-Facto design has been used in this study.

4-2 statistical sample and population

Statistical population

Esfahan Melli bank entity client who received financial services and returned or did not returned the money and its profit to the bank (from 20 March 2013 to 20 march2014) considers as statistical population. Companies with more than 3 months after the last repayment consider as bad account (default) company while companies with less than 3 months after the last repayment regard as good account (without default) company. In this study, random sample has been selected among 400 companies.
Regarding client risk credit dependent variable which is the relative number ranging from 0 to 1, the Cochran formula has been used as equation1.

$$n \geq \frac{\frac{z\alpha^{2}}{2}\ 0.25}{D^{2}} \qquad \text{Equation (1)}$$

Where 0.25 denotes quality distribution variance, α represents the first type error probability equal 5%, D is the estimation error equal 5& and n denotes the population ratio.

Sampling

In this research, Simple random sampling has been used for the reason that information details related to statistical population are so confidential. Therefore, company has been coded, statistical simulation method among all codes (400 codes) selected and the companies corresponding to these codes considered as random sample.

4-3) method and instruments of date analysis

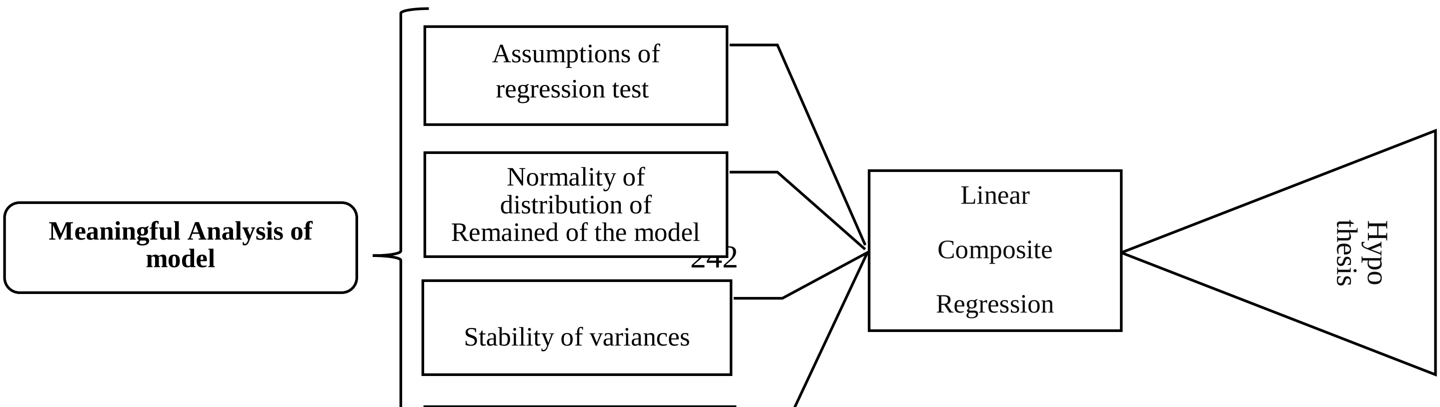
- Due to the normal distribution of data, descriptive statistics has been used in a descriptive mode.
- Kolmogorov- Smirnov nonparametric test has been used for normal distribution of dependent and independent variables.
-Watson camera statistics has been used for assessing independent remaining or error estimation by regression model.
-Pearson linear correlation coefficient has been used for assessing independent linear variables
-homogeneity of variances test (White) along with fisher and chi-square criterion has been used for examining the null hypothesis for homogeneity of variances test versus non homogeneity of variances test as anti hypothesis.
-Error distribution histogram has been developing for assessing regression estimation equation normal error distribution.

Statistical methods

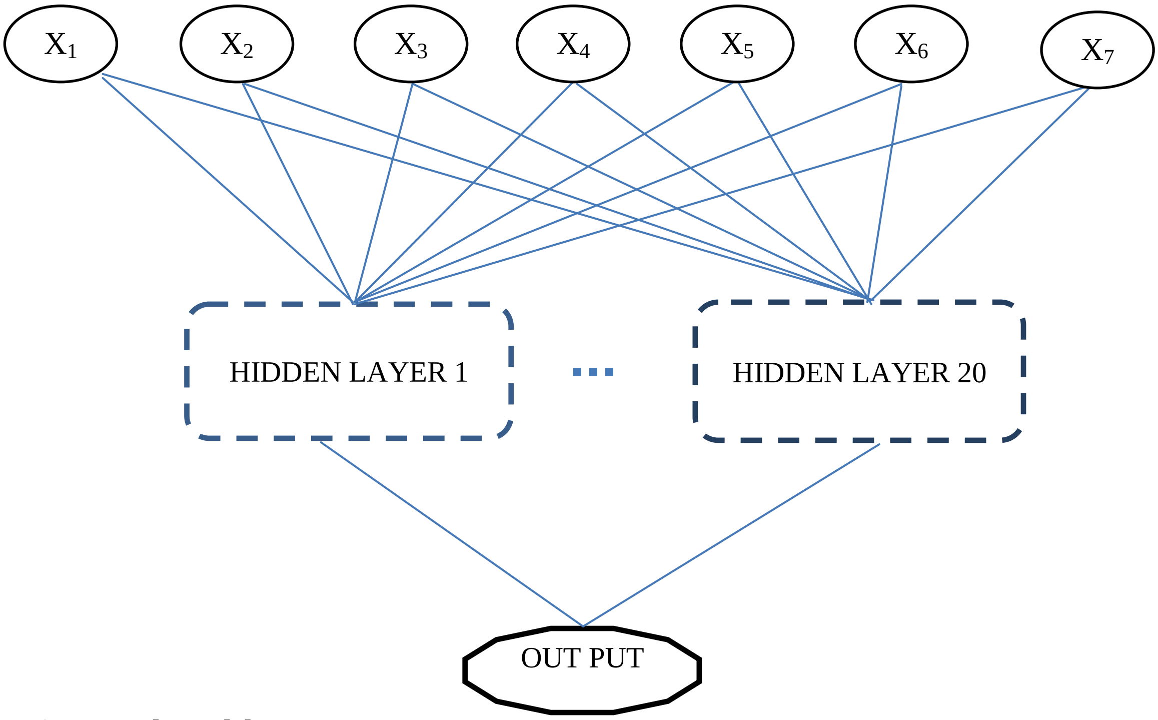
Multi -variable regression

Non- statistical method
MLP neural network

4-4) Conceptual model



Conceptual models of neural networks



4-5) research model

Examined variables in a conceptual model and explanation of variables measurement

1. General equation Y=f(X1, X2, X3, X4, X5)

2. Variables definition

Y=Credit risk prediction $\begin{cases} y1 = regression\ method \\ y2 = neural\ network\ method \end{cases}$

X1=ranking correspondence based on logistic regression method

X2= ranking correspondence based on logistic neural method

3. Variables classification

F(X1) = dependent variable

X1…X7= independent variable

4. Variables measurement

Variables definition: **Y** denotes client credit risk considering as relative coefficient current state and qualitatively in some banks. In this study, relative coefficient has been estimated 0 -1 or indeed 0-. /3.
X1 presents client total calculated default cheques
X2 is property pledge considering as received services value and it is about 1/625 in the sample bank.
X3 denotes every client received services amount.
X4 presents the combination of client creditor circulation regarding bank documents from settlement and previous services set to zero
X5 presents the time after default account

5. Equations for variables

Mathematical equations for variables along with similar relating research based on assessing economy have been presented by a linear relationship in equation 2.

F= LN$\left(\frac{Y}{1-Y}\right)$ = C+$\beta 1X1 + \beta 2X2 + \beta 3X3 + \beta 4X4 + \beta 5X5$

Equation 2

Simulation with neural network is known as nonlinear and complex equation which is the function of simulation process.

6. F Calculation

In assessing economy method, random sample client performance has been examined by Y and Xj values in which mathematical equations defined based on linear parametric equation and βj equation parameter has been estimated base don regression calculation. Besides, neural network parameter method and nonlinear equation have been stimulated optimally.

5) Research findings

5-1 findings structure

Research total structure has been organized based on statistical sample description, findings description, pre-hypothesis analysis and findings analysis including client risk validation in both neural simulation method and regression method. Assessed pre-hypothesis and similar or related researches have been examined by complex linear regression in order to estimate variables equation.
In this research, Excel software and MATLAB & SPSS statistical software have been applied for primary data analysis and findings analysis or description, respectively.

5-2 findings description

Research variables or data have been described regarding related distributive central statistical indexes. Calculated statistical indexes involve mean, medium, standard deviation, minimum and maximum presenting in table 1.

Description	Minimum	Maximum	Mean	Standard deviation	Curvature coefficient	Elongation coefficient
Credit record	2	5000	258	692	3.61	14.69
Modified risk	-4.60	-0.85	-1.8	0.69	-0.04	0.09

Property pledge value	190	6428283	227001	56175	1.63	4.96
Services amount	117	3955867	139693	345652	6.92	59.44
Creditor circulation	4	1777918	25535	11283	10.95	153.17
Default cheque amount	000	26162	7648	6339	0.57	-0.04
Credit risk	0.01	0.30	0.16	0.07	0.03	-0.08

Table1. Findings description

5-3 Pre-hypothesis analysis

In this research as well other similar studies, neural networks simulation and complex linear regression method have been used for Isfahan Melli bank entity clients' validation. For this purpose, pre-requisites to using methods including independent and functional variables normal distribution, model estimated remaining normal distribution, variances stability, variables linear independence and estimated coefficient extent or tendency to one have been measured before applying validation methods. Assessing results of these pre-hypothesis are mentioned in the research findings description.

-Normal distribution of variables

Kolmogrov-Smirnov test has been used for examination of normal distribution of dependent variable. This test used for client credit risk variable and credit modified risk as a dependent variable results in normal distribution of dependent variable. Statistical software K-S test output of this variable has been shown in table2.

Variable		Kolmogrov-Smirnov Z statistic	Meaningful level	result
Credit risk	Y	0.025	0.875	Normal distribution
Modified risk	F	0.125	0.452	Normal distribution
Default cheque amount	X1	0.165	0.1950	Normal distribution
Property pledge value	X2	0.145	0.1990	Normal distribution
Services amount	X3	0.179	0.1782	Normal distribution
Creditor circulation	X4	0.185	0.1576	Normal distribution
Credit record	X5	-0.235	0.2154	Normal distribution

Table 2: Kolmogrov-Smirnov test for dependent variable, its modified amount and independent variables

Regarding the above table and K-S Z statistic and due to meaningful level (0.452,0.875)is more than 0/05, H0 hypothesis ha been accepted. Therefore, dependent and independent variable or client ratio credit risk in the sample company and also credit modified risk have all a normal distribution (95% certainty).

- Error independence test

Using complex linear regression for remaining independent or estimated error based on regression model is known as another pre-hypothesis. For this purpose, Watson camera statistic has been used testing serial correlation between regression errors remaining based on the following statistical null hypothesis.
H0: no correlation between errors
H1: correlation between errors

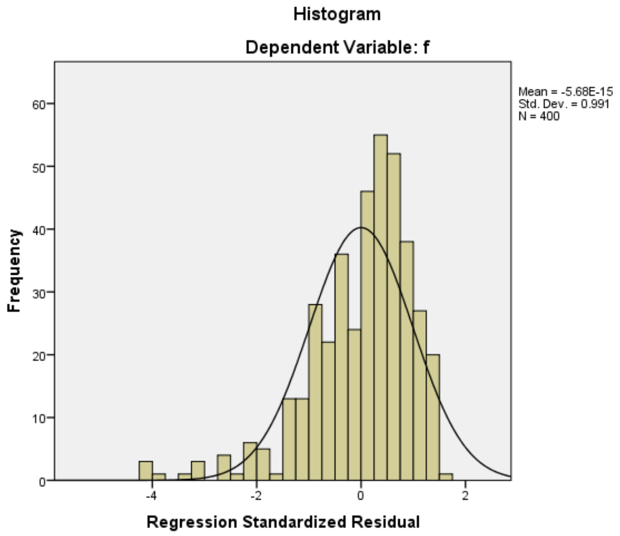
Determination coefficient	Modified determination coefficient	Standard error	Watson camera statistic
0.068	0.052	0.9211	1.8542

Table 3: Error independence test

Regarding table 3, Watson camera statistic for current research regression model equals to 1/854 located between 1/5 and 2/5 distances. As a result, H0 hypothesis based on complex linear regression has been accepted regarding no correlation between errors.

-Normal distribution of errors

Regression estimated equation error as independent and dependent variable having normal distribution is known as another pre-hypothesis of complex linear regression. For this purpose, we compare error distribution histogram with normal curve. As shown in plot 1, error distribution mean in estimated regression model approximately equals to zero and standard deviation is about 0/994. Therefore, regression model error has normal distribution.



Plot 1: Normal distribution evaluation of regression estimated model errors

- Linear independence of independent variables

Using complex linear regression for linear independence of independent variables is another pre-hypothesis. Pearson linear correlation coefficient criterion has been used for evaluation of linear independence of independent variables. Based on the obtained results:

1) For the reason that calculated correlation coefficient for all dependent variables is positive, there is a direct relationship between all independent variables.

2) There is a week linear relationship between independent variables except client received services amount and property pledge value.

3) Since calculated correlation coefficient for client received services amount and received pledge value equals to 1, there is a perfect linear correlation between these two variables, for the reason that client received pledge value is based on provided services coefficient and 162/5 percent regarding Melli bank regulations.

-variances homogeneity test

White homogeneity test based on chi-square and Fisher criterion has been used in this research. Null hypothesis for homogeneity of variances test versus non homogeneity of variances test consider as anti hypothesis. The obtained results have been summarized in table4.

Test criterion	Test statistic	Meaningful level	Test result
Fisher test	5.2154	0.0000	variances homogeneity has been accepted
Chi-square test	84.2345	0.0000	variances homogeneity has been accepted

Table 4: variances homogeneity test (White)

As shown in table 4, chi-square and Fisher test level have a tendency to zero and they are less than 5 &1 percent. As a result, null hypothesis regarding variance homogeneity has been certainly accepted in 95% and 99% test level.

5-4 Variables relationship analysis

Regression parameters estimation

Logistic regression parameter for client credit risk prediction has been summarized in table 5.

Description	symbol	coefficient	Standard deviation	Standard coefficient	T statistic	Meaningful level
X	α	-1.865	0.114	----	-16.359	0.000
Default cheque	$\beta 1$	0.00009	0.000	0.849	1.312	0.190
Pledge value	$\beta 2$	0.0000	0.000	-0.843	-1.127	0.260
Services amount	$\beta 3$	0.0000007	0.000	0.090	1.750	0.081
Creditor circulation	$\beta 4$	0.0000004	0.000	0.065	1.071	0.285

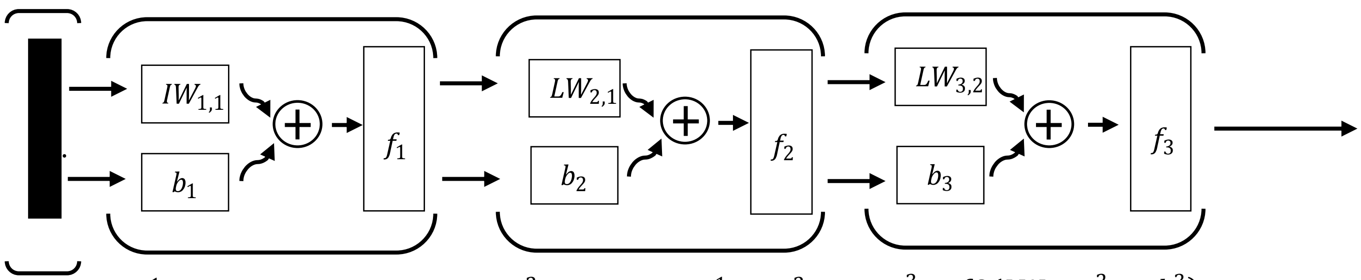
Credit record	$\beta 5$	0.001	0.001	0.663	0.891	0.373

Table 5: Summerised results of regression parameters estimation

As shown in table 5, we can paraphrase the relationship between independent variables with entity client credit modified risk dependent variables. Generally, if estimated coefficient or independent variable slop is positive, there is a direct relationship between dependent variables and related independent variables. On the other hand, if estimated slop is negative (less than zero), there is a reverse or indirect relationship between independent and functional variables.

Estimating of neural network

The model used in the Neural Network section of current project, is a three layered neural network, which contains of input vector with 5 variations: Dishonored cheques, Amounts of received facilities by customers, value of received collaterals from legal customers, Creditor turnover of current account of customers.
Network Model is trained by training algorithms in the tools bar of artificial neural networks in MATLAN software, and with trial and error method within existing algorithms in Liebenberg-Marquardt in comparison with other algorithms, led to the best simulation for model.
In this work, network, which has been used, had three recursive spread algorithms with three-layered. In this algorithm, computational layer or Zk is calculated with eq. 5:
Equation 5:
Zk = f2$\{B_0 + \sum_{k=1}^{n}[W_k f_1(|B_{HK} + \sum_{i=1}^{m} W_{ik} P_i|)]\}$
Where B_0 is the bias related to the output layer, Wk is the weight of relation between neuron» in the hidden layer and single neuron of calculation layer. BHk bias neuron k in the hidden layer k: 1,2,3,…,n , Wik is the weight of relation between the variation i:1,2,3,…,m and neuron k in the hidden layer, Pi is the input variation I , $f1(\square)$is the transformation function of each neuron for each output neurons. Mentioned transformation functions of sigmoid functions are as equation 6:
Equation 6:
$f_N(\lambda) = \frac{1}{1+e^{-\lambda}}$ for N=1, 2
Data are dividing randomly to three sets of training (85%), test (10%), and validation (5%). After repetition of 1000 learning cycle, finally, the structure of the neural network three-layer perception, with 7 neurons in the input layer, 20 neurons in the middle layer and a neuron in the output layer and Tangent-Sigmoid function



$a^1 = f1(IW_{1.1}\, p + b_1)$ $a^2 = f2(LW_{2.1}\, a^1 + b^2)$ $a^3 = f3(LW_{3.2}\, a^2 + b^3)$

In the middle layer and linear transferring function in the output layer are selected by post-spread algorithm. Designing, training and testing of neural network model are conducting via MATLAB ver. 7.1.
In this study, the minimum numbers of layers and neurons are selected in a way that dynamic anticipated parameters in each three experiment, test, validation sets are compatible with main data in maximum way. For this purpose, various error indexes comprising of mean absolute error(MAE), Mean Biased Error(MBE), mean squared error(MSE), root mean-square error(RMSE) and correlation coefficient(IOA) for three sets(train, test, ver) are defined and minimizing these error indexes and maximizing correlation coefficients for three sets are considered.

Model Validation

Validation of estimated results based on correlation coefficients and errors within performed calculation are summarized in Table 6 for each subset of data:

Table 6 Validation to estimated models with error indexes and correlation coefficients

Error Description	Training Set	Test Set	Validation Set
Total error of IOA	0.9850	0.9841	0.9748
Total error of MBE	0.6890	0.2466	1.0098
Total error of MAE	0.6890	0.2466	1.0098
Total error of MSE	3.1389	0.3510	0.2649
Total error of RMBE	1.7717	0.5925	0.5146

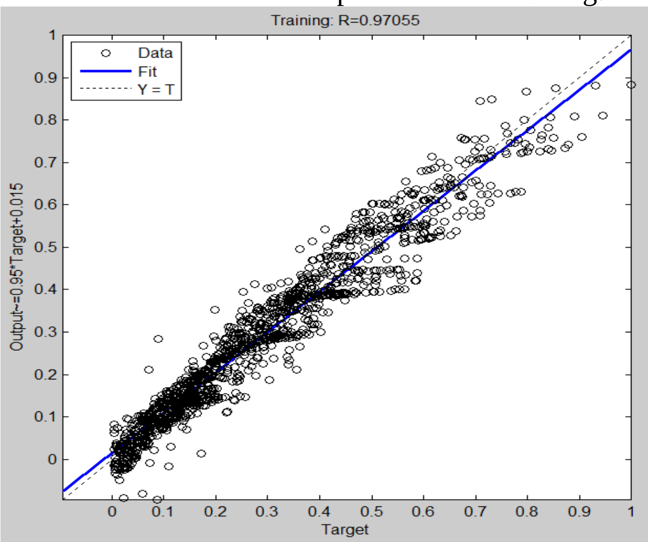
Calculations showed that the bias of output layer is estimated to 73.827.

5-5 summery

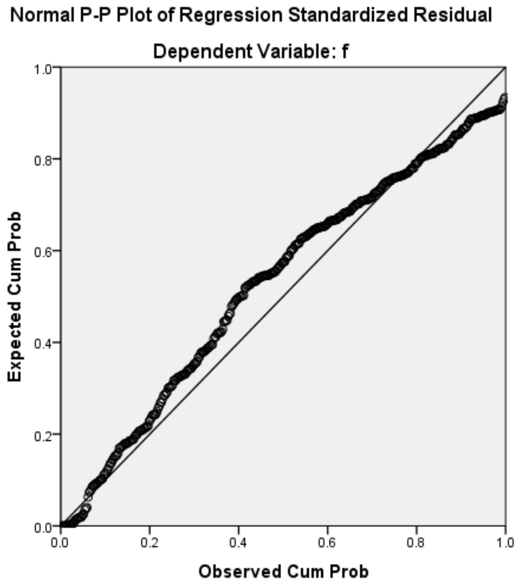
In this research, some criteria such as default cheque, clients received services amount, received pledge value of entity clients, clients current account creditor circulation, credit record have been used for entity client evaluation examination of Isfahan Melli bank branches.

Pre- hypothesizes used in linear regression including normal distribution of data, independent variables linear independence, normal distribution of the remaining and variances homogeneity test have been examined after data analysis and random sample description.

Finally, based on neural network and logistic regression method, Melli bank entity clients have been validated in a random sample .The results obtained have been compared in the following:



Based on neural network and logistic regression model, comparison of client real credit risk with estimated risk has been shown in plots 2 and 3.Based on above plots, client real risk and client estimated risk can be mostly corresponded by using neural network (a more adapted bisector45 in plot 2 than plot 3).



Based on linear logistic regression, estimated determination coefficient and changes equal to 6/8% and 5.2 %, respectively, in usual and normal state. Regarding neural network, estimated determination coefficient acquired from square of the correlation coefficient equals to 94.2 % and has a tendency to 1 or 100 % in which client credit risk and operative validations have a deep relationship.

1- According to Table 7:

Errors	Total changes	Free level	Changes mean	F statistic	Meaningful level
Intergroup	0.372	4	0.0931215		
Intragroup	2.955	394	0.0061192	5.218	0.253
Total	3.327	398			

Table 7: Variance analysis

Based on table 7, Fisher test and T Student value are in a meaningful and corresponding level regarding variance analysis in which the mentioned values are more than 1 and 5% and linear relationship between clients credit risk and operative validations has been rejected based on every confidence levels. Therefore, using neural network comparing relationship between variables based on 20 neurons rather than 1 level and also nonlinear in three levels for entity clients credit risk prediction in Isfahan Melli bank branches, makes more accurate and reliable prediction.

6. Conclusion

Based on linear logistic regression estimation, determination coefficient and changes equal to 6.8% and 5.2%, respectively, in usual and normal state. Regarding neural network, estimated determination coefficient acquired from square of the correlation coefficient equals to 94.2 % and has a tendency to 1 or 100 % in which client credit risk and operative validations have a deep relationship.
Generally, Fisher test and T Student value are in a meaningful and corresponding level regarding variance analysis in which the mentioned values are more than 1 and 5% and linear relationship between client credit risk and operative validations has been rejected based on every confidence levels. Therefore, using neural network comparing relationship between variables based on 20 neurons rather than 1 level and also nonlinear in three levels for entity clients credit risk prediction in Isfahan Melli bank branches, makes more accurate and reliable prediction.
Research results show that:
“Due to nonlinear complex relationships between operative and client credit risk validation, using neural network makes more accurate and reliable prediction.”

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