Fuzzy Adaptive Networks in credit rating and loan approval

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Abstract: Fuzzy adaptive network (FAN) is proposed to help decision makers in credit scores and to assign the amount of loan. By combining with neural networks to incorporate the learning ability, FAN provides an alternative approach for the imprecision and fuzziness of the credit rating system. A loan approval example is given and the performance of FAN is compared with the regression algorithm. The results show that FAN is favored than regression in this financial application.

Key-words: Fuzzy adaptive network (FAN); Inference system; Credit rating; Loan approval; Regression

1 Introduction

Today, most financial loan analyses, including time and cost related problems for financial institutes, relied on human experts or expert systems. The credit analysts usually focus on the company’s financial statements using rough rules of thumb, which are based on financial ratios such as leverage, liquidity, efficiency, profitability, and market value ratios. Experienced experts are often preferred for the job since they usually provide better decisions. However, training human experts costs and requires a time commitment, and issues due to subjective opinions are inevitable. On the other hand, the evaluations generated by expert systems are cheaper. Expert systems also provide less biased decisions than the human experts since they won’t be affected by human factors such as competitive pressure. Actual and potential applications of expert systems to financial management have received extensive coverage in the financial press. However, when the decision process is not well-structured and is dependent on incomplete, vague, or error-prone information, expert systems cannot provide necessary insight for solutions.

Over the past decade, alternatives in artificial intelligence as expert systems in financial management have drawn great attention. A fuzzy neural system simulates the process by human learning and intuition. Unlike an expert system, a fuzzy neural system does not rely on a preprogrammed knowledge base. Rather, it learns through experience and is able to continue learning as the problem changes. The fuzzy neural system is well suited to deal with unstructured problems, inconsistent information, and real-time output. A fuzzy neural system with the ability to accommodate the real world’s changing economy is the desired objective of this study.

2 Credit rating and loan approval

A bank has to decide if a customer/firm is good enough to give him a credit/loan, or how much credit/loan can be given to a specific customer/firm. Credit score systems should carry a health warning. Sources of customer’s information can be obtained from a customer database, by examining the history of the bank’s relationship to that customer, or from an external database. A rating falls into the latter category. Each of the three types of information has its problems: the data given by the customer may contain incorrect information; the business history may not be long enough to be reliable; an external database is usually for bigger companies, but not individuals, and may be expensive to assess. Banks and credit departments of industrial firms use mechanical credit scoring systems to cut the costs of assessing commercial credit applications. One of the scoring systems is to use neural networks. However, neural networks require a great amount of data and proper training. The database of banks normally contains more good than bad creditors because the banks usually accept the good customers and reject obvious bad customers. Neural networks trained by such a database may not be able to identify bad customers since there is not enough data. Fuzzy neural networks with additional rules may improve the training process.
2.1 Credit Scores
Credit scoring is a method creditors use to help determine whether to give the applicants credit and how much to give. Personal information and their credit history such as payment history (late payments and collection actions), the number and type of accounts, outstanding debt, and the age of accounts, is collected from the credit application forms and the credit reports. Creditors then compare this information to the credit performance of consumers with similar profiles usually by a statistical model that assigns credit scores to the applicants. The factors that help predict who is likely to repay a debt are evaluated and awarded a score. The total credit score is summed up by all the scores. This number, named a credit score, is assumed to be able to predict the credit worthiness of applicants and how likely it is for the applicants to repay a loan and make the payments when due.

Credit scoring is a scientific method that uses statistical models to assess an individual’s credit worthiness based on their credit history and current credit accounts. The credit scoring system is popular because it is considered as an objective method, which does not vary when applied by different individuals. Credit scoring was originally developed in the 1950s, but only had come into increasing use in just the last two decades.

The most popular credit scoring method consists of a FICO score (Fair, Isaac Company score) which assesses an individual’s credit worthiness. It is calculated by comparing your current credit history and current credit accounts to statistical models. Quick, objective analysis is made and a score is issued. This score is then used as a risk indicator by credit grantors to determine whether or not to offer you credit.

Creditors frequently treat so-called FICO scores as an important factor in the decision whether or not to offer credit. The scores range from 375 to 900 points, but those numbers mean little on their own. They become meaningful and useful within the context of a particular lender’s own cutoff points and underwriting guidelines.

In general, it is likely to be considered as less of a credit risk if the FICO score is high. Under mortgage lending guidelines, for example, a score between 620 and 650 (average FICO scores fall into this range) indicates basically good credit, but also suggests to lenders that they should look at the potential borrower to assess any particular credit risks before extending a large loan or high credit limit. People with scores in this range have a good chance at obtaining credit at a good rate, but may have to provide additional documentation and explanations to the lender before a large loan can be approved. This means that their loan closing may take longer, making their experience more like that of borrowers in the days before credit scoring, when every individual was researched. A difference of 40 points in credit score is considered as double risk. That is, lending money to someone scores 520 is twice more risk than someone scores 560. A more detailed classification is as in Table 1.

FICO or the Credit Bureau score is based on information drawn from the credit report. About 30 individual factors are used to determine the score. These can be categorized in five areas: (1) Payment history (35%); (2) Outstanding debt (30%); (3) Credit history (15%); (4) Pursuit of new credit (10%); and (5) Types of credit in use (10%). In this study, FICO is used for demonstration.

<table>
<thead>
<tr>
<th>Range</th>
<th>Meaning</th>
</tr>
</thead>
<tbody>
<tr>
<td>720+</td>
<td>Perfect Credit</td>
</tr>
<tr>
<td>700 - 719</td>
<td>Superior Credit</td>
</tr>
<tr>
<td>680 - 699</td>
<td>Excellent Credit</td>
</tr>
<tr>
<td>640 - 679</td>
<td>Outstanding Credit</td>
</tr>
<tr>
<td>620 - 639</td>
<td>Good Credit</td>
</tr>
<tr>
<td>600 - 619</td>
<td>Average Credit</td>
</tr>
<tr>
<td>580 - 599</td>
<td>Fair Credit</td>
</tr>
<tr>
<td>560 - 579</td>
<td>Some Credit Issues</td>
</tr>
<tr>
<td>540 - 559</td>
<td>Impaired Credit</td>
</tr>
<tr>
<td>Below 540</td>
<td>Serious Credit Issues</td>
</tr>
</tbody>
</table>

2.2 Neurofuzzy Methods
Due to the fact that many factors are used in the decision making, the credit scores are usually vague or not well-defined, and the relative importance between different variables must be determined in order to obtain the overall scores. Neurofuzzy systems have the potential of improving the rating procedure. Some attempts have been made to accomplish various applications utilizing fuzzy representation and learning ability of Neural networks.

Rast and Martin [1] demonstrated that for two financial applications, price forecasting and customer credit rating, the Fuzzy Neural Network approach improves the network quality. This type of network faces fewer problems than the classical network approach, yet the use of this approach is limited to large amounts of data. Piramuthu [2] evaluated financial
credit-risk with neural and neurofuzzy systems. Credit approval, loan default, and bank failure prediction data were studied and used to compare the performance of neural and neurofuzzy systems. He concluded that neural networks performed somewhat better than neurofuzzy systems in credit rating.

Malhotra and Malhotra [3] suggested the integration of artificial intelligence, expert systems, neural networks, and fuzzy logic for reducing the complexity and increasing the accuracy in credit approval, but a detailed description of the approach is not included. Extension of their efforts on evaluating customer loan was done by neural networks [4].

West [5] investigated the credit scoring accuracy of five neural network models: multilayer perception, mixture-of-experts, radial basis function, learning vector quantization, and fuzzy adaptive resonance. Results are compared with more traditional methods considering financial applications including linear discriminate analysis, logistic regression, k-nearest neighbor, kernel density estimation, and decision trees. It was demonstrated that the multilayer perceptron may not be the most accurate neural network model, and that both the mixture-of-experts and radial basis function neural network models should be considered for credit scoring applications. Logistic regression is found to be the most accurate of the traditional methods.

A recent work is done by Julia, et al. [6], who applied neural networks on Modeling of sovereign credit ratings and found neural networks are highly effective classifiers.

### 3 Fuzzy adaptive network

Cheng and Lee [7] and [8] proposed the architecture of the fuzzy adaptive network (FAN), which is essentially a fuzzy inference system employing the neural network learning technique. In this section, the FAN is briefly summarized. More detailed discussions can be found in the literature [7].

A fuzzy inference system basically consists of three conceptual components: a rule base, which contains a set of fuzzy if–then rules; a database, which defines the membership functions used in the fuzzy rules; and a reasoning mechanism, which performs the inference procedure based on the rules and a given condition for deriving a reasonable output [7] and [9].

Various fuzzy inference systems can be constructed depending on the fuzzy if–then rules and the aggregation procedure. The FAN is a network representation of the Takagi and Sugeno fuzzy inference model [10]. The network provides a comprehensive visualization and adaptability system, retaining both the representation ability of fuzzy systems and the learning ability of neural networks.

The FAN is a five-layered feed-forward network. Each node in the FAN performs a particular mode function on the incoming signals, which is characterized by a set of parameters. The main difference from a pure neural network is that some of the nodes contain parameters to be adjusted. The following Gaussian membership functions are used in these nodes:

\[
\mu_{F_{j},h}(x) = \exp\left(-\frac{(x_j - v_{j,h})^2}{\sigma_{j,h}}\right)
\]

(3)

where \(x_j\) is the input to this node; \(F_{j,h}\) is the \(h\)th fuzzy set associated with the input \(x_j\); \(H_{j,h}\) is the membership function defined for \(F_{j,h}\), and \((v_{j,h}, \sigma_{j,h})\) are the Gaussian parameters.

The FAN is a powerful approximation tool for fuzzy systems, whose objective is to infer an association between specific input–output pairs. These input–output pairs are usually referred to as training data that characterizes the system to be identified. The training procedure is actually a sequence of adjustments of the parameters in the network, including both consequence and premise parameters.

**Performance measure.** The performance of the FAN is measured by the following sum of least squares error (LSE):

\[
E = \frac{1}{N} \sum_{i=1}^{N} \left[ (y_i - \hat{y}_i)^2 + (e_i - \hat{e}_i)^2 \right]
\]

(4)

where \(Y_i\) is the desired output and \(\hat{Y}_i\) is the FAN estimated output, both outputs are assumed to be symmetric triangular fuzzy numbers, \(Y = (y, e)\), where \(y\) and \(e\) are the mode or center and spread, respectively.

**Learning algorithms.** The FAN uses two sets of adaptive parameters: the premise parameters and the consequence parameters. Consequently, the learning process includes the learning of both sets of parameters. The usual back-propagation is used for the training of the premise parameters and the consequence parameters are trained by solving a fuzzy linear programming problem based on Tanaka’s fuzzy regression approach [11].
4 Application of FAN in credit rating and loan approval

In practical terms, the banks determine whether to lend money or not based on both subjective opinions (judgment) and objective financial scores. The basic assumption is that the future will resemble the past. The banks compare applicants to their past experiences and will only grant credit to acceptable risks. There are usually two types of applicants: individuals and small to middle size companies. Criteria vary from financial institutions to financial institutions. In this application, we deal with small businesses with net worth of 1-5 Million.

Based on the credit score, the decision maker can determine how much credit to grant: maximum, average, or minimum credit line in the score range. If the decision maker knows the applicants and believes in their potential, they might receive a higher credit line than average. In other words, the individual difference of decision makers will affect the amount of credit.

In this study, the FICO credit score and the judgment of the decision makers (DM) are considered as the most important factors to the determining of the credit line. Suppose the FICO scores (Score) can be divided into three levels: High, Average, and Low; the judgment of the decision maker (Judgment) is either positive, neutral, or negative. This “Judgment” is in fact influenced by the DM’s observation and judgment regarding the overall economic environment and to the company’s potential. The objective is to determine the credit line (Y) base on the FICO score and the DM’s judgment. To apply Fuzzy Adaptive Network, the following rules are generated:

\[
\begin{align*}
R_1: & \text{ IF (Score is Low and Judgment is Negative),} \\
R_2: & \text{ IF (Score is Low and Judgment is Neutral),} \\
R_3: & \text{ IF (Score is Low and Judgment is Positive),} \\
R_4: & \text{ IF (Score is Average and Judgment is Negative),} \\
R_5: & \text{ IF (Score is Average and Judgment is Neutral),} \\
R_6: & \text{ IF (Score is Average and Judgment is Positive),} \\
R_7: & \text{ IF (Score is High and Judgment is Negative),} \\
R_8: & \text{ IF (Score is High and Judgment is Neutral),} \\
R_9: & \text{ IF (Score is High and Judgment is Positive),}
\end{align*}
\]

Then \( Y = Y' = c_0 + c_1 \text{Score} + c_2 \text{Judgment} \), where \( i=1 \ldots 9 \) corresponding to \( R_i \).

For the reasons of business secrets and privacy protection, the data are confidential and thus are not publicly accessible. However, a limited amount of individual cases as samples or technique demos are available from the Internet. Those samples are used as reference so that the data generation will not be too far from reality. For example, one of the samples for a middle size business company had a so-called “commercial credit score” of 347 (101-660) and resulted in about $46,913 of credit. The score of 347 is converted to equivalent FICO score (375-900) of 607. Loan amounts using the credit scoring system for small to medium sized business usually range from $5,000 to $150,000. Above that, a hybrid method of a credit score and some traditional commercial loan criteria will often be used. The training data are generated by Excel random number generator. The FICO score is in a range from 375 to 900. For crisp classification, scores less than 620 are considered as Low; scores between 620 and 650 are considered Average; scores larger than 650 are considered as High. One thing we learn from those credit bureaus is that most applicants’ scores fall into the Average range.

The numerical values of Judgment are generated by Excel as well using uniform distribution with \((\text{min, max}) = (1, 7)\). The values of judgment 5 ~ 7 are considered as positive, 3 ~ 5 as neutral, and 1 ~ 3 as negative. The data for amounts of business loans approved are retrieved from the 1998 database of U.S. Small Business Administration (SBA). Due to the limit of Fortran calculation ability, only part of the data are averaged and used. The amount of approved loans between $5,000 and $15,000 (maximum amount is $150,000) are adopted. The overall data retrieved are exponentially distributed with a mean of 21,600 and a shift of 5,000 (because minimal amount approved is $5,000). That is, the data used for calculation only belong to the lower part of the overall data available. Therefore, it is assumed that these applicants would score less than 640 (good credit). As the result, the scores are generated by a normal distribution with a mean of 500 and a standard deviation of 80. Scores that exceed 640 or below 375 are discarded. The membership functions of credit scores are re-defined: 375 ~ 450 as Very Low, 450 ~ 550 as Low, and 550 ~ 640 as Average. The 9 rules stated above need to be modified by replacing Low, Average, and High with Very Low, Low, and Average. The examples of training data are shown in Table 2. Note that the data of the two independent variables are generated by a random number generator, not actual values. The spread is calculated by \( \frac{1}{4} \) of the loan approved.

To train the Fuzzy Adaptive Network, \( \alpha \) is set to be 0.1, the initial Gauss parameters are arbitrarily set as:

\[
\begin{align*}
\text{Credit Score:} & \quad (400, 30), (500, 30), (600, 30)
\end{align*}
\]
A Fortran coded computer program was used for training. Due to the calculation difficulty of Fortran linear programming solver, the amounts of the loan approved are transformed by taking nature log as well as the spread. Therefore, the training data for the computer program actually consists of four columns: Credit score, Judgment, mode of Loan approved, and spread of loan approved. The output of the FAN model is plotted in Fig.1. The FAN’s prediction of mode well followed the trend of actual data, while apparently the spread is overestimated. The reason for the over-fitting is that Tanaka’s fuzzy linear regression is intended to cover all possible areas and hence resulted in the overestimating of spreads.

Table 2 Examples of training data for credit rating

<table>
<thead>
<tr>
<th>Data</th>
<th>Credit Score</th>
<th>Judgment</th>
<th>Loan approved</th>
<th>Spread</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>375</td>
<td>3</td>
<td>5000</td>
<td>1250</td>
</tr>
<tr>
<td>2</td>
<td>382</td>
<td>2</td>
<td>5000</td>
<td>1250</td>
</tr>
<tr>
<td>8</td>
<td>410</td>
<td>3</td>
<td>5000</td>
<td>1250</td>
</tr>
<tr>
<td>9</td>
<td>419</td>
<td>6</td>
<td>5200</td>
<td>1300</td>
</tr>
<tr>
<td>10</td>
<td>420</td>
<td>2</td>
<td>5300</td>
<td>1325</td>
</tr>
<tr>
<td>91</td>
<td>628</td>
<td>5</td>
<td>14300</td>
<td>3575</td>
</tr>
<tr>
<td>92</td>
<td>630</td>
<td>5</td>
<td>14500</td>
<td>3625</td>
</tr>
<tr>
<td>93</td>
<td>630</td>
<td>5</td>
<td>14700</td>
<td>3675</td>
</tr>
<tr>
<td>94</td>
<td>630</td>
<td>2</td>
<td>14900</td>
<td>3725</td>
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<tr>
<td>95</td>
<td>630</td>
<td>6</td>
<td>15000</td>
<td>3750</td>
</tr>
<tr>
<td>100</td>
<td>635</td>
<td>3</td>
<td>15000</td>
<td>3750</td>
</tr>
</tbody>
</table>

The training result for the membership function is the following:

Credit Score: (399.457, 28.995), (504.304, 38.674), (606.114, 19.725)
Judgment: (3.802, 3.409), (4.999, 1.1), (7.957, 0.229).

To find out how good the FAN fitting is, regression analysis is performed to predict the mode as an indicator. Using the same variables and with a 95% confident interval, the regression model has a multiple R-square of 0.943 and an adjusted R-square of 0.887. The comparison of the FAN output and regression analysis on mode prediction is visualized in Fig.2. The FAN (SSE = 75,550,000) seems to perform better than regression (SSE = 90,420,529) numerically since the SSE of FAN is smaller. The prediction equation of regression can be written as:

\[
\text{Amount of Loan} = -9989.85 + 36.50922 \times \text{Credit Score} - 50.6207 \times \text{Judgment}. \quad (5)
\]

The p values for the parameters show the significance (p < 0.0001) of the coefficients. The p value for judgment (p = 0.322) is not significant. If it’s significant, the negative coefficient of judgment means that when Judgment is higher, the amount of loan approved will be lower, which would not be reasonable.

5. Discussion

FAN slightly underestimated the amount of loan approved, but the overall error is smaller than regression. Both FAN and regression underestimated the amount of loan approved when the credit score is lower than 390 or higher than 625.

Because regression is trying to find a linear combination of variables to present the dependent variable, when the target is not linear the error generated may be larger. To find a good regression model, trial and error method is necessary. That is, use different transformation of independent variables (such as square, log, exponential, etc.) by experience or simply guessing. In this scenario, FAN is advantageous just like neural networks because it’s a non-parameter approach and the only thing to be done is feeding data.

Reference

[6] Bennell, Julia A.; Crabbe, David; Thomas, Stephen; Gwilym, Owain ap, Modelling sovereign


Fig.1 Comparison of FAN Prediction with Target. Note Mode and Spread are observations.

Fig.2 Comparison of FAN Output with Regression Results.