Fuzzy Type 2 Inference System for Credit Scoring

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Abstract: - Credit scoring is regarded as a core assessment tool of Lenders during the last few decades and has been widely studied in the areas of statistics, and artificial intelligence. Nowadays credit risk appraisal is an area of renewed interest due to recent financial crises. Many novel approaches have been proposed to increase the accuracy of credit scoring. In this paper, a Fuzzy Type 2 Inference System (FT2IS) is proposed to deal with the credit scoring problem.

Key-Words: - Type 2 Fuzzy Logic, Credit Scoring

1 Introduction

The name *bank* traces its origins back to the Ancient Roman Empire, where moneylenders would set up their stalls in the middle of enclosed courtyards called *macella* on a long bench called a *bancu*, from which the words *banco* and *bank* are derived. A bank is an institution whose primary activity is to act as a payment agent for customers to borrow and/or lend money while managing a set of multi-dimensional risks associated with operating risks, liquidity, foreign exchange rates, capital adequacy and etc.

The Lenders, such as banks and credit card companies, needs to evaluate the potential risk posed by lending money to consumers and to mitigate losses due to bad debt. In credit risk evaluation, credit scoring is one of the key techniques based on the analysis of a consumer's credit files, to represent the creditworthiness of that consumer. The objective of credit scoring is to assign credit applicants to either "good" or "bad" risk groups. For this purpose intuitive experience, statistics method such as integer programming in [1], logit and discriminant analysis in [2], probit analysis in [3], linear programming in [4], nearest neighbour by [5] and [17], emerging techniques, such as neural networks in [6], [7] and [25], genetic algorithm in [8], [9], [18] and [23] , fuzzy logic in [10], [23], support vector machine in [11-15], [19], [20] and [21], data mining in [19] and fuzzy type 2 interface system in [16] been used by researchers and lenders.

Fuzzy Type 2 Inference System (FT2IS) are proven to be most effective in situations, where there are difficulties in defining initial memberships for fuzzy terms used in human generated fuzzy models. The difficulties are related to uncertainties regarding the exact shapes of membership functions. To allow considerations of uncertainties in initial data, they are described by Fuzzy Type 2 membership functions.

Fuzzy Type 2 approach to designing fuzzy inference systems, neural networks, and neuro-fuzzy systems are comprehensively described in literature [27-29]. Turksen, presents a review of Fuzzy and Fuzzy Type 2 inference models of the past and future in [30]. The more advantageous features of Fuzzy Type 2 systems as compared to Fuzzy Type 1 systems are better description of uncertainty and higher computational power. These two features make them:

1. Capable of catching complex input-output relationships of real-world systems allowing uncertainties in input data and
2. Better suitable for revealing experts knowledge and constructing fuzzy models in human tractable form. However, due to computational difficulties they found fewer application areas than ordinary (Type 1) fuzzy systems as yet.

The aim of this work is to design a FT2IS for credit scoring. The proposed system has been created in software and a number of computational experiments done. This paper is organized as follows. Section 2 describes the FT2IS. Section 3 sets the FT2IS for credit scoring. Finally, a conclusion made in Section 4.

2 Fuzzy Type 2 Inference System

The structure of the FT2IS [16] for credit scoring is shown in Fig. 1. The FT2IS uses arbitrary number of Fuzzy Type 2 input variables and arbitrary number of Fuzzy Type 1 output variables. The input variable's Fuzzy Type 2 terms are described as:

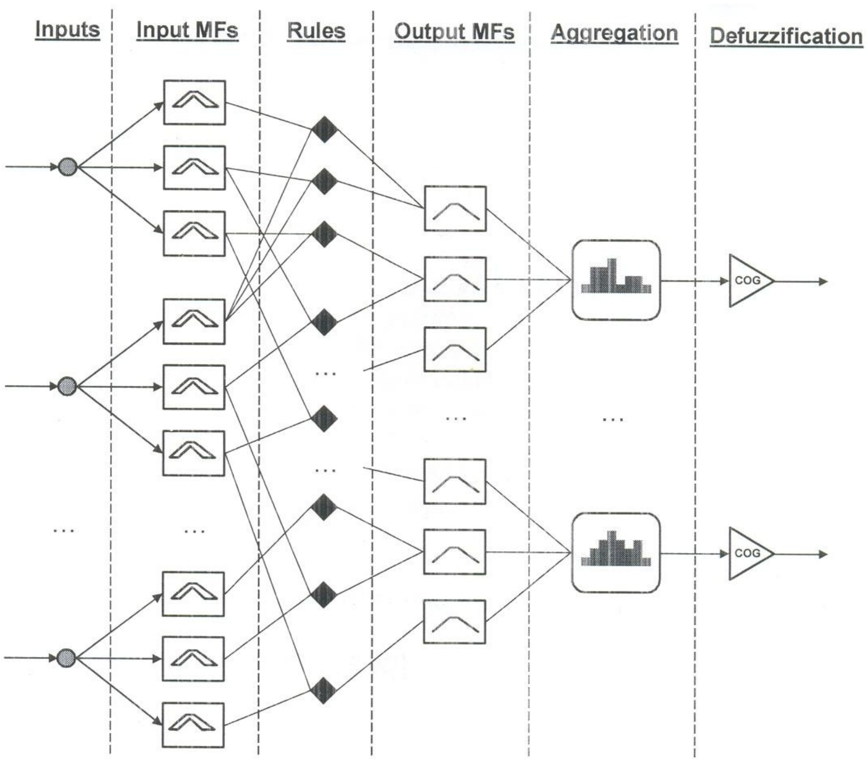

Fig. 1 Structure of Fuzzy Type 2 Inference System

$$\begin{aligned} &\tilde{\tilde{A}} = \{x / \tilde{\mu}_x\}, x \in X \subset \Re \\ &\tilde{\mu}_x = \{m/1\}, m \in M_x \subset [0,1] \end{aligned} \quad (1)$$

where

$$\begin{aligned} &M_{xL} = \text{lowerof}([m_{x1}, m_{x2}], [m_{x3}, m_{x4}]) \\ &m_{x1} = \max\left(\min\left(1, \frac{RL - x}{RL - ML}\right), 0\right) \\ &m_{x2} = \max\left(\min\left(1, \frac{RR - x}{RR - MR}\right), 0\right) \\ &m_{x3} = \max\left(\min\left(1, \frac{x - LL}{ML - LL}\right), 0\right) \\ &m_{x4} = \max\left(\min\left(1, \frac{x - LR}{MR - LR}\right), 0\right) \end{aligned} \quad (2)$$

and we calculate the lower of two intervals [a,b] and [c,d] (the operator “lowerof” used above) as follows:

$$\text{lowerof}([a,b],[c,d]) = \begin{cases} [a,b], \text{if}\left(\frac{a+b}{2} < \frac{b+c}{2}\right) \\ [c,d], \text{elsewise} \end{cases} \quad (3)$$

LL, LR, ML, MR, RL and RR (LL ≤ LR ≤ ML ≤ MR ≤ RL ≤ RR) are parameters defining the “shape” of Fuzzy Type 2 membership functions. An example of Fuzzy Type 2 input value defined in this way ([0.25, 0.75], [1.25, 1.75], [2.25, 3.00]) is shown in Figure 2. As can be seen, a Fuzzy Type 2 number can be composed on the basis of three intervals [LL, LR] (a left interval, indicated by letter L in the figure), [ML, MR] (a medium interval, indicated by letter M in the figure), and [RL, RR] (a right interval, indicated by letter R in the figure). As can be seen from Fig. 2 input term membership functions can be considered as interval valued membership functions (interval membership values for two values of x are shown: x=1 and x=2.5).

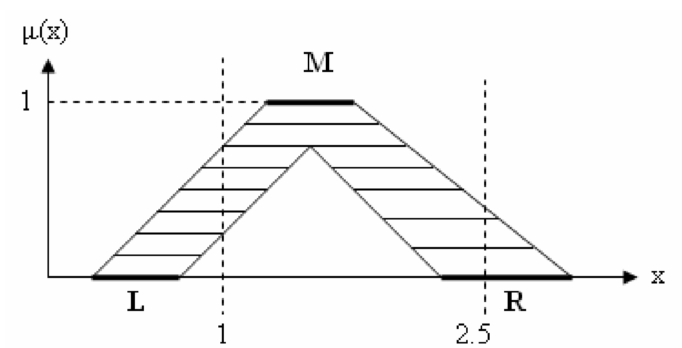

Fig. 2 A Fuzzy Type 2 term value

The output variable’s Fuzzy Type 1 terms are ordinary Fuzzy Type 1 trapezoidal fuzzy numbers:

$$\tilde{B} = [L, ML, MR, R] = [[L, L], [ML, MR], [R, R]] \quad (4)$$

Zadeh's implication procedure used to compute output membership functions. After the implication procedure, two piecewise linear membership functions get for every output variable:

$$\tilde{\tilde{y}}_i = \{y / [\mu_{Li}(y), \mu_{Ri}(y)]\} \quad (5)$$

Type reducing is performed on the basis of center of gravity (COG) defuzzification procedure:

$$\begin{aligned} COG(\tilde{\tilde{y}}_i) &= \{y / [COG(\mu_{Li}(y)), COG(\mu_{Ri}(y))]\} \\ &= \{y / [y_{Li}, y_{Ri}]\} \end{aligned} \quad (6)$$

The final defuzzification is performed as follows:

$$y_i = \frac{y_{Li} + y_{Ri}}{2} \quad (7)$$

Such fuzzy sets can be produced, for example, as result of fuzzy inference having used fuzzy terms with trapezoidal membership functions in both antecedent and consequent parts of fuzzy IF-THEN rules.

$$\begin{aligned} &X = \{x_i / m_i\}, i = \overline{1, n} \\ &m_i = \mu(x_i) \end{aligned} \quad (8)$$

By definition:

$$x_{defuzz} = \frac{\int_{x_1}^{x_n} x\mu(x)dx}{\int_{x_1}^{x_n} \mu(x)dx} \quad (9)$$

any (linear) part of $\mu(x)$ in an interval $[x_i, x_{i+1}]$ can be represented as:

$$\mu(x) = \frac{m_{i+1} - m_i}{x_{i+1} - x_i} x + \left(m_i - \frac{m_{i+1} - m_i}{x_{i+1} - x_i} x_i \right) \quad (10)$$

Then, the above integrals are calculated as:

$$\begin{aligned} &\int_{x_1}^{x_n} \mu(x)dx = \frac{(m_i + m_{i+1})(x_{i+1} - x_i)}{2} \\ &\int_{x_1}^{x_n} x\mu(x)dx = \frac{(2m_i x_i + 2m_{i+1}x_{i+1} + m_i x_{i+1} + m_{i+1}x_i)(x_{i+1} - x_i)}{6} \end{aligned} \quad (11)$$

For a single interval $[x_i, x_{i+1}]$:

$$x_{defuzz} = \frac{(2m_i x_i + 2m_{i+1}x_{i+1} + m_i x_{i+1} + m_{i+1}x_i)}{3(m_{i+1} + m_i)} \quad (12)$$

For the whole domain $[x_i, x_{i+1}]$:

$$x_{defuzz} = \frac{1}{3} \frac{\sum_{i=1}^{n-1} (2m_i x_i + 2m_{i+1}x_{i+1} + m_i x_{i+1} + m_{i+1}x_i)(x_{i+1} - x_i)}{\sum_{i=1}^{n-1} (m_i + m_{i+1})(x_{i+1} - x_i)} \quad (13)$$

The error value of the network is calculated as:

$$E = \sum_p \sum_i \left| y^*_{pi} - y_{pi} \right| \quad (14)$$

where y^*_{pi} is the desired value for output i when applied input value vector x_p and y_{pi} is the actual network output for the same input vector.

To lead the FT2IS network to the state with minimum error, genetic algorithm (GA) is used. The parameters LL, LR, ML, MR, RL, RR for all input terms and the parameters L, ML, MR, R for all outputs terms are undergone genetic algorithm adjustment. The fitness function is set to comply with the current network error E.

3 Empirical analysis

The data used for this study is "Australian Credit Approval" dataset obtained from UCI Repository of Machine Learning Databases [26].

The Australian Credit Approval dataset consists of 690 samples in which 307 samples of creditworthy applicants and 383 samples where credit is non-creditworthy applicants. It contains 14 attributes, where six are continuous attributes and eight are categorical attributes and one class attribute (good, bad).

Australian Credit Approval dataset concerns credit card applications. All attribute names and values have been changed to meaningless symbols to protect confidentiality of the data. This dataset is interesting because there is a good mix of attributes -continuous, nominal with small numbers of values, and nominal with larger numbers of values. There are 37 cases (5%) had one or more missing values. These were replaced by the mode of the attribute (categorical) and mean of the attribute (continuous).

The brief type 2 fuzzy logic rules used for "Australian Credit Approval" dataset are as follows:

IF A1 IS "LOW" AND A2 IS "AVR" AND A3 IS "LOW" AND A4 IS "LOW" AND A5 IS "HGH" AND A6 IS "AVR" AND A7 IS "AVR" AND A8 IS "HGH" AND A9 IS "HGH" AND A10 IS "AVR" AND A11 IS "HGH" AND A12 IS "AVR" AND

A13 IS "AVR" AND A14 IS "AVR" THEN Accept IS”HGH"

IF A1 IS "LOW" AND A2 IS "AVR" AND A3 IS "LOW" AND A4 IS "AVR" AND A5 IS "HGH" AND A6 IS "AVR" AND A7 IS "LOW" AND A8 IS "HGH" AND A9 IS "LOW" AND A10 IS "LOW" AND A11 IS "LOW" AND A12 IS "AVR" AND A13 IS "HGH" AND A14 IS "HGH" THEN Accept IS "VHGH"

IF A1 IS "HGH" AND A2 IS "HGH" AND A3 IS "HGH" AND A4 IS "AVR" AND A5 IS "HGH" AND A6 IS "HGH" AND A7 IS "AVR" AND A8 IS "HGH" AND A9 IS "HGH" AND A10 IS "LOW" AND A11 IS "HGH" AND A12 IS "AVR" AND A13 IS "AVR" AND A14 IS "AVR" THEN Accept IS "AVR"

IF A1 IS "LOW" AND A2 IS "LOW" AND A3 IS "LOW" AND A4 IS "LOW" AND A5 IS "LOW" AND A6 IS "LOW" AND A7 IS "LOW" AND A8 IS "LOW" AND A9 IS "LOW" AND A10 IS "LOW" AND A11 IS "LOW" AND A12 IS "LOW" AND A13 IS "LOW" AND A14 IS "LOW" THEN Accept IS "LOW"

The type 2 fuzzy membership functions for some inputs after the network is trained using genetic algorithm are as follows.

Termset A13 (input):
"LOW"= [[0, 1], [5, 10], [15, 20]]
"AVR"= [[17, 25], [100, 200], [250, 280]]
"HGH"= [[260, 300], [400, 500], +infinity]

Termset A14 (input):
"LOW"= [[0, 5], [50, 70], [80, 90]]
"AVR"= [[80, 150], [500, 1500], [2000, 5555]]
"HGH"= [[5550, 5600], [5650, 5700], +infinity]

The proposed approach credit scoring and the class attribute are given in Table 1 for some of the applicants. Three evaluation criteria are used to measure the classification results as shown in Table 2. Table 2 reveals an 84.49% average correct classification rate for proposed approach.

4 Conclusion

The primary activity of the lenders is to act as a payment agent for customers to borrow and/or lend money while managing a set of multi-dimensional risks. The task of the credit scoring is to classify credit applicants into good and bad risk groups. Different credit evaluation processes developed for credit approval.

Table 1 Sample evaluated cases

Applicant	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10	A11	A12	A13	A14	A15	PA
1	1	22.08	11.46	2	4	4	1.585	0	0	0	1	2	100	1213	0	0
2	0	22.67	7	2	8	4	0.165	0	0	0	0	2	160	1	0	0
3	0	29.58	1.75	1	4	4	1.25	0	0	0	1	2	280	1	0	0
4	0	21.67	11.5	1	5	3	0	1	1	11	1	2	0	1	1	0
5	1	20.17	8.17	2	6	4	1.96	1	1	14	0	2	60	159	1	1
6	0	15.83	0.585	2	8	8	1.5	1	1	2	0	2	100	1	1	0
7	1	17.42	6.5	2	3	4	0.125	0	0	0	0	2	60	101	0	0
8	0	58.67	4.46	2	11	8	3.04	1	1	6	0	2	43	561	1	1
9	1	27.83	1	1	2	8	3	0	0	0	0	2	176	538	0	0
10	0	55.75	7.08	2	4	8	6.75	1	1	3	1	2	100	51	0	0
11	1	33.5	1.75	2	14	8	4.5	1	1	4	1	2	253	858	1	1

PA: results of the proposed approach

Table 2 Classification results using the FT2IS

Observed group	Predicted group			Accuracy
	Good	Bad	Total	Overall%
Good	204	103	307	66.45
Bad	379	4	383	98.96
Total	583	107	690	84.49

In this paper, we have presented an application of Fuzzy Type 2 Inference System (FT2IS) for credit scoring. Australian Credit Approval financial dataset from the UCI machine learning repository is selected to evaluate the proposed method. This dataset is interesting because there is a good mix of attributes - continuous, nominal with small numbers of values, and nominal with larger numbers of values. There are also a few missing values. Each instance contains 6 nominal, 8 numeric attributes, and 1 class attribute (accepted or rejected). The experimental accuracy results of the FT2IS for credit scoring based on this dataset has been described.

Future studies should aim to collect more datasets and use other techniques to test the FT2IS accuracy results.

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