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Credit Risk Assessment by Means of Fuzzy Logic Prediction

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***Abstract*—The goal of this paper is to provide information about the fuzzy logic prediction in general and develop a fuzzy logic prediction system for credit risk assessment using data from local bank in Almaty city.**

Keywords—credit risk assesment; credit risk prediction; fuzzy logic; fuzyy logic prediction

I. *Introduction*

The entire human society's history is marked by the exposure to risks of all kinds and the efforts undergone by humans to deal with the risks. From ancient time, at the emergence of species, the human practiced risk management in order to survive. The practice of survival instincts lead to the avoidance of risks threatening to extinct the human kind. The very existence of human kind today is the proof of the success of applying risk management strategies by our ancestors. Risks are uncertainties. In the banking universe, there are a large number of risks. As the goal of any privately own company, the main goal of bank's management is to maximize the shareholders' value. Bankruptcies in the financial sector are costly, not only for the equity and debt holders of banks' but often also for taxpayers. In order to avoid that the banks are constantly under pressure and have to assume high risks and at the same time manage the risks in order to avoid, or at least minimize losses.

Due to financial crises, credit risk assessment has been the major focus of financial and banking industry. Especially for any credit-granting institution, such as commercial banks and certain retailers, the ability to discriminate good customers from bad ones is crucial. The need for reliable models that predict defaults accurately is imperative so that the interested parties can take either preventive or corrective action [1].

Therefore, credit risk evaluation becomes very important for sustainability and profit of enterprises. Furthermore, an accurate prediction of credit risk could be transformed into a more efficient use of economic capital in business.

To asses credit risk the fuzzy logic prediction is used, a so-called expert system. This expert system makes use of expert rules, which contain fuzzy statements. An example of an expert rule is IF "monthly salary is high" AND "credit history is good" THEN "credit risk is low". Sugeno's singleton fuzzy inference model is used to apply these rules to the input variables in order to predict the output price.

II. *Fuzzy prediction*

Several methods exist to predict an output variable with different input variables. A common used technique is regression analysis. Any regression analysis requires a set of assumptions such as linearity, normality and homoscedasticity [2]. Furthermore, regression techniques are not capable of digesting linguistic fuzzy data. The fuzzy set theory allows to include unavoidable imprecision in the data records. Fuzzy inference is the actual process of mapping with a given set of input variables and output through a set of fuzzy rules. The essence of the modeling is to set up relevant fuzzy rules. The following steps are necessary for successful application of modeling through a general fuzzy system [3].

1) Fuzzification of the input and output variables by considering appropriate linguistic subsets such as high, medium, low, heavy, light, hot, warm, big, small.

2) Construction of rules based on expert knowledge and/or the basis of available data. The rules relate the combined linguistic subsets of input variables to the convenient linguistic output subset. Any fuzzy rule includes statements of "IF.THEN." with two parts. The first part that starts with IF and ends before the THEN is referred to as the predicate (premise, antecedent) which combines in a harmonious manner the subsets of input variables. Consequent part comes after "THEN" which includes the convenient fuzzy subset of the output based on the premise part. This implies that there is a set of rules which is valid for a specific portion of the inputs variation domain. The input subsets within the premise part are combined most often with the logical "and" conjunction whereas the rules are combined with logical "or".

3) The implication part of a fuzzy system is defined as the sharping of the consequent part based on the premise (antecedent) part and the inputs are fuzzy subsets.

4) The result appears as a fuzzy subset and therefore it is necessary to defuzzify the output for obtaining a crisp value.

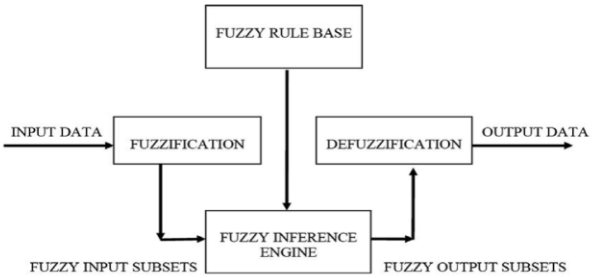

Fig. 1. *General structure of a fuzzy system.*

III. *Credit risk assessment*

The credit risk depends on many different factors. Risk may vary depending on the average income of a person, credit history, character of a person, stability of his job, concurrent credits from other banks, etc [4]. The accuracy of a fuzzy prediction system depends on input variables as well as the expert rules and the membership functions; therefore it is important for them to be chosen carefully. In our case the credit risk prediction is made using four variables, and data was provided by local bank of Almaty. The input variables used are average monthly income of a person for the past 6 months, credit history, stability of his job and concurrent credits from other banks. As you can see three out of four variables are fuzzy, and were given as a number between 0 and 5, 0 being bad and 5 being good.

IV. *Sugeno's singleton inference model*

Sugeno's singleton inference model is similar to the most popular Mamdani method in many respects. In fact the first two parts of the fuzzy inference process, fuzzifying the inputs and applying the fuzzy operator, are exactly the same. The main difference between Mamdani fuzzy inference and Sugeno's singleton is that the output membership functions are constant for Sugeno's singleton fuzzy inference [6].

A typical rule in a Sugeno fuzzy model has the form: if x and y are inputs, then ouput $z = ax+by+c$. For a zero-order Sugeno model (used in our case), the output level z is a constant $(a=b=0)$. The output level z_i of each rule is weighted by the firing strength w_i of the rule.

For example, for an AND rule with inputs x and y, the firing strength is $w_i = AndMethod(F_1(x),\ F_2(y))$, where $F_1(x)$, $F_2(y)$ are the membership functions for inputs x and y.

The final output of the system is the weighted average of all rule outputs, computed as follows: $output = \sum_{i=1}^{N} w_i z_i \,/\, \sum_{i=1}^{N} w_i$, where N is the number of rules.

V. *Membership functions*

Once the variables are included in the system, their membership functions can be defined. In our case defining membership function was done based on basis of statistical data obtained from the same bank. Each variable is subdivided into three categories.

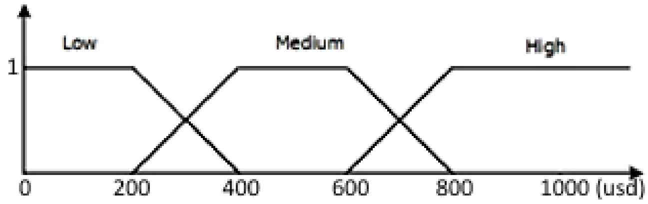

Fig. 2. *Membership functions for average monthly income.*

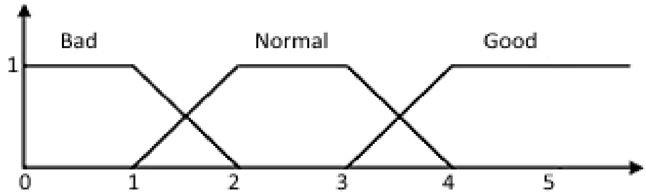

Fig. 3. *Membership functions for credit history.*

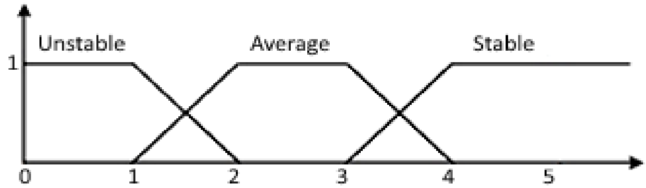

Fig. 4. *Membership functions for job stability.*

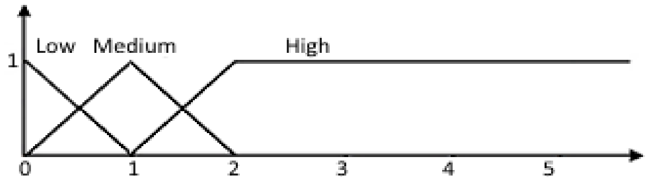

Fig. 5. *Membership functions for amount of concurrent credits.*

VI. *Data*

The sample of 500 credit cases was provided by local bank of Almaty. The data was divided into 2 parts; first 350 randomly selected entries were used to generate rules and remaining 150 entries were used for testing purpose.

VII. *Generating rules*

Rules where generated based on 2/3 of the input data. The following algorithm was used to generate rules. Note that generated rules are for Sugeno's singleton inference model; therefore the conclusions of the rules are crisp numbers.

1) *For each possible combination of input fuzzy sets, find among the data instances ones where input variables fall into those fuzzy sets.*

2) *For each possible combination of input fuzzy sets, the average and standard deviation will be computed for selected inputs.*

3) *For each possible combination of input fuzzy sets, if majority is more than 80% then this combination with result as majority will be added to the rules.*

TABLE I. GENERATED RULES

Average monthly income	***Credit history***	**Job stability**	***Amount of concurrent credits***	**Credit**
low	bad	unstable	high	0
low	bad	unstable	medium	0
low	normal	unstable	low	0
low	normal	stable	low	1
low	good	unstable	low	1
low	good	stable	low	1
low	good	stable	medium	1
average	bad	unstable	low	0
average	normal	unstable	low	0
average	normal	stable	low	1
average	good	unstable	low	1
average	good	average	low	1
average	good	stable	low	1
average	good	stable	medium	1
high	bad	unstable	high	0
high	normal	unstable	low	1
high	normal	stable	high	1
high	normal	stable	medium	1
high	good	average	low	1
high	good	stable	high	1
high	good	stable	low	1

VIII. *Results*

After applying Sugeno's singleton inference model and obtaining output results, simple comparison to original outputs showed that 83.3% answers were correct, which is greater by 10% comparing to simple linear regression which showed only 73.3% correct outputs.

IX. *Conclusion*

Due to the huge outstanding amount and increasing speed of bankruptcy filings, credit risk assessment has attracted much research interests from both academic and industrial communities. A more accurate, consistent, and robust credit evaluation technique can significantly reduce future costs for the credit industry.

This paper describes usage of fuzzy logic prediction system in credit risk assessment. As results show, the developed model predicts the outcome fairly well, achieving almost 84% of correct answers, which can be further enhanced by increasing number of inputs variables and sample of data used for generating rules.

In general, fuzzy logic prediction model can provide a promising solution to credit risk analysis and other prediction problems.

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