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Prediction of Dumping a Product in Textile Industry

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ABSTRACT

Fuzzy Decision Trees (FDT's) are one of the most popular choices for learning and reasoning from dataset. They have undergone a number of alterations to language and measurement uncertainties. However, they are poor in classification accuracy. In this paper, Neuro -fuzzy decision tree (a fuzzy decision tree structure with neural like parameter adaptation strategy) improves FDT's classification accuracy and extracts more accuracy human interpretable classification rules. In the forward cycle fuzzy decision tree is constructed and in the feedback cycle, parameters of fuzzy decision tree have been adapted using stochastic gradient descent algorithm by traversing back from leaf to root nodes. In this paper, the system may predict whether a product in dumped or not for the textile industry is explained.

Index Terms - *Fuzzy Decision Tree, Neuro-fuzzy decision tree, Fuzzy ID3.*

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1. INTRODUCTION

Many early-warning systems are available in our society and in many other fields and found to be very beneficial. The textile industry also needs such a system to reduce the risks. At the present time, most of the existing dumping and warning systems are directly based on human common sense and knowledge which are sometimes inaccurate, unreliable, and incomplete.

FDT is a successful method for accurate prediction. It facilitates human inspection or understanding. But it is poor level of predictive accuracy. Neuro-Fuzzy Decision Trees [1] is a Fuzzy Decision Tree structure with neural like parameter adaptation strategy. In the forward cycle, we construct Fuzzy Decision Trees using any of the standard induction algorithms like fuzzy ID3. In the feedback cycle, parameters of Fuzzy decision trees have been adapted using stochastic gradient descent algorithm by traversing back from leaf to root nodes. With this strategy, during the parameter adaptation stage, keep the hierarchical structure of fuzzy decision trees intact. This approach of applying back propagation algorithm directly on the structure of fuzzy decision trees improves its learning accuracy without compromising the comprehensibility (interpretability).

2. FUZZY ID3 ALGORITHM

ID3 algorithm [2], [3] applies to a set of data and generates a decision tree for classifying the data. Fuzzy ID3 algorithm is extended to apply to a fuzzy set of data (several data with membership grades) and generates a fuzzy decision tree using fuzzy sets defined by a user for all attributes. A fuzzy decision tree consists of nodes for testing attributes, edges for branching by test values of fuzzy sets defined by a user and leaves for deciding class names with certainties. Fuzzy ID3 is very similar to ID3, except ID3 selects the test attribute based on the information gain, which is computed by the probability of ordinary data but ours by the probability of membership value for data.

Assume that we have a set of data D, where each data has θ numerical values for attributes A_1, A_2….A_θ and one classified class C = {C_1, C_2, …..C_q} and Fuzzy Sets f_{i1}, f_{i2}, ….f_{in} for the attribute A_j (the value of m varies on every attribute). Let D^{C_k} to be a fuzzy subset in D whose class is C_k and |D| the sum of the membership values in a fuzzy set of data D[4]. Then an algorithm to generate a fuzzy decision tree is in the following:

1. Generate the root node that has a set of all data, i.e., a fuzzy set of all data with the membership value 1.
2. If a node 't' with a fuzzy set of data D satisfies the following conditions:

   (i) the proportion of a data set of a class C_k is greater than or equal to a threshold θ_r, that is, $\frac{|D^{C_k}|}{|D|} \geq \theta_r$

   (ii) The number of a data set is less than a threshold θ_n that is $|D| < \theta_n$,

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(iii) there are no attributes for more classification, then it is a leaf node and assigned by the class name (more detailed method is described below).

3. If it does not satisfy the above conditions, it is not a leaf node and the test node is generated as follows:

3.1 For A_i's (i=1,2,…,*l*), calculate the information gains $G(A_i, D)$, to be described below, and select the test attribute A_{max} that maximizes them.

3.2 Divide D into a fuzzy subsets D_1, D_2, …….D_m according to A_{max}, where the membership value of the data in D_j is the product of the membership value in D and the value of $f_{max,\, j}$ of the value of A_{max} in D.

3.3 Generate new nodes t_1, t_2,……t_m for fuzzy subsets D_1, D_2, …. D_m and label the fuzzy sets $f_{max,\, j}$ to edges that connect between the nodes t_j and t.

3.4 Replace D by D_j (j=1,2,…..m) and repeat from 2 recursively.

The information gain $G(A_i, D)$ for the attribute A_i by a fuzzy set of data D is defined by

$$G(A_i, D) = I(D) - E(A_i, D) \quad (1)$$

where

$$I(D) = -\sum_{k=1}^{n} (p_k . \log_2 p_k) \quad (2)$$

$$E(A_i, D) = \sum_{j=1}^{m} \left(p_{ij} . I\left(D_{fq}\right)\right) \quad (3)$$

$$p_k = \frac{\left|D^{C_k}\right|}{|D|} \quad (4)$$

$$p_q = \frac{\left|D_{f_q}\right|}{\sum_{j=1}^{m} \left|D_{f_q}\right|} \quad (5)$$

As for assigning the class name to the leaf node, we propose three methods as follows:

(a) The node is assigned the class name that has the greatest membership value, that is, other than the selected data are ignored.

(b) If the condition (a) in step 2 in the algorithm holds, do the same as the method (a). If not, the node is considered to be empty, that is, the data are ignored.

(c) The node is assigned by all class names with their membership values, that is, all data are taken into account [5].

3. NEURO-FUZZY DECISION TREE

Due to the size and performance of FDT is severely affected by fuzziness control parameter (α-cut) and leaf selection threshold (β_{th}), however, guide rules of selecting α and β_{th} are very hard to find in the existing fuzzy decision tree literature. Neuro-FDT incorporates the merits of neural learning algorithms into the feedback cycle of hierarchical FDT. The method significantly improves the classification accuracy of FDT without compromising the comprehensibility, the FDT structure has been kept intact during the parameter adaptation stage.

Rajen. B Bhatt and M. Gopal [1] proposed back propagation learning to be applied directly on FDT structure by traversing back from each leaf node to root node. Neuro-FDT includes one forward cycle of FDT induction and then several back propagation iterations of tuning the FDT parameters (membership functions and leaf certainties). This strategy doesn't disturb the hierarchical structure of FDT and effectively tune the tree parameters, while preserving the interpretability [6].

The figure 2 shows the basic Neuro-FDT structure with two summing nodes added to it to carry out inference. From all the leaf nodes, certainty factors corresponding to class 1 (Yes) are summed up to calculate y_1. Same way, certainty factors corresponding to class 2 (No) are summed up to calculate y_2. For an arbitrary pattern, the firing strength of l^{th} class at m^{th} leaf node is given by

$$\mu^i_{path\ m} \times \beta_{ml} \quad (6)$$

Each $path_m (m = 1,...,6)$ is defined on the premise space composed of input features available in traversing from root node to m^{th} leaf node, where $\mu^i_{path\ m}$ is membership degree of $path_m$. Which can be calculated as,

$$\mu^i_{path\ m} = \prod_{j=1,2,3} \mu F_{jm}\left(s^i_j\right) \quad (7)$$

β_{ml} $(0 \le \beta_{ml} \le 1;\ l = 1, 2)$ is the degree of certainty, with which $path_m$ can classify the class *l*.

In Figure 2, $path_6$ can classify 'Yes' with the certainty of β_{61} and classify 'No' with the certainty of β_{62}. F_{jm} is j^{th} variable's membership function available on m^{th} path.

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Firing strengths of all the leaf nodes for a particular class *l* are summed up to calculate the prediction certainty $y_l^i(l=1,2)$ of the pattern through FDT

$$y_l^i = \sum_{m=1}^{6} \mu_{path_m}^i \times \beta_{m1} \qquad (8)$$

where $0 \le y_l^i \le 1$. For example, in figure 2, prediction certainties for 'Yes' (y_1), 'No' (y_2) are to be calculated by,

$$y_1^i = \sum_{m=1}^{M} \mu_{path_m}^i \times \beta_{m1}\ ; \quad y_2^i = \sum_{m=1}^{M} \mu_{path_m}^i \times \beta_{m2}$$

When classification to unique class is desired, the class with the highest membership degree has to be selected i.e., classify given pattern to class l_0, where

$$l_0 = \arg\max_{l=1,2} \{y_l^i\} \qquad (9)$$

The class corresponding to maximum prediction certainty will be selected $l_0 = \arg\max\{y_1^i, y_2^i\}$

To fuzzify input attributes, the method we select Gaussian membership functions out of many alternatives [7], due to its differentiable property. For i[th] pattern membership degree of $path_m$ can be calculated by

$$\mu_{path_m}^i = \prod_j \mu F_{jm}(s_j^i) = \prod_j \exp\left(\frac{(s_j^i - c_{jm})^2}{2\sigma_{jm}^2}\right) \qquad (10)$$

where c_{jm} and σ_{jm} are center and standard deviation (width) of Gaussian membership of j[th] input attribute on m[th] path of F_{jm}.

The method defines as the error function of the FDT a differentiable function like the mean-square-error E,

$$E = \frac{1}{2n} \sum_{l=1}^{q} \sum_{i=1}^{n} \left(d_l^i - y_l^i\right)^2 \qquad (11)$$

Where n the total number of training patterns and d_l^i and y_l^i is the desired class of i[th] pattern through Neuro-FDT respectively.

The necessary condition for the minimization of error is that its differentiations with respect to the parameters Gaussian center locations, Gaussian widths, and certainty factors are all vanish. The leads to the parameter update rule,

$$\theta^{\tau+1} = \theta^{\tau} - \eta \frac{\delta E}{\delta \theta} \qquad (12)$$

For FDT structure with Gaussian membership functions, we obtain the following update rules for the adaptation of the parameters centers, widths and certainty factors.

$$\beta_{ml}^{\tau+1} = \beta_{ml}^{\tau} + \frac{\eta}{n} \sum_{i=1}^{n} \left(d_l^i - y_l^i\right) \mu_{path_m}^2 \qquad (13)$$

4. Construction of Fuzzy Decision Tree:

The export textile products dataset from January to August in 2012 are considered. Fuzzy set of dataset D shown in table 1.

Table 1: Export Textile Dataset

M	μ	S_1	S_2(%)	S_3(%)	C
1	1.0	Middle	36	16.0	Yes
2	0.8	High	28	18.0	No
3	0.2	High	37	17.0	No
4	0.7	Low	46	17.5	Yes
5	1.0	High	37	16.0	No
6	0.3	Low	46	17.5	No
7	1.0	Middle	56	16.5	No
8	0.5	Middle	27	18.0	Yes

M, S_1, S_2, S_3 represents respectively months production capacity of import country, market share and china's textile products export growth rate.

Fuzzy sets low, middle and high in the attribute S_3, fuzzy sets small, middle and big in S_2, and fuzzy sets strong and weak in S_1 are defined as

$$\text{Low} = \left\{\frac{1}{16}, \frac{0.8}{16.5}, \frac{0.5}{17}, \frac{0.2}{17.5}\right\}$$

$$\text{Middle} = \left\{\frac{0.5}{16.5}, \frac{1}{17}, \frac{0.8}{17.5}, \frac{1}{18}\right\}$$

$$\text{High} = \left\{\frac{0.2}{16.5}, \frac{0.5}{17}, \frac{0.8}{17.5}, \frac{1}{18}\right\}$$

$$\text{Small} = \left\{\frac{1}{36}, \frac{0.8}{46}, \frac{0.5}{27}, \frac{0.2}{37}\right\}$$

$$\text{Middle} = \left\{\frac{0.5}{56}, \frac{1}{27}, \frac{0.5}{37}\right\}$$

$$\text{Big} = \left\{\frac{0.2}{46}, \frac{0.5}{27}, \frac{0.8}{37}, \frac{1}{28}\right\}$$

$$\text{Strong} = \left\{\frac{1}{middle}, \frac{0.3}{low}\right\}$$

$$\text{Weak} = \left\{\frac{0.6}{low}, \frac{1.0}{high}\right\}$$

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Note that we can define fuzzy sets of the continuous membership functions.

First, we calculate the information I(D). Since we have $|D| = 5.5$, $|D^{C_1}| = 2.2$ and $|D^{C_2}| = 3.3$, we have $I(D) = \frac{2.2}{5.5}\log_2\frac{2.2}{5.5} - \frac{3.3}{5.5}\log_2\frac{3.3}{5.5}$ =0.971.

Next, we calculate the expected information for all $A_1^{'}s$. For S_3, using the step 3.2 in the algorithm, we have the fuzzy sets of data $D_{S_1,low}$, $D_{S_2,middle}$, $D_{S_3,high}$ shown in table 2.

Tale 2: Fuzzy Sets data

M	Low	mid	High	S_3(%)	C
1	1	0	0	16.0	Yes
2	0	0	0.8	18.0	No
3	0.1	0.2	0.1	17.0	No
4	0.14	0.35	0.56	17.5	Yes
5	1	0	0	16.0	No
6	0.06	0.15	0.24	17.5	No
7	0.8	0.5	0.2	16.5	No
8	0	0	0.5	18.0	Yes

The membership value is calculated by the product of μ in D and the membership value of the fuzzy sets low, middle and high of the value of the S_3 in D.

Ten for low, we have $|D_{S_3,low}| = 3.1$, $|D^{C_1}_{S_3,low}| = 1.14$, $|D^{C_2}_{S_3,low}| = 1.96$, and $I(D_{S,high}) = \frac{1.14}{3.1}\log_2\frac{1.14}{3.1} - \frac{1.96}{3.1}\log_2\frac{1.96}{3.1} = 0.949$

$|D_{S_3,middle}| = 1.2$, $|D^{C_1}_{S_3,middle}| = 0.35$, $|D^{C_2}_{S_3,middle}| = 0.85$, and $I(D_{S_3,middle}) = 0.871$

for high, we have $|D_{S_3,high}| = 2.4$, $|D^{C_1}_{S_3,high}| = 1.06$, $|D^{C_2}_{S_3,high}| = 1.34$, and $I(D_{S_3,high}) = 0.990$

Now we can calculate the expected information after testing by the S_3 as

$$E(S_3, D) = \frac{3.1}{6.7}\times 0.949 + \frac{1.2}{6.7}\times 0.990 = 0.950$$

Thus we have the information gain for the attribute S_3 as

$$G(S_3, D) = I(D) - E(S_3, D) \text{=0.971-0.950 =0.021}$$

By similar analysis for S_2 and S_1, we have G(S_2,D) =0.118, G(S_1,D) =0.164. Since we select the attribute that maximize the gain, we have as the test attribute. We apply the same process until it holds the leaf condition (1), (2) or (3)in the step 2 in the algorithm. For this data, we have the fuzzy decision tree shown in figure 1.

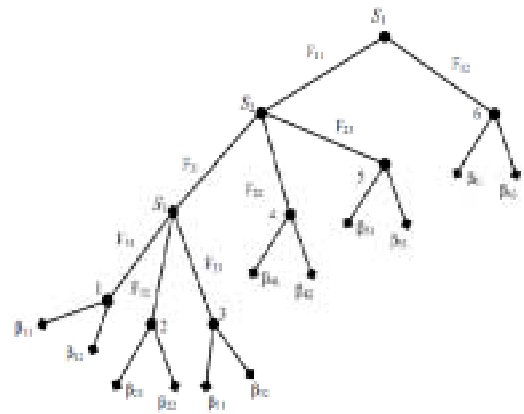

Figure 1: Fuzzy Decision Tree

Then, we may get neuro-fuzzy decision tree using the method [1]. For the export textile products dataset, to classify given pattern to either 'Yes' or 'No', 'Yes' represents dumping and 'No' represents no dumping. It shows in figure 2.
Using the pseudo code of the Neuro-FDT strategy to train and get degree of certainty β shown below.

$$\begin{bmatrix} \beta_{11} & \beta_{12} \\ \beta_{21} & \beta_{22} \\ \beta_{31} & \beta_{32} \\ \beta_{41} & \beta_{42} \\ \beta_{51} & \beta_{52} \\ \beta_{61} & \beta_{62} \end{bmatrix} = \begin{bmatrix} 0.61 & 0.59 \\ 0.53 & 0.97 \\ 0.66 & 0.84 \\ 0.7 & 0.84 \\ 0.71 & 0.79 \\ 0.86 & 0.84 \end{bmatrix}$$

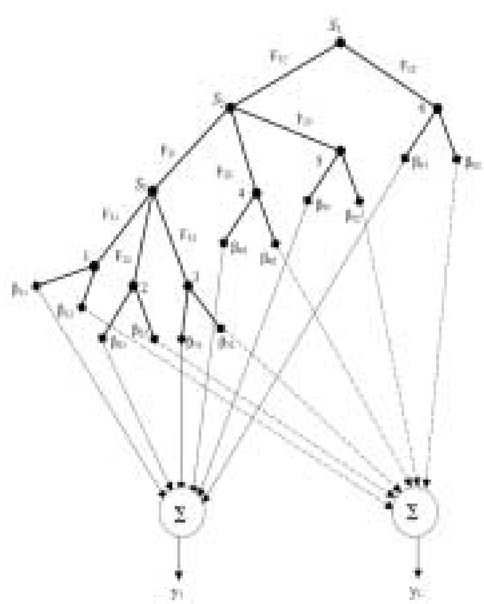

Figure 2: FDT for back propagation

5. CONCLUSION

This paper proposed a method for the early warning system may predict whether a product in dumped or not. The method is more validated for predicting a product to dump than other methods. Neuro-FDT has many advantages such as fairly simple but powerful strategy for improving the classification accuracy of FDT without compromising the comprehensibility.

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