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Generating fuzzy rules from training instances for fuzzy classification systems

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Abstract

In recent years, many methods have been proposed to generate fuzzy rules from training instances for handling the Iris data classification problem. In this paper, we present a new method to generate fuzzy rules from training instances for dealing with the Iris data classification problem based on the attribute threshold value α, the classification threshold value β and the level threshold value γ, where $\alpha \in [0,1]$, $\beta \in [0,1]$ and $\gamma \in [0,1]$. The proposed method gets a higher average classification accuracy rate than the existing methods.

Keywords: Fuzzy rules; Fuzzy sets; Fuzzy classification systems; Iris data; Membership functions

1. Introduction

In recent years, some methods have been presented to generate fuzzy rules from training instances for handling the Iris data (Fisher, 1936) classification problem (Castro, Castro-Schez, & Zurita, 1999; Chang & Chen, 2001; Chen & Chang, 2005; Chen & Chen, 2002; Chen & Fang, 2005a, 2005b; Chen & Lin, 2000, 2005a, 2005b; Chen & Tsai, 2005; Chen, Wang, & Chen, 2006; Hong & Chen, 1999; Hong & Lee, 1996, 1999; Ishibuchi & Nakashima, 2001; Tsai & Chen, 2002; Wu & Chen, 1999).

Castro et al. (1999) presented a method to generate fuzzy rules from training data to deal with the Iris data classification problem. Chang and Chen (2001) presented a method to generate weighted fuzzy rules to deal with the Iris data classification problem. Chen and Chang (2005) presented a method to construct membership functions and generate weighted fuzzy rules from training instances. Chen and Tsai (2005) presented a method to generate fuzzy rules from training instances to deal with the Iris data classification problem. Chen et al. (2006) presented a method for generating weighted fuzzy rules from training data for dealing with the Iris data classification problem. Chen and Chen (2002) presented a method based on genetic algorithms to construct membership functions and fuzzy rules to deal with the Iris data classification problem. Chen and Fang (2005a) presented a method for handling the Iris data classification problem. Chen and Fang (2005b) presented a method to deal with fuzzy classification problems by tuning membership functions for fuzzy classification systems. Hong and Lee (1996) presented a method for inducing fuzzy rules and membership functions from training instances to deal with the Iris data classification problem. Wu and Chen (1999) presented a method for constructing membership functions and fuzzy rules from training instances to deal with the Iris data classification problem. Hong and Lee (1999) discussed the effect of merging order on performance of fuzzy rules induction. Hong and Chen (1999) presented a method to construct membership functions and generate fuzzy rules from training instances by finding relevant attributes and membership functions to deal with the Iris data classification problem. Chen and Lin (2005a) presented a method to generate weighted fuzzy rules from training instances to deal with the Iris data classification problem.

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Chen and Lin (2005b) presented a method to generate weighted fuzzy rules from numerical data based on genetic algorithms to deal with the Iris data classification problem.

In this paper, we present a new method to generate fuzzy rules from training instances for dealing with the Iris data classification problem. The proposed method constructs the membership functions and generates fuzzy rules from training instances based on the attribute threshold value α, the classification threshold value β, and the level threshold value γ to deal with the Iris data classification problem, where $\alpha \in [0,1]$, $\beta \in [0,1]$, and $\gamma \in [0,1]$. The experimental results show that the proposed method gets a higher average classification accuracy rate than the existing methods.

The rest of this paper is organized as follows. In Section 2, we briefly review basic concepts of fuzzy sets (Zadeh, 1965). In Section 3, we present a new method to generate fuzzy rules from training instances for handling the Iris data classification problems. In Section 4, we use an example to illustrate the fuzzy rules generation process of the proposed method. In Section 5, we make an experiment to compare the average classification accuracy rate of the proposed method with the existing methods. The conclusions are discussed in Section 6.

2. Basic concepts of fuzzy sets

In this section, we briefly review basic concepts of fuzzy sets from (Zadeh, 1965).

Definition 1. Let U be the universe of discourse, $U = \{x_1, x_2, \ldots, x_n\}$. A fuzzy set A of the universe of discourse U can be represented as follows:

$$A = \mu_A(x_1)/x_1 + \mu_A(x_2)/x_2 + \cdots + \mu_A(x_n)/x_n, \tag{1}$$

where μ_A is the membership function of the fuzzy set A, μ_A: $U \to [0,1]$, $\mu_A(x_i)$ denotes the grade of membership of x_i belonging to the fuzzy set A, and $\mu_A(x_i) \in [0,1]$.

Definition 2. Let A and B be two fuzzy sets defined in the universe of discourse U. The union operation between the fuzzy sets A and B, denoted as $A \cup B$, is defined as follows:

$$\mu_{A\cup B}(x) = \max(\mu_A(x), \mu_B(x)), \quad \forall x \in U, \tag{2}$$

where μ_A and μ_B are the membership functions of fuzzy sets A and B, respectively, μ_A: $U \to [0,1]$, and μ_B: $U \to [0,1]$.

Definition 3. Let A and B be two fuzzy sets defined in the universe of discourse U. The intersection operation between the fuzzy sets A and B, denoted as $A \cap B$, is defined as follows:

$$\mu_{A\cap B}(x) = \min(\mu_A(x), \mu_B(x)), \quad \forall x \in U, \tag{3}$$

where μ_A and μ_B are the membership functions of fuzzy sets A and B, respectively, μ_A: $U \to [0,1]$, and μ_B: $U \to [0,1]$.

Definition 4. Let A be a fuzzy set defined in the universe of discourse U. The complement of the fuzzy set A, denoted as $\overline{A}$, is defined as follows:

$$\mu_{\overline{A}}(x) = 1 - \mu_A(x), \quad \forall x \in U, \tag{4}$$

where μ_A and $\mu_{\overline{A}}$ are the membership functions of fuzzy sets A and $\overline{A}$, respectively, μ_A: $U \to [0,1]$, and $\mu_{\overline{A}}$: $U \to [0,1]$.

3. A new method to generate fuzzy rules from training instances for handling fuzzy classification problems

In this section, we present a new method to generate fuzzy rules from training instances to deal with the Iris data (Fisher, 1936) classification problem. The Iris data contains 150 instances having four input attributes, i.e., Sepal Length (SL), Sepal Width (SW), Petal Length (PL) and Petal Width (PW) as shown in Table 1. There are three species of flowers, i.e., Iris-Setosa, Iris-Versicolor and Iris-Virginica, and each species has 50 instances. Assume that the ith training instance a_i has four input attribute values $x_{i,\text{Sepal Length}}$, $x_{i,\text{Sepal Width}}$, $x_{i,\text{Petal Length}}$, $x_{i,\text{Petal Width}}$, and one output attribute value y_i, shown as follows:

$$a_i = ((x_{i,\text{Sepal Length}}, x_{i,\text{Sepal Width}}, x_{i,\text{Petal Length}}, x_{i,\text{Petal Width}}), y_i),$$

where $x_{i,\text{Sepal Length}}$ denotes the attribute value of the attribute "Sepal Length" of the ith training instance, $x_{i,\text{Sepal Width}}$ denotes the attribute value of the attribute "Sepal Width" of the ith training instance, $x_{i,\text{Petal Length}}$ denotes the attribute value of the attribute "Petal Length" of the ith training instance, $x_{i,\text{Petal Width}}$ denotes the attribute value of the attribute "Petal Width" of the ith training instance, y_i denotes the species of flower of the ith training instance, $y_i \in$ {Iris-Setosa, Iris-Versicolor, Iris-Virginica}, and $1 \leqslant i \leqslant 150$. The type of membership functions used in this paper is the triangular membership function and trapezoidal membership function, as shown in Fig. 1. In Chen et al. (2006) and Chen and Chen (2002), Chen et al. presented the definition of "the degree of entropy" v_i of an input attribute X_i as follows:

$$V_i = \frac{\text{PD}}{|\text{WD}|} \tag{5}$$

where v_i denotes the degree of entropy of the input attribute X_i and $1 \leqslant i \leqslant 4$. First, Chen et al. found the whole domain WD of the input attribute X_i. Then, they found the individual domain of the input attribute X_i for each species of flower. PD contains a set of intervals $I_1, I_2, \ldots, I_p$ which are not overlapped with the individual domain of the input attribute X_i for each species of flowers, and $|\text{PD}| = |I_1| + |I_2| + \cdots + |I_p|$, where $|I_j|$ denotes the length of the interval I_j, and $1 \leqslant i \leqslant p$; $|\text{WD}|$ denotes the length of the whole domain WD.

Assume that the attribute threshold value given by the user is α, the classification threshold value given by the user is β, and the level threshold value given by the user is γ, where $\alpha \in [0,1]$, $\beta \in [0,1]$ and $\gamma \in [0,1]$. The attribute threshold value α is used to test which attributes can be used to deal with the classification, where $\alpha \in [0,1]$; the classification threshold value β is used to test whether the