Algorithm of Fuzzy Support Vector Machine based on a Piecewise Linear Fuzzy Weight Method

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ABSTRACT

This article describes how fuzzy support vector machines (FSVMs) function well with good anti-noise performance, which receives the attention of many experts. However, the traditional center-distance fuzzy weight assignment method assigns support vectors with a small value of a membership degree and this weakens the role of support vectors in classification. In this article, a piecewise linear fuzzy weight computing method is proposed, in which boundary samples are assigned with a larger value of membership degree and samples far from the mean vector are assigned a smaller value of membership degree. The proposed method has a good classification performance, because the influence of noise samples is weakened and meanwhile the support vectors are paid much more attention. The experiments on the UCI database and MNIST data set fully verify the effectiveness of the proposed algorithm.

KEYWORDS

Anti-Noise Performance, Fuzzy Support Vector Machine, Membership Degree, Piecewise Linear Fuzzy Weight

1. INTRODUCTION

Fuzzy Support Vector Machine (FSVM) theory was firstly proposed by Lin, etc. (Lin & Wang, 2002). Its main idea is to introduce the concept of fuzzy weights to the original sample, enhancing the noise resistance of this algorithm. Currently, this algorithm is widely applied in the fields of network intrusion detection (Lun, University, & Beijing, 2005; Yang, Yu, Xie, & Zhang, 2011), face recognition (Leng & Wang, 2008; Liu & Chen, 2007), text classification (Wang & Chiang, 2007, 2009) and credit risk evaluation (Wang, Wang, & Lai, 2005).

For the fuzzy support vector machine, the original sample \((x_i, y_i)\) is usually expressed as \((x_i, y_i, s_i)\), where \(s_i\) stands for the fuzzy weight of samples. Fuzzy support vector machine weakens the effect of noise samples for classification results through introducing fuzzy weight. Fuzzy support vector machine algorithm can be achieved by solving the following optimization problem:

\[
\begin{aligned}
\text{Min.} & \quad \frac{1}{2} w^T w + C \sum_{i=1}^{l} s_i \xi_i \\
\text{s.t.} & \quad y_i (w \cdot \Phi(x_i) + b) \geq 1 - \xi_i, \quad \xi_i \geq 0, \quad i = 1, \cdots, l
\end{aligned}
\]

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Different from the traditional support vector machine algorithm, in the fuzzy support vector machine model, the misclassification penalty $\xi$ of samples is influenced by fuzzy weight $s_i$ and so the effects of noise samples for classification can be reduced by setting reasonable fuzzy weights. The key of fuzzy support vector machine algorithm is to assign the fuzzy weights, and currently the commonly applied approach is the center distance fuzzy weight assignment method. The specific calculation formula is as follows:

$$
 s_i = \begin{cases} 
 1 - \left( \frac{\|m_i - x\|}{r_i + \delta} \right) & y_i = 1 \\
 1 - \left( \frac{\|m_2 - x\|}{r_2 + \delta} \right) & y_i = -1 
\end{cases}
$$

(2)

where $m_i$ and $m_2$ denote the sample center of the two kinds of sample, and $\delta > 0$ is used to avoid $s_i = 0$. $r_i$ and $r_2$ denote the radius of the two kinds of samples, and they can be defined as follows:

$$
 r_i = \max_{(x,y) = 1} \|m_i - x\| \\
r_2 = \max_{(x,y) = -1} \|m_2 - x\|
$$

(3)

As the center distance fuzzy weight assignment method assigns smaller ambiguity to boundary samples, the effect of the noise samples is weakened. However, at the same time the role of support vector in classification is weakened as well. In view of the drawback of the center distance fuzzy weight assignment method, this paper proposes a new fuzzy weight assignment method, namely, the piecewise linear fuzzy weight computing method.

The main idea of this method, on the one hand, is to assign the fuzzy weight based on the possibility of the sample being noise for the non-border area which is far away from the center sample; and on the other hand, is to assign the fuzzy weight according to the chance of the sample being support vector for the border area. This method can effectively weaken the influence of the noise samples, while retaining the role of the support vector samples. Thus, its performance is better than the center distance fuzzy weight assignment method.

For convenience, in this paper we denote the fuzzy support vector machine algorithm corresponding to the center distance fuzzy weight assignment method as FSVMCD, and denote the fuzzy support vector machine algorithm based on piecewise linear fuzzy weight computing method as FSVMPLF.

The remainder of this paper is organized as follows: Section 2 puts forward a piecewise linear fuzzy weight computing method and the corresponding FSVMPLF algorithm. In Section 3, we test the proposed FSVMPLF algorithm on some UCI standard data sets (Blake, 1998) and the MNIST digital recognition data sets (Yu, Yang, & Xie, 2014), and compare its performance with FSVMCD. The experimental results and the detail analysis are also given in this part. Section 4 concludes the whole paper.

**2. THE PIECEWISE LINEAR FUZZY WEIGHT COMPUTING METHOD**

As mentioned in Section 1, the center distance fuzzy weight assignment method weakens the influence of noise samples, but at the same time it also reduces the role of support vector samples in classification. For this shortage, this section presents a new fuzzy weight calculation method, namely piecewise linear fuzzy weight computing method. Similar to the center distance fuzzy weight assignment method, in this paper, the piecewise linear fuzzy weight computing method also thinks the samples that are away from the center vector are more likely to be noise, hence should be given less fuzzy weights.
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