An Improved Second Order Training Algorithm for Improving the Accuracy of Fuzzy Decision Trees

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ABSTRACT

Fuzzy decision tree (FDT) is a powerful top-down, hierarchical search methodology to extract human interpretable classification rules. The performance of FDT depends on initial fuzzy partitions and other parameters like alpha-cut and leaf selection threshold. These parameters are decided either heuristically or by trial-and-error. For given set of parameters, FDT is constructed using any standard induction algorithms like Fuzzy ID3. Due to the greedy nature of induction process, there is a chance of FDT resulting in poor classification accuracy. To further improve the accuracy of FDT, in this paper, the authors propose the strategy called Improved Second Order- Neuro- Fuzzy Decision Tree (ISO-N-FDT). ISO-N-FDT tunes parameters of FDT from leaf node to roof node starting from left side of tree to its right and attains better improvement in accuracy with less number of iterations exhibiting fast convergence and powerful search ability.

KEYWORDS

Classification, Fuzzy Decision Tree, Fuzzy ID3, Levenberg Marquardt, Second Order Training

INTRODUCTION

Machine learning algorithms like multi-layer perceptron, radial basis function (RBF) networks, neural networks and support vector machines are widely used for nonlinear pattern classification problems. In spite of having several advantages like relative ease of applications and abilities to provide gradual responses, these algorithms lack human interpretability, which can be a problem especially if users need to justify and understand their decisions. In such cases, only decision trees (DTs) managed to get satisfactory results. Decision tree is one of the most widely used classification technique due to its hierarchical representation of classification knowledge. Various decision trees are developed over the years, namely CART (Breiman et al. 1984), ID3 (Interactive Dichotomiser3), Quinlan (1986), C4.5 (Quinlan 2014), SPRINT (Shafer et al. 1996), SLIQ (Mehta et al. 1996), etc., However, crisp decision tree algorithms are criticized for their sensitivity towards the small changes in attribute values.

To address the problem related with crisp decisions, various researchers have introduced Fuzzy Decision Tree (FDT) induction algorithms (Weber. 1992; Maher and Clair, 1993; Umano et al., 1994; Yuan and Shaw, 1995; Jeng et al., 1997; Hayashi et al., 1998; Janikow, 1998; Yeung et al., 1999; Chiang & Hsu, 2002). A comprehensive survey of these FDT induction techniques can be found in Chen et al. (2009). The most important task in induction of FDT is to use an appropriate
and efficient attribute selection measure. Average fuzzy classification entropy is one such measure used by Quinlan (1986) for induction of Fuzzy ID3 algorithm. Yuan and Shaw’s (1995) introduced average fuzzy classification ambiguity of attribute(s) as the measure for the induction of FDT. Both the fuzzy entropy measure and the fuzzy ambiguity measures essentially use the ratio of uncertainty to measure the significance of fuzzy conditional attributes. Further, Yeung et al. (1999) proposed the average degree of importance of attribute(s) as a novel attribute selection criterion for FDT induction. An analytic and experimental comparison of these three measures for generating FDT is given by Wang et al. (2001). Two other algorithms have been proposed by Bhatt & Gopal (2004), named as fuzzy-rough interactive dichotomizers ver. 1.1 and ver. 1.2, where they use dependency degree using fuzzy-rough hybrid method for induction of fuzzy decision tree. The description of the proposed measure is given by Bhatt & Gopal (2006). Wang & Borgelt (2004) proposed to use information gain as a splitting criterion and came up with some improvements for the same. Jensen & Shen (2005) proposed to use a fuzzy rough set based splitting criterion for FDT induction. Bhatt & Gopal (2008) proposed an attribute selection measure using fuzzy rough hybrids and produced a novel fuzzy-rough classification trees. Zhai (2011) also used fuzzy-rough technique, in which expanded attributes are selected by using significance of fuzzy conditional attributes with respect to fuzzy decision attributes. Lertworaprachaya (2014) proposed look-ahead based fuzzy decision tree induction method for constructing decision trees using interval-valued fuzzy membership values.

As other variant of traditional FDTs, Wang et al. (2015) proposed a new framework for FDT induction using fuzzy rules. The proposed method helps to minimize the size of the trees and it is also employed to produce leaves of high purity. Few research works also focused on the generation of the appropriate membership functions for the fuzzy partitioning of attributes. For example, Xizhao & Hong (1998) discretized continuous attributes using fuzzy numbers and probability theory. Pedrycz & Sosnowski (2005) employed context-based fuzzy clustering for generating proper membership functions. Bhatt et al. (2012) proposed two heuristic algorithms for obtaining triangular and trapezoidal fuzzy membership function parameters from FCM clustered data. Chen and Wang (2013) presented a new fuzzy ranking method based on the α-cuts of interval type-2 fuzzy sets and further proposed a new method for fuzzy multiple attributes decision making. He & He (2015a) investigated the properties of extended Atanassov’s intuitionistic fuzzy interaction Bonferroni mean (EIFIBM) and the extended weighted Atanassov’s intuitionistic fuzzy interaction Bonferroni mean (EWIFIBM), and applied them to multiple attributes decision making problems. As another variant, He et al.(2015b) designed hesitant fuzzy set for situations in which it is difficult to determine the membership of an element to a set because of ambiguity between a few different values. They have defined the ith order polymerization degree function and proposed a new ranking method to further compare different hesitant fuzzy sets. Lee and Chen (2015) proposed a new fuzzy decision making method and fuzzy group decision making method based on the proposed likelihood-based comparison relations of hesitant fuzzy linguistic term. He et al. (2015c) considered the interactions between the membership function and non-membership function of different Intuitionistic Fuzzy sets and developed the intuitionistic fuzzy interaction Bonferroni mean (BM) and the weighted intuitionistic fuzzy interaction Bonferroni mean, as complement to the existing generalizations of BM under intuitionistic fuzzy environment. Wan et al. (2015) investigated the prioritization relationship of attributes in multi attribute decision making with trapezoidal intuitionistic fuzzy numbers and also presented a new lexicographic ranking method for trapezoidal intuitionistic fuzzy numbers.

The other FDT induction related works tried to improve the accuracy of the FDT by applying optimization and back propagation techniques. Wang et al. (2000) proposed optimization methods based on minimizing the total number of leaf nodes and average depth of leaves. They have also proved that the construction of a minimum FDT is a NP-Hard problem. Pedrycz & Sosnowski
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