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IFC-Filter: Membership function generation for inductive fuzzy classification

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ABSTRACT

Fuzzy classification can be defined as a method of computing the degrees of membership of objects in classes. There are many approaches to fuzzy classification, most of which generate sophisticated multivariate models that classify all of the input space simultaneously. In contrast, methods for membership function generation (MFG) derive simple models for fuzzy classification that map one input variable to one fuzzy class; therefore, by minimizing complexity, these models are very understandable to human experts. The unique contribution of this paper is a method for membership function generation from real data that is based on inductive logic. Most existing MFG methods apply either parameter optimization heuristics or unsupervised learning and clustering for the definition of the membership function. In contrast to heuristic methods, our method can approximate membership functions of any shape. In comparison to clustering, our approach can make use of a target signal to learn a membership function supervised from the association between two variables. Compared to probabilistic methods, which translate frequency information, i.e., normalized histograms, directly into membership degrees, our approach applies inductive reasoning based on conditional relative frequencies, which are called likelihoods. According to the law of likelihood in inductive logic, it is the *ratio between the likelihoods* of the data that is of interest when evaluating two alternative hypotheses, not the likelihoods themselves. The greatest advantage of our method is its understandability to human users and thereby the potential for visual analytics. However, experimental evaluation did not show reproducible significant effects on the predictive performance of conventional multivariate regression models. Given that there are already many very accurate multivariate models for fuzzy classification, the practical implication is that IFC-Filter can unfold its unique potential mainly for explaining data, specifically, associations between analytical and target variables, to human decision makers. Lessons learned from two case studies with industry partners demonstrate that IFC-Filter can extract interpretable and actionable knowledge from data.

1. Introduction

Concepts that do not have sharp boundaries can be seen as fuzzy classification: the class distinction is uncertain and, thus, fuzzy. Not only are the boundaries of fuzzy classes vague; they are also gradual in the sense that there are degrees of membership. Language abounds with examples of fuzzy concepts. For instance, the concept "near" is a fuzzy classification of space. How can precise meaning be assigned to such gradual classes? *Fuzzy set theory* (Bellman, Kalaba, & Zadeh, 1964, 1965) proposes the concept of *membership functions* to map mathematically precise definitions to fuzzy concepts by assigning gradual *membership degrees* between zero and one to objects in classes. *Approximate reasoning* (Bellman & Zadeh, 1977) thus supports *fuzzy propositions* with gradual truth values. The basis for the precise specification of fuzzy classification is thereby gradation instead of dichotomy.

The manual definition of membership functions can be applied in *expert systems* to capture expert knowledge on gradual concepts. This can be applied in information systems for *fuzzy classification in databases* (Meier, Schindler, & Werro, 2008). When membership

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functions are explicitly defined a priori, the process of classification corresponds to a mapping from data to membership degrees. In addition, the question that motivated the research for this paper was how these membership functions can be induced from data to discover implicit knowledge in databases. As a result, this paper describes a machine learning algorithm for fuzzy classification by *membership function generation* and a prototype implementation with evaluation (Kaufmann, 2014) that can extract membership functions and visualize the corresponding graphs for application in analytics. To generate membership functions, the algorithm automates inductive logic based on likelihoods. For this use of *inductive reasoning* in fuzzy classification, Kaufmann (2014) uses the term *inductive fuzzy classification* (IFC). Because the transformation of input variables is called attribute filtering, the method presented in this paper is termed *IFC-Filter.*

This paper is structured as follows: Section 2 surveys the current literature on fuzzy classification, analyzes similar approaches and, based on that analysis, situates our contribution. Section 3 describes our concept of IFC based on inductive logic. Section 4 presents an implementation of the concept as an extension of the *Weka machine learning workbench* (Hall et al., 2009). Section 5 provides a case-based, idiographic evaluation of our approach. Section 6 discusses the pros and cons of the IFC-Filter and indicates areas for further research.

2. Literature survey and contribution

Fuzzy classification can be defined as computing the degrees of membership of objects in classes. The first account of the term in the literature is by Bellman et al. (1964), who described fuzzy classification as constructing estimates of the characteristic functions $f_A, f_B: \Omega \rightarrow [0, 1]$ of two disjoint fuzzy sets A and B in a space Ω based on knowledge of samples of n points $\alpha^1, \alpha^2, \ldots, \alpha^n$ that are known to belong to A and m points $\beta^1, \beta^2, \ldots, \beta^m$ that are known to belong to B. This definition describes a task of supervised inductive learning of fuzzy classification from existing examples. In general, fuzzy classification can be inductive (generated from data) or deductive (derived from predefined models). Inductive fuzzy classification can be generated in a supervised or in an unsupervised manner. As defined above, supervised fuzzy classification means the learning of models from labeled data. The unsupervised learning of fuzzy classification from data without category labels is called *fuzzy cluster analysis* (Yang, 1993). In contrast, deductive fuzzy classification means classifying by using membership functions predefined by human experts, e.g., (Meier et al., 2008). Such fuzzy expert systems are based on domain knowledge reflected in membership functions and domain ontologies (Lee & Wang, 2011). The approach to fuzzy classification proposed in this paper computes estimates of membership functions from labeled data inductively to automate the definition of expert knowledge.

Fuzzy classification has been applied in a wide range of domains where gradual and multiple class assignments are required. For example, the gradual and overlapping assignment of objects to classes is useful when classifying geographical images as vegetation, soil or water (Wang, 1990) because regions can contain all three to different degrees. In marketing analytics, it can bridge art and science by uniting linguistic variables with their mathematically precise definitions (Meier & Donzé, 2012). In neurobiology, it can help classify neurons: Because living cells do not adhere to artificial human classifications, there are so-called atypical forms (edge cells) of neurons. To cope with this fuzziness, Gutch, Battaglia, Karagiannis, Gallopin, and Cauli (2013) proposed the gradual classification of neurons using fuzzy classification. Other applications include biometric voice identification (Dustor & Kłosowski, 2013), home energy management for smart grids (Lin & Tsai, 2014), predicting protein interactions in biomedical analytics (Sriwastava, Basu, & Maulik, 2015), and power system security assessment (Luo et al., 2015).

In the relevant literature, several classes of models for fuzzy classification can be identified by their distinctive features. In Table 1, an overview of these approaches is presented, together with the properties that separate the model classes. For the distinction of model class characteristics, eight criteria (in columns) have been applied. Thus, we could identify nine classes of models (labeled A to I) for fuzzy classification frequently cited in the literature. Of course, this approach to theorizing presents a rough generalization, in which many less frequently published approaches are not reflected. Additionally, the classes are not disjoint, and several approaches can be combined. However, these categories can serve as a guideline for categorizing different model classes for fuzzy classification so that the area of contribution of this paper can be situated.

A. *Fuzzy cluster analysis* (Yang, 1993) is an approach to the unsupervised learning of fuzzy classification. Fuzzy clustering algorithms aim at modeling patterns from unlabeled data (Baraldi & Blonda, 1999a). An overview of five different approaches can be found in (Baraldi & Blonda, 1999b). Many fuzzy clustering models compute fuzzy partitions of object spaces by optimizing objective functions, such as intra-cluster proximities. In contrast to hard clustering, objects can be assigned many clusters gradually. The most prominent fuzzy clustering method is *fuzzy c-means,* (FCM) (Bezdek, 1981), of which new and improved versions exist, e.g., (Jiang et al., 2015; Zhu, Chung, & Wang, 2009).
B. *Fuzzy rule-based systems* (FRBS) map an input space to fuzzy classes by transforming the input to the domain of linguistic variables with fuzzy truth values and applying approximate reasoning based on a set of rules. For example, *Takagi–Sugeno type fuzzy systems* (Takagi & Sugeno, 1985) map objects to membership degrees by applying a set of standardized rules containing conjunctions of fuzzy restrictions as antecedents and fuzzy class memberships as consequents of fuzzy implications. FRBS can classify the input space deductively, if the fuzzification functions and rule bases are predefined by human experts. Furthermore, FRBS can be learned from data inductively (Hühn & Hüllermeier, 2009; Roubos, Setnes, & Abonyi, 2003; Wang & Mendel, 1992). Often, model generation is accomplished by parameter fitting using biomimetic methods, e.g., (Berlanga, Rivera, del Jesus, & Herrera, 2010; Del Jesus, Hoffmann, Navascues, & Sanchez, 2004; García-Galán, Prado, & Muñoz Expósito, 2015; Setnes & Roubos, 2000; Trawinski, Cordon, & Quirin, 2014).
C. *Neuro-fuzzy systems* combine artificial neural networks (ANN) with approximate reasoning and fuzzy logic (Mitra & Hayashi, 2000). The aim is to combine the advantages of ANN, namely massive parallelism, data-driven learning and optimal generalization, with the descriptiveness and interpretability of fuzzy logic systems. Examples include the use of neural networks as fuzzy classifiers (Mitra & Pal, 1994), fuzzy inference networks that retain more of the logical structure of fuzzy systems (Pedrycz & Smith, 1997), generic self-organizing fuzzy neural networks (Tung & Quek, 2002), rough neuro-fuzzy structures (Nowicki, 2009) and fuzzy min–max neural networks (Davtalab, Dezfoulian, & Mansoorizadeh, 2014; Simpson, 1992)