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Symbolic Approximate Reasoning with Fuzzy and Multi-valued Knowledge

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Abstract

Knowledge-based systems have nearly become omnipresent in various sectors to facilitate decision-making. Their aim is to get close to human induction. For that, dealing imprecise knowledge is essential since human thinks imprecisely. The principal logics that allow manipulating this kind of knowledge in intelligent systems are fuzzy logic and multi-valued logic. Up to now, according to our knowledge, knowledge-based systems manage separately either fuzzy knowledge or multi-valued knowledge. However, modeling heterogeneous knowledge (fuzzy and multi-valued) in the same inference engine should ensure more flexibility and freedom to the user. In that context, our aim is to allow the use of fuzzy and multi-valued knowledge at once. We propose a new approach to convert fuzzy knowledge into symbolic knowledge by projecting fuzzy inputs over the x-axis that corresponds to the universe of discourse of fuzzy variable. In order to demonstrate its applicability, our proposal is tested within a rule-based system. A numerical example is then provided.

Keywords: Approximate reasoning ; Fuzzy logic ; Multi-valued logic ; Knowledge conversion ; Inference ; Rule-based systems ; Imprecision

1. Introduction

In conventional information processing method, it is expected that the information is well defined and always available. However, in real-world knowledge-based systems, knowledge is often associated with different types of imperfection such as imprecision or uncertainty. Uncertainty means that the event occurrence is subject of question. Whereas, imprecision describes the event vagueness to measure the degree in which an event occurs. Imperfection can ensue because the information is not defined enough, or only by partial and imprecise evidence or due to the inaccuracy of instruments used to evaluate the observation[1]. Among the widely used modeling frameworks to represent and manage imperfect knowledge, we cite fuzzy logic[2] and multi-valued logic[3]. The former is based on fuzzy set theory, which allows intermediate degrees between the full membership and the non-membership and it is based on a numerical domain. Whereas, the latter is founded on multi-set theory and it allows a symbolic representation of terms. Despite of its performance, fuzzy logic was criticized by different authors[4,5,6].

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According to them, defining a numerical membership function for abstract data (such as evaluation of the exam difficulty, level of intelligence, etc.) is often artificial and difficult to apply since they does not refer naturally to numerical scales. In that case, multi-valued logic allows the expert to use adverbial terms (little, more-or-less, very, etc.) which are evidently part of our natural language. Even when handled knowledge are quantitative, person often uses linguistic adverbs to evaluate knowledge imprecision, even uncertainty, rather than numbers. For example, when evaluating the age of a person, we generally say that he is very young instead of saying that he has 2 years, 3 month old. This is since the human reasoning lacks in nature of precision. However, fuzzy logic requires a numerical modeling and treatment of knowledge. Furthermore, fuzzy logic is characterized by an inherent computational complexity. This is due to the need of computing fuzzy sets of multi-dimensional Cartesian products especially for nontrivial applications. Furthermore, while applying for example the compositional rule of inference defined by Zadeh[7], the complexity of matrix computation is very high. Indeed, for finite universes X and Y with $|U| = m$ and $|V| = n$, the inference requires O(mn) operations. For that, the use of multi-valued logic is advantageous, especially when manipulated knowledge are qualitative. This will enforce an inference process closer to human reasoning, and it will produce a more comprehensible output for the user.

The expert is often in need of different types of imperfection (uncertainty as well as imprecision) to model its knowledge. To manage uncertainty, different approaches were proposed, for example when fuzziness and ignorance are prevalent or when both stochastic and fuzzy uncertainties coexist[8]. Nonetheless, it is unavoidable to deal with imprecision in knowledge-based systems. That is why many numeric and symbolic techniques were proposed. Several types of imprecise knowledge may coexist in real systems. However, as far as we know, no work has treated different types of imprecision within the same knowledge-based system. Up to now, the commonly knowledge-based systems manage separately either fuzzy knowledge[9,10,11,12] or multi-valued knowledge[13,14,15]. However, modeling heterogeneous knowledge (fuzzy and multi-valued) in the same inference engine should ensure more flexibility to the user since he is no longer limited to just a qualitative or quantitative information to evaluate imprecise knowledge. The challenge is to deal with both multi-sets and fuzzy sets at once such in the following rule: "*If the driver is tired then the reflex speed is weak"* where *driver* and *reflex speed* are linguistic variables, *tired* is a multi-set, and *weak* is a fuzzy set. The multi-set *tired* can have a truth-degree among the set {not-at-all, little, moderately, very, entirely}. The fuzzy set *weak* can have a trapezoidal membership function in the interval [1ms, 3000ms]. The problem that arises is, having an observation, how such knowledge can be managed in the same inference process and how can we deduce a new fact. In this context, we propose a new modeling approach of fuzzy knowledge to be expressed in a multi-valued one. The idea is to convert fuzzy inputs into multi-valued knowledge using a *fuzzy-to-symbolic conversion* method. In other words, we try to translate a given fuzzy set into a generated multi-set. This choice is supported by the criticism of fuzzy logic cited above. The knowledge-based system will then deal only with multi-valued information. Consequently, the original symbolic modeling of qualitative knowledge is preserved. On the other hand, the conversion of quantitative knowledge is made by the projection of corresponding fuzzy sets over the X-axis of its membership function while minimizing as well as possible the information loss that could lead. As an example of application, we tried to integrate our approach in a rule-based system where data from different types and different nature are processed. Rule based-systems, which present a branch of knowledge-based systems, have been recently presented in several areas[16] such as agriculture, risk management, etc. Then, it seems important to enhance the manner in which inputs are integrated into. We are interested to apply our approach on symbolic inference systems based on symbolic approximate reasoning. We adopt precisely those based on linguistic modifiers[17]. We note that our approach can easily be integrated in any knowledge-based system in multi-valued context, and not only in a rule-based system. It will be the first stage of the multi-valued system. This is to insure the translation of any fuzzy knowledge to multi-valued knowledge before the execution of the others phases of the multi-valued system.

The remainder of this paper is organized as follows: the second section outlines how imprecise knowledge are modeled and processed. We focus on fuzzy and symbolic knowledge. The third section describes our proposed methodology consisting on standardizing input knowledge by converting them from fuzzy to multi-valued. In the fourth section, a numeric application of reasoning based on heterogeneous knowledge validates our approach. The fifth section concludes the paper and outlines future works.