What Does Fuzzy Logic Bring to AI?

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The term "fuzzy logic" often refers to a particular control-engineering methodology that exploits a numerical representation of commensense control rules in order to synthetize, via interpolation, a control law. This approach has many features in common with neural networks. It is currently concerned mainly with the efficient encoding and approximation of numerical functions and has less and less relationship to knowledge representation issues. This is, however, a very narrow view of fuzzy logic that has little to do with AI. Scanning the fuzzy set literature, one realizes that fuzzy logic may also refer to two other topics: multiple-valued logics and approximate reasoning. Although the multiple-valued logic stream is very mathematically oriented, the notion of approximate reasoning as imagined by Zadeh is much more closely related to the program of AI research: he wrote in 1979 that "the theory of approximate reasoning is concerned with the deduction of possibly imprecise conclusions from a set of imprecise premises." In the following, we use the term "fuzzy logic" to mean any kind of fuzzy set-based method intended to be used in reasoning systems.

Fuzzy logic is 30 years old and has a long-term misunderstanding with AI. As a consequence, fuzzy logic methods have not been considered to belong to mainstream AI tools until now, although an important part of fuzzy logic research concentrates on issues in approximate reasoning and reasoning under uncertainty. Some reasons for this situation may be found in the antagonism which existed for a long time between purely symbolic methods advocated by AI and the numerically oriented approaches that were involved in fuzzy rule-based systems. Besides, fuzzy sets were a new emerging approach not yet firmly settled, but apparently challenging the monopoly of probability theory on being the unique proper framework for handling uncertainty. In spite of the fact that fuzzy sets have received more recognition recently, there is still a lack of appreciation by AI researchers of what fuzzy logic really is, as, for instance, recently exemplified by Elkan [1994].

Encoding Similarity and Interpolation

In the mid-70's, when MYCIN was becoming a landmark among rule-based expert systems dealing with uncertainty, the first fuzzy rule-based system was designed by Mamdani's group at Queen Mary College in London following an idea suggested by Zadeh shortly before. This system is the direct ancestor of most of the fuzzy control systems that became so widely used in the early 1990's. What is at work in rule-based fuzzy control is a simple device for interpolating between numerically valued conclusions of parallel rules. This interpolation is made on the basis of degrees of matching of the current situation with respect to the fuzzy-condition parts of the rules. These degrees estimate the similarity between the current situation and prototypical values that constitute the core of the fuzzy sets describing the firing conditions of the rules. Such coefficients, obtained through a matching procedure, were quite different from the certainty factors attached to facts and rules in the MYCIN-like expert system. However, AI expert systems and fuzzy rule-based controllers did share the idea that the rules were encoding expert knowledge. This view has more or less disappeared in the recent neuro-fuzzy-based methods, where fuzzy rules are just a convenient format for synthesizing control laws from sets of input/output pairs and thus for approximating functions and tuning them locally. Then the knowledge representation and approximate reasoning aspects are no longer the main features of the approach in its present development. However, the basic notions of similarity and interpolation might be useful in other, more AI-oriented, applications such as case-based reasoning and for retrieving cases and extrapolating from them by means of gradual rules of the type "the more x is A, the more y is B." Similarity reasoning should encode commonsense inferences of the form: if "p is close to p'" and "p implies q" then "q is not far from being true." Fuzzy set theory is a natural framework for modeling such inference patterns.

Modeling Uncertainty and Preference

Apart from similarity, two other basic semantics can be addressed by fuzzy set-based methods, namely uncertainty and preference: uncertainty pervading available information in reasoning problems, preference among more or less acceptable values in a decision-oriented perspective. Possibility theory offers a framework for dealing with uncertainty when the available information is no longer precise and certain, but is represented by means of fuzzy sets. With fuzzy sets, uncertainty is estimated by means of two dual measures of possibility and necessity. This framework has merits for the representation of states of partial of total ignorance. Another interesting feature of possibility theory is that it requires only purely ordinal scales for the assessing of uncertainty. It provides a very qualitative approach and facilitates the elicitation of the uncertainty levels. Based on possibility theory, a possibilistic logic (which should not be confused with the fully compositional calculus of fuzzy set membership degrees) has been developed both at the syntactic and semantic level. In this logic, classical logic formulas are associated with lower bounds of necessity measures expressing the level of certainty, or equivalently of epistemic entrenchment of the formulas. It has been established that rational nonmonotonic inference relations (in the sense of Lehmann) can be represented in possibilistic logic, where a default rule "if p then q generally" is understood as the constraint that the possibility measure of "p and q" is strictly greater than the possibility of "p and not q." Connections with other approaches to nonmonotonic reasoning, including one based on infinitesimal probabilities, have been laid bare. Possibilistic logic is a genuine extension of classical logic that encodes an uncertainty calculus. Possibilistic assumption-based truth maintenance systems provide simple implementations of nonmonotonic reasoning. Possibilistic logic can be used as well for reasoning from multiple sources of information having different reliability levels. The corresponding data fusion tools have been developed.

When fuzzy sets model preference among values according to flexible constraints, rather than imprecise and uncertain information, possibility theory offers a natural framework for extending the constraint satisfaction problem paradigm to soft and prioritized constraints. Scheduling provides a good example of application of these techniques where, for instance, due dates are often somewhat elastic. Moreover, some parameters such as the duration of operations (which are not under our control) may be pervaded with uncertainty. In this situation a trade-off has to be made between a high level of satisfaction of constraints and the need to cope with unlikely but potentially dangerous states of the world. Possibility theory can be used as the basis for a qualitative utility theory that tackles such a decision problem (including computation with ill-known numerical quantities).

Interfacing Symbolic Labels with Numerical Data

Finally, an important feature of fuzzy sets is to provide a framework for interfacing in a nonrigid way with classes with numerical values. In classification problems the use of fuzzy classes obviates the need for arbitrarily classifying borderline cases at the beginning of a reasoning stage. Numerical data can be summarized by means of linguistically labelled fuzzy sets so as to feed symbolic reasoning machinery. These issues come close to learning, another subfield of AI in which this aspect of fuzzy sets might be particularly interesting, even if only a rather small amount of work is currently being done in this direction.

In conclusion, it must be stressed that it is the formalization of some forms of commonsense reasoning that has motivated the development of fuzzy logic; as such, fuzzy logic has some relevance to AI. What fuzzy sets typically bring to AI is a mathematical framework for capturing gradedness in reasoning devices. Such a theory of gradedness is not necessarily numerical, contrary to what many people tend to believe, but can be purely ordinal (lattice-based). Moreover, gradedness can take various forms: similarity between propositions, levels of uncertainty, and degrees of preference. In our opinion, fuzzy logic will have a chance for full acceptance as part of AI research when people start believing in its capability to handle these various types of gradedness in a mathematically sound and computationally tractable way.

FOR FURTHER READING

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