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ScienceDirect

Fuzzy Sets and Systems 274 (2015) 18–23

FUZZY sets and systems

www.elsevier.com/locate/fss

In memory of Professor Hideo Tanaka: A tennis match that never happened

Abstract

I recall sweet memories of Professor Hideo Tanaka during my academic research career on fuzzy theory, as well as elaborate on how his applied works have inspired me on my subsequent theoretical research concerning fuzzy modeling and decision-making.
2014 Published by Elsevier B.V.

Fig. 1. A retirement party for M. Sugeno and H. Tanaka.

At the very first International Fuzzy Systems Association (IFSA) Conference in Palma de Mallorca (1985), I first met Professor Hideo Tanaka while attending his organized session on Fuzzy Linear Regression and Programming in Industrial Engineering. I was very impressed by his view of coarse data which can be modeled by fuzzy sets in many practical engineering problems. Inspired by his view, I later considered coarsening schemes as one aspect of human intelligence where, when facing difficult decisions under uncertainty, humans always coarsen their precise ranges of actions in order to arrive at needed decisions. Applying these views to expert systems, we realize that coarsening schemes, which allow experts to express their reliable knowledge in the process of expert knowledge elicitation, play a central role in designing ways to obtain experts' knowledge, including experts' prior information in generalized Bayesian inference. Moreover, fuzzy data, as used in fuzzy regression, bring out the essential feature that what matters in using natural language information, as models by fuzzy sets, is the shapes of membership functions. It is well-known that if we do theoretical research, we should read empirics (and vice versa!). My exposure to Professor Tanaka's

http://dx.doi.org/10.1016/j.fss.2014.04.018
0165-0114/2014 Published by Elsevier B.V.

empirical research in fuzzy regression, exemplified by his joint work with K. Asai and S. Uejma [19] has influenced my view on developing methods for incorporating (combining) various types on uncertain data, as exemplified by my later work on random fuzzy sets (Nguyen et al. [14]), as one way to take into account of both randomness and fuzziness.

Before starting my sweet story about Professor Hideo Tanaka, let me pause here to elaborate a little bit on my views on fuzzy modeling and decision-making, inspired from his applied works.

Fuzziness in natural language concepts such as “high income” is a type of uncertainty which is often confused with randomness, especially from a Bayesian viewpoint, since, essentially, membership functions are assigned to fuzzy concepts somewhat subjectively, just like subjective probability distributions assigned to unknown (but not random) parameters in statistical models, in Bayesian statistics.

This situation is illustrated by the objection of Dennis Lindley when he talked in Zadeh’s Seminar at UC Berkeley, in 1982, later published as “Scoring rules and the inevitability of probability” (Lindley [11]). Perhaps, this is one of the reasons why probabilists and statisticians are not impressed with fuzzy data, although Lindley’s paper has been later rigorously analyzed by Goodman, Nguyen and Rogers [10].

Another possible reason that the scientific community, especially intelligent system folks, is skeptical with the use of fuzzy sets in system analysis is the paper by Charles Elkans [5] “The paradoxical success of fuzzy logic”, although this “misleading” paper has been answered by Nguyen, Kreinovich and Koshelva [13], as well by Gehrke, C. and E. Walker [6].

Clearly, while fuzzy concepts in natural language are well understood, it is their mathematical (quantitative) modeling (for applications) which created debates among practitioners. Specifically, it seems that some main issues are: Where do we actually “run into fuzzy sets” (data) in real applications? Does fuzzy set theory improve anything? How to obtain membership functions for fuzzy data? Is there a statistical inference theory for treating fuzzy data?

Inspired by practical works of Professor H. Tanaka, I was led to conduct some theoretical research to address the above questions, centering on fuzzy modeling and decision-making with fuzzy data.

Where do we run into fuzzy sets?

In general, besides numbers, we use natural language to impart our knowledge. As such, naturally, we run into fuzzy concepts in it. It is often said that many phenomena in economics, for example, are fuzzy in nature, but they have been, or still treated as if they were crisp. At an artificial level, fuzzy concepts (and their quantitative modeling) appear in successful applications such as in fuzzy c-means algorithm for cluster analysis (Bezdek [3]), and in fuzzy control (Takagi and Sugeno [18]). The essence of fuzzy control rules is the coarsening of measurements on a domain into a fuzzy partition. Coarsening is a natural intelligent behavior of humans. When we cannot make precise measurements, or answer questions with certainty, we coarsen our domains into partitions (fuzzy or not) to make decisions which are imprecise but often correct. In particular, a coarsening scheme on a domain Θ aims at facilitating answers for experts in the knowledge extraction process. As such, each $A \subseteq 2^{\Theta}$ contain localization information about the true (but unknown) parameter of interest, and hence smaller sets contain more information than larger ones, i.e., the “information order relation” is A is more informative than B (written as $A \succeq B$) if $A \subseteq B$ (recall $I(A) = -\log P(A)$: $A \subseteq B \Longrightarrow I(A) \geq I(B)$). It is precisely this “information order” (extended to fuzzy subsets) which forms the basis for treating fuzzy data in statistical inference, in a rigorous fashion. Coarsening schemes are also used to generalizing Bayesian statistics. Note that, the mathematical theory of evidence (Shafer [17]) is based on a (crisp) coarsening of the domain of interest.

Another striking example where there is a need to consider fuzzy sets is this. In the context of coalitional games, there are effectively situations where we need to consider partial coalitions, based upon, say, the percentages of workforce committed to coalitions of “players”. This is known as fuzzy games (Aubin [1]), see also Aumann and Shapley [2].

How to obtain membership functions?

Having spelled out various situations where fuzzy concepts (e.g., “high income”) appear naturally and should be taken into account for decision-making, the next practical question is how to model them, i.e., how to assign membership functions to them? Recall that, unlike distributions of random variables, membership functions of fuzzy