COMMONSENSE REASONING BASED ON FUZZY LOGIC

L.A. Zadeh Computer Science Division University of California Berkeley, California 94720

ABSTRACT

Although most human reasoning is approximate rather than precise in nature, traditional logical systems focus almost exclusively on those modes of reasoning which lend themselves to precise formalization. In recent years, however, in our attempt to design systems which are capable of performing tasks requiring a high level of cognitive skill, it has become increasingly clear that in order to attain this goal we need logical systems which can deal with knowledge that is imprecise, incomplete or not totally reliable.

Prominent among the systems which have been suggested for this purpose are those based on default reasoning (Reiter, 1983), circumscription (McCarthy, 1980), nonmonotonic reasoning (McDermott and Doyle, 1980, 1982), and probabilistic logic (Nilsson, 1984). These and related systems are basically extensions of first-order predicate calculus and probability theory, and are rooted in bivalent logic.

In a departure from reliance on bivalent logical systems, we have developed an approach to commonsense reasoning based on fuzzy logic (Zadeh, 1983, 1984). In this approach, a central role is played by the concept of dispositionality and the closely related concept of usuality. Furthermore, an extensive use is made of syllogistic reasoning (Zadeh, 1985), in which the premises are propositions containing fuzzy quantifiers such as most, many, usually, etc.

The point of departure in the fuzzy-logic-based approach to commonsense reasoning is the assumption that commonsense knowledge consists for the most part of dispositions, that is, propositions which are preponderantly, but not necessarily always, true. For example:

Birds can fly.
Slimness is attractive.
Glue is sticky if it is not dry.

Typically, a disposition contains one or more implicit fuzzy quantifiers. For example, birds can fly may be interpreted as most birds can fly or, equivalently, as usually (if X is a bird then X can fly). A proposition of the general form

usually (p) or usually (if p then q), where p and q are propositions, is said to be usuality-qualified. In this sense, commonsense knowledge may be viewed as a collection of usualityqualified propositions in which the fuzzy quantifier usually is typically implicit rather than explicit.

Our approach to inference from commonsense knowledge may be viewed as an application of fuzzy logic, under the assumption that a disposition may be expressed in the canonical form QA's are B's, where Q is a fuzzy quantifier, e.g., most, almost all, usually, etc., and A and B are fuzzy predicates such as small, tall, slim, young, etc. Fuzzy logic provides a basis for inference from dispositions of this type through the use of fuzzy syllogistic reasoning (Zadeh, 1985). As the name implies, fuzzy syllogistic reasoning is an extension of classical syllogistic reasoning to fuzzy predicates and fuzzy quantifiers. In its generic form, a fuzzy syllogism may be expressed as the inference schema

in which A, B, C, D, E and F are interrelated fuzzy predicates and Q_1 , Q_2 and Q_3 are fuzzy quantifiers.

The interrelations between A,B,C,D,E and F provide a basis for a classification of fuzzy syllogisms. The more important of these syllogisms are the following $(\land \triangleq conjunction, \lor \triangleq disjunction)$:

(a) Intersection/product syllogism:

$$C=A \land B, E=A, F=C \land D$$

(b) Chaining syllogism:

$$C=B$$
, $E=A$, $F=D$

(c) Consequent conjunction syllogism:

$$A=C=E, F=B \land D$$

(d) Consequent disjunction syllogism:

$$A = C = E, F = B \lor D$$

(e) Antecedent conjunction syllogism:

$$B=D=F$$
, $E=A \land C$

(f) Antecedent disjunction syllogism:

$$B=D=F$$
, $E=A \lor C$

In the context of expert systems, these and related syllogisms provide a set of inference rules for combining evidence through conjunction, disjunction and chaining (Zadeh, 1983).

One of the basic problems in fuzzy syllogistic reasoning is the following: Given A, B, C, D, E and F, find the maximally specific (i.e., most restrictive) fuzzy quantifier Q_s such that the proposition Q_s E's are F's is entailed by the premises. In the case of (a), (b) and (c), this leads to the following syllogisms:

Intersection/Product Syllogism.

$$Q_1 A's \text{ are } B's$$

$$Q_2 (A \text{ and } B)'s \text{ are } C's$$

$$(Q_1 \otimes Q_2)A's \text{ are } (B \text{ and } C)'s$$

where \otimes denotes the product in fuzzy arithmetic (Kaufmann and Gupta, 1985). It should be noted that (4.1) may be viewed as an analog of the basic probabilistic identity

$$p(B,C/A) = p(B/A)p(C/A,B)$$

A concrete example of the intersection/product syllogism is the following:

most² students are young and single

where $most^2$ denotes the product of the fuzzy quantifier most with itself.

Chaining Syllogism.

$$Q_1A$$
's are B 's
$$Q_2B$$
's are C 's
$$(Q_1 \otimes Q_2)A$$
's are C 's

This syllogism may be viewed as a special case of the intersection product syllogism. It results when $B \subset A$ and Q_1 and Q_2 are monotone increasing, that is, $\geq Q_1 = Q_1$, and $\geq Q_2 = Q_2$, where $\geq Q_1$ should be read as at least Q_1 , and likewise for Q_2 . A simple example of the chaining syllogism is the following:

most students are undergraduates

most undergraduates are single

most2 students are single

Note that undergraduates \subset students and that in the conclusion F = single, rather than young and single, as in (2).

Consequent Conjunction Syllogism.

The consequent conjunction syllogism is a example of a basic syllogism which is not a derivative of the intersection/product syllogism. Its statement may be expressed as follows:

where Q is a fuzzy quantifier which is defined by the inequalities

$$0 \otimes (Q_1 \oplus Q_2 \ominus 1) \le Q \le Q_1 \otimes Q_2 \tag{4}$$

In which \mathbb{O} , \mathbb{O} , \mathbb{O} , and Θ are the operations of \vee (max), \wedge (min), + and - in fuzzy arithmetic.

An illustration of (3) is provided by the example

most students are young

most students are single

Q students are single and young

where

$$2most \ominus 1 \leq Q \leq most.$$

This expression for Q follows from (4) by noting that

most ⊗ most = most

and

$$0 \, \textcircled{0} \, (2most \, \ominus 1) = 2most \, \ominus 1$$

The three basic syllogisms stated above are merely examples of a collection of fuzzy syllogisms which may be developed and employed for purposes of inference from commonsense knowledge. In addition to its application to commonsense reasoning, fuzzy syllogistic reasoning may serve to provide a basis of rules for combining uncertain evidence in expert systems (Zadeh, 1983).

ACKNOWLEDGMENTS

Research supported in part by NASA Grant NCC-2-275 and NSF Grant IST-8320416.

REFERENCES

- Kaufmann, A. and Gupta, M.M. (1985). Introduction to Fuzzy Arithmetic. Van Nostrand, New York.
- McCarthy, J. (1980). Circumscription: non-monotonic inference rule. Artificial Intelligence 13, 27-40.
- McDermott, D.V. (1980). Non-monotonic logic, I. Artificial Intelligence 13, 41-72.
- McDermott, D.V. (1982). Non-monotonic logic, II: non-monotonic modal theories. *Journal of the Association for Computer Machinery* 29, 33-57.
- Moore, R.C. and Hobbs, J.C. (eds.) (1984). Formal Theories of the Commonsense World. Ablex Publishing, Harwood, N.J.
- Nilsson, N. (1984). Probabilistic logic. SRI Technical Note 321, Menlo Park, CA.
- Reiter, R. and Criscuolo, G. (1983). Some representational issues in default reasoning. Computers and Mathematics 9, 15-28.
- Zadeh, L.A. (1983). The role of fuzzy logic in the management of uncertainty in expert systems. Fuzzy Sets and Systems 11, 199-227.
- Zadeh, L.A. (1984). A Theory of Commonsense Knowledge (H.J.S. Skala Termini and E. Trillas, eds.). Reidel, Dordrecht.
- Zadeh, L.A. (1985). Dispositions. IEEE Transactions on Systems, Man and Cybernetics SMC-15, 754-763.
- Zemankova-Leech, M. and Kandel, A. (1984). Fuzzy Relational Data Bases A Key to Expert Systems. Verlag TUV Rheinland, Cologne.

AUTHOR'S BIOGRAPHY

LOTFI A. ZADEH is a member of the Computer Science Division, Department of EECS, University of California, Berkeley. He received the M.S. degree from M.I.T. in 1946 and the Ph.D. degree from Columbia University in 1949. From 1946 to 1959 he was a member of the Electrical Engineering faculty at Columbia, and in 1956 was a visiting member of the Institute for Advanced Study in Princeton. In 1959, Dr. Zadeh moved to Berkeley and served as Chairman of the Department of Electrical Engineering from 1963 to 1968. He was a Visiting Professor of Electrical Engineering at M.I.T. in 1963 and 1968, and held NSF Senior Postdoctoral Fellowships in 1956 and 1962, as well as a Guggenheim Fellowship in 1967. In 1968, 1973 and 1977 he was a visiting member of the IBM Research Laboratory, San Jose, and in 1981 was a visiting scholar at the Artificial Intelligence Center, SRI International, in Menlo Park. Dr. Zadeh is a member of the editorial boards of a number of journals and is serving as a member of advisory committees associated with academic institutions and governmental agencies. He is a member of the National Academy of Engineering, a Fellow of the IEEE and AAAS, a Fellow of the World Council on Cybernetics, and a member of ACM, AMS, Society for Engineering Science, American Association for Artificial Intelligence, Association for Computational Linguistics, the North American Fuzzy Information Processing Society and the International Fuzzy Systems Association. In 1973 he was awarded the Education Model by the IEEE and was a recipient of the Centennial Medal in 1984. In 1986 he was awarded a doctorate honoris causa by Paul-Sabatier University in France in recognition of his development of the theory of fuzzy sets and its applications.

Lotfl A. Zadeh
Computer Science Division
Department of Electrical Engineering and Computer Science
University of California
Berkeley, CA 94720, U.S.A.
(415) 642-4959