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Fuzzy sets based knowledge systems and knowledge elicitation

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Abstract. Fuzzy sets are adequate forms of knowledge representation when the information is uncertain due to vagueness and imprecision. Knowledge structures using fuzzy sets are similar to those implemented in non-fuzzy systems. Classical knowledge elicitation methods can be used in combination with techniques to develop membership functions. The fuzzy set representation has several advantages, including flexibility in expressing uncertain knowledge during elicitation, representation of the knowledge and its uncertainty as a unique entity, easy interfacing with classical systems, and a more robust system in ill-defined domains. These advantages result in increased system reliability.

1. Introduction: randomness and fuzziness

Fuzzy sets (Zadeh 1965), a mathematical tool to model uncertainty, has been proposed as a knowledge representation technique for expert systems (Zadeh 1983). In order to understand the need for this representation, one must first understand the sources of uncertainty.

If a deterministic environment is assumed, uncertainty results from the limitations in human information processing due to difficulties in perception, storage, decision making, and response. For example, if all factors related to the tossing of a coin were known, the outcome could be determined. However, in most cases all the information is not available. Even if it was, modeling the whole process would be cumbersome, and in the case of chaotic events it would take at least as long as the event itself (Jensen 1987). Consequently, individuals tend to maximize performance as the optimal combination of precision and effort. This is the best alternative in a complex environment limited in time and resources.

When uncertainty results from unmeasured variables of frequent phenomena, it is called randomness, for example, tossing a coin. It can be quantified either by repeating the event numerous times, or by soliciting subjective probabilities; the latter approach assumes individuals can perform as measurement instruments. On the other hand, if uncertainty is due to vagueness and imprecision in perception, it is referred as fuzziness, for example, the definition of gray in a scale of darkness. Its measurement is discussed in a subsequent paper.

From this point of view, fuzzy sets and probabilities are two different languages to express uncertainty, each of them with their own axiomatic framework, advantages, and disadvantages. Guidelines for selecting among these methods are limited and even contradictory. There are three main reasons for this: first, the choice depends strongly on the analyst, his perception of the problem, and his previous experience; second, it is domain-dependent; and lastly, there are combinations between probability theory and fuzzy sets ('fuzzy probabilities' and the 'probability of fuzzy events') making the transition less pronounced. The graphical taxonomy in figure 1 is a beginning. One should expect that increased use of these tools will provide additional information. In the meantime, the following conditions tend to indicate the use of fuzzy sets: vagueness and imprecision, linguistic variables, qualitative information, lack of sufficient physical measurements, the need for a 'real' model instead of a 'normative' one, values of variables restricted to ill-defined ranges, and complex casual hierarchies. At first glance, these conditions characterize many domains for which knowledge-based systems are considered to be appropriate.

The remainder of this paper examines knowledge-based systems that use fuzzy sets to represent uncertain knowledge. The structure and internal operation of these systems are presented. Then knowledge acquisition methods and difficulties are discussed.

2. Fuzzy sets in knowledge-based systems

Knowledge-based systems (KBS) are abstractions, models of reality, consequently the theory of similarity applies. Hence, not all aspects of reality can ever be captured in the system, and dimensions left aside create uncertainty in the model. This concept is depicted in figure 2 where a two-dimensional entity is modeled by only one dimension. If no uncertainty is captured in the model, either range (a,b) or (c,d) must be chosen. In both cases the system would be

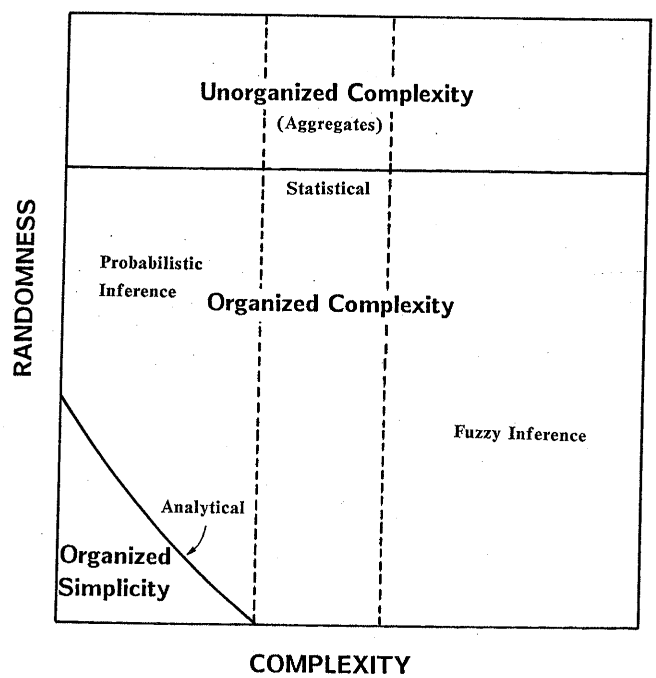

Figure 1. A taxonomy for uncertainty (from Blockley *et al.* 1983).

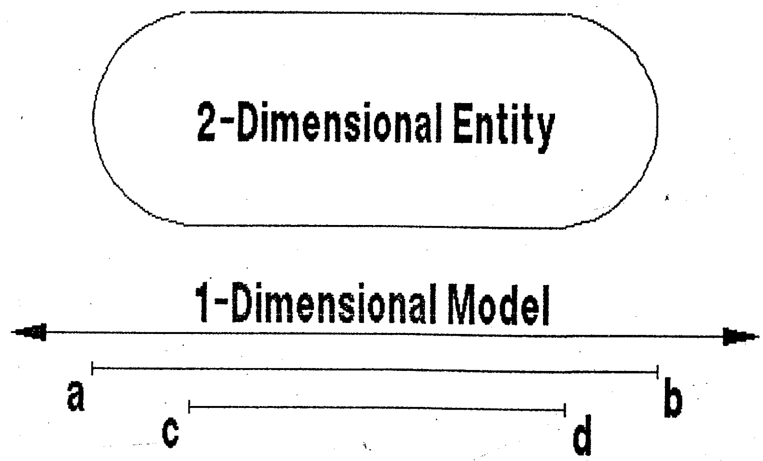

Figure 2. KBS, abstractions and uncertainty.

brittle on the extremes. Paradoxically, it seems that only by taking uncertainty into consideration can the reliability of knowledge systems be increased.

Fuzzy sets can be used to represent uncertain knowledge: not only a numerical model is provided, but also an axiomatic framework to manipulate these representations (albeit a flexible one). This section summarizes the knowledge structures that have been used with the fuzzy set form of knowledge representation, and describes the operations involved when interfacing with the user or other software, i.e., coding and decoding.

2.1. *Knowledge structures and search*

There are several potential alternatives to structure fuzzy knowledge. While all of them can be seen as generalizations of structures used in artificial intelligence, the characteristics of fuzzy sets provide for particular features. Fuzzy knowledge-based systems that have been implemented can be grouped in one of the following structures (Zadeh 1978, Zimmermann 1985, Santamarina and Chameau 1988, Blockley and Baldwin 1987):

1. Fuzzy logic: operates on the bases of generalized inference rules like modus ponens and modus tolens, connectives like conjunctions and disjunctions, and negation.
2. Fuzzy rule-based systems: implementations of fuzzy logic.
3. Fuzzy graphs: based on fuzzy relations in conjunction with graph theory.
4. Fuzzy semantic networks: consist of fuzzy links joining fuzzy statements at the nodes.
5. Fuzzy constraints–stacks: alternatives in the solution set are defined in terms of fuzzy constraints, arranged in multi-dimensional stacks; search proceeds by constraint satisfaction.

The choice of a knowledge structure depends on the characteristics of the domain, on the problem-solving method used by the expert, and on the previous experience and perception of the knowledge engineer.

Operationally, all these structures lead to solution spaces, which in most implementations are exhaustively searched; for example, Negoita (1985) finds the solution to a goal by a 'pull out from the structure of the tree' implemented with a depth-first search approach. However more efficient searches can be conducted, in particular, heuristic-based searches. For example, improved search of hypergraphs can be accomplished as follows: assume, for simplicity, that all fuzzy sets involved in an AND–OR graph are monotonic functions discretized in 'n' intervals so that the cardinality 'c' ranges between 0·0 to n. Then the following rules can be used to reduce the search space:

- AND-node (minimization is assumed): set $c_{min}=n$; (*a*) if the solution of any branch results in $c=0{\cdot}0$, then stop the search of that node and assign 0·0 to all membership values; (*b*) if the partial solution of any branch guarantees a result with $c=c_{min}$ obtained from previous branches in the node, then discontinue the search of the branch; and (*c*) when a branch is solved, compare its cardinality with c_{min} and assign this value to c_{min}.
- OR-node (maximization is assumed): set $c_{max}=0$; (*a*) if the solution of any branch results in $c=n$, then stop the search of that node and assign 1·0 to all membership values; (*b*) if the partial solution of any branch guarantees a result with $c=c_{max}$ obtained from previous branches in the node, then discontinue the search of the branch; and (*c*) when a branch is solved, compare its cardinality with c_{max} and assign this value to c_{max}.

The second check is done recursively, bringing partial results to the level of the given node, and the process is repeated for all branches. A more general implementation of this algorithm could use other measures of similarity. In any case, the important observation to be made is that these improved searches do not require additional information, and are based only on the information contained in the representation of the knowledge.

2.2. *Coding and decoding*

Once a fuzzy set representation of knowledge has been selected, the designer needs to define the internal code-format to be used by the system. Then, the *input-encoding* and the *decoding-output* translation algorithms are defined. There are three basic analytical forms for coding: (*a*) continuous, defined by an equation, (*b*) discrete, defined as a list of membership values, and (*c*) short-form, in which the membership function is characterized by a set of two to four characteristic values, e.g., beginning, peak, and end. The discrete form is particularly attactive for programming in LISP. The short-form can be manipulated with efficient algorithms.

Translation algorithms facilitate the communication with the user as well as with other parts of the knowledge system based on non-fuzzy knowledge. They operate with a 'dictionary', which consists of a list of words and their membership functions (figure 3). Input-to-code translation replaces words with their equivalent fuzzy set, which is then affected by any existing modifier such as: very, not, and maybe. For example:

Mary is very old
Mary is very (0/40, 0·2/50, 0·4/60, 0·8/70, 1·0/80, 1·0/90)
Mary is (0/40, 0·1/50, 0·2/60, 0·4/70, 0·7/80, 1·0/90)

where each entry u/n in the lists represents the membership value u that

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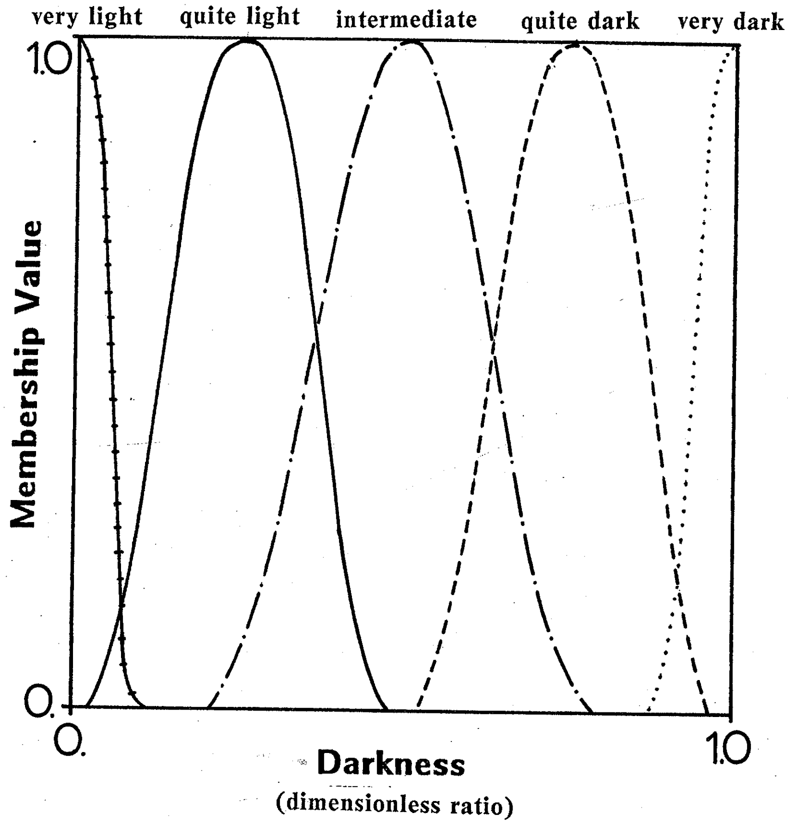

Figure 3. A dictionary for darkness.

corresponds to the support value n; in this case n is the age in years.

Code-to-output translation is more difficult; it is based on pattern matching between the answer (in the form of a fuzzy set) and the membership functions of the words in the dictionary. The result depends on the quality of the algorithm and the extent of the dictionary, and may include modifiers.

3. Knowledge acquisition (KA)

Even though extensive effort has been dedicated to automate KA, most elicitation still involves the interaction between the expert, the knowledge engineer, and the computer system. Knowledge acquisition requires (a) the 'adaptation' to the expert and his domain, and to the rigid computer structure, (b) the 'extraction' of relevant, correct, and complete knowledge from the expert, and (c) the 'implementation' of this information in a computer system. The better the adaptation/interaction, the less information is lost or altered, the easier the elicitation process, and the higher the probability of developing a reliable system.

3.1. *Methods and difficulties in KA*

Two periodic international workshops (Banff, Canada, and European), one journal, several books, and a large number of papers in the literature have been dedicated to KA methods, their advantages and limitations. Furthermore, techniques that were not developed for KA, and that are not included in this body of knowledge, may also prove useful to KA (e.g., several methods listed in the creativity literature). Appendix 1 summarizes KA strategies that can be used in the development of expert systems.

Objections have been found for every KA method. Psychological, philosophical and even physical considerations have been argued. Appendix 2 is an attempt to summarize the underlying foundations for these limitations. Some of the listed difficulties (for example, KA considered as a measurement task: it will always affect the 'measurand') lead to the profound conclusion that *KA is inherently biasing*. The analysis of KA methods and difficulties (Appendices 1 and 2) stimulates the following observations:

A combination of more than one method is needed to minimize limitations due to different memory allocations, variety of knowledge representations (human and computer), and different stages in system development, among others.

None of the existing methods can directly elicit knowledge used in automated tasks. This information can be obtained indirectly by means of the strategies listed under 'Describing the domain' (Appendix 1), and during performance feedback. It is also not possible to detect 'blind' knowledge (Appendix 2).

The elicited knowledge does not reflect the best expertise unless a realistic environment is provided. This limitation applies to all methods including those under 'Problem solving' (Appendix 1).

Difficulties in verbalization affect all methods, except the observational method.

The effects of biases in decision making are difficult to filter. Experts are less affected but not immune to these biases (e.g., 'following common practice' or availability heuristic).

Elicited knowledge is distorted by the type of knowledge representation, problem-solving models and inference procedures available in the system.

Communication – sharing meaning – is restricted by the knowledge engineer's comprehension of domain. Communication-based difficulties are probably accentuated in computerized KA. Searl's Chinese room metaphor can be extended to KA (Searle 1990).

Converting expert's verbalized knowledge into a computer representation is a 'translation' task. Limitations smilar to those found for machine translation in the early 1960s apply to computer-based KA.

The variety of evaluation functions used in human decision making cannot be replaced by a unique operator in all but the simplest domains.

The time consuming nature of exhaustive elicitation and costly expert's time set major constraints and requirements on KA.

3.2. *Current trends*

Two major trends can be distinguished in knowledge acquisition. The first one, computerized KA, is an attempt to develop powerful systems that will adapt to the expert and the characteristics of the domain, without the need for the knowledge engineer. Boose (1989) summarizes available systems. Unfortunately, some results indicate that it may not be possible to develop all-purpose computer systems for KA (see for example, Gaines 1986). Similar development can be traced in other AI endeavours such as GPS, text interpretations, vision, et cetera. The second trend is led by individuals middle-skilled in a domain who bypass the knowledge engineer and develop systems based on their knowledge and that of their peers, i.e., the human side adapting to computer systems. The important marketing effort for AI products, and the accessibility of personal computers support this KA direction.

Other trends can be noticed, e.g., developing new KA strategies, or using computerized knowledge acquisition as intelligent interfaces to ease the use of powerful shells. Finally, it may also be possible to develop architectures and to use knowledge representations that facilitate knowledge acquisition. If fuzzy sets are considered for this task, KA must be coupled with methods to measure membership functions.

3.3 *KA for fuzzy sets based knowledge systems*

Several methods to measure membership functions can be found in the fuzzy set literature: point estimation, interval estimation, exemplification, pairwise comparison, statistical, adaptable molds, and transition between extremes. Usage, advantages, and disadvantages of each method are summarized in Table 1. Chameau and Santamarina (1987) made a comparative study and found that the interval estimation is not only preferred by assessors but it is also the one that produces membership functions of lowest fuzziness. The authors concluded that fuzziness is always reflected in the answer. Similarly, Kochen and Badre (1974) found that consistency prevailed when assessors were allowed to be fuzzy in their answers to imprecise questions. These findings point to the need for knowledge acquisition methods that facilitate the expression of uncertain knowledge.

The limited number of documented cases precludes a detailed set of guidelines for the combination of KA strategies with the methods to measure membership functions. Only few suggestions can be anticipated.

Fuzzy logic and rules are adequate for modeling fuzzy causal relations, and building decision trees and graphs. The Mercalli Intensity Scale for earthquakes can be implemented with a network consisting of a number of fuzzy relations, conjunctions, and disjunctions, conforming to a decision tree. (A typical relation, in linguistic form states: *IF walking was very difficult, THEN the Mercalli Intensity was about 6 or 7*). Fuzziness is also present in users' criteria when interacting with a computer (e.g., Karwowski *et al.* 1989). Appropriate methods for such problems are those that seek for symptomatic events or for goals listed under 'Dissecting the domain' in Appendix 1, in combination with the method based on the 'Transition between extremes' (table 1) for the determination of membership functions.

Decision making based on fuzzy constraints has the highest potential for the implementation of classification systems. Experts can be interviewed by following the methods listed under 'Describing the domain' in Appendix 1, in combination with 'Interval estimation' or 'Membership function exemplification' (table 1). Similar approaches can be used when the selected knowledge structure is a semantic network. An additional method to obtain knowledge could be the propagation of fuzzy constraints from a 'training set' onto a 'generic mold'. The last two approaches are described in the following example.

Table 1. Methods for developing membership functions.

Method	Point estimation–selecting categories	Interval estimation	Membership function exemplification	Pairwise comparison
Procedure	Individuals select the element or label within a list that best answers the question.	Individuals select a reasonable range of possible values that best answers the question.	Individuals provide the object's membership function, in discrete or continuous form.	Assessors estimat the relative degre by which two objects possess tl quality being analysed (Saaty 1974, 1977).
Typical question	What is the age that best represents the set of old people?	Give the IQ range that best represents the set of very smart people.	Give the degree of belongingness of A for each level of the variable.	Which object, A or B, has propert X more strongly, and how much more?
Response mode	Selection of a category, yes-no, others.	Graphical or numerical.	Numerical or graphical.	Numerical
Advantages	Easy to respond.	Simple, flexible, fast; individuals can manifest the fuzziness of their perception in the answer, preferred by assessors, leads to least fuzziness in answer.	Fast determination of the membership function.	Precision
Disadvantages	Poor representation of the assessor's perception, sensitive to the number of labels in the list, statistically based (either using many assessors, or one assessor and repetition of the stimuli).	Either statistical methods are used (several assessors or repetitions) or the shape of the membership function needs to be assumed, or more information is solicited (like in Kuz'min 1981).	Assessors must understand concepts in fuzzy sets, similar difficulties with other direct methods. Assumes assessors can perform as measurement instruments.	Membership ma not exist in a rai scale (Norwich and Turksen 1984), the extremes of the variable need to be included, cumbersome, complexity is proportional to the square of th number of elements.

ip functions.

Membership function exemplification	Pairwise comparison	From statistical data	Adaptable molds	Transition between extremes
Individuals provide the object's membership function, in discrete or continuous form.	Assessors estimate the relative degree by which two objects possess the quality being analysed (Saaty 1974, 1977).	Available statistical data in the form of a histogram is normalized by converting the highest ordinate to one.	Individuals are provided with full windows representing the most important dimensions of the prototype, and are asked to mold it to a special case by adding constraining information.	Assessors indicate the extreme values of the variable, then, unimodal or monotonic membership functions can be obtained for equidistant linguistic values, following specified guidelines.
Give the degree of belongingness of A for each level of the variable.	Which object, A or B, has property X more strongly, and how much more?	n/a	Depends on implementation.	Provide the extreme values of the variable under consideration.
Numerical or graphical.	Numerical	n/a	Depends on implementation.	Numerical, in general (Santamarina and Chameau 1987).
Fast determination of the membership function.	Precision	Use of available information.	The method resembles learning by proceduralization; it can be automatically implemented using a training set of cases.	General validity, simple, minimum data is solicited, uses all the fuzzy logic framework.
Assessors must understand concepts in fuzzy sets, similar difficulties with other direct methods. Assumes assessors can perform as measurement instruments.	Membership may not exist in a ratio scale (Norwich and Turksen 1984), the extremes of the variable need to be included, cumbersome, complexity is proportional to the square of the number of elements.	Conditioned by the possibility-probability consistency principle (Civanlar and Trussel 1986; Dubois and Prade 1980, 1983).	It may need support from one of the other methods.	Individuals must have a perception of the extremes of the variable, difficulties may arise in 'linearizing the scale.

3.3.1. *Example: Pre-qualifying Presidential candidates:* In this task, vague information plays a decisive role. Therefore, knowledge acquisition must allow flexibility of expression. It is assumed that the 'classification system' to be developed will be based on the satisfaction of fuzzy constraints. The following knowledge acquisition strategy is suggested:

1. Interview experts on 'presidents' qualifications' using methods listed under 'Describing the domain' in Appendix 1. For example, ask assessors to list the most relevant dimensions to be considered in the selection of a president. The result in this case will be a list of attributes such as: level of prior political involvement, IQ, seriousness, concern for human aspects, aggressiveness in international affairs, etc.
2. Prepare a questionnaire including these dimensions and a segment representing each of them.

Attribute		*Segment*	
IQ	*50*	---------------- ----------------	*200*
Seriousness	*clown*	---------------- ----------------	*stiff*

3. Ask assessors to represent on the segment the range that best characterizes a good president (Interval estimation – table 1).

IQ	*50*	-------------<<- ---->>----------	*200*
Seriousness	*clown*	---------------- <<-------->>----	*stiff*

4. Develop the membership functions: add the ranges provided by different assessors for the same dimension X, and normalize (Chameau and Santamarina 1987). This is the membership function for the fuzzy constraint that characterizes a good president on the attribute X.
5. Repeat for all dimensions. The set of all membership functions represents a 'good president'.

In order to use this simple system, one would ask: How much 'attribute X' has candidate Y? and compare the response with the corresponding fuzzy constraint in the database (different measures of distance can be used; Dubois and Prade 1980). Repeat the question/comparison for all dimensions for each candidate, and for all candidates. The result will be a relative ranking of the candidates.

An alternative method to develop the knowledge base would be by means of a training set of past presidents. In this case, the knowledge engineer would interview experts on past presidents and ask them to describe a selected set of presidents according to preselected attributes (similar to steps 1 and 2, above). Then, *a generic mold of a president would be adapted* to this training set. The simplest form of 'adaptation' could be modeled with fuzzy union, as depicted in figure 4. Note that the result of this approach may differ from the previous database: in the first case the fuzzy constraints would represent the conditions to be 'a good president', while in the second case it would be the conditions to be 'a president'.

This example of a KBS for pre-qualifying presidential candidates presumes that 'an expert is he who has assimilated the nature of a phenomenon'. Then the

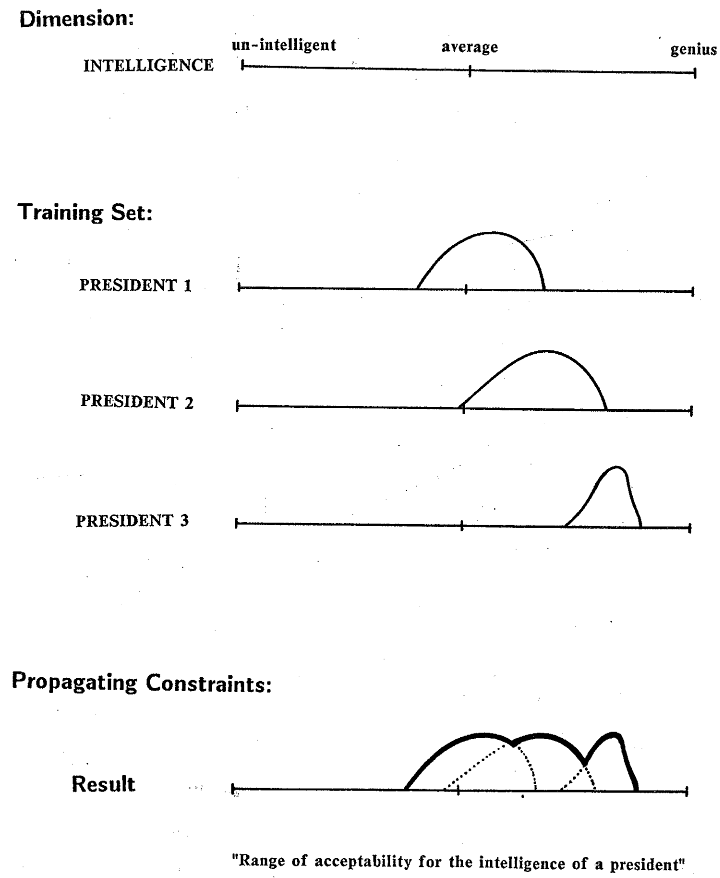

Figure 4. Knowledge acquisition by propagating fuzzy constraints.

goal is to extract the expert's mental model, i.e., the essence of the phenomenon he is expert in, and not his decision process *per se*. However, it is also possible to envision the elicitation and modeling of procedural knowledge by means of fuzzy sets.

4. Advantages of fuzzy sets in KBS and KA

Three analogies were discussed in this paper. KBS as models, KA as measurement, and encoding as translation. The purpose was to emphasize that (*a*) KBS necessarily involve uncertainty, and that uncertainty must be modeled to increase system reliability, and that (*b*) KA is inherently biasing, and a strategy with relaxed structure may facilitate KA and improve the quality of the acquired knowledge.

Fuzzy sets facilitate the elicitation and encoding of uncertain knowledge. Uncertainty is the result of the human trend to improve performance, while optimizing the balance between effort and quality in decision making. Sources of uncertainty in KA include (from Appendix 2): difficulties in retrieving, different levels in the comprehension of attributes and phenomena, different human/computer representation schemes, unrealistic situations and elicitation contexts, difficulties in verbalization, and poor communication between expert and knowledge engineer. There may be other advantages, for example, it is known that intermediate stages in group decision-making are characterized by the fuzzification of initially crisp statements (McDaniel Johnson 1980). Then fuzzy sets may be used to facilitate consensus when information is elicited from groups.

Knowledge systems have performed well in clearly bounded domains, becoming brittle as the task approaches the boundaries. Fuzzy sets facilitate the development of systems that are more flexible and forgiving at the bounds (figure 2). The result is a more robust tool, that performs better for a wider variety of conditions and users. From an encoding point of view, fuzzy sets support the representation of knowledge and its uncertainty as a unique entity. The resulting representation is very flexible, it can be easily coupled with non-fuzzy forms of knowledge representation, and can be manipulated with a variety of evaluation functions. Depending on the knowledge structure, the representation is very transparent, facilitating system refinement by direct system examination as well as by automated search for lacunae. These advantages reflect in increased system reliability.

Appendix 1. Knowledge acquisition methods

Problem solving

Protocol: record of the expert's behaviour while solving a problem. It may involve verbalizations or just actions.

Retrospective probing: expert responds to specific questions after the completion of the task.

Procedural simulation or problem analysis: expert solves real problems while being occasionally probed for the reasoning process (Grover, 1983, Waterman 1986).

On-site observation: the expert is watched solving a problem on-site and the underlying process is inferred.

Forward scenario simulation: expert chooses a case and verbalizes the reasoning process in reaching the goal (Grover 1983).

Introspective reports: experts try to explain their knowledge, skill and decision process.

Teacher-student and teachback: the knowledge engineer learns from the expert through problem soving or observation. The roles may be reverted occasionally, and the elicitor presents aspects of the acquired knowledge to the expert.

Dissecting the domain

Distinguishing events: the characteristics of a symptom are discovered by distinguishing the events that could cause it from those that could not (Kahn *et al.* 1985, Hart 1986).

Dividing goals: goals are successively broken down into subgoals to the level of observable facts (Hart 1986, Grover 1983).

Grouping symptoms: symptoms are listed and successively grouped until the final goal is reached (Hart 1986). Alternatively, the interview is driven towards the construction of rules which help to classify observations into more specific objects and activities (Grover 1983).

ETS—Repertory grid: elicitation is guided to develop a grid of constructs – hierarchical breakdown (Boose 1986). 'Laddering' is a related technique used to get superordinate, subordinate, or equal-level concepts (Cordingley 1989).

Path division: seeks a cause on the path linking a diagnosable event with an already reported symptom (Kahn *et al.* 1985).

Path differentiation: seeks to find whether an event is the result of overlapping causal paths or non-overlapping ones (Kahn *et al.* 1985).

Frequency conditionalization: seeks for conditions that will make a symptom more or less likely to occur (Kahn *et al.* 1985).

Differentiation: finds symptoms that distinguish diagnosable events (Kahn *et al.* 1985).

Describing the domain

Problem discussion: expert discusses information and procedures needed to solve problems (Waterman 1986).

Characteristics and decisions: expert lists characteristics and decisions; then he is asked to match sets (Hart 1986).

Problem description: expert describes characteristic problems for each type of answer.

Critical incident technique: expert describes interesting or difficult cases that he recalls (Hart 1986).

System improvement

System refinement: expert provides problems to be solved with elicited knowledge (Waterman 1986).

System examination: expert examines system's knowledge and structure (Waterman 1986),

Performance feedback (Gaines 1986).

System validation: cases solved by expert and system are presented to other experts (Waterman 1986)

Groups of assessors

Crawford slip method: groups of individuals respond to questions on slips of paper (from Boose 1986).

Delphi: structured form of communication, with controlled feedback for re-evaluation, oriented to facilitating consensus.

Brainstorming: individuals list potential ideas which are then evaluated.

Other methods or categories

Induction: knowledge is extracted from a 'training set' (Hart 1986).

Constraint propagation: constraints defining cases in a training set are propagated to establish the constraints that characterize the alternative solutions.

Interviewing (category): Several of the methods listed above are part of this broad category of elicitation methods. Depending on the format, they can also be classified as unstructured, focused, or structured interviewing (Cordingley 1989).

Idea generation: Some methods for the generation of creative ideas are applicable to KA, particularly if they are based on association. Crawford Slip Method and brainstorming form part of this broad group. Other techniques include cognitive browsing, contrast, addition, Gordon Technique, sketching, vicarious thinking (see Santamarina and Akhoundi 1990 for a complete list). Sorting techniques, systematic organization of information, and matrix structuring can also be considered in this category.

Appendix 2. Some difficulties in knowledge acquisition

Human dimensions

Memory allocation: it is believed that information is kept in different memory allocations: declarative, working, and procedural memories (Kyllonen and Allouisi 1987). Unfortunately, much human activity may not be accessed by awareness (Dixon, 1981, from Gaines 1986).

Human knowledge representation: different theories or models for information storage have been suggested: verbal (rules, schemas, semantic networks), spatial arrangements, acoustic, motor kinesthetic patterns, mental models (Evans 1988 discusses the validity of some of these models). The coexistence of one or more of these representations calls for KA strategies to access them.

Level of aptitude: there are three basic categories or levels of human behavior: skill-based or automated, rule-based controlled by stored procedures, and knowledge-based for unfamiliar situations (Rasmussen 1983). Automation results after frequent repetitions of a process; intermediate steps are not kept in short term memory and are not available for verbalization (Ericsson and Simon 1980). Acquiring information from the three levels is important to computer modeling (Garg-Janardan *et al.* 1987).

Type of knowledge: There are two main categories: (*a*) process knowledge which encompasses strategies and procedures used in solving a problem; and (*b*) content knowledge which includes domain specific information (Garg-Janardan and Salvendy 1987). Both types of knowledge may be needed to develop a system.

Blind knowledge: what the expert does not know that he does not know.

Uncertain knowledge: all stored knowledge has some level of uncertainty associated to it. Not allowing for the expression of uncertainty during KA enforces biasing.

Performing, retrieving and the environment: the quality of a decision and the ability to retrieve it depend on the environmental conditions, including motivation, reality of the task, etc. (Eshelman *et al.* 1986). The acquisition methodology must be adaptable to the dynamically evolving conditions during elicitation.

Problems in verbalization: this group includes: timing or the effects of concurrent or retrospective reporting, a priori theories, probing method, specificity of requested information, completeness, consistency, context and noise (Ericsson and Simon 1980, Nisbett and Wilson 1977). Verbal data may be of limited use in many cases.

Communication: more than just transmitting information between a source and a receiver, communication is sharing meaning (Parry 1967). A knowledge engineer not trained in the domain under study can have only limited communication with experts in the domain. This difficulty may not only result in loss of information but also in hindering the experts' positive attitude to express their knowledge.

Response mode: graphical, numerical, verbal, certain-vague, etc. In the case of eliciting probabilities, a probability wheel, or the use of odds instead of probabilities may be preferred (e.g., elicitation of extreme values).

Cognitive limitations and systematic biases: there are numerous well-documented biases and inherent limitations in human decision making (Cleaves 1987, Jacob *et al.* 1986, Evans 1987, 1988). Many of them related to the perception of probabilities have been identified, leading to the conclusion that man is a poor intuitive statistician. Corrective procedures must be used during KA to minimize these effects (e.g., alternative response modes, requesting justifications, demanding group consensus).

Computer dimensions

Knowledge representation: current methods for knowledge representation in expert systems are: productions, semantic networks, frames, scripts, and conceptual dependency. New approaches and systems (e.g., Darwinian methods, neural nets) have not yet had a major effect in knowledge systems. The type of knowledge representation affects the acquisition of information and imposes alterations during encoding.

Problem solving: even though several techniques have been implemented (goal driven, data driven, means-ends, constraint própagation, others) most expert systems operate on the bases of one or at most two, while real experts often use a combination. In addition, it has been observed that experts use a multiplicity of evaluation functions (Wallsten 1980), but most KBS use a unique evaluation function.

Fundamental human–computer discrepancy: supporters for this position are increasing in number, both from inside AI as well as from other fields such as communications, neurology, philosophy, and physics (e.g., Weizembaum 1976, Winograd and Flores 1987, Penrose 1989, Searle 1990).

Other dimensions

Measurement: a postulate of measurement theory is that the measurement always affects the measurand. Extrapolating to KA, the elicitation process itself alters the elicited knowledge.

Goals and purposes: besides the general elicitation of information, other goals are: refining, completing, reaching consensus, resolving conflicts, and the generation of ideas. The elicited information may be used for different purposes, for example, decision making and training.

Type of problem: analysis or synthesis, intellectual or manual, repetitive or random, etc.

Eliciting information from groups and printed material

Stage in system development: different types of information are needed whether the stage of the systems is feasibility analysis, prototype development, or refining and validating a production model.

Form of communication: this includes direct verbal communication and indirect observation.

Encoding: difficulty in converting elicited knowledge into the computer representation.

Time: time constraints during elicitation and for system development/refinement.

Characteristics of the domain: This is a group of subdimensions which include intellectual demand, repetitiveness, and complexity.

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