Yugoslav Journal of Operations Research
1 (1991), Number 1, 79-89

AN APPROACH FOR SELECTING APPROPRIATE METHODS FOR TREATING UNCERTAINTY IN KNOWLEDGE BASED SYSTEMS

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Abstract. The problem of representation of and reasoning with uncertain data and knowledge is of importance in a broad range of disciplines, e.g. artificial intelligence and expert systems, decision theory and information systems development. The aim of this paper is to review the four developed uncertainty management systems (UMS), which are in most common use: Bayes (Probability) Theory, Fuzzy Logic, Certainty Factors Method and Dempster-Shafer Theory. The main features of each method are presented along with their strengths and weaknesses. A number of diferent sources of unceratinty are identified. The power of each of the four systems in dealing with these different types of uncertainties is examined. In the second part, a methodology for appropriate UMS selection is proposed. Selection is based on types of uncertainty inherent in a given application.

Key words and phrases: Uncertainty management systems, Bayes theory, fuzzy logic, certainty factors, Dempster-Shafer theory

1. INTRODUCTION

Recent years have seen a growing necessity for including uncertain, imprecise and incomplete data and relations between them in a broad range of domains. Uncertainty is incorporated into all knowledge based system components: knowledge base, data base, inference engine and user-interface. Dealing with uncertainty has been debated widely in the literature. Still, it is evident that the management of uncertainty presents complex and not yet fully understood problems. The term uncertainty has been given a wide interpretation and appears to be used whenever reasoning by strict logical implication is not considered possible.

The presence of uncertain information can be associated with various causes. Most complex applications domains involve multiple types of uncertainty. Several approaches for treating uncertainty hae been developed. The four most well-known and commonly used uncertainty management systems (UMS) are: (1) Bayes (probability) theory, (2) Fuzzy logic, (3) Certainty factors method and (4) Dempster-Shafer theory. Each of these methods treats the uncertainty inherent in a problem from a different point of view and each addresses the uncertain information in a different way.

Development of knowledge based systems in many cases relies crucially upon the method(s) of handling uncertainty used. The selection of the appropriate UMS influences the system performance, efectivness and reliability. The objectives of the work outlined in this paper are to examine some of the issues involved in managing uncertainty and to assess the power of the four UMS in handling the various types of unceratinty which occur in practice. This is done with a view to developing an approach for selecting appropriate methods.

2. SOURCES OF UNCERTAINTY

The notion of uncertainty is very important in knowledge based systems. However, the nature of uncertainty is not yet well defined. Different sources of uncertainty can be distinguished (Bonisone and Tong, 1985). The distinctions between the types of uncertainty that arise even in simple systems are often subtle and difficult to detect. Interactions between them produce difficulties in their classification.

Although it is not possible to give an exhaustive list of all possible types of uncertainty, some of the key ones that arise are now outlined:

(1) *noisy data*. Sources of noisy data are, for example, unreliable communication channels and measuring devices with limited accuracy.

(2) *lexical imprecision*. Concepts and definitions used in description of domain knowledge are often vague, ill-defined, imprecise and ambiguous.

(3) *descriptive (formal, rule-representation) langugage*. Ambiguities in natural language are rarely clarified during translation to a descriptive language for knowledge representation. Sometimes, input data and knowledge have to be reduced into a more compact format and this leads to a loss of information.

(4) *random processes*. Stochastic processes are encounterd in some domains. Prediction of future events, outcomes or future state of a system creates uncertain data.

(5) *incomplete data*. All required data are not always available. Sources of incomplete data are, for example, unsuccessful records of past events, unknown interactions in systems and the high price of gathering all necessary information. Inference in such case must draw a conclusion based on incomplete data.

(6) *contradictory data*. Inference based on contradictory data generates uncertain conclusions.

(7) *uncertain knowledge*. Inference in knowledge based systems is very often based on heuristics. It means that evidence and hypotheses are only partially correlated, i.e. causal links between them are not certain.

(8) *aggregation of rules from different knowledge sources and experts*. Combining the views of multiple experts into a consensus knowledge base can be difficult and sometimes impossible. A system commonly attaches a weighting to each expert and inferences the composite conclusion. However, no systematic way of obtaining such weightings exists.

3. REVIEW OF FOUR UMS

For more than three hundred years scientists, philosophers, mathematicians and statisticians have used the concept of probability to describe degrees of uncertainty. Nevertheless, many doubts concerning the appropriateness of the use of probability in knowledge based systems have arisen during the last few decades. As a result several developed UMS have evolved (Mamdani, Efstathiou and Pang, 1985, Henkind and Harrison, 1988). Each of the four reviewed UMS has a different perspective of uncertainty. Although, they all propose a numerical approach, the numbers they attach to uncertainty have different meanings.

3.1. Bayes Theory

A huge amount of theoretical results and experiences concerning the applicability of probability theory in different fields of human knowledge has been accumulated. Probability can be used in uncertainty modeling in different ways. For example, Barr and Zehno (Barr and Zehno, 1983) present a classical probability approach, and Weichselberger and Pöhlmann (Weichselberger and Pöhlmann, 1990) examine a new methodology for uncertainty which operates with probability given by intervals and not by real numbers. In this paper the classical probability approach based on Bayes rule is reviewed.

In Bayes theory uncertainty is viewed as probability, where probability can be interpreted as a relative frequency, as a degree of belief or in some other manner. Propagation of probabilities is performed through a system by Bayes rule:

$$p(H_i|E) = \frac{p(E|H_i) \cdot p(H_i)}{\sum_{j=1}^{m} (p(E|H_j) \cdot p(H_j))}$$

where:

H_j, $j = 1, \dots, m$ are disjoint hypotheses,

E is observed evidence,

$p(H_i)$ is a priori probability of hypothesis H_i,

$p(E|H_i)$ is conditional probability of E given H_i,

$p(H_i|E)$ is conditional probability of H_i given E, i.e. revised probability of hypothesis H_i.

Hypotheses H_j, $j = 1, \dots, m$ are ranked according to posterior probabilities calculated by Bayes rule.

Strengths of Bayes approach in treating uncertainty can be summarized as follows:

- Method is based on the well-known probability theory axioms.
- There are no restrictions concerning domains in which method can be applied.

Undesirable features of the method include:

- Method requires huge number of a priori and conditional probabilities for revision of hypotheses probabilities. The consequence is computational costliness. There are several approaches to Bayes method which introduce additional assumptions in order to reduce the number of input data required. However, those assumptions are not always applicable.
- Determination of a priori probabilities is based on statistical analysis and requires a massive amount of data. If data are not available, determination of a priori probabilities is based on subjective estimations of experts.
- There is no adequate way of representing ignorance. One way of representing incomplete information is to assign equal a priori probabilities to all hypothesis. In that case, there is no possibility of make a distinction between ignorance and equal a priori belief in all hypotheses.
- Probability of hypothesis negation H depends on probability of hypothesis H, according to the very well-known axiom: $p(H) + p(\neg H) = 1$. This restriction is not appropriate for cases where belief in negation of hypothesis should not be influenced by belief in the hypothesis.

3.2. Fuzzy Logic

Principles of fuzzy sets and fuzzy logic were layed by L. A. Zadeh, in 1965 (Zadeh, 1965). Since then, fuzzy sets and fuzzy logic have been developing and applied to various fields (Klir and Folger, 1988).

Fuzzy set theory is the extension of conventional set theory. It eliminates the sharp boundary which divides members of the set from non-members. Transition from a member of a set to a non-member appears gradual. Mebership in a set is expressed along a continuum from 0 to 1, where 0 means "not in the set", 1 means "in the set".

The main features of fuzzy logic which are important in treating uncertainty in knowledge based systems are now mentioned. Propositions truth values such as true, very true, more-or-less true are represented by fuzzy sets, i.e. appropriate membership functions. Fuzzy logic operates with fuzzy predicates (e.g. large number, tall person, expensive system) and fuzzy quantifiers (e.g. as most, almost all, almost always). An important concept in fuzzy logic is the linguistic variable. Values and relationships between linguistic variables are described using imprecise terms. Propositions can be qualified in three ways:

— truth qualification (for example: proposition p is very true),

— probability qualification (for example: proposition p is quite probable),

— possibility qualification (for example: proposition p is very possible).

Advantages of treating uncertainty by fuzzy logic include:

- Fuzzy logic is suitable for representing imprecise and ill-defined concepts of knowledge.
- Fuzzy logic is a very flexible theory. Operators and inference rules for fuzzy sets can be defined in various ways.

Some disadvantages of fuzzy logic are:

- Construction of fuzzy set is context dependent. The function which represents a fuzzy set is determined by subjective evaluation, using statistical data or is composed by standard functions.
- Choice of appropriate operator definitions for a given application may be a problem because there is little guidance as to which definitions should be selected.
- There are many approaches in fuzzy reasoning, but it is not always clear which approach should be used.

3.3. Certainty Factors

Certainty factors method has been developed for medical diagnostic expert system MYCIN (Shortliffe and Buchanan, 1984). The basic idea of this method is based on confirmation theory. Certainty factors measure the confidence that can be placed in any given hypothesis as a result of an observed evidence. A certainty factor is the difference between two component measures:

$$\mathrm{CF}[H,E] = \mathrm{MB}[H,E] - \mathrm{MD}[H,E]$$

where:

$\mathrm{CF}[H,E]$ is the certainty of the hypothesis H given evidence E,

$\mathrm{MB}[H,E]$ is a measure of belief in H given E,

$\mathrm{MD}[H,E]$ is a measure of disbelief in H given E.

Certainty factors can range from -1 (completely false) to $+1$ (completely true). Zero reflects ignorance or balance of evidence for and against hypothesis.

Propagation of uncertainty is based on several combining rules. They define the calculi for MB and MD in the case of incrementally acquired evidence, which can be certain or uncertain and calculi for conjunction and disjunction of hypotheses.

Some positive features of certainty factors method are:

- Calculation of certainty factors is simple and efficient. Limitations of certainty factors method include:
- Storing both values, MB and MD, is computationally expensive.
- Evaluation of a certainty factor for an hypothesis depends on the construction of rules. Logically equivalent rules constructed in different ways can produce different resulting certainty factors for the same hypothesis.
- Rules for certainty factor calculation are not based on a firm mathematical theory.

- Certainty factors are defined for a particular medical context. Definitions of the rules for certainty factor calculations are influenced by the characteristics of this medical domain. For example, one of the limitations is rapidity with which measures of belief and disbelief converge to 1.

- Single piece of negative evidence can overwhelm several pieces of positive evidence or vice versa. Because of these properties certainty factors calculi is not appropriate for many types of problems.

3.4. Dempster-Shafer Theory

The theory was first set by A. Dempster in the 1960's and subsequently extended by G. Shafer. Its relevance to the problem of treating uncertainty has been recognized recently (Gordon and Shortliffe, 1984).

Investigation into applying Dempster-Shafer theory to knowledge based systems is motivated by two limitations of Bayes approach:

- ignorance can not be represented explicitly,

- commitment of belief to hypothesis implies commitment of the remaining belief to its negation.

The basic idea of Dempster-Shafer theory is in introducing the set of hypotheses as a power set of all possible events. The set of all mutually exclusive and exhaustive hypotheses is denoted by 2^{θ}. The impact of each distinct piece of evidence on the subsets of θ is represented by a function called a basic probability assignment (bpa). The quantity bpa(A) is a measure of that portion of the total belief commited exactly to A, where A is an element of 2^{θ} and the total belief is 1. The bpa function is a generalization of the traditional probability density function.

A belief function, denoted Bel, corresponding to a specific bpa, is a measure of the total amount of belief in A:

$$\mathrm{Bel}(A) = \sum_{B \subseteq A} \mathrm{bpa}(B) \qquad A, B \in 2^{\theta}.$$

Given two belief functions based on two independent observations, but with the same set of hypotheses, Dempster's combination rule computes a new belief function that represents the impact of the combined evidence. Strengths of Dempster-Shafer theory include:

- Possibility of representing ignorance explicitly. Ignorance is represented by assigning belief to a large subset of hypotheses.

- Belief in a negation of an hypothesis is not constrained by belief in a hypothesis.

Weaknesses include:

- Assumption that independent evidence is not applicable in every domain.

- There is no mathematical justification for the correctness of Dempster's combination rule.

- Method requires great amount of input data, i.e. a bpa has to be assigned to every subset of possible events.

4. POWER OF EACH UMS

Although each of the UMS has its strong points, none of them can handle all of the sources of uncertainty outlined above. The main disadvantage of each UMS is that it provides a single framework for handling uncertainty without storing information about the source and type of uncertainty under consideration. Table 1. displays the power of each UMS in representing and reasoning with different types of uncertainty.

The power of each UMS is estimated by three terms:

- Y (Yes) indicates high suitability of method for treating the particular type of uncertainty.
- M (Maybe) indicates that given type of uncertainty might be represented by the particular UMS, but it usually requires either modification of the method or further resarch and application in real problems. We shall explain this for two cases.

1. Simple Bayes theory does not provide a way of representing contradictory information. However, modification of Bayes method which is implemented in the expert system PROSPECTOR is designed to handle inconsistency. The PROSPECTOR method operates with two values: sufficiency factor LS and necessity factor LN. Factor LS measures the support for a hypothesis. It is used in the alteration of a priori odds of hypothesis if evidence is true. Factor LN measures the support against an hypothesis and is used if evidence is untrue. This method treats inconsistency of the form: the presence of evidence enhances the odds on hypothesis (LS > 1), but the absence of evidence has no effect (LS = 1).

TABLE 1. Power of each UMS in treating different types of uncertainty

	UMS			
Sources of uncertainty	Bayes	Fuzzy logic	Certainty factors	Dempster-Shafer
1. noisy data	M	M	M	N
2. lexical imprecision	N	Y	N	Y
3. descriptive language	M	M	M	M
4. random processes	Y	N	M	M
5. incomplete data	M	N	N	Y
6. contradictory data	M	N	N	Y
7. uncertain knowledge	Y	Y	Y	M
8. aggregation of experts	M	M	M	Y

2. This concerns the power of descriptive language used in fuzzy logic. PRUF is a meaning representation language based on fuzzy logic. It translates imprecise

premisses expressed in a natural or synthetic language into a form to which the inference rules in fuzzy logic may be applied. PRUF considers representation of common sense knowledge, which usually involves a lot of uncertainty, as a set of dispositions. Disposition is a term which is often, but not necessarily, true. In fuzzy logic, dispositions are represented via fuzzy quantifiers. However, PRUF procedures require further formalization in order to be implemented in a real application.

- N (No) denotes method inappropriateness for management of given type of uncertainty.

As one would expect, terms presented in the table are subjective in nature. They also migh be expressed on a subjective scale from 0 to 10, where 0 marked complete lack of appropriateness and 10 marked complete appropriateness of method in dealing with the given type of uncertainty. Still, it is quite clear that each of the UMS is suitable for reasoning with only small number of uncertainty types. Also, some types of uncertainty are not successfully treated by developed UMS. For example, combining rules which calculate a measure of uncertainty based on different observations never takes into account the kind of mutual dependence of the two observed facts.

5. METHODOLOGY OF UMS SELECTION

Complex real-world problems usually involve several types of uncertainty. For researchers who design knowledge based systems the questions as to which method of measuring uncertainty has to be addressed (Rothman, 1989).

We describe one approach for selecting UMS. It consists of two steps. The first step is to generate the vector P_i, $i = 1, \dots, 8$, which represents the problem under consideration with respect to the 8 identified types of uncertainty. The presence of each type of uncertainty is measured on the subjective scale from 0 to 10. The second step evaluates the degrees of similarity between vector P and each column of the matrix U, represented by Table 1. Evaluation can be performed in different ways. The following two are proposed:

- Spearman's correlation test (Langley, 1968). Each vector of marks is converted into a vector of rank values. Correlation factor is calculated according to the formula:

$$\mathrm{R1}_j = 1 - \frac{6 \cdot \sum_{i=1}^{n} d_i}{n^3 - n}, \qquad j = 1, \dots, 4, \quad d_i = \bar{P}_i - \bar{U}_{ij}$$

where:

n is the length of correlated vectors, i.e. the number of different types of uncertainty ($n = 8$),

$\bar{P}$ is vector of ranked values which describes the given problem,

$\bar{U}_{-j}$ is vector of ranked values which describes the j-th UMS, $j = 1, \dots, 4$.

- Using minimum operator for each type of uncertainty. Appropriateness of each

UMS for given problem is calculated by formula:

$$R2_j = \sum_{i=1}^{n} \min(P_i, U_{ij}), \qquad j = 1, \ldots, 4.$$

The highest $R2_j$ corresponds to the most suitable UMS.

6. IMPLEMENTATION OF METHOD FOR UMS SELECTION

The approach described above for selecting appropriate UMS was implemented using the CRYSTAL shell which runs under MS-DOS. The consultation with the developed system unfolds in the following way:

(1) The system queries the user for information about the problem under consideration. The user inputs subjective marks which describe the problem with respect to the different types of uncertainty. A help facility which explains the types of uncertainty is also available.

(2) The user selects the method of ranking.

(3) The system outputs ranking of the four UMS. On user request, system can explain why the highest ranked method is the most appropriate for the given problem.

The system has been successfully tested on 3 already developed knowledge based systems; for example on SPARTA, an expert system for advising on stocks of spare parts (Petrović and Petrović, 1990), which incorporates fuzzy logic, on an expert system for investment appraisal (Sweeney, 1991) which operates with certainty factors and on an expert system for statistical process control with reasoning based on Bayes theorem.

In the following some details related to the example of spare parts inventory and SPARTA expert system are presented. Spare parts inventory problems are a very good example where the incompleteness, inconsistency, imprecise terms and uncertainty always appear. Each problem descriptor is characterized by linguistic parameters which have words as their values and an imprecise relation between them. For example, the unit price of some part may be said to be very high, high, moderate, low. Similarly, the essentiality of parts may be graded as high, medium, low. Further, the stock of spares should, of course, be influenced by the possibilities for providing additional spares on the market. Even the parameters of the stochastic demand processes which depend on the random failures of the components are very often sufficiently unknown. Therefore, the selection of an appropriate UMS in knowledge-based systems for spare parts problem is of the highest importance.

In accordance with the methodology proposed, it is necessary to assume the presence of each type of uncertainty and the vector P should be deterimined. In this case, let P be (7,10, 1, 7, 6, 1, 10, 1), which means that: (a) main types of uncertainty in spare parts problems are lexical impression and uncertain knowledge, (b) there are practically no descriptive uncertainties, contradictory data or necessity to aggregate a rule from different knowledge sources or experts, (c) noisy data, random processes and incomplete data appear significantly.

Spearman's correlation test gives the following order of the four UMS: fuzzy logic ($R1_2 = 0.786$), certainty factors ($R1_3 = 0.263$), Bayes theory ($R1_1 = 0.129$) and Dempster-Shafer theory ($R1_4 = -0.540$). The following order of applicability of methods is recommended using minimum operator. Fuzzy logic ($R2_2 = 30$), Bayes theory ($R2_1 = 28$), Dempster-Shafer theory ($R1_4 = 23$) and certainty factors ($R2_3 = 20$). It is interesting that both ranking methods recommend fuzzy logic as the most appropriate UMS to apply in the given problem. This is just the UMS that the SPARTA expert system used for treating uncertainty in solving the spare parts problem.

7. FUTURE DIRECTIONS

The representation of and reasoning with uncertain data and knowledge is the theme of various on-going projects. By way of conlusion to this paper two directions for further reseach are suggested:

(1) The methodology for UMS selection outlined can be improved taking additional factors into account. For example, selection of UMS might also depend on the importance of providing an explanation to the user. Very often UMS do not reflect the way in which domain experts reasons under uncertain conditions. In such cases, it is difficult to justify performed calculi for uncertainty.

(2) The UMS presented in the paper have proven their worth in several domains. To enable the treatment of different types of uncertainty in a single framework, it is necessary to develop hybrid UMS which will combine good features of already developed UMS (Baldwin, 1991).

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