

# Managing Uncertainties in Interactive Systems

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## INTRODUCTION

To adapt users' input and tasks an interactive system must be able to establish a set of assumptions about users' profiles and task characteristics, which is often referred as user models. However, to develop a user model an interactive system needs to analyze users' input and recognize the tasks and the ultimate goals users trying to achieve, which may involve a great deal of uncertainties. In this chapter the approaches for handling uncertainty are reviewed and analyzed. The purpose is to provide an analytical overview and perspective concerning the major methods that have been proposed to cope with uncertainties.

### Approaches for Handling Uncertainties

For a long time, the Bayesian model has been the primary numerical approach for representation and inference with uncertainty. Several mathematical models that are different from the probability prospective have also been proposed. The main ones are Shafer-Dempster's Evidence Theory (Belief Function) (Shafer, 1976; Dempster, 1976) and Zadeh's Possibility Theory (Zadeh, 1984). There have also been some attempts to handle the problem of incomplete information using classical logic. Many approaches to default reasoning logic have been proposed, and study of non-monotonic logic has gained much attention. These approaches can be classified into two categories: numerical approaches and non-numerical approaches.

1. *Probability and Bayesian Theory*. There is support for the theoretical necessity and justification of using a probability framework for knowledge representation, evidence combination and propagation, learning ability, and clarity of explanation (Buchana and Smith, 1988). Bayesian processing remains the fundamental idea underlying many

new proposals that claim to handle uncertainty efficiently.

In all the practical developments to date, the Bayesian formula and probability values have been used as some kind of coefficients to augment deterministic knowledge represented by production rules (Barr and Feigenbaum, 1982). Some intuitive methods for combination and propagation of these values have been suggested and used. One such case is the use of Certainty Factors (CF) in MYCIN (Shortliffe and Buchanan, 1976). Rich also use a simplified CF approach in user modeling system GROUNDY (Rich, 1979).

However, some objections against such probabilistic methods of accounting for uncertainty have been raised (Karnal and Lemmer, 1986). One of the main objections is that these values lack any definite semantics because of the way they have been used. Using a single number to summarize uncertainty information has always been a contested issue (Heckerman, 1986).

The Bayesian approach requires that each piece of evidence be conditionally independent. It has been concluded that the assumptions of conditional independence of the evidence under the hypotheses are inconsistent with the other assumptions of exhaustive and mutually exclusive space of hypotheses. Specifically, Pednault *et al.* (1981) show that, under these assumptions, a probabilistic update could take place if there were more than two competing hypotheses. Pearl (1985) suggests that the assumption of conditional independence of the evidence under the negation of the hypotheses is over-restrictive. For example, if the inference process contains multiple paths linking the evidence to the same hypothesis, the independence is violated. Similarly, the required mutual exclusiveness and exhaustiveness of the hypotheses are not very realistic. This assumption would not hold if more than one hypothesis occurred simultaneously and is as restrictive as the single-default assumption of the simplest

diagnosing systems. This assumption also requires that every possible hypothesis is known *a priori*. It would be violated if the problem domain were not suitable to a closed-world assumption.

Perhaps the most restrictive limitation of the Bayesian approach is its inability to represent ignorance. The Bayesian view of probability does not allow one to distinguish uncertainty from ignorance. One cannot tell whether a degree of belief was directly calculated from evidence or indirectly inferred from an absence of evidence. In addition, this method requires a large amount of data to determine the estimates for prior and conditional probabilities. Such a requirement becomes manageable only when the problem can be represented as a sparse Bayesian network that is formed by a hierarchy of small clusters of nodes. In this case, the dependencies among variables (nodes in the network) are known, and only the explicitly required conditional probabilities must be obtained (Pearl, 1988).

2. *The Dempster-Shafer Theory of Evidence.* The Dempster-Shafer theory, proposed by Shafer (Shafer, 1976), was developed within the framework of Dempster's work on upper and lower probabilities induced by a multi-valued mapping (Dempster, 1967). Like Bayesian theory, this theory relies on degrees of belief to represent uncertainty. However, it allows one to assign a degree of belief to subsets of hypotheses. According to the Dempster-Shafer theory, the feature of multi-valued mapping is the fundamental reason for the inability of applying the well-known theorem of probability that determines the probability density of the image of one-to-one mapping (Cohen, 1983). In this context, the lower probability is associated with the degree of belief and the upper probability with a degree of plausibility. This formalism defines certainty as a function that maps subsets of a proposition space on the  $[0,1]$  scale. The sets of partial beliefs are represented by mass distributions of a unit of belief across the space of propositions. These distributions are called the basic probability assignment. The total certainty over the space is 1. A non-zero BPA can be given to the entire proposition space to represent the degree of ignorance. The certainty of any proposition is then represented by the interval characterized by upper and lower probabilities.

Dempster's rule of combination normalizes the intersection of the bodies of evidence from the two sources by the amount of non-conflictive evidence between the sources.

This theory is attractive for several reasons. First, it builds on classical probability theory, thus inheriting much of its theoretical foundations. Second, it seems not to over-commit by not forcing precise statements of probabilities: its probabilities do not seem to provide more information than is really available. Third, it reflects the degree of ignorance of the probability estimate. Fourth, the Dempster-Shafer theory provides rules for combining probabilities and thus for propagating measures through the system. This also is one of the most controversial points since the propagation method is an extension of the multiplication rule for independent events. Because many applications involve dependent events, the rule might be inapplicable by classical statistical criteria. The tendency to assume that events are independent unless proven otherwise has stimulated a large proportion of the criticism of probability approaches. Dempster-Shafer theory suffers the same problem (Bhatnager and Kanal, 1986).

In addition, there are two problems with Dempster-Shafer approach. The first problem is computational complexity. In the general case, the evaluation of the degree of belief and upper probability requires exponential time in the cardinality of the hypothesis set. This complexity is caused by the need for enumerating all the subsets of a given set. The second problem in this approach results from the normalization process presented in both Dempster's and Shafer's work. Zadeh has argued that this normalization process can lead to incorrect and counter-intuitive results (Zadeh, 1984). By removing the conflicting parts of the evidence and normalizing the remaining parts, important information may be discarded rather than utilized adequately. Dubois and Prade (1985) have also shown that the normalization process in the rule of evidence combination creates a sensitivity problem, where assigning a zero value or a very small value to a basic probability assignment causes very different results.

Based on Dempster-Shafer theory, Garvey *et al.* (1982) proposed an approach called Evidential Reasoning that adopts the evidential interpretation of the degree of belief and upper probabilities. This approach defines the likelihood of a proposition as a subinterval of the

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