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Interactive Systems and Sources of Uncertainties

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INTRODUCTION

Today's e-commerce environment requires that interactive systems exhibit abilities such as autonomy, adaptive and collaborative behavior, and inferential capability. Such abilities are based on the knowledge about users and their tasks to be performed (Raisinghani, Klassen and Schkade, 2001). 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.

Uncertainty refers to a set of values about a piece of assumption that cannot be determined during a dialog session. In fact, the problem of uncertainty in reasoning processes is a complex and difficult one. Information available for user model construction and reasoning is often uncertain, incomplete, and even vague. The propagation of such data through an inference model is also difficult to predict and control. Therefore, the capacity of dealing with uncertainty is crucial to the success of any knowledge management system.

Currently, a vigorous debate is in progress concerning how best to represent and process uncertainties in knowledge based systems. This debate carries great importance because it is not only related to the construction of knowledge based system but also focuses on human thinking in which most decisions are made under conditions of uncertainty. This chapter presents and discusses uncertainties in the context of user modeling in interactive systems. Some elementary distinctions between different kinds of uncertainties are introduced. The purpose is to provide an analytical overview and perspective concerning how and where uncertainties arise and the major methods that have been proposed to cope with them.

Sources of Uncertainties

The user model based interactive systems face the problems of uncertainty in the reference rule, the facts, and representation languages. There is no widely accepted definition about the presence of uncertainty in user modeling. However, the nature of uncertainty in a user model can be investigated through its origin. Uncertainty can arise from a variety of sources. Several authors have emphasized the need for differentiating among the types and sources of uncertainty. Some of the major sources are as follows:

(1) The imprecise and incomplete information obtained from the user's input. This type of source is related to the reliability of information, which involves the following aspects:

- Uncertain or imprecise information exists in the factual knowledge (Dutta, 2005). The contents of a user model involve uncertain factors. For instance, the system might want to assert "It is not likely that this user is a novice programmer." This kind of assertion might be treated as a piece of knowledge. But it is uncertain and seems difficult to find a numerical description for the uncertainty in this statement (*i.e.*, no appropriate sample space in which to give this statement statistical meaning, if a statistical method is considered for capturing the uncertainty).
- The default information often brings uncertain factors to inference processes (Reiter, 1980). For example, the stereotype system carries extensive default assumptions about a user. Some assump-

tions may be subject to change as interaction progresses.

- Uncertainty occurs as a result of ill-defined concepts in the observations or due to inaccuracy and poor reliability of the measurement (Kahneman and Tversky, 1982). For example, a user's typing speed could be considered as a measurement for a user's file editing skill. But for some applications it may be questionable.
- The uncertain exception to general assumptions for performing some actions under some circumstances can cause conflicts in reasoning processes.

(2) Inexact language by which the information is conveyed. The second source of uncertainty is caused by the inherent imprecision or inexactness of the representation languages. The imprecision appears in both natural languages and knowledge representation language. It has been proposed to classify three kinds of inexactness in natural language (Zwick, 1999). The first is generality, in which a word applies to a multiplicity of objects in the field or reference. For example, the word "table" can apply to objects differing in size, shape, materials, and functions. The second kind of linguistic exactness is ambiguity, which appears when a limited number of alternative meanings have the same phonetic form (*e.g.*, bank). The third is vagueness, in which there are no precise boundaries to the meaning of the word (*e.g*., old, rich).

In knowledge representation languages employed in user modeling systems, if rules are not expressed in a formal language, their meaning usually cannot be interpreted exactly. This problem has been partially addressed by the theory of approximate reasoning. Generally, a proposition (*e.g.,* fact, event) is uncertain if it involves a continuous variable. Note that an exact assumption may be uncertain (*e.g.*, the user is able to learn this concept), and an assumption that is absolutely certain may be linguistically inexact (e.g. the user is familiar with this concept).

(3) Aggregation or summarization of information. The third type of uncertainty source arises from aggregation of information from different knowledge sources or expertise (Bonissone and Tong, 2005). Aggregating information brings several potential problems that are discussed in (Chen and Nocio 1997).

(4) Deformation while transferring knowledge. There might be no semantic correspondence between one representation language to another. It is possible that there is even no appropriate representation for certain expertise, for example, the measurement of user's mental workload. This makes the deformation of transformation inevitable. In addition, human factors greatly affect the procedure of information translation. Several tools that use cognitive models for knowledge acquisition have been presented (Jacobson and Freiling, 1988).

CONCLUSION

Generally, uncertainty affects the performance of an adaptive interface in the following aspects and obviously, the management of uncertainty must address all of the following aspects (Chen and Norcio, 2001).

- How to determine the degree to which the premise of a given rule has been satisfied.
- How to verify the extent to which external constraints have been met.
- How to propagate the amount of uncertain information through triggering of a given rule.
- How to summarize and evaluate the findings provided by various rules or domain expertise.
- How to detect possible inconsistencies among the various sources and,
- How to rank different alternatives or different goals.

REFERENCES

Barr, A. and Feigenbaum, E. A., *The Handbook of Artificial Intelligence 2*. Los Altos, Kaufmann , 1982.

Bhatnager, R. K. and Kanal, L. N., "Handling Uncertainty Information: A Review of Numeric and Nonnumeric Methods," *Uncertainty in Artificial Intelligence*, Kanal, L. N. and Lemmer, J. F. (ed.), pp2-26, 1986.

Bonissone, P. and Tong, R. M., "Editorial: Reasoning with Uncertainty in Expert Systems," *International Journal of Man-Machine Studies*, Vol. 30, 69-111 (2005)

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