HUMAN PERFORMANCE IN AUTOMATED SYSTEMS: CURRENT RESEARCH AND TRENDS

Edited by

Mustapha Mouloua, Ph.D.
Cognitive Science Laboratory
The Catholic University of America
Washington, DC 20064

Raja Parasuraman, Ph.D.
Cognitive Science Laboratory
The Catholic University of America
Washington, DC 20064

LEA LAWRENCE ERLBAUM ASSOCIATES, PUBLISHERS
1994 Hillsdale, New Jersey Hove, UK

Capturing Uncertainties in Human Performance with Rough Sets

Wei Wang, Qiyang Chen, A.F.Norcio
Department of Information Systems
University of Maryland, Baltimore County

ABSTRACT

In user modeling, stereotyping or classifying a user is based on incomplete and imprecise information about the user. The acquisition of inference knowledge has been considered a bottleneck problem. Also the problem of uncertainty and inconsistency must be taken into account. Rough sets provides an alternative way to deal with this problem. This paper discusses several features of rough sets such as approximate classification, feature selection and knowledge dependency and their application in user modeling. We suggest that rough set approach provide very useful tools for data analysis, so the inference rules in user modeling could be constructed from imprecise and ambiguous data in a more effective, efficient, and robust manner.

INTRODUCTION

A user model is a representation of the characteristics of a user that are relevant to the goal of supporting an effective and graceful human-computer interaction(Brajnik,et al.,1990). The notion of 'user model' is employed in different sense in artificial intelligent research and human computer interaction. There are three different types of models that are called 'user models'(Fischer,1991):

- ***users' model:*** the model that users have of systems and tasks, the individual's own personal idiosyncratic model;
- ***designers' model:*** the generalized 'typical user' model (canonical user model) that designer develops to help in the formulation of the design model;
- ***system's model about user:*** an intelligent program constructs of the person with which it is interacting.

In artificial intelligence, the notion of 'user model' is only used in the last sense in terms of reconstruct the user's belief, goals, preference in sufficient detail during the on-going interaction. The different characteristics of user model between AI and HCI are: individual vs. canonical, explicit vs. implicit, dynamic(automatic) vs. static.

User models have recently attracted much research interest in the field of artificial intelligence dialog systems and complex system. They have become important components of cooperative dialog systems and adaptive system. It has become evident that flexible user-oriented behavior in terms of tailoring the system's response can be achieved only if the system has access to a model of the user containing assumptions about his/her background knowledge as well as his/her goals and plans.

The basic process of user modeling includes acquisition and maintenance of user data. Acquiring knowledge about the user uses default reasoning to make a large number of plausible inferences based on a small number of observations of user's performance. Maintenance involves incorporating new facts about an individual user into an existing model. Thus, the problem of uncertainty and inconsistency must be resolved(Chin,1989, Rich,1989). Most research in user modeling discusses these issues and proposes several approaches that can be used to deal with these problems(Chen,1992, Chin,1989, Rich,1989). However a great number of inherent uncertainty problems in user modeling need to be explored further or still remain unsolved.

In the remainder of this paper, we will first discuss the uncertainty problems of acquiring inference knowledge, then we will propose rough sets method to deal with the problems. Finally, we conclude this paper by highlighting the advantage of rough sets approach to user modeling and discuss several further issues of adaptation and learning based on rough sets theory.

PROBLEMS OF CONSTRUCTING INFERENCE RULES IN USER MODELING

The content of a user model naturally varies from application to application. The knowledge embedded in a user model may be the system's believes about the user's goal and plans, the user's personal traits, or the user's domain knowledge and beliefs(Chin,1989, Finin,1989, Norcio,1989, Rich,1983). Current user modeling research exhibits great varieties depending on the application domain. In order to construct a user model efficiently and effectively, many researches in user modeling classify a user as belonging to one of several generic classes or stereotypes, in other words, the user's interaction with the system is classified as being of a particular type by comparison with known examples of that type. The purpose of classification in user modeling is to predict user behavior and to provide effective interaction(Allen,1990). The uncertainty problem arises during this process because of two reasons. First, the process of user modeling is to reason with incomplete information. Second, the classification and inference rules are based on the designer's intuition and assumption(Rich,1983). Besides the difficulty of constructing user models, another important issue is how can accurate domain dependent knowledge base and stereotypes be developed for the system. If information is incorrect or inaccurate, all user modeling efforts would be futile. However in user modeling, where user's behaviors may vary dramatically and unexpectedly, it's more difficult to ensure completeness and correctness. Because of this dilemma, the acquisition of inference knowledge has been considered a bottleneck problem. The main issues are what kind of knowledge is required to make inferences and how can this knowledge be acquired, represented and applied. When building a user modeling system, the following problems need to be considered:

- *Knowledge Source*: Unlike an expert system where the expertise is available for a relatively narrow domain of discourse, a user modeling system usually lacks the support of expert knowledge. Human performance is so complicated and different. It's difficult to define the relation between observed behavior data especially incomplete and its implications about the user's characteristics. In a specific domain, how to define stereotypes and construct domain-specific inference rules and default assumptions are not easy. In a user modeling system, some knowledge could be acquired from common sense and experienced domain experts. But most make direct observations during experiments, in other words, from data. That is, data represents experience that originated from historical cases.
- *Predefine Problems*: Although, stereotypes provide a mechanism for organizing information about classes of users in a way that make possible rapid inference about users, individual users are so different, they usually do not completely fit any one stereotype(Brajnik,1990, Chen,1992). These pre-defined rules might be inappropriate for any specific user performing any specific task. On the other hand, it is difficult to classify user precisely based on the partial and limited information provided by users. It is difficult to pre-define accurate stereotypes; in other words, imprecise categories can not be precisely defined by available knowledge.
- *Measures of Uncertainty*: Because the user modeling system should be able to predict or infer a user's characteristics based on incomplete and imprecise information about the user, these inferences are uncertain; usually it requires that the system be able to judge the certainty of its inferences. How to set the certainty value or assign probability measures of the inference is a major problem.
- *Learning and Adaptation*: User modeling cannot rely solely on its pre-knowledge of user's behavioral patterns, because a set of pre-defined rules could never cover all possibilities. On the other hand, to

respond to the user's specific needs, we need to extract user knowledge dynamically from the dialogue history. In order to react flexibly and individually to the performance of the user, an effective system should have learning and adaptation ability. In the traditional stereotype approach, only fairly simple modifications can be made. Facets cannot be added or deleted, only the value of a facet and its rating can change. We suggest the system should have the function to learn from experience. The adaptation includes modifying the certainty measures and deleting or creating evidence or rules on the basis of each experience with a user.

We propose that rough sets approach can be used as an efficient tool for capture, analyze, and discover the relation from this information which is incomplete, ambiguous, and imprecise. It can be expected to solve above problems.

ROUGH SETS APPROACH TO CONSTRUCT INFERENCE RULES

Recently, the rough sets approach is gaining popularity in classification, pattern recognition, and cluster analysis. The inherent learning capability of rough sets, which generalize from specific examples to principles, enable them to act as an efficient technique for knowledge acquisition and machine learning(Pawlak,1991, Pawlak,1988).

In a rough set approach to user modeling, a user is viewed as an object described by a set of multi-valued task related attributes, containing features which determine the classification, in the universes U(potential user community and their attributes). Each user is also associated with some classes or stereotypes. Suppose we only have partial knowledge about the universe U; i.e. we know characteristics of the user in a subset E U. Then the problem of identifying a stereotype is reduced to the problem of determining whether an individual belongs to a particular subset based on the description of the individual contained in a test sample E. If the descriptions of the individual users are sufficient and precise enough with respect of a given stereotype or class, one can unambiguously describe the class or a subset of objects. However, the available knowledge in the user modeling situation is often incomplete and imprecise. Under such circumstances, one can only provide an approximate characterization of a subset of objects based on their attribute values.

Rough sets are quite useful for constructing inference knowledge and stereotypes with respect to the following aspects.

Approximate classification

We assume that each individual user in the universe of discourse U is characterized by a set of attribute values:

Let A= $\{a_1, a_2, \ldots, a_n\}$ be a set of attributes.

Let V= $\{v_1, v_2, \ldots, v_n\}$ be the domains of these attributes.

Let R$\subset$ U×U be an equivalence relation on U.

Let R*=$\{X_1, X_2, \ldots, X_n\}$ be the partition induced by R, where X_i is an equivalence class of R (a combination of attributes called an elementary concepts).

The problem is to define a stereotype S$\subset$U in terms of the elementary concepts(user characteristics) $X_1, X_2, \ldots, X_n$ in U. In other words, given an individual described by X_i , one would like to decide if this user belong to S or not. If all the users with the same description belong to S (see X_1, X_2 in Figure 1), we can conclude unambiguously that any user with description X_1, X_2 definitely belongs to S. However, in a user modeling system, not all the individuals with the same description belong to S because of incomplete information. It is apparent that a user category is not definable based on partial observations in an interaction. In this case, the user may or may not be a member of S. Therefore, we cannot precisely define a stereotype S based on the descriptions of the objects alone. Instead, one can only approximately define the set S (vague categories). For any subset S$\subset$U, we can define the R-lower $\underline{R}S$ and R-upper $\overline{R}S$ approximations as follows:

$$\underline{R}S = \bigcup_{X_i \subseteq S} X_i \qquad (1)$$

$$\overline{R}S = \bigcup_{X_i \cap S \neq \phi} X_i \qquad (2)$$

That is, $\underline{R}S$ is the union of all those elementary sets(user characteristics) in A, which is individually contained by S, whereas $\overline{R}S$ is the union of all those X_i of which has a non-empty intersection with S. (see Figure 1).

If F=$\{S_1, S_2, \ldots, S_n\}$ is a family of non empty sets(stereotypes), then $\underline{R}F = \{\underline{R}S_1, \underline{R}S_2, \ldots, \underline{R}S_n\}$ and $\overline{R}F = \{\overline{R}S_1, \overline{R}S_2, \ldots, \overline{R}S_n\}$ are called the R-lower and the R-upper approximation of the family F. The accuracy of approximation of F by R is defined as:

$$\alpha_R(F) = \frac{\sum card \underline{R}S_i}{\sum card \overline{R}S_i} \qquad (3)$$

The quality of approximation of F by R is the following:

$$\gamma_R(F) = \frac{\sum card \underline{R}S_i}{card U} \qquad (4)$$

The accuracy of classification expresses the percentage of possible correct decision when classifying users employing the knowledge R. The quality of classification expresses the percentage of users which can be correctly classified to classes of F employing knowledge R.

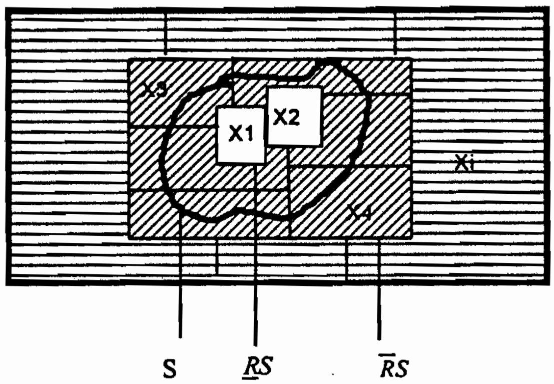

Figure 1. A concept S in knowledge representation space

U	a_1	a_2	a_3	a_4
u_1	V_{11}	V_{21}	V_{31}	V_{41}
u_2	V_{12}	V_{22}	V_{32}	V_{42}
u_3	V_{13}	V_{21}	V_{33}	V_{42}
u_4	V_{11}	V_{22}	V_{33}	V_{41}
u_5	V_{11}	V_{21}	V_{31}	V_{43}
u_6	V_{13}	V_{23}	V_{33}	V_{42}
u_7	V_{13}	V_{22}	V_{32}	V_{42}
u_8	V_{12}	V_{22}	V_{32}	V_{43}

Table I. An example of value distribution of user's attributes

An simple example of a user's attributes representation system is given in Table 1. In this table we have a subset of users in the universe U=$\{u_1, u_2, \ldots, u_8\}$ which is characterized by means of the set A=$\{a_1, a_2, a_3, a_4\}$. Suppose v_{ij} is the value of each attribute. In this case, users u_1, u_5 cannot be distinguished by attribute a_1, a_2, a_3. Some elementary sets defined in Table 1 are as follows:

$\{a_1\}$elementary sets:

$$X_1 = \{u_1, u_4, u_5\},\quad X_2 = \{u_2, u_8\},\quad X_3 = \{u_3, u_6, u_7\}$$

$\{a_1, a_2, a_3\}$elementary sets:

$X_1 = \{u_1, u_5\},\ X_2 = \{u_2, u_8\},\ X_3 = \{u_3\},\ X_4 = \{u_4\},\ X_5 = \{u_6\},\ X_6 = \{u_7\}.$

$\{a_4\}$ elementary sets:

$$S_1 = \{u_1, u_2\},\ S_2 = \{u_2, u_3, u_6, u_7\},\ S_3 = \{u_5, u_8\}$$

Let F={S_1, S_2, S_3 } be a partition of U defined by as conclusion and let R=a_1, a_2 and a_3 be conditions which generate the following classification on U, according to formula (1) and (2), we obtain:

$$\underline{R}F = \{\{u_4\}, \{u_3, u_6, u_7\}, \{\}\},\ \text{and}$$

$$\overline{R}F = \{\{u_1, u_4, u_5\}, \{u_2, u_3, u_6, u_7, u_8\}, \{u_1, u_2, u_5, u_8\}\}$$

This means that users with the same description of u_4 definitely belong to category S_1 , but if a user with the same description of u_1 or u_5, this user may be a member of category S_1 , or may be a member of The quality of classification according to (4) is:

$$\gamma_R(F) = \frac{card\underline{R}S_1 + card\underline{R}S_2 + card\underline{R}S_3}{cardU} = \frac{1+3+0}{8} = 0.5$$

That means, if a user is defined by attribute a_1, a_2 and a_3, the percentage of users which can be correctly classified to classes of S_1, S_2 and S_3 is 50%.

Determining the dependencies of user's characteristics

When building a user model, we will make some assumptions and inferences based on the user's input. This allows the system to define defaults about the user's other implicit characteristics. Because the user's attribute values are somehow correlated in the sense where the dependencies between them can range from relevant to consistence or from contradictory to irrelevant. More precisely, a user's characteristics Q is derivable from the user's other characteristics P, if Q can be defined in terms of some attributes value of P. The derivation (dependency) can also be partial, which means that only part of attributes value in Q is derivable from user's other attributes value in P. Rough set can be used for detecting the dependencies or significance among all the attributes. Let U be the user community, R be user's characteristics and P, Q $\subset$ R, we say that knowledge Q depends in a degree k from knowledge P:

$$k = \gamma_P(Q) = \frac{card\underline{PQ}}{cardU} \qquad (5)$$

These features are very useful in modeling human performance where the available information is not adequate to characterize the user fully. Because of the inherent uncertainty in stereotype-based inferences, it is important to assign explicit measures of certainty and possibility. Using a rough sets approach, the generated rules are categorized as certain and possible rules. For instance, it can be easily verified from Table 1 and formula (5) that:

$$\{a_1, a_2, a_3\} \xrightarrow{0.5} a_4$$
$$\{a_1, a_2\} \xrightarrow{0.5} a_4$$
$$\{a_1\} \xrightarrow{0.375} a_4$$
$$\{a_2\} \xrightarrow{0.125} a_4$$

This means that a user's attributes a_1, a_2 and a_3 is not sufficient to predict the user's other attributes such as a_4 in all instances, in other words, attribute a_4 partially depends on attributes a_1, a_2 and a_3. Also we can determine that attribute a_1 is relatively significant in deciding a_4. The dependency analysis of the user's characteristics is very useful in user modeling. Given limited information, we can predict or infer other information about the user with possibility.

Reduction of user's attributes

When acquiring knowledge to construct a user model, we assume a set of attributes which can describe an individual user. A problem arises that whether all the attributes are always necessary to define some categories. Very often, some of the attributes may be redundant in the sense that they do not provide any additional information about the users. In rough set, the concepts a reduct and the core are very useful. It can capture essential factors affecting the classification result and do not take irrelevant factors into account. It can eliminate superfluous or "noisy" data. A reduct of user's attributes is its essential part, which suffices to define all basic characteristics occurring in the considered user information, whereas the core is in a certain sense its most important part. From Table 1, it should be noted that attribute a_3 is redundant or superfluous because the removal of the attribute a_3 from the knowledge base would not affect the dependency between attributes a_1, a_2 and attribute a_4. This function enable to get minimal subsets of the essential characteristics of users that are needed to design user models accurately.

CONCLUSION

In this paper, we propose an rough sets approach to user modeling, especially, emphasize on detecting and discovering the relationships between users' characteristics and their classification.

We suggest that rough sets approach be appropriate to get user modeling knowledge because:

- *Approximate Classification:* It is impossible to classify a user precisely according to a limited information about the user. Rough sets provide a natural way to deal with uncertainty in terms of vague classification.
- *Feature Selection:* Information used to construct a user model is generally incomplete, imprecise, and inconsistency, and it may contain useless details. Rough sets provide a series of tools for data analysis, so knowledge from imprecise and ambiguous data can be acquired in a more effective, efficient, and robust manner.
- *Identification non-deterministic systems and incorporation probabilistic information:* Because of the inherent uncertainty in stereotype-based inferentes, it is important to assign explicit measures of certainty and probability. A rough sets approach can estimate such measures, the produced rules are categorized into certain and possible.

In a rough sets approach, the generalized rules are inferred from a training set of samples. The test sample has to be carefully chosen. The initial rules captured from training set may not correctly describe or predict the great variety of human behavior. However, it is not critical because rough sets provide efficient algorithms for machine learning.

An important problem is the maintenance of knowledge in a dynamic environment. Because user performance and characteristics are so varied, there is a possibility that current knowledge would have to be altered when a new piece of information is delivered with a new user. The reducts play an essential part of the knowledge such as functional dependencies. It should be noticed how large alterations could be triggered by the addition of one object. The computational complexity of the problem of reducts enumeration is, in the worst case, exponential with respect to the number of attributes. Therefore we need to explore an improved algorithm(Orlowska,1992) or make assumptions about the size of the sample set of objects with a fixed set of attributes, the only issue of the latter method is the evaluation of the computational complexity of the problem.

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