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# Uncertainty Indentification, Representation and Measurement in User Modeling: A Methodology

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**ABSTRACT**

*User modeling, which is the task of learning user interest, knowledge, preference and intention from the different characteristics of a user and patterns of user interaction, is a typical problem with inherent uncertainty. This paper focuses on uncertainty identification, representation, inference and measurement in user modeling in the context of human computer interaction. A system architecture, as a methodology for building user modeling systems, is presented. It does not only provide the functional requirements but also it incorporates components to handle and measure the uncertainty due to vagueness and imprecision using fuzzy theory and possibility theory as the theoretical foundation. The architecture is also illustrated with examples from a business to customer e-commerce system.*

**1. INTRODUCTION**

User Models are collections of information and assumptions about individual users (as well as user groups), which are needed in the adaptation process. User modeling (UM) is a process for constructing user models comprises of acquisition, representation, inference and maintenance [1-3]. One of the research problems in user modeling is handling the inherent nature of uncertainty in user models and environments. Information pertaining to a user model may be incomplete, imprecise, vague, contradictory, or deficient in some other way; and may cause different types of uncertainty.

There are various meanings associated to uncertainty. According to Parsons and Hunter [4] uncertainty is defined as a measure of the certainty of something and is thus modeled using a numerical value denoting falsity and truth, usually 0 and 1. Presently, it is realized that uncertainty is a multidimensional concept. These dimensions are related to the different categories of uncertainty including uncertainty due to randomness (stochastic uncertainty), uncertainty due to ambiguity, and uncertainty due to vagueness and imprecision [5]. These different type of uncertainty may coexist in user models and propagate in the modeling process. At this point, stochastic uncertainty is the one which is well studied using a probabilistic or Bayesian approach, e.g., [6-9]. Another dimension of uncertainty is uncertainty due to imprecision and vagueness that are identified with the lack of sharp or precise distinctions in the world. For handling this uncertainty type, fuzzy set theory and possibility theory provide the appropriate mathematical framework. This uncertainty type is not well studied in user modeling and adaptive information systems. A few examples are [10-13]. In these studies measures of uncertainty for adaptation decisions, and application of machining learning based upon existing user data are not considerably investigated.

Therefore, this paper focuses on identifying, representing, and measuring uncertainty due to vagueness and imprecision in user models and modeling; and the application of uncertainty measures in adaptation decision. After identifying the requirements for effective uncertainty handling in section 2, a user modeling methodology is proposed and discussed in section 3.

**2. REQUIREMENTS FOR HANDLING UNCERTAINTY IN USER MODELING SYSTEMS**

In addition to the basic functional and non-functional requirements of a user modeling system, the following characteristics are additional requirements for effective uncertainty handling [1, 13, 14]:

- Detailed description about the evidence to the level that it is possible to describe its uncertainty.
- Transparent uncertainty representation for describing uncertainty input and getting interpretable uncertainty output.
- Second-order measures of uncertainty that measure the uncertainty of evidence and conclusion as well as the uncertainty of the representation of the uncertainty.
- Effective computational algorithms.

Based upon previous studies such as [5, 10, 14-18], and analyzing of the structure and features of a user model and the user modeling process, a preliminary taxonomy of uncertainty is proposed in Table 1. It is by no means complete and needs further investigation.

*Table 1: Taxonomy of Uncertainty in User Models*

Source in UMS	Causes of Uncertainty	Type of Uncertainty	Examples	Formalism
Users' facts and action events	Incompleteness and imprecision	Information-based imprecision	Time of browsing a site; number of clicks	Fuzzy Theory and Possibility Theory
Users' facts and action events	Vagueness due to inexactness of the representation language	Linguistic imprecision	Rich Customers; Customer Level of Interest in Products	Fuzzy Theory and Possibility Theory
Users' facts and action events	Contradictory information	Ambiguity /Conflict	Two different Ranks to an item at different time	Evidence Theory
Assignment of default assumptions to user model	Incompleteness and imprecision; vagueness; or Erroneous	Information-based imprecision	User's Interest level ranked as very high	Fuzzy Theory and Possibility Theory
Future Users' facts/actions prediction	In-deterministic nature at the present	Randomness or Stochastic nature of facts	A chance for a user to buy a product within a month	Probability Theory

Figure 1: User Modeling System Architecture for Handling Uncertainty

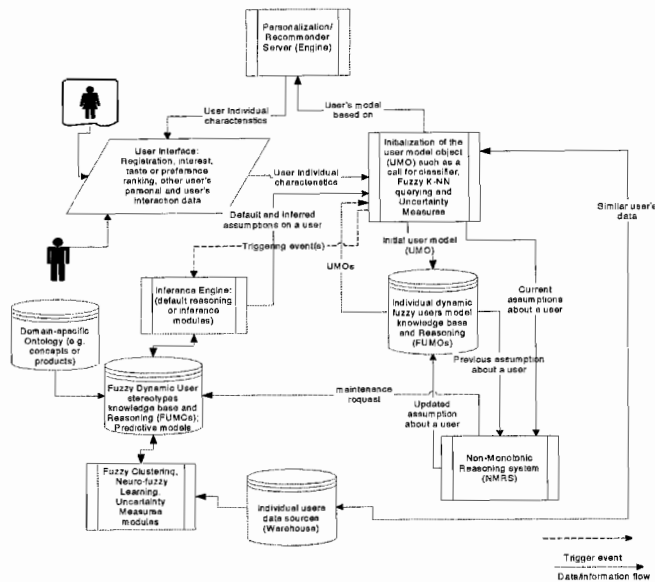


Figure 2: Generic Structure of Fuzzy Stereotype or User Classes (FUMC's)

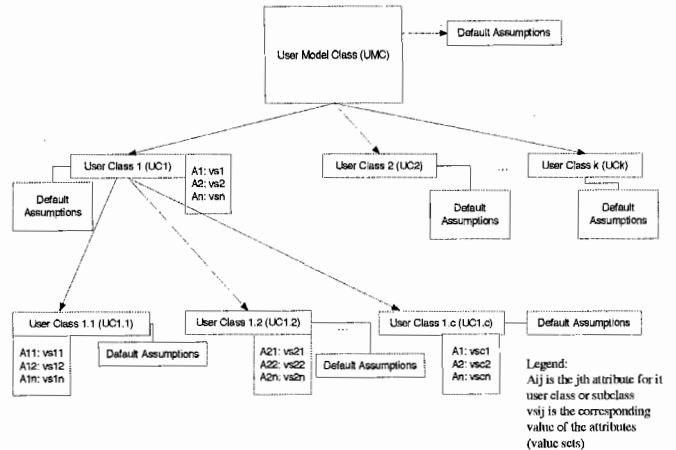
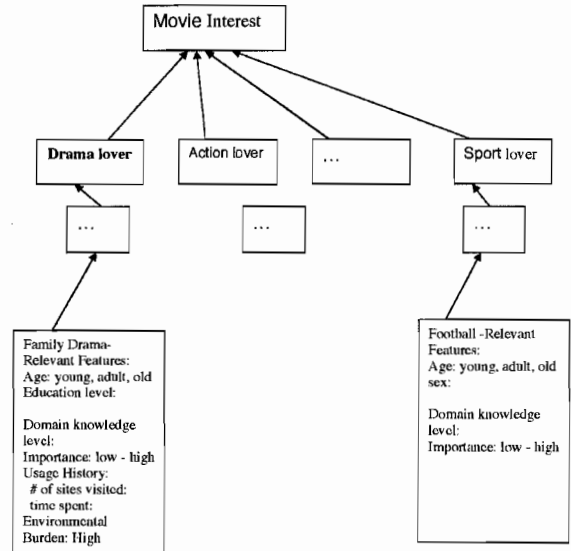


Figure 3: An Example of FUMCs for a Movie Recommender System



### 3. PROPOSED USER MODELING SYSTEM ARCHITECTURE

In order to support the requirements stated in section 2, based upon the conventional user modeling architecture (e.g. [2, 12]), the user modeling methodological architecture in Figure 1 is proposed. The architecture's components and their functions and interactions are described and illustrated using examples from user modeling in e-commerce domain in the next subsections.

#### 3.1 Acquisition and Representation

One of the components of the system architecture is the fuzzy user model class or stereotype (FUMC). Each of FUMC mainly consists of user features or attributes and its corresponding values, default assumptions, and trigger conditions or methods for activating and deactivating assumptions about users in the class. Default assumptions are shared assumptions assigned to all member of a class in the absence of evidence to differentiate one from another.

FUMCs can be organized in hierarchy forming class-subclass fuzzy relations. FUMCs' attributes and values can be represented using fuzzy set, relation, and rule; and FUMCs' inference methods employ fuzzy relations, calculus, and fuzzy logic. In addition, the stereotypes can have different predictive models, classifiers, and rule-based inferences that construct assumptions about users, Figures 2 and 3 are examples. A formal definition of FUMC is:

A fuzzy user model class is defined by a quintuple  $(n, S, C, A, M)$  in which  $n$  is the identity of the class;  $S$  is the fuzzy set of its parent classes;  $C$  is the fuzzy set of its child classes;  $A$  is the fuzzy set of its class attributes; and  $M$  is the different methods including those for reasoning and measures of uncertainty computed based upon  $A$ .

Where  $A_i = \{ \langle x_i, \mu_{A_i}(x_i) \rangle \mid x_i \in X_i \text{ for } I \text{ from } 1 \text{ to } N \}$ ; and  $N$  is the total number of attributes in the class.

Domain -specific ontology consists of knowledge about specific entity are needed to impose a structural relationship among the FUMCs. For instance in the e-shop domain, the ontology refers to the knowledge and relation about the products (items or services) to be put up for sale. The hierarchical relationships in FUMCs are the result of a mirror of the user data over the domain knowledge description and relations.

The FUMCs can be defined heuristically by domain experts, determined analytically or determined empirically from data. In the latter case, different machine learning techniques such as clustering,

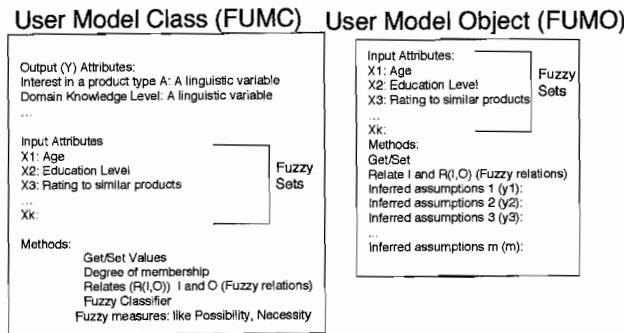
artificial neural networks and genetic algorithms can be used. In this study, an ANN is proposed as learning approach whenever there are labeled data and expert rules. Further, fuzzy clustering is proposed as learning approach whenever there are unlabeled data.

The fuzzy user models knowledge or objects (FUMOs) are attributes and value sets of individual users. The object obtains some of its features and values from the user during system interaction. Additional assumptions, both predicted and default assumptions, are assigned to FUMOs from the FUMCs by the inference engine (similar to the content-based approach employed in current recommender systems), Figure 4 is an example. The formal definition of a FUMO is:

A fuzzy user model object, FUMO is defined by a quintuple  $(o, S, B, M)$  in which  $o$  is the identity of the object;  $S$  is the fuzzy set of its classes (set of FUMC);  $B$  is the fuzzy set of its object attributes; and  $M$  is the different methods including those for reasoning and measures of uncertainty computed based upon  $B$ . Where  $B_i = \{ \langle x_i, \mu_{B_i}(x_i) \rangle \mid x_i \in X_i \text{ for } I \text{ from } 1 \text{ to } K \}$ ; and  $K$  is the total number of attributes in the object.

The user interface component of the application can be used for registering a user, eliciting explicit interest, ranking preferences, and

Figure 4: Structures of User Model Class and User Model Object



recording implicit usage behavior while the user is interacting with the system. Based on these individual user characteristics as well as the characteristics of other similar users (like collaborative approach), a user's FUMOs can be initialized and updated using online learning techniques such as fuzzy k-nearest neighbor algorithm and neuro-fuzzy classifier. Algorithms that incorporate these standard learning routines need to be developed and used for initializing and updating FUMOs based upon the FUMCs and observed user data.

**3.2. Inference**

The principles of default, stereotype-based, and secondary reasoning in a user modeling system are incorporated in this framework. These includes:

- activating FUMCs to assign or generate assumptions to FUMOs when trigger conditions are true,
- deactivating FUMCs to retract assumptions assigned to FUMOs when retraction conditions are true, and
- aggregation of assumptions from lower levels FUMCs to higher levels FUMCs in the hierarchy.

These inference mechanisms are implemented as methods in FUMC and FUMO. They can be activated by the different triggering events. For instance, in e-commerce shopping sites, the events that trigger the inference methods fire when new users register, change their features, etc. When these events indicators are significant, the trigger conditions fire appropriate methods to update user models. Moreover, to maintain the current user model based on new evidences, and to correct conflicting and inconsistent assumptions about a user, a non-monotonic reasoning approach [19] is proposed in the framework, referred as non-monotonic reasoning component (NMRC).

Client applications such as Adaptive/Personalization/Recommender Engine can use FUMOs for personalized or adaptive services for an individual user, and FUMCs for groups of users. The user modeling system provides clients with results of inference about users such as users' interest or domain knowledge level related to (i) a specific item; (ii) other related items; and (iii) higher level class of items.

In future studies in addition to uncertainty due to vagueness and imprecision, there is a need for identifying and analyzing other uncertainty types, and incorporating them in the user models and user modeling systems. Moreover, the agent oriented development approach can be pursued for the implementation of the system.

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