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An Associative Approach in Dynamic User Modeling

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Abstract

A research framework for building a user model by utilizing artificial neural networks (ANN) is presented. The limitations of stereotype-based user modeling are discussed which underlie the motivations of introducing ANN approaches. An associative user modeling approach is proposed which is incorporated in a blackboard processing environment.

1. Introduction

In order to capture a user's individual characteristics in task performance, a user modeling mechanism has been recognized as an important component in adaptive interface systems [7]. An interface equipped with a user model helps the system tailor its response to individual users. It not only exhibits a wide range of cooperative functionality, but also improve system efficiency and effectiveness [4].

In order to make a large number of inferences based on a small number of evidence or observations, it has been common practice in user modeling to have a set of pre-defined stereotypes associated with a particular user. The assumed information about users and the tasks they perform are represented in a generalization hierarchy. Along with certain types of confidence measurements, this information can be further classified in terms of its persistency or temporal extent and its sources, and the degree of specification [9]. In next section we will highlight some of the issues that motivates our approach.

2. Limitations of Stereotyping Approaches

Stereotyping provides a simple way for obtaining initial information about a user. The modeling process proceeds with a stereotype assignment in terms of default or evidential reasoning. Default reasoning allows the modeling process to maintain stereotypical information about a user in the absence of evidence to the contrary, whereas evidential reasoning assigns and revises the belief values to the facts held by the model [1].

2.1 Default modeling process

In the stereotyping approach, rule-based reasoning is conducted with extensive default assumptions that may conflict with the new evidence during the interaction. Therefore, techniques such as truth maintenance and ad hoc approaches are necessary for handling inconsistencies in a non-monotonic process. However, since these approaches examine one piece of evidence at a time, they may fail to detect inconsistent inputs that should be ignored. For example, a database query from a user may imply a conflict with system's original belief about this user's understanding of the contents of the database; this may be due to misusing the grammar of query language. This conflict may have nothing to do with user's belief about database contents; therefore it should be ignored in the modeling process. Thus, without examining the continuity and *overall behavior pattern* in task performance, the modeling process may not reflect the real situation and the current effort of maintaining consistency may bring some new conflicts in the subsequent interaction. Meanwhile, model construction may frequently fall into a non-monotonic process of conflicts-resolution [3].

2.2. Evidential Modeling Process

If the model construction is driven by evidential reasoning, specifying the belief values for both evidence and rules become very difficult. Even if one can identify the correlation between observed user's behavior data and its implications, it is still difficult to assign probabilistic values. In addition, even with a well understood situation, it is still likely to fail maintaining probabilistic formalisms (e. g. independence of probabilities) over the whole production system.

Some user modeling systems utilize techniques for handling uncertainties as a learning mechanism in which the model is refined by modifying the belief values until adequate modeling performance is obtained. It is obvious that off-line tuning is both time consuming and inexact. It is often based on inadequate tests and a subjective judgment of how the interaction is pursuing, and local improvement obtained by tuning one capability of the modeling process might be detrimental to other capabilities. Moreover, if such a revision is not based on a view of the behavior pattern, the modeling process may face the dilemma of frequent conflict-resolution.

2.3. Representation Power of Generalization Hierarchy

It is efficient to build an initial user model through stereotype hierarchy. However, its inherent structure limits the degree of individualizing a user. Since the pre-defined properties are framed within each stereotype and can be only inherited through the hierarchy, there is no effective way to update those properties that are no longer significant in the context of task performance. It is not an extreme situation that a user may fail to fit any set of stereotypes, so that the modeling process fails to associate any system beliefs to that user. However it would be better to extract some of the properties or assumptions distributed among the stereotypes to characterizing a particular user.

A hierarchical stereotyping approach also provides a natural way for classifying a user's long-term characteristics [9]. However, in a real time interaction, a user's performance primarily reveals short-term characteristics which change over time and exhibit many varieties regarding the current task. It is difficult to classify short-term characteristics through a pre-defined hierarchy. For example, a user may exhibit both expert and novice traits in a task performance. Therefore the classification of long-term characteristics via few dimensions might not help system's adaptation to the current context [7]. Besides modeling long-term characteristics of user provides no direct insight with respect to the context of task and underlying goals [4]. We suggest that modeling process should emphasize short-term racteristics of the user because it results in more efficient system adaptation to the current (than modeling long-term characteristics. In addition, the short-term model is temporal to context of interaction so that it is less risky than a long-term model [5].

Modeling Users with Associative Approach

. Viewing User-Task Information through User's Behavior Patterns

It seems more appropriate to represent knowledge about a user and the task in a form of terns as well as their associations. Since a user's behavior data in an interaction is highly ited in a context of task and mixed with noise, all the aspects of the pattern have to be mined before any decision can be made. However, the conventional stereotype, in which inference proceeds a step at a time through sequential logic, may become seriously dequate for describing such pattern-formatted knowledge and the workload of recovering n inconsistency might be very heavy [8].

In our approach, the user's information is viewed and organized as a set of patterns. ious ANN techniques can be used to analyze the patterns, which requires the ability of t tolerance, graceful degradation and signal enhancement. Some ANN operation nitives have been suggested for user modeling process [2,3]. In this paper, we are more cerned about modeling user with associative memories.

Auto-associator

This ANN primitive can be implemented by various paradigms of associative memory. It ures the associations between input and output patterns despite incomplete or inconsistent ts. The associative memory that has only a single set of interconnected units can be one ie implementations. Each unit serves as both an input unit and an output unit. Its feature :lf-organizing is especially useful in recognizing user-task context.

Suppose a state transition diagram is used to define the user's task performance. It can be :formed into a stored pattern in associate memory in which each state is represented by a and the transitions are mapped to weighted connections. During an interaction, a user's ations involving several units can be organized as an stimulus vector. The associative iory can produce a relatively complete path of state transitions as a prediction for gating the user toward task accomplishment. This provides a basis for comparing the s real action with the predicated one and then modifying corresponding user models. This erty can also be used in plan recognition while some relevant traits are observed.

Associative memory also provides a way to model what the user knows. Considering a s problem solving as a procedure of associative thinking, the representation power of a model could be enhanced by adjusting the pattern of weights or propagating activation s through interconnected concepts to reflect the real time change of the user's mental :l or the beliefs. Thus a user model can be updated dynamically and consistently. In the :ling process, the stimulus from a user can trigger some assumptions about what a user dy knows and then the corresponding units are fired. The spreading activation rule can ually create two network states: the network reaches a single, stable state, or it reaches a : in which it cycles through a constant series of states. The set of those units reaching the words, it can be expected that a series of concepts is the likely result of a particular stimulus. Usually the activation and propagation rules are ad hoc and the activated nodes compete with each other in a multiple-winners-take-all fashion.

3.3. Associative User Modeling

In our approach, the associations are established among the system's beliefs about the task-related characteristics of all possible users. Unlike the stereotype approach, these beliefs are not framed within any structure. All elementary properties and underlying assumptions about users and their tasks are viewed to be associative to each other in a spectrum which is valued from negative to positive (i. e. contrary to consistent). Stereotype hierarchy limits the representation of the associations so that it is impossible to extract properties from different stereotypes to form a new profile (i.e. a set of new stereotypes) about the current user or task.

Associative user modeling reduces the workload of knowledge acquisition, because it is much easier to identify the casual relationship between two system beliefs than to define complete stereotypes with respect to a user's task. Learning processes can be conducted in term of automatically revising weights, adding or deleting a unit representing an assumption. It proceeds locally so that the change to the network can be limited to the minimum.

In associative user modeling, there is no explicitly pre-defined stereotype involved. All assumptions are organized into associative memories in which the relationship among the assumptions are weighted under certain conditions. The activity level of network units at each propagation phase is considered to be a prediction of the possibility of relevance to the user's current task. After filtered by a threshold function at the end of iteration, the fired units that represent assumptions reach the value of 1. The weights can be initially set by the following equation [6]

$$w_{ij} = -\, ln \frac{p(x_i = 0 \cap x_j = 1)\, p(x_i = 1 \cap x_j = 0)}{p(x_i = 1 \cap x_j = 1)\, p(x_i = 0 \cap x_j = 0)}$$

In the original version of this equation, p is derived from a Bayesian analysis of the probability that unit x_i is fired given unit x_j is fired and vise versa. However, in our approach, we loosely define value of p as the value of plausibility which may not satisfy the probability formalism, because it is often difficult to assign precise probabilistic values and maintain the formalism for the casual relationships among assumptions used in user modeling.

The pattern of weights reveals three aspects of the relationships: if the two assumptions tend to be on and off together, then the weight will be a large positive value; if the two assumptions come on and off independently, then the weight of their connection is almost zero; if the two assumptions are somehow contrary which is implied by a larger value difference of corresponding units, then the weight takes on a negative value. In addition, a constant bias is given by

$$bias_i = -\, ln \frac{p(x_i = 0)}{p(x_i = 1)}$$

Using a bias can help detect the significance of an assumption within the context of task.

If an assumption is usually fired, it has a positive bias; and if it equally often on and off, it has zero bias. If it is usually off then it has negative bias.

In associative memory, the pattern of fired assumptions underlies a user's profile. If network contains n units then there are 2^n possible binary states (i.e. stored patterns) in which system could potentially settle. Thus the capacity of representation in associative user modeling is much greater than stereotyping approach that has same number of initial assumptions.

4. A Blackboard Structure of User Modeling System

As a component of an adaptive interface, our associative user modeling framework is shown in Figure 1. In order to tailor system response to an individual user, the characteristics about the tasks must be also captured. Therefore, two knowledge sources are necessary in an interaction: user profiles and the task profiles. Accordingly two networks are utilized: one that incorporates the user's task-related characteristics and one that stores the assumptions underlying system actions or responses. From the view point of system adaptation, one network addresses *when to adapt*, while another addresses *how and what to adapt*. The generated responses vary based upon the types of application systems (e.g. database retrieval, tutorial system, etc.).

A blackboard structure is appropriate for knowledge representation and reasoning. The objects in blackboard can be manipulated cooperatively in terms of sending or receiving stimulus vectors, or utilized independently depending on the control information appearing in the blackboard. The dynamics of networks are interpreted and stored in the knowledge bases of the user profile and the task profile. This blackboard system supports a multilevel user modeling process in the sense that it incorporates procedures of preprocessing, updating and post-processing a user model in an interaction [3].

It is acknowledged that associative memories cannot accomplish all procedures of user modeling. Production systems processing both user and task profiles are necessary to coordinate the multilevel process, which are implemented in the control module. Its major functions are forming task-related user images delivered to the networks, analyzing and interpreting network outputs, and supporting response generation. However, there is no non-monotonic reasoning involved in symbolic reasoning. Meanwhile the declarative information about both user and task profiles are manipulated and stored in knowledge bases.

The patterns stored in networks are viewed as blackboard objects, while the user and task profiles as well as related production systems are underlying knowledge sources. User modeling proceeds with dynamics of networks, making changes to both blackboard objects and knowledge sources. As data appears on the blackboard, the network modules produce increasingly accurate information. The system dynamically chooses a focus of attention in current modeling process. If the focus of attention is a knowledge source, a blackboard object is activated as the context of its invocation. If the focus of attention is a blackboard object, a knowledge source that can process that object is chosen. If the focus of attention is both a source and an object, a complete modeling process is executed within the current context. The stored patterns in networks are continuously invoked as interaction progresses. Once the networks reach a stable status, some contents of the model are established with respect to the current context. This fulfills the dynamic process of user modeling.

5. Conclusions

The inherent features of conventional stereotype approaches limit user modeling in the aspects of reasoning mechanisms, capabilities of individualization, and learning, It is suggested that the concepts and the techniques of pattern recognition be utilized to capture task-related characteristics of a user. Some ANN primitives, especially associative memories have shown the promise of enhancement in modeling process. The proposed framework not only possesses all advantages of stereotyping approach but also provides a flexible platform for overcoming the limitations of the conventional approach. A prototype system and related experiment is under implementation. Further research is aimed at verifying that this framework can scale to large, complex applications in which various associative paradigms are investigated in terms of their efficacy in user modeling.

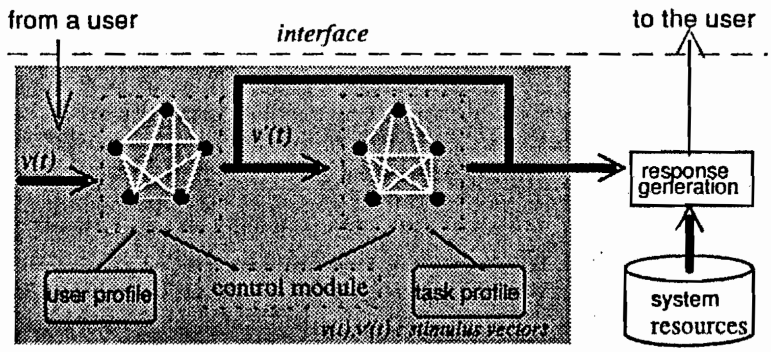

Figure 1. ***Blackboard structure for user modeling***

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