USER MODELLING FOR INTENT PREDICTION IN INFORMATION ANALYSIS

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User modelling is a key element in successfully assisting intelligence analysts who must gather information and make decisions without being overloaded by the massive amounts of data available on a daily basis most of which are irrelevant. Furthermore, with user modelling, we can predict the goals and intentions of the analyst in order to better serve their information seeking tasks by providing better re-organization and presentation of data as well as pro-actively retrieve novel and relevant information as it arises. Our goal is to provide a dynamic user model of an analyst and work with him as he goes about his daily tasks.

Introduction

Our effort in user modelling for analyst intent prediction is a part of the OmniSeer project involving Global InfoTek, Inc., University of Connecticut, and University of South Carolina. OmniSeer focuses on research, evaluations of technology, and explorations of algorithms and processes necessary to develop a revolutionary agency-based framework, architecture, and system concept that will assist analysts not only in dealing with massive data, but also in making prior and tacit knowledge explicit, allowing for modification and update of the analyst's current cognitive state. In this paper, we focus on the user modeling effort being led by the University of Connecticut.

The novelties of our approach are the structure of the user model, the dynamic nature of the construction process and the services offered to other analysis processes. Our dynamic user model clearly delineates a user's interests, preferences, and context especially as they change over time. This decomposition of the user model allows us to systematically construct and critically analyze the behavior and performance of such a sophisticated system as OmniSeer. While other previous efforts have focused exclusively on learning any one aspect of information seeking and processing, none of the previous approaches has attempted to integrate all three aspects together for determining and understanding a user's goals and intentions. We show that our user model will not only elicit the analyst's interests and preferences but also provides a good explanation toward *why* the analyst wants to focus on the given information. We demonstrate that the services provided by our user model can be used by other analysis processes in OmniSeer to better serve the analyst in analyzing and detecting important information. By constructing the user model "on-the-fly", we adapt quickly to the changes in the goal and approaches used by the analyst and thus improve the quality of the retrieval process and analyst's experience with the system.

The rest of the paper is organized as follows. The next section discusses background and related work. We dedicate the next two sections to describing our model of intent prediction and the components of our cognitive model. Next, the evaluation methods are presented. We conclude with an overview of the current status of our efforts and future work.

Background and Related Work

This work is derived from our earlier attempts with two predecessor systems, Clavin (Santos et al 1999) and Kavanah (Nguyen et al 2000, Santos et al 2001, Santos et al 2003), and our recent work on adversary intent inferencing (Surman et al 2003). Clavin proposed initial ideas on how a dynamic user model can help expand queries, while in Kavanah, the user model is evaluated in an information retrieval application focusing on the medical domain. We learned from our initial empirical evaluation of Kavanah that the user model does improve the retrieval process and does not add an extra cognitive workload to the users (Santos et al 2003). As for the Adversary Intent Inferencing Model, it helps an analyst capture an enemy's intent and provides the context as to why he/she is pursuing it.

In our approach, we focus on the representation of each component in the user model, and the integration of these components. Regarding the former issue, research work in knowledge representation (Clark and Porter 1997) is closely related to our representation of *why* the analyst chooses to pursue their current goal. Another related effort is from the InfoSleuth group (Hwang 1999) which used the relations between concepts to help with information retrieval applications. Regarding the latter issue, a lot of work from interface agents have focused on using interests or preferences to help with the retrieval process (Decker and Sycara 1997, Widyantoro et al 1999).

OmniSeer and Analyst Intent Prediction

Our primary objective is to develop and evaluate dynamic cognitive context models that support a comprehensive behavioral model, which captures and fuses many, possibly conflicting, behavioral motivations, such as user role, task, preferences, and interests. In particular, we are exploring models of analysts and their decision-making with both reactive and autonomous tools. At a high level the effort includes:

-How to capture an analyst's interests, preferences, and knowledge.

-How to assist an analyst's information seeking tasks.

-How to provide intelligent what-ifs, challenge user beliefs, and mitigate an analyst's bias.

-How to provide user model explanation via knowledge nuggets.

The primary components/services that the user model must provide to assist the analyst include:

-User Model Component Networks: Each user model (UM) of an analyst consists of three basic components: ***Interests*** (What is the analyst focusing on?), ***Context*** (Why is the analyst focused on the interests?), and ***Preferences*** (How does the analyst seek and view information?)

-User Model Loading: Used to initialize a user model at the start of an analyst's information-seeking session. For example, this recalls a prior model for a returning analyst; and selects a user model template for new analysts.

-User Model Updating: Updates the user model of the analyst based on observation of an analyst's information-seeking activities and feedback from the analyst and other services.

-User Model Query: Supports other services by providing information on analyst's current goals and interests; disseminates "knowledge nuggets" regarding an analyst's intentions. The term "query" here refers to the queries asked by other services such as value information or surprise detection.

-User Model Explanation: Provides detailed feedback to analysts and other services regarding decisions made by the user model and facilitates the exchange of knowledge among analysts.

-Analyst Query Modification: Analyst's information queries are proactively modified and new queries may be recommended to the analyst based on the current user model. The term "query" here refers to the queries issued by an analyst in an information-seeking task.

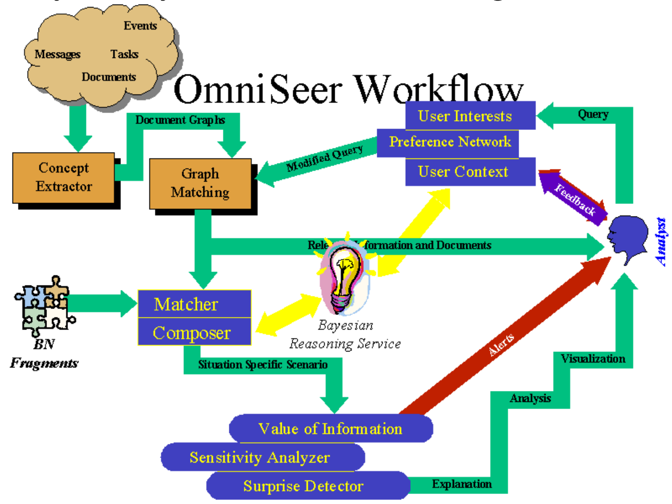

Figure 1: User model in OmniSeer system

The user model is integrated in the OmniSeer system as shown in Figure 1. We will illustrate how this model works by an example. Assume that an intelligence analyst is searching for information on weapons of mass destruction in Iraq and that he has been using the system for some time. When he starts the system, his user model is loaded by **User Model Loading** module which recalls prior information about his information seeking behaviors such as his interests in Iraqi Weapons of Mass Destruction. He then issues a query which will be processed through the **Analyst Query Modification** component to be modified according to what the system understands about the analyst's intent captured in **User Model Component Networks**. For example, the analyst asks about "Facilities for Weapons of Mass Destruction in Iraq". The modified query will contain WMD in Iraq and Biological Weapons in Iraq because his user model shows that WMD is an abbreviation for Weapons of Mass Destruction, and Biological Weapons is a kind of weapon of mass destruction. Next, the modified query will be matched against every document gathered from events, tasks, messages and documents circulated within the organization. Each of these documents is processed through a concept extractor component where the concepts and the relations between them are extracted (such as "mass destruction weapon *isa* weapon". The OmniSeer system will return those documents with matching scores greater than a predefined threshold set by the analyst. Interested readers are referred to (Santos et al 2003) for more detail. The analyst then goes through the returned results and indicates which documents are relevant. This relevant information will be fed to the **User Model Updating** component where each of the component networks will be updated correspondingly. The information contained in the user model, such as analyst's interests, can then be used to activate some cases in the BNFragments components where all possible cases are stored. In this case, for example, some scenarios regarding how Iraqi weapons of mass destruction are hidden from UN inspectors are activated. These cases will go through several other services/analysis processes in which information is valued, sensitivity analysis is performed and surprise factors are detected. These services/analysis processes can then alert the analyst and he/she can view the outputs of these analyses. Based on how the analyst assesses these, he will then provide feedback to the user model to update the user model accordingly.

Dynamic Cognitive User Modelling

At the heart of this effort is the user model component networks which provides our dynamic user modeling capabilities. The user model is situated between the analyst and the intelligent software tools which in OmniSeer, are tailored to the specific analyst's needs to better enhance and support analyst activities (Brown et al 1999; Santos et al. 2001). The user model continuously monitors analyst's activities and pro-actively predicts and explains analyst's goals and intentions. The results from intelligent software tools that support the analyst can also provide essential domain feedback and knowledge for the user model to better model the analyst with respect to his/her tasks and specific domains of operation. As the analyst performs his/her functions, the results from the user model will serve as input to the various software tools.

Messages communicated to and from the user model consist of knowledge nuggets. Knowledge nuggets are directed graphs which are probabilistic in nature, and contain concepts and relationships among the concepts. These include messages from services such as behavioral explanation, behavioral prediction, external feedback, etc. Typical knowledge nuggets are derived from the individual behavioral model as well as domain model information and ontological information. For example, if the analyst is conducting a document retrieval task, knowledge nuggets would be directed acyclic graph representing relevant documents [Santos et al. 1999; Nguyen et al.2000; Santos et al. 2001]:

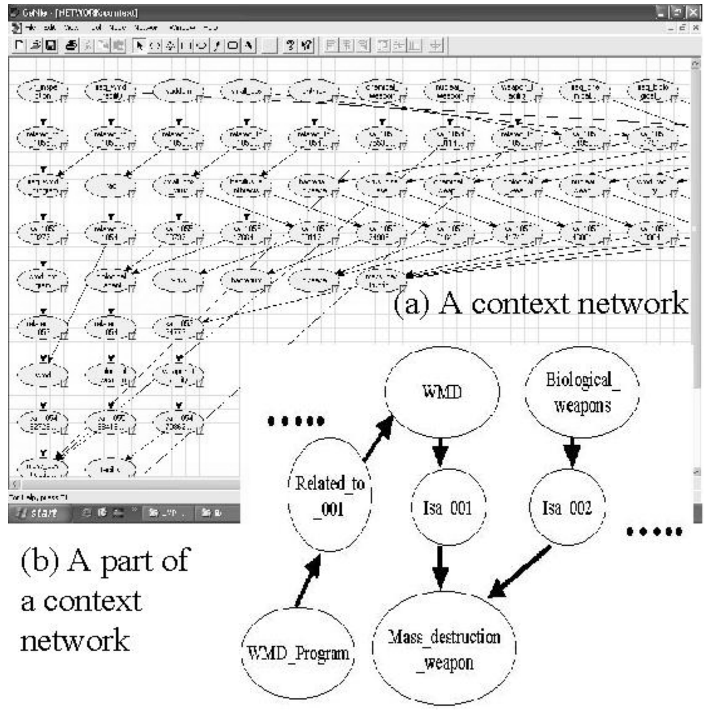

Figure 2: An example of context network

As we mentioned above, in order to provide a sufficiently fine-grained dynamic cognitive model within OmniSeer that effectively captures the analyst's goals and intention, we must construct a unified and dynamic model of the user's interests, preferences, and context. The user model also focuses on the interactions among them in a dynamic fashion. We capture the analyst's interests by keeping track of his/her topics of interests as well as how much the system thinks he/she is interested in these topics. This information is a result of a reasoning process over the context network which represents analyst's knowledge. As the analyst's interests are changing over time, we incorporate a fading function to make irrelevant interests fade away. Denote each interest concept as a and each level of interest for this concept as L(a). We compute $L(a)$ after each query by $L(a) = 0.5\times(L(a)+ n/m)$ in which n, m are number of relevant documents containing concept a and number of relevant documents, respectively. The user context network is constructed dynamically from the relevant documents. An example of a context network is shown in Figure 2. The user context is stored in a directed acyclic graph. Each node has a weight which indicates the user's level of interests in the concept represented by the node. When a node, for example "Biological weapons" or "WMD" in Figure 2, is set as evidence, other nodes will be activated and their weights will be computed based on how far it locates from the evidence node. The basic rule is that a node that is located far from the evidence node will be of less interest to the user.

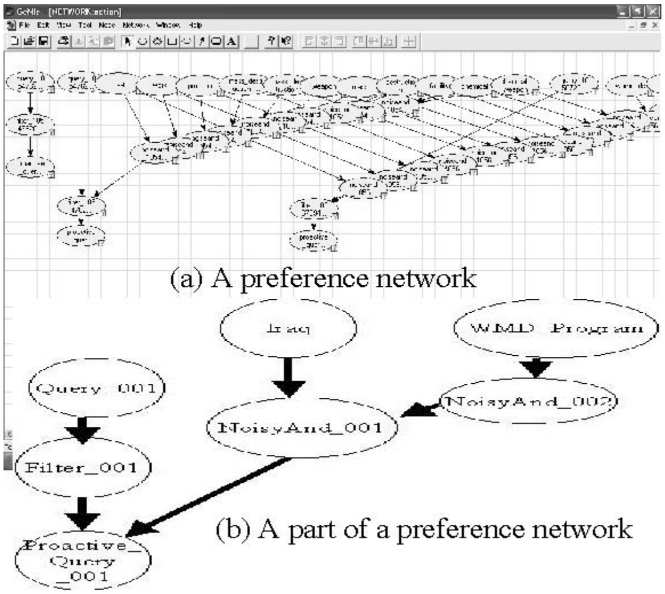

Figure 3: An example of preference network

Lastly comes the user preference network (Figure 3) which represents how the user wants to modify the original query based on previous queries and search behaviors. Depending on each tool (narrowing down or broadening up semantically the current query) is selected, the current query is modified appropriately.

In addition to using the information contained in these components to modify the analyst’s query, our focus is on deriving and learning the analyst’s working context or what we term, the user ontology by discovering the relations which are not explicitly defined in the documents or present in previous knowledge nuggets. This is done by gathering statistical information on linguistically related concepts. Most existing methods tacitly assume that all users share a single common ontology that they use in their information retrieval search. This implies that all analysts have the same level of understanding, organization, and beliefs as expressed in a common ontology. We posit that users understand information and how it interacts in their own individual fashion. This arises from many factors ranging from analyst experience and expertise to basic differences in user style and operation. This serves as a primary element in ultimately capturing the differences between users in their information seeking requirements and approaches.

Evaluation and Performance Metrics

Proper evaluation of the user model’s effectiveness is crucial for assessing and analyzing its usefulness in dealing with the massive data. To evaluate the user model’s effect in the OmniSeer system, we evaluate the accuracy of each component of the user model, accuracy of adaptation decision made by doing inference on user model, and the analyst’s satisfaction.

We evaluate the accuracy of each component in the user model by making sure that it is created and updated properly. For example, the Interests set has to capture what the analyst is currently focusing on; the context network has to correctly represent the analyst’s knowledge on certain topic; the relations being inserted into the context network has to make some senses; and the preference network has to truly reflect the analyst’s responses and gives reasonable suggestions on action being taken.

Secondly, we need to evaluate the accuracy of the adaptation decision made by using our user model. As our final goal is to use the user model to adaptively change the analyst’s queries based on his/her interests, context and preferences, it is very important to measure the impacts of the user modeling in assisting the analysts with their jobs. We need to validate the retrieval quality because a major part of the analyst’s job is to assess documents returned. We use the traditional recall and precision metrics (Salton and McGill 1983) to measure the retrieval quality and we compare these metrics of the system without user model against the one with it. We compute the average gain in precision and recall metrics every time the adaptation decision is made.

$$AveragePrecision(Recall)gain = \sum \frac{n-m}{\#adaptation\_made}$$

$$FrequencyOfAdpatation = \frac{\#adapted\_queries}{\#queries}$$

in which *n*, *m* are precision(recall) for the system running with and without user model respectively.

Lastly, in our user satisfaction evaluation, we focus on measuring the analyst’s knowledge gain versus his/her efforts in two main types of tasks which are retrieval task and assesses information from intelligent software tools in OmniSeer. We measure the analyst’s gain and analyst’s effort objectively and subjectively. Objectively, the analyst’s gain can be measured by how close he/she reaches a pre-set goal, and his/her efforts can be measured by how much time he/she spends on complete the task. Subjectively, the analyst’s gain is how he/she feels about the process of searching for certain information and doing analysis based on the searching results, how satisfied he/she is with the results from intelligent software tools in OmniSeer. And the analyst’s effort is how hard he/she thinks he/she has to try to finish the task.

Current Status and Future Work

Currently, we have a running system written in Java with 262 documents which are collected from public web sites with topics on Weapons of Mass Destruction. These documents have been used for the first test run of the system for retrieval purposes. Our current user model consists of all the three major components in our user model architecture, i.e. Interests, Preferences, and Context. Our model is powered by a Bayesian network engine (thanks to SMILE [1]). We believe that the user acts based on the goal that he/she wants to achieve and the environment in which the action is going to be carried out. The preference network captures the user's actions, the pre- and post-conditions of the environment, and gives suggestions to the analyst on the decision being made. Since the user is not working in a static environment, a Bayesian network model is appropriate here to capture the uncertain, causal relationship between the pre-conditions, goals and actions. This provides information on the user's knowledge and deeper motivations behind the goals upon which the individual is focused and illuminates connections between goals. The analyst can see from our system, at any time, the current status of the user model about his/her interests, preferences and context.

Even though the first version of our user model in OmniSeer is up and running, there are still a couple of issues to be addressed. First, the preference network and the context network will grow rapidly as the analyst keeps using the system, proper fading functions are necessary for both networks to ensure the efficiency of the whole system. Together with the fading process we now have for the user interests, this will help us to better reflect the process of shifting user interests, and changes in their search strategies. Second, we only consider relevant documents. We will also consider irrelevant documents indicated by the user to build the context and preference networks.

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[1] Smile is a Bayesian network library developed by Decision System Laboratory at University of Pittsburgh http://www.sis.pitt.edu/~genie/.

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