A Multi-agent Smart User Model for Cross-domain Recommender Systems

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ABSTRACT
This paper describes our approach to the next generation of open, distributed and heterogeneous recommender systems using *Smart User Models (SUM)*. Our work focuses on integrating multiple agent-based services based on a unique representation of the user in what is called a *Multi-agent Smart User Model*. Intelligent agents are used in order to obtain a single user model instead of having several versions of the same user spread throughout various services. A methodology has been developed using incremental aggregation of information, which favors non-intrusive behavior of the user model in order to determine objective, subjective and emotional user features.

Keywords
User modeling, cross-domain recommender systems, incremental learning, Smart User Models.

INTRODUCTION
The development of smart adaptive systems [1] is a cornerstone for personalizing services for the next generation of open, distributed and heterogeneous recommender systems. Agent Technology has contributed to the integration of services [11], but this integration has mainly been performed from a service point of view and is not usually centered on the user. Over the last years, our research group has been working with distributed services on the Internet using Agent Technology [9]. Currently we are dealing with challenges concerning: 1) the development of a unique, reusable and adaptive user model regarding objective, subjective and emotional user features ; 2) mapping user preferences from specific applications in several domains to this unique user model.

The next generation of recommender systems will have a moderately portable user model, which will interact with services in several open, distributed and heterogeneous environments to communicate user preferences in several domains. This requires the definition of the *Smart User Model (SUM)* and the corresponding infrastructure to integrate the user information across several services.

This paper is organized as follows: First, we define the *SUM* components. Second, we describe the mechanism for incremental aggregation of information in the *SUM*. Third, we explain the multi-agent framework in which it operates. The paper concludes with some contributions and plans for further research.

SMART USER MODEL
We have carried out work based on creating an adaptive user model [8] that should be able to pick up any type of objective, subjective or emotional user features (explicit or implicit). For this purpose, [4] defines the following *SUM* as the collection of attribute-value pairs that characterize the user. Where the collection of attribute-value pairs represents objective *(O)*, subjective *(S)* and emotional *(E)* features of the user. These sorts of features form three components in the user model: U^O, U^S and U^E. To summarize:

$$SUM_i = \left\langle U^O, U^S, U^E \right\rangle$$

This definition is useful in order to develop the mechanism for incremental aggregation of user information.

MAPPING USER FEATURES IN SEVERAL DOMAINS
From the *SUM* definition, we propose a methodology that can be applied to both learn user features from user information stored in recommender systems and deliver the user features to other recommender systems. In order to use the *SUM* in several application domains, we first define the user model *(UM)* in a given existing application domain $_i$ as follows:

$$UM_i = \left\{ AD_i, AI_i, AU_i \right\}$$

Where *AD* is the set of domain characteristics, *AI* is the set of user interests and *AU* is the set of socio-demographic features of the user *i* required by the application. Then, we establish a relationship between the *SUM* and the UM_i by means of a weighted graph, *G (SUM,* UM_i*)*. This graph connects *SUM* user features with particular user features

Workshop: Beyond Personalization 2005
IUI'05, January 9, 2005, San Diego, California, USA
http://www.cs.umn.edu/Research/GroupLens/beyond2005

required in the application domain UM_i. In particular, *SUM* emotional features modify the weights used on the graph according to the emotional state of the user (For more details see [4]). The methodology is based on the combination of machine learning methods: inductive methods (generalization) and deductive methods (specialization). For details on *SUM* management see ([5]). Therefore, instead of making the user fill out the *UM* of each application, we shift information from and to *UM*s of different domains according to the graphs that are defined by each application.

MULTI-AGENT FRAMEWORK

We exploit the synergy between the flexibility of multi-agent systems and the learning capabilities of smart adaptive systems in order to develop a *Multi-agent Smart User Model.* Our approach to user modeling includes the *interoperability* and *coordination* [3] of several autonomous agents with an incremental learning process based on Support Vector Machines [2]. Our framework of *Multi-agent Smart User Model* is able to provide information about the user when a new application in the environment requires it (reactivity); it is able to search for new applications in which the user could be interested (pro-activity); and it can interact with other user models to obtain recommendations in a collaborative way [7]. It is based on two groups of agents: The *Web Service Agents* group *(WSA)* and the *Ubiquitous Agents* group *(UA)*. The WSA provides autonomy capabilities regarding automatically finding services in a specific domain. The UA provides initialization, identification, interoperability, control, coordination, management and storage of the user preferences allowing flexible and autonomous human-agent interaction. The UA integrates a new generic and portable user model that works in accordance with [10] and our *SUM* definition. Coordination between the WSA and UA is established mainly by two mechanisms. First, the WSA requests personalized information from the UA in order to deal with the recommender systems in the environment. Second, the UA receives information from the WSA regarding the success or failure of the application interaction. This relevance feedback is used by the UA to learn about the user's interests, so the corresponding *SUM* and the graph *G (SUM, UMi)* of the application is updated.

CONCLUSIONS AND FUTURE WORK

The next generation of open environments will use *Smart User Models*, which include, among other attributes, the emotional factor [6] of the human being who they represent. The implementation of the *Multi-agent Smart User Model* makes transferring knowledge feasible (i.e. user preferences) from one domain, in which the user has already been profiled, to another, with which the user has never interacted before. The methodology developed can be used to learn user features from user information stored in recommender systems, and deliver the user features to other recommender systems. We are currently testing our hypothesis on the use of kernel-based methods [12] in order to construct automatic mapping of user features into the high-dimensional feature space of several domains. We think that in the near future our model will provide a rich workbench to test learning methods (acquisition and information shifts of user features) in open environments.

ACKNOWLEDGMENTS

This research project has been supported by the Spanish project DPI2001-2094-C03-01 of the Science and Technology Ministry (MCYT).

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