Smart User Models for Tourism:
A Holistic Approach for Personalised Tourism Services

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Abstract. This research focuses on the development of methodologies of tourism-related integration services. The authors define an adaptive Smart User Model and develop a methodology to build and manage this Smart User Model in the next generation of open environments in order to offer the user a variety of highly personalized services. In addition, the *Smart User Model* is able to capture any type of explicit or implicit information concerning the user from several domains in order to add to its knowledge of user preferences and interests.

Keywords: Recommender systems, smart user models**,** tourism services, user modelling, user models management.

1 Introduction

The important role of tourism in many regions of Europe has led to a growing number of tourism-related web sites through which users can directly access tourist information for themselves (Wöber, 2003). Recently, the tourism industry has discovered the advantage of providing personalised, *tailor-made* information to users since it increases the quality of the information presented to them and at the same time, reduces the total amount of data they receive (Rumetshofer, 2003). Personalisation, however, involves elaborating user models that require information from the user (Brusilovsky, 2001). Several machine learning techniques have been developed aimed at avoiding user disenchantment while still providing personalised information (Billsus and Pazzani, 1999; Burke, 2002; Montaner, 2003; McDonald and Ackerman, 2000). Particularly, collaborative systems try to take advantage of user communities to enrich knowledge on individual users (Ricci, et al., 2003) and user behaviour-based systems try to explain decision-making process in *open environments* such as Internet, the Worl-Wide-Web, Web-Services and Peer-to-Peer services (Dholakia and Bagozzi, 2001).

Such techniques, however, are constrained to a single domain. In the near future, mobile phones, smart cards and wireless devices will be used by more flexible travellers who will require all sorts of tourism services, anytime, anywhere and with no previous history of their use (Umlauft, et al., 2003; O'Brien & Burmeister, 2003). To meet this challenge, new personalisation mechanisms need to be developed to achieve full, ubiquitous computing that supplies users with the relevant service in the right place at the right time, while avoiding, as much as possible, bothering the user with initialisation procedures.

In this line, the authors have carried out exploratory work based on creating an adaptive user model, which aims to capture user information in a generic way: a *Smart User Model (SUM)*. The aim of the SUM is to make it feasible to transfer knowledge, i.e., user data, from one domain, in which the user has already been profiled, to another, with which the user has never before interacted.

For reasons of clarity, the authors focus on user models for recommender systems. The current scenario in recommender systems involves the interaction of *one user model* with *one recommender system* (see for example (Delgado and Davidson, 2002)). This means that there needs to be a number of user models, depending on the number of applications with which the user interacts (see Figure 1). In this scenario, users must provide personal information whenever they need a service from the different recommender systems. In addition, the user models in each recommender system do not share a common structure or vocabulary. These limitations mean that the portability of the user model and the possibility of sharing it in different domains are not yet feasible.

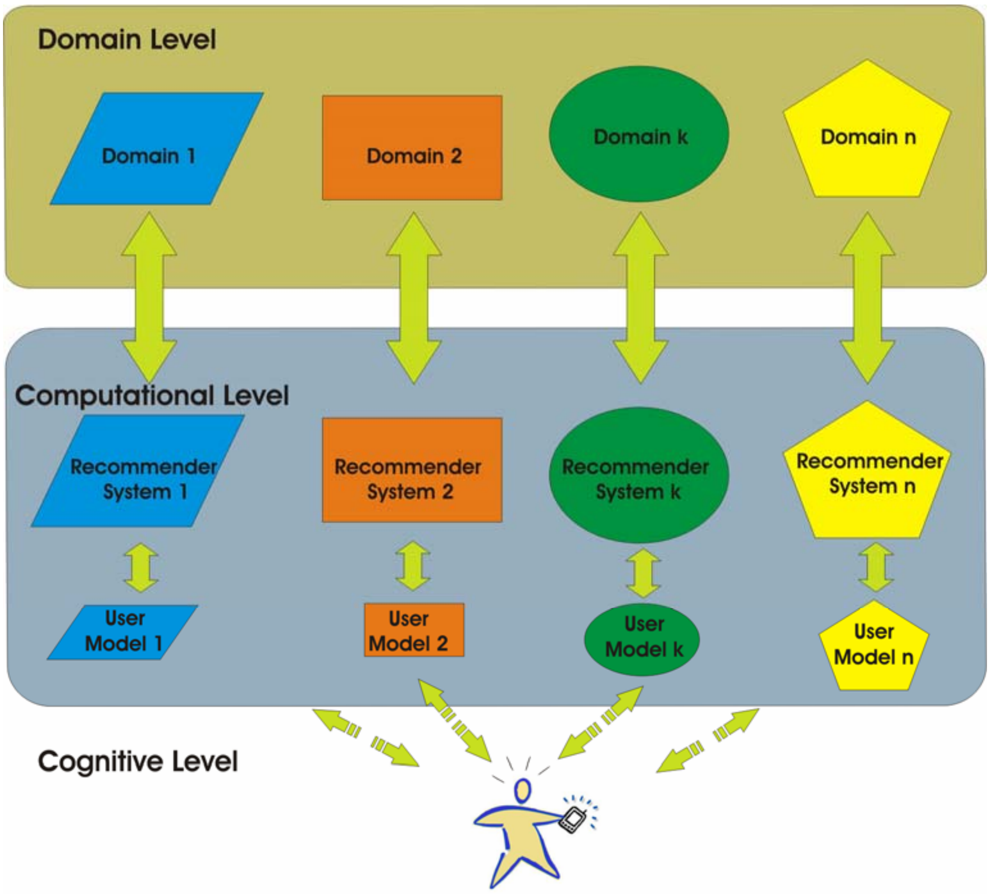

Figure 1. The current scenario in Recommender Systems.

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, using ontologies in order to communicate user preferences in several domains (see Figure 2).

For example, imagine that the user has interacted with a restaurant and a cinema recommender system in the past, but has never interacted with a marketing recommender system. On the one hand, the following user profile has been captured by the restaurant system:

- Objective information: Name: Juan Valdez; age: 37 years old; male, Spanish
- Preferences (subjective information): he likes attractive places; he likes imaginative cuisine; efficient service is not very important to him.

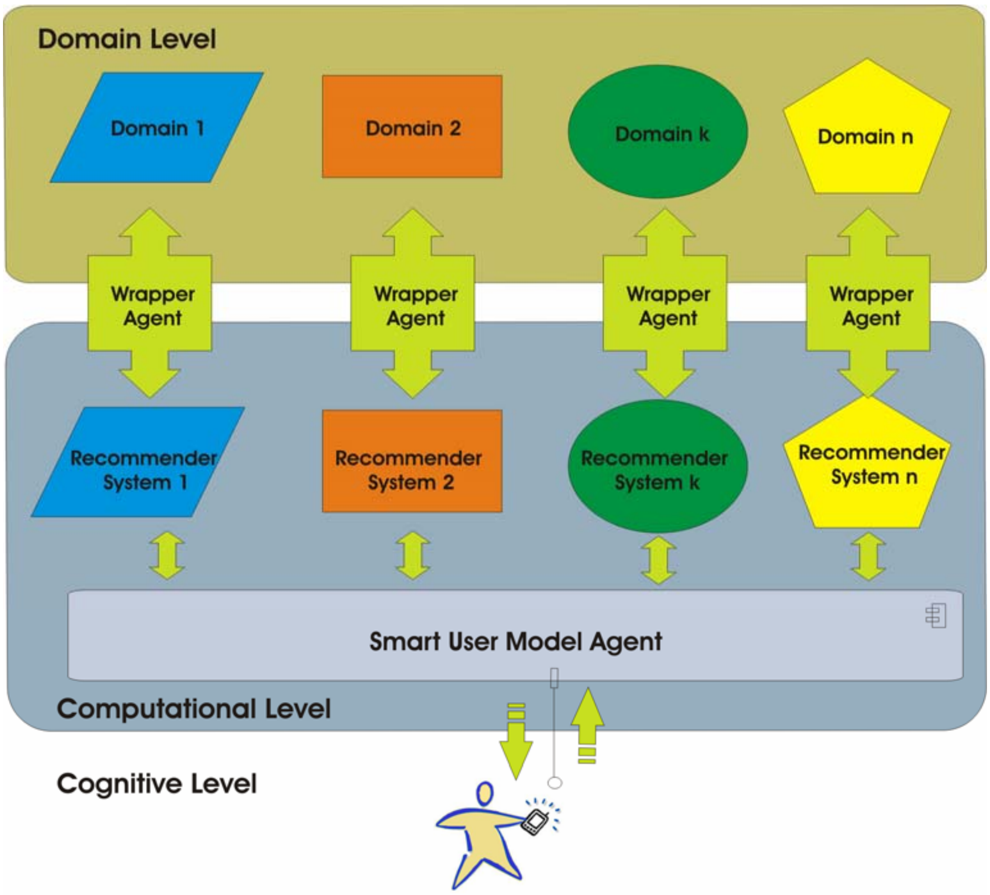

Figure 2. The Next Generation of Recommender Systems

On the other hand, the marketing system needs the following information to provide personalised recommendations: age, sex, income, nationality, and preferences on novel, useful products and creative and dynamic marketing campaigns. Is it possible to take the information known about Juan Valdez from the restaurant and movie domain in order to provide some recommendations in the marketing domain? Our aim is to provide an affirmative answer to this question by means of Smart User Models which are obtained by the methodology proposed and explained in this paper

This paper is organized as follow: first, related works in user modelling are presented. Then, the different representational levels of the user information are introduced and a possible definition of the *SUM* is given. In section 4, a methodology is proposed in stages in order to describe the *SUM* through formal representations. In section 5, the proposed technique is illustrated with an example. Finally, some conclusions are put forward regarding Smart User Models in the next generation of distributed and open environments, as well as in existing applications.

2 Related Work

User modelling is a wide research area in personalisation. The complex-process to model the user has been studied in research areas such as Adaptive Hypermedia (Kobsa, et. al, 2001), Educational Hypermedia (Tsiriga and Virvou, 2002), Human-Computer Interaction (Eisenstein and Rich; 2002), Kansei Engineering (Tomofumi, et. al, 2202), Software Engineering (Wooldridge and Jennings, 1999), Emotional Intelligence (Pickard, 1997; Kopecek, 2001) and Artificial Intelligence (Delgado, et.

al, 1999; Webb, et. al, 2001). In a previous work (González, et. al, 2003) we have implemented a holistic study of research on user models, in which we analyze the recent advances in all these disciplines. Case-base approach (Ha and Haddawy, 1998) has been used in preference elicitation and clustering implementing distance measures in movies recommender system. Collaborative Filtering (Herlocker and Konstan, 2001) is used in several kinds of task-focused recommender systems to provide content-independent suggestions based on both interests rating and item associations. Knowledge-based reasoning (Burke, 2000) implements a complementary approach to user modelling in recommender systems without requiring that the users make their ratings explicit. Interactive Learning Agents approach (Shearin and Lieberman, 2001) builds user profiles from continuous interaction with the user without need to store preferences in the user model and to use large data sets to learn particular interests and preferences of the user. More recently hybrid approaches has been implemented in recommender systems as multi-attribute utility theory (MAUT) (Bauer et. al, 2002) and Case-based methods (Ha and Haddawy, 1999; Ha, 2001) to make recommendations to decision makers. Other approaches have been developed applying Decision Theory to build software-tools for decision maker's preferences (Bhargava, et. al, 1999; Wöber et. al, 2000). The common current challenge to all of them arises in modelling the user in open, distributed, heterogeneous, large-scale and interconnected systems networks in where the interactions with the user can be dynamic in multiple domains. Our research is concerned in the development of user models with objective, subjective and emotional features of the user in those environments.

3 Representational Levels

In order to provide a formal definition of *Smart User Models* the authors distinguish three representational levels about the knowledge of the user: the Cognitive level, the Computational level and the Domain level (see Table 1).

The cognitive level relates the capability of perceiving, individual learning and developing through individual or social interaction with the environment. At this level the user perceives, stores, processes, and retrieves information. In terms of human personality, (Miller, 1991) propose three dimensions for the cognitive level:

a. Cognition : Thinking (knowing, understanding);

b. Affect : Emotion (attitudes, predispositions, emotions, feelings) and

c. Conation : Volition (intentions to act, reasons for doing).

This cognitive model recognizes that the mind receives information and manifests action through the body. Body can be considered in terms of biological or genetic influences, bodily functioning and overt behaviour or output. The model also recognizes there is a feedback loop between overt responses (or behaviour) and resulting stimuli from the environment. In summary, the cognitive level can be defined as *"the act or process of knowing including both awareness and judgment"* (Merriam Webster's Dictionary).

Table 1. Representational levels in the Smart User Models.

Cognitive Level (Human beings)	Computational Level (Machine)	Domain Level (Entity / Service)
Mental States	Programs / Agents	Composition
Mental representations (Features, thinking, understanding, knowing, attitudes, predispositions, emotions, feelings)	Data Structures / Ontologies (Classes, Instances, Attributes, Relations / Terms and Definitions, Axioms, Relationships)	Characteristics (Objects, properties)
+	+	+
Algorithms (Behaviours, Volition)	Computational Procedures (Methods/Communicative Acts, Interaction Protocols, Content Languages)	Organization (Operation)
= Cognition of objective, subjective and emotional features and behaviours of a user	= Running Programs / Agents acting on behalf of user	= Available Items, objects / Services in a domains with attributes

The aim is then to achieve an artificial cognitive representation of the user. For doing it at the computational level there are the set of data structures, attributes, its relations, axioms, mathematical formulations and methods that allow representing the cognitive information of the user into readable and comprehensible meta-data for a software information system.

The domain level is the particular environment in the real world in which the user is modelled. It is marked by specific characteristics and organization according to design goals of the software applications.

Following notation is given to represent formally the mental features of a user at the different levels.

3.1 Cognitive Level

Let be a user defined by his/her features and behaviours ***F***.

Let ***F*** be the ***space*** of **features** and **behaviours** of a user composed by three dimensions:

$$F = O \cup S \cup E$$

O is the finite set of objective attributes of user. These can be provided by the user or acquired from any database. Relate the name, age and socio-demographic information of the user.

$$O = \{o_1, o_2, o_3, \ldots, o_i, \ldots, o_n\}$$

S is the finite set of subjective attributes of user. These are the personal judgment that the user performs according to her/his impressions, feelings and opinions or an arbitrary expression of his/her private preferences. These features can only be acquired through user interaction with the external environment and the system.

$$S = \{s_1, s_2, s_3, \ldots, s_j, \ldots, s_m\}$$

E relates psychological traits and personality, such as joy, surprise, sadness, anger, disgust, etc. Emotional traits can be acquired through the Emotional Intelligence Test (González, et. al, 2002).

$$E = \{e_1, e_2, e_3, \ldots, e_k, \ldots, e_l\}$$

3.2 Computational Level

Let be ***L*** the ***set*** of ***attributes,*** which represent the *features,* and *behaviours* of a user, ***F***, at the computational level. ***O****,* ***S*** *and* ***E*** are then mapped at the computational level by the corresponding set of attributes:

$$A^O = \{a_1^O, a_2^O, a_3^O, ..., a_i^O, ..., a_n^O\}$$

$$A^S = \{a_1^S, a_2^S, a_3^S, ..., a_j^S, ..., a_m^S\}$$

$$A^E = \{a_1^E, a_2^E, a_3^E, ..., a_k^E, ..., a_\ell^E\}$$

Each attribute can take values in a given domain, using the following notation:

$$v_i^O = value(a_i^O)$$

$$v_j^S = value(a_j^S)$$

$$v_k^E = value(a_k^E)$$

Domains of objective attributes are easily to define, since they correspond to the typical ones that can found in a database. That is, strings for the name, integers for the age, and so on. Regarding subjective attributes, the representation of preferences and interest of the user is not a trivial issue. There are some previous works, as (Osgood et. al, 1957; Roberts, 1979; Valls and Torra, 1999; Zeynep, 2003) that deal with methods to measure the meaning of an object. In this line, based on the semantic differential method and the interval scales, the authors have defined the domain of each subjective attribute in the interval [0,1] based on the following set of labels {Very not, not, a little bit not, normal, a little bit, very, very much}. Table 2 shows the different intervals assigned to each label in the [0,1] interval. For the sake of extension, we are not detailing in this paper on how the semantic differential method is and we suggest the reader to consult the papers before above mentioned.

Finally, domains of emotional attributes are defined in the [0,1] interval according to a psychological-base method explained in (González, et.al, 2004).

Table 2. Labels and values of the perceptions about the user interests

Very Not	Not	A little bit Not	Normal	A little bit	Very	Very much
[0, 0.14)	(0.14, 0.28)	(0.28, 0.42)	(0.42, 0.57)	(0.57, 0.78)	(0.71, 0.85)	(0.85, 1]

With those set of attributes, A^O, A^S and A^E it is possible to define a *Smart User Model* as follow:

Definition 1: A *Smart User Model*, *SUM,* is the collection of attributes-value pairs that characterize at the user.

$$SUM = \left\langle \begin{array}{l} \left[\left(a_1^O, v_1^O\right), \left(a_2^O, v_2^O\right), \ldots, \left(a_i^O, v_i^O\right), \ldots, \left(a_n^O, v_n^O\right)\right], \\ \left[\left(a_1^S, v_1^S\right), \left(a_2^S, v_2^S\right), \ldots, \left(a_j^S, v_j^S\right), \ldots, \left(a_m^S, v_m^S\right)\right], \\ \left[\left(a_1^E, v_1^E\right), \left(a_2^E, v_2^E\right), \ldots, \left(a_k^E, v_k^E\right), \ldots, \left(a_\ell^E, v_\ell^E\right)\right] \end{array} \right\rangle$$

From the above definition, it is possible to distinguish the following partition:

$$\begin{aligned} U^O &= \left[\left(a_1^O, v_1^O\right), \left(a_2^O, v_2^O\right), \ldots, \left(a_i^O, v_i^O\right), \ldots, \left(a_n^O, v_n^O\right)\right] \\ U^S &= \left[\left(a_1^S, v_1^S\right), \left(a_2^S, v_2^S\right), \ldots, \left(a_j^S, v_j^S\right), \ldots, \left(a_m^S, v_m^S\right)\right] \\ U^E &= \left[\left(a_1^E, v_1^E\right), \left(a_2^E, v_2^E\right), \ldots, \left(a_k^E, v_k^E\right), \ldots, \left(a_\ell^E, v_\ell^E\right)\right] \end{aligned} \quad \textbf{(3.1)}$$

Then, we get the following alternative definition:

$$SUM = \langle U^O, U^S, U^E \rangle \qquad \textbf{(3.2)}$$

3.3 Domain Level

Let be ***D*** a set of attributes that define a given domain.

$$D = \{a_1, a_2, ..., a_h, ..., a_p\}$$

Let be $A^D \subset D$ the set of characteristics, properties and organization or operation of an item (object or service) in a given domain *D*.

$$A^D = \{a_1^D, a_2^D, ..., a_h^D, ..., a_p^D\}$$

Let be $A^I \subset D$ a set of interests of a user in particular objects or services in a domain *D*.

$$A^I = \{a_1^I, a_2^I, ..., a_i^I, ..., a_p^I\}$$

Let be A^U the socio-demographic features of the user in the domain *D*, normally introduced in a "login" procedure.

$$A^U = \{a_1^U, a_2^U, ..., a_k^U, ..., a_r^U\}$$

4 Smart User Model Management

From the *SUM* definition, the authors propose in this section a methodology to both, learn user features from user information stored in recommender systems and deliver the user features to other recommender systems. In this sense, they use the term "*known domain*" to specify domains in which the user has interacted with, and so the corresponding recommender system kept information about the user interests and preferences. Conversely, the authors call "*unknown domain*" the ones to which the user has never interacted with them. The methodology concerns objective and subjective features. Emotional features of the user are something more complex and require a different methodology. See (Nasoz, et al., 2003; González, 2003; El-Nasr, et al., 1999; Roseman, et al., 1990; Ortony, et al., 1988; Ekman, 1982) for preliminary approaches.

Then, our methodology is based on the following steps:

1. **Acquisition-generalization method.**

   Such method allows the information shift from a known domain to the *SUM*.

2. **Acquisition-specialization method.**

   For information transfer from the *SUM* to an unknown domain.

3. **Update method.**

   The authors use this method to change the *SUM* according to the results obtained by the recommender systems.

In the following sections, all methods are provided according to the objective and subjective attributes of the *SUM*.

4.1 Acquisition-generalization method

In this section, the authors propose a method to shift user information from existing applications to other ones, thanks to the *SUM*.

4.1.1 Acquisition-generalization method for objective attributes

In order to acquire the *SUM* features from existing user information in a given domain. The authors propose the development of a ρ^O graph. ρ^O is defined as a directed graph that relates the values of the socio-demographic attributes of the user, A^U, in the *Smart User Model (SUM).*

A directed graph is a tuple, *G = (V, E)* in which *V* = { $v_1, v_2, \ldots, v_i, \ldots, v_n$ } is a set of vertex or nodes; *E* is a set of edges or arcs, $E \subseteq V \times V$; so each $e_i \in E$ is $e_i(v_i, v_j)$ is the arc from v_i to v_j.

In the case of ρ^O, the vertex of graph are the attributes A^U and A^O, and the edges, $E \in A^U \times A^O$. So arcs define pairs that describe a binary relationship between the socio-demographic attributes and objective attributes from a user on a given domain, $(a_i^U \in A^U)$, to the ones at the *Smart User Model*, $(a_i^O \in A^O)$.

Regarding the set of objective attributes at SUM, A^O, they are generated as the union of the socio-demographic attributes of the user at the domain level, A^U. Thus, when there is only one single domain, it holds that: $A^O = A^U$

Successively, when there exists *n* domains, with *n* set of attributes regarding the socio-demographic attributes of the user, $A^{U_1},\dots,A^{U_n}$; the objective attributes at SUM are the following:

$$A^O = \bigcup_{i=1}^{n} A^{U_i}$$

Finally we want to stress that this generalisation procedure is not excepted from problems caused by synonymous, confusing and overlapping terms. We expect, however, that such problems will disappear in a near future with the use of tourism ontologies (see (Missikoff et. al, 2003)).

4.1.2 Acquisition-generalization method for subjective attributes

To shift the information contained in the *SUM* to a particular domain, the authors propose the use of a directed weighted graph, ρ^S. A directed weighted graph can be defined as a tuple *G = (V, E, W)* in which *V* = { $v_1, v_2, \dots, v_i, \dots, v_n$ } is a set of vertex or nodes; *E* is a set of weighted edges or arcs, $E \subseteq V \times V \times W$; so each $e_i \in E$ is $e_i(v_i, v_j, w_i)$ is the arc from v_i to v_j where its cost is $w_i \in W$. *W* = { $w_1, w_2, \dots, w_i, \dots, w_n$ } is a set of weights $w_i \in \Re$.

In the case of ρ^S the vertex are the attributes A^I and A^S , and the edges are defined in $A^I \times A^S$. So arcs define pairs that describe a binary relationship between the user interests-attributes and subjective attributes at the domain level, $(a_i^I \in A^I)$ and the ones at the *Smart User Model*, $(a_i^S \in A^S)$. Weights are computing according to the value of the attribute at the domain level. So,

$$w_i = normalized\_value\left(a_i^I\right) \quad \in [0,1] \qquad \textbf{(4.1)}$$

4.2 Acquisition-specialization method

In this section, the authors introduce a methodology to obtain the information of the *SUM* and project it to unknown domains.

4.2.1 Acquisition-specialization method for objective attributes

In order to acquire objective attributes, the authors propose to develop a φ^O graph. φ^O is defined also as a directed graph, *G = (V, E)*. In this case the vertex of graph are the attributes A^O and A^U, and the edges, $E \in A^O \times A^U$. So, arcs define pairs that describe a binary relationship between the objective attributes and socio-demographic attributes of the *Smart User Model* and the socio-demographic attributes at the domain level.

It is interesting to note, here, that the authors are not creating the attributes of the domain level (D in the formal definition), but the corresponding contents for the user at hand. Probably only part of the attributes of the domain level will be fulfilled, that is, the attributes that are known at the SUM: $A^U = A^O \cap D$. However, this partial information could be enough in order to start a recommendation process.

4.2.2 Acquisition-specialization method for subjective attributes

To shift preferences and interests of the user from the SUM to the domain level, a graph ρ^S is required. ρ^S, is defined as a directed weighted graph, in which each vertex is the subjective attributes in the *Smart User Model* (a_i^S) and the others vertex are the item-attributes of interest in the domain level with unknown values. Weights are computing according to the value of the attribute at the domain level. So,

$$w_i = normalized\_value\left(a_i^I\right) \qquad \in [0,1] \qquad \textbf{(4.2)}$$

Regarding subjective attributes, some problems arise when two or more arrows from attributes at the SUM, a_i^S, a_j^S converge to a single attribute, a_k^I, at the domain level. In such a situation, a multi-criteria decision process should be established to determine the value of a_k^I. One of the most simplistic approaches could be to assign to a_k^I the average of the values of a_i^S, a_j^S. However, average measures tend to neutralize the meaning of the attributes. For avoiding such situation, the authors have chosen as a starting point the maximum value. As a future work, they need to explore alternative measures (see for example (Valls and Torra, 2002)).

4.3 Update method

In this section, the authors introduce a methodology for to update the information of the *SUM* accordingly to the user interaction with a given recommender system.

4.3.1 Update method for objective attributes

Objective attributes represent socio-demographic features that are measurable with a certain degree of certainty. So the only change expected from the system is due to new attributes values. In this case, the new values are then updated.

4.3.2 Update method for subjective attributes

The feedback of the system can be used to update the weight values of the graph involved in the recommendation process.

So, each weight of the corresponding relationship between interest-attributes (domain level) and subjective attributes (computational level) are rewarded or punished according to the following equation.

$$w_i = \varphi w_i + (1 - \varphi) * Feedback \qquad \textbf{(4.3)}$$

Feedback is a value between [0, 1] and φ is a parameter of the system evolution dynamics. The authors have experience in the use of this update method in a recommender environment (Montaner, et. al, 2002).

This update process is quite important for subjective attributes due to the semantic transfer of preferences from a domain to another. That is to say, it could be the case that the value for "attractive" has different meaning in a restaurant than from a "movie" environment. Then, if the attractive value is acquired from the restaurant domain, and lead to unsuccessful results at the movie environment, the successive application of the update method would tune to the appropriate value for the attractive attribute at the movie application (see for example (Yu, et. al, 2003) for other studies on feature weighting).

5 Case Study

In this section, the authors illustrate with an example on city tourism the methodology proposed. The authors will assume that the user Juan Valdez has interacted with a restaurant and a movies recommender systems. The authors want to acquire a *SUM* and use it in another domain, namely the *marketing domain*. In this section, they present the cases study to illustrate how the formal definitions and methods can be used in order to develop a *Smart User Model*. For a better understanding of the example, the authors have distinguished three cases: Restaurants is one single known domain; movies is also a known domain and marketing is an unknown domain.

5.1 Objective Features

In this section, the authors will focus on the methods for objective features (see Figure 3).

Case a. Generalization from the restaurant domain

In the restaurant domain, the following socio-demographic features have been defined:

$$A^U = \{age, sex, country, region, city\}$$

Then, ρ^O_{a1} is defined from the restaurants domain to the *SUM* as follow:

$$\rho^O_{a1} = \{(\text{age, age}), (\text{sex, sex}), (\text{country, country}), (\text{region, region}), (\text{city, city})\}$$

Assume that, Juan Valdez (*JV*), has the following profile at the domain level:

value (age) = 57

value (sex) = male

value (country) = spain

value (region) = Catalonia

value (city) = Girona

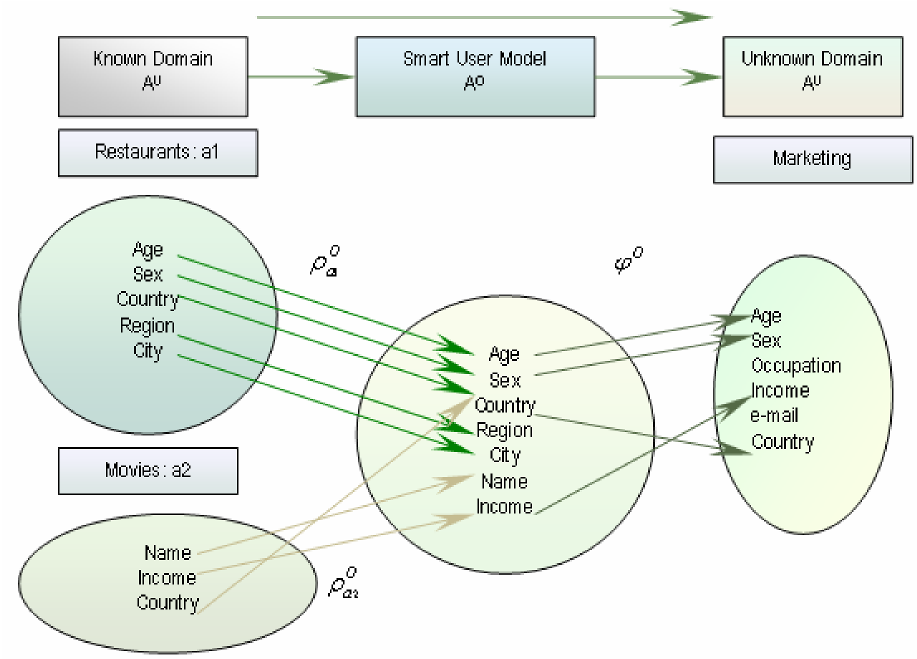

Figure 3. Graphical representation of the weighted graph ρ^O and φ^O for objectives attributes of the Smart User Model

The authors use A_{JV}^{U} to note all values of Juan Valdez at the domain level:

A_{JV}^{U} = {57, male, Spain, Catalonia, Girona}

According to ρ_{a1}^{O} the *SUM* acquired from the domain level for Juan Valdez is then following:

$$U^{O} = \left[(age, 57), (sex, male), (country, Spain), (region, Catalonia), (city, Girona)\right]$$

Case b. Specialization to the marketing domain.

Let's suppose the following socio-demographic features are defined in the unknown domain (marketing):

$$A^{U} = (age, sex, occupation, income, e\text{-}mail, country)$$

At the *SUM*, the current information of the user, A^{O}, is the following:

$$A^{O} = \{age, sex, country, region, city\}$$

The corresponding graph φ^{O} is the following:

$$\varphi^{O} = \{(age, age), (sex, sex), (country, country)\}$$

In our example, Juan Valdez has the following values at the *SUM*:

$$U^O = \left[(age,57),(sex,male),(country,Spain),(region,Catalonia),(city,Girona)\right]$$

Since Juan Valdez has never interacted with the marketing domain, no values for each attributes are known for him. After applying φ^O for Juan Valdez, we get the following values at the marketing domain.

value (age) = 57

value (sex) = male

value (occupation) = nil

value (income) = nil

value (e-mail) = nil

value (country) = Spain

Case c. Generalization from the restaurants and movies domain

In the example, the authors have two known domains (restaurants and movies) with the following user demographics attributes:

A_{a1}^U = *{age, sex, country, region, city}* (Restaurants domain)

A_{a2}^U = *{name, income, country}* (Movies domain)

Then, the final set of objective attributes at the *SUM* is:

$$A^O = \{name, age, sex, income, country, region, city\}$$

According to these sets of attributes A^U_{a1}, A^U_{a2} and A^O, the following graphs are defined:

$$\rho^O_{a1} = \{(\text{age, age}), (\text{sex, sex}), (\text{country, country}), (\text{region, region,}), (\text{city, city,})\}$$

$$\rho^O_{a2} = \{(\text{name, name}), (\text{income, income}), (\text{country, country})\}$$

In our example, Juan Valdez, has the following attributes in the two domains:

$A^U_{JVa1} = \{57, \text{male, Spain, Catalonia, Girona}\}$

$A^U_{JVa2} = \{\text{Juan Valdez}, 36000, \text{Spain}\}$

So, at the *SUM* we get:

$$U^O = \begin{Bmatrix} (name, JuanValdez), (age, 57), (sex, male), (income, 36000), \\ (country, Spain), (region, Catalonia), (city, Girona) \end{Bmatrix}$$

5.2 Subjective features

In this section, the authors apply the methodology for dealing with subjective features (see Figure 4).

Case a. Generalization from the restaurants domain

In our example, suppose that the restaurants recommender system has the following interests' attributes to capture user interests:

$$A^I = \{attractive\ place,\ imaginative\ cuisine,\ efficient\ service\}$$

The corresponding attributes at the *SUM* are A^S = *{attractive, imaginative, efficient}*

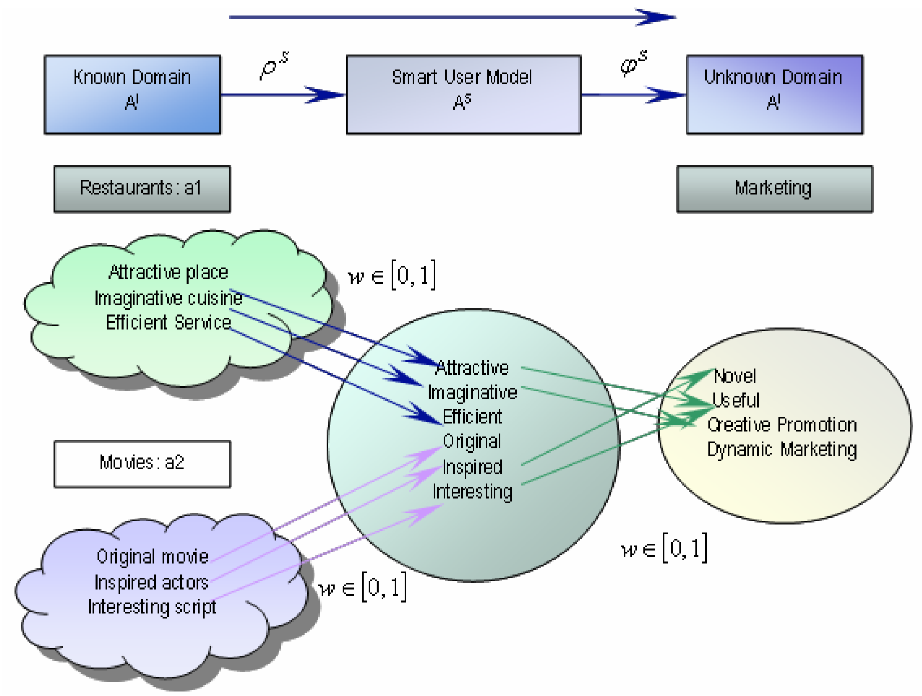

Figure 4. Graphical representation of the weighted graph ρ^S and φ^S for subjective attributes of the Smart User Model

Our user, Juan Valdez, has been modelled according to these initials interests with the following values:

value (attractive-place) = 0.7

value (imaginative-cuisine) = 0.8

value (efficient-service) = 0.1

In a summarized form:

$$A_{JV}^{I} = \{0.7, 0.8, 0.1\}$$

The corresponding graph, ρ^{S} is the following:

ρ_{JV}^{S} = {(attractive place, attractive, 0.7), (imaginative cuisine, imaginative, 0.8), (efficient service, efficient, 0.1)}.

Then, the component U^{S} of the Smart User Model will be:

$$U^{S} = \{(attractive, 0.7), (imaginative, 0.8), (efficient, 0.1)\}$$

Case b. Specialization to the marketing domain

Initially the characteristics of the *SUM*, A^{S}, are the following:

A^{S} = *{attractive, imaginative, efficient}*

At the domain level, the marketing recommender system expects information of the user regarding the following interests:

A^{I} = {novel product/service, useful, creative promotion, dynamic market}.

For the user Juan Valdez, these interests are unknown.

The graph corresponding to the shift of information from the *SUM* to the marketing domain according to ρ^S is the following:

ρ^S_{JV} = {(attractive, useful, 0.7), (Imaginative, Creative, 0.8), (Inspired, Novel, 0), (Interesting, useful, 0)}.

Then, the profile of Juan Valdez contains the following information:

$$A^I_{JV} = \{0.7, 0.8, 0, 0\}$$

Case c. Generalization from the restaurants and movies domain

In the example, the following sets of subjective characteristics in the restaurants and the movie domains are correspondingly considered:

$A^I_{a_1}$ = *{attractive place, imaginative cuisine, efficient service}*

$A^I_{a_2}$ = *{original movie, inspired actors, interesting script}*

The subjective features at the *SUM* are the following:

A^S = *{attractive, imaginative, efficient, original, inspired, interesting}*

The corresponding graphs are:

ρ_{a1}^{S} = *{(attractive place, attractive, 0.7), (imaginative cuisine, imaginative, 0.8), (efficient service, efficient, 0.1)}*

ρ_{a2}^{S} = *{(original movie, original, 0.8), (inspired actors, inspired, 0.5), (interesting script, interesting, 0.5)}*

Table 3. Values of subjective attributes of the Smart User Model of Juan Valdez in his Smart User Model.

A_{a1}^{I}		A_{a2}^{I}		A^{S}	
Attributes	Values	Attributes	Values	Attributes	Values
Attractive place	0.7	original movie	0.8	Attractive place	0.7
Imaginative cuisine	0.8	inspired actors	0.5	Imaginative cuisine	0.8
Efficient service	0.1	interesting script	0.5	Efficient service	0.1
				original movie	0.8
				inspired actors	0.5
				interesting script	0.5

In the example, the authors have the following information of Juan Valdez at the restaurant and movie domains (see Table 3):

$$A_{JVa_1}^{I} = \{0.7, 0.8, 0.1\}$$

$$A_{JVa_2}^{I} = \{0.8, 0.5, 0.5\}$$

The values of Juan Valdez *Smart User Model* from two domains are the following:

$$U_{JV}^{S} = \{(attractive, 0.7), (\text{imaginative}, 0.8), (\text{efficient}, 0.1), (\text{original}, 0.8), (\text{inspired}, 0.5), (\text{interesting}, 0.5)\}$$

6 Conclusions

In this paper, a new approach towards defining a Smart User Model is presented, with the aim of obtaining personalized tourism services that take advantage of previous information known about the user. Then, a methodology is described, designed and developed by the authors, for obtaining the user features for the Smart User Model. This methodology can be used to learn user features from user information stored in recommender systems as well as deliver the user features to other recommender systems. The methodology is illustrated with case studies that represent the objective and subjective characteristics of the user model. The methodology proposed allows the information about the user to be utilized in an unknown domain. An important advance in *on-the-move* tourism information is, when arriving at an unknown place, the user is able to receive relevant, personalized information from an unknown recommender system, thanks to his/her Smart User Model (SUM). Finally, it is important to note the possible correlation of this work with research on context-aware user models. Knowledge of the current situation of a user, combined with the knowledge provided by his/her Smart User Model may provide some remarkable results in the field of recommenders systems for tourism, in line of the work started by (Console, et al., 2002).

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10 Figures List

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