Personalized Recommendation of TV Programs*

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Abstract. This paper presents the user modeling and recommendation techniques applied in Personal Program Guide (PPG), a system generating personalized Electronic Program Guides for digital TV. The PPG recommends TV programs by relying on the integration of heterogeneous user modeling techniques.

1. Introduction

The advent of Internet and Word Wide Web makes now available to the users a large amount of information, products and services. Therefore, users get "lost in the hyperspace" and recommendation techniques [15] are often presented as a solution to the information overload problem by helping the users to filter relevant items on the basis of their needs and preferences. Recommender systems address these problems by applying artificial intelligence techniques such as user modeling, content-based and collaborative filtering, case-based reasoning, etc. With the recent expansion of TV content, digital TV networks and broadband, smarter TV entertainment is needed as well. As there are several hundreds of available programs every day, users need to easily find the interesting ones and watch such programs at the preferred time of day. Electronic Program Guides (EPGs) should recommend personalized listings, but they should also be deeply integrated in the TV appliance, in order to facilitate the access to the user's digital archive. For details, see [3].

This paper presents Personal Program Guide, a user-adaptive EPG that tailors the recommendation of TV programs to the viewer's interests, taking several factors into account. The PPG captures an individual model for each registered user and employs

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it to generate an EPG whose content and layout are tailored to the user watching TV[1]. The personalized recommendation of programs is based on the integration of user modeling techniques relying on explicit user preferences, stereotypical information about TV viewer preferences, and the unobtrusive observation of the user's viewing habits. As the PPG has been designed to run within a Set-Top box, the user's behavior can be continuously monitored, in contrast to the Web-based EPGs, which can only track the interaction while the user browses them. In particular, we preferred to focus on the observation of real user's behavior and to implement the PPG on the client-side. Basing the system on a server-side architecture would support the application of social recommendation techniques, such as collaborative filtering, but would waste the rich information coming from the direct observation of the user's behavior.

The rest of this paper is organized as follows. Section 2 gives an overview of the facilities offered by the system, Section 3 sketches the system architecture and then faces with the management of the sources of information about the users, Section 4 discusses the recommendations of TV programs, Section 5 describes the results of an evaluation, Section 6 presents related works and Section 7 concludes the paper.

2. Overview of the facilities offered by the system

The PPG acts as a personal assistant offering advanced TV services. The PPG is designed for a set-top box, but it is currently implemented in a simulator running on desktop environments for demonstration purposes. In order to make our description more concrete, we will use an example of the GUI of this prototype: see Figure 1.

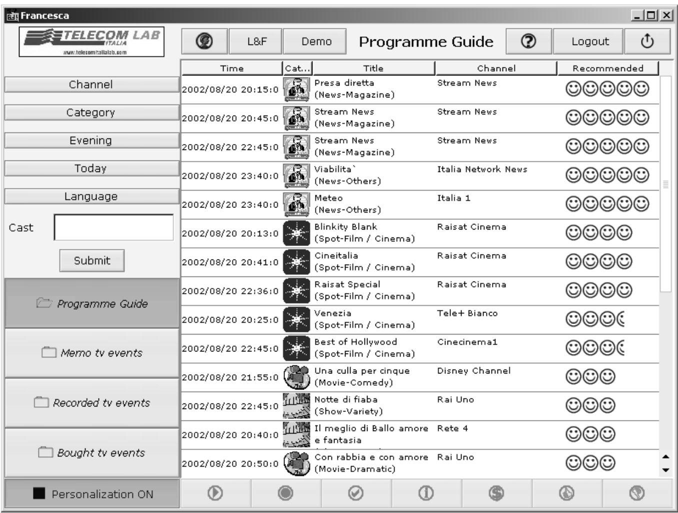

Figure 1. Personal Program Guide: PC simulator main window

[1] At the current stage, we have focused on the personalization of the EPG to individual TV viewers. The management of household viewing preferences is part of our future work.

The system offers advanced facilities for browsing the TV events: programs can be searched by channel, category, viewing time, etc.. Moreover, the user may ask for details about a program (e.g., cast, content description), record it, ask to be advised when the transmission of the program starts (memo), and so forth. The archived programs are retrieved by means of functions that enable the user to get the list of programs she has asked to be alerted about (Memo TV events button), she has recorded (Recorded TV Events), or she has bought (Bought TV Events). By default, the PPG works in personalized mode (Personalization ON): the less suitable programs are filtered out and the most promising ones are shown at the top of the recommendation list. The recommendation degree of a program is represented by a list of smiling faces close to the program description, in order to make the ranking information independent of the visualization criterion (time, channel, etc.). The personalization facility can be switched off by the user.

3. Sketch of the system architecture and management of the information about the user

The general architecture of the PPG and its main components are reported in Fig. 2. In particular, the Recommendation Module makes use of the information about TV programs and preferences of the users (managed by the UMC Manager).

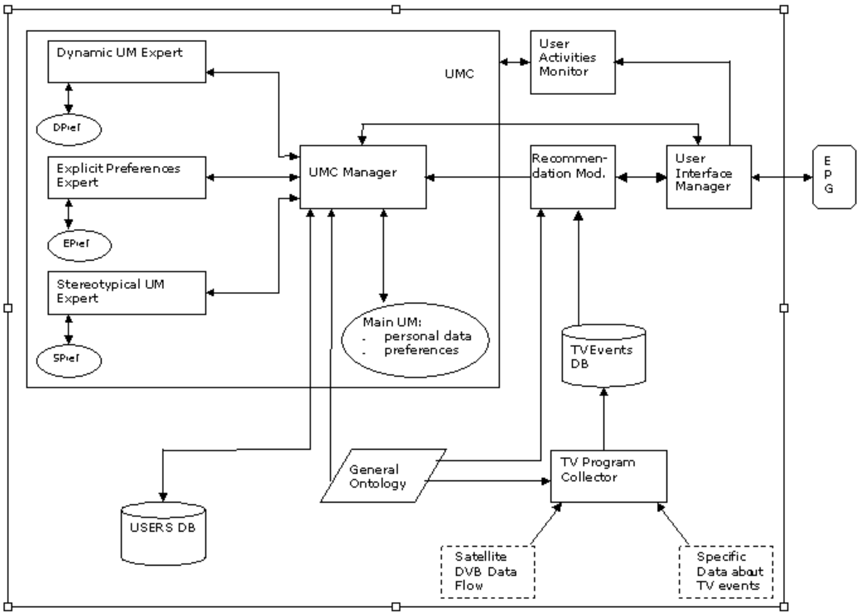

Figure 2: Architecture of the Personal Program Guide

The representation of TV programs is an extension of the Digital Video Broadcasting standard [8][2]. Each program is described by a set of fields describing data such as the starting time of the program, the transmission channel and the stream content (video, audio or data). The descriptor also includes one or more program categories representing the program content and format: e.g., Movie, Serial, News; see [2]. The program categories are organized in a taxonomy, the General Ontology, which includes several broad categories, such as Serial, and specializes such categories into more specific ones, such as Soap Opera, Science Fiction Serial, etc.

The management of the user model is aimed at achieving a precise description of her interests and viewing preferences, during different times of day (and weekdays). In the design of the user model (UM), we considered the following information:

- *Explicit preferences* for categories of TV programs (e.g., movies, documentaries, etc.) that the user may want to notify the system about.
- The *estimates on the viewing preferences* for the program categories (related to the number of programs the user watches, for each category).
- *Socio-demographic information*, such as her age, occupation, and so forth.
- Information about the user's general *interests and hobbies*.
- *Prior information about the preferences of stereotypical classes of TV viewers*.

Such different types of information provide multiple points of view on the user, useful for personalization, but require a separate information management. To this purpose, we have designed the User Modeling Component of the PPG as an agent that exploits three specialized user modeling modules (Explicit Preferences Expert, Stereotypical UM Expert, Dynamic UM Expert), each one managing a separate user model that reflects the viewpoint of the module (see Figure 2):

- The *Explicit User Model* stores the whole information elicited from the user in an explicit way: her personal data, interests, and preferences for TV program categories.
- The *Stereotypical User Model* stores the prediction on the user's preferences inferred by exploiting general information about TV viewer categories.
- The *Dynamic User Model* stores the system's estimates on the user's preferences, as observed by analyzing the individual user's viewing behavior .

Each expert manages a different TV program ontology depending on the information about user preferences available to the expert. Then, mapping rules are exploited to relate the different TV program characterizations to the categories of the General Ontology.

The User Modeling Component (UMC) maintains a Main User Model as a synthesis of such views, used by the system to personalize the interaction with the TV viewer. The UMC integrates the predictions provided by the experts into the Main User Model by taking the experts' confidence in the predictions into account (based on the estimation of the quality of the data used to generate the prediction). For space reasons, we skip the description of the Explicit User Model, which merely manages in a direct way the explicit user's preferences (and interests), and we focus on the other two user models, where inference mechanisms play a major role.

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[2] The DVB has been defined at the international level to specify global standards for the global delivery of digital television and data services.

3.1. The Stereotypical User Model

We used the Sinottica lifestyle study conducted by Eurisko data analyzers [9] as basis for the specification of characteristics and preferences of stereotypical TV viewer classes. Since the Eurisko survey relates homogeneous group of users and their corresponding interests and preferences, we structured the stereotypes in two parts: *i)* classification data characterizing the individuals of the represented stereotype, and *ii)* prediction part, containing the typical preferences of such individuals. Regarding the prediction part of stereotypes, we further analyzed a survey on the exposure to the TV, made by Eurisko and Auditel [4], which measures the audience of each lifestyles class. For more details about the knowledge engineering approach applied to collect and to process all the gathered data, see [10]. We defined a *Stereotype Ontology* defining the TV program categories to be considered as far as the stereotypical preferences are concerned. Mapping rules relate the preferences of the Stereotype Ontology to those ones of the General Ontology. The representation of the stereotypes is the one adopted in the SeTA system [1]; see the Housewife lifestyle in Fig. 3:

Classification data

Age *[personal data]*:	*Importance*: 1, *Values*: (< 15, 0) (15/24, 0) (25/34, 0) (35/44, 0.5) (45/54, 0.5) (55/64, 0) (> 64, 0)
Gender *[personal data]*	*Importance*: 1, *Values*: (male, 0) (female, 1.0)
Books*[interest]*:	*Importance*: 0.6, *Values*: (low, 0.8) (medium, 0.2) (high, 0)

Prediction part

movies-sentimental, Interest degree: 1; *serial-soap*, Interest d.: 1; *TV news* Interest d. : 0,2; *fashion programs*, Interest d.: 0,5; *cooking program,* Interest d.: 1, etc;

Figure 3: The “Housewife” stereotype

Each classification datum (socio-demographic feature, user interest) is represented as a slot with three facets: the *Feature Name*, the *Importance* (relevance of the feature to the description of the stereotype) and the *Values* (a frequency distribution on the values of the feature). For instance, the interest for *Books* has medium importance to the characterization of the users of the “Housewife” class (Importance is 0.6). Moreover, 80% of the “housewives” have low interest in reading books (frequency is 0.8); some have medium interest (0.2), but no one is highly interested in this activity.

The slots in the *prediction part* describe the preferences (for categories of the Stereotype Ontology) of the typical user belonging to the represented stereotype. A prediction slot is represented as follows: the *Program category* specifies the TV program category. The *Interest degree* represents the user’s interest in the category and takes values in [0,1], where 0 denotes lack of interest and 1 is the maximum interest. E.g., the *Housewife* really likes sentimental movies, soap opera and cooking programs; she moderately likes fashion programs and does not like TV news.

To estimate the user preferences, the Stereotypical UM Expert first classifies the user with respect to the stereotypical TV viewer classes. This is aimed at estimating which lifestyle descriptions are best suited to predict her preferences. The classification is performed by matching the user’s classification data with the stereotypical descriptions, according to the approach described in [1]. The result of the classification is a *degree of matching* with respect to each stereotype: this is a number in [0, 1], where 1 denotes perfect matching (the user data perfectly match the classification of a stereotype), while 0 denotes complete mismatch.[3]

Preferences for TV program categories		Degrees of matching with stereotypes	
Movie-All 0.65	conf: 0.43[4]	Colleagues	0.34
Movie-Sentimental 0.65	conf: 0.43	Engaged women	0.24
Movie-Comedy 0.65	conf: 0.43	Refined women	0.26
Movie-Detective 0.65	conf: 0.43	Dolphins	0.16
News All 0.65	conf: 0.43		
Serial Fiction 0.65	conf: 0.43		

Figure 4– Portion of Francesca's Stereotypical User Model

Given the user's stereotypical classification, the predictions on the user's preferences (Spref in Fig. 2) are estimated by taking the contribution of each stereotype into account, proportionally to the degree of matching associated to the stereotype. Let's consider a program category C and the stereotypes $\{S_1, \ldots, S_n\}$. The user's degree of interest in C (*Interest_C*) is evaluated by means of the following weighted sum:

$$Interest\_C = \Sigma_{i=1..n}\, DM_{Si} * Interest\_C_{Si}$$

$Interest\_C_{Si}$ is the degree of interest in C predicted by a stereotype S_i and DM_{Si} is the degree of matching between the classification data of the user and S_i. Fig. 3 shows the classification of a user Francesca and the stereotypical predictions on her preferences.

3.1.1. Confidence in the stereotypical predictions

The confidence in the stereotypical predictions depends on the confidence in the user classification that, in turn, depends on the amount of information about the user available at classification time and on "how stereotypical" is the user.

Confidence in the user classification with respect to a stereotype. The user's degree of matching with respect to a stereotype S is considered reliable if it is based on complete information about her classification data. The confidence in the classification is thus evaluated by considering the minimum and maximum degrees of matching the user might receive, if complete information about her were available:

- The lower bound of the degree of matching (DM_{min}) is evaluated by pessimistically assuming that, for each classification datum she has not specified, the user matches the value(s) less compatible with the stereotype. For instance, several values of Age in Housewife have a compatibility equal to 0 (see Fig. 3). Thus, the lower bound of the compatibility of Age is 0.

[3] For each datum F (e.g., "Age"), the suitability of the stereotype S is captured by a *compatibility value*, evaluated by matching the value v of F specified by the user (e.g., "35/44") with the corresponding datum in S. This match depends on the frequency of users belonging to S fitting the v value (e.g., 50% "housewives" are between 35 and 44) and on the importance of F in S. The *degree of matching* of the user with respect to the stereotype is then evaluated by combining the compatibility values of her classification data by means of a fuzzy AND operation; see [1] for details.

[4] This confidence derives from the confidence in stereotypical classification. The confidence values are the same because they correspond to program categories fully specified by the stereotypes. Other preferences, not shown in the figure, have lower confidence (0 for the preferences not specified by the stereotypes).

- The upper bound (DM_{max}) is evaluated by optimistically assuming that, for each missing classification datum, the user matches the most compatible value (0.5 for Age in Housewife, see Figure 2).

The lower and upper bounds define the interval of admissible values for the matching degree (*DM*), given the user data: $DM_{min} \leq DM \leq DM_{max}$. The larger is the interval the lower is the confidence in the classification. Thus, the confidence can be evaluated as:

$$conf_S = 1 - (DM_{max} - DM_{min} / \Delta_{max})$$

where Δ_{max} is the maximum distance between DM_{max} and DM_{min} and corresponds to the case where no classification datum is set.

Confidence in the predictions on the user's preferences. To evaluate the confidence in the predictions on the user's preferences, an overall assessment of the quality of the user classification is needed, which takes all the stereotypes into account. We noticed that the estimates on the user preferences are accurate if she matches few stereotypes, while the predictions downgrade if she loosely matches many stereotypes. Thus, we evaluate such confidence by combining the average confidence in the stereotypical classification ($Conf_{stereotypes}$) with an evaluation of its focalization degree (*Focus*).

$$StereotypicaExpertConfidence = Conf_{stereotypes} * Focus$$

The focalization degree is derived from the evaluation of Shannon's entropy on the degree of matching of the stereotypes. Suppose that the $\{S_1, \ldots, S_n\}$ stereotypes receive the following matching degrees $\{DM_1, \ldots, DM_n\}$. Then, the entropy is:

$$Entropy = \sum_{i=1..n} - DM_i * \log_2 DM_i$$

As the number of stereotypes is fixed, the entropy may be normalized in [0,1], therefore obtaining a normalized entropy *normEntropy*. The focalization degree is:

$$Focus = 1 - normEntropy$$

The focalization degree is 0 when the entropy is maximum, i.e., the classification is extremely uncertain. In contrast, when a single stereotype matches the user, the focalization degree is 1. In turn, the confidence in the prediction is high when the classification relies on complete information about the user and is very focused.

3.2. The Dynamic User Model

The Dynamic User Model specifies the user preferences for the program categories and subcategories of the General Ontology and for the channels available. Different from the other UM experts, the preferences can be related to different contexts because the expert has direct access to the user's behavior . In particular, this expert monitors user actions such as playing a TV program, recording a program, and all the actions available at the interface (see Fig. 1). In order to face the uncertainty in the interpretation of the user's viewing behavior a probabilistic approach is adopted, where discrete random variables encode two types of information: preferences and contexts (viewing times). The sample space of the preference variables corresponds to the domain of objects on which the user holds preferences; the corresponding probability distributions represent a measure of such preferences (degrees of interest). The sample space of every context variable is the set of all possible contexts. We encoded this type of information by exploiting Bayesian Belief Networks (BBNs).

Fig. 5 shows the structure of the BBN representing the user preferences. The network models the contextual information by means of context variables representing the conditions in which the user preferences for the TV programs may occur, the root nodes. We describe a context with temporal conditions, represented by the two variables "DAY" and "VIEWINGTIME" encoding, respectively, the 7 days of the week and the 5 intervals of time in which the day can be subdivided (morning, noon, ..., night). The leave nodes of the BBN represent the user's contextual preferences, providing the probabilities for every program category, subcategory and channel.

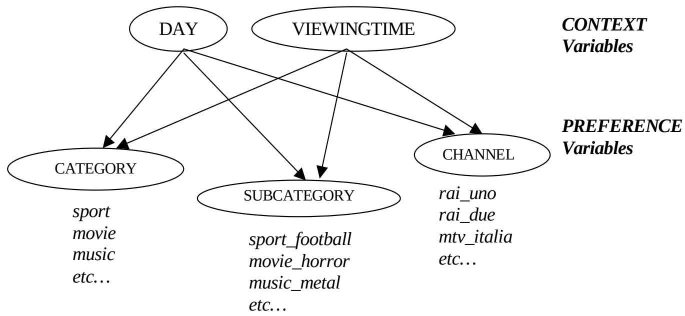

Figure 5: Portion of the BBN that represents the Dynamic User Model

For each individual user, the BBN is initialized with a uniform distribution of probabilities on its nodes where all values assumed by the preference variables have equal probability. The BBN is updated by feeding it with evidence about the user's actions, starting from the first time she watches the TV. Each time the user interacts with the program guide (to record a TV program, play it, etc.), the category and the subcategory of the event and its transmission channel are retrieved. Then, the BBN is fed with evidence that a new observation for that category is available. Not all the user actions have the same impact on the learning phase: e.g., playing a TV program provides more important evidence about the user's preferences than asking for more information about the same TV program. This fact is reflected in the definition of different learning rates for the possible user actions. The BBN exploited has been implemented using the Norsys' Netica toolkit [14], which provides algorithms for general probabilistic inference and parametric learning.

Confidence in the predictions of the Dynamic UM Expert. The confidence of the Dynamic UM Expert in the predictions on the user's preferences is based on the amount of evidence about the user's viewing behaviour provided to the BBN since the first user interaction. At the beginning, the expert has low confidence in its predictions. As the number of observations increases, the Dynamic UM Expert becomes more confident. In fact, although noise can be present in the user's behaviour, the BBN tolerates such noise much more in the presence of a large corpus of data. A sigmoid function is used to define the confidence, given the number of events observed within the context. This function is normalized in the interval [0,1] and is defined as follows:

$$Conf(x) = \frac{1}{1 + e^{(k-x)*s}}$$

The function returns a confidence close to 0 if no user-events are observed in a specific context. Moreover, the function returns a confidence of 0.5 after *k* events are observed and the confidence gets close to 1 after the observation of 2**k* user-events. The *s* coefficient (in [0, 1]) defines how steep has to be the function (*s* has been set to 0.1).

3.3. Integration of the predictions provided by the User Modeling Experts

The Main User Model is instantiated by merging the predictions on the user's preferences provided by the Explicit, Stereotypical and Dynamic UM Experts. For each preference *P*, the predictions on *P* ($Interest_1, \ldots, Interest_3$) are combined into an overall *Interest* as follows:[5]

$$Interest = \frac{\sum_{e=1}^{n} Conf_e * Interest_e}{\sum_{e=1}^{n} Interest_e}.$$

The formula merges the predictions in a weighted way, on the basis of the experts' confidence, in order to privilege estimates based on higher quality information about the user. The confidence may change along time and eventually, the Dynamic UM Expert influences the predictions in the strongest way, providing an estimation of the user's long-term viewing preferences.

4. Personalized recommendation of TV programs

The Recommendation Module (Fig. 2) suggests TV programs as follows:

- the TV programs satisfying the user's search query are retrieved from a local database storing the information about available programs[6];
- the programs are ranked on the basis of the user's preferences (Main User Model). The score associated to each the program is used to sort the recommendation list and to enrich the presentation with smiling faces representing the expected degree of appreciation;
- if several programs are retrieved from the user query, the rank associated to the items is exploited to filter out the worst programs, therefore reducing the length of the recommendation list.

Indeed, the generation of the scores for the TV programs is performed by taking into account both the user's preferences for the program category of the event and her preference for the transmission channel. The former type of information is the basis for the recommendations, but we use the latter to refine the score associated to the items, and thus the system's suggestions, with evidence about the user's viewing habits. The integration of these information sources is useful because the preferences for program categories do not support the comparison between individual programs

[5] The Explicit and the Stereotypical UM experts do not predict the preferred channels; thus, the confidence in such predictions is 0. Moreover, we assume that their predictions (which are a-contextual) are the same in all the viewing contexts.

[6] The local database is populated by the TV Program Collector that downloads from the MPEG-2 satellite stream information about the TV programs available in a restricted time interval and integrates such information with data retrieved from the providers' web sites.

belonging to the same category. In contrast, the preference for the channel (per viewing time) enables the system to take the user's preferences for individual programs into account, without explicitly modeling the characteristics of such programs. In fact, the system relies on the criteria applied by the provider in the selection of the programs to be shown: the scheduling of palimpsest (and of advertisements) is based on the supposed TV audience in a given time slot that influences the quality and the characteristics of the programs.

5. The evaluation of the system's recommendation capability

In this initial phase of the project we carried out a formative evaluation of the system's recommendation capability. As the Dynamic UM Expert's predictions are not available at moment (this expert requires observing real user's behavior for a significant amount of time) we focused on the other experts. 62 subjects, 22-62 aged, have been interviewed to collect their socio-demographic data, their interests and preferences for categories (Movies, News, etc) and subcategories (Action Movies, Cooking Programs, etc) of TV programs. Then, the so collected information has been entered into the system to evaluate the validity of the user classification and the accuracy of the recommendations.

Concerning the first point, we have compared the system classification with the classification of two domain (human) experts. The comparison showed that 70% of the users have been correctly classified by the system, while the remaining 30% have been incorrectly classified for two main reasons:

- the system classification fails when the user's interests are different from those evaluated according her socio-demographic data;
- the data provided by Eurisko does not cover the whole Italian population.

The TV program predictions generated by the system have been then compared to the explicit preferences expressed by the users. As outlined before, this testing has mainly evaluated the recommendations provided by the Stereotypical UM expert in conjunction with the Explicit UM expert. In this case, when the user explicit preferences are not available, the system takes in consideration just the Stereotypical expert. This situation is not unusual, since it is well known [7] that users do not like spend time filling questionnaire and evaluating items because they would get their immediate task done. Moreover, users are usually uncomfortable in answering personal questions. To test the performance of the system, we evaluated the distance between the system predictions and the users' preferences by means of mean absolute error (*MAE*[7], for details see [11]) while to test the accuracy of the selection process we measured the *precision*[8] of the collected data.

We obtained a mean absolute error value of 0,10 (the values are expressed on a scale ranging from 0 to 1) with a precision of 0.50. These values have confirmed our hypothesis about the validity of an integration of different sources of information. We

[7] The MAE metric evaluates the distance between the system predictions and the user's opinion by means of rate vectors. A smaller value means more accurate system's predictions.

[8] The precision is defined as ratio between the user-relevant contents and the contents presented to the user.

believe that the contribution of the Dynamic UM Expert and a broader coverage of the stereotypical KB can still improve these measures.

6. Related work

Several recommender systems are exploited in Web stores, electronic libraries and TV listing services. For instance, see [15][12][13] for an overview. The PPG differs from such systems in two main aspects: our system integrates multiple preference acquisition techniques for the identification of the user preferences and the consequent recommendation of items. Moreover, the system privileges the local execution of tasks with respect to a centralized management of the EPG. In particular, the decentralization of the system execution supports the generation of precise user models (the TV viewers are frequent users of the TV) and limits the amount of explicit feedback required from the user, because her behavior can be analyzed at any time she watches the TV. In contrast, if a central server manages the EPG, the user's interaction with the TV is carried out in a distinct thread and can only be monitored while she browsers the program guide, unless special hardware is used to connect the TV to the internet in a continuous way. See, for instance, [16].

Some recommender systems integrate multiple prediction methods by evaluating their precision, given the user's reactions to the system's recommendations (programs she watches, etc.). For instance, Buczak et al. [6] fuse three recommenders by means of a neural network. In contrast, the PPG currently merges the predictions provided by different UM Experts on the basis of their confidence in the predictions (where the confidence depends on the quality of the user data used to make the predictions). Indeed, we want to exploit relevance feedback to fuse our UM Experts, as well. However, we will combine such feedback with the experts' confidence, because in this way the system can benefit from an informed tuning parameter during its whole lifecycle. In fact, as the confidence depends on the amount of information about the user available to the system, it can be employed since the first interaction, while relevance feedback takes a significant amount of time before being effective.

7. Conclusions

This paper has presented the Personal Program Guide (PPG), a prototype system generating personalized EPGs, which we are developing in a joint project between Telecom Italia Lab and the University of Torino. A demonstrator of the PPG running on a PC simulator of the Set-Top Box environment is available.

The PPG integrates different user modeling techniques for the recognition of the TV viewer's preferences and the consequent generation of personalized recommendation listings. The management of different perspectives on the recognition of the user's preferences, and the cooperation/competition between the different user modeling methods has revealed to be fruitful to enhance the system's recommendation capabilities. As expected, the personalization based only on stereotypical suggestions is problematic, because not always people match stereotypes in a precise way. At the same time, the recommendations based on explicit user information are subject to failures: users often refuse to declare their real preferences or they provide the system with weak information about themselves. Finally, the recommendations based on the observation of the user behavior suffer from the *cold start* problem and, mirroring the user's usual selections, do not support the variety in the system's recommendations. The integration of three (or more) user modeling techniques enhances the reliability and richness of the system's predictions.

The system offers a client-based personalization, which solves several privacy and security problems to be taken in account when using personal information about the user. In fact, this approach avoids the propagation of the information about the user to other information sources or in the Internet. Moreover, the personal use of the application (which requires logging in), preserves the user from the possibility that other users (e.g., in the household environment) access her model.

REFERENCES

1. Ardissono, L., and Goy, A.: 2000, Tailoring the Interaction with Users in Web Stores. User Modeling and User-Adapted Interaction 10(4), 251-303.
2. Ardissono L., Portis F., Torasso P., Bellifemine F., Chiarotto A., Difino A.: 2001, Architecture of a system for the generation of personalized Electronic Program Guides. Proc. UM'01 Workshop on Personalization in Future TV, Sonthofen, Germany.
3. Ardissono L. and Buczak, A.: 2002 TV' 02: the 2nd Workshop on Personalization in Future TV, Malaga, Spain, 2002, http://www.di.unito.it/~liliana/TV02/.
4. Auditel : 2000, http://www.auditel.it
5. Billsus D., and and M. Pazzani: 1999, A Personal News Agent that Talks, Learns and Explains. Proc. 3rd Int. Conf. on Autonomous Agents (Agents '99), Seattle, WA, 268-275.
6. Buczak, A., Zimmerman, J. and Kurapati, K.: 2002, Personalization: Improving Ease-of-Use, Trust and Accuracy of a TV show Recommender. Proc. of the AH'02 Workshop on Personalization in Future TV, Malaga, Spain, pp. 3-12.
7. Carroll, J.M. & Rosson, M.B.: 1987, The Paradox of the Active User. In J.M. Carrol (Ed.), Interfacing Thought: Cognitive Aspects of Human-Computer Interaction. (pp.80-111). Cambridge, MA: MIT Press.
8. DVB: 2000, Digital video broadcasting. http://www.dvb.org.
9. Eurisko: 2000, Sinottica. http://www.eurisko.it .
10. Gena C.: 2001, Designing TV Viewer Stereotypes for an Electronic Program Guide. Proceedings of the Eight International Conference on User Modeling, 274-276.
11. N. Good, J. B. Schafer, J. A. Konstan, A. Botchers, B. M. Sarwar, J. L. Herlocker, and J. Ricdl : 1999, Combining collaborative filtering with personal agents br better recommendations, Proc. of the 16th National Conf. on Artificial Intelligence, pp. 439-446.
12. GroupLens: 2002, http://www.cs.umn.edu/Research/GroupLens.
13. Kobsa, A., Koenemann, J. and Pohl, W.: 2001, Personalized Hypermedia Presentation Techniques for Improving Online Customer Relationships. The Knowledge Engineering Review 16(2):111-155.
14. NETICA: 2001, Application for Belief Networks and Influence Diagrams, User's Guide, www.norsys.com
15. Resnick, P., and Varian, H. R.: 1997, Communications of the ACM: Special Issue on Recommender Systems 40.
16. Smyth, B., Cotter, P., Ryan, J.: 2002, Evolving the Personalized EPG-An Alternative Architecture for the Delivery of DTV Services, Proc. of the AH'02 Workshop on Personalization in Future TV, Malaga, Spain, pp .