TV Program Recommendation for Groups based on Muldimensional TV-Anytime Classifications

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Abstract — *The advent of Digital TV and Personal Digital Recorders promise to change the way people watch TV. The higher efficiency of digital coding will lead to increasing the number of contents offered to the user, demanding automatic tools for content recommendation. In the other hand, digital recorders will permit a non-linear consumption model, enabling the creation of (automatic) personalized schedules that combine the appealing contents for a specific user or group of users. This paper presents an approach to content recommendation for groups of people, based on TV-Anytime descriptions of TV contents and semantic reasoning techniques*[1].

Index Terms — Digital TV, TV-Anytime, recommender system, group recommendations.

I. Introduction

Digital television (DTV) is nowadays being deployed all around the world, offering many advantages to end users such as improved quality of audio and video, interactivity, mobility and a higher efficiency that permits to increase the number of broadcast channels or enable high definition.

In parallel, digital settop boxes with local storage are emerging (the *Personal Digital Recorder* or PDR), being able to record hundreds of hours of video, (automatically) schedule recordings or even merge contents to compound a virtual channel. This will change the traditional linear nature of TV, multiplying the possibilities available to the final user who can be easily overwhelmed by this new landscape.

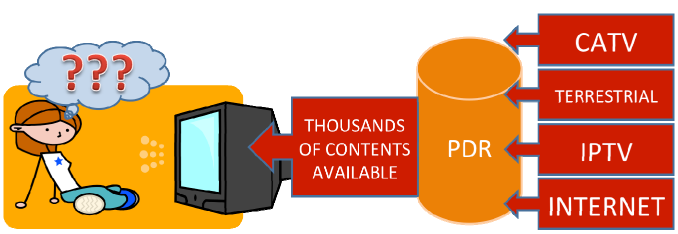

Fig.1. New TV technological advances can bring confusion to users.

In this context, it is necessary to develop agents that recommend programs to the users, thus improving their viewing experience. These agents employ several strategies to compare the broadcast contents to the users' profiles and their usage history, providing them with recommendations or even a personal channel (using automated recording capability).

Past proposals [1] are mainly focused on *personal* recommendations, based on the profile of a *particular consumer*. The number of televisions per household has increased in the last decades, allowing that the members of the household watch TV individually. In addition, many new technologies (for instance, broadcasting for personal devices) allow a personal experience when watching TV, stressing the relevance of this recommendation model.

However, television viewing is very often a group experience because people watch TV with their families or friends. Masthoff [2] citates some works that establishes that (i) television is the medium most often shared with family, (ii) watching television together is top of the list of activities shared between parents and children, (iii) young people would like to watch television with friends, and (iv) television is the most popular conversation topic of young people with friends.

Since a recommendation for an individual may not be adequate or optimal for all the members of the group, it is necessary to develop new recommendation engines that focus on the different kind of groups that watch television.

Chorianopoulos [3] points out that further research is needed in the field of recommending TV contents for groups and that a very promising area is the application of recommendation methods within small networks of affiliated groups of TV viewers (e.g. friends and family), in order to enhance the shared experience of TV.

Some approaches were recently introduced [4, 5, 6] based on merging strategies from Social Choice Theory [2]. Such engines consider the personal profiles and usage history of every individuals of the group. However, they are usually more useful for groups of people with similar interests, maybe the case of friends (*homogeneous groups*). This is not generally the case of families, where the individual user profile of the father, mother and childs probably differ (*heterogeneous groups*). In this case, the former processes lead to poor recommendations. Consequently, much more work needs to be done to define algorithms and tools able to cope with such differences derived from group composition.

In this regard, this paper introduces a new evolution of the tool AVATAR, a well-known TV recommender that now has been powered with the capability to make group recommendations, identifying and applying different processing techniques as per the group characterization.

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In the remains of the paper, section II presents an overview of different technologies that will play an important role in the implementation of the forthcoming TV models; section III highlights the main aspects of the AVATAR recommender; section IV presents some previous work and achievements in the field of group recommendation; section V describes our approach to built successful recommendations for groups, especially in the case of heterogeneous ones. Finally, section VI draws some conclusions and suggests future work.

II. Technological Landscape

In the last years, several interesting technologies (coming as much from the TV field as from the computer area) have been normalized that will play a central role in the evolution of DTV. These technologies, initially developed in an isolated way, have now reached a maturity level that permits significant synergies to arise from their integration.

The most important of these technologies is the Multimedia Home Platform (MHP) [7]. This standard, developed by the DVB Consortium, defines a generic common framework to enable inter-operable applications to be broadcast and executed on receivers with specific hardware and software implementations from any manufacturer. MHP normalizes the application model, the integration with the software of the DTV receiver and the API (*Application Programming Interface*) to access the hardware resources in any compliant equipment.

If MHP provides normalized computing TV applications, the TV-Anytime [8] metadata standard normalizes a common data format to describe TV contents, users and content consumption. TV-Anytime Phase 1 specifications standardize multimedia services based on digital storage in consumer platforms, combining the immediacy of the television with the flexibility of the Internet. This way, TV-Anytime allows the user to find, navigate and manage contents from a wide variety of sources, including traditional broadcasting, interactive TV, Internet, and local storage in a PDR, as depicted in Fig. 2. Besides, TV-Anytime describes procedures for rights management and protection of contents, and mechanisms to reference contents regardless of their location and broadcast time.

While TV-Anytime Phase 1 is mainly focused on unidirectional networks, Phase 2 takes into account bidirectional aspects introducing, for instance, the capability to exchange personal profiles. Particularly, this capability allows: (i) providers to receive detailed and comprehensive data from a wide range of PDR devices from different users, (ii) PDRs to directly exchange profiles as needed, and (iii) consumers to "carry" their profiles and other personal data [9]. TV-Anytime permits the development of web services that can retrieve user information, paving the way for PDR and service to communicate. Since personal information is sensitive, TV-Anytime requires the user to specify who is authorized to request his personal profile, and provides the security mechanisms [10]. This permits the PDR to gather the users' profiles needed to offer recommendations for a group of users watching TV together (*group recommendation*).

Unlike MHP (officially approved and deployed in many countries), TV-Anytime is still in an embryonic phase. It is clear that more projects and innovative applications are needed to propel its deployment, especially those ones improving the TV consumer experience in a *realistic consumer oriented way*.

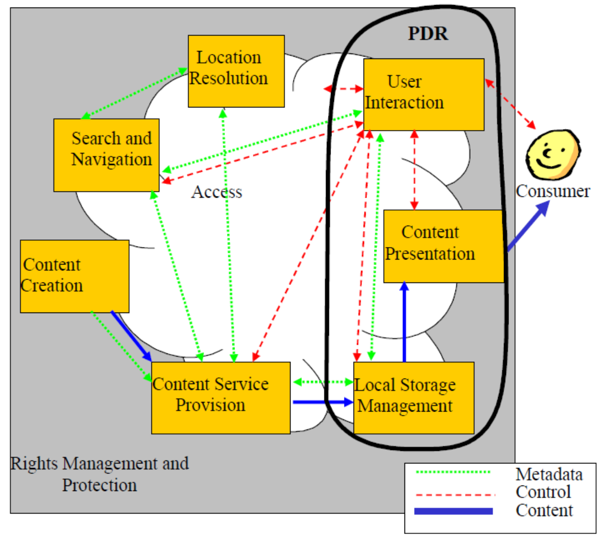

Fig. 2. Some capabilities supported by TV-Anytime specifications[2]

In this regard, media personalization using TV-Anytime is gaining momentum nowadays as a promising mechanism that lays the foundations of novel business models in the provision of personalized services for DTV, whose utility is undoubted in view of the content overload available in the digital stream. Traditional personalization strategies are mainly based on syntactic techniques, thus leading to very poor recommendations [11]. In order to fight these limitations, it is necessary to reason about the semantics of the available TV programs and to discover hidden relationships between these contents and the viewer's preferences, beyond a simple syntax-based comparison. These reasoning processes –traditionally adopted in the field of Semantic Web– require a formal representation of the domain knowledge (named *ontology*), where the semantic descriptions of the TV programs and relationships existing among them are modeled. The synergy between recommender systems and ontologies has been already explored in [12], showing significant increases in the recommendation accuracy. As a consequence, in TV recommender systems, ontologies are tools to favour the development of processing algorithms that improve the quality of current personalized recommendations, so completing the framework composed of PDRs (hardware), MHP (software), and TV-Anytime (data).

III. AVATAR: A Recommender System for Individual Viewers

This section summarizes the internals of the strategy for individual viewers adopted in the AVATAR recommender

[2] This figure has been extracted from TV-anytime metadata specifications [8].

system (see [13] for algorithmic details), which has been conveniently extended to deal with recommendations for a group of viewers watching TV together. These extensions include the TV-Anytime-compliant multidimensional ontology and the user modeling technique described next, along with the group recommendation strategy we will explain in section V.

A. A Muldimensional TV Ontology

Taking into account the most of the TV-Anytime capabilities, we have devised an enhanced ontological model that reflects the multidimensional content classification scheme of TV-Anytime. The descriptions of the programs to be broadcast are received in TV-Anytime format including their classifications in these schemes (as created by content producers). The instances of the scheduled programs are added to the system database, linking and classifying them in one or several of our hierarchies, enabling comparisons in multiple dimensions in order to compute similarity. Regarding these dimensions, our current implementation works with four hierarchies extracted from the classification schemes *Intention, Format, Content* and *IntendedAudience* defined in TV-Anytime standards.

Our ontology also includes other semantic attributes of the TV programs, such as topic, time and geographical information, and involved credits, as depicted in Fig. 3, where we can see a *documentary* about the use of *steamers* in *Spain* during the Industrial Revolution involving *Gerardo Melia* as director. As we will explain later, these attributes will permit semantic reasoning to discover semantic relationships among contents, thus leading to enhanced recommendations.

B. User Modeling

In our approach, the viewer profiles consist of excerpts from the multidimensional TV ontology containing the programs that a given individual has rated in the past, each one attached to a numerical index called DOI (*Degree Of Interest*) that quantifies his/her liking of it. As explained in [14], the DOI for a given program can be explicitly entered by the viewer, or inferred from indirect measures such as the time he/she spends watching it.

DOI indexes take values in the range [-1,1], with -1 representing the greatest disliking and 1 representing the greatest acceptance. From the DOI index of each program, our approach infers the level of interest of the user both in the attributes of this program and in the classes under which it is categorized in our multidimensional TV ontology. Specifically, the DOI indexes of the program propagate through each hierarchy of classes and the attributes of the programs as follows:

- The DOI of an attribute is taken as the average of the DOI indexes of the programs it is linked to.
- Similarly, in each one of the four hierarchies considered in our TV ontology, the DOI indexes of the most specific classes are computed as the average of the DOI indexes of the programs classified under them. Upwards in the hierarchy, each class C contributes to the DOI of its immediate superclass with a value given by (1), where $sib(C)$ is the number of sibling classes of C.

$$\frac{DOI(C)}{1+sib(C)} \qquad (1)$$

In sum, our viewer profiles store a list of TV programs the user viewed in the past, and each program is associated to a vector of values containing the DOI indexes of (i) this program, (ii) its attributes, and (iii) its classes in the TV ontology.

C. Our Recommendation Strategy for Individual Viewers

The recommendation strategy adopted in AVATAR combines two of the most popular filtering techniques in order to decide whether a target program *TP* is suggested to a given user *U*:

- **Content-based filtering**: This technique suggests *TP* to the *U* if it is similar to the contents this viewer has enjoyed in the past.
- **Collaborative filtering**: On the contrary, the collaborative filtering suggests the content *TP* to *U* if this program has been appealing to other individuals with similar preferences (hereafter, his/her *neighbors*).

As we will detail in the next sections, the research contribution of this recommendation strategy is the fact that both filtering techniques are enhanced with semantic reasoning processes about the TV ontology. These processes infer new knowledge about the viewer's preferences from the ontology, going beyond the pure syntax-based approaches adopted in traditional recommender systems (see [11] for an in-depth study). This way, our reasoning-based strategy leads to diverse and improved recommendations, including programs strongly related to the viewer's preferences (e.g. our reasonings associate a program about *fauna* with other one about *flora* because both are related to *Nature*, even when their respective attributes are different).

D. Our Content-based Filtering

This filtering process quantifies a matching value between the target program *TP* and the user *U*, by measuring the resemblance between the program and each content included in his/her profile. To this aim, we have proposed a similarity metric enhanced by semantic reasoning, which we refer to as *semantic similarity metric*. As shown in (2), the matching value between *TP* and *U* is computed by averaging the levels of semantic similarity between *TP* and each program c_i stored

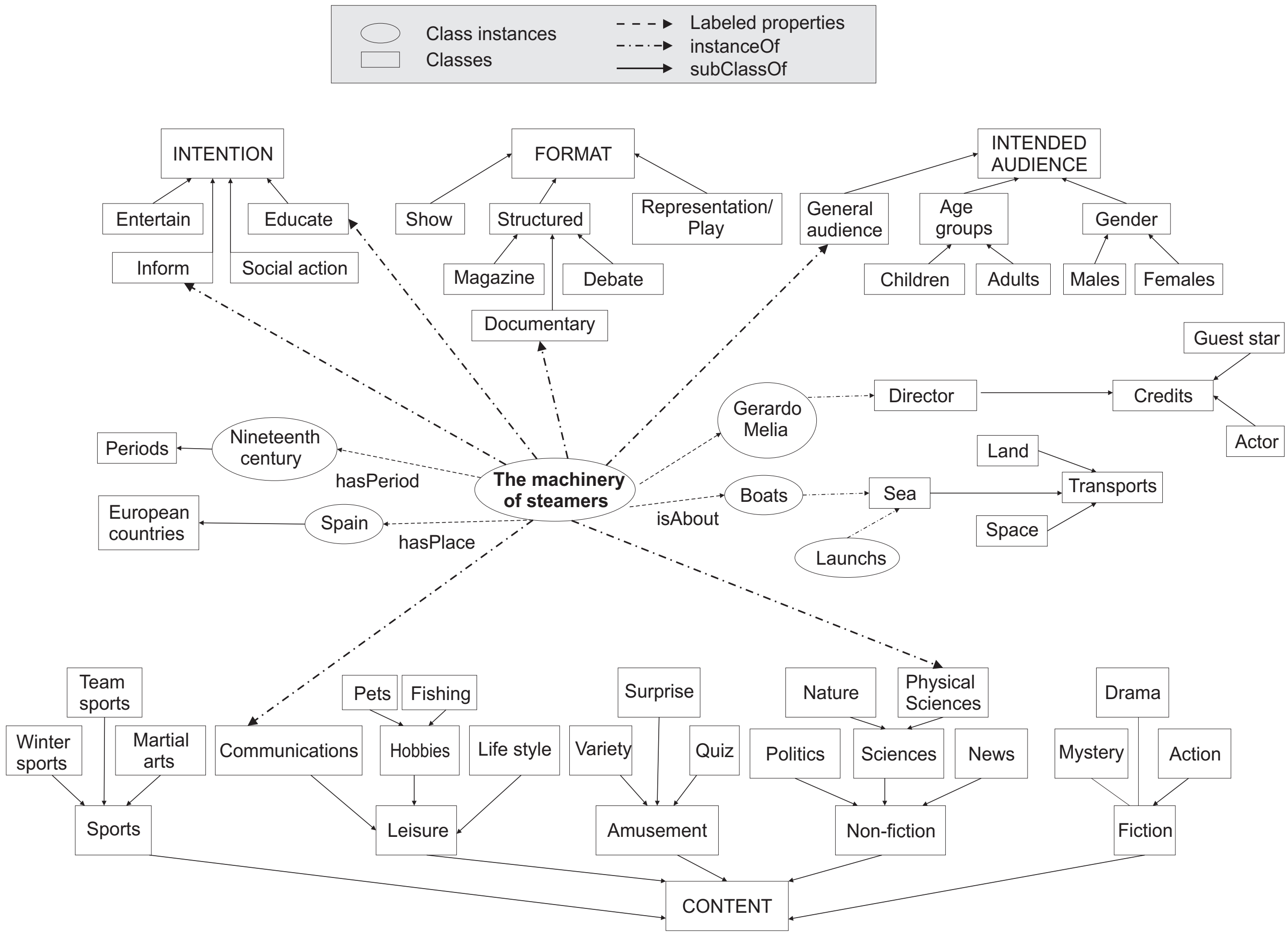

Fig. 3. A brief excerpt from our TV-Anytime-compliant multidimensional ontology including hierarchies corresponding to *Intention*, *Format*, *Intended Audience* and *Content* of TV programs.

in U's profile, weighted by their respective DOI indexes. Intuitively, the resulting matching value is high when TP is very similar to contents that have been very appealing to the user.

$$matching(U,TP) = \frac{1}{N_U} \cdot \sum_{i=1}^{N_U} DOI_U(c_i) \cdot SemSim(TP,c_i) \quad (2)$$

Our semantic similarity metric quantifies resemblance between contents considering two components:

- The first one (named *hierarchical similarity* or Sim_{Hie} (TP,c_i)) measures their closeness in each one of the four hierarchies considered in our TV ontology (see Fig. 2). This closeness is computed by (3), where the *depth* of a program is its level in the hierarchy, and *LCA* of two programs identifies their *Lowest Common Ancestor* in that hierarchy. In fact, the hierarchical similarity between the user's preferences and the target program will be computed for each hierarchy and later averaged.

$$Sim_{Hie}(TP,c_i) = \frac{depth(LCA(TP,c_i))}{Max(depth(TP), depth(c_i))} \quad (3)$$

- The second component (named *inferential similarity* or Sim_{Inf} (TP,c_i)) discovers associations between programs that share attributes semantically related to each other: specifically, *identical attributes* and *sibling attributes* (e.g. *Boats* and *Launchs* in Fig. 3, which share the parent class *Sea* - *Transports*).

  This approach leads to (4), where $DOI_U(SA_j)$ is the level of interest of the user U in the shared attributes (SA). As explained in section III-D, this level is automatically obtained from the specific ratings the user has assigned to the programs related to those attributes.

$$Sim_{Inf}(TP,c_i) = \frac{1}{\# SA} \sum_{j=1}^{\# SA} DOI_U(SA_j) \quad (4)$$

Once similarity between TP and each program c_i in U's profile has been computed, we obtain the components $Sim_{Hie}(TP,c_i)$ and Sim_{Inf} (TP,c_i), finally weighted and added by a configurable parameter, whose value depends on both the application context of the recommender system that adopts our filtering strategy, and the domain ontology used for reasoning. This value is finally included in (2), so that the resulting matching level permits to decide whether *TP* is recommended to the viewer *U*.

E. Our Collaborative Filtering

The goal of our collaborative filtering is to predict the level of interest of the user *U* in the target program by exploiting his/her neighbors' preferences and the multidimensional TV ontology. If the predicted level of interest is greater than a configurable threshold, the program *TP* is finally suggested to the *U*.

In order to form *U*'s neighbourhood, we have defined a *taxonomy-based approach* that exploits the hierarchical structure of our multidimensional ontology to discover overlap between the preferences of two users, even when both have viewed different TV programs. Specifically, our approach uncovers resemblance between the preferences of two viewers when they have rated programs categorized under a *common ancestor* in the hierarchies modelled in the multidimensional TV ontology. For instance, our approach detects that a viewer who has enjoyed a documentary about animals (classified under the *Nature* class in Fig. 3) and a viewer who has liked a program about mechanical engineering (belonging to *Physical Sciences*) are neighbours because both of them share interest in *Sciences* ancestor of *Content* hierarchy. Leaving apart the algorithmic details, the higher the number of common ancestor between the profiles of two viewers, the greater the correlation value measured between their respective preferences. Finally, the individuals whose correlation values (with regard to the user *U*) are greater than a given threshold are selected as his/her neighbors.

Once *U*'s neighbourhood has been created, our collaborative filtering predicts what would be his/her rating for the target program *TP*. To this aim, we average the DOI indexes of each neighbor N_k in the program *TP*, weighted by the correlation values measured between *U* and those neighbors, as shown in (5), where *M* is the neighborhood size.

$$\Pr edRating(U,TP) = \sum_{k=1}^{M} corr(U,N_k) \cdot DOI_{N_k}(TP) \qquad (5)$$

From this explanation, it follows that the rating of *U* in *TP* is high when this program has been very appealing to this viewer's neighbors, and when their respective preferences are strongly correlated. In this scenario, *TP* also seems to be an interesting program for *U*.

IV. PREVIOUS WORK IN GROUP RECOMMENDATION

A. Groups

Past years have witnessed a strong research activity in automated personal recommendation systems, especially fostered by the amazing raising of the commercial activity in Internet.

However, as highlighted in the introduction, when designing a recommendation system for TV, we must consider the frequent fact that users watch television in groups.

Even though the most common case is watching television with other members of the home (usually the family), we can find a lot of scenarios where TV viewing is (wanted or not) a social activity. It is not unusual at all, especially among young people, to meet to watch a movie, a football match, a chapter of a series, a talk-show or a entertainment program.

We can easily conceive other cases where program recommendation for groups is undoubtedly useful: for instance, long-distance public transportation and leisure centers. We can even think in applications related to modernist phenomenon like Internet social networks, where some content can be automatically identified and recommended to the group to raise a debate.

The range of interesting fields is even wider if we extend group recommendation to other products or services: tourist groups in a short visit to a big town, making a menu for a shared dinner, or ambient music selection, just to name a few.

An important factor to take into account when working with groups is their characterization regarding the similarity of their members. This way, if we want to generate TV program recommendations for a group, the first thing to be done is to classify it as a homogeneous or a heterogeneous group according to the interests and characteristics of its members.

Generally speaking, a family (see Fig. 4) will be a heterogeneous group, as the particular interests of the father use to be dissimilar to those of the mother, both of them dissimilar to those of the kids, and these ones dissimilar among themselves depending on the age differences.

Fig. 4. Heterogeneous group. A family is usually constituted by individuals with different ages and gender, and consequently different interests.

On the other hand, we can imagine that the interests of a group of friends will be similar (see Fig. 5). That is, interests will not be *identical*, but *similar*. The user profiles of each member will be alike. This is a much easier group to recommend, since we can substitute the group for a virtual user and still have a good recommendation.

Fig. 5. Homogeneous group. The individuals of a group of friends share many characteristics that result in common interests.

B. *Previous research work*

In literature it is possible to find some works about elaboration of group recommendations. In [2], Masthoff classified the different strategies adopted to predict the group satisfaction for viewing a TV program, as per the satisfaction of each member in the set (named merging techniques).

In one of these techniques, each member votes for his preferred alternative and that with the most votes wins, while in other each user can vote for as many alternatives as they wish. Other approaches make a new list of ratings with the minimum (or maximum) of the individual ratings. However, from the experiments described in [15, 16], it follows that the best merging technique in terms of group recommendation accuracy is the so-called *Average Without Misery*, where a new list of ratings is made averaging the individual ratings but without considering the values lower than a given threshold.

These merging techniques have been widely adopted in recommender systems bound to diverse domains of applications, such as Intrigue [17] and Travel Decision Forum [18] (in order to plan vacation for a group of tourists traveling together), MusicFX [19] (that adjusts the selection of music played in a fitness center as per the people present in the room), Browse [20] (that recommends web pages to a group of two or more users that browse together the Internet), and Polylens [21] (that suggests movies to a group of viewers), just to name a few possibilities.

Differently from our proposal, these approaches to group recommender systems exploit neither the TV-Anytime capabilities for exchange of viewers' profiles nor the semantic reasoning capabilities in order to select enhanced recommendations for the group.

C. *Other relevant work on Group Recommendation*

User profile merging has been extensively studied in last years in different domains: environment setting [22], information delivering [23], student group formation [24] or virtual communities [25].

Specially interesting in our context is the work described in [4], focused on recommending TV contents to a group. There, three strategies are clearly identified:

(i) *Group agent*: the users register a common account for them, having a common profile (difficult to apply if members change frequently).
(ii) *Merging recommendations*: it recommends for each user and then performs the merging.
(iii) *Merging user profiles*: it merges all user profiles to generate a common user profile to recommend.

According to their experiences the last is the best strategy, as confirmed by the work presented in [26]. Notwithstanding, this merging process is critically depending on two fundamental decisions:

- *Feature selection*, whose task is to determine whether a feature should be included in the target common user profile.
- *Weight assignment*, which means how should be weighted a selected feature.

Although experiences described in [4] establish that strategy (iii) is better than (ii), the results show that the system makes good recommendations only if people with similar preferences compose the group. If the group is heterogeneous, good recommendations are difficult to achieve.

As we understand that the most frequent situation when watching TV in groups is still the family scenario (usually an heterogeneous group), it is clear that much work remains to be done to achieve useful tools for group recommendation.

V. Our Group Recommendation Strategy

Our first step to make group recommendations is to characterize the group of users watching TV together: recall that we deal with *homogeneous groups* when all the members share similar preferences; otherwise, *heterogeneous groups* are considered. Specifically, for each pair of members U_j and U_k of a group G, we measure their resemblance by the taxonomy-based approach proposed in section III-E.

- First, we create four rating vectors for the users U_j and U_k, including their ratings in the categories of the four hierarchies modeled in the TV ontology, that is, *Format (F)*, *Intention (I)*, *Intended Audience (IA)* and *Content (C)*.
- Next, we compute the value of correlation C_{jk} between the rating vectors of U_j and U_k for each hierarchy (denoted by $C_{jk\text{-}F}$, $C_{jk\text{-}I}$, $C_{jk\text{-}IA}$ and $C_{jk\text{-}C}$). Then, we average the four resultant values as shown in (6), where the average is properly weighted depending on the importance we want to assign to each classification in our recommendation strategy.

$$C_{jk} = w_F \cdot C_{jk-F} + w_I \cdot C_{jk-I} + w_{IA} \cdot C_{jk-IA} + w_C \cdot C_{jk-C} \quad (6)$$

- Finally, we characterize the group of users G as per the resulting correlation value: if C_{jk} is greater than a threshold for every pair of members U_j and U_k, G is a homogeneous group. If any of these correlation values is below that threshold, we will say thay the group is heterogeneous.

Once the group has been characterized this way, two different approaches are followed in our algorithm depending on the case, to take into account the important differences between both kind of groups.

In the following, we present these two different treatments.

A. Homogeneous Group

In this case, as the members of the group have similar interests, we then define a *virtual user* representing the group, whose profile is the merging of all the individual profiles, as shown in Fig. 6.

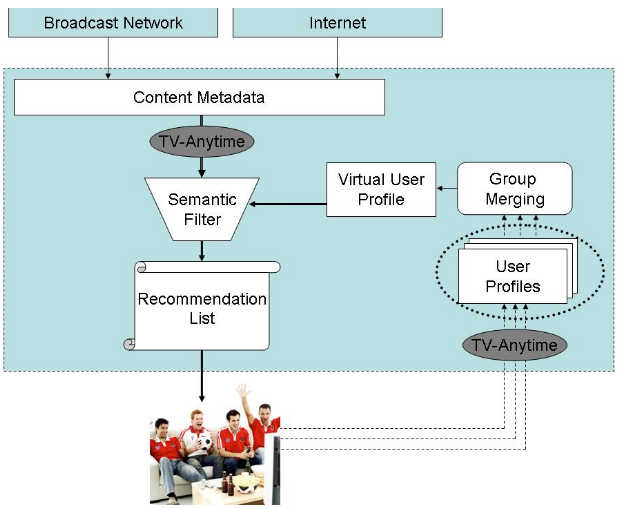

Fig. 6. Recommending to homogeneous groups.

The merging is computed by the *Average without Misery* technique[3]: for each class, the resultant DOI will be -1 if DOI is negative for this class for any member; otherwise, it will be the average of DOI indexes of the class for all the group members.

Then, our group recommendation strategy suggests to this virtual viewer using the content-based filtering technique adopted in the original AVATAR process for individuals (see section III-D).

This strategy has been proved to be adequate to predict satisfaction with the content recommended, while avoids recommending a category of content that somebody in the group dislikes.

B. Heterogeneous Group

In the case we are processing a *heterogeneous group* (that is, some of the correlations between the members of the group are not high enough), the users' interests are not compatible.

In this situation, the rating vectors representing the users point to very dissimilar directions. Thus, the above method or similar ones will not be adequate because the resultant of averaging the individual vectors will be next to the origin –the (0,0,0,…,0) point– and all information about individual users would be lost. Such a recommendation would be very poor, since richness of the description of each user would be much diminished.

Bearing this in mind, we decide to use our collaborative filtering technique to process the group, but starting from its members, as depicted in Fig. 7.

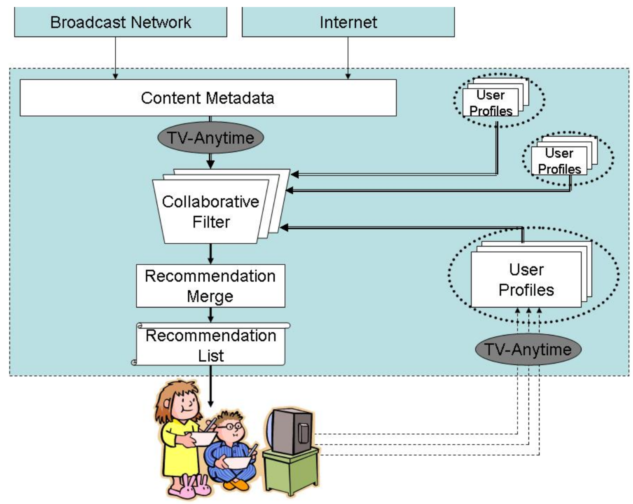

Fig. 7. Recommending to heterogeneous groups

For the previous purpose, we proceed as follows:

- First, we find the neighborhood N_j of *each* member U_j of the group G. As per what we said in section III-E, N_j includes all users U_k such that the correlation measure C_{jk} is above a threshold. Note that these neighbors can be in any group registered in the system.
- Then, we look for known groups G_m in the system whose members V_{mn} are all of them included in one (at least) of the neighborhoods found. That is, $\exists i \,/\, \forall n, V_{mn} \in N_i$. As it is natural, this means that G and G_m are similar groups, as for each member U of G, there is some member V of G_m with similar individual tastes. The set of G_m thus obtained will be considered the neighborhood of G.

At this point, supposing we have a new program TP to be broadcast soon, we must decide which groups can be interested in this target content.

- Our first stage is to compute the adequacy of TP for each member V_m of all groups G_m. In case a member had seen this program, we use his/her DOI index; otherwise, the adequacy level is predicted by semantic reasoning. To this aim, we exploit our content-based

[3] We have chosen this merging technique because it allows to obtain the best results in terms of recommendation accuracy, as shown the experiments carried out in [2].

filtering technique and compute the matching level between the member V_m and the target program TP by means of (2). This approach leads to the below equation.

$$\text{Adequacy}(TP, V_m) = \begin{cases} DOI_{V_m}(TP) \text{ if V}_m \text{ has seen } TP \\ matching(V_m, TP) \text{ otherwise} \end{cases} \quad (7)$$

- Next, we compute the matching between every G_m and TP using the *Average without Misery* strategy applied to all the members of the group G_m.
- Finally, averaging all matchings of the neighbor groups, we obtain the predicted interest of G for the content TP.

From this it follows that we recommend TP to a group if it was appreciated by groups with similar members.

VI. Conclusions And Future Work

In this paper, a method to predict the interest of a group of people for an audiovisual content has been presented that allows us to make accurate recommendations for the group. We defined homogeneous and heterogeneous groups and considered different appropriate algorithms for each kind of group, what reflects real habits of TV consumption.

As a requirement for the development of interoperable consumer electronic equipment, TV-Anytime metadata is extensively used to guarantee (i) the availability of detailed-enough content descriptions, and (ii) the viability of compatible mechanisms to annotate and collect users' profiles.

In addition, our personalization approach exploits synergies between the multidimensional classification of contents based on TV-Anytime metadata schemes, and semantic reasoning techniques about a domain ontology formalized from these classifications. This way, we greatly improve the accuracy of current similarity metrics and traditional approaches to TV recommender systems, discovering hidden relationships between the new programs and the viewer's preferences, beyond a simple syntax-based comparison.

As future work, we are planning to enhance our present algorithm with considerations from real TV consumption experience.

We are studying to add the possibility to automatically identify and give more weight to the leader(s) of the group, comparing the individual preferences to the contents finally watched. As well, members in special situations (i.e. a child's birthday) should result in an increase of their weight.

Contents may have a cost and this may be a factor of decision, not yet considered. Finally, similarly to [17], we are exploring the relevance of searching homogeneous groups inside the heterogeneous groups, and take this fact into account in the collaborative techniques of our recommendation strategy.

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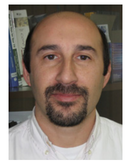

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