AVATAR: An Improved Solution for Personalized TV based on Semantic Inference

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Abstract — *The generalized arrival of the Digital TV will bring a significant increase in the amount of channels and programs available to end users, with many more difficulties for them to find interesting programs among a myriad of irrelevant contents. Thus, automatic content recommenders should receive special attention in the following years to improve the assistance to users. Current approaches of content recommenders have important well-known deficiencies, which difficult their wide acceptance. In this paper, a new approach for automatic content recommendation is presented, based on the so-called Semantic Web technologies, that significantly reduces those deficiencies. The approach has been implemented in the AVATAR tool, a hybrid content recommender that makes extensive use of well-known standards, such as MHP, TV-Anytime, or OWL[1].*

Index Terms — Digital TV, recommender systems, MHP, Semantic Web.

I. Introduction

The denomination of digital television (DTV) has been traditionally linked to greater quality of audio and video, which led many people to confusing DTV technology with high-definition TV (HDTV). But DTV has a unique strength that lies within its capability to transmit data and telematic applications along with the audiovisual contents. Those applications, running on the users' receivers, are envisaged to cause a revolution in the very conception of the television.

To enable the execution of telematic applications, the new DTV receivers will be endowed with interactive and computational capabilities that will turn them into vehicles to access the Information Society. This way, it will be possible to fight the worrisome digital divide that is starting to show up in the developed countries, due to the limited penetration of the Internet in homes. Nowadays, the Information Society is mostly accessed through Internet-enabled personal computers, and, as proved by data from InternetWorld Stats (recovered from http://web.archive.org), the penetration figures in homes seem to be reaching their peak (around 35% in Europe and 67% in the USA) as the growing rate is slowing down (from 29% in 2001 to 19% in 2004 in Europe, and from 14% to 7% in the USA). Bearing this in mind, the fact that television is present in nearly every household in developed countries –being a familiar device for everyone– leads to thinking of DTV as the means to overcome the commented barrier.

On another hand, after the establishment of the DVB (Digital Video Broadcasting) broadcasting standards, it is foreseeable that the normalization in the DTV field will focus on the telematic applications, to overcome the current incompatibility problems between software and receivers from different providers. Thus, the market should evolve into a truly horizontal model with well-defined roles (content providers, service providers, digital platforms, network operators, receiver manufacturers and users), contributing to reducing costs and attain greater acceptance of these technologies.

In this new scenario, the users will have access from their homes to a great number of channels and services from different providers. This fact will have a greater impact in Europe, as long as the greater bandwidth available in DTV has been used to lodge a greater number of channels; in the USA and Japan, conversely, the greater capacity has been mostly devoted to the emission of high-definition formats, as noted in [1]. Resembling what happened with the growth of the Internet, this huge number of channels will cause the users to be disoriented: even though they may be aware of the potentiality of the system, they lack the tools to exploit it, not managing to know what contents and applications are available and how to find them. Successful search engines arose on the Internet, ranging from the syntactic matching processes of the mid-90s to the more recent approaches to the Semantic Web, which are nowadays the subject of intensive research [2].

Taking advantage from the experiences carried out on the Internet, both regarding the syntactic search engines and the most recent studies on the Semantic Web, this paper presents an application called AVATAR (AdVAnced Telematic search of Audiovisual contents by semantic Reasoning). This is a personal assistant that values the adequacy of the contents offered by different providers to the preferences of every user. The aim of this system is to furnish a highly-personalized viewing experience that prevents from bewildering the users in an increasingly growing offer of TV channels.

This paper is organized as follows: Section II presents an overview of the techniques being used by the current recommenders of audiovisual contents. Section III comments the most important technologies in the DTV field, with special interest for those underlying the AVATAR system, which is

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described in Section IV. Section V details a sample use of AVATAR. Finally, Section VI provides a discussion of the features of AVATAR, including the main conclusions from this work and motivating directions of future work.

II. Related Work

Recommender systems are computing applications intended to offer automatically to the users personalized suggestions according to their preferences and needs.

In the last two decades, recommender systems have achieved a growing interest in the research community. This is supported by a great diversity in the approaches that can be found both in the TV domain [3] and outside of it [4]. However, two personalization strategies can be highlighted because of their outstanding popularity: *content-based methods* and *collaborative filtering*. The former recommend to the target users contents similar to the ones they liked in the past, whereas the latter suggest to each user contents appealing to spectators with similar preferences [5].

Content-based methods require a metrics to quantify the similarity between the users' profiles and the programs candidates for recommendation. To define such metrics, it is necessary to define appropriate descriptions of the considered contents, which is usually a time consuming task. Despite their successful application, by their own nature, these methods suggest contents too similar to those ones known by the user, which leads to limited diversity in the recommendations. This problem is especially serious regarding the new users of the system, as the suggestions offered to them are based on immature profiles containing a reduced set of programs.

On another hand, by its very own, the collaborative approaches offer more diverse recommendations, as they are based on the experience of users with similar preferences (named *neighbors*). Besides, collaborative filtering does not require the aforementioned resource-demanding content descriptions, as they search correlations among the ratings the users assign to contents. For these reasons, the collaborative strategy has been successfully experienced in systems such as Movielens and Moviefinder [6].

Notwithstanding, some limitations can also be identified in the collaborative filtering techniques. On one hand, this technique requires that some users have watched and rated a specific content for it to be recommended. Because of this, a significant *latency* is observed since a new content arrives to the system until it is suggested to some viewer, as it is necessary that a meaningful number of users rate the new content. On the other hand, the lack of flexibility to estimate similarity among users (usually based on direct overlapping among the programs in their personal profiles) leads to the so-called *sparsity problem*. In this case, as the number of contents in the system increases, the probability that two users have watched the same programs is lower. This reduced overlapping among the users' profiles greatly hampers the discovery of like-minded users, a critical step in collaborative approaches.

With the aim to combine the advantages of each technique and minimize their drawbacks, a significant number of systems can be found in the literature that use *hybrid approaches* [7]. These approaches offer more accurate recommendations than those suggested by each strategy individually. Some of the most important hybrid TV systems are PTV and PTVPlus [8].

Nevertheless, due to the fact that the existing TV recommender systems are focused on searching processes lacking in semantic inference capabilities, the quality of their suggestions is clearly limited, just as it happens with the Internet search engines. Specifically, with the goal of improving the recommendation quality, our proposal presents an improved hybrid approach, based on the experienced gained in the so-called Semantic Web. This approach combines a content-based algorithm with a collaborative filtering one, increasing their accuracy thanks to the addition of semantic inference capabilities. This strength permits us to define a new and flexible metrics to assess the semantic similarity between two specific TV contents, whose value depends on the semantic relationships discovered between them. Even though this hybrid personalization strategy has been incorporated into the AVATAR system –a recommender of audiovisual contents and telematic applications for DTV– its flexibility allows to reuse it in other application domains.

III. Technological Landscape

Leaving apart the advantages and drawbacks that the digital TV transition brings to our society, the most relevant characteristic of this evolution is the appearing of a myriad of technologies and formats in a field traditionally characterized by its stability. This stability is especially significant regarding signals and formats, where absolute compatibility has been kept for decades in the large TV markets.

This stable market now faces significant changes, mainly derived from the introduction of software and computer-like technologies. In this scenario, normalization will play a fundamental role to achieve compatible products that keep high the user's confidence in this user-friendly device.

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 digital TV and in the resolution of the problems introduced in the previous sections. 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) [9]. 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 (named Set-Top Box or STB) and the API (Application Programming Interface) to access the hardware resources in any compliant equipment. Two types of applications have been initially defined: procedural ones, based on the Java language (DVB-J), and declarative ones, based on a mark-up language (DVB-HTML) closely related to the Internet well-known language. In the MHP standard, several successful previous APIs have been adopted, as can be JavaTV from Sun Microsystems, HAVi and DAVIC.

The adoption of the MHP standard has been announced by a large set of countries, with several degrees of commitment (see http://www.mhp.org for up-to-date data), including the US cable industry. In addition, a new initiative has been recently launched named GEM (*Globally Executable MHP*) to integrate MHP and the other major normalization initiatives (ATSC and ARIB) under a common umbrella. This initiative intends to define a common core for all of them, specifying functional equivalents for the technology or market specific parts of each standard. This will reduce differences among standards and establish predefined paths for portability of applications, setting the foundations for a world-wide market.

If MHP provides normalized computing TV applications, the TV-Anytime [10] standard normalizes a common data format to describe TV contents. TV-Anytime is an initiative of the most important actors in the multimedia contents industry that normalizes XML applications describing generic TV contents, specific instances of programs, user profiles, content segmentation information, and mechanisms to reference contents regardless of their location and broadcast time. The main goal is twofold: to separate the information that describes the contents from the information needed for obtaining them, and to make the whole independent of the transport mechanism.

These technologies (MHP and TV-Anytime) are two fundamental tools to promote the deployment of a new generation of *personal video recorders* (PVR), as foreseen by the DVB. As these new receivers work with digital signals, they are usually referred to as *digital video recorders* (DVR) or *personal digital recorders* (PDR). These devices are expected to implement a new set of functions a step ahead of current PVRs, enhancing the user's watching experience and issuing serious challenges to the traditional broadcasting models based on the linear viewing of the programs selected by operators. In addition to the well-known time-shift feature of current PVRs, the new digital devices will be able to provide random access within a recorded TV program, assembling of virtual channels based on user's preferences, instant reply of program highlights, recording functions based on a trailer, or tailored advertisement insertion. These functions will require an important normalization effort to achieve compatibility, a must for market success. In this sense, the DVB has already started the work to include in their standards the necessary signalling to carry TV-Anytime metadata in the service information, and the specifications of the necessary APIs for the MHP applications to access to these metadata in a normalized way.

In addition to these technologies (already mature and only pending of imminent deployment), it is necessary to highlight the increasing effort being dedicated to the development of mobile TV, which will make TV ubiquitous through handheld devices in the near future. In this regard, the broadcast industry (supporting DVB-H: Digital Video Broadcasting – Handheld [11]) and the mobile telecommunications one (supporting MBMS: Multimedia Broadcast and Multicast Services [12]) are immersed in a dramatic race to develop and deploy the necessary technology as soon as possible. Two other players, DMB developed by the Korean industry and MediaFLO [13] from Qualcomm, are also competing for being the winning standard in this lucrative business. Even though MBMS has significant limitations regarding the number of TV channels available (as it shares bandwidth with voice and data), it represents the cheaper approach because it is based in the 3G network infrastructure and it does not need to develop a new dedicated network like DVB-H, DMB and MediaFLO. However, if immediate availability is a winning factor, DVB-H has an important advantage in this regard, since multiple trials are already being carried out in the USA and all along Europe (Finland, UK, Germany, France, Italy, Spain…).

Looking at the specific domain of automatic personalized recommenders, the problem about the lack of reasoning capabilities described in Sect. II has been detected time ago in the Internet search field, where a large consensus exists about the limitation of syntactical searches to set the foundations of a smarter Internet. In that *intelligent* network, advanced applications should be provided to solve the user's problems when finding appropriate information or looking for commercial services, and taking into account the personalized user's characteristics. In this context, the Semantic Web initiative has been promoted which tries to provide the bases for a more detailed and structured description of Web resources through metadata. In addition, the Semantic Web also resorts to the development of appropriate knowledge ontologies to establish hierarchies and significant relationships among the involved entities. The aforementioned detailed descriptions and the ontologies permit an enhanced reasoning process to infer new knowledge through the combination of the relevant facts of the problem, the user's profile and restrictions, and the services infraestructure. In this regard, several independent works developed in recent years have been integrated by the W3C in the OWL standard (Web Ontology Language [14]). This standard offers a suitable tool to represent in a formal way all the relevant information about a specific domain, opening the door to further processing. Specifically, the synergy between recommender systems and ontologies has been already explored in [15], showing significant increases in the recommendation accuracy. As a consequence, in TV content recommenders, ontologies are tools to favour the development of processing algorithms that improve the quality of current personalised recommendations, so completing the framework composed of PDRs (hardware), MHP (software), and TV-Anytime (data) over any available fixed or mobile network.

IV. The AVATAR Recommender System

In this section, we present the main design decisions behind our system, as well as its general architecture.

AVATAR is designed for an environment in which the STB is permanently connected to a broadband network. Thus, the user can download data from the service provider and send information at any time. This model has been adopted because it is being quickly implanted in market, due to the increasing use of access technologies such as xDSL and cable.

In addition, in order to fulfill the planned goals, our design took into account the following requirements:

(1) The application must be broadcast through a TV service. For that reason, our system has been implemented as a DVB-J-type MHP application.

(2) To promote an extensive use of our system, we have adopted normalized formats and technologies (such as MHP, TV-Anytime and OWL).

(3) Finally, AVATAR was designed according to a modular architecture that allows both to add new personalization techniques easily, and to adopt future standards.

A. A Hybrid Personalization Technique

As we mentioned in Sect. II, we propose a hybrid recommendation technique that combines the content-based methods with the collaborative filtering. Our main contribution with respect to previous approaches is the capability to infer new knowledge from the semantics of TV contents and the user's preferences.

In order to represent formally the knowledge about the TV domain on which our inferential process is applied, we have implemented an ontology by the OWL language. This ontology stores classes, instances and properties hierarchically organized, that identify resources and relationships commonly used in the TV domain: categories of TV programs, cast, genres, topics of programs, etc. Bearing in mind that the TV programs in AVATAR are described by TV-Anytime metadata, the attributes of TV programs included in our ontology are very close to those that this specification defines. This way, the mapping process between TV-Anytime contents and specific instances in our OWL ontology is clearly facilitated. In Fig. 1 we show a brief excerpt from our TV ontology with some of their instances, classes and properties (the complete ontology is available in http://avatar.det.uvigo.es, section Software).

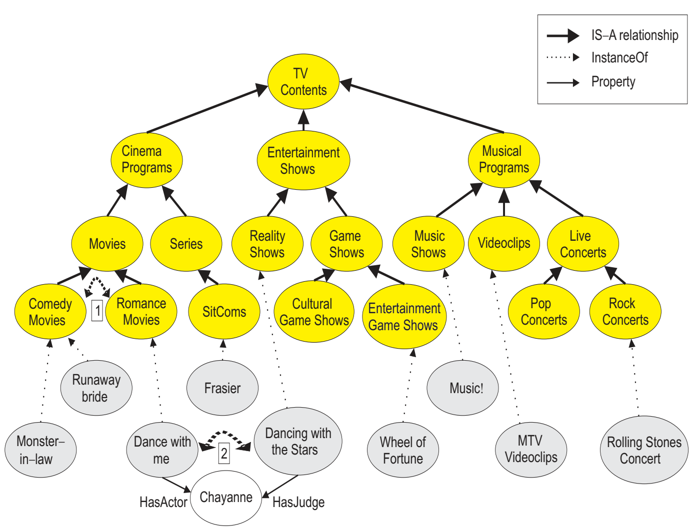

Fig. 1. An excerpt from our TV ontology

As one of the most relevant advantages of the ontologies is their capability to reuse the represented knowledge [16], we have resorted to our TV ontology to model the users' preferences. As a consequence, each one of the user's profile in AVATAR –named ontology-profile– stores a hierarchical structure in which the programs the user likes (or dislikes), along with their attributes –named semantic characteristics– are identified by instances, classes and properties already formalized in the OWL ontology.

Besides, in order to quantify the level of interest of a user in relation to each class and instance contained in his/her profile, we have assigned a index –named DOI (Degree Of Interest)– to each one of them. The index computed for a program suggested by AVATAR depends on several factors, such as: (i) the acceptance or rejection of the user to the suggestion, (ii) the percentage of the program watched by the user, and (iii) the time elapsed until the user decides to watch the offered program. A detailed description of the computation of the DOI and other indexes is explained in [17].

Once the mechanisms for representing the information required in the recommendation process have been introduced, we present the proposed personalization strategies. In the last sub-section, we describe how the results of our two techniques are fused to offer a final hybrid suggestion to the users.

Content-based Strategy: The goal of this strategy is to suggest to a target user TV contents semantically related to those he/she watched in the past. For that purpose, we propose a metrics that quantifies the semantic similarity between the content to suggest (named *target content*) and those contents stored in the user's profile. Our semantic similarity is based on inferring semantic relationships between the matched programs. This way, the stronger the inferred relationships between two specific contents, the higher the value of their similarity. The proposed semantic similarity considers two kinds of relationships:

- *Hierarchical Semantic Similarity:* This component takes into account the IS-A hierarchy that our OWL ontology defines *explicitly* to classify the TV contents. So, the closer two programs are in this hierarchy, and the deeper their nearest common ancestor in it, the stronger the hierarchical relationship between both contents. As a consequence, if the nearest common ancestor of the two matched programs is the hierarchy root class (*TV Contents*), their hierarchical similarity is null. In Fig. 1, we can identify a relationship of this type between the comedy movies *Dance with me* and *Runaway bride* (represented as relation 1).
- *Inferential Semantic Similarity:* The inferential similarity is based on discovering *implicit* relations between the matched contents. These relations are inferred between programs that share semantic characteristics (e.g. cast, genres, topic, etc.). Thus, we

say that there exists a relationship between two contents when both of them are associated by properties to instances –equal or different– of the same class of the TV ontology. Specifically, if the common instance is the same, this is named *union instance*; otherwise, the relation is established by different instances of a *union class*. In Fig. 1, we can identify the relationship 2 established through a *union instance*. So, it is possible to relate the comedy *Dance with me* to the reality show *Dancing with the Stars*, because both of them involve the actor and dancer *Chayanne*. Obviously, the greater the number of common instances between the matched programs, the stronger their semantic relationship, and therefore, the higher the inferential similarity value.

According to what we have just explained, our approach computes the semantic similarity between the target content and all of the programs stored in the analyzed user's profile. Thus, AVATAR obtains a *semantic matching level* between the target content and the user's preferences. Logically enough, if this content is very similar to those programs the viewer most liked, the level should be high. Because of this, our approach computes this *matching level* by weighing the semantic similarity values commented before according to the DOI indexes of each program in the analyzed user's profile.

Collaborative Strategy: The goal in this strategy is to suggest to a target viewer programs appealing to other like-minded viewers. For that purpose, it is necessary to find users with similar preferences to the target user's ones, whom we hereafter refer to as his/her neighbors.

In order to form this neighborhood, our proposal defines the so-called *rating vectors* for all of the users. Their components are the DOI indexes stored in each user's profile for the classes of the TV content hierarchy sketched in Fig. 1. Next, our collaborative strategy computes the *Pearson-r* correlation [18] between the rating vectors, resulting in the highest values for those users interested in programs (instances) belonging to the same hierarchy classes. This approach alleviates greatly the *sparsity problem* presented in Sect. II, since it is not necessary that two users had watched exactly the same programs in order to detect similarity between their respective preferences.

Once the target user's neighborhood has been formed, AVATAR checks if the target content is appealing for each one of these neighbors. For that purpose, our approach uses different values depending on whether these neighbors know the target content or not. In case they do, our proposal uses the DOI indexes of this program, stored in their respective profiles. Otherwise, AVATAR estimates the level of interest for each neighbor by computing the semantic similarity between the target content and his/her preferences, as we explained previously.

Finally, AVATAR computes a value, named *semantic prediction*, that estimates the level of interest of the target user in relation to the considered content, according to his/her neighbors' interest. Thus, the predicted value is greater when the target content is appealing to more the users' neighbors, and when their respective preferences are strongly correlated.

Final Recommendation: In order to fuse the content-based and collaborative strategies described before, AVATAR uses a "two-chance" mechanism based on the following idea: if the target content is similar to the ones the user most likes, this program is directly suggested to him/her; otherwise this user becomes a candidate for the collaborative strategy. In this second chance, our approach predicts whether the target content is appealing to most of the neighbors of the considered user, and, in that case, the program is finally recommended; otherwise, it is discarded. This process is described in Algorithm 1, where the two functions used return the aforementioned *semantic matching* and *semantic prediction* values, respectively. Note that we use two thresholds in the range [0,1] for deciding if these values are significant enough.

Algorithm 1

Recommend (*target-content*, *user-profile*) {
  if (*semantic_matching* (*target-content, user-profile*) $\geq \beta_{Match}$)
    return TRUE
  elseif (*semantic_prediction*(*target-content*, *user-profile*) $\geq \beta_{Pred}$)
    return TRUE
  else return FALSE
}

B. The Architecture

In Fig. 2, we show the architecture of the AVATAR system, which is composed of four main agents.

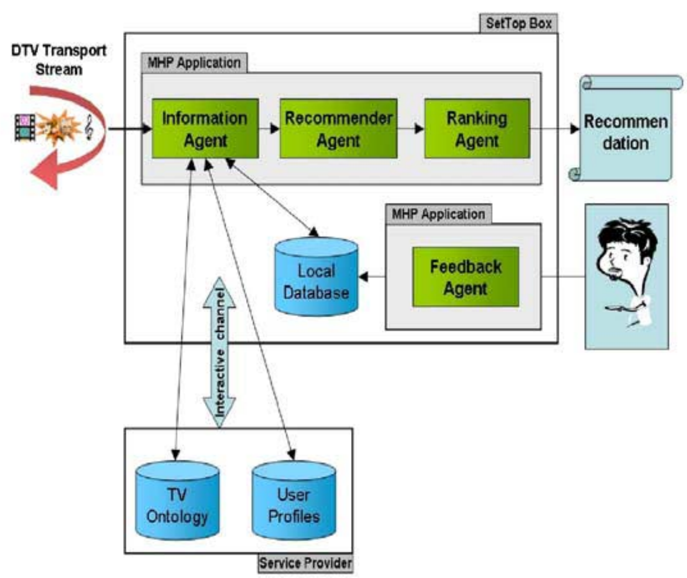

Fig. 2. Architecture of the AVATAR system

Recommender Agent: It carries out the recommendation strategy described in Algorithm 1. Thus, it returns the set of TV programs that are appealing to the users.

Ranking Agent: This agent takes the programs selected by the recommender agent and it sorts them as a ranking. For that purpose, it considers both the *semantic matching* and *semantic prediction* values computed by AVATAR, and the user's context: age, languages he/she knows and language of the suggested programs, etc.

Information Agent: This agent accesses to the TV ontology and to the database where the service provider stores the user's profiles. Besides, it manages the information received through the interactive channel, formatted according to TV-Anytime. In short, it is in charge of providing the required information by the recommender system.

Feedback Agent: It updates the user's ontology-profile according to the following information: (i) the data extracted from the viewing behavior of the user and, (ii) the success or failure in the recommendations previously elaborated by AVATAR. This process allows to refine the knowledge about the user's preferences by modifying the DOI indexes stored in his/her profile, thus resulting in more accurate suggestions.

The above agents are included in two MHP applications due to their different life-time. On one hand, the feedback agent must be permanently monitoring the user actions. On the other one, the recommender, ranking and information agents only run when a personalized suggestion is required.

The agent-based architecture of our system permits to add new recommendation strategies and mechanisms for information management without significant changes in its general structure. In this regard, note that new recommender agents that cooperate in the system can be incorporated into the proposed architecture. For that purpose, it is only necessary to modify conveniently the ranking agent, so that it fuses the recommendations offered by each one of them.

V. An Example

In this section, we describe an application scenario, consisting of a specific target content and a set of users to whom AVATAR suggests this TV program. This example evidences differences between the recommendations elaborated by our hybrid strategy and those offered both by the existing collaborative systems and the conventional content-based methods.

Due to space limitations, some simplifications are assumed. So, we have greatly reduced both the number of semantic characteristics of each TV content, and the size of the user neighborhood used in the collaborative strategy. In spite of these simplifications, the shown example highlights the utility of semantic inference to compare the user's preferences, and the advantages of our method for the neighborhood formation. In this scenario, we assume that the target content is *Dancing with the Stars*, a reality show in which several celebrities (the singer *Robbie Williams* and the actress *Jennifer Lopez*, among others) are coupled with professional dancers and evaluated by a judging panel of dancing experts, chaired by *Chayanne*. On another hand, we consider that the target user is U and his/her neighbors are the viewers N_1, N_2, and N_3. The TV programs contained in their profiles, as well as their respective DOI indexes, are shown in Table I.

TABLE I
SOME TV CONTENTS DEFINED IN USERS' PROFILES

USER U	USER N_1	USER N_2	USER N_3
Rolling Stones Concert (0.8)	Music! (0.9)	**Dancing with the Stars (0.6)**	Wheel of Fortune (0.7)
Runaway bride (0.9)	Dance with me (0.85)	Videoclips (0.8)	Friends (1)
Frasier (0.85)	Desperate housewives (0.65)	Monster-in-law (0.85)	About celebrities (-0.8)

Note that all these programs refer to positive preferences of the users, except the show *About the Celebrities* that we suppose was suggested to N_3 and rejected by him/her; hence its negative DOI index. The TV contents shown in Table I are represented together with some semantic characteristics in Fig. 3. So, for instance, we can identify the sitcom *Friends* involving the actors *Jennifer Aniston* and *Matthew Perry,* and the comedy movie *Monster-in-law* starring *Jennifer Lopez*.

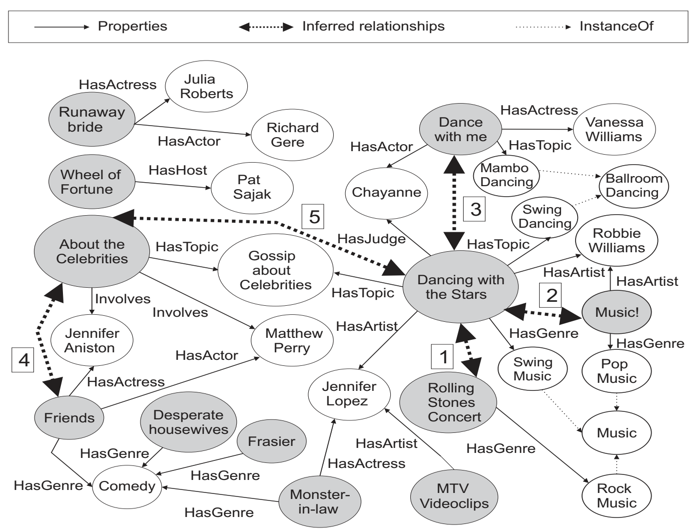

Fig. 3. Subset of instances and semantic relationships inferred from our OWL ontology.

As shown in Table I, our approach detects that the neighbors of U are N_1, N_2, and N_3, although none of them has watched exactly the same programs than U. Indeed, the *Pearson-r* correlation between U, N_1 and N_2 is high because the three viewers are interested in instances of several subclasses related to *Musical Programs* (*Rock Concerts*, *Music Shows* and *Videoclips*, respectively in Fig. 1). Regarding N_3, the sitcoms are appealing programs both to this user and U, given that they have watched *Friends* and *Frasier*, respectively.

A. A Conventional Content-based Recommendation

The traditional content-based approaches would suggest to U programs excessively similar to those he/she already knows. The origin of this lack of diversity lies in the similarity metrics used, which is based on selecting programs belonging to the same categories of this user profile (concerts, movies, and sitcoms) and involving the same people (e.g. *Julia Roberts* or *Richard Gere* in this example). Specifically, because of this metrics, the conventional content-based approaches would never select *Dancing with the Stars* for U (see Table I).

B. A Conventional Collaborative Recommendation

The existing collaborative filtering approaches would suggest *Dancing with the Stars* to U if most of his/her neighbors had watched and enjoyed this show. In our scenario, as shown in Table I, only the neighbor N_2 knows this program, and besides, his/her level of interest is medium. Therefore, the reality show would not be finally recommended to U.

C. A Hybrid Recommendation by AVATAR

In this section, we will see how the semantic inference capabilities incorporated in AVATAR detect that *Dancing with the Stars* is a show appealing both the user U and those neighbors who have not watched it yet.

Let us start describing the implicit semantic relationships inferred by AVATAR from the user preferences shown in Table I (represented by numbered arrows in Fig. 3). Next, we will describe how the discovered knowledge is used in the recommendation process.

- Although the TV-Anytime metadata define different musical genres for the contents *Dancing with the Stars* and *Rolling Stones Concert* (*Swing Music* y *Rock Music*, respectively), our approach relates them by the join class *Music* (relationship 1 in Fig. 3).
- The reality show and *Music!* are semantically related because both contents share the musical genre and involve the artist *Robbie Williams* (relation 2 in Fig. 3).
- The implicit relationship between *Dancing with the Stars* and the movie *Dance with me* (relationship 3 in Fig. 3) is due to the fact that these contents involve different ballroom dancings (swing and mambo, respectively), and, besides, *Chayanne* participates in both of them. Obviously, approaches based on simple syntactic comparisons between the attributes of the considered programs would not uncover this kind of relationships.
- *Dancing with the Stars* and *Wheel of Fortune* are explicitly related in the content hierarchy defined in our ontology, because both of them are entertainment shows (in Fig.1 we see that the two programs are instances of the classes *Reality Shows* and *Game Shows,* subclasses of *Entertainment Shows*).
- *About the Celebrities* is related to the sitcom *Friends*, given that this show includes news about the personal lifes of the actors *Jennifer Aniston* and *Matthew Perry*, main characters in the sitcom (relationship 4 in Fig. 3).
- Finally, AVATAR also infers an implicit relation between *Dancing with the Stars* and *About the Celebrities*, because both contents have a common topic, detected by the instance *Gossip about celebrities* (relation 5 in Fig. 3).

The Content-based Strategy in AVATAR: As shown in the first row of Table II, our system compares U's preferences against the reality show *Dancing with the Stars*. According to Fig. 1, the hierarchical similarity between these programs is null because of the non-existence of a common ancestor between their respective classes other than *TV Contents*. On another hand, the inferential similarity is not significant because AVATAR is able to infer only one relationship between the *Rolling Stones* concert watched by U and the reality show (relationship 1 mentioned before). Note that this relation is established by means of an only instance of the join class *Music*. For that reason, our approach quantifies a very low similarity between the U's preferences and the reality show. The combined value of both components is not high enough to exceed the threshold β_{Match} in Algorithm 1. Therefore, the reality show is not offered to U, and so this user is evaluated in the collaborative phase of our approach. This process is summarized in the remaining rows of Table II.

The Collaborative Strategy in AVATAR: Opposite to what happens with the conventional approaches, our strategy considers all the neighbors of U in the collaborative phase, both those who have watched the reality show, and those who do not know this content. In our scenario, given that N_1 and N_3 have not watched *Dancing with the Stars*, AVATAR predicts a specific level of interest for them by computing the semantic similarity between their preferences and the reality show.

Regarding N_1, the aforementioned relationships 2 and 3 are used to compute this value, as shown in Table II. Before describing this process, note that the respective semantic characteristics of the contents *Music!* and *Dance with me* (see Fig. 3) are of interest for N_1, because both programs are very appealing to him/her. Specifically, considering the join instances and classes existing between both contents (*Robbie Williams*, *Chayanne*, *Music* and *Ballroom dancing* in Fig. 3) and their high level of interest in N_1's profile, our approach estimates a significant inferential semantic similarity. As a consequence, a semantic matching value greater than β_{Match} is computed. Therefore, *Dancing with the Stars* is offered to N_1. In accordance with what we explained in Sect. V-A, the conventional content-based approaches would never offer this show to N_1, in spite of being semantically related to his/her preferences, as our approach discovers. This is because, according to the similarity metrics used, this reality show is excessively dissociated from N_1's preferences.

TABLE II
AN EXAMPLE OF RECOMMENDATION OFFERED BY AVATAR

USER	HIERARCHICAL SEMANTIC SIMILARITY		INFERENTIAL SEMANTIC SIMILARITY			SEMANTIC MATCHING	SEMANTIC PREDICTION	RECOMMEND TARGET CONTENT?
	Value	Common Ancestor	Value	Relations in Fig. 3	Union Class/Instances			
U	Null	TV Contents	Low	1	Music	$< \beta_{Match}$	-	No
N_1	Null	TV Contents	High	2, 3	Robbie Williams, Chayanne, Music, Ballroom dancing	$\geq \beta_{Match}$	-	Yes
N_3	Low	Entertainment Shows	Low	4, 5	Gossip about celebrities, Jennifer Aniston, Matthew Perry	$< \beta_{Match}$	-	No
U	Null	TV Contents	Low	1	Music	$< \beta_{Match}$	$\geq \beta_{Pred}$	Yes

Regarding the user N_3, although *Dancing with the Stars* belongs to the same category of *Entertainment Shows* than the programs *Wheel of Fortune* that this user enjoyed, the semantic inference capabilities of AVATAR allow to discover that this reality show is not a program of interest for him/her. This way, as shown in the next-to-last row of Table II, our approach uses both the relationships 4 and 5 mentioned before and N_3's negative preferences in order to compare the programs this user has watched to *Dancing with the Stars*. On one hand, given that AVATAR suggested the show *About the Celebrities* to N_3 and this user rejected it, our approach assigns a negative DOI index to this content in his/her profile (-0.8 in Table I). This value is also used to set the DOI values of their respective semantic characteristics (*Jennifer Aniston*, *Matthew Perry* and *Gossip about celebrities* in Fig. 3). The DOI index of the former instance is the negative value assigned to the show *About the Celebrities*. According to the relation 4 in Fig.3, the two remaining instances are already contained in the user N_3's profile, associated as semantic characteristics of the sitcom *Friends*. This way, their DOI values are just slightly reduced, because N_3 has not accepted *About the Celebrities*, in which both actors also participate.

On another hand, note that the aforementioned relationship 5 uncovers an association between *About the Celebrities* and the target reality show by the instance *Gossip about celebrities*. According to what we have just explained, this instance is not appealing to N_3, because of its negative DOI index. As a consequence, this level of interest leads our approach to estimate a negative value of inferential semantic similarity between N_3's preferences and *Dancing with the Stars*. For that reason, this content is not suggested to this viewer.

Once all of the neighbors of U have been analyzed, our collaborative strategy predicts that *Dancing with the Stars* is an appealing show to this user. As shown in the last row of Table II, this prediction value is high enough to exceed the threshold β_{Pred}, because most of U's neighbors (specifically, N_1 and N_2) are interested in this reality show. In addition, their preferences are strongly correlated to this user's ones. Note that the interest of N_1 in the reality show would be omitted in the existing collaborative approaches.

Lastly, as we said in Sect. V-B, the existing collaborative approaches would not offer the reality show to U until most of his/her neighbors had watched and liked this program (i.e. until N_1 and N_3 had watched this show). Considering that *Dancing with the Stars* was suggested to the neighbor N_1 thanks to the novel semantic inference capabilities of AVATAR, it is clear that the existing proposals would never recommend this show to this viewer. Therefore, the reality show would neither be recommended to U, although our inference process discovers that it is appealing to both viewers.

VI. CONCLUSION

TV is currently facing a near future plenty of significant changes and challenges in its technical foundations and business models, mainly derived from the introduction of software and computer-like technologies. In addition, the digital switchover will make available to the users much more channels and contents than today. As a result, assistance mechanisms will be needed to help the users to find appealing contents, avoiding interesting programs going unnoticed.

Nowadays, in the field of automatic recommenders important drawbacks have been identified even in the more elaborated tools. In this paper, we have presented a hybrid recommendation strategy for a TV intelligent assistant, based on mixing the most successful personalization approaches up-to-date: content-based methods and collaborative filtering. Our approach complements these personalization techniques with a novel process of knowledge inference starting from the user's preferences and the TV content semantics. Our algorithms discover *complex semantic relationships* that relate the user's preferences to the finally suggested contents. The formalization makes extensive use of TV standard technologies as TV-Anytime and MHP, and is based on data structures (ontologies) and languages (OWL) extracted from the Semantic Web field to build the inference framework.

The proposed hybrid strategy greatly reduces the *sparsity problem* of the collaborative filtering approaches, thanks to a technique that uses a hierarchy to identify the general categories which the user's preferences belong to, instead of identifying specific programs. This way, we exploit this hierarchical structure in order to generate overlapping between profiles containing different TV contents. In addition, this technique also alleviates the *latency problem* of the collaborative systems, since whenever a new content arrives to the system this can be suggested to the users with no delay.

To alleviate the lack of diversity usually associated to the content-based methods, we have defined the *semantic similarity*, a new flexible metrics to compare TV contents based on inferring semantic relationships between programs. These relationships are discovered between programs that share semantic characteristics relevant for the users (e.g. cast, genres, topics, etc.). So, the greater the number of common semantic characteristics, the higher the measured similarity.

Finally, the paper presents an example of the kind of reasoning carried out by our tool, highlighting interesting conclusions achieved thanks to the new strategy that could not be discovered in traditional approaches.

Our main future work is to continue the experimental evaluation of the presented hybrid strategy that is being carried out with undergraduate students at the University of Vigo. The first results of these experiments can be found at the website *http://avatar.det.uvigo.es/experiments.html*. Even though the first results are encouraging, more comparisons with current traditional approaches must be undertaken for final conclusions to be drawn.

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