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Procedia Computer Science 22 (2013) 561 – 570

Procedia Computer Science

17th International Conference in Knowledge Based and Intelligent Information and Engineering Systems - KES2013

A TV program recommender framework

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Abstract

In the area of intelligent systems, research about recommender systems is a critical topic and has been applied in many fields. In this paper, we focus on TV program recommender systems. We give an overview of literature research about TV program recommender systems and propose a smart and social TV program recommender framework for Smart TV, which integrates the Internet and Web 2.0 features into television sets and set-top boxes. In addition, we also address several issues, such as accuracy, diversity, novelty, explanation and group recommendations, which are important in building a TV program recommender system. The proposed framework could be used to help designers/developers to build TV program recommender systems/engines for smart TV.

Keywords: Intelligent system, recommender systems, TV Program recommendation ;

1. Introduction

With the development of Internet and increasing information overload, personalized recommender systems become more and more important and useful for both consumers and business. The main aim of a recommender system is to predict consumers' preferences based on implicit feedback or explicit feedback, or both of them and recommend the most favorite items which are likely to be interested by consumers [1]. From consumers' point of view, recommender systems can help them find information or preferable products faster and more accurate than a system without recommender. On the other hand, from businesses/provider's point of view, they can benefit from recommender systems in terms of revenue, attracting consumers, obtaining users' trust and loyalty and so on [2].

TV program recommender systems are one important application of personalized recommender systems. With the development of Smart TV and expansion of TV program/contents, hundreds of channels from cable or satellite provider, along with great Internet-based content providers like Netflix, Hulu, YouTube, are available

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doi:10.1016/j.procs.2013.09.136

to users. The tremendous TV program/contents, on one hand, may bring users many choices; on the other hand, users may sometimes feel confused and it is not easy to find interesting TV program because of the massive amounts of TV program. Hence, TV program recommender systems/engines have become more and more important and have been adopted by many famous television makers and content providers, such as Google TV, Apple TV, Sony TV, YouTube and so on

To address these situations, there are many related research papers published in the academic world. For instance, paper [3] addressed some main research questions of TV program recommendation, such as profiling methods, recommendation algorithms, and group recommendation issue. In paper [4], they proposed an Internet based personalized TV recommender, which uses a mixture of case-based reasoning and collaborative filtering as a means of learning users' preferences in order to generate recommendations. Paper [5] proposed a multi-agent TV program recommender to capture the evolving personal TV preferences of a viewer by incorporating machine learning techniques. The proposed recommender is made up of explicit recommender agent, implicit recommender agents and feedback agent. Paper [6] proposed a hybrid TV program recommender system --- AIMED recommender which is based on user properties such as Activities, Interests, Moods, Experiences, and Demographic information. The AIMED data is fed into a neural network model to predict TV viewers' program preferences. In [7], the authors proposed an extended personal video recorder (PVR) with a generic recommendation system based on a Bayesian classifier and adapted it for the use in the application area of television. The system analyzes the user's TV watching behavior to present new choices of content. On the other hand, in the industry, many Television/Set-top makers, such as SONY Bravia, Apple TV, Google TV, and TV program/contents providers, such as Netflix, YouTube, Hulu, have also adopted TV program recommender systems/engines in their products/service.

Most of these previous researches about TV program recommender systems are mainly based on the concept of traditional television sets. For example, those television sets are not connected to internet or recommendation algorithms are just based on TV program contents. And researchers mainly focus on increasing the accuracy of TV program recommendations, ignoring the importance of diversity, novelty, explanation of recommendations. With the development and widespread of Smart TV, much more smart and open TV program recommender systems proposals are needed. Hence, this paper aims at giving a comprehensive literature review about TV program recommender systems and proposing a smart and social TV program recommender system. The proposed TV program recommender consists of TV program content analysis module, user profile analysis module and user preference learning module. These modules not only treats TV program content and users' direct feedback, but also suggests extracting related information such as TV watching statistics information, users' preference/interest for the other contents from social media or relevant organization. In the preference learning module, we suggest three user preference learning approaches: leaning from individual's past experience, learning from implicit network and learning form explicit network. In addition to the proposed TV program recommender framework, we also address several issues, which are important in the building of a TV program recommender system, such as accuracy, diversity, novelty, explanation and group recommendation.

In the following sections, we firstly give a survey of TV program recommendation systems research. Next, we propose an integrated framework for a novel TV program recommendation architecture. Then, we discuss several important issues for the proposed TV program framework. Finally, we give some concluding remarks and future work plan.

2. Research relevant to TV program recommendation

Much work has been done in the area of recommender systems and they have been applied to a wide range of disciplines, and personalized TV program recommendation is one important application of them.

In [4], the authors used a mixture of case-based reasoning and collaborative filtering as a means of learning users' preferences in order to generate recommendations. Their personal TV (PTV) recommender initially let users state their preferences about channel, genre, and viewing time while registering with the system and then infers users' preferences as they enter their feedback on TV shows they have watched.

In [5], the authors proposed a multi-agent TV program recommender to capture the evolving personal TV preferences of a viewer by incorporating machine learning techniques. The proposed recommender is made up of explicit recommender agent, implicit recommender agents and feedback agent. Among them, the explicit recommender agent takes a person's explicit profile as input and generates program recommendations and explicit profile comprises a list of features, and their associated user-specified ratings. The implicit agents use the Bayesian classifier approach to compute the likelihood that the viewer will like or dislike a particular TV program and use the Decision Tree (DT) approach to compute program recommendation scores. The feedback agent works in collaboration with the implicit and explicit recommender agents and helps them fine-tune their recommendation quality.

In [7], they proposed an extended personal video recorder (PVR) with a generic recommendation system based on a Bayesian classifier and adapted it for the use in the application area of television. The system analyzes the user's TV watching behavior to present new choices of content. The content is stored on an internal hard disc drive where it is recorded for the user to watch. They built two types of user profiles: initial user profile which a static profile, where the user defines contents he or she is interested in during the beginning of the system, and adaptive user profile which is created continuously on the basis of the user's viewing behavior. They used Bayesian classifier to generate recommendations based on initial user profile and adaptive user profile.

In [8], they developed a recommender engine which tracks users' TV-preferences and delivers accurate content recommendations. The recommender engine contains two recommenders: implicit recommender and explicit recommender. The implicit recommender generates profiles based on users' viewing histories. They use both Bayesian and Decision Tree methods to produce implicit recommendations. And explicit recommender generates recommendations based on users' input profile and feedback. And finally they use artificial neural network to fuse the outputs of the different recommenders into a single set of improved recommendations.

In [9], they introduced a personalized TV program recommendation system ----- queveo.tv. The proposed hybrid approach combined content-filtering techniques with those based on collaborative filtering, and also provides all typical advantages of any social network such as comments, tags, ratings, etc. They used vector space model to generate content-based recommendations. And they used SVD (Singular Value Decomposition) in order to reduce the dimension of the active item's neighborhood, and then it executes the item-based filtering with this low rank representation to generate its predictions. According to their research, the hybrid method which integrates content-filtering techniques and collaborative filtering could solve first-rater, cold-start, sparsity and overspecialization problems.

In [10], they developed a PTV (Personalized Television Listings—http://www.ptv.ie) system which tackles the information overload associated with modern TV listings data, by providing an Internet-based personalized listings service. PTV is capable of automatically compiling personalized guides to match the likes and dislikes of individual users based on a combination of user profiling, case-based reasoning and collaborative filtering techniques. From their experiment, they found that the PTV system is in high level in terms of accuracy. And meanwhile, the response time is also acceptable.

In [11], they developed a PPG system, which presents the recommendations from the Explicit- and the Implicit Profile, which contain the favorite genres, sub genres and events of an individual user. The paper highlights the generation of a Recommendation Index for genres, sub genres and events by using implicit and explicit profiles. The explicit setting of the individual preferences of a user is done throw an interface, which is called "Profile Generator". With this interface each user is able to set her/his favorite genres, sub genres and events. The implicit generation is done by different equations, which logs the viewing behavior of each individual user and offer the opportunity to separate the obtained information into three different parts: genre, sub-genre and event.

In [12], they presented a personalized electronic program guides (PPG) for digital TV. The PPG manages a user model that stores the estimates of the individual user's preferences for TV program categories and channels. The user model results from three sources of information: The user's explicit preferences that may be declared by the user; Information about the viewing preferences of stereotypical TV viewer classes; and the user's viewing behavior. Accordingly, they designed three modules to manage these three kinds of information: The Explicit User Model stores the information elicited from the user; The Stereotypical User Model stores the prediction on the user's references inferred from prior information about TV viewer categories; The Dynamic User Model stores the estimates on the user's preferences inferred by observing her viewing behavior.

3. Proposed TV program recommender framework

Based on the survey studies of the previous section, we propose a novel integrated TV program recommendation framework, which contains three components (Fig. 1): TV program content analysis module, user profile analysis module and user preference learning module. Each of these components has its specific tasks and aims. This part addresses the specific definition of each component.

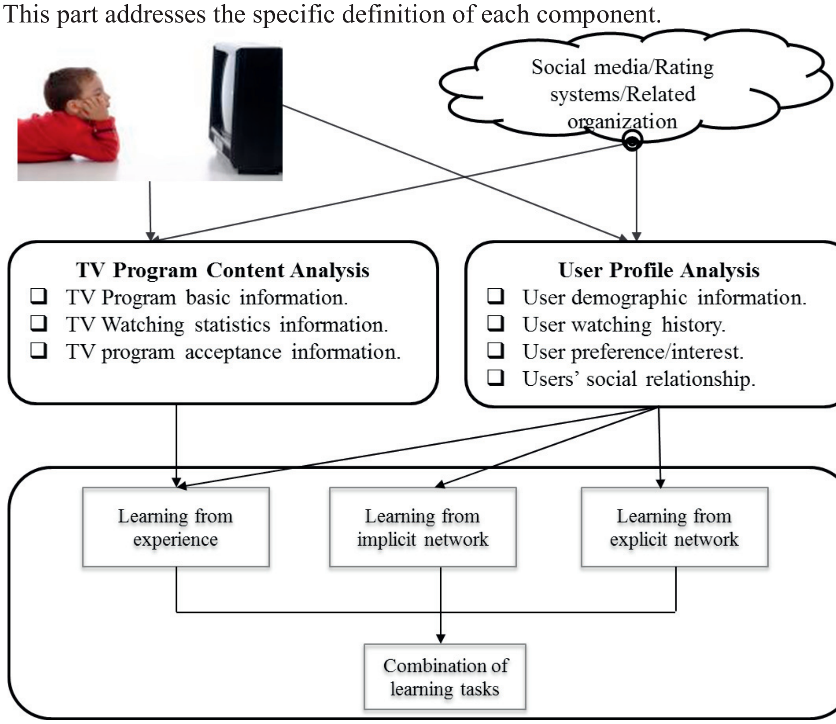

Fig. 1. The framework of proposed TV program recommender systems

3.1. TV Program information analysis component

The main task of TV program content analysis module is to obtain TV program basic content information, watching statistics information and program acceptance information.

- TV program basic information: the basic information of a TV program could be channel, title, genre /sub-genre, keywords, actors and so on. Among them, keywords mean the main terms, which are used to describe the main contents of the TV program. This type of information can be extracted from the description of the TV program provided by broadcast/content provider and stored in XML files or database.
- TV watching statistics information: this type of information can be collected from related companies, research institutes, and TV program providers. TV watching statistics are important for a TV program recommender, because that the statistics can reflect the macro characteristics and trend of TV watching behaviors of users which could be important factors in learning and predicting individual's preference. For example, in one report of A.C. Nielsen Co. (http://www.nielsen.com/content/corporate/us/en.html), the program Big Bang Theory is ranked 5th which means it is a popular TV program in USA, so we can use this information to predict a user's preference for the program if the user is interested in comedy.
- TV program acceptance information: this type of information means users' perception, feeling or opinion for a TV program and can be extracted by text/data mining algorithms/tools from online social media or other sources. There are many online rating systems/databases, such as AngiesList (http://www.angieslist.com/), for different products or services such as hotels, restaurants, movies, music, and TV program and so on. Most of these rating systems enable users to give ratings and reviews/comments for specific products or service. From the average rating received by a TV program, we can infer the average acceptance of the TV program, and from the reviews/comments, we can extract the main sentimental terms which reflect users' perception for the TV program.

3.2. User profile analysis component

The main task of user profile analysis component is collecting and extracting users' demographic information, watching histories, preference/Interest and social relationship.

- Demographic information: this type of information means users' name/nickname, age, sex, occupation, income and so on. Demographic information is proved to be a factor can influence viewers' program preferences. Currently, many program recommendation systems use this variable to predict users' program preferences. Demographic information classifies viewers into separate preference sets and then maps them to appropriate program styles.
- Watching history: users' past watching history may reflect their interests and watching habits. This type of information could tell that a user watched what TV program at what time and how long the user watched the program and rating/feeling for the program. The time user spent watching TV programs indicates the user's watching habit. How long the user watched the program and rating indicates the users' preference for the program.
- Preference/Interest: this type of information means users' preference for other contents such as movies, music and books. With the development of smart TV, users could watch movies, listen music and read books through relevant applications. Users' preference for these movies, music and books could be used to predict users' preference for TV program. For example, if a user like watching comedy movies, then he/she may like comedy TV program as well.
- Social network (relationship): Users' preferences tend to be influenced by their friends/family/colleagues, so it is reasonable to take users' social relationship's preference into account. Users' social network could be extracted from relevant social media such as Facebook or twitter.

3.3. User preference learning component

There are three main learning task of user preference learning component: learning from individual's past experience, learning from implicit network and learning form explicit network.

- Learning from individual's past experience: users' past watching histories reflect their TV program preferences and watching habits. For example, if a user often watches comedy drama in the night, we can infer that he/she likes comedy drama and his/her TV program watching habit is at night. Then when there is a new comedy drama, the recommender could recommend it to the user. In addition, users' preference/interest for the other contents such as movies and music through relevant applications also could be used to predict users' preference. For example, if a user used to watch comedy movies on Netflix and videos on YouTube, when there is a new comedy drama in TV program, the recommender can predict the user may like it.
- Learning from implicit network: Users may have similar preference for TV programs even if they don't know each other. So there is an implicit network between users based on their preference for TV program. For example, there is a group of users, who don't know each other, used to watch comedy drama and gave high ratings to comedy drama, then we can predict the preference of one of them based on the other users' preferences.
- Learning form explicit network: explicit network means users are connected through real relationship (friends/family/colleague) or social network. Individual's preference for relevant contents (movies, music, TV program) may be influenced by his/her social relationship. For example, a user has watched The Big bang Theory and likes it, and then he/she may recommend the drama to his friends or colleague. On the other hand, if most of the user's friends think the drama is good, the user may also like the drama.

Different learning task may need different algorithms. For example, learning from experience task could use content-based filtering methods such as Bayesian classifier, Case-based reasoning, and vector space model and so on. Learning from implicit network task and learning from explicit network task can use collaborative filtering methods such as user/item-based filtering, Matrix Decomposition method, and so on. The final recommendations presented to users are the combination of the three learning results.

4. Important issues

In addition to the TV program recommender framework, we also address some import issues: accuracy, diversity, novelty, explanation and group recommendation, which are indispensable for building a TV program recommender.

4.1. Accuracy

Prediction accuracy is by far the most important metric to measure the quality of recommender systems and most discussed property in the recommendation system literature. Accordingly, recommending TV program that match consumers' preferences accurately is the most important aim of a TV program recommender, since the accuracy of recommendations will directly influence users' perception for the recommender. For example, paper [2] and [13] proved that perceived recommendation accuracy significantly influence perceived usefulness of recommender systems. Hence, the more accurate TV program recommendations a recommender provides, the more useful of the recommender users may feel. On the other hand, a TV program recommender which often misses users' preference and provides the wrong TV program list, may noise users and make them lose their confidence in the TV program recommender and even in the television itself.

There are many approaches to improve the accuracy of TV program recommendations. One way is developing new algorithms based on related techniques such as data mining, machine learning, and complex network by incorporating related resources such as TV program contents, users' watching behavior. Another alternative way is combining current recommendation algorithms. For example, the authors proposed a hybrid recommendation algorithm for TV program recommender by combining Bayesian classifier and Decision Tree through neural network in [8]. In [4], they showed a hybrid by combining case-based reasoning and collaborative filtering together. In our TV program recommender framework, we propose incorporating both of the two ways talked above. On one hand, we suggest developing three main algorithms: learning from individual past experience, learning from implicit network and learning from explicit network. And on the other hand, we propose combining the results of the three learning task we talked above.

4.2. Diversity

Diversity refers to how different the items in the recommendation list are with respect to each other. Diversity measures the diversity level of recommendations and is one of the metrics to evaluate the quality of a recommender system. Current research in recommender systems has been focusing on improving the diversity of recommendations. In [14], the authors addressed that providing accurate recommendations is not enough, the other aspect such as diversity of recommendations should be taken into account. For example, recommending a list of very similar TV programs may be of little useful for a user, even though this list's average accuracy might be high. The importance of diverse recommendations has been emphasized in several recent studies [2], [15]. For instance, in [2], they proved that diversity of recommendations is positively correlated with perceived usefulness of a recommender.

To provide diverse TV program recommendations, the main approach is by selecting the TV program that has maximum similarity with users' preference and, at the same time, has minimum similarity with other TV programs in the recommendation list. For example, paper [15] presented a novel method called topic diversification which is designed to balance and diversify personalized recommendation lists in order to reflect the user's complete spectrum of interests. Paper [16] proposed an approach to diversity in recommendations called Social Diversity which utilizes social networks in recommender systems to leverage the diverse of underlying preferences of different user communities to introduce diversity into recommendations.

4.3. Novelty

The novelty of a piece of information generally refers to how different it is with respect to "what has been previously seen", by a specific user, or by a community as a whole [17]. With respect to recommender systems, novelty of recommendations is defined with respect to the end-user as the proportion of known and unknown relevant items in the recommended list. The core concept of novelty is related to the recommender's ability to educate consumers and help them discover new items [2]. With the development of recommender systems and consumers' requirements, there is an increasing realization in the recommender systems field that novelty and diversity are fundamental qualities of recommendation effectiveness and added-value [17]. It is not enough providing accurate recommendations and consumers need to be recommended novel items that may "surprise them". Paper [2] proved that recommendation novelty is positively related to perceived usefulness of recommender systems.

Several research has mentioned novelty issues in recommender systems. In [18], the authors proposed a taxonomy-based recommender system that utilizes cluster based topic-to-topic associations to improve its recommendation quality and novelty. The proposed recommender utilizes techniques from association rule mining to find how different topics are associated with each other in a given user cluster. Based on the discovered topic associations, the recommender suggests items with topics that are strongly linked to the taxonomy profile of the target user.

4.4. Explanation

Explanation of recommendations means reasons for recommending particular items to particular users. There are several recommender systems provide explanations for their suggestions in the form of similar items the consumer has rated highly, like Amazon, or keywords describing the item caused it to be recommended [19]. Explanations help users to decide whether to accept the recommendations or not and to understand the incorrect reasoning when a prediction is inaccurate. In [20], they found that a good CF algorithm that generates accurate recommendations is not enough to constitute a useful system from the consumers' perspective and the system needs to convey to the consumer its inner logic and why a particular recommendation is suitable for them. In paper [13], they found that some users were curious to know more about how the system was achieving such good recommendations (music).

With respect to TV program recommender systems, we also propose that giving explanation of recommendations will make users trust the systems and increase their satisfaction for the systems. For instance, According to [2], [21], [20], the role of transparency in a recommender system is very important, and the recommender system can convey its inner logic to the user via the explanation interface. Paper [21] proposed that explanations showing how the system works make recommender systems much transparent and good explanations could help increase consumers' satisfaction, making it quicker and easier for consumers to find what they want, and persuade them to try or purchase recommendations. In [22], they argued that the contribution of explanation is not only to convince consumers to adopt recommendations, but also allow them to make more informed and accurate decision about which recommendations to utilize, and eventually affect consumers' satisfaction to recommender systems.

4.5. Group recommendation

As entertainment devices, televisions are often viewed by a group of users, such as a family or viewers at public places. For example, people in one family may have different preference and habits for TV program. The housewife may often watch TV in the afternoon, children may often watch cartoon in the evening and the husband may often watch news in the night. But when they watch TV program in the weekend, they might watch the preferable TV program for everyone. So the TV recommender systems should not only provide personalized programs for individuals, but also be able to recommend programs to multiple viewers taking care of the preferences of the majority of viewers, in the case where the viewers are watching TV at the same time, and in the same spot [23].

Group recommendation is one of hot research topic in the area of TV program recommendation. In [24], they discussed different strategies for combining individual user models to select TV items to suit groups of viewers and arrive at a recommendation decision to a group of users through combining individual user ratings on whole programs rather than features. In [25], the authors proposed a user interest aggregation method for group recommendation by allowing the current member optionally to view (and perhaps copy) the preferences already specified by other members. Paper [26] suggested user profile merging algorithm, which merges individual profiles so as to form a common user profile that reflects most and consistent preferences of the group.

5. Conclusion

This paper presents a literature overview of TV program recommender systems. Based on related the research, we propose a smart, and social TV program recommender framework which consists of TV program content analysis module, user profile analysis module and user preference learning module. The proposed framework not only processes TV program content and users' direct feedback, but also suggests extracting related information such as TV watching statistics information, users' preference/interest for the other contents from social media or relevant organization. In the preference learning module, we suggest three user preference learning approaches: leaning from individual's past experience, learning from implicit network and learning form explicit network. In addition to, we also address several issues, which are important in the building of a

TV program recommender system, such as accuracy, diversity, novelty, explanation and group recommendation and show some corresponding solutions for these issues. The proposed framework could be used to help designers/developers to build TV program recommender systems/engines for smart TV.

In the future, we will continue to work on this topic and improve the proposed TV program recommender framework and give specific recommendation algorithms to promote the performance of TV program recommender systems in terms of accuracy, diversity, novelty, explanation and group recommendation. Furthermore, we will design and build a prototype of TV program recommender system based on the proposed framework and conduct a user survey to verify the proposal.

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