POI ENHANCED VIDEO RECOMMENDER SYSTEM USING COLLABORATION AND SOCIAL NETWORKS

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Abstract: Every day, the number of videos available in the world increases. For instance, there is a vast amount of video websites, like Youtube and NetFlix, VOD services, as well as PVR devices that automatically record videos, 24 hours a day. Apparently this situation allows a large possibility of choice for the user, on the other hand, it creates an overload problem, i.e., a difficulty to find the correct content for the user needs. One of the ways to treat such an overload is the use of recommender systems, which filter the content in order to deliver what is most interesting to the user. This paper presents an approach that allows the annotation of points of interest on videos on the Web. Through this, users can mark their most interesting points on the videos. This information can thus be used in conjunction with the user profile and interests to provide recommendations. The differential of this paper is to show how points of interest can be used to enhance video recommender systems and how to design social networks of users with common interest points.

1 INTRODUCTION

Every day the number of videos available in the world increases. For example, there is a vast amount of video websites (e.g. Youtube, NetFlix, TerraTV, etc.), and VOD services (Video On Demand), as well as devices that automatically record videos, known as PVR's (Personal Video Recorders), 24 hours a day. Just on YouTube, the leader website of online video sharing on the Web, 48 hours of video were daily added every minute on the Website in 2010 (Google, 2012).

It poses an important issue for the user: the overload of video content. One way to treat such an overload consists on the use of recommender systems, which filters the content in order to deliver what is most interesting to the user.

The typical approach used by filtering systems consists on a hybrid recommender system, i.e., one that uses both content-based and collaborative filtering, minimizing the problems that these approaches have individually. Additionally, in order to create new recommendation models or to improve recommendation, new approaches have been proposed, such as the use of context information (Naudet, Mignon, Lecaque, Hazotte and Groues, 2008), information from social networks (Golbeck and Hendler, 2006), annotations of content with tags (Hung, Huang, Hsu and Wu, 2008), among others. In the video recommendation area, recent works have focused on the annotation of Points of Interest (POI). Through this, users can mark points on the video that are more interesting for them.

This paper presents an approach to use POI to enhance video recommender systems, and shows how a social network of users with POI in common can be created and used to perform recommendations. In such approach, the user participates more interactively and actively through collaboration.

The rest of this paper is organized as follows. Next section presents related work. In section 3, recommender system's theory and concepts are presented. Section 4 gives an example of a video recommender system that is extended in sections 5 and 6 in order to use POI to enhanced recommendation and to build social networks of user who have POI in common. In the last section, we present our conclusions and discuss future works.

2 RELATED WORKS

There are many works about video recommender

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systems. For instance, Qin, Menezes and Silaghi (2010) extract information about video's relationship using a network formed from reviews left as comments in videos from YouTube. A network of videos is created, and it is used as the basis of a recommender system. Analogously, this paper shows how to create a network using POI.

Nathan, Harrison, Yarosh, Terveen, Stead and Amento (2008) present a system named CollaboraTV, which was made to study new ways to watch TV and new interaction approaches among viewers. In this system, the user can put temporal linked annotations on videos or TV programs. One kind of annotations is POI. When the user is watching a video, he/she can mark positive or negative interest points in the current position of the video stream. These points are used to build interest profiles for users and communities of users. The paper suggests that the most popular positive interest points of different TV programs can be used to produce a new program. The system offer recommendation of the most popular TV programs and encourages the exchange of recommendations between users. Their authors suggest that annotations could be used to generate recommendations in a future work. In this paper, is actually presented how to use interest points in recommendation.

Chakoo, Gupta and Hiremath (2008) exploit the fact that users tend to like more of particular segments of the viewed content than the rest. The extraction of these segments and their information is used to enrich user experience, improving the quality of video recommender systems. The user must mark each segment pointing its beginning and ending in the video stream. Additionally, the user can rate each segment. With this information, an user profile of scene interest is built. Their authors focus on development of a method to extract scene segments from the viewed content and on the presentation of a framework capable of presenting recommended content visibility. Differently, this paper focus on the classic item recommendation and presents and analyzes a generic way of marking interest points, which can be done not only in viewed content, but also in content being viewed.

The aforementioned works showed that interactivity and collaboration can be used to improve video recommenders systems. In addition, current research in this field shows that the combined use of content and collaboration is better. Therefore, the most-used approach is to combine content-based filtering (CBF) and collaborative filtering (CF) in a hybrid approach. For instance, Lekakos and Caravelas (2008) present experiments showing that the accuracy of a hybrid approach is greater than the one using these base filtering approaches alone. Based on this fact, this paper shows how to enhance these hybrid recommenders using POI.

3 RECOMMENDER SYSTEMS

Recommender systems help users identify items of interest. These recommendations are generally made by two types of filtering: collaborative filtering (CF) and content-based filtering (CBF).

CBF takes the descriptions of the previously evaluated or currently accessed items by the user to calculate the similarity between items, and, then, recommend items of interest to the user. This type of filtering enables personalized recommendations for users, however it has two main disadvantages (Nguyen, Rakowski, Rusin, Sobecki and Jain, 2007): (i) it depends on one objective description of the items; and (ii) it tends to overspecialize recommendations.

CF calculates the similarity between users and recommends items that are liked by similar users. This uses ratings given by users in the past to find the best item. It has two main disadvantages (Sarwar, Konstan, Borchers, Herlocker, Miller and Riedl, 1998): (i) the early-rater problem that occurs when an user is the first from his/her neighborhood to rate an item; and (ii) the sparsity problem that is caused when there are few ratings for the items.

These filtering types can be combined in a hybrid recommender system that takes the advantages of both in order to overcome their disadvantages alone.

4 VIDEO RECOMMENDER SYSTEMS

Often called movie recommender systems, the most popular ones apply a hybrid approach. The CBF component uses descriptive features of the videos. These features can be, for instance, title, genre, language, duration, producer, actors and plot keywords. These features can also be used to describe the user's preferences in an user profile. In this case, the recommendation task consists on matching item features and user preferences.

To make the recommendations a CBF component evaluates the similarity between the current item that the user is accessing (or items accessed in the past) and other existent items. Similarity can be measured in different ways. A simple one checks if the genre of the video is in the user profile. If so, the item is a candidate to be recommended. More complex ways use similarity metrics as the cosine measure. In this metric each item is represented by a vector, the length of which is equal to the number of non-unique features of all available items. The elements of the vector state the existence or non-existence (boolean) of a specific feature in the description of the item. This metric, which is presented bellow (1), is used by Lekakos and Caravelas (2008).

$$\mathrm{sim}(a',b') = \frac{a'.b'}{|a'|*|b'|} = \frac{\sum_i a_i b_i}{\sqrt{\sum_i {a_i}^2}\sqrt{\sum_i {b_i}^2}} \quad (1)$$

In this equation, a_i and b_i are the values of the i_{th} elements of vectors a' and b'. The result is a numeric value used to calculate the of CBF component prediction.

The CF component uses user ratings of items. The typical approach used is a neighbourhood-based algorithm, divided in 3 steps: (a) computation of similarities between the current user and other users, (b) neighbourhood development, and (c) computation of prediction based on weighted average of the neighbours' ratings on the target item.

For the first step, typically the Pearson's Correlation Coefficient is used. In (2) presented the adapted Pearson's Correlation Coefficient utilized in Lekakos and Caravelas (2008) is presented.

$$sim(X,Y) = \frac{n\sum_i X_i Y_i - \sum_i X_i \sum_i Y_i}{\sqrt{n\sum_i {Y_i}^2 - (\sum_i Y_i)^2}\sqrt{n\sum_i {X_i}^2 - (\sum_i X_i)^2}} \quad (2)$$

In this equation, X_i and Y_i are the ratings of users X and Y for item i, and X, Y refer to the mean values of the available ratings for the users X and Y. At the neighbourhood development step, neighbours with positive correlation to the active user are selected. Finally, to compute an arithmetic prediction for an item, the weighted average of all neighbours' ratings is computed using following equation (3).

$$Ki = K' + \frac{\sum_{J \in Neigboors}(J_i - J')r_{K_j}}{\sum_J |r_{K_j}|} \quad (3)$$

Here, K' is the average mean of usr's ratings, J_i is the rating of neighbour J for the item i, J is the average mean of neighbour J's ratings and r_{Kj} is the Pearson correlation measure for the user and neighbour J, and K_i is the prediction for item *i* in the CF component.

A hybrid approach can be applied by combining the CBF and CF components using some of the hybridization methods. For instance, the Switching method (Burke, 2007) can be used. Both components can make its predictions and a switching criterion choose the prediction that will be used to make the recommendation. This switching criterion can be, for instance, the number of CF predictions: if it is above a threshold the CF component will be used, otherwise the CBF will be used.

5 POI VIDEO RECOMMENDER SYSTEM

Natan et al. (2008) and Chakoo et al. (2008) showed that interactivity and collaboration of users can be used to improve a recommender system. The first allow users to mark their current position on the video stream with positive or negative interest points. The second allows users to mark segments on a viewed video. The user tends to like particular segments of the video more than the rest. In the remaining of this paper, a segment of video will be called as POI.

A POI of an user in a video can have intersection with a POI of another user or users. When the number of intersections within a single video exceeds a certain threshold, and it occurs between different videos among couples of users, it is suspected that these users have common interests, or similar taste, about videos. Faced with such evidence, the following proposition is released: "interest points can be used to find similar people, or who have common interests, or taste like, about videos, and this similarity can be used to enhance a video recommender systems". One of the goals of this work is to verify if this proposition is true.

Figure 1 shows how the POIs can be arranged along a video timeline. In this example, four users, identified by U_1, U_2, U_3 and U_4, share their interest points about one video. The interest points of some users have intersections with the interest points of other users. Above a threshold of intersections, it is said that users are similar. Although to have more certainty on this similarity, that analysis should be extended to different videos, also considering a certain number of videos.

Figure 2 shows the analysis on an extended set of videos. In this figure, it is observed that users U_2 and U_4 are the most similar in the group of users for a minimum of three videos and two intersections (i_m) in each video ($video_n$).

It is also possible that users have not marked any interest points in a video or have never seen the video. It is also possible that when re-watching a video, the user mark new interest points or want to clear existing ones.

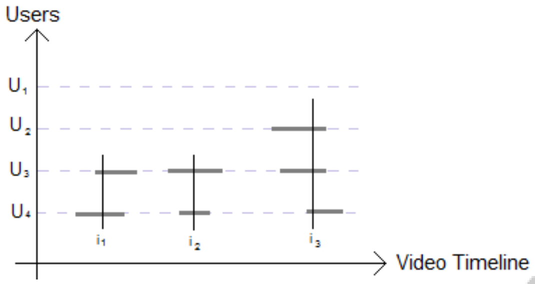

Figure 1: users' POI in a video and their intersections showing common interests between users.

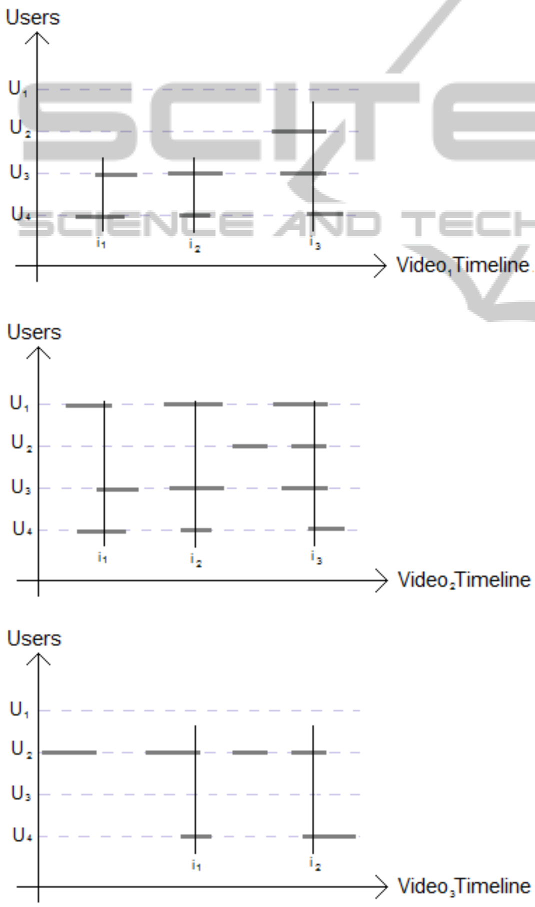

Figure 2: users' POI in different videos.

5.1 Enhancing a Video Recommender System with POIs

To calculate the similarly between users, a utility function will be used. This function will use the intersection on interest points about video of a couple of users to calculate a value between 0 and 1 that correspond to the degree of similarity between a couple of users. When the value is 0 the two users don't have similar interest, or taste, about any video; when the value is 1 the two users have the highest degree of similarity of interest, or taste, about a video. This function will be used to enhance the similarity calculated by the CF component, using equation (4).

$$sim^{CFe}(a,b) = sim^{CF}(a,b) * \left(1 + sim^{POI}(a,b)\right) \quad (4)$$

Here, $sim^{CFe}$is the enhanced similarity of CF component, sim^{CF} is the similarity of the CF component and sim^{POI} is the utility function. If the value computed by the utility function is 0 the CF similarity doesn't change; if this value is greater than 0 it acts increasing the sim^{CF} as percentage value.

5.2 Marking POIs

POIs are marked by the user while he/she watches the video. The user interface of the system must provide a widget with options to collect POIs.

For instance, the webpage showed in the Figure 3, that was built to make a preliminary study about POI marking in this work, can be used to mark POIs. In this page when the user starts the presentation of the video a new area is displayed, where there are options to mark POIs. It can be done through 3 buttons ("10 seconds", "20 seconds" and "30 seconds"). When the user click in one of this buttons, for instance "20 seconds", a POI is marked from the current position on the media stream until the point 20 seconds before the current position of the media stream. For instance, if the current position of the media stream is 50 seconds and the user click on the button "20 seconds" the POI will start at position 30 seconds and finish at the position 50 seconds. The POI can be logged using an asynchronous HTTP request running on background. This approach to mark POIs is fast and easy to do and it doesn't need to come back the media stream.

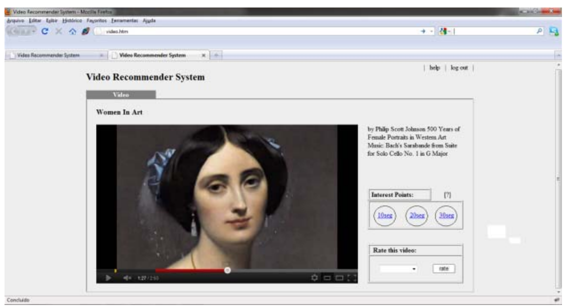

Figure 3: A webpage where the video is presented, and the user can mark POIs.

(In the preliminary studies made in this work about POI marking people marked interest points seconds after it occurs on the video stream and with no long duration, and without losing the attention on video due to interaction. So, it is expected that 10, 20 and 30 seconds could be adequate to a complete study.)

6 POI SOCIAL NETWORK AND COLLABORATION

Social networks are composed of users who have common interests and share information among themselves. Users can share experiences, interact with others, learn and disseminate knowledge (Zanda, Menasalvas and Eibe, 2011).

Through the similarity between users calculated by the intersection of interest points, users with similar interest or taste about videos can be found. Based on this evidence the following proposition is released: "the similarity between users based on interest points, which must be expressed in numerical value, can be used to build a social network. Through this network the person can meet others similar to him/her and receive (or exchange) more precise recommendations, person to person". Other goal of this work is to verify if this proposition is true.

A POI social network is presented in the Figure 4. The nodes are users; an edge is established between two users if they have at least one intersection of interest point. The user is the central node, the rest of nodes are the existing users similar to he or she. They are connected by edges. Each edge has a numeric value, calculated by the utility function (Section 5.1), and its value correspond to width (weight) of the edge between the nodes. Users with higher degree of similarity are more closer, and with lower degree are more distant at the social network graphic presentation.

An user viewing your social network can meet users like he/she, and seek advice, or even, exchange recommendations directly with another user. For example, U_1 could access the U_{16} and see the "Top 10 rated videos by U_{16}," could "exchange recommendations by chat or e-mail," or even "see what the user is watching now" if the user U_{16} is online (and permits it). This approach employ a simple yet powerful mechanism, follow the Informational Social Influence that tells to user that when he or she do not know what to do, he or she often times copy other users (Aronson, Wilson and Akert, 2005).

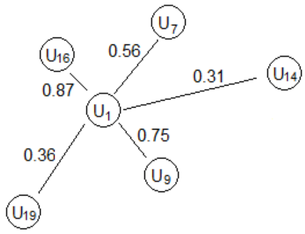

Figure 4: A POI social network formed by users with interest points in common about video.

For instance, the webpage showed in the Figure 5, that was built to make a preliminary study about POI social network presentation in this work, can be used to present a POI social network. When the user access other user the system shows a tooltip with its user profile (photo, name, age, gender, country, city, status) and some options to interaction: see the "Top 10 best rated videos", "chat" and "e-mail" to exchange recommendation of videos, and "watching now" to see what video the user is currently watching. This three last option are active when the user is logged in the system.

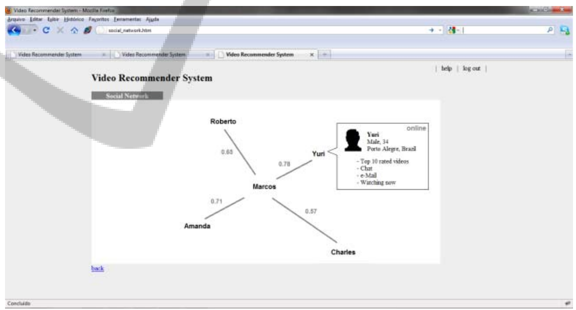

Figure 5: A webpage with a POI social network and options to access or exchange video recommendations with other user with similar interests about video.

7 CONCLUSIONS AND FUTURE WORKS

This paper presented an approach that allows the annotation of points of interest (POI) on videos on the Web. Through this, users can mark their most interesting points on the videos. This information can thus be used in conjunction with the user profile and interests to provide recommendations. Moreover, this paper showed how POI can be used to enhance video recommender systems and how to create social networks of users with common interest points and use it to perform recommendations. In this approach, the user participates more interactively and actively through collaboration.

Furthermore, this approach can be applied in different scenarios, and not only on the Web, but in video on demand (VOD) services and on devices such as Personal Video Recorder (PVR), on TV and in mobile devices.

An important point is the POI marking, it is influenced by the system design, and especially, by the design of interface and of interaction.

For future works a prototype and the POI utility function will be developed to validate the propositions made. YouTube will be used as a video source through its integration API. If the propositions are positively confirmed, the approach will be extended to other types of media (audio, text, picture and TV program). In the case of audio and TV programs the same approach used to mark interest points on video can be used in audio and TV programs. In the case of text the approach to mark interest point will be made similarly as it is done with a highlight text pen. In the case of one picture the approach to mark interest points will be made by the delimitation of interest regions on the picture. Other approaches to mark interest points in video will be tested as mark the beginning and the ending of interest point in the video stream, that is indicated to environments where the user can rewind the video or review its, as on Distance Education.

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