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A Novel Advertisement Recommendation System For Online Video Portals

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Abstract

Online Video portals like YouTube, Vimeo, NetFlix, Vube, Twitch, etc., usually display advertisements before playing videos to its users based on the category to which the user belong to. However, due to the varied interests of the user, visibility of such advertisements is restricted. In this paper, we propose a novel technique which helps bring the right advertisement to the right users. We have implemented this idea using two collaborative algorithms. To satisfy this purpose we have designed a local video portal with a new recommendation system which benefits both users as well as the advertisers. Results show that 68.35% of viewers were interested in the advertisements that were displayed using our proposed technique

Keywords: Advertisements, Collaborative Filtering, Recommender System, Video Portals.

Introduction

There are more than 70 online video portals[13]which are targeted by advertisers to showcase their wares. The advertisements are usually added as an overlay over the video being viewed. Due to the varied interests of the user many of these advertisements are skippedwhich results in loss of revenue to the advertiser. Pricing flexibilities exist to help out the advertiser [14] in this scenario, but it is much more beneficial for the advertiser to target the right viewer. Therefore, it is now essential to find a best way for displaying advertisements on online video portals such that it is helpful for both the video portal viewer as well as the advertisers.

In this paper we propose a novelrecommendation system that is able to bring the right advertisement to the target audience, even if they are guest users. We have generated a dataset based on a thorough survey over a restricted age group which we have used to train our system. Our recommendation system suggests relevant advertisements out of a large number of advertisements available by analysing the viewers' behaviour. Collaborative filtering [1, 2, 4] techniquessuch as user based and item based are some of the most widely used methods in recommendation. In such areas, the dataset generated through the survey helps in finding the taste of the users. Identifying viewers' interest levels through an innovative tracking technique also helps improve viewership when integrated with the collaborative algorithm.

This paper is focused on the various video advertisements displayed on the video portal and does not take into account the various text and image based advertisements.Further, we define that a 'guest user' is one who is currently not logged in to the video portal and as a result we have no statistics regarding the viewers' preferences. Also, in the interest of brevity, for the rest of our paper, we will shorten the word "advertisement" to "ad" / "ads".

The paper is organised as follows section 2 describes the existing system by taking a popular video portal as a case, section 3discusses the proposed technique section 4 elaborates the proposed technique with various observations on the technique. Finally we conclude the paper in section 5 and also explore possible extensions of the technique described.

Existing System
For our research, we have analysed the working and design of one of the most popular video portals - youtube.com [9, 14].YouTube plays a vital role in marketing by means of advertisements which are not only segregated based on the demography of the viewer, but also on advertiser preferences and viewer recommender statistics of registered viewers.These advertisements or ads are displayed as pre, mid, and post rolls before the desired video is played [15, 16].

Once an advertisement begins, YouTube gives viewers 5 seconds to decide whether to continue watch or skip the advertisement. If the user wants to skip an advertisement SKIP AD button must be clicked and proceeding to it displays the actual video that was chosen.

There are a few issues with this approach.

1. Once the actual video begins the viewer cannot go back to the ad that was skipped.
2. Recommending an ad based on demography or category does not ensure proper viewership.

So to overcome this we suggest the technique of Advertisement shuffling.

Proposed System
We propose an efficient way of shuffling the advertisements using collaborative filtering and identifying even guest user preferences using an innovative tracking technique. Figure 1 shows the high level design of our proposed system.

The research can be viewed as three interlinked modules.

- Data Collection
- Recommendation system
- Identifying Viewer Preference

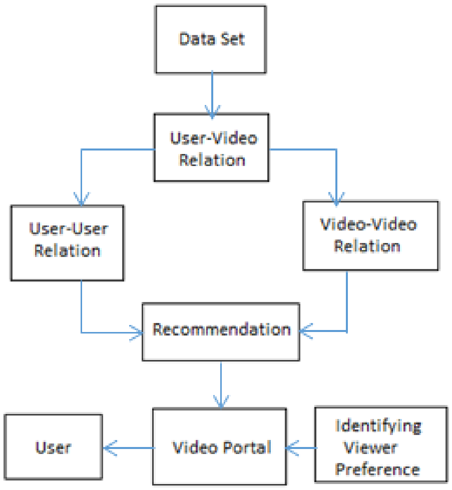

Figure 1: Architecture Diagram

Data Collection Methodology

Our dataset consists of a set of videos and ads which were rated initially by an equal number of male and female registered viewers within the 20-25 age groups. As the viewership frequency is quite substantial within this age group [17]. A simple video portal was developed which mirrored the user interface of a popular video portal. Each registered user was then requested to login to the developed portal and view videos. The videos ranged from technical lessons to short humour and popular music. Advertisements of a wide range were also overlaid over videos in a randomized manner.

The individual user preferences were first selected based on the user who skipped a particular advertisement. In the dataset, -1 implied that the user had skipped an ad and so did not like it while 1 denoted that the user liked the ad and watched it completely. This led to the creation of various user-video, video-video and user-user relations which are detailed in section 3.2.

Recommendation System

This system mainly uses the collaborative filtering in two ways

1. Item-based Collaborative Filtering
2. User-based Collaborative Filtering

Item-based Collaborative Filtering

Item-based collaborative filtering [8] is a model-based algorithm for making recommendations. For this research, the various 'videos' are the ads available for view. We use the correlation values between the video that is skipped by the guest user and other videos present in our dataset. The correlation value is calculated by using Pearson correlation formula,

$$\text{simil}(x,y) = \frac{\sum\limits_{i \in I_{xy}} (r_{x,i} - \bar{r_x})(r_{y,i} - \bar{r_y})}{\sqrt{\sum\limits_{i \in I_{xy}} (r_{x,i} - \bar{r_x})^2 \sum\limits_{i \in I_{xy}} (r_{y,i} - \bar{r_y})^2}}$$

Equation 1: Pearson Coefficient [12]

Here r_x denotes the correlation coefficient of skipped video and r_y denotes the correlation coefficient of the other videos.

User-based Collaborative Filtering

User-based collaborative filtering [11] finds other users whose past rating behaviour is similar tothat of the current user which is found using the Pearson Correlation Formula (Equation 1) and use their ratings on other items to predict what the current user will prefer.

Identifying Viewer Preference

For our research we have categorised the viewer into 3 classes, namely

1. Registered Viewers
2. Newly Registered Viewers
3. Non-Registered Viewers

The method of recommendation varies among these classes. The following sub-sections detail these methods.

Registered Viewers

As the viewer begins to watch a video, the first ad that is displayed will be recommended by user based Collaborative Filtering. And if viewer watches the complete ad then we update the particular user-video cell in the relation table with value 1 and then play the actual video that was chosen.On the other hand, if the user skips the advertisement then we update the table with value -1 and use the user-based collaborative algorithm to recommend another ad.

Newly Registered Viewers

When the viewer chooses a video to watch, the first advertisement displayed will be random one, as we don’t have any history about his past browsing. If the viewer watches the advertisement then we update the user video relation table as 1 and the actual video is played else if the viewer skips the ad, a new ad is displayed using user-based collaborative algorithm and finally an update is made in the table correspondingly.

Non-Registered Viewers

These viewers are also known as guest users. Statistics state that the majority of video portal users are non-registered users [18]. Such viewers do not have any historical data or even a user identification field for the user based collaborative filtering technique to work. Therefore we have customised our video portal to attract these viewers. It is also well known that when there is a sudden change [19], people usually become more curious about it. So we tried to identify the viewer boredom or negative preference based on his mouse movement. Once we identify that an active guest user demonstrates a negative preference to the ad displayed, we replace the ad with another. For this replacement of ad we use item-based collaborative filtering which is more appropriate for this category as it only requires the video-video correlation value.

We assume that the viewer is “bored” by the ad played if the mouse moves towards the ‘skip’ button. Our aim is to shuffle / replace the ad if the mouse is moved towards the skip button. To aid this concept of “shuffling”, our video portal consists of two containers c1 and c2 around the skip ad button as shown in Figure 3.

To ensure that the viewers’ mouse pointer intends to skip an ad and not just rest on screen, we calculate the speed of the mouse pointer at each container. s1 and s2 are the calculated speeds at containers c1 and c2 respectively. With the speed s1 and s2 we decide whether the viewer skips the ad or not and this is discussed in the following cases.

Case1 (s1 > s2): The mouse pointer passes over the skip ad button and does not stop on the skip ad button.

Case2 (s1< s2): The mouse pointer is slowing down near the skip ad button, so assume that the user is skipping the ad.

Case3 (s1==s2): There is no change in the video and the user has not yet decided to skip the ad.

If the advertisement is skipped, we have included a ‘back’ button as an overlay over the video for 5 seconds if the user wants to continue to view the previously displayed advertisement.

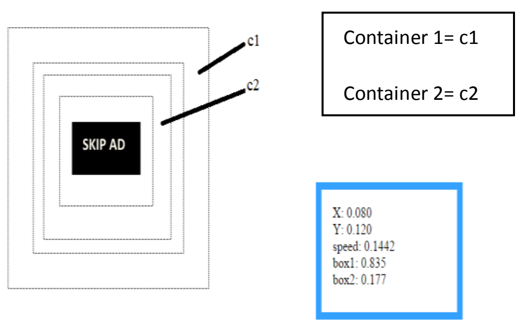

Figure 2: Skip AD Button with 2 Containers

Observation and Result

Based on the initial dataset, the correlation coefficient value for each video given by every user is calculated. This coefficient value is considered as an input for calculating the correlation similarity between two users using Pearson Correlation Formula (Equation 1). Table 1 shows the recommendations derived using user-based Collaborative Filtering, where the videos 9, 7,10, 67, 78 are recommended to the user 1 (for instance) and are ordered in decreasing order of preference values.

Table 1: Videos recommended to the user 1 using User based CF

Video ID	Preference Value
9	2.267949
7	2.0717967
10	2.0717967
67	2.0717967
78	2.0

In case of non-registered or guest viewers, the item based collaborative filtering is used to recommend ads. Table 2 shows the recommendations derived using Item based collaborative filtering, where 5,3,14,34 are the videos that are similar to the video 1 and their correlation similarity are 1.0,1.0,1.0,0.95 respectively.

Table 2: Video Similarities using Item based CF

Video ID	Recommended Video ID	Item Similarity (resp.)
1	5,3,4	1.0,1.0,1.0
7	4,2,3	1.0,1.0,1.0
9	10,11,15	1.0,1.0,0.95
10	9,11,15	1.0,1.0,0.95
11	9,10,15	1.0,1.0,0.95

Based on a survey we found that 66.7% of male candidates and 70% of female candidates completely watched the ads recommended by this technique. On an average we found that 68.35% of viewers completely viewed the recommended ads without skipping.

Conclusion and Future Work

This paper puts forward a technique improve the visibility of video advertisements on popular video streaming websites. Experimental results and user study shows that this technique ensures that the advertisements reach the intendant audience, thereby increasing the viewership and benefiting both the advertiser and viewer.

As the correlation dataset grows, the technique proposed in this paper recommends ads with increasing accuracy. However, the downside is the high level of computation required. Parallel and distributed algorithms may provide an effective solution. Future research will be in this direction.

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