



Embedding user preferred advertisement in video playback in ecommerce

Dr.J.Dafni Rose,
Head of the Department,
Computer Science and Engineering
St. Joseph's Instituter of Techonology
Chennai, India.
jdafnirose@yahoo.co.in

Andrews D. Newton, S. Hari Prasad
Student, Computer Science and Engineering
St. Joseph's Instituter of Techonology
Chennai, India
andrewsnewton14@gmail.com

Abstract— The prevalence of online videos provides an opportunity for e-commerce companies to recommend their products in videos. In this paper, we propose an online video advertising system named Video Advertisement Embedding In Video Playback Using Ecommerce, to exhibit appropriate product ads to particular users at proper time stamps of videos, which takes into account video semantics, user shopping preference, and viewing behavior feedback. First, an incremental co-relation regression (ICRR) model is novelly proposed to construct the semantic association between videos and products. To meet the requirement of online advertising, ICRR is implemented in an incremental way to reduce the time complexity. User preference diffusion (UPD) is induced under the framework of heterogeneous information network to construct user-product association from two different e-commerce platforms, Tmall and MagicBox, which alleviates the problems of data sparsity and cold start. A video scene importance model (VSIM) is proposed to model the scene importance by utilizing the user viewing behavior, so that ads can be embedded at the most attractive positions in the video stream. To combine the outputs of ICRR, UPD, and VSIM, a unified distributed heterogeneous relation matrix factorization (DHRMF) is applied for online video advertising, which is efficiently conducted in parallel to address the real-time update problem, so that the whole system can be performed in real time.

Keywords:

I. INTRODUCTION

An advertisement is a notice or announcement in a public medium promoting a product. Advertising plays significant role in the introduction of a new product in the market. It stimulates the people to purchase the product. In this paper, we propose a novel personalized Online Video Advertising System is presented to recommend product ads from ecommerce sites to users of online video hosting. In the existing model advertisements are randomly chosen and are displayed to all the users the same ads. This will be frustrating for most of the users because they were not interested on the displayed advertisement. Most of the time the users will skip the ads because they were not interested to see that. The most used button in online is the skip ad button. In the proposed model the advertisements are shown according to the user's interests. For that first we have to find the user's preference. This can be mined from an ecommerce site. For that we have to analyze each user's behaviors of ecommerce sites. Whenever the user starts to use a product specification the

amount of time the user spends to see the product is calculated. After collecting the each user preference, we have to identify the semantic association between videos and products and construct the association between key frames and products. The relation between the videos and products can be identified by splitting the videos and searching the products from the frames. When user plays the video and if the user preferred product is present in the video then the user preference advertisement are shown in the video in proper timestamps. That is as long as the product is present in the video the advertisement will be displayed in the video without interrupting the video playback.

II. LITERATURE SURVEY

Jun Wang, Arjen P. de Vries, Marcel J.T. Reinders et al 1996 [12] "Unifying User-based and Item-based Collaborative Filtering Approaches by Similarity Fusion" proposed that Memory-based methods for collaborative filtering predict new ratings by averaging (weighted) ratings between, respectively, pairs of similar users or items. In practice, a large number of ratings from similar users or similar items are not available, due to the sparsity inherent to rating data. Consequently, prediction quality can be poor. This paper reformulates the memory-based collaborative filtering problem in a generative probabilistic framework, treating individual user-item ratings as predictors of missing ratings. The final rating is estimated by fusing predictions from three sources: predictions based on ratings of the same item by other users, predictions based on different item ratings made by the same user, and, third, ratings predicted based on data from other but similar users rating other but similar items. Existing user-based and item-based approaches correspond to the two simple cases of our framework. The complete model is however more robust to data sparsity, because the different types of ratings are used in concert, while additional ratings from similar users towards similar items are employed as a background model to smooth the predictions. Experiments demonstrate that the proposed methods are indeed more robust against data sparsity and give better recommendations.

Paridhi Jain, Ponnurangam Kumaraguru, Anupam Joshi et al 2015 [19] "Identifying Users across Multiple Online Social Networks" proposed that an online user joins multiple social networks in order to enjoy different services. On each joined

social network, she creates an identity and constitutes its three major dimensions namely profile, content and connection network. She largely governs her identity formulation on any social network and therefore can manipulate multiple aspects of it. With no global identifier to mark her presence uniquely in the online domain, her online identities remain unlinked, isolated and difficult to search. Literature has proposed identity search methods on the basis of profile attributes, but has left the other identity dimensions e.g. content and network, unexplored. In this work, we introduce two novel identity search algorithms based on content and network attributes and improve on traditional identity search algorithm based on profile attributes of a user. We apply proposed identity search algorithms to find a user's identity on Facebook, given her identity on Twitter. We report that a combination of proposed identity search algorithms found Facebook identity for 39% of Twitter users searched while traditional method based on profile attributes found Facebook identity for only 27.4%. Each proposed identity search algorithm access publicly accessible attributes of a user on any social network. We deploy an identity resolution system, Finding Nemo, which uses proposed identity search methods to find a Twitter user's identity on Facebook. We conclude that inclusion of more than one identity search algorithm, each exploiting distinct dimensional attributes of an identity, helps in improving the accuracy of an identity resolution process.

Sheng Zhang, Weihong Wang, James Ford, Fillia Makedon et al 2004 [21] "Learning from Incomplete Ratings Using Non-negative Matrix Factorization" proposed that we use a low-dimensional linear model to describe the user rating matrix in a recommendation system. A non-negativity constraint is enforced in the linear model to ensure that each user's rating profile can be represented as an additive linear combination of canonical coordinates. In order to learn such a constrained linear model from an incomplete rating matrix, we introduce two variations on Non-negative Matrix Factorization (NMF): one based on the Expectation-Maximization (EM) procedure and the other a Weighted Nonnegative Matrix Factorization (WNMF). Based on our experiments, the EM procedure converges well empirically and is less susceptible to the initial starting conditions than WNMF, but the latter is much more computationally efficient. Taking into account the advantages of both algorithms, a hybrid approach is presented and shown to be effective in real data sets. Overall, the NMF-based algorithms obtain the best prediction performance compared with other popular collaborative filtering algorithms in our experiments; the resulting linear models also contain useful patterns and features corresponding to user communities."

Zaem Hussain Mingda Zhang Xiaozhong Zhang Keren Ye Christopher Thomas Zuha Agha Nathan Ong Adriana Kovashka et al 2010 [28] "Automatic Understanding of Image and Video Advertisements" proposed that there is more to images than their objective physical content: for example, advertisements are created to persuade a viewer to take a certain action. We propose the novel problem of automatic advertisement understanding. To enable research on this

problem, we create two data sets: an image dataset of 64,832 image ads, and a video dataset of 3,477 ads. Our data contains rich annotations encompassing the topic and sentiment of the ads, questions and answers describing what actions the viewer is prompted to take and the reasoning that the ad presents to persuade the viewer ("What should I do according to this ad, and why should I do it?"), and symbolic references ads make (e.g. a dove symbolizes peace). We also analyze the most common persuasive strategies ads use, and the capabilities that computer vision systems should have to understand these strategies. We present baseline classification results for several prediction tasks, including automatically answering questions about the messages of the ads.

Tao Mei, Xian-Sheng Hua, Linjun Yang, Shipeng Li et al 1999 [23] "VideoSense – Towards Effective Online Video Advertising" proposed that with Internet delivery of video content surging to an unprecedented level, online video advertising is becoming increasingly pervasive. In this paper, we present a novel advertising system for online video service called VideoSense, which automatically associates the most relevant video ads with online videos and seamlessly inserts the ads at the most appropriate positions within each individual video. Unlike most current video-oriented sites that only display a video ad at the beginning or the end of a video, VideoSense aims to embed more contextually relevant ads at less intrusive positions within the video stream. Given an online video, VideoSense is able to detect a set of candidate ad insertion points based on content discontinuity and attractiveness, select a list of relevant candidate ads ranked according to global textual relevance, and compute local visual-aural relevance between each pair of insertion points and ads. To support contextually relevant and less intrusive advertising, the ads are expected to be inserted at the positions with highest discontinuity and lowest attractiveness, while the overall global and local relevance is maximized. We formulate this task as a nonlinear 01 integer programming problem and embed these rules as constraints. The experiments have proved the effectiveness of VideoSense for online video advertising.

Michail Dimopoulos, Thomas Winkler et al 2005 [17] "Image Warmness— A New Perceptual Feature For Images and Videos" proposed that many basic, but very useful features, for characterizing an image or calculating the similarity between two images are based on color information. Psychological studies show that beyond the tone of color, different colors are also associated with different emotions. Thus, two colors that trigger the same impression are most likely considered to be more similar than two colors which trigger the opposite impression. We introduce a new feature called image warmness. It is based on the cold or warm impression that a single color triggers in the brain of the beholder. Image warmness provides a measure about how cold or warm an entire image is perceived by humans based on colors it contains. In a survey and evaluation with 90 images and 101 participants we show that the values of image warmness calculated by the proposed formula are close to the average rating of the survey participants.

III. SYSTEM ARCHITECTURE

Initially the admin logs in into administrator's account and uploads videos. In the second step, the videos are converted into frames. At last every single frames are taken and are searched for key frames which resembles the product if the threshold value is crossed.

Now the user creates a profile for the ecommerce site and logs into the ecommerce site and searches for some products. While searching the product, the specification of that product is viewed. By calculating the amount of time the user viewing the product and the number of times the product viewed, the user preference can be calculated.

The preferred product can be either added to the cart for purchasing later or can be ordered. Here the items that are added into the cart is considered to be the most preferred product. The product that is ordered is removed from the preference list. While the product inside the cart is not viewed for a long time the product gets removed from the preference list. While ordering the product the user is redirected into the banking site where the user creates an account to pay the bill through online transaction.

Now the user creates an account for the video steaming site and logs in. Now the user selects a video and plays the video. If the user preferred object is present in the video, then for particular timestamps the product advertisement is displayed.

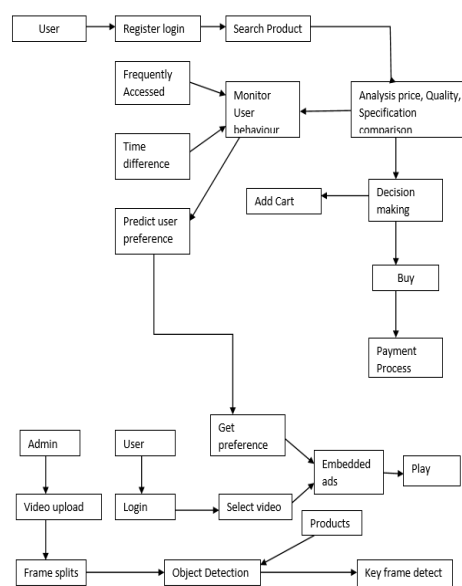


Fig 3.1 Architecture diagram of embedding the ad in the video

3.1 Video Uploads and Frame Splits

In the module, Video content provider's admin login his account and uploads video based on category in Server. Video displays based on the frame rate. The frame rate is the number of frames or images that are projected or displayed per

second. Frame rates are used in synchronizing audio and pictures. To show the ads, we need to find the relationship between videos and products. By using ffmpeg tool, videos are splitted into frames.

3.2 Product Based Key Frame Detection

In this module, we determine the semantic association between videos and products. Using surf Detector algorithm, Classify video frames based on products. Surf Detector is an algorithm, which extracts the some unique key points and descriptor from the product and frame. It matches the product key points and frame key points. If the matches reach the particular threshold, it is confirmed that the product present in the image. Surf Detector processes all frames one by one and finds the key frame for each products. The user registers his details and creates an account. The user watches the videos, this videos are uploaded by admin. In the database a table contains every video and all the products that are present in the video. It also contains the number of the frames in which the particular products appear.

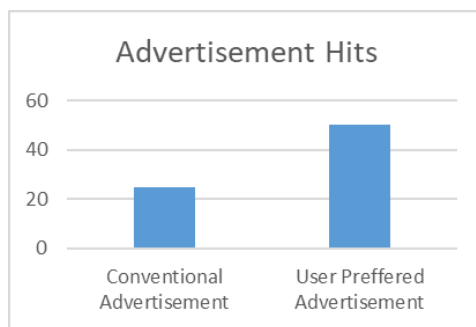
3.3 User Preference Mining

In this module, we determine the user preference based on the user's behavior. The user registers his details in ecommerce site and creates an account. User login his account and search products based on his requirements. Once the user enter his account, the user behaviors are observed till the user logs out of his account. User behavior analysis based on frequently search the product and how long user watches the product. User wants to buy a product, he spends more time to view the specification and at the same he clicks the product more number of times to view the specification, price etc. These techniques used to find the user preference. We find the user preference and give priority (Example: Priority will be given to newly updated product in the cart). When user buys a product it will go to payment process. User creates a bank account and credit money into the account. A OTP is sent to the user for payment verification. If the entered OTP is correct and if the account contains enough amount to buy the product the payment may complete successful.

3.4 Embedded ads on video

In this module, we embedded the advertisement in video in proper timestamps. After analyzing the user preference, User login into the video content provider site where the user preference are get from the ecommerce site. After user select any video, the system will verify is there any user preferred products will be available on the video. If it is present, it calculates the key frame and the respective products ads will be display on the video in particular key frame for particular timestamps.

IV. RESULTS



The above graph 4.1 shows the difference in the advertisement hits which is surveyed by 60 numbers of persons

V. CONCLUSION

To develop the proposed system we have to know some software language and the tools that are required for the process and the results that are obtained from it is being discussed here. The platform used here is JAVA. The basic Knowledge of the platform is to be provided so that only one can able to develop the required application. All the tools that are used for the development of the system is being explained in detail.

The System is being developed in a Windows platforms with the help of an Integrated Development Environment (IDE) where we can able to develop a system with the help of software languages and the tools for storing the data. The Tools required for storing the data is MySQL which is a Structured Query Language which would help to store the data in the local disk and make use of it for the development process. With the help of Query Language we can able to retrieve, process the data according to the need of the end user.

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