Application of multi factor comparison model to populate the trending videos from cross domain

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ABSTRACT

A Predicting the top-N popular videos and their future views for a large batch of newly uploaded videos is of great commercial value to online video services (OVSs). Although many attempts have been made on video popularity prediction, the existing models has a much lower performance in predicting the top-N popular videos than that of the entire video set. The reason for this phenomenon is thatmost videos in an OVS system are unpopular, so models preferentially learn the popularity trends of unpopular videos to improve their performance on the entire video set. However, in most cases, it is critical to predict the performance on the top-N popular videos which is the focus of this study. The challenge for the task are as follows. First, popular and unpopular videos may have similar early view patterns. Second, prediction models that are overly dependent on early view patterns limit the effects of other features. To address these challenges, we propose a novel multifactor differential influence (MFDI) prediction model based on multivariate linear regression (MLR). The model is designed to improve the discovery of popular videos and their popularity trends are learnt by enhancing the discriminative power of early patterns for different popularity trends and by optimizing the utilization of multi-source data. We evaluate the proposed model using real-world YouTube data, and extensive experiments have demonstrated the effectiveness of our model. Index Terms—Popularity Prediction, Top-Npopular videos, Cross-domain

INTRODUCTION

P Opularity prediction of online videos, especially the prediction of the top-N popular videos is of great importance to support the development of online video services (OVSs). From the perspective of better user experience, the ability to identify the top-N popular videos is beneficial to video services, such as caching and recommendation. From the perspective of commercialization, identifying the top-N popular videos helps the video service providers to maximize their profits, as advertisers are more likely to pay more for popular videos. Although many attempts have been made on popularity prediction of online videos [18][14][1][17][4], because most of the videos in an OVS system are unpopular; consequently, models preferentially learn the popularity trends of these unpopularvideos to achieve better performance on the video set as a whole. Prediction of the top-N popular videos remains a challenging problem for the following reasons. First, popular and unpopular videos may have similar early view patterns, and this similarity limits the performance benefit of video classification based on early view patterns [6]. Second,

Zhiyi Tan and Ya Zhang are with the Cooperative Medianet Innovation Center, Shanghai Jiao Tong University, Shanghai 200240, China (e-mail: skt1zytan@qq.com; ya zhang@sjtu.edu.cn). Ya Zhang is the corresponding author. existing studies show that the strong correlation between early views and long-term popularity dominates the training of the prediction models. This overdependence on early view patterns prevents models from finding popular videos based on multisource data [8][13]. To address the above problem, we present a novel popularity prediction model named multi-factor differential influence (MFDI) based on multivariate linear regression (MLR). We first enhance the ability of early view patterns to identify different popularity trends. We conduct a large-scale analysis of statistical data of early viewers' attitude-related behavior and the long-term popularity of videos. We find that the increase in the future popularity of videos follows an approximate Rayleigh distribution with respect to the degree of contradiction between early viewers with different attitudes. Based on this discovery, by combining early views with knowledge of early viewers' attitudes, we construct early rating patterns that offer better discriminative power for identifying popularity trend and use these rating patterns to replace early view patterns as the input to the proposed model. Furthermore, we incorporate the popularity of the videos' content on a social network to help the proposed model to discover popular videos and to learn their popularity trends. To overcome the restrictions on multi-source data utilization, we propose a timeaware trade-off mechanism to control the model's relative dependence on enhanced early patterns and social network data. The time-aware trade-off applies higher decay to earlier enhanced patterns and correspondingly increases the degree of denpendence of the model on social network data over time. We evaluate the proposed model using real-world data consisting of videos from YouTube and social network data from Twitter. Our experimental results show that the proposed model outperforms state-of-the-art models, thereby confirming the benefits of our efforts to improve the prediction performance for the top-N popular videos. The main contributions of this paper can be summarized as follows: • We propose a model for predicting the top-N popular videos. By enhancing the ability of early patterns to distinguish among popularity trends and optimizing the model's utilization of multi-source data, we develop a model that achieves the promised performance; • By using the tags of videos as indicators of their content and jointly training a multi-layer perceptron (MLP) network on the popularity data of videos and their related social content, we estimate the contribution of the popularity of a video's content on a social network to the long-term popularity of the video. 1This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TMM.2018.2845688, IEEE Transactions on Multimedia

RELATED WORKS

Since the popularity of online videos has been proven to be predictable through the statistical analysis of large-scale YouTube data [25][3], numerous related studies have been conducted. Szabo and Huberman (S-H) proposed a content-scaling (CS) model based on log-transformed relations between a video's long-term popularity and its early popularity [18]. Their conclusion is one of the most important foundations of popularity prediction research and has been succeed by many related works [24][1][2]. All of the approaches cited above achieved initial success, but their shortcomings has been uncovered by subsequent research. Pinto and Almeida discovered that videos with similar popularity at a given time may exhibit distinct popularity behaviors in the future. Based on this discovery, they proposed a new multivariate radial basis function (MRBF) model by investigating the view patterns during the early period instead of the cumulative views up to a given time [14]. The MRBF model showed better performance than the models of the SH paradigm and has been prven to have good extensibility and generalizability by subsequent research [13][7][10][23]. However, existing studies have focused on achieving high prediction performance on the entire video set, whereas the prediction of the top-N popular videos has been largely ignored. Unlike top-N video identification for video recommendation [9][5], the prediction of the top-N popular videos is concerned with the overall popularity in the entire video set rather than being oriented toward individual users. For services such as online advertising, knowledge of the top-N popular videos is of great commercial value for improving the profit-budget ratio. However, the prediction of the top-N popular videos remains a critical problem because the performance of existing models for predicting the top-N popular videos is far worse than their performance on the video set as a whole. This problem is caused by the Pareto distribution of videos' popularity, as most of the views received by a video set are associated with only a few popular videos. Therefore, to reduce the prediction error over the entire video set, models will preferentially learn the popularity trends of the unpopular videos, hence sacrificing prediction performance on popular videos. Some recent studies have attempted to more deeply analyze the dynamics of video popularity and have related the popularity dynamics to various factors [16][15][21]. Although some of these studies have improved the prediction performance through the leveraging of multiple factors, their experimental results also show that the utilization of multisource data is a critical problem due to the dominance of early patterns in the training of prediction models [4][20]. Enlightening research was performed by Wu and Zhou [22], who modeled the reactions of users and the information cascade as two hidden processes and attempted to fit the evolution of video popularity using a combination of these two processes. Although the Evo model is far from being suitable for real application in popularity prediction, the experimental results of Wu and Zhou's study illustrate that the modeling of additional early features is a feasible way to improve a model's ability to learn different popularity trends.

Symbols	Definitions
v_{ij}	views of video i over the period $(j-1, j]$
x_{ij}	enhanced pattern corresponding to v_{ij}
t_s	range of the observed data
t_r	target time point of video popularity prediction
t_T	target time point of retweets prediction
$\widetilde{N}_i(t_s, t_r)$	predicted accumulative views of video i up to t_r
$N_i^*(t_r)$	real accumulative views of video i up to t_r
$N_i(t_s)$	real accumulative views of video i up to t_s
R_{ij}^p	proportion of viewers with positive attitude in v_{ij}
R_{ij}^n	proportion of viewers with negative attitude in v_{ij}
$\mathcal{F}_{ij}^{pos}$	positive attitude entropy of video i in jth interval
$\mathcal{F}_{ij}^{neg}$	negative attitude entropy of video i in jth interval
$f(R_{ij}^p, R_{ij}^n; \Phi)$	weight function on early views
$g(j; \theta)$	normalized decay function for early patterns
$s_i(t_j)$	retweets count of tweet i in $(t_{j-1}, t_j]$
$S_i(t_j)$	accumulative retweets count of tweet i in $[t_1, t_j]$
$O_i^{(t)}$	Occupy vector of tweet i's tag list
$D_i^{(y)}$	weight vector of video i's tag list
$G^{(t)}$	popularity weight vector of tags for tweets
$G^{(y)}$	popularity weight vector of tags for videos

TABLE I: Definitions of symbols

I. **MFDI MODEL** A. Problem Statement and Related Definitions Our task is to predict the cumulative views of online videos at given time tr, based on the observed data from ts < tr, and to retrieve the Top-N popular videos at tr. Such task requires the prediction performance focusing on popular videos rather than the entire video set. Definitions of variables used in this article are listed in Table I. B. Framework of MFDI MLR is a widely adopted mathematical model in popularity prediction. The typical framework of MLR based models combines a regression on early view patterns {vij} ts j=t1 with an optional compensation B(Ψi) based on video i's side information Ψi [14], which can be formulated as

$$\widetilde{N}_i(t_s, t_r) = \sum_{j=t_1}^{t_s} \omega_j v_{ij} + \omega_b B(\Psi_i),$$

where Ψi denotes the side information of video i. The shortcoming of (1) is that {vij} does not have sufficient capability to represent different popularity trends, but for the Pareto distribution of popular videos, {vij} nevertheless appears to be strongly correlated with the prediction target N∗ i (tr). This strong correlation causes the model to focus on unpopular videos and greatly weakens the contribution of B(Ψi) to the prediction performance. To overcome this shortcoming, we propose to enhance the discriminative power of vij for different popularity trends and to balance the dependence of the model on early patterns and side information of videos. The proposed MFDI model can be formulated as follows.

$$\widetilde{N}_i(t_s, t_r) = \sum_{j=t_1}^{t_s} g(j;\theta)\omega_j v_{ij} f(R^p_{ij}, R^n_{ij}; \Phi) + \omega_b B(\Psi_i) \int_{j=t_1}^{t_s} [1 - g(j;\theta)] dj.$$

EXPERIMENTS AND ANALYSIS

Data Preparation The video data were obtained from YouTube using the YouTube API 3.0 (https://developers.google.com/youtube/v3/). We obtain the basic information on each video including the –id‖, –title‖, –description‖ and –tags‖, and the timeaware data including –views‖, –likeCount‖, –dislikeCount‖ and –favorites‖ for every 24 hours. A typical example of the data collected for a video is shown in Table IV. To track the popularity of tweets that shared tags with the collected videos, we obtained their –retweets‖ data at the same frequency using Rest API 2.01 . Specifically, we first search for videos uploaded over the previous three days and obtained 216,000 different videos. Then, we extracted the tags of each video and created a tag set containing the 9341 most frequently appearing tags (we extracted only the first 5 tags of each video). Next, we used the Twitter API to search for tweets with tags that appeared in the tag set, identifying 3314 tags from 38114 tweets. Then, we tracked the –retweets‖ of each identified tweet every 24 hours for the next week. We tracked only the –retweets‖ of the 3734 tweets with the 126 most frequently appearing tags. The crawled tag set covers 20.3% of the filtered videos. Based on the

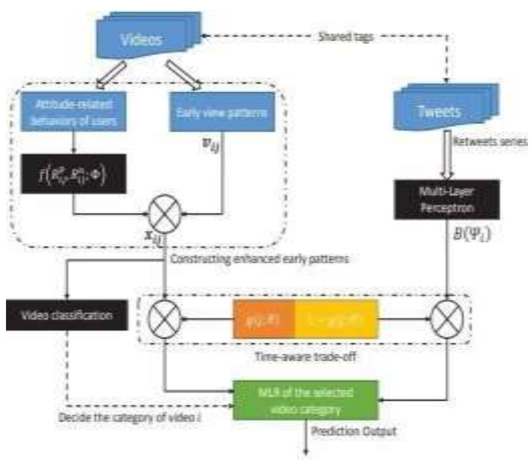

Fig. 1: Framework of MFDI model

crawled data, we removed videos that received no views on at least one week and those with too few cumulative views. The final video set contains 48,369 videos. B. Evaluation Metrics and Experimental Settings The experiments reported here consist of two parts: performance evaluation and result analysis. For the performance evaluation, we choose two metrics. The first is the widely adopted mean relative squared error (mRSE). mRSE = 1 Mv X Mv i=1 Nei(ts, tr) − N∗ i (tr) N∗ i (tr) !2 , (22) where Mv is the total number of videos and Ni(ts, tr) and N∗ i (tr) are the predicted popularity and real popularity of video i, respectively. The other metric is the average precision (AP). AP@N = N Recall N , (23) where N Recall is the number of top-N videos identified in the prediction result of the model. Because the maximum range of our collected popularity data is three weeks, we use related data of the first five days after the publication of a video as the early data, and the prediction target is the popularity 21 days 1https://dev.twitter.com/rest/public after publication. The results are obtained via 5-fold crossvalidation. As suggested in most related studies, we consider two tradeoff functions: a negative exponential function and a type-I Pareto function. The experiments show that the performance of the proposed model with the type-I Pareto function is slightly better than the performance of the model with the negative exponential function. Thus, the experimental results presented in this article are those obtained with type-I Pareto function as the trade-off function. The values of σ and γ in f(R p ij , Rn ij ; Φ) are set to 0.96 and 1.02, respectively, based on a fit of the training data to a Rayleigh distribution. To avoid becoming trapped in local optima, we use a simulated annealing algorithm (SAA) to control the optimization process. The annealing factor and the acceptance threshold of the SAA are set to 0.45 and 0.7, respectively. Meanwhile, the l2 norm factor κ is set to 0.01, as in many related works. The dual learning rates for MLP training are set to υ (y) = 0.372 and υ (t) = 0.628 for the final result. The values of the other manually adjusted parameters are set as follows: α = 3.734 and β = 1.52. C. Baseline Models Three baseline models are considered in the evaluation of the proposed model. The first is the widely adopted MRBF model:

$$\widetilde{N}_i(t_s,t_r) = \sum_{j=t_1}^{t_s} \omega_j v_{ij} + \sum_{c=1}^{k} RBF(V_i^{t_s}, V_c).$$

CONCLUSION

In this article, we have investigated the problem of top-N popular video prediction and have proposed a novel MFDI prediction model. The proposed model predicts the top-N popular videos by enhancing the ability of early patterns to identify different popularity trends and by optimizing the model's utilization of multi-source data. Experimental results obtained using real-world data demonstrate that the proposed model outperforms other models, including the state-of-the-art model. This article is our initial study on popularity prediction for Top-N popular videos. To the best of our knowledge, this study is the first popularity prediction research to focus on top-N popular videos. Our study still has room for improvement. Possible improvements include leveraging additional related early features and discovering more precise mathematical correlations between the attitudes of early viewers and future popularity trends. For example, in this study, the early viewers' This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TMM.2018.2845688, IEEE Transactions on Multimedia 10 attitudes are inferred from only the three explicit behavior factors; however, early viewers' attitudes may also be reflected in many implicit ways. If more data related to early viewers' attitudes or similar features could be well modeled, they would be helpful for further improving the model's prediction performance, especially on the top-N popular videos.

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