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VIDEO PROMOTION USING CROSS NETWORK

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Abstract: *The rapid exploration of various social media networks have changed the way how video contents are created, used, distributed and consumed in sharing portals. Nowadays, online videos can be accessed from beyond the internal mechanism of the video sharing portals, such as internal search and front page highlight. Nowadays marketing the you tube video at various networking sites are became a trend and it is very useful for increasing the popularity of video among viewers. In this paper, we implemented a cross-network collaborative application among you tube and twitter. By using common user of both sites we tried to advertise a video by optimal advertiser (celebrity with same domain of video) for the particular video which we get from the twitter. The person (followee) with maximum followers in the twitter is optimal followee for the video which having same domain as the person. For example; the person with sport background having maximum followers are suitable for sports videos.*

Keywords*: empirical Bayes, variational methods, probabilistic graphical models, automatic image annotation, image retrieval*

1. INTRODUCTION

With the advance of social media, the style people can get access to the video contents is changing. Instead of only relying on the internal mechanisms provided by the traditional video sharing portal to access the videos, more and more people now prefer to directly watch videos from their involved social media networks.

Recently, it has been reported that over 700 YouTube videos are shared in Twitter each minute and Twitter has allowed users to embed videos in their tweets by posting video links.

Followers to these users then receive the tweet feed and become the potential viewers of these videos.

Under this followee-follower structure, Twitter followees, especially those with a lot of followers (which we refer to as popular followee), play important roles under social media circumstances by: acting as “we media”, via the control of information dissemination channels to millions of audiences, and acting as influential leaders, via their potential impact on the followers’ decisions and activities.

In this context, if we can identify “proper” followees to help disseminate videos, their significant audience accessibility and behavioral impact will guarantee the promotion efficiency. Therefore, the problem of this work is: For specific YouTube video, to identify proper Twitter followees with goal to maximize video dissemination to the followers.

2. RELATED WORK

A. Analyzing Cross-System User Modeling on the Social Web

This project analyses tag-based user profiles, which result from social tagging activities in Social Web systems and particularly in Flickr, Twitter and Delicious. The characteristics of tag-based user profiles within these systems examine to what extent tag-based profiles of individual users overlap between the systems and identify significant benefits of cross-system user modeling by means of aggregating the different pro les of a same user.

B. Modeling Annotated Data

The problem of modelling annotated data data with multiple types where the instance of one type (such as a caption) serves as a description of the other type (such as an image). We describe three hierarchical probabilistic mixture models which aim to describe such data, culminating in correspondence latent Dirichlet allocation, a latent variable model that is effective at modeling the joint distribution of both types and the conditional distribution of the annotation given the primary type. We conduct experiments on the Corel database of images and captions, assessing performance in terms of held-out likelihood, automatic annotation, and text-based image retrieval.

C. Maximizing product adoption in social networks

A model that factors in a user's experience (or projected experience) with a product. It adapts the classical Linear Threshold (LT) propagation model by defining an objective function that explicitly captures product adoption, as opposed to influence. In this model, adoption maximization is NP-hard and the objective function is monotone and sub modular, thus admitting an approximation algorithm.

D. Latent dirichlet allocation

(LDA), a generative probabilistic model for collections of discrete data such as text corpora. LDA is a three-level hierarchical Bayesian model, in which each item of a collection is modeled as a finite mixture over an underlying set of topics. Each topic is, in turn, modeled as an infinite mixture over an underlying set of topic probabilities. In the context of text modeling, the topic probabilities provide an explicit representation of a document. It present efficient approximate inference techniques based on variational methods and an EM algorithm for empirical Bayes parameter estimation. We report results in document modeling, text classification, and collaborative filtering, comparing to a mixture of unigrams model and the probabilistic LSI model.

3. EXISTING SYSTEM

Latest statistics show that, for the world's largest video sharing portal YouTube, 100 hours of videos are uploaded within every minute which results in an estimate of more than 2 billion videos totally. However, in spite of the massive videos generated in YouTube, it exhibits limited propagation efficiency with the internal video-centric mechanisms and many high quality videos may remain unknown to the wide public. According to research, YouTube video view count distribution exhibits a power-law pattern with truncated tails. Most videos have a short active life span, receiving half of the total views in the first 6 days after being published, and with fewer and fewer access thereafter. On the other hand, the followee-follower architecture and fast diffusion characteristic of the social micro blogging service Twitter [21] has established itself as a great external platform to promote and engage with the audiences and distinguished itself with significant information propagation efficiency. In this paper, we focus on how to utilize the auxiliary Twitter social network to help promote videos in traditional video sharing portal YouTube.

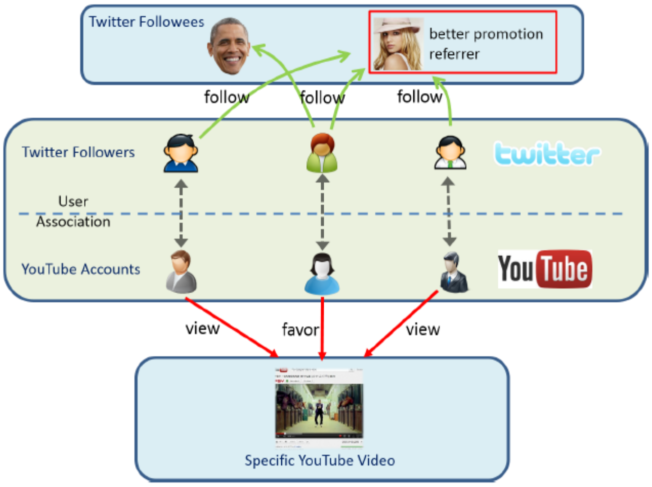


Fig1: video dissemination

Recently, it has been reported that over 700 YouTube videos are shared in Twitter each minute and Twitter has allowed users to embed videos in their tweets by posting video links. Followers to these users then receive the tweet feed and become the potential viewers of these videos. Under this followee-follower structure, Twitter followees, especially those with a lot of followers (which we refer to as popular followee), play important roles under social media circumstances by:

(1) Acting as "we media", via the control of information dissemination channels to millions of audiences, and

(2) Acting as influential leaders, via their potential impact on the followers' decisions and activities. YouTube video "Gangnam Style" went viral to become the first web video that reaches one billion views in 5 months, resulting mainly from its successful strategy of roping in some popularly followed musicians on Twitter, such as Britney Spears, Justin Bieber and Katy Perry. In this context, if we can identify "proper" followees to help disseminate videos, their significant audience accessibility and behavioral impact will guarantee the promotion efficiency. Therefore, the problem of this work is: For specific YouTube video, to identify Proper Twitter followers with goal to maximize video dissemination to the followers (as shown in Fig 1).

4. PROPOSED SYSTEM

The key lies in how to establish a reasonable cross-network association between YouTube and Twitter. Inspired by the fact that the same individual usually involves with different social media networks and different social media networks share remarkable percentage of overlapped users 3, if we know the corresponding Twitter accounts of YouTube users who show interest to a given video (e.g., upload, favorite, add to playlist), it is confident to identify the Twitter followee that these Twitter accounts jointly followed as the optimal promotion referrer. Therefore, we propose a brand new way to establish the cross-network association by leveraging the collective intelligence of the observed overlapped users. Since YouTube video generally distributes on specific semantic level, a direct way to associate the YouTube and Twitter spaces is from the content level where the YouTube video content and Twitter users' generated tweets are used to capture the association. However, this kind of association can only capture the semantic correlation between the two spaces and still suffers from the discrepancy issue in topic granularity. Therefore, we also make further exploration with a more flexible and heterogeneous kinds of association under which the YouTube video content and the network structure of the Twitter users are correlated.

5. MATHEMATICAL MODEL

Given a collection of YouTube videos V where each video v ∈ V is represented by its contained textual words and visual key frames [WV, fv], and a collection of Twitter users UT where each user u ∈ UT is represented by his/her followee collection and

INPUT (In) & OUTPUT (Out) OF EACH STAGE.

Stage 1

In: YouTube video v ∈ V: [WV, fv];

Twitter user u ∈ UT: [Ufolloweeu, Utweetu].

Out: YouTube video distri. V: p (zY |v);

Twitter user tweet distri. UTt: p (zTt |u);

Twitter user followee distri. UTf: p (zTf |u).

Stage 2

In: V, UTt, UTf; YouTube, Twitter and

Overlapped user set UY , UT , Uo;

YouTube user interested videos Vu ⊂ V.

Out: Semantic-based assoc. func. Fs: uY → uTt ;

Network-based assoc. func. FN: uY → uTf.

(UY: the aggregated YouTube user distri.)

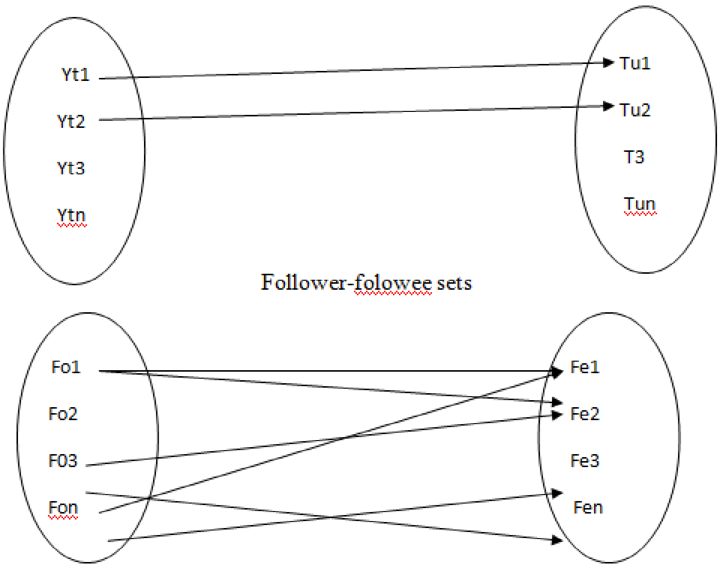
Stage 3

In: Fs, FN; Test video set VT;

Twitter followee set Ufollowee.

Out: Twitter followee rank for v ∈ VT: ψv (•).

Generated tweet collection [Ufollowee u, Utweet u], the followees of these Twitter users (Tu1, Tu2, Tun) construct the Twitter followee (Fe1, fe2...Fen) user collection Ufollowee ⊂ UT and part of the corresponding YouTube (Yt1,Yt2..Ytn) user accounts are also known.



Formally, let DY = {dY1, · · ·, dYjDj}, DT = {dT1, · · ·, dTDj} denote the coupled user factors in YouTube and Twitter, where |D| is the number of the latent user attributes. By forcing overlapped user's YouTube and Twitter distributions share the same coefficients after projected to the coupled factors, we have the following optimization objective function:

SYnon, STnon are user factor coefficients for the non-overlapped users in YouTube and Twitter, SY = [So, SYnon], ST = [So, STnon], λ3, λ4, λ5 are tuning parameters controlling the factor distribution sparsely.

6. ALGORITHM

Alternative Learning Algorithm for LA all

Input: Users' topic distributions UY = [UYo, UY non],

UT = [UTo, UT non]; the weighting parameters λ3, λ4, λ5.

Initialize: DY, DT.

Repeat

1. Fix other variables so.

2. Fix other variables, learn SY non, STnon.

3. Fix other variables, update DY and DT until convergence or reach maximum iteration.

Return: user factors DY and DT. Since unique user shares the

7. CONCLUSION

We have proposed an overlapped user-based association solution framework, to address the novel cross-network YouTube video promotion problem. To better capture the cross-network association from different perspectives, we conduct both semantic-based and network-based associations in a unified ranking scheme. Alternative methods have been developed and evaluated, to demonstrate the effectiveness of exploiting user collaboration towards heterogeneous knowledge association. The proposed framework is quite flexible, and can be generalized to other cross-network collaborative problems. We hope that this paper could serve as a good chance to emphasize the collective utilization of social media sources and further the agenda of cross-network analysis and application in social multimedia research.

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