Cross-Network YouTube Video Promotion: A Survey

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Abstract
The emergence and rapid proliferation of social media networks have reshaped the way how video contents are generated, distributed and consumed in traditional video sharing portals. Nowadays, online videos can be accessed from far beyond the internal mechanisms of the video sharing portals, such as internal search and front page highlight. Recent studies have found that external referrers, such as external search engines and other social media websites, arise to be the new and important portals to lead users to online videos. In this paper, a novel cross-network collaborative application is introduced to help drive the online traffic for given videos in traditional video portal YouTube by leveraging the high propagation efficiency of the popular Twitter followees. YouTube videos and Twitter followees distribute on heterogeneous spaces, and presenting a cross-network association-based solution framework. In this framework, first represent YouTube videos and Twitter followees in the corresponding topic spaces separately by employing generative topic models. Then, the cross-network topic spaces are associated from both semantic-based and network-based perspectives through the collective intelligence of the observed overlapped users. Based on the derived cross-network association, finally match the query YouTube videos and candidate Twitter followees in the same topic space with a unified ranking method.
Keywords:
Video promotion, Cross-network analysis, Social media

1. Introduction

With the rise of social media, the way 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 [12]. Social media brings in much possibility to the traditional video sharing portals and it is very fascinating to explore the innovation sparkles generated when these two meet with each other. 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 [6]. 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 [8]. On the other hand, the followee-follower architecture and fast diffusion characteristic of the social microblogging 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, it focus on how to utilize the auxiliary Twitter social network to help promote videos in traditional video sharing portal YouTube. Recently, it has been reported that over 700 YouTube videos are shared in Twitter each minute [28] 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, 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 followees with goal to maximize video dissemination to the followers* (as shown in Fig. 1).

Three challenges are mainly concerned with our problem: (1) In our scenario, whether a Twitter followee is proper for the promotion task is actually decided by the interest his/her followers show to the YouTube videos. However, the Twitter followee and YouTube video distribute in completely different social platforms and no explicit association exists between them; (2) We can only know the followers' activities on Twitter, based on what

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only the demographics or interests on the general level can be inferred [27], [34]. While, the YouTube videos are known to distribute more on specific semantic level [19]. The discrepancy in topic granularity makes it impractical to directly evaluate Twitter followers' interest to YouTube videos; (3) Although more popular Twitter followees (with more followers) can result in higher coverage to the general audiences, what video promotion cares is the number of "effective" audiences, who are likely to show interest to the video and with higher probability to take subsequent consuming actions like watch, reshare, etc. Besides, the more popular the Twitter followee is, the more cost is needed to get him/her to help. Therefore, both the audience coverage and virtual cost should be considered when measuring the "properness" of Twitter followees for specific YouTube videos.

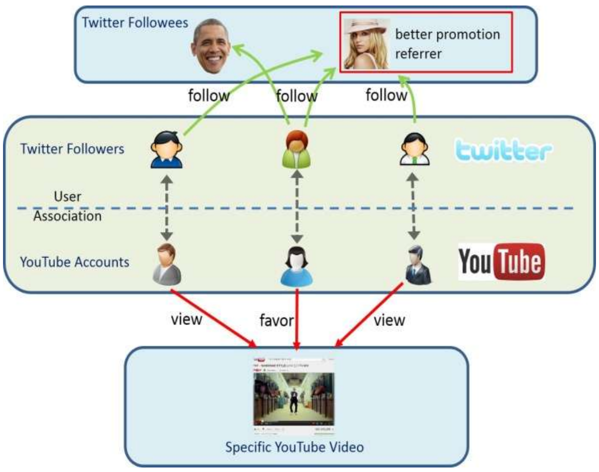

Figure. 1. Problem illustration: to identify proper Twitter followees (Twitter users who are followed by others) to help promote the YouTube videos.

1.1. Contributions in this work can be summarized as follows:

Problem-wise introduce a new problem of YouTube video promotion on Twitter platform by identifying proper Twitter followees. There exist both trends and demands in exploring external referrers towards promoting social media content.

Solution-wise a cross-network association-based solution framework is presented, under which different kinds of associations are explored and integrated. Alternative methods have been examined and introduced a novel and promising perspective by exploiting the overlapped users as bridge to obtain the association (which is inspired by crowd wisdom). To the best of our knowledge, this is the first attempt to mine the cross-network association under a user-bridged scheme. The extension in this paper includes three aspects: (1) Except for the network-based association in [35], we also add a new semantic-based association parallelly by leveraging users' generated tweet information. Each stage for this new association is also designed and evaluated separately; (2) We explicitly present a unified ranking framework to integrate both semantic-based association and network-based association for better Twitter referrer identification. (3) More quantitative experiments are conducted to validate the flexibility and effectiveness of our proposed solution framework, including: (a) A direct *Semantic Match* method is added as a baseline. (b) A new intuitive user coverage (*Cov*) metric is added to evaluate the performance of different methods in terms of the actual size of users who will adopt the target videos. (c) A more focused comparison and analysis between single semantic-based association and network-based association are made.

2. Related Work

Cross-network Collaboration

With various social media networks growing in prominence Cross-network collaborative applications have recently attracted attentions. One line is on cross-network user modeling, which focuses on integrating various social media activities. YouTube video recommendation solution by incorporating user information from Twitter. Another line is devoted to taking advantage of different social networks' characteristics towards collaborative applications. Our work belongs to the second line, where a collaborative application is designed to exploit the propagation efficiency of Twitter to meet the YouTube video promotion demand.

Social Media Influencer Mining

Previous analysis on Twitter has found that popular users with high in-degree are not necessarily influencers for propagation, which calls for research onto the problem of influencer mining. One line is to identify the domain or topic experts. Representative solutions include the extensions to PageRank by considering topical similarity. Another line is concerned with maximizing influence spread by initializing some seed users. first defined this problem, which is then applied to product adoption and viral marketing. Our introduced problem of Twitter followee identification can be viewed as a special case of influencer mining. The existing influencer mining methods mainly focus on single network and need an explicit relevance metric, e.g. the topical relevance between follower and followee, and the accept rate between the propagation item and follower. In our problem, the relevance of influencer is designed by items distributed on another network. It is difficult to explicitly define the relevance metric between cross- network knowledge. Moreover, to focus on addressing cross-network association, we pay no attention to the complicated social network structure as in the standard maximizing influence problems. What we care is actually about the propagation efficiency in the first level of followee-follower network.

Heterogeneous Topic Association

The core of our solution lies in the heterogeneous topic association between Twitter followee and YouTube video. Typical applications of existing heterogeneous topic association work include heterogeneous face recognition and cross-media retrieval, where invariant feature extraction and subspace learning based solutions are extensively investigated. Invariant feature extraction methods are devoted to reducing. The heterogeneous gap by exploring the most insensitive feature patterns. In our work, we propose a solution framework based on user's collaborative involvement in heterogeneous topics. This avoids low-level analysis and can be viewed as a high-level crowdsourcing strategy.

3. Framework of Proposed System

The proposed system follows three stages: Heterogeneous Topic Modeling, Cross-network Topic Association and Referrer Identification.

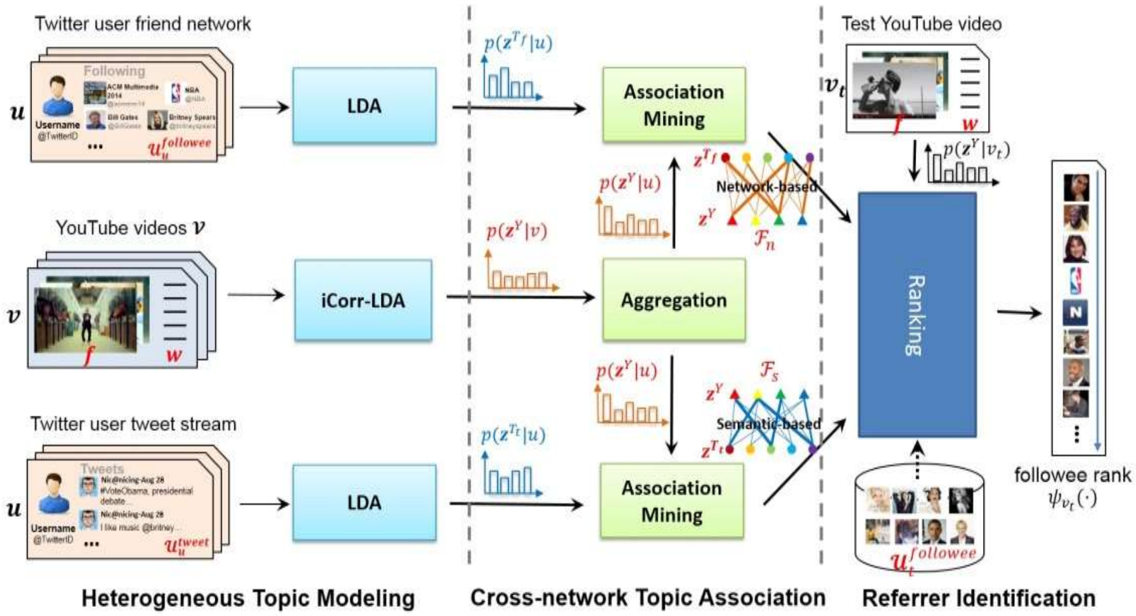

Figure. 2 This flow diagram gives an overview of our solution framework, which consists of three parts: heterogeneous topic modeling, cross-network topic association and referrer identification

Stage 1 is to discover the latent structure within YouTube video and Twitter user spaces, and facilitate the subsequent analysis and applications in topic level. We conduct this by employing generative topic models, with video as document, textual word and visual feature of keyframes as the multimodal word in YouTube. In Twitter, a semantic-based and a network-based topic spaces are constructed simultaneously via topic models, with user as document, tweet word or followee as word, respectively. Through this stage, each YouTube video and Twitter user can be represented as distributions in the derived corresponding topic spaces. The explicit association between the cross-network topic spaces prevents from direct analysis.

Stage 2 is designed to address this issue by mining the cross-network topic association. To obtain a flexible association that goes beyond the traditional semantic-based criteria, we propose a user-contributed solution that first aggregates YouTube video distribution to user level, and then exploits the overlapped users among different networks as bridge for association mining. The basic premise is that: if the same group of users heavily involve with topic A in network X and topic B in network Y, it is very likely that topic A and B are closely associated. To address the topic discrepancy issue between cross-network topic spaces, both semantic-based association and network based association are conducted separately under this scheme. With the derived topic association, topical distribution transfer between different networks is enabled, i.e., given users' topical interest in YouTube videos, we can infer (1) for semantic-based association: their most favorite Twitter tweet semantic topics; (2) for network-based association: their most probably followed Twitter followee topics. Since the ultimate goal is to match video to followee. After the offline Stage 1 and Stage 2, in the online Stage 3, we view each test video as a virtual YouTube user who holds identical topical distribution. It is easy to understand that the virtual user actually represents the typical users in YouTube showing significant interest to the test video, who are exactly potential fans and thus the targeted users. Therefore, after topical distribution transfer, it is promising to identify the Twitter followee that best matches both the Twitter tweet semantic and Twitter followee topical distributions of the targeted users as the optimal promotion referrer for the video.

4. Advantage of proposed system

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. 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

5. 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.

References

[1] F. Abel, S. Ara´ujo, Q. Gao, and G.-J. Houben, "Analyzing cross-system user modeling on the social web," in WebEngineering. Springer, 2011, pp. 28–43.
[2] S. Bhagat, A. Goyal, and L. V. Lakshmanan, "Maximizing product adoption in social networks," in WSDM 2012. ACM,pp. 603–612.
[3] D. M. Blei and M. I. Jordan, "Modeling annotated data," in SIGIR 2003, pp. 127–134.
[4] D. M. Blei, A. Y. Ng, and M. I. Jordan, "Latent dirichlet allocation," the Journal of machine Learning research, vol. 3,pp. 993–1022, 2003.
[5] M. Cha, H. Haddadi, F. Benevenuto, and P. K. Gummadi, "Measuring user influence in twitter: The million follower fallacy." ICWSM, vol. 10, pp. 10–17, 2010.
[6] M. Cha, H. Kwak, P. Rodriguez, Y.-Y. Ahn, and S. Moon, "I tube, you tube, everybody tubes: analyzing the world's largest user generated content video system," in IMC 2007, pp. 1-14.
[7] W. Chen, C. Wang, and Y. Wang, "Scalable influence maximization for prevalent viral marketing in large-scale social networks," in KDD 2010. ACM, pp. 1029–1038.
[8] X. Cheng, C. Dale, and J. Liu, "Statistics and social network of youtube videos," in IWQoS 2008, pp. 229–238.
[9] X. Cheng, H. Li, and J. Liu, "Video sharing propagation in social networks: Measurement, modeling, and analysis," in INFOCOM, 2013 Proceedings IEEE. IEEE, 2013, pp. 45–49.
[10] Z. Deng, J. Sang, and C. Xu, "Personalized video recommendation based on cross-platform user modeling," in ICME 2013.IEEE, pp. 1–6.
[11] E. Elhamifar and R. Vidal, "Sparse subspace clustering: Algorithm, theory, and applications," Pattern Analysis and Machine Intelligence, IEEE Transactions on, vol. 35, no. 11,pp. 2765–2781, 2013.
[12] F. Figueiredo, J. M. Almeida, M. A. Gonc¸alves, and F. Benevenuto, "On the dynamics of social media popularity: A youtube case study," arXiv preprint arXiv:1402.1777, 2014.
[13] S. Ghosh, N. Sharma, F. Benevenuto, N. Ganguly, and K. Gummadi, "Cognos: crowdsourcing search for topic experts in microblogs," in SIGIR 2012. ACM, pp. 575–590.

[14] T. L. Griffiths and M. Steyvers, “Finding scientific topics,” Proceedings of the National academy of Sciences of the United States of America, vol. 101, no. Suppl 1, pp. 5228–5235, 2004.
[15] J. A. Hartigan and M. A. Wong, “Algorithm as 136: A k-means clustering algorithm,” Applied statistics, pp. 100–108,1979.
[16] K. J¨arvelin and J. Kek¨al¨ainen, “Cumulated gain-based evaluation of ir techniques,” ACM Transactions on Information Systems (TOIS), vol. 20, no. 4, pp. 422–446, 2002.
[17] T. Joachims, “Optimizing search engines using clickthrough data,” in KDD 2002. ACM, pp. 133–142.
[18] D. Kempe, J. Kleinberg, and ´ E. Tardos, “Maximizing the spread of influence through a social network,” in KDD 2003.ACM, pp. 137–146.
[19] J. R. Kender, M. L. Hill, A. P. Natsev, J. R. Smith, and L. Xie, “Video genetics: A case study from youtube,” in ACM Multimedia 2010, pp. 1253–1258.
[20] B. F. Klare, Z. Li, and A. K. Jain, “Matching forensic sketches to mug shot photos,” Pattern Analysis and Machine Intelligence, IEEE Transactions on, vol. 33, no. 3, pp. 639–646, 2011.
[21] H. Kwak, C. Lee, H. Park, and S. Moon, “What is twitter, a social network or a news media?” in Proceedings of the 19th international conference on World wide web. ACM, 2010, pp. 591–600.
[22] H. Lee, A. Battle, R. Raina, and A. Y. Ng, “Efficient sparse coding algorithms,” Advances in neural information processing systems, vol. 19, p. 801, 2007.
[23] Z. Lei, M. Pietikainen, and S. Li, “Learning discriminant face descriptor,” 2013.
[24] H. Li, H. Wang, J. Liu, and K. Xu, “Video requests from online social networks: Characterization, analysis and generation,”in INFOCOM, 2013 Proceedings IEEE. IEEE, 2013, pp. 50–54.
[25] J. Liu, F. Zhang, X. Song, Y.-I. Song, C.-Y. Lin, and H.-W. Hon, “What’s in a name?: an unsupervised approach to link users across communities,” in WWW. ACM, 2013, pp. 495–504.
[26] M. Osborne, S. Petrovic, R. McCreadie, C. Macdonald, and I. Ounis, “Bieber no more: First story detection using twitter and wikipedia,” in TAIA 2012, vol. 12.
[27] D. Rao, D. Yarowsky, A. Shreevats, and M. Gupta, “Classifying latent user attributes in twitter,” in SMUC 2010, pp. 37–44.
[28] S. Roy, T. Mei, W. Zeng, and S. Li, “Towards cross-domain learning for social video popularity prediction,” IEEE Transactions on Multimedia, vol. 15, no. 6, pp. 1255–1267, 2013.
[29] S. D. Roy and G. Lotan, “Detecting geo-spatial weather clusters using dynamic heuristic subspaces,” in Information Reuse and Integration (IRI), 2014 IEEE 15th International Conference on. IEEE, 2014, pp. 811–818.
[30] S. D. Roy, T. Mei, W. Zeng, and S. Li, “Social transfer: cross-domain transfer learning from social streams for media applications,” in ACM Multimedia 2012. ACM, pp. 649–658.
[31] R. Vidal, “A tutorial on subspace clustering,” IEEE Signal Processing Magazine, vol. 28, no. 2, pp. 52–68, 2010.
[32] J. Weng, E.-P. Lim, J. Jiang, and Q. He, “Twitterrank: finding topic-sensitive influential twitterers,” in WSDM 2010. ACM, pp. 261–270.
[33] C. Xu, C. Dale, and J. Liu, “Understanding the characteristics of internet short video sharing: Youtube as a case study,” arXiv preprint arXiv:0707.3670, 2007.
[34] Z. Xu, R. Lu, L. Xiang, and Q. Yang, “Discovering user interest on twitter with a modified author-topic model,” in WI-IAT2011, pp. 422–429.
[35] M. Yan, J. Sang, and C. Xu, “Mining cross-network association for youtube video promotion,” in Proceedings of the ACM International Conference on Multimedia. ACM, 2014, pp. 557–566.
[36] J. Yang, Z. Wang, Z. Lin, S. Cohen, and T. Huang, “Coupled dictionary training for image super-resolution,” Image Processing, IEEE Transactions on, vol. 21, no. 8, pp. 3467–3478, 2012.