Neurocomputing 172 (2016) 53–63

Contents lists available at ScienceDirect

Neurocomputing

journal homepage: www.elsevier.com/locate/neucom

Web video topics discovery and structuralization with social network

Juan Cao [a], Yongdong Zhang [a], Rongrong Ji [b], Fei Xie [c], Yu Su [c]

[a] Institute of Computing Technology, Chinese Academy of Science, Beijing, China
[b] Department of Cognitive Science, School of Information Science and Engineering, Xiamen University, Xiamen, China
[c] Communication and Technical Bureau, XinHua News Agency, Beijing, China

ARTICLE INFO

Article history:
Received 26 November 2013
Received in revised form
1 September 2014
Accepted 27 October 2014
Available online 9 May 2015

Keywords:
Topic discovery
Topic structuring
Social network
Community
Web video analysis

ABSTRACT

The prevailing of Web 2.0 techniques has led to the boom of web video content as well as its social network. To overcome the information overload problem, effective web video topic discovery and structuring techniques are highly demanded. To this end, existing works go to two respective directions: video topic discovery based on content or community detection in social network, with limited interplay between topics and network structures. In this paper, we construct the video social network based on web user interactions over videos. By comparing the topics and communities discovered on this network, we unveil the loose correspondence relationship between content and social network, and correspondingly propose a novel community-driven web video topic discovery model, which regularizes the topic model in relaxed community-level. Quantitatively analysis on real-world YouTube data shows that our model has achieved a significant improvement over the purely content-based or network-based baselines. Meanwhile, we propose a community-based topic structuralization framework, which decomposes a topic in social network space, and tracks the spreading trajectory of this topic among different communities on the time line. This structuralization can help users to catch the important facets of topics, such as "Who is interested with this topic" and "How does it propagate among the communities", which provide valuable insights in related applications such as web monitoring and market development.

1. Introduction

Topic detection is a good solution to effectively organize the dramatically growing web videos, and has been widely adopted by various video websites like the "Video Playlist" of YouTube[1] and the "Video Album" of Youku.[2] However, different from the conventional data mining where videos are simply connected based on original content similarity (*e.g.* visual similarity), the web videos are diversely connected in a network. As shown in Fig. 1, when a conventional video collection has been shared in a social network and interacted by web users, the videos are indirectly connected by users' various interactions such as uploading, viewing and commenting *etc*. Therefore, the conventional sparse video collection has been converted to a video social network with heterogeneous social correlations [28–30]. These social network information influence web video topic in the following two aspects:

From topic discovery perspective: It is a task that aims to group together the materials that discuss the same event [1]. By studying many topic cases, we find that the related web videos can grow to hot topics with two kinds of reasons. One kind of topics becomes "HOT" because their contents are very popular and general, so that everybody can produce related contents or follow them. *e.g.* "Bush was attached by shoes" and "Dog's video". We call them *Content-contributed Topic*. The other kind of topics becomes "HOT" because they have significant distribution on the social network, where their contents are so specific that only can be produced and propagated by a limited user group. These topics are generally related to specific or sensitive events like "Makeup tutorial", we call them *Network-contributed Topic*. These kinds of topics play an important role in practical web monitoring. However, for their content are not as popular as *Content-contributed Topic*, they are relatively difficult to be discovered by pure content-based methods. So we can expect that leveraging social network information and video content will improve the performance web video topic discovery.

From topic structuralization perspective: it is a task that aims to structuralize the materials within a topic. Generally, a topic is dynamically evolving over time in different spaces, such as content space, geographic space and social network space. Mining the evolution path of a topic can give users a global view about the topic, and help them to predict its evolution trend. Most of the previous works [6,25,4] focus on the topical evolution and organization in the content space, and model their life cycles in the

[1] http://www.youtube.com.
[2] http://www.youku.com.

http://dx.doi.org/10.1016/j.neucom.2014.10.103
0925-2312/

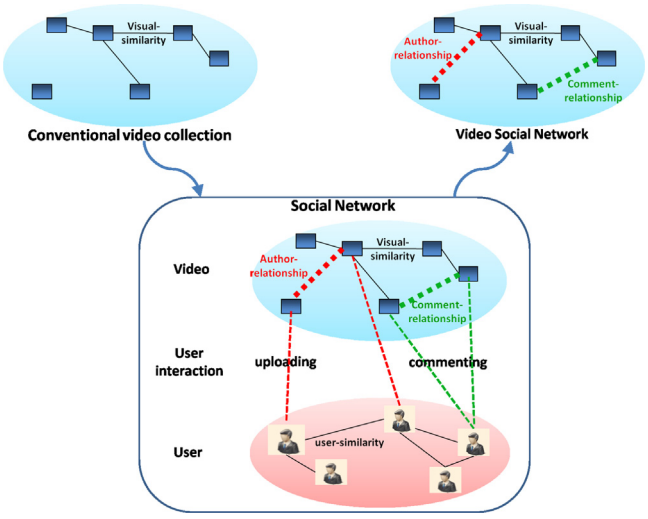

Fig. 1. Toy example of video social network.

time line as topic trajectories. Recent works in [19,27] propose to investigate the geographical propagation phenomenon of video topics on the web, and mine the hot topics for different regions. It is notable that topic is also propagating among the users of social network. So in this paper, we focus on tracking the evolution trajectory of topics on social network, and explore "Who is interested with this topic" and "How does it propagate among the users".

Based on the above analysis, the key problem of this paper is *how we can leverage the social network information and video content wisely for web video topic discovery and structuralization*. A valuable tool in the analysis of large scale social network is community detection, which attempts to identify the groups of vertices that are more densely connected to each other than to the rest of the network [20]. Several recent work have verified the effectiveness of community structure for social media analysis such as the social media classification [22], web video retrieval [14] and text topic discovery [12].

However, as shown later in Section 4.2, by comparing the topic structure discovered based on content and the community structure extracted from video social network, we find that there is low coherency between both structures. Because in the video social network, except the common interests on content, users can be connected by various other reasons like friends, families and colleagues. From this perspective, how to effectively utilize such network information for topic discovery is still an open problem. In this paper, we investigate the relationship between topic and community, and correspondingly propose a community-driven topic discovery and structurization method. In general, our contributions are three-fold:

- By constructing video social networks based on user interactions over 80,000 YouTube videos, we unveil the relationship between topic structure of video content and the community structure of their social network: (1) The community in video social network has low content consistency. (2) Within the topics with network structure, they usually converge on limited communities (three in our experimental settings). This discovery provides valuable insights for many network-based web video applications, such as video retrieval, reranking and recommendation.
- Based upon the above findings, we propose a community-driven web video topic discovery algorithm. By dynamically regularizing the topic model of videos with the community structure of their users, it not only outperforms the purely content based and social network based methods, but also can discover both the traditional *content-contributed hot topics* and the *network-contributed hot topics* as defined in Section 1.
- Finally, we propose a community-based topic structuring framework, which can discover the community structure within a specific topic, and visualize its spreading trajectory among the communities.

The rest of this paper is organized as follows: Section 2 reviews related work on web video topic discovery and structurization. Section 3 introduces the definition and creation of video social network. Section 4 analyzes the relationship between topic structure and community structure. Based on the analysis, Section 5 proposes a community-driven web video topic discovery model. Then Sections 6 and 7 show the experimental results for topic discovery and case study for topic structuralization, respectively. Finally Section 8 concludes our work.

2. Related work

2.1. Web video topic discovery

Compared with conventional video collection, social video has two important characteristics. Its large scale size leads to the typical sparse phenomenon among videos [22], and how to solve the sparse problem is a key issue. Meanwhile, the web user interactions result in a heterogeneous social network among videos [20], and how to utilize the rich social network information is an active field in recent year. Following we introduce the existing efforts for both problems in web video topic discovery.

Different from the task of Topic Detection and Tracking (TDT) [1] in text field, the textual annotations of web videos are sparse and noisy [11,18,4], and tracking video topics by using sparse texts and limited visual cues is becoming a new challenge for TDT. One of the pioneering work is [11], in which Liu et al. proposed a bipartite graph reinforcement model to overcome the sparse-text problem. Their main idea is to densify sparse texts of videos by information propagation through disclosing the bi-directional correlations between videos and texts. In [18], Shao et al. utilized a star-structured K-partite graph to represent the rich multi-modal features, and then introduced a co-clustering process to discover the web video topics. In recent work [4], they extracted the global trajectory feature to overcome the noisy problem of conventional discrete features, and discovered the hot topics by selecting the optimal paths in a global topic evolution graph. Experiments verified that the global feature is robust to process the noisy web videos.

However, all the above methods only considered content, and ignored the social characteristics of web videos. As the socialization of web media becomes more and more important, many researchers try to integrate the network structure to help various content analysis tasks. For example, in [3], Benevenuto et al. characterized the user response interactions from YouTube with statistical models; in [16], Roelof et al. recommend photos based on their subscription network; and in [2], Becker et al. clustered events by combining text with author and location annotations. In [22], Tang et al. combined the content and social relationships as a heterogeneous network, and extracted the *Latent Social Dimension* from this network to implement media classification. One of the most similar work to us is from [12]. They first verified the effectiveness of network structure for text content analysis on the co-author academic publication network, then proposed to regularize the statistical topic models in the whole network. Meanwhile, they also disclosed an interesting observation in a co-author academic publication network: unlike the hot research