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Personalized Video Recommendation Based on Cross-Platform User Modeling

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Most personalized video recommendation methods are based on single-platform user modeling, which suffers from data sparsity and cold-start issues. In this paper, we introduce cross-platform user modeling as a solution by smartly aggregating user information from different platforms. Unlike traditional recommendation methods where sufficient user information is assumed available in the target platform, this proposed method works well when there is little knowledge about users' interests in the target platform.

Introduction

Currently, most of the user modeling strategies are based on single platform. However, the available user information in one single platform is limited, which deteriorates the notorious "cold-start" problem. On the other hand, many network users create and maintain multiple accounts across different web2.0 platforms. User's behaviors on different platforms reflect the user's preference from different prospective and jointly contribute to in-depth user understanding.

One obstacle in cross-platform user modeling is the acquisition of associated user accounts, i.e., which account in one platform and which in another platform correspond to the same user. Fortunately, many users are willing to provide their separate accounts in different platforms, when registering into social network sites or using social media account management tools (e.g. Aboutme), which enables cross-platform user modeling and provides opportunities to advanced applications.

We address the personalized video recommendation problem by introducing cross-platform user modeling. We use YouTube as the target platform where to perform the recommendation task, and Google+ as the auxiliary platform where user information is transferred. Two strategies are designed to strengthen the understanding of user interest in the target platform: one is profile enrichment and the other is collaborative relationship transfer.

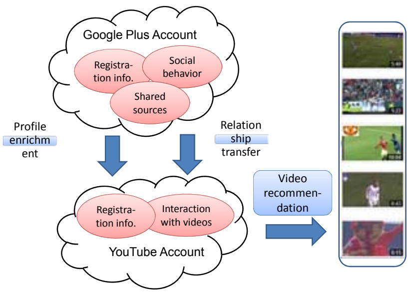

Fig. 1. The framework of our proposed approach.

The framework is illustrated in Fig. 1. The inputs include user profiles in Google+ and YouTube, and the output is the generated video recommendation list. According to the aforementioned two strategies, the framework contains three components, namely the social relationship transfer, the user profile enrichment and the video recommendation.

Cross-platform user modeling

Social relation transfer

We assume that users who have similar profiles in Google+ are very likely to have similar profiles in YouTube, so we transfer the collaborative relationship in Google+ to YouTube. Furthermore, we model the user similarity in Google+ from different perspectives and assign different weights to them.

Users on social network are associated with heterogeneous data. The challenge is how to effectively combine these data to model user similarity. Note that we can measure user similarity under different modalities [1], which is analogous to a kernel function in the kernel machines. This inspires us to adopt the multiple kernel learning (MKL) scheme [2] to integrate the multiple modalities, which is regarded as one of the principle way to combine heterogeneous data sources.

User similarity by registration information

Since registration information is abundant in Google+ and is adequate for user understanding, we take it as a modality to model user similarity. To represent the registration information of a user. We collect all the tags in registration information and build a tag space. The tags of a user are converted into a feature vector by the traditional TF-IDF method. The user u_i can be represented by a vector $\mathrm{x}_i \in R^d$. The normalized linear kernel to measure the user similarity is denoted as:

$$K^1(u_i,u_j) = \frac{\mathbf{x}_i^T\mathbf{x}_j}{\sqrt{\mathbf{x}_i^T\mathbf{x}_i}\sqrt{\mathbf{x}_j^T\mathbf{x}_j}} \quad (1)$$

User similarity by comments

The interaction between a user and activities reflects the user preference. If two users have similar tagging behaviors, it's very likely that they have similar interests. Therefore, we also model user similarity by their comments on activities. User similarity K^2 is modeled in the same way as Eq. 1.

User similarity by common activities

Google+ users often release and share videos, photos and articles. If two users share many common sources, they could be regarded to have similar interests. Meanwhile, we take the different modalities of sources into consideration and model user similarity by videos, photos and articles separately. We extract the tags associated with these sources and adopt the bag-of-word model to represent each user in specific domains, i.e., video, photo and article. And then the similarity $K^{3\sim5}$ is measured by cosine similarity as Eq. 1.

Optimal combination of multiple kernels

As we want to obtain the user similarity in YouTube, we will give higher weights to the modalities that can reflect user characteristics in YouTube. In practice, linear combination is effective and robust; hence we will determine a linear combination of multiple kernels to fuse all modalities to measure user similarity, parameterized by a weight vector, parameterized by a weight vector $\varphi \in R^{N_K}$

$$K(u_i,u_j;\varphi) = \sum_{a=1}^{N_k}\varphi_a K^a(u_i,u_j) \quad (2)$$

Where K^a is the kernel defined under the ath view of the users, and N_K is the number of modalities.

Given the target matrix **Y**, we adopt the kernel alignment to measure the quality of kernel **K** with respect to the target matrix **Y**. Note that the kernel matrices need be centered before kernel alignment and the step is as follows.

$$[\mathbf{K}]_{ij} = K_{ij} - \frac{1}{N_u}\sum_{i=1}^{N_u}K_{ij} - \frac{1}{N_u}\sum_{j=1}^{N_u}K_{ij} + \frac{1}{N_u^2}\sum_{i,j=1}^{N_u}K_{ij} \quad (3)$$

where N_u is the number of users.

The alignment between **K** and **Y** is defined by

$$\rho(\mathbf{K},\mathbf{Y}) = \frac{\mathbf{E}[tr\mathbf{KY}]}{\sqrt{\mathbf{E}[tr\mathbf{KK}]\mathbf{E}[tr\mathbf{YY}]}} \quad (4)$$

Given the target graph represented by matrix **Y**, we maximize the alignment ρ over **K** to solve the kernel. The matrix **Y** is observed from the YouTube platform. The solution of φ^* of the optimization problem is given by

$$\varphi^* = arg\ min \varphi^T \boldsymbol{M}\varphi - 2\varphi^T \mathbf{b} \quad (5)$$

User profiling

User profile in YouTube

The users' profiles are built up by extracting the tags and categories associated with these videos (like "upload" , "favor" or "add to playlist") as well as the registration information. For the representation of visual feature, we adopt the Spatial Pyramid Matching (SPM) model.

User profile enrichment

We utilize user registration information from Google+ to enrich their profiles in YouTube. Besides, we extract the video-related behaviors of users from Google+ to enrich their profiles in YouTube.

Experiments

(1) Recommend only by YouTube Profile (S1);
(2) Recommend by Profile Enrichment (S2);
(3) Recommend by YouTube Profile with Collaborative Transfer (S3);
(4) Recommend by Profile Enrichment with Collaborative Transfer (S4).
(5) Profile Enrichment with Collaborative relationship in YouTube (S5)

Table 3. The linear parameters by KTA

Kernel	1	2	3	4	5
Name	Registration	Comment	Video	Photo	Article
Weight	0.266	0.125	0.204	0.020	0.385

The comparison of average F-score by different strategies is illustrated in Fig. 2 ~ Fig. 5.

References:

[1] J. Zhuang, T. Mei, S.C.H. Hoi, X.S. Hua, and S. Li, "Modeling social strength in social media community via kernel-based learning," in *Proceedings of the 19th ACM international conference on Multimedia*. ACM, 2011, pp. 113–122.
[2] G.R.G. Lanckriet, N. Cristianini, P. Bartlett, L.E. Ghaoui, and M.I. Jordan, "Learning the kernel matrix with semidefinite programming," *The Journal of Machine Learning Research*, vol. 5, pp. 27–72, 2004.

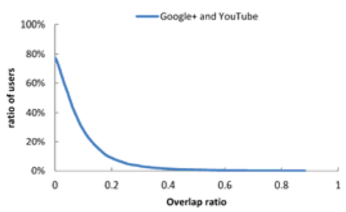

Fig. 2. Overlap of user profiles across platforms.

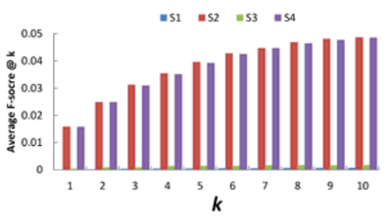

Fig. 3. The performance of different strategies.

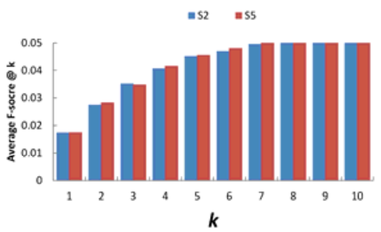

Fig. 4. The performance of utilizing user similarities in YouTube.

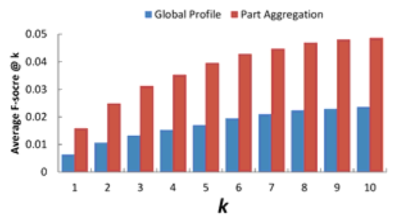

Fig. 5. The performance of profile enrichment.