Demographic Attribute Inference from Social Multimedia Behaviors: A Cross-OSN Approach

Liancheng Xiang[1,2], Jitao Sang[1,2], and Changsheng Xu[1,2(✉)]

[1] National Lab of Pattern Recognition, Institute of Automation, CAS, Beijing 100190, China
{liancheng.xiang,jtsang,csxu}@nlpr.ia.ac.cn
[2] University of Chinese Academy of Sciences, Beijing 100049, China

Abstract. This study focuses on exploiting the dynamic social multimedia behaviors to infer the stable demographic attributes. Existing demographic attribute inference studies are devoted to developing advanced features/models or exploiting external information and knowledge. The conflicts between dynamicity of behaviors and the steadiness of demographic attributes are largely ignored. To address this issue, we introduce a cross-OSN approach to discover the shared stable patterns from users' social multimedia behaviors on multiple Online Social Networks (OSNs). The basic assumption for the proposed approach is that, the same user's cross-OSN behaviors are the reflection of his/her demographic attributes in different scenarios. Based on this, a coupled projection matrix extraction method is proposed for solution, where the cross-OSN behaviors are collectively projected onto the same space for demographic attribute inference. Experimental evaluation is conducted on a self-collected Google+ and Twitter dataset consisting of four types of demographic attributes as gender, age, relationship and occupation. The experimental results demonstrate the effectiveness of cross-OSN based demographic attribute inference.

Keywords: Cross-OSN · Stable demographic attribute inference · Dynamic behavior

1 Introduction

Along with the explosive prevalence of social media, more and more people are now being engaged in various Online Social Networks (OSNs) to create and share huge volume of multimedia information. Towards the goal of efficient digital information management and customized social media services, user modeling from the social multimedia behaviors has become more urgent and important than ever before. User models distribute in different aspects, ranging from demographic attributes (e.g., age, gender, marriage status, occupation), personal interests (e.g., politics, technology, music, sports), to social networking status, mobility patterns, consuming patterns, emotional orientation, etc. Among them,

L. Amsaleg et al. (Eds.): MMM 2017, Part I, LNCS 10132, pp. 515–526, 2017.
DOI: 10.1007/978-3-319-51811-4_42

demographic attributes recording the basic and intrinsic user information constitute the most fundamental dimensions to build generic user models, and thus are widely applied in practical information services.

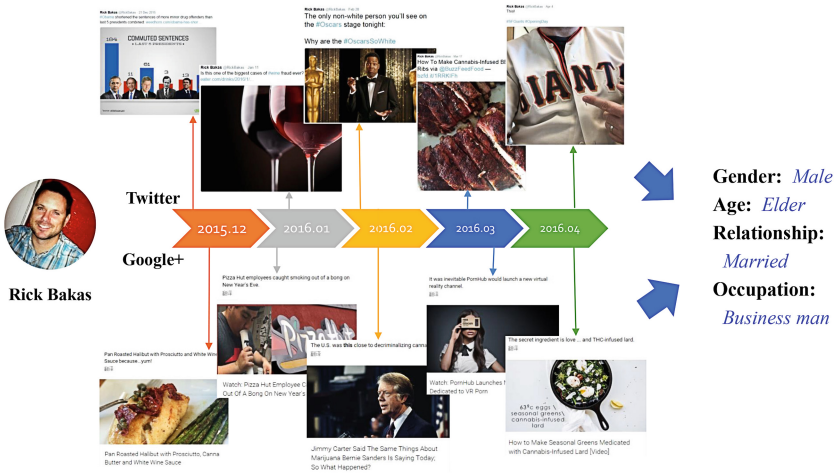


Fig. 1. An illustrative example to infer demographic attributes of a common user "Rick Bakas" from social multimedia behaviors.

Recent years have witnessed extensive studies on inferring user demographic attributes from their social multimedia behaviors [2,4,7,9,10,14]. Most of these studies either developed advanced features and models or exploited external information and knowledge. For example, Rao et al. [10] exploited sociolinguistic features and n-gram models to infer users' demographic attributes including gender, age and regional origin from their Twitter behaviors. Fang et al. [4] identified the inter-relation between different demographic attributes and proposed a multi-task learning scheme for relational attribute inference on Google+. However, so far as we know, a critical problem has been ignored and remained unexplored till now: *the contradiction between the dynamicity of observed social multimedia behaviors and the relative stable demographic attributes*. As illustrated in the left of Fig. 1, users' social multimedia behaviors are significantly dynamic with changing focuses from time to time. On one hand, the above existing demographic attribute inference studies generally take user dynamic behaviors at different time periods as a whole, which inevitably leads to information loss in user modeling and fails to capture the underlying correlation between the dynamic behaviors and the stable demographic attributes. On the other hand, studies in personal interest modeling have tackled the dynamicity problem by separating user behaviors into different time sessions to estimate the evolving interests over time [12]. In the context of demographic attribute inference, since the demographic attributes such as gender, age, marriage status and occupation

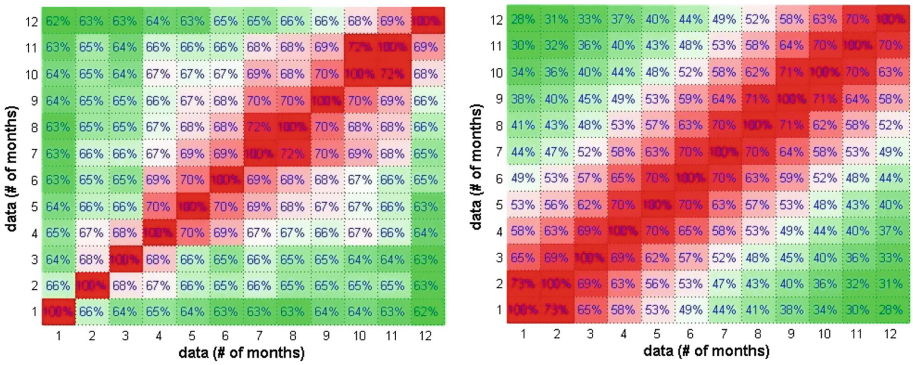
are static or remain unchanged during a long period of time, the methodologies from dynamic interest modeling also cannot be directly used.

The solution goes to two lines to address the contradiction between dynamic behaviors and stable demographic attribute: one is to discover the stable patterns from user behaviors during an enough long time, and the other is to identify the shared patterns from user behaviors under different circumstances. This exploratory study is focusing on solution along the second line. Today's social media users are now using a multitude of OSN services, e.g., following real-time hot events on Twitter, communicating with his/her friends on Facebook/Google+, and subscribing and watching videos on YouTube, which has called attention from bunches of researchers. Abel et al. [1] introduced a cold-start recommendation solution by aggregating user proles in Flickr, Twitter and Delicious. In [11], the real-time and socialized characteristics of the Twitter tweets was exploited to facilitate video applications in YouTube. Deng et al. [3] incorporated user information from Google+ to facilitate personalized YouTube video recommendation. Yan et al. [13] proposed a united YouTube video recommendation framework via cross-network collaboration in which users auxiliary information on Twitter are exploited to address the typical problems in single network-based recommendation solutions. This cross-OSN scenario also provides a natural testbed to explore the shared user behavior patterns towards demographic attribute inference. It is reasonable to assume that it is the unique and stable demographic attributes that explain and lead to the disparate and dynamic social multimedia behaviors on various OSNs (illustrated in Fig. 1).

We propose a cross-OSN demographic attribute inference approach to realize the above assumption. In particular, we consider Google+ and Twitter, the popular Social Networking Site (SNS) and microblogging site, as the test OSNs in our study. In either of them, users are allowed to post texts, pictures, and videos. The training stage of the proposed approach consists of two steps. Firstly, users' social multimedia behaviors are processed to construct user feature representation for each OSN. Secondly, with the ground-truth demographic attribute as supervision, we utilize a coupled projection matrix extraction method to identify the shared patterns among the same individual's OSN respective representations and obtain the correlation between the demographic attribute space and the behavior feature spaces. At the test stage, given the observed user behaviors on different OSNs, we first extract user features and then infer his/her demographic attributes by mapping onto the derived coupled projection matrixes. Experiments on a real-world dataset demonstrate the superior performance of cross-OSN demographic attribute inference over the single-OSN based solutions.

The main contributions of this paper can be summarized as follows:

- We propose and tackle with the problem of stable demographic attribute inference from dynamic social multimedia behaviors.
- A cross-OSN approach is presented to identify the shared behavior patterns towards demographic attribute inference.



(a) (b)

Fig. 2. The user behavior similarities between different time pairs in Google+ and Twitter from 2014.12 to 2015.12.

2 Data Collection and Analysis

In this section, we first introduce how we collect our cross-OSN user dataset, and then conduct some quantitative analysis on investigating the dynamicity of users' social multimedia behaviors.

2.1 Data Collection

To construct a dataset with user account linkage between different OSNs, we start from Google+ website where users are willing to share their user accounts on other OSNs, and collect 1,478 users with accounts on both Google+ and Twitter. These 1,478 users are recorded as *common users* in the rest of this paper. For each of the common users, we further download his/her recent 2,000 social posts (including both the texts and attached images) and the user profile from Google+ and Twitter, respectively. As a result, the collected cross-OSN dataset consists of 1,622,247 social activities in Google+ and 2,572,546 multimedia tweets in Twitter for the 1,478 common users.

2.2 User Behavior Analysis

Due to the changing of user's interest or focus, the typical user behaviors will change with time. In this subsection, we further examine the dynamicity of the typical user behaviors in the collected dataset. We investigate this characteristic by measuring the similarities of the same users' social activities between different time periods on Google+ and Twitter, respectively. Specifically, we collect all the behavior data of the common users from December 1st, 2014 to December 1st, 2015 and calculate the average user activity similarity between each time-time pair over all users in a monthly granularity, given as follows:

$$sim(t_i, t_j) = \frac{1}{|\mathcal{U}|} \sum_{u \in \mathcal{U}} \cos(\mathbf{f}_u^{t_i}, \mathbf{f}_u^{t_j})$$

where t_i, t_j denote two different time periods (i.e., months), and $\mathbf{f}_u^{t_i}, \mathbf{f}_u^{t_j}$ are user u's derived feature representations[1] in time period t_i, t_j. $\cos(\cdot, \cdot)$ is the cosine similarity metric.

In Fig. 2, we plot the normalized similarities between all the possible time pairs with a heatmap. Both axes represent the time intervals (i.e., months) from December 1st, 2014. Red color indicates high similarity while green means dissimilarity. We can observe that in both OSNs the red-color points are mostly along the diagonal line, and the similarities get smaller when the points get farther from it. This indicates that the user behaviors are continuously changing with time going on, and just considering all user's behaviors as a whole will inevitably lead to an information loss.

3 Approach

Problem Definition: Given a collection of common users $\mathcal{U}$, we represent each user $u \in \mathcal{U}$ as a three-dimensional tuple $[\mathbf{f}_u^g, \mathbf{f}_u^t, \mathbf{a}_u]$, where $\mathbf{f}_u^g, \mathbf{f}_u^t$ are the feature representations of user u in Google+ and Twitter, respectively. $\mathbf{a}_u$ denotes the labeled user attribute set. The goal is to make use of the users' cross-OSN features $\mathbf{f}_u^g, \mathbf{f}_u^t$ and their corresponding attribute set $\mathbf{a}_u$, to learn a mapping function $\mathcal{F}(\mathbf{f}_u^g, \mathbf{f}_u^t) \rightarrow \mathbf{a}_u$ between the users' behavior feature spaces and demographic attribute space for user attribute inference.

3.1 User Feature Extraction

Textual Features: We use the stemming method and stop words elimination, and remove words with a corpus frequency less than 15 in the whole text set. To reduce the number of dimensions for feature representation, we further use an entropy-based method for discriminative word selection for each attribute category. The basic idea is to measure each word by the mutual information entropy, and choose the top 10,000 words with the highest scores. TF-IDF term weighting method is applied to weight feature appropriately.

Visual Features: Convolutional neural networks (CNNs) have become more and more popular for extracting visual features from images recently. In this work, we use the widely used VGG16 model trained on ImageNet and extract a 1000-dimensional visual feature from the top fully connected layer with Caffe [8] for each image. Since one user generally has more than one image in his/her social posts, we apply a max-pooling method on the image representations to obtain an aggregated 1000-dimensional feature vector for each user.

Finally, we concatenate the textual and visual features and obtain the final feature representation for each user.

[1] The feature extraction is introduced in Sect. 3.1.

3.2 Coupled Projection Matrix Extraction

In each OSN, we assume that the correlations between the user's behavior feature space and demographic attribute space are embedded in a projection matrix W, based on which the user's demographic attribute representation $\mathbf{s}_u$ can be inferred by directly projecting his/her social behavior features $\mathbf{f}_u$. This assumption can be formulated as: $\mathbf{f}_u = W\mathbf{s}_u$. The task is thus to learn this projection matrix W with observations of the training users' social behavior features and their corresponding user attribute set. This can be realized by solving an optimization problem as follows,

$$\min_{W,S} ||F - WS||_F^2 + \lambda_1 ||S - A||_F^2 + \lambda_2 ||W||_F^2 \tag{1}$$

where $F = [\mathbf{f}_1, \mathbf{f}_2, \cdots, \mathbf{f}_N]$ denotes the social behavior features which is introduced in Sect. 3.1. $A = [\mathbf{a}_1, \mathbf{a}_2, \cdots, \mathbf{a}_N]$ denotes the discrete attribute representations of all the N users in the training set, by directly expanding each user's labeled attributes as a one-hot vector, which is 0 in most dimensions and 1 in a single dimension. In this case, the $\boldsymbol{i}$th attribute value will be represented as a vector which is 1 in the $\boldsymbol{i}$th dimension. For example, with regard to gender, a male user would be $[1, 0]$ while a female user would be $[0, 1]$. $S = [\mathbf{s}_1, \mathbf{s}_2, \cdots, \mathbf{s}_N]$ denotes the continuous demographic attribute representations of users, which has the same size with the discrete attribute representation A. Here we update the discrete attribute representation A to a continuous form S, to better indicate the user's relative strength on different attribute types.

However, in this formulation, the contradiction between the dynamicity of observed social behaviors and relatively stable demographic attributes is not considered. To address this problem, the basic premise of our solution is to discover the shared patterns from multiple user behaviors in different OSNs. Therefore, we further modify the continuous attribute representation S in Eq. (1) as a shared factor extracted from both Google+ and Twitter, and obtain the following objective function:

$$\begin{aligned} \min_{W^g, W^t, S} \|F^g - W^g S\|_F^2 + \left\|F^t - W^t S\right\|_F^2 \\ +\lambda_1 \|S - A\|_F^2 + \lambda_2 \|W^g\|_F^2 + \lambda_3 \left\|W^t\right\|_F^2 \end{aligned} \tag{2}$$

where F^g, F^t are the social behavior features of all the N users in Google+ and Twitter, respectively. W^g, W^t are the coupled projection matrices in different OSNs, and λ_1, λ_2, λ_3 are three regularization parameters. In this way, the derived attribute representation S is shared across different OSNs and can reflect some stable activity patterns.

Since there are multiple variables in the objective function, we adopt an alternative algorithm to find optimal solutions for the three variables W^g, W^t and S. The key idea is to minimize the objective function w.r.t one variable while fixing the other variables, as similar to [6]. The partial derivatives of the objective function can be derived as:

$$\frac{\partial}{\partial W^g} = 2W^g(SS^{\mathrm{T}} + \lambda_2 I) - 2F^g S^{\mathrm{T}} \tag{3}$$

$$\frac{\partial}{\partial W^t} = 2W^t(SS^{\mathrm{T}} + \lambda_3 I) - 2F^t S^{\mathrm{T}} \tag{4}$$

$$\frac{\partial}{\partial S} = 2MS - 2[(W^g)^{\mathrm{T}} F^g + (W^t)^{\mathrm{T}} F^t + \lambda_1 A] \tag{5}$$

where $M = (W^g)^{\mathrm{T}} W^g + (W^t)^{\mathrm{T}} W^t + \lambda_1 I$.

Let the partial derivative equals zero, we can obtain the final updating rules as below,

$$W^g = F^g S^{\mathrm{T}}(SS^{\mathrm{T}} + \lambda_2 I)^{-1} \tag{6}$$

$$W^t = F^t S^{\mathrm{T}}(SS^{\mathrm{T}} + \lambda_3 I)^{-1} \tag{7}$$

$$S = M^{-1}[(W^g)^{\mathrm{T}} F^g + (W^t)^{\mathrm{T}} F^t + \lambda_1 A] \tag{8}$$

Based on this, we update W^g, W^t and S iteratively until convergence or maximum iteration.

3.3 User Attribute Inference

With the derived coupled projection matrices W^g and W^t, given a new user with his/her social behavior features $\mathbf{f}^g$ and $\mathbf{f}^t$, we can estimate the user's unique demographic attributes as:

$$\mathbf{s}^* = \min_s \ \|\mathbf{f}^g - W^g \mathbf{s}\|_F^2 + \left\|\mathbf{f}^t - W^t \mathbf{s}\right\|_F^2 \tag{9}$$

Besides, when the projection matrices are obtained, we can also roughly infer the demographic attributes for the typical users with observed social behaviors in one single OSN, by solving the objective function as follows:

$$\mathbf{s}^* = \min_{\mathbf{s}} \|\mathbf{f} - W\mathbf{s}\|_F^2 \tag{10}$$

where $\mathbf{f}$ and W correspond to the user's social behavior features and the projection matrix in single Google+ or Twitter.

With the estimated user attribute representation $\mathbf{s}$ for each user, we rank the attribute values in each attribute type and choose the biggest one as the final inference result for the attribute type.

4 Experiments

4.1 Experimental Setting

We consider four types of user demographic attributes, i.e., gender, age, relationship, and occupation. The attribute values are defined according to a comprehensive study on Google+ and Twitter data and a survey of previous work on user attribute inference [4,5,10], shown in Table 1. Gender, age and relationship are binary attributes, while occupation is classified into 15 groups, such as student, IT person and entertainer. Since there is no available groundtruth of user attribute values, we build the evaluation dataset by manually labeling the attributes for each user. To ease the annotation task, some user platforms such as Facebook[2], Wikipedia[3] are utilized as referenced sources for accurately

[2] http://www.facebook.com/.
[3] http://www.wikipedia.org/.

Table 1. User attribute definition.

Attribute name	Attribute values
Gender	1-Male; 2-Female
Age	1-Young ($\leq$30); 2-Elder (>30)
Relationship	1-Unmarried; 2-Married
Occupation	1-Student; 2-IT person, Software Engineer, Geek; 3-Entertainer, Actor, Comedian, Musician, Model, TV show host; 4-Writer, Journalist Editor, Blogger, TV news host, Critics Lawyer; 5-Politician; 6-Ath-lete; 7-Business man, Economist, Entrepreneur; 8-Scientist; 9-Photographer; 10-Doctor; 11-Chef, eater, cook; 12-Engineer, Specialist, Designer; 13-Teacher; 14-Artist, Religious people, Critic; 15-Other

annotating the user attributes. Each user is annotated by three active social network users, and their attribute values are determined as ground-truth only when at least two annotators agree on it.

In this paper, we introduce a cross-OSN demographic attribute inference approach which can infer stable demographic attributes using dynamic social multimedia behaviors. Each of the four attributes is inferred independently. To demonstrate the effectiveness of the proposed coupled projection matrix extraction (CPME) method, we compare it with the popular support vector machine (SVM) method and projection matrix extraction (PME) method using features extracted from single Google+ or Twitter. And a cross-OSN approach, the SVM method using features concatenating the two OSNs' features, acts as a comparison as well. All are listed as follows:

- **Support Vector Machine Using Google+ Feature or Twitter Feature (SVM_Google+/SVM_Twitter):** The method uses features extracted from Google+ or Twitter to train an attribute classifier for each attribute type.
- **Support Vector Machine Using Both OSNs Feature (SVM_Both OSNs):** This is a contrastive cross-OSN attribute inference method which uses a joint feature of Google+ feature and Twitter feature.
- **Projection Matrix Extraction Using Google+ Feature or Twitter Feature (PME_Google+/PME_Twitter):** This refers to the single-OSN attribute inference method described in Eq. (1). It represents the typical method which does not consider the dynamicity problem.

In all experiments, we use 10-fold cross-validation to compare different methods and adopt *accuracy* as the final evaluation metrics. As for the parameters of the proposed model, we find the optimum parameter values according to a separate validation set, i.e., $\lambda_1 = 0.1$, $\lambda_2 = \lambda_3 = 0.3$.

4.2 Experimental Results and Analysis

Table 2 shows the *accuracy* of different methods for inferring user demographic attributes, from which we can make the following observations. (1) Different OSNs contribute differently to the inference of these four types of attributes. For both the SVM and PME methods, age attribute and occupation attribute can be more accurately inferred from Google+, while gender attribute and relationship attribute benefit more from Twitter. A proper selection of typical OSNs is thus important in inferring the user demographic attributes. (2) The SVM method leverages the rich cross-OSN user data do not shows obvious advantage comparing with SVM method using features extracted from single Google+ or Twitter. The accuracy of gender attribute even drops when using both OSNs feature. (3) Although the PME method is not that effective compared with the SVM method in exploiting the same single-OSN information, the proposed CPME method can further improve the performance not only over all the single-OSN methods but also the cross-OSN SVM method. This in turn shows the advantage of the proposed method in addressing the contradiction problem between the dynamic user behaviors and stable demographic attributes from a cross-OSN view. (4) As a binary classification problem, the accuracy of relationship attribute seems relatively low no matter which method is used. It is a rather difficult problem to infer user relationship attribute because of the comparatively weak correlations between users behavior and relationship attribute. Even so, the proposed CPME method has greatly enhanced the relationship attribute inference accuracy 5.95% than that of the SVM method using cross-OSN user data which achieves highest accuracy in baselines.

Table 2. Accuracy of different methods for user demographic attribute inference.

	Gender	Age	Relationship	Occupation
SVM_Google+	0.74737	0.69333	0.58301	0.39104
SVM_Twitter	0.76003	0.68000	0.58492	0.37258
SVM_Both OSNs	0.75748	0.71667	0.58758	0.41238
PME_Google+	0.74245	0.66301	0.56092	0.38161
PME_Twitter	0.75521	0.65710	0.57236	0.36681
CPME	**0.79325**	**0.75085**	**0.62250**	**0.48070**

In Fig. 3, we present some demographic attribute inference by the proposed CPME model. Some users use different images as profile photo in different OSNs, while some users use the same images. We can see that the model accurately infers most of the user attributes, such as attribute “male”, “young”, “unmarried”, “IT person” and so on.

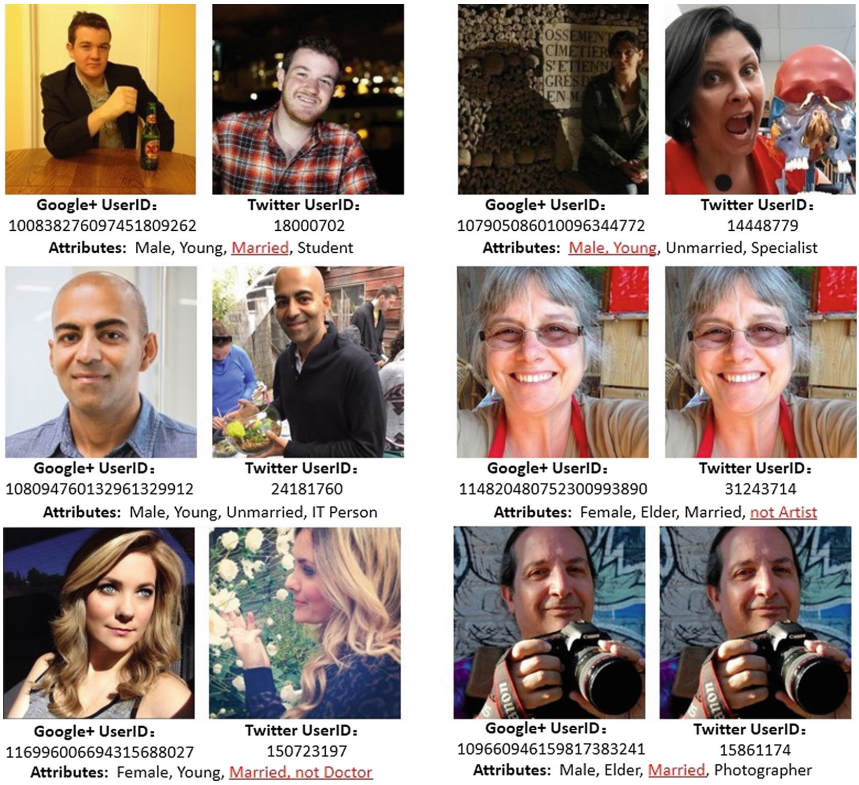


Fig. 3. Predicted user demographic attributes of the testing sample users. Failure instances are highlighted with red. (Color figure online)

4.3 Discussion

In the above-mentioned comparison experiment, more user data in both OSNs are used in the cross-OSN method when testing, which may not be a fair comparison indeed for single-OSN methods. Moreover, it is also very difficult to collect the cross-OSN user data for every user. In a real-world application, we usually can only get access to the user data in one single OSN for attribute inference. As illustrated in Sect. 3.3, with the derived coupled projection matrices, the proposed CPME method can also handle this kind of users with single-OSN behavior data. Therefore, we further test the accuracy of the proposed CPME method on three different user settings, i.e., given test users' data only on Google+, only on Twitter, and on both of them. The result is shown in Table 3, we can see that: (1) Even only with user data in one single OSN for inference, the performance is still higher than the single-OSN methods in Table 2, which may be due to the reason that the potential and stable relevance between different OSN feature spaces are captured in the proposed coupled projection matrix extraction

Table 3. Performance comparison of the proposed CPME method on three different user settings when inferring.

	Gender	Age	Relationship	Occupation
Google+	0.77227	0.738176	0.61200	0.41988
Twitter	0.78495	0.74324	0.59620	0.45270
Both OSNs	**0.79325**	**0.75085**	**0.62250**	**0.48070**

method. (2) By providing more user data in both OSNs, the performance can be further improved. This indicates that more user data available for inference contributes to more accurate attribute prediction.

5 Conclusion

In this paper, we introduce a cross-OSN approach for demographic attribute inference from social multimedia behaviors. The proposed approach is validated to effectively discover the shared stable behavior patterns and achieve superior performance. We also explored the potential of employing single-OSN behavior data for robust demographic attribute inference by utilizing the implicit correlations between users' cross-OSN behaviors. In the future, we will be working along three lines: (1) The cross-OSN approach in dynamic user attribute inference can be compared and examined. (2) The stable patterns from long-time user behaviors for demographic attribute inference can be identified. (3) The proposed method shows its superiority in user demographic attribute inference compared to the SVM method, even if the SVM method is a standard classification method while the proposed method with square loss function is not a strict classification method. Hence, we will try to use more distinguishing features and other suitable loss function.

Acknowledgements. This work is supported by National Natural Science Foundation of China (Nos. 61432019, 61225009, 61303176, 61272256, 61373122, 61332016).

References

1. Abel, F., Araújo, S., Gao, Q., Houben, G.-J.: Analyzing cross-system user modeling on the social web. In: Auer, S., Díaz, O., Papadopoulos, G.A. (eds.) ICWE 2011. LNCS, vol. 6757, pp. 28–43. Springer, Heidelberg (2011). doi:10.1007/978-3-642-22233-7_3
2. Chen, X., Wang, Y., Agichtein, E., Wang, F.: A comparative study of demographic attribute inference in twitter. In: Ninth International AAAI Conference on Web and Social Media (2015)
3. Deng, Z. Sang, J. Xu, C.: Personalized video recommendation based on cross-platform user modeling. In: 2013 IEEE International Conference on Multimedia and Expo (ICME), pp. 1–6. IEEE (2013)

4. Fang, Q., Sang, J., Xu, C., Hossain, M.S.: Relational user attribute inference in social media. Multimedia IEEE Trans. **17**(7), 1031–1044 (2015)
5. Filatova, E., Prager, J.: Occupation inference through detection and classification of biographical activities. Data Knowl. Eng. **76**, 39–57 (2012)
6. Gao, H., Tang, J., Hu, X. Liu, H.: Content-aware point of interest recommendation on location-based social networks. In: AAAI, pp. 1721–1727 (2015)
7. Huang, Y., Yu, L., Wang, X., Cui, B.: A multi-source integration framework for user occupation inference in social media systems. World Wide Web **18**(5), 1247–1267 (2015)
8. Jia, Y., Shelhamer, E., Donahue, J., Karayev, S., Long, J., Girshick, R., Guadarrama, S. Darrell, T.: Caffe: convolutional architecture for fast feature embedding. In: Proceedings of ACM International Conference on Multimedia, pp. 675–678. ACM (2014)
9. Pennacchiotti, M. Popescu, A.-M.: Democrats, republicans and starbucks afficionados: user classification in Twitter. In: Proceedings of 17th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, pp. 430–438. ACM (2011)
10. Rao, D., Yarowsky, D., Shreevats, A., Gupta, M.: Classifying latent user attributes in Twitter. In: Proceedings of 2nd International Workshop on Search and Mining User-Generated Contents, pp. 37–44. ACM (2010)
11. Roy, S.D., Mei, T., Zeng, W., Li, S.: Socialtransfer: cross-domain transfer learning from social streams for media applications. In: Proceedings of 20th ACM International Conference on Multimedia, pp. 649–658. ACM (2012)
12. Sang, J., Lu, D., Xu, C.: A probabilistic framework for temporal user modeling on microblogs. In: Proceedings of 24th ACM International on Conference on Information and Knowledge Management, pp. 961–970. ACM (2015)
13. Yan, M., Sang, J., Xu, C.: Unified YouTube video recommendation via cross-network collaboration. In: Proceedings of 5th ACM on International Conference on Multimedia Retrieval, pp. 19–26. ACM (2015)
14. Zheleva, E. Getoor, L.: To join or not to join: the illusion of privacy in social networks with mixed public and private user profiles. In: Proceedings of 18th International Conference on World Wide Web, pp. 531–540. ACM (2009)