Pattern Recognition Letters 116 (2018) 121–126

Contents lists available at ScienceDirect

Pattern Recognition Letters

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

Evaluating attributed personality traits from scene perception probability

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ARTICLE INFO

Article history:
Received 26 March 2018
Available online 3 October 2018

Keywords:
Personality prediction
Attributed personality traits
Scene perception probability
Convolutional neural network

ABSTRACT

People tend to have different preferences for image scenes, which are indicative of their personality traits. Inspired by the relationship between users' attributed personality traits and preferred image scenes, this letter proposes a personality prediction method based on image scene perception probability. Firstly, image scenes are recognized based on the convolutional neural network. Secondly, the probability distribution of perceived image scenes is calculated. Finally, a regression model is trained using the scene probability distribution features to predict the attributed personality traits. The experimental results on the annotated PshycoFlickr dataset show that the proposed method is superior to the state-of-the-art approaches.

1. Introduction

Personality psychology aims to study the relationship between individual's behavior and personality traits through the analysis of the stable and continuous behavior [1]. With the prevalence of mobile internet, the social network (e.g., Facebook, Flickr, and WeChat) is becoming more and more inseparable in people's daily life. As one of the most popular mediums in social networks, images are widely used in sharing people's activities and express their opinions. Images may contain rich semantics, such as scenes and objects, including animal, people, house, sky and mountain, etc., which are indicative of the users' preferences. For example, if a user likes images with people in a party, the user tends to be extroversive. If a user likes images containing a quiet room, the user tends to be introversive. This makes it possible to model users' personality traits based on their liked images [2,3]. Personality prediction is useful in advertising, personalized recommendation system, and mental health assessment.

Studies have shown that people with the same personality tend to have similar behaviors, which indicates that their behavior habits are closely related to their mental activities [4,5]. Human personality traits can be divided into the Big-Five (BF) kinds, namely: Openness, Conscientiousness, Extroversion, Agreeableness and Neuroticism [6]. The traditional method for personality assessment is mainly based on the questionnaire [7]. However, questionnaire is time-consuming, labor-intensive, and is easily affected by the knowledge and cultural background of the assessors. Users often shy away from the truth when the questionnaire has negative consequences, which leads to inaccurate results. For example, when the question "I tend to find fault with others" appears in the questionnaire, users often choose "disagree" to show that they are easy to get along with. Therefore, it is necessary to build computational models that can predict the BF personality traits automatically and in a more user-friendly way.

Personality computing addresses two basic problems: Automatic Personality Recognition (APR) and Automatic Personality Perception (APP) [8]. While automatic personality recognition aims to infer self-assessment personality traits, automatic personality perception is the task of inferring personality traits that are attributed by others. Since APR is for self-assessment, the evaluation results are often not objective. APP is for attribution, which is evaluated by others and the results are more objective. Sociologists have demonstrated that the social identity of a person is determined not only by the actual personality but also by others' impressions [9]. Therefore, this letter focuses on user's attributed personality traits.

2. Related work

There are two main APP approaches: nonverbal behavioral cues-based methods and social media-based methods [8]. The former methods predict attributed personality traits by observing human expressions, such as extrinsic expressions and gesture [10–12].

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https://doi.org/10.1016/j.patrec.2018.09.027
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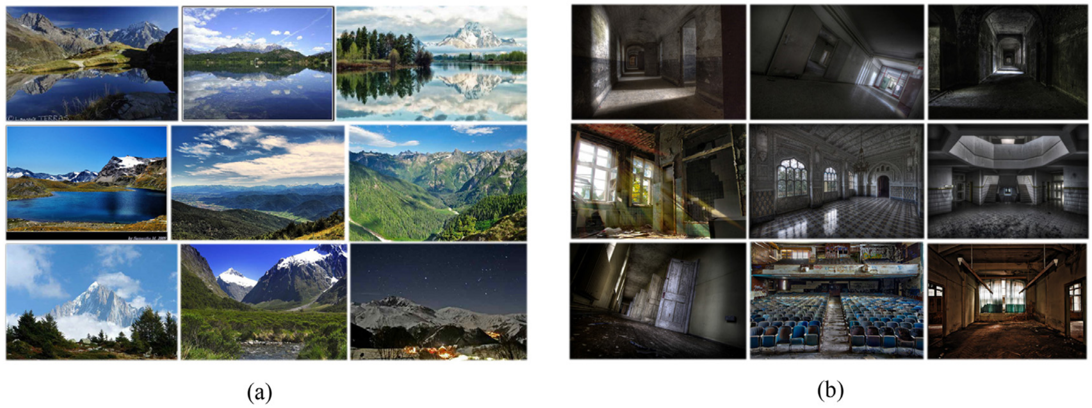

Fig. 1. Example images liked by users with different personality traits: (a) images liked by users with high Agreeableness; (b) images liked by users with high Neuroticism.

The latter methods predict personality traits using images/videos on the social network or relevant comments [13–15,17]. With the prevalence of social media, the huge amount of multimedia information makes it possible to study users' personality traits. Therefore, this letter focuses on modeling personality traits based on social media.

A few works have been done towards APP based on social media. Fitzgerald et al. [13] investigated the agreement between attributed personality traits and selfie content (body portion, facial expression, appearance and gaze). In [14], a bimodal deep learning method, which combines the complementary information from the two modalities (audio and video), is used to predict the first impression of users in a short video. Cristani et al. [15] proposed a method to build an intermediate representation of images that were tagged as favorite by a group of Flickr users. The LASSO [16] regression model is used for personality prediction based on the relationship between low-level image features (color, composition, texture, etc.) and BF personality traits. Based on [15], Guntuku et al. [17] further added high-level semantic features that have better representation of users' like. This method takes into account the fact that users with different personality traits have different favorite contents contained in the liked images. However, the high-level semantic features used in [17] are hand-crafted ones, and one of them (gender identification) needs manual annotation. In addition, the low-level and high-level features in [15,17] are extracted from all images and simple average is calculated to produce the final feature. This may be problematic, because different images have different semantic features, which are not equally important for personality prediction.

Although the aforementioned approaches have achieved some success, APP is still in its infancy. According to [18], since APP is a user-centric prediction problem, it is not sufficient to solve this problem by the image-centric methods [15,17], which is to infer users' personality traits based on a single image. Therefore, a sufficient number of images should be used for users' personality prediction. In [19], Moss et al. showed that users with different personality traits have different preferences for image contents. As semantic content, image scenes have reliable correlation with people's personality traits. In [20], Riskoa et al. also found that personality trait is a robust predictor of an individual's preferences for scene-viewing. These findings have shown that the scenes of images play a significant role in users' preferences. Fig. 1 shows two sets of user liked images from the PsychoFlickr database [15], where the users' BF personality traits have been labelled by the questionnaire [7]. Images liked by users with high Agreeableness are shown in Fig. 1(a), which indicates that affable users tend to like natural scenes (mountains and lakes, etc.). Fig. 1(b) shows the liked images of users with high Neuroticism, which indicates that neurotic users usually prefer dark and closed rooms. Therefore, it is reasonable to infer users' personality traits from perceived scenes. Inspired by the above observation, this letter presents a new method for personality prediction based on image scene perception probability, which is calculated from a number of images liked by the users. The proposed method uses high-level semantic features for APP, and it outperforms the state-of-the-arts.

The main contributions of this work are two folds. First, we investigate the relation between image scenes and user personality, based on which we propose a personality prediction method based on image scene perception. Second, the statistical features of image scenes, which are recognized by pre-trained deep learning model, are used to solve the user-centric prediction problem. The proposed approach takes into account the statistical characteristics of a group of user liked images, which has a better representation of the users' preferences than the simple average strategy used in [15,17]. Furthermore, the semantic features used in the proposed method are automatically extracted using the pre-trained deep learning model, so no human interaction is needed.

3. Proposed approach

The framework of the proposed approach is shown in Fig. 2. Convolutional neural network (CNN) is first employed to recognize the scenes contained in user liked images. The scene probability distribution is then calculated, based on which a linear regression model is trained with the associated attributed personality scores. Finally, we evaluate the performance of the proposed method based on the public PsychoFlickr database [15], which provides user liked image and the associated ground truth personality scores collected using the BFI-10 questionnaire [7].

3.1. Image scene recognition

In this letter, the pre-trained scene recognition model based on the Places365 image database [22], which delivers the best performance so far, is used to recognize the scenes of user liked images. Fig. 3 shows several test results by the pre-trained CNN model on the PsychoFlickr database. From Fig. 3(a), it is clear that pre-trained model can correctly identify the scenes such as snow mountains and glaciers, and the responses are consistent with the real scenes. Fig. 3(b) shows that images are identified as catacomb and burial chamber and the recognized scenes of the images are also highly consistent with human perception.

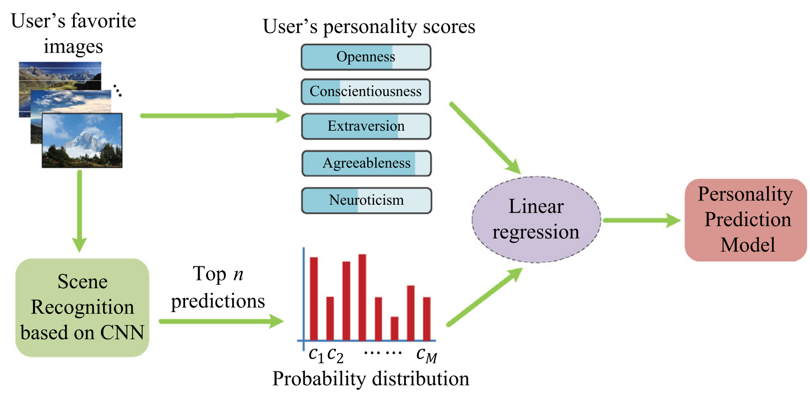

Fig. 2. The framework of the proposed personality prediction method based on image scene perception probability.

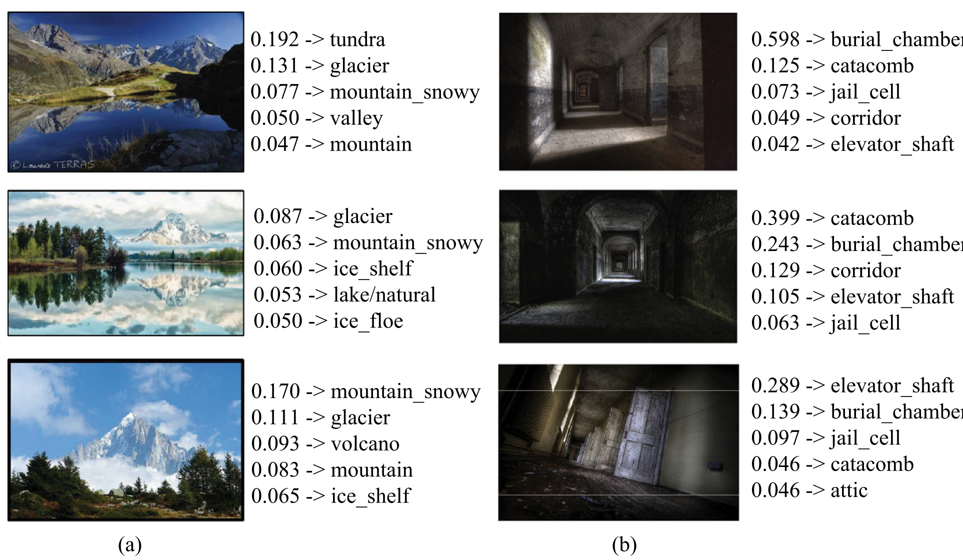

Fig. 3. The top 5 scenes and probabilities of users liked images using the pre-trained scene recognition model. (a) High agreeableness; (b) High neuroticism.

3.2. Personality prediction method

The Place365 image database [22] contains more than 8 million images, comprising 365 scenes that are commonly encountered in daily life. Based on the pre-trained CNN model in this database, the top n scenes of an image can be recognized. Let $\boldsymbol{x}_i$ denote the set of scenes in the ith image liked by a user

$$\boldsymbol{x}_i = [c_1, c_2, c_3, \ldots, c_M], \tag{1}$$

where M is equal to 365, and $c_m (m = 1, 2, 3, \ldots, M)$ indicates whether the mth scene is recognized in the image. If the mth scene is recognized from the image, then c_m is set to 1; otherwise, it is set to 0.

It is known that the personality trait of a user is the stable and complicated expression of his preferences [1]. The recognized scenes of a single image is not sufficient for representing these characteristics. Therefore, all the scenes contained in a large number of images liked by the user should be used. Then the scene probability distribution of the user is calculated as follows

$$\boldsymbol{X} = \frac{1}{N} \sum_{i=1}^{N} a_i \boldsymbol{x}_i, \tag{2}$$

where a_i is the weight that measures the relative importance of the ith image to the overall personality prediction, and N is the number of user liked images.

After obtaining the scene probability distribution $\boldsymbol{X}$, a regressor is employed for modeling the personality traits. Let Y denote the actual personality score of the user, which can be formulated as

$$Y = \boldsymbol{W}\boldsymbol{X}^{\mathrm{T}}, \tag{3}$$

where $\boldsymbol{W}$ is a $1 \times M$ matrix, and each column represents the weight of each scene probability. This problem can be regularized by LASSO, which adds the L1-norm to the object function and makes most elements of $\boldsymbol{W}$ to be zero [16]. Consequently, LASSO is particularly suitable for this regression problem, since it has been shown in Fig. 1 that only a few of the scenes are correlated with a given personality trait [20]. In this way, the most active scenes for each personality trait can be determined. By contrast, the other regression models cannot achieve effective feature selection. Hence, $\boldsymbol{W}$ can be obtained by minimizing the mean square error of the predicted personality score and actual personality score,

$$\boldsymbol{W}^* = \arg\min_{W} \left(\sum_{i=0}^{U_{tr}} \left(Y - \boldsymbol{W}\boldsymbol{X}^{\mathrm{T}}\right)^2 + \lambda \parallel \boldsymbol{W} \parallel_1 \right), \tag{4}$$

where λ is the coefficient of the L1-norm regularization used to limit the weight to avoid over-fitting, and U_{tr} is the number of users used for model training.

To predict the personality of a given user, the pre-trained CNN model is first used to recognize the scenes of the liked images. Then the scene probability distribution $\boldsymbol{X}$ of all liked images can be calculated using Eq. (2). Finally, the predicted personality trait score $Y^{'}$ can be obtained by

$$Y^{'} = \boldsymbol{W}^{*}\boldsymbol{X}^{\mathrm{T}}. \tag{5}$$

4. Experimental results

4.1. Experimental setting

(*1) Database*: The performance of the proposed method is evaluated on PsychoFlickr database [15], which contains 60,000 favorite images of 300 users (200 images per user) on Flickr. The BFI-10 questionnaire [7] was used to obtain the attributed personality traits of each user. The questionnaire contains 10 questions, every two of which are correlated with a trait, and each question has five options from "Strongly Disagree" to "Strongly Agree". Therefore, the attributed personality scores of users are in the range $[-4, 4]$. The users' attributed personality traits, which are O: Openness, C: Conscientiousness, E: Extraversion, A: Agreeableness and N: Neuroticism, were evaluated by the average results of 12 independent observers.

(*2) Setup for model training*: In this work, the pre-trained ResNet model [21] on the Places365 image database [22], which is implemented using PyTorch [23], is used for recognizing image scenes. LASSO [16] is used as the linear regression method. By using the grid search method, the hyper-parameter λ is set to 0.01. It should be noted that the proposed method can achieve very stable performance when λ is in the range [0.001, 0.1]. For simplicity, we suppose that all liked images are equally important for a user, so $a_i (i = 1, 2, 3, \ldots, N)$ are all set to 1. In regression, the 300 users are randomly divided two groups, i.e., 80% users for model training and the remaining 20% for prediction. To avoid bias, the training-test process is repeated 100 times, and the average results are reported in this work.

(*3) Criteria for prediction performance*: Similar to [17], Spearman Rank Order Correlation Coefficient and Root Mean Square Error are employed to evaluate the performance of the proposed method. In order to measure the dispersion degree of the 100 times of training-test processes, the Coefficient of Variation, which indicates the percentage of standard deviation and average value, is also reported.

- Spearman Rank Order Correlation Coefficient (SROCC) is used to evaluate the prediction monotonicity and is computed by

$$SROCC = 1 - \frac{6\sum_{i=1}^{U_{te}} d_i^2}{U_{te}\left(U_{te}^2 - 1\right)}, \tag{6}$$

where U_{te} is the number of users for prediction, and d_i is the difference between the ranks of the actual and predicted personality scores, which is defined as

$$d_i = R_i - R_i^{'}, \tag{7}$$

where R_i and $R_i^{'}$ denote the score ranks of the ith user in actual and predicted personality scores, respectively.

- Root Mean Square Error (RMSE) is used to measure the prediction accuracy and is calculated by

$$RMSE = \sqrt{\frac{1}{U_{te}}\sum_{i=1}^{U_{te}}\left(Y_i - Y_i^{'}\right)^2}, \tag{8}$$

where Y_i and $Y_i^{'}$ denote the actual personality score and the predicted personality score of the ith user for prediction, respectively.

- Coefficient of Variation (CV) is adopted to measure the dispersion of SROCC (CV_s) and RMSE (CV_r) and is computed by

$$CV = \frac{\sigma}{\mu} \times 100\%, \tag{9}$$

where σ and μ denote the standard deviation and average value of 100 test results, respectively.

Table 1
Comparison of the results on PsychoFlickr database.

Personality	Metric	SROCC	CV_s	RMSE	CV_r
O	Cristani [15]	0.3486	21.23%	0.5632	20.01%
	Guntuku [17]	0.3865	22.03%	0.5568	19.27%
	Proposed	**0.5376**	**14.60%**	**0.4167**	**17.29%**
C	Cristani [15]	0.5140	17.55%	0.4032	21.45%
	Guntuku [17]	0.5349	16.30%	0.3840	20.91%
	Proposed	**0.6376**	**13.49%**	**0.2870**	**17.30%**
E	Cristani [15]	0.6178	19.45%	0.7872	**11.63%**
	Guntuku [17]	0.6815	14.70%	0.6144	14.81%
	Proposed	**0.7198**	**8.37%**	**0.5025**	16.28%
A	Cristani [15]	0.4877	18.65%	0.5184	20.34%
	Guntuku [17]	0.5112	17.01%	0.4928	20.27%
	Proposed	**0.6439**	**11.65%**	**0.3819**	**17.94%**
N	Cristani [15]	0.6066	13.90%	0.5184	17.28%
	Guntuku [17]	0.6191	12.00%	0.4992	16.96%
	Proposed	**0.6994**	**9.44%**	**0.4101**	**16.75%**

Higher value represents better performance for SROCC, while lower value indicates better performance for RMSE and CV.

(4) Baseline Methods: In order to verify the performance of our method, comparative experiments are conducted with the state-of-the-art methods [15,17]. In [15], the low-level image features (color, composition, texture, etc.) are used for personality prediction based on the LASSO regression. In [17], combining with the low-level image features, the semantic features of image contents are applied to predict personality traits.

4.2. Performance evaluation

Table 1 summarizes the experimental results of the three methods on the PsychoFlickr database. It can be seen that the SROCC values of the proposed method are much higher than those of the other two methods, which indicates that the prediction monotonicity of our method is significantly better. Meanwhile, the RMSE values of our method are lower than the other two methods, especially for Openness, Extroversion and Agreeableness. The users with high Openness like unconventional image scenes, which is difficult to represent by the traditional image features, but can be accurately recognized by pre-trained CNN model. Therefore, the SROCC value of the proposed method is significantly better than the other two methods by an amount of 0.15. The CV values of the three methods are less than 23%, which indicates that the average results of SROCC and RMSE are stable and effective [24]. By contrast, the CV values of the proposed method are the smallest except for Extroversion, which indicates that the proposed method can achieve the most stable results.

In order to verify the effect of the top n scenes used in the proposed method, the performance of the proposed method is tested under different number of scenes. The experimental results are shown in Fig. 4. We can observe that the SROCC values are higher when $n > 5$. For Conscientiousness and Neuroticism, the SROCC values reach the maximum and keep approximately constant when n is about 20. For Openness, the highest SROCC values are obtained when n is about 21. For Extraversion and Agreeableness, the SROCC values reach the maximum when n is about 25. Therefore, when n is in the range [20, 25], the proposed method can achieve the best overall performances. In implementation, we set the parameter n to 21.

4.3. Discussion

To verify that users with the same personality traits usually like images with similar scene perception characteristics, we fur-

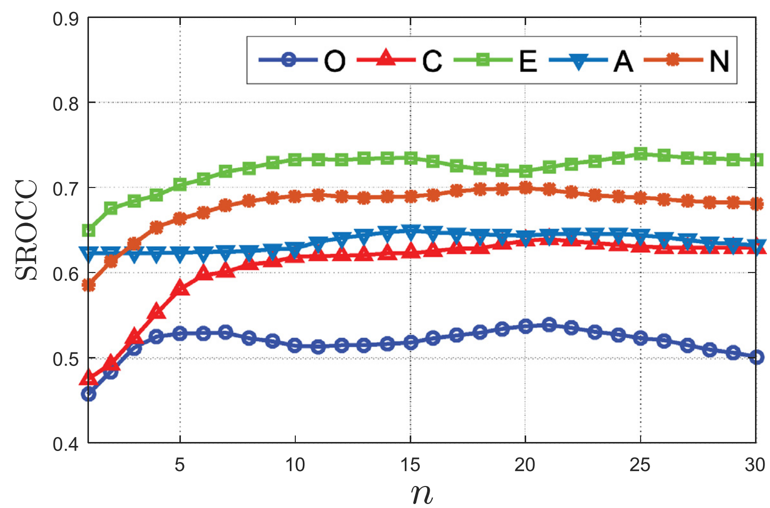

Fig. 4. Performances of the proposed method with different number of scenes (n) used.

Table 2
Top 10 scenes and probabilities with high Extroversion and low Extroversion on PsychoFlickr database.

Extroversion	Probability and scene	
High	**User 1**	**User 2**
	0.480 → Beauty salon	**0.345 → Beauty salon**
	0.395 → Dressing room	**0.250 → Dressing room**
	0.325 → Discotheque	**0.115 → Discotheque**
	0.145 → Stage/indoor	**0.115 → Stage/outdoor**
	0.135 → Jail cell	0.095 → Shower
	0.110 → Shower	0.095 → Jail cell
	0.110 → Arena/performance	0.090 → Stage/indoor
	0.095 → Veterinarians office	0.085 → Street
	0.095 → Martial arts gym	0.070 → Watering hole
	0.065 → Dorm room	0.065 → Arena/performance
Low	**User 3**	**User 4**
	0.265 → Jail cell	**0.475 → Elevator shaft**
	0.200 → Burial chamber	**0.475 → Jail cell**
	0.180 → Catacomb	**0.385 → Burial chamber**
	0.115 → Elevator shaft	**0.260 → Catacomb**
	0.090 → Sky	0.145 → Basement
	0.090 → Barn door	0.115 → Staircase
	0.085 → Cemetery	0.110 → Attic
	0.085 → Alcove	0.105 → Sky
	0.080 → Forest/broadleaf	0.100 → Corridor
	0.080 → Basement	0.075 → Subway station

Table 3
The most positively and negatively correlated scenes with BF personality traits.

Personality	Positive scenes	Negative scenes
O	Artists loft	Fishpond
	Sky	Pet shop
	Museum/indoor	Veterinarians office
C	Slum	Burial chamber
	Sky	Driveway
	Staircase	Dorm room
E	Water park	Burial chamber
	Stage/outdoor	Catacomb
	Martial arts gym	Barndoor
A	Playground	Burial chamber
	Slum	Volcano
	Candy store	Basement
N	Basement	Tundra
	Burial chamber	Museum/outdoor
	Jail cell	Conference center

ther conduct a qualitative analysis of the relationship between the users' personality traits and preferred scenes. Table 2 shows the top 10 scenes and the corresponding scene probabilities of 200 images liked by two users with the highest Extroversion and two users with the lowest Extroversion on PsychoFlickr database. We can find that the top four scenes with the highest probability of the two extrovert users are in the same order of beauty salon, dressing room, discotheque, and stage. And the semantic information associated with these scenes is also consistent with the preferences of extroverts. The top four scenes with the highest probability of the two introverted users are jail cell, elevator shaft, burial chamber and catacomb. And the semantic information associated with these scenes is also in line with the preferences of introverts. We have also done similar experiments on the other four personality traits, and similar results have been obtained. Therefore, modelling users' personality traits from the scene probability distribution is reasonable and effective.

After the linear regression, the most active scenes for each personality trait can be obtained based on the largest or smallest weights of scenes. Table 3 lists the three most active scenes that are positively or negatively related to specific personality traits. It can be observed that the burial chamber that is positively correlated with Neuroticism is correlated negatively with Conscientiousness, Extroversion and Agreeableness. The users with high Openness show preferences for the arts and skies, which indicates that they have creative thinking. The scenes of fishpond and pet shop indicate that users with high Openness seem to not like animals. People that like images with the scene of slum tend to be higher in Conscientiousness and Agreeableness. The water park and stage/outdoor, meaning play and competition in outdoor places, are associated with high Extroversion. The natural scenes have the most negative correlation with Neuroticism. The above analysis shows that the semantic information of scenes has a high consistency with the BF personality traits.

5. Conclusion

In this letter, a personality prediction method based on image scene perception has been proposed. The scenes of user liked images are extracted by the pre-trained CNN model and the scene probability distribution is used for personality prediction. It is basically based on the observation that users with the same personality traits tend to like images with similar probability distribution of scenes. To this end, a linear regression model is built using the scene probability distribution features for predicting the attributed personality traits. The experimental results have demonstrated that the predicted personality traits of the proposed method are more consistent with the actual personality traits, and it outperforms the state-of-the-art personality prediction methods.

While the scene probability distribution has a better performance in capturing the users' preferences, the image scenes are simply recognized by pre-trained CNN model and all liked images are supposed to have equal contribution to the personality prediction, which may not be optimal. How to measure the relative importance of user liked images to the personality prediction [25] and design the problem-specific deep neural network for personality prediction [26] need further explorations. What is more, since there is only one public database for users' personality analysis so far, building a new image database of users' personality traits would be helpful for validating the generalization ability of the personality prediction models.

Acknowledgments

This work was supported by the Natural Science Foundation of Jiangsu Province (BK20181354), National Natural Science Foundation of China (61771473 and 61379143), the Six Talent Peaks High-level Talents in Jiangsu Province (XYDXX-063) and the Qing Lan Project (2016, 2017).

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