Personality Modeling Based Image Recommendation

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Abstract. With the increasing proliferation of data production technologies (like cameras) and consumption avenues (like social media) multimedia has become an interaction channel among users today. Images and videos are being used by the users to convey innate preferences and tastes. This has led to the possibility of using multimedia as a source for user-modeling, thereby contributing to the field of personalization, recommender systems, content generation systems and so on. This work investigates approaches for modeling personality traits (based on the Five Factor Modeling approach) of users based on a collection of images they tag as 'favorite' on Flickr. It presents several insights for improving the personality estimation performance by proposing better features and modeling approaches. The efficacy of the improved personality modeling approach is demonstrated by its use in an image recommendation system with promising results.

Keywords: semantic features, personality modeling, big five factor.

1 Introduction

Modeling users' personality based on content (images and videos) they like has widespread applications in recommender systems, personalization, novel content generation systems, and target advertising systems and so on. The key factors to address this problem effectively are the source for acquiring users' personality and the model used to facilitate the right mapping between them. In this work we look at positive implicit feedback (likes) on images as the source for modelling users personality, because images are universal in expression even when users speak different languages.

Assessing the personality of users by looking at images they liked has been studied in the literature [1]. To do this, images tagged as 'favorite' by a group of Flickr users were collected. Next the users were asked to answer the BFI-10 questions [2] to get their personality profile based on the Big Five Factor personality modeling approach [3]. 'Psychology experts' were asked to look at the images liked by the users and answer the same BFI-10 questions. The idea was to get the experts' opinion regarding the users' personality profile (a different perspective from self-assessment). The process of automatically assessing the personality profile of users involved learning a regression model (LASSO [4]) mapping low-level image features to their personality profile. A summary of the features used in [1] is depicted Table 1. Each users personality is modeled based on a training set of images liked by the user. The ability of the model to

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predict personality was evaluated based on a test set of images liked by the user. Difference in self-assessment of personality and the assessment given by experts was studied and the following observations were made.

- With a reasonable level of accuracy, personality profiles assessed by experts can be modelled from low-level features extracted from images users liked.
- However users' self-assessed personality profiles are difficult to model and the learned model does not generalize well.

Based on the above observations it was concluded that because self-assessed personality profiles tend to be more noisy, they are difficult to generalize. The noise is ascribed to the fact that users may not be able to assess their personality properly. However it must be noted that the above conclusions are based on the following two implicit assumptions.

- Users' self assessment of personality profile was based only on the images they have liked.
- Experts assessment of users personality goes beyond the clues presented by the images, based on which they made their assessment.

We note that the above assumptions may not be true because the experts rating of the users personality is based on the limited set of images shown to them. The expert can only work within the bounds of information provided to him. Conversely, when users are assessing their personality, it's based on factors which certainly go beyond the images they like. So what is indicated as noise in the self-assessed personality profiles can very well be additional information that the images do not capture. Note that the users are answering the BFI-10 questions which probably capture more information than that contained in the images. Also it is not really clear that the low-level features used to map from features to personality profiles are indeed representative in predicting highly semantic concepts as the Five Factor (Openness, Conscientiousness, Extraversion, Agreeableness and Neuroticism) personality profiles.

In view of the above observations we first look at answering a few questions that would help us identify a better approach to modelling users personality from a set of images the user has liked and also see how we can generalize better. The questions we attempt to answer are as follows:

- Is the set of features used in [1] sufficient to describe user's interests. How about looking at more semantic features?
- Is there an approach which leverages upon users' likes on images to model their personality, which goes beyond their likes on images?
- If experts can better assess personality by looking at images liked by the user, how can we leverage on this fact to improve personality profile prediction on self assessed data? Does the expert knowledge help generalize well?

After conducting a detailed investigation of the above questions we identify a useful set of features and approach that helps better model the user personality profile. This forms the basis for addressing the recommendation problem which is basically, given a user, answering what kind of images would the user like?

Fig. 1. Need for including Semantic Features. Left: High score on Conscientiousness; Center: Low score on Extraversion; Right: High score on Neuroticism.

Contributions. We conduct a detailed investigation of estimating users personality profile from a collection of images that were liked by the user presenting recommendation for features that need to be considered and also the modeling approach that can generalize well. We show the need for using high level user understandable features and also demonstrate the efficacy of a F2A (Features-to-Answers) +A2P (Answers-to-Personality) approach compared to the usual F2P (Features-to-Personality) approach that has been taken by existing works. Once we have a better approach for modeling personality from images we demonstrate their usefulness in an image recommendation system. Here the Big Five Factors for personality modeling form a latent space for mapping images and users.

Table 1. List of Features (with newly added features are bolded)

List of Features used	
Use of Light	**Head and Upperbody recognition**
HSV statisctics	**Face and Pose recognition**
Emotion-based	**Gender identification**
Entropy	**Scene Classification**
Regions using mean shift segmentation	**Computer Graphics vs. Natural image**
Low Depth of Field (DOF)	**Saliency**
GIST Descriptors	**Black & White vs. Color image**
#Edges	**Visual Clutter**
Tamura	
Wavelet Textures	Colorfulness
Rule of thirds	GLCM-features
Objects: Deformable Parts model	Image Parameters

2 Enhancing Personality Modeling

In this section we investigate how the personality modeling approach based on mapping low-level images features to personality profile can be improved. We also investigate the difference between self-assessed and expert assessed personality profiles in helping model the Five Factor personality profiles.

Fig. 2. Sample of the images 'faved' by users with different personality profiles. Left: High score on Openness; Center: High score on Extraversion; Right side: High score on Agreeableness.

2.1 Adding Semantic Features

As aforementioned, Table 1 lists the features used in [1]. We note that most of these features are low-level features. Hence we first investigate adding more semantic features that might provide a better representation of the users' preferences and hence their personality. Table 1 depicts these additional features in (**bold**).

For images to reflect user's personality, they (or the features extracted from them) should be representative of a universal set of possible images (or features), that help model a diverse set of tastes (associated with different personality profiles). As building a universal set of images is infeasible, the features chosen to represent the limited set of images, should be able to convey semantics that is well representative of characteristics that everybody can relate to.

Depending on a person's psychophysical nature, one is drawn to different 'kinds' of images. To make this distinction, some amount of domain knowledge has to be included to capture the differences in what different people look at. For example, images on the left side of collage (Figure 1) show images liked by a user with a score of 4 on conscientiousness (for a range of [-4,4]). This trait reflects in socially prescribed impulse control and a sense of thoughtful behavior. Images of such users consist of carefully planned and timed shots and many black & white images (which is shown to be a sign of focus, subtlety of tones and versatility [5]). While people with high score on extraversion have images with a lot of people, people with a low score, have opposite preference - consisting of scenic backdrops, without faces or objects to focus upon (images in the middle of the same collage). Also, people with a high score on neuroticism are characterised by anxious and tense behavior. They seldom relax. This is conveyed by the images they like (images on the right side of the collage), most of which have a high level of clutter [6].

Personality traits should ideally be influenced by high level semantic concepts, each dealing with multiple facets of human behavior [7,8]. For example, a person with a high score on Openness factor tends to appreciate art, come up with distinctive-looking work and home environments etc. Figure 2 shows some random images liked by 3 users from the PsychoFlickr data-set [1] (to be described in Section 3.1). The left part of the collage show images 'faved' by a user with a score of 4 on Openness factor. These images show a bias towards dance, music and artistic photography. This is just a representative set. The original dataset can be accessed at [1]. Images of a user having a score of 4 on Extraversion are shown in the middle. This trait reflects in energetic approach towards social and material world. This means that the user is expected to have high affinity towards friends and partners - the images liked by the user can be seen to convey, in this case, a liking towards people of opposite gender. The right part shows images liked by a user with a score of 4 on Agreeableness, which reflects in traits such as altruism, tender-mindedness and trust, and in behavior like consoling friends who are upset etc. The images liked by the user convey a similar inclination.

Each of the five personality traits convey specific innate tastes of users which lead to certain behavioral attributes. Capturing the wide spectrum of personality traits with features extracted from data is a challenge. But, the features can be used to detect the above mentioned behavioral attributes (which are usually less subtler than personality traits) which can give us clues about the user's personality.

Based on this analysis, we have found that while aesthetic features capture a lot of information in the images as mentioned in literature [9], features which are more interpretable are needed to capture a person's tastes. Aesthetics, which formed the majority of the features used in [1], fail to convey these high level semantic characteristics. Especially, when we are trying to find the right user-image match, a more concrete relationship between person's profile and content profile is needed to give the users what they like [10].

2.2 Looking Beyond Existing Approaches

Most of the works in automatic personality modeling have taken the approach of extracting features from data (related to users) and using them directly to model personality of users (termed as Features-to-Personality - F2P). But research in psychology [2] shows that personality is ascertained by the asking users a set of well-designed questions. The answers to these questions are converted into a score, for each of the 5 personality traits (termed as Features-to-Answers, Answers-to-Personality - F2A+A2P). Taking this approach with features extracted from data was shown to be more effective than predicting the personality scores directly [11]. The intuition is that non-experts understand and hence answer the BFI-10 questions better than scoring themselves on a scale of -4 to 4 for personality profiling.

F2A+A2P Model. Personality prediction is divided into two stages, namely transforming features to answers (F2A) and mapping the answers to trait scores (A2P). For the first stage, i.e, transforming the feature space into answers, a Sparse and Low-rank Transformation (SLoT) algorithm was [11] used here. The motivation for using the sparse and low rank transformation is twofold. (a) The answers to the questions may have some overlap with each other (i.e., a social and outgoing person would want to be thorough in work as this might attract others; a low rank constraint is needed in the regression problem to capture these correlations between the answers). (b) Each answer might only be influenced by a few features (leading to a sparsity constraint). And for the second stage, the BFI 10 scoring scheme [2] is used to predict the personality profiles.

SLoT Formulation. The transformation to BFI-10 answers from features contains both low-rank and sparse structure. In addition to minimizing the regression error, specific matrix norms are therefore used to learn the transformation.

The answers are represented by Z - a $10 \times N_{tr}$ matrix and the features of training images by F_{tr}. Regression model's parameters are represented by W - a $10 \times N_f$ matrix.

Estimation of the transformation matrix W, with sparse and low-rank structure from the training images (F_{tr}, Z), can be formulated as the following objective function,

$$\min_{W} \left\{ \frac{1}{2} \|Z - WF_{tr}\|_F^2 + \lambda_1 \|W\|_* + \lambda_2 \|W\|_1 \right\}. \quad (1)$$

where $\|\cdot\|_F$ is matrix Frobenius norm, $\|\cdot\|_*$ - matrix nuclear norm, a convex surrogate for the matrix rank, and $\|\cdot\|_1$ is the matrix ℓ_1 norm , a convex surrogate for the matrix ℓ_0 norm. Predictions on test samples are obtained as $Z_{tes} = WF_{tes}$, where F_{tes} is the feature matrix for the test samples. Details on solution of Eq. 1 are elaborated in [1].

2.3 Expert vs. Self-assessed Profile

In [1] it was claimed that modeling experts-assessed personality profiles of users performs better than self-assessed profiles. We note that this is subject to what kind of features are chosen as relevant and what learning approach is used to build the personality prediction model. Since the personality profiles are histograms over quantized bins it needs to be understood that the actual value of prediction error (deviation) can have a significant bearing on the the above claim. More specifically, if the error is less than the quantization interval we can expect no error. Hence we believe that with a better choice of features and model learning approach self-assessed personality modeling can be closer to what experts give. This can be used to predict the user's self-assessed scores, even without explicitly asking the users to answer the BFI-10 questionnaire which can be aid in non-intrusive personality acquisition techniques [12].

Moreover it would be interesting to note how well the expert knowledge based model generalizes in being able to predict self-assessed personality models. After all we cannot expect every user to fill up a questionnaire to indicate his profile. Rather we would want to use the knowledge of a few experts to build a model that generalizes well for unknown users for whom only the images they have liked are known. A better approach and better features should help to generalize better.

3 Experiments

In this section we investigate the efficacy of using more semantic features, evaluate a F2A+A2P personality modeling approach unlike the standard F2P approach, study the relationship between self assessed and expert based personality modeling, and finally assess the effectiveness of our investigations on the performance of a personality modeling based image recommender system.

3.1 The PsychoFlickr Dataset

The PsychoFlickr data set consists of Flickr images. The data set consists of 60,000 images where 200 images are tagged as favorite by 300 'pro' users. For every user, personality assessment was done as described in Section 1.

Experimental Set Up. We divide the dataset into training and test sets to validate the results of the different modeling approaches. For all the experiments, unless specified otherwise, the data split is 75% training with 5 fold cross validation and 25% for testing. Results are reported on testing data. In the experiments, 'old features' refers to the features used in [1] and 'new features' refers to the combined set of semantic features and old features (Table 1). The semantic features were extracted using default parameters of softwares provided by the cited works. The traits, for which performance of models is being reported, are: O: Openness, C:Conscientiousness, E:Extraversion, A:Agreeableness and N:Neuroticism. Results obtained are statistically significant ($p < 5\%$).

3.2 Comparing Modeling Approaches

LASSO regression was taken as the baseline approach for modeling users personality based on a their 'faved' images. Note that this was also the model chosen in [1].

Sparse Support Vector Regression. To account for sparsity in the data a sparse SVM modeling approach was chosen to evaluate its efficacy. We also hope that the model captures non-linearities in the data better.

F2A+A2P. The previous two approaches modeled personality scores directly based on the features (F2P). Recent results [11] have shown that the alternative of F2A+A2P gives a better prediction model for modeling profiles of individuals inside video segments. Note that the set of features used in [11] apply to inferring personality profiles of people in the videos whereas in this work we use features to model personality profiles of users who like a set of images. Hence although the modeling approach is the same, the two scenarios are different - a) [11] deals with perception of personality profiles of characters in videos whereas our work deals with both recognition and perception [13] of users personality profile based on the images they like.

Table 2. Results of predicting personality-profiles of users for both F2A+A2P and F2P approaches, represented in terms of RMSE

With Old Features			
Trait	LASSO	sparse SVR	F2A+A2P
O	1.698	1.774	**0.982**
C	1.789	1.684	**0.898**
E	2.077	1.836	**0.971**
A	1.669	1.399	**0.831**
N	2.208	2.356	**1.197**

With New Features			
Trait	LASSO	sparse SVR	F2A+A2P
O	1.796	1.718	**0.913**
C	1.704	1.652	**0.830**
E	1.859	1.820	**0.905**
A	1.441	1.379	**0.719**
N	2.299	2.317	**1.114**

However, we must note that the PsychoFlickr data set does not contain the ground truth for users and experts answers to the BFI-10 questions. In the BFI-10 scoring scheme[2], out of the 10 questions, 2 distinct questions contribute to the scoring of every personality trait in a linear relationship as defined below.

$$P_i = (A_i + (6 - A_{i+5}))/2 \ \forall i \in [1, 5], \tag{2}$$

Table 3. Measuring actual deviations in prediction of personality scores (which are converted into High, Medium, Low categories based on threshold)

Classification Accuracy (in %)		
Trait	F2P	F2A+A2P
O	62.40	66.10
C	58.10	**70.50**
E	53.70	**69.70**
A	64.30	**72.30**
N	50.70	**61.50**

where P_i (dependent variable) is the personality score for trait i and A_i (independent variable) is the i-th BFI-10 answer. Note that we know P_i and our goal is to get an estimate of the A_i's. Hence we rewrite the equation with P_i as the independent variable and A_i's as the dependent variables. This gives us a new set of linear equations parameterized by the A_i's which can be represented in their polar form as

$$r_i = |2 * P_i - 6|/\sqrt{2}, \tag{3}$$
$$\theta_i = 135^o \text{ if } r_i > 0, \tag{4}$$
$$= 315^o \text{ if } r_i < 0, \tag{5}$$
$$= 0 \text{ if } r_i = 0, \tag{6}$$

where $r_i = \sqrt{A_i^2 + A_{i+5}^2}$ is the distance of the line (with P_i as intercept) from the origin and $\theta_i = \pi/2 + \tan^{-1}(A_{i+5}/A_i)$ is the angle the line subtends with the positive x-axis. So for every set answers, we have a corresponding mapping in the polar space. A model is then trained to predict the values of r_i and θ_i which are then converted back into personality scores based on the BFI scoring scheme (from which these values were derived). We trained LASSO, sparse SVR and F2A+A2P models using the old features as the input and self-assessed personality scores as the output. Table 2 shows that F2A+A2P approach is better than F2P approach with significant performance gains. Even RMSE of traits using sparse SVR is lesser than that using LASSO. It also shows that F2A+A2P can bring huge gains in modelling personality scores, reducing the error by 40-50%. The same experiment was repeated using new features. Adding new semantic features led to a 5-15 % increase in performance (Table 2). We also measure the actual deviation w.r.t to the exact personality score values. The scores were divided into low, neutral and high levels. This is to highlight, as discussed previously, how bining influences the actual performance. Table 3 shows that F2A+A2P is better by about 7-15% at predicting all the traits except for Openness. It should be noted that the images were tagged as favorite by Flickr 'pro' users, who pay a fee for using privileged features on Flickr. This means that the users' interests would be highly inclined towards art, photography and the like as mentioned in Section 2.1, thereby skewing the traits' distribution. This bias in the Openness trait is a possible reason for the inferior performance of F2A+A2P.

3.3 Expert vs. Self-assessed

The analysis made in [1] show that a model on personality scores given by experts performed better than model on self assessed personality scores. We tried to see if the increased performance in modeling self-assessed scores using F2A+A2P can decrease the difference between the error in modeling expert-assessed and self-assessed scores. The performance in terms of errors made by the models' is shown in Table 4. Note that the RMSE on both expert and self-assessed scores falls below 1. As in the previous section, we evaluated the accuracy on actual deviation from the three bins as well. On experts scores (training+testing), F2A+A2P could classify almost all the samples in the right range (90% accuracy). And on self-assessed data (training+testing), the performance of F2A+A2P is as shown in Table 3. The accuracy can go as high as 75%. As mentioned in Section 2.3, this deviation is more meaningful to observe and reduce, and we see that F2A+A2P is able to do so for all the traits of both experts and self-assessed scores. F2P approaches used in previous personality modeling literature show good performance for Extraversion and Conscientiousness traits as they can be easily perceived [14]. But when the approach of mapping features to answers is used and personality scores are predicted using the BFI scoring scheme, it results in significant gains in performance for all traits as seen in this section and also previous section. This can be attributed to the fact that the relationship between features and answers are less non-linear and also that we are using the BFI scoring scheme, which is the standard method used in psychology, for personality assessment.

Table 4. Results of F2A+A2P method on modeling experts' scores and self-assessed scores, shown in terms of RMSE

Trait	Experts	Self-assessed
O	0.406	0.913
C	0.062	0.830
E	0.895	0.905
A	0.679	0.719
N	0.194	1.114

Generalization. Often it is found that we have a lot of information about the data related to users, but no information about their personality profiles. It is also infeasible, in many cases, to ask the users to answer the BFI 10 to be able to build their profile. But it is less troublesome to get psychology experts to build the personality profile of the users by asking them to examine the data.

To verify if we can bridge the gap between expert scores and the self-assessed scores, we checked the capability of the F2A+A2P model trained on experts scores as output to generalize on self assessed scores. Comparing Table 4 with Table 5 shows the ability to generalize for all the traits except for Openness and Agreeableness (in line with previous experiments in our work and also in literature). Very low error in conscientiousness can be explained by the observation that the cues associated with this trait, mentioned in Section 2.1, are comparatively easy to notice.

Table 5. Evaluating generalization of training on experts' scores to test on self-assessed scores using F2A+A2P, terms of RMSE. Column under On Experts represents train/test on experts scores and under On Self-assessed represents training on experts' scores and testing on self-assessed scores.

Trait	On Experts	On Self-assessed
O	0.406	1.163
C	0.062	0.146
E	0.895	0.743
A	0.679	0.891
N	0.194	0.482

We see that F2A+A2P can be used to predict the user's self-assessed scores, even without explicitly asking the users to answer the BFI-10 questionnaire. This can be a huge step forward in non-intrusive personality acquisition techniques, which was shown to be preferred the most by users in [12].

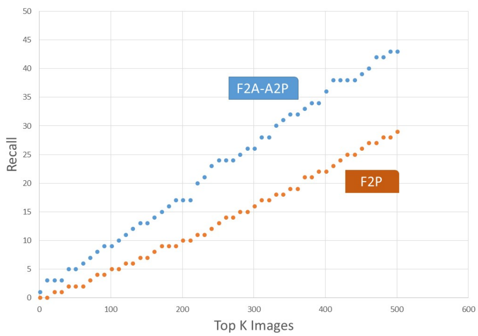

Fig. 3. Mean Recall (for all users) using top-k images retrieved by F2P and F2A+A2P

3.4 Image Recommendation System

For the recommendation problem given a user, we tried to predict which image will the user like. For this, our goal is, given a user profile, evaluate recall at top-K for all test images. Note that in the given data-set, we only have information about the images that were tagged as favorite by every user. We do not know if a user has seen the images tagged as favorite by remaining users. Therefore, although we cannot reject the possibility that the images tagged as favorite by other users could be his 'favorite' as well, we prefer to be more strict in our evaluation and the performance evaluation forms a lower bound on accuracy.

For these experiments we used the models for both F2P (sparse SVM) and F2A+A2P as described in previous sections. We took a total of 2000 images (for which user assignments are known and different from training set) as the test set and ranked the

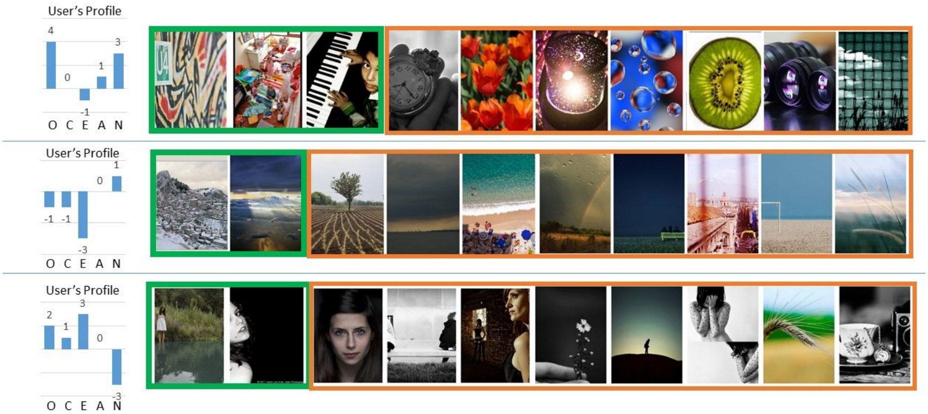

Fig. 4. Top 10 Images retrieved by F2A+A2P for a sample of users based on their Personality Profile. The images with green border are 'faved' by the user. Retrieved images not belonging to the user's faved set can be seen to have lot of similarity w.r.t cues associated with the corresponding personality traits. Explained in Section 3.4.

images based on RMSE between the predicted profile and users profile. The performance evaluation is based on recall for top-K (where K $\in \{1, 2, \ldots\}$). Figure 3 shows that F2A+A2P is able to retrieve a higher number of images (in top-K) when compared with F2P model. It is definitely a possibility that some images that were highly ranked by the model but were not counted towards recall might have been 'faved' by the user. Even without taking this into account, we see a steep increase in the recall using F2A+A2P when compared to F2P.To verify this we visually inspected the top 10 images retrieved by the model for a few users, out of which 3 are shown along with the corresponding user profile in Figure 4. The images bounded by green are 'faved' by the users. The first user has a high score on Openness and Neuroticism traits and the images are very colorful (which was found to be a common characteristic of images depicting custom work/home environments (image 2 from the left) and artistic photography). Some of the images retrieved have high clutter (images 1 and 10 from the left), which is a characteristic of images 'faved' by neurotic users. Second user has a very low score on extraversion and corresponding images retrieved have scenic backdrop without any explicit objects.

This confirms that a) representing images through semantic features helps in mapping images to users and b) F2A+A2P approach is highly effective in modeling personality profiles from images with high generalization.

4 Conclusions

In this paper, the problem of image recommendation has been studied from a personality modeling perspective. It was seen that F2A+A2P approach outperforms F2P. Also, it was verified that high level semantic features outperform low-level features (used in [1]) in capturing the tastes of users.

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