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On the Relationship Between the Five-Factor Personality Model and the Color-Brightness and Statistical Characteristics of Images Published in Social Networks

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Abstract. The purpose of the article is to study the relationship of personality traits with the content of images posted in social networks. The paper attempts to identify informative features and appropriate ways to configure artificial neural networks. The developed technique includes obtaining several color-bright-based and statistical characteristics of image collections in the form of histograms and BoW dictionaries with further construction of classifiers based on artificial neural networks to test the hypothesis about the interrelation between the available graphic data and the five-factor personality model of the tested. The questionnaire, which allowed the formation of training and test samples, was carried out by employees of the Psychological Institute of RAE with the "NEO-FFI" test, which included 60 questions. The collections of images used are datasets that published by users of the "VKontakte" social network. The problems of determining personality factors were experimentally solved with using classifying and predictive artificial neural networks. The work confirmed the prevailing opinion that there is no significant interrelation (correlation) between placed images and "Big Five" personal factors. With the help of published images, the factors "Openness" and "Agreeableness" are predicted best, worst of all – "Neuroticism". The results of forecasting personality recognition traits improve as the number of layers of neural networks grows, up to overtraining moment.

Keywords: Personality Traits, Big Five, Published Images, Social Network, Questionnaire, Artificial Neural Network.

1 Introduction

One of the topical researches conducted by psychologists, together with engineers and mathematicians, is related to establishing the connection between personal factors (traits) and graphic content published in social networks. It is believed that a person can be described by five traits or the "Big Five" model: openness to experience, intelligence ("Openness" or "O"-factor); consciousness, self-awareness, integrity ("Consciousness" or “C”-factor); extroversion, vigor, proneness to contact (“Extraversion” or “E”-factor); goodwill, sweetness, ability to get together (“Agreeableness” or “A”-factor); neuroticism, emotional instability, anxiety, low self-esteem (“Neuroticism” or “N”-factor). Foreign sources were the first to mention the existence of such a connection. For example, using a convolution artificial neural network (ANN) of the “VGG-Net” model in [1], we obtained a general evaluation of the connection between personality factors and various features using Pearson's correlation. Table 1 presents the results.

Table 1. Correlation between the “Big Five” factors and attributes.

Features	O	C	E	A	N
Colors	0.284	0.352	0.293	0.317	0.398
All Images	0.448	0.479	0.369	0.336	0.593
Text	0.168	0.059	0.223	0.111	0.261

From here, it becomes clear that the account of images and their characteristics can make quite a particular contribution to the prediction of personality traits. In combination, the two modalities (text, image) provide a more accurate assessment of personality, revealing what may be lost by individual modality.

We may refer to studies that have attempted to examine the relationship between a person and the content of published images. Thus, for example, in [2] studied personal factors in the context of the bodies of “Twitter” images. It is shown, for example, that users with a high degree of openness towards experience value art, which manifests itself in the publication and approval of sketches or images containing musical instruments. Analyzed a total of 34,875 pictures of 232 “Twitter” users. In order to assign points to each user in the evaluation of personal traits of the “Big Five”, an automatic text regression method was used [3]. Also took into account such features as color and content of photos. Researches have shown that colors can cause emotions and influence psychological states. The HSV color model (Hue, Saturation, Value) was used to analyze the color components of images. Used various histograms and a standard deviation of HSV values to predict personal factors. The results of the correlation analysis (according to Pearson) of the interrelation of features and factors are presented in Table 2.

Table 2. Correlation between factors, colors and image content.

Factors	O	C	E	A	N
Colors and image content					
Grayscale	0.039	-0.139	-0.128	-0.152	0.262
Brightness	-0.108	0.040	0.124	0.027	-0.020
Saturation	-0.017	0.023	0.102	0.076	-0.077
Pleasure	-0.0017	0.932	-0.079	0.037	-0.024
Arousal	-0.007	0.005	0.119	0.048	-0.054
Dominance	0.005	-0.013	0.113	0.010	-0.021
Hue Count	-0.094	0.040	0.118	0.085	-0.103

Used single-factor correlation tests to identify the relationship between image characteristics and personality. The results of the analysis of the relationship between color components of images and personal factors made it possible to establish in the most general way the relationship between the model factors.

The study [4] attempts to define personality traits based on the fact that users take photos, share photos, and apply different photo filters to adjust the appearance of the image in the "Instagram" network. Among the 113 participants and 2,298 extracted photographs, distinctive features (e.g., hue, brightness, saturation) that are associated with personality traits were found. In the online survey, participants completed the widely used "BigFive Inventory" (BFI) personal questionnaire and provided access to the content of their "Instagram" accounts. The results show the relationship between personality traits and how users want their photos to look. Descriptors based on the color in the HSV color space were extracted for each image in the collection. The article obtained descriptive results linking each personality trait with the corresponding characteristics of personality factors based on color and brightness characteristics. Average values of attributes were used to calculate the correlation matrix (see Table 3).

Table 3. Correlation matrix of personal factors and image characteristics.

Feature	O	C	E	A	N
Red	-0.06	0.02	0.17	-0.05	0.03
Green	0.17	0.14	0.23	0.03	-0.12
Blue	-0.01	0	0.17	0.02	-0.01
Yellow	0.01	0.04	0.01	0.14	-0.07
Orange	-0.03	-0.07	-0.16	0.02	0.06
Violet	0	-0.06	-0.09	-0.07	0.06
Bright.mean	-0.25	-0.1	-0.19	-0.07	0.22
Bright.var	0.06	0	0	-0.07	0.05
Bright.low	0.28	0.09	0.16	-0.05	-0.16
Bright.mid	-0.09	0.06	0.04	0.15	-0.06
Bright.high	-0.2	-0.12	-0.18	-0.08	0.21
Sat.mean	0.16	0.06	0.03	-0.04	0
Sat.var.	0.2	0.16	0.19	0.1	-0.05
Sat.low	-0.08	0.02	0.02	0.07	0.01
Sat.mid	0.08	0.09	0.02	0.07	0.01
Sat.high	0.13	0.1	0.04	-0.01	0.01
Warm	-0.05	-0.04	-0.2	0	0.03
Cold	0.05	0.04	0.2	0	0.03
Pleasure	-0.19	-0.08	-0.18	-0.09	0.22
Arousal	0.23	0.09	0.1	0	-0.08
Dominance	0.28	0.11	0.17	0.05	-0.18
Number of faces	-0.16	0.03	0.11	-0.11	-0.03
Number of people	0.22	-0.05	-0.07	-0.01	0.07

There is no doubt that the results obtained are primary and require further research on other image bodies while involving in the evaluation of the identity of proven information technology based on surveys and automated image analysis.

2 Research Objectives

The present work checks the hypothesis about the existence of a significant connection between features of a five-factor model of the person with color-brightness and statistical characteristics of collections of images. The check is carried out based on data from the social network "VKontakte" and the results of the questionnaire obtained by psychologists from the Psychological Institute of RAE (test "NEO-FFI", 60 questions [5]). The expert data on the personality model represent five values in the range of 0-48. Image collections are presented as sets of graphic files containing thematic collections of images published by users in social networks. The entire data set, which contains expert information and graphics files of the people under test, available for analysis, includes information on 1,346 people under test. During the experiment, 859 representatives of the image collection with three or more files were selected from this set.

We wish to solve the following problems.

1. The first task is to determine personal factors using classifying direct distribution ANN. The solution is associated with the construction of a feature space based on histograms of the distribution of color and brightness characteristics for each class of images separately; ANN training is carried out based on the obtained histograms. An alternative can be probability distributions: mathematical expectation, dispersion value, function type are determined.

2. The second task is to determine personal factors with the help of predictive ANN. The solution is related to building BoW dictionaries (Bags Of Words) based on KAZE descriptors, that been extracted from images in user profiles [6]. Training and test vectors formed with the help of such dictionaries, or BoW descriptors, are information records indicating the presence/absence of certain visual words in the images of the user. Approach description: extraction of a training sample of KAZE descriptors from images, their clustering, and formation of bags of visual words; based on the extracted BoW descriptors, the multilayer neural network of direct propagation of trait prediction is trained. Training is carried out using user profiles of the selected social network.

The following factors determine the complexity of both approaches: 1) nonnumerical data should be converted into numeric data, 2) lack of sufficient representation by the values of individual attributes.

3 The Method of the Classifying ANN

For each of the personal factors, three classes are formed corresponding to the limited ranges of expert data values: a high score (33-48 points), an average score (21-32 points), and a low score (0-20 points). Histograms for image collections are constructed in RGB, HSV, and grey shades. Thus, the data of seven histograms go to the input of neural network classifier. Statistical data for histogram construction for each tested user of the social network are collected based on all images presented in his/her collection.

The neural network classifier is a multilayer perceptron with one hidden layer containing 150 neurons. The input layer contains 1,716 neurons (7 histograms, values ranging from 0 to 1), and the output layer contains three neurons corresponding to the presented classes. The sigmoid is used as an activation function. An independent classifier is built for each of the "Big Five" factors during testing. The general structure of the samples database is presented in Table 4.

Table 4. Overall samples database structure.

Factor	Number of class representatives		
	Low value	Medium value	High value
O	88	525	246
C	376	347	136
E	381	357	121
A	132	503	224
N	140	305	414

Also, when training neural network classifiers (for each of the factors), the sample of 859 representatives is divided into two non-intersecting parts: the training and test samples. Neural network qualifiers are trained by backward error propagation for one million iterations. Further, in Tables 5-9, the test results for each personality factor are presented.

Table 5. Classification results for the "O" factor.

Training samples					
Sent to ANN input, class	Classification result			Total classified samples	Classified correctly, %
	Low	Average	High		
Low	27	14	3	44	61.36
Average	9	249	4	262	95.03
High	8	16	99	123	80.48
				429	87.41
Test samples					
Sent to ANN input, class	Classification result			Total classified samples	Classified correctly, %
	Low	Average	High		
Low	11	22	11	44	25.00
Average	35	151	77	263	51.41
High	23	69	31	123	25.20
				430	44.88

Table 6. Classification results for the "C" factor.

Training samples					
Sent to ANN input, class	Classification result			Total classified samples	Classified correctly, %
	Low	Average	High		
Low	174	14	0	188	92.55
Average	19	154	0	173	89.01
High	11	3	54	68	79.41
				429	89.04
Test samples					
Sent to ANN input, class	Classification result			Total classified samples	Classified correctly, %
	Low	Average	High		
Low	102	64	22	188	54.25
Average	76	68	30	174	39.08
High	30	27	11	68	16.17
				430	42.09

Table 7. Classification results for the "E" factor.

Training samples					
Sent to ANN input, class	Classification result			Total classified samples	Classified correctly, %
	Low	Average	High		
Low	184	6	0	190	96.84
Average	11	167	0	178	93.82
High	10	1	49	60	81.66
				428	93.45
Test samples					
Sent to ANN input, class	Classification result			Total classified samples	Classified correctly, %
	Low	Average	High		
Low	83	86	22	191	43.45
Average	90	66	23	179	36.87
High	22	28	11	61	18.03
				431	37.12

Table 8. Classification results for the "A" factor.

Training samples					
Sent to ANN input, class	Classification result			Total classified samples	Classified correctly, %
	Low	Average	High		
Low	58	4	4	66	87.87
Average	6	242	3	251	96.41

High	9	10	93	112	83.03
				429	91.60
Test samples					
Sent to ANN input, class	**Classification result**			**Total classified samples**	**Classified correctly, %**
	Low	**Average**	**High**		
Low	10	35	21	66	15.15
Average	55	145	52	252	57.53
High	21	69	22	112	19.64
				430	41.16

Table 9. Classification results for the "N" factor.

Training samples					
Sent to ANN input, class	**Classification result**			**Total classified samples**	**Classified correctly, %**
	Low	**Average**	**High**		
Low	61	2	7	70	87.14
Average	10	134	8	152	88.15
High	10	4	193	207	93.23
				429	90.44
Test samples					
Sent to ANN input, class	**Classification result**			**Total classified samples**	**Classified correctly, %**
	Low	**Average**	**High**		
Low	21	23	26	70	30.00
Average	36	43	74	153	28.10
High	52	69	86	207	41.54
				430	34.88

From the obtained tables, we can see that the recognition results of the training samples are significantly higher than the corresponding results of the test samples. In general, this can be explained by 1) the ANN's ability to memorize and generalize information; 2) a low correlation between factors and color-brightness representations, which corresponds to the results [1-4].

4 The Method of the Predicting ANN

From each image of the user with the given threshold of sensitivity (KAZE-Response), the own set of KAZE-descriptors is calculated, each descriptor represents a vector with numbers with a floating point, invariant to rotation, displacement, and changes in lighting. In this study, the threshold selected is 0.005. Then clustering of KAZE descriptors of the training sample using the k-average method is performed [7]. In this case, the expected number of clusters at the output of the clustering algorithm is set. distAVG, or the average distance from the descriptors to their winning clusters, is considered throughout the training sample to cut off the KAZE descriptors farthest from the selected clusters. The obtained distance is further used to sift out those descriptors that are far from the clusters, consider them random outliers.

The remaining image descriptors in the profiles of individual users of the social network are used to form averaged occurrence vectors of KAZE descriptors on images – generalizing BoW user descriptors (Bags of visual Words). The size of a BoW descriptor is determined by the number of clusters used. In the first step of computing BoW descriptors, it is proposed to write the number of detected KAZE descriptors with a distance to the nearest cluster center, not exceeding distAVG, in the form of a vector. In the second step, the obtained vectors are normalized by dividing by the number of images in user profiles. Based on the obtained data, an additional vector from the maximum normalized values is fixed. The vector is used at the final, third step, to obtain values of BoW descriptor vectors within the specified range. This pre-processing is necessary for normalization of the ANN operation, including by avoiding zeroes in BoW-descriptors of the training sample.

Training of the feed-forward ANN is based on the "Microsoft Cognitive Toolkit" (CNTK) library version 2.6 [8]. In the experiments, the size of the dictionary varied from 64 to 16,384 items to achieve high accuracy of the predictive ANN on the test samples database. The choice of the best configurations was made by testing different configurations of the ANN; it varied: number of layers, number of neurons, and other settings. The activation functions supported by CNTK [9] and PolyWog wavelet functions were tested [10]. The list of learning optimizers was limited to the set supported in CNTK [11].

The first variant of ANN architecture:

– an input layer, 125-1,000 neurons;
– dropout layer with a 0.01 probability of triggering [12];
– an output layer with 5 neurons.

The variant with 2,048 dictionary elements and 250 input layer neurons with ReLU-function of activation $f(x) = \max(0, x)$, for the output layer, $f(x) = x$ showed the best result; the ANN was trained by Adam-optimizer [13] with coefficients L1- and L2-regulation 0.0001 and 0.01 respectively (see Table 10).

Table 10. Joint prediction of five factors (first architecture option).

Teaching samples					
	O	**C**	**E**	**A**	**N**
Average standard deviation values for individual "Big Five" factors:	0.29	0.32	0.35	0.32	0.27

Average standard deviation value by individual factors:	0.31		**Average standard deviation value by individual users:**	0.28	
Accuracy of selection of the most clearly expressed factor (from 0 to 1):	1.00		**Accuracy of the least pronounced factor (0 to 1):**	1.00	
Test samples					
	O	**C**	**E**	**A**	**N**
Average standard deviation values for individual "Big Five" factors:	12.54	14.36	12.40	11.65	15.99
Average standard deviation value by individual factors:	13.39		**Average standard deviation value by individual users:**	12.43	
Accuracy of selection of the most clearly expressed factor (from 0 to 1):	0.24		**Accuracy of the least pronounced factor (0 to 1):**	0.29	

Second variant of the ANN architecture:
– an input layer, 64-1,000 neurons;
– a dropout layer with a 0.01 probability of triggering;
– a hidden layer, 50-800 neurons;
– a dropout layer with a 0.01 probability of triggering;
– a hidden layer, 35-600 neurons;
– a dropout layer with a 0.01 probability of triggering;
– an output layer with 5 neurons.

The variant with 1,536 dictionary elements, the neural network in its layers contained 250, 200 and 150 neurons with ReLU activation function showed the best result; Adam-optimizer with L1- and L2-regulation coefficients 0.0001 and 0.01 respectively was used, the output layer also without activation function (see Table 11).

Table 11. Joint prediction of five factors (second architecture option).

Teaching samples					
	O	**C**	**E**	**A**	**N**
Average standard deviation values for individual "Big Five" factors:	0.62	0.56	0.56	0.69	0.51
Average standard deviation value by individual factors:	0.59		**Average standard deviation value by individual users:**	0.52	
Accuracy of selection of the most clearly expressed factor (from 0 to 1):	0.98		**Accuracy of the least pronounced factor (0 to 1):**	1.00	
Test samples					
	O	**C**	**E**	**A**	**N**
Average standard deviation values for individual "Big Five" factors:	10.89	13.73	11.11	10.87	15.11
Average standard deviation value by individual factors:	12.34		**Average standard deviation value by individual users:**	11.40	
Accuracy of selection of the most clearly expressed factor (from 0 to 1):	0.21		**Accuracy of the least pronounced factor (0 to 1):**	0.31	

Summarizing the results obtained, it should be noted that the addition of additional layers to the ANN improved the standard deviation indicator in the test sample (from 12.4-13.39 to 11.40-12.34). At the same time, the accuracy of the extraction of the factors fluctuates insignificantly. The optimal number of neurons in the first layer of both networks is 250. In this regard, it was decided to increase the number of layers, preserving the architectural features of the ANN and other experimental conditions. The third variant of the ANN contained 400, 350, 300, 250, 200, and 150 neurons in the layers (interspersed with the dropout layers), 1,536 dictionary elements were used. The number of layers was selected experimentally. The test results are shown in Table 12.

Table 12. Joint prediction of five factors (third architecture option).

Teaching samples					
	O	**C**	**E**	**A**	**N**
Average standard deviation values for individual "Big Five" factors:	1.00	0.77	0.83	0.98	0.68
Average standard deviation value by individual factors:	0.85		**Average standard deviation value by individual users:**	0.75	
Accuracy of selection of the most clearly expressed factor (from 0 to 1):	0.98		**Accuracy of the least pronounced factor (0 to 1):**	0.95	
Test samples					
	O	**C**	**E**	**A**	**N**
Average standard deviation values for individual "Big Five" factors:	8.74	12.64	8.97	9.92	13.85
Average standard deviation value by individual factors:	10.82		**Average standard deviation value by individual users:**	9.98	

Accuracy of selection of the most clearly expressed factor (from 0 to 1):	0.21	**Accuracy of the least pronounced factor (0 to 1):**	0.38

From the received tables, we can see that the results of the forecasting of personal features of recognition improve with the growth of the number of layers of the ANN.

5 Conclusion

In conclusion, in general terms, here are the results of the formulated tasks.

1. On training samples, the average recognition accuracy of a classification ANN is within the range of 87-93%, while on test samples, the recognition accuracy drops to 34-44%. It suggests that when training neural network classifiers on the existing data set, we encounter the effect of the ANN retraining. In this case, the neural network classifier functions more as a model of associative memory than a regression model. At the same time, it can identify some weak regularities in the processed data. When classifying test data, errors associated with the unbalanced training samples are observed. Based on the obtained results, it can be concluded that there is no significant connection between the color-brightness characteristics of image collections and the “Big Five” factors. Thus, the hypothesis that there is a significant relationship between the available graphic data and the five-factor personality model of the tested in the first part of the study has not yet been confirmed. It should be noted that for more accurate analysis, a significant increase in training samples and balancing of classes are required.

2. To compare the results of the predictive ANN with the previous achievements, let us refer to [14]. The results obtained in this paper show that the prediction of personal factors by BoW descriptors is inferior to the prediction of direct image processing using neural networks in the selection of the least expressed factors. In [14] on the test sample, the accuracy of the most clearly expressed factor selection was 0.19-0.21, which is consistent with the results of this study. In both works “Openness” and “Agreeableness” are well predicted, which confirms the previous conclusions about the connection of images placed by users of a social network with these personal factors. The poorest prediction is that of neuroticism.

Thus, the following conclusion can be drawn throughout the series of studies carried out by the authors, including the works [14,15]. In essence, it was possible to confirm the information about the absence of a significant relationship (correlation) between the placed images and personal factors given in the works [1-4]. It can be partially explained by the complexity and ambiguity of the interpretation of the graphic content, as well as the small volume of the original sample. The authors hope to expand the sample further and conduct a new cycle of research, taking into account not only the color and brightness characteristics but also the content of published images.

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