Predicting Users' Personality from Instagram Pictures: Using Visual and/or Content Features?

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ABSTRACT

Instagram is a popular social networking application that allows users to express themselves through the uploaded content and the different filters they can apply. In this study we look at personality prediction from Instagram picture features. We explore two different features that can be extracted from pictures: 1) visual features (e.g., hue, valence, saturation), and 2) content features (i.e., the content of the pictures). To collect data, we conducted an online survey where we asked participants to fill in a personality questionnaire and grant us access to their Instagram account through the Instagram API. We gathered 54,962 pictures of 193 Instagram users. With our results we show that visual and content features can be used to predict personality from and perform in general equally well. Combining the two however does not result in an increased predictive power. Seemingly, they are not adding more value than they already consist of independently.

CCS CONCEPTS

• **Information systems** → *Recommender systems*; • **Human-centered computing** → *User models*; *User studies*;

KEYWORDS

Personality, Instagram, picture content, social media

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1 INTRODUCTION

Personality is considered a stable construct to capture individual characteristics to explain behavioral differences with [27]. These personality-based individual differences has shown to be a useful factor to rely personalization strategies on. Hu and Pu [19] showed that personality-based systems are more effective in increasing users' loyalty towards the system and decreasing cognitive effort compared to systems without personality information. In addition, the domain independent nature of personality allows it being incorporated across domains [1]. Hence, once personality is known of a user, it can be incorporated into different platforms.

Given the usefulness of personality traits to personalize experiences in systems, research has started to give attention to map the relations between personality and behaviors (e.g., health [18, 32], education [3, 26], movies [4], music [6–9, 14, 15, 33], marketing [28]). Although there is an increased interest in identifying the relationships between personality and behaviors, the question remains on how to obtain users' personality for incorporation. A common approach is to use self-report measurements: a questionnaire is being used in order to assess the user's personality. However, questionnaires are time consuming and intrusive; it interrupts the flow between the user and the system.

To overcome the intrusiveness of using questionnairs to measure users' personality traits, several researchers have made an attempt to predict personality from the digital footprint that users leave behind. The usefulness of social networking sites (SNSs) as an external information source to predict personalities from becomes especially apparent through the increased interconnectedness of systems. Through single sign-on (SSO) buttons users are given the opportunity to easily register and login to the system with their SNS account. Besides providing convenience to users, it also allows access to information that can be exploited for personality acquisition and thereby circumvent the usage of questionnaires.

SNSs such as Facebook, Twitter, and Instagram consist of an abundance of additional information that can be used to infer personality traits from: Golbeck, Robles, and Turner [17] looked at Facebook profiles to make a personality predictor, and Quercia et al. [29] used Twitter messages to indicate personalities of users. In this work we focus specifically on personality predictions from Instagram pictures. Instagram is a popular mobile photo-sharing application with currently over 800 million users. [1] With the use of picture filters, Instagram allows its users to create and express a distinct personal style by adjusting and manipulating the appearance of the content they want to share. Previous work of Ferwerda et al. [12, 16] on predicting personality traits from Instagram pictures extracted the visual features of Instagram pictures and showed that these properties consist of personality information of users. A few

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[1] https://instagram.com/press/ (accessed: 08/12/2017)

other works showed that personality can be predicted from pictures. However they mainly focus on content features instead of the visual features. For example, Celli et al. [2] analyzed compositions of Facebook profile pictures (e.g., facial close-ups, facial expressions, alone or with others) for personality prediction.

The contributions of this work to personality research comes in two fold: 1) we extend prior research by Ferwerda et al. [12, 16] by exploring the predictive value of personality in the content features of Instagram pictures, and 2) we explore whether combining visual features with content features improves personality prediction of Instagram users.

2 RELATED WORK

There is an increasing body of work that looks at how to implicitly acquire personality traits of users. Since all kind of information can relate to personality traits, even information that is not directly relevant for a specific purpose may still contain information that is useful for the extraction of personality (e.g., Facebook [11], Twitter [29, 31], and Instagram [10, 12, 13, 25]). The increased connectedness between SNSs and applications through SSO buttons provide an abundance of information that can be exploited to implicitly acquire personality traits of users. Except for basic information, SSOs often gain access to other parts of the user's profile as well [5].

Quercia et al. [29] looked at Twitter profiles and were able to predict users' personality traits by using their number of followers, following, and listed counts. With these three characteristics they were able to predict personality scores with a root-mean-square error 0.88 on a [1,5] scale. Similar work has been done by Golbeck, Robles, and Turner [17] on Facebook profiles. They looked at the sentiment of posted content and were able to create a reliable personality predictor with that information. More comprehensive work on the prediction of personality and other user characteristics using Facebook likes was done by Kosinski, Stillwell and Graepel [24].

Besides posted content on SNSs, the features of pictures has shown to consist of personality information as well. Work of Ferwerda, Schedl, and Tkalcic [12, 16] on Instagram pictures, showed that the way filters are applied to create a certain distinctiveness can be used to predict personality traits of the poster. Others (e.g., [2, 30]) have focused on the content of pictures. They showed that compositions of Facebook profile pictures consist of indicators of users' personality. This makes us believe that the content of Instagram pictures may consist of useful information as well about the poster's personality. Additionally, Skowron et al. [31] showed by combining linguistic and picture features they were able to improve predictions with 10-20% in each trait. Hence, besides exploring the content features of pictures for personality information, we further explore combining the content and visual features of pictures as well.

3 METHOD

To investigate the relationship between personality traits and picture features, we asked participants to fill in the 44-item BFI personality questionnaire (5-point Likert scale; Disagree strongly - Agree strongly [21]). The questionnaire includes questions that aggregate into the five basic personality traits of the FFM: openness, conscientiousness, extraversion, agreeableness, and neuroticism. Additionally, we asked participants to grant us access to their Instagram account through the Instagram API [2] to crawl their pictures.

We recruited 193 participants through Amazon Mechanical Turk, a popular recruitment tool for user-experiments [23]. Participation was restricted to those located in the United States, and also to those with a very good reputation (≥95% HIT approval rate and ≥1000 HITs approved) [3] to avoid careless contributions. Several control questions were used to filter out fake and careless entries. Pictures of each participant were crawled after the study. This resulted in a total of 54,962 pictures. The Mahalanobis distance was calculated to further identify outliers. This left us with 134 completed and valid responses. Age (18-64, median 31) and gender (60 male, 74 female) information indicated an adequate distribution. From hereon, we define the term "picture-collection" as all the Instagram pictures of a single user.

3.1 Visual Features

For each picture in a picture-collection that was crawled, we extracted several features. The extracted features are discussed below. Most of the features are color-based, some are content-based. For color-based features we use the color space that is most closely related to the human visual system, i.e., the Hue-Saturation-Value (HSV) color space [34].

3.1.1 Brightness. For each picture, we calculated the average brightness and variance across all the pixels in the picture. Pictures that have a high average brightness tend to be bright, obviously. These features represent how light/dark a picture is and how much contrast there is in the picture, respectively. Pictures that have a high variance tend to have both dark and light areas, whereas pictures with a low variance tend to be equally bright across the picture. Furthermore, we divided the brightness axis into three equal intervals and counted the share of pixels that fall into each of these intervals (low/mid/high brightness). Pictures that have a high value in the *low brightness* feature tend to be darker, those that have a high value in the *mid brightness* feature tend to have mostly neither dark nor bright areas, while those pictures that have a high value in the *high brightness* feature tend to have lots of bright areas.

3.1.2 Saturation. We calculated the average saturation and the variance for each picture. Pictures with low average saturation tend to be bleak, colorless, while pictures with high saturation have more vivid colors. Pictures with a high saturation variance tend to have both bleak and vivid colors. Here we also divided the saturation axis into three equal intervals and calculated the share of pixels that fall into each interval (low/mid/high saturation). pictures that have a high value in the *low saturation* tend to have more bleak colors, those with a high value in the *mid saturation* feature tend to have neither bleak nor vivid colors while those pictures that have a high value in the *high saturation* feature tend to have vivid colors across most of the picture area.

3.1.3 Pleasure-Arousal-Dominance (PAD). As the filters on Instagram intend to create a certain expression, we adopted the PAD model of Valdez and Merhabian [35]. They created general rules of

[2] https://www.instagram.com/developer/

[3] HITs (Human Intelligence Tasks) represent the assignments a user has participated in on Amazon Mechanical Turk prior to this study.

the expression of pleasure, arousal, and dominance in a picture as a combination of brightness and saturation levels:

(1) Pleasure = .69 Brightness + .22 Saturation
(2) Arousal = -.31 Brightness + .60 Saturation
(3) Dominance = -.76 Brightness + .32 Saturation

3.1.4 Hue-related features. We extracted features that represented the prevalent hues in pictures. We chose features that represent various aspects of the hues. For each of the basic colors (red, green, blue, yellow, orange, and violet) we counted the share of pixels that fall into each color. As the discrete color clustering of the hue dimension is nonlinear and subjective, we divided the hue into 10 equal intervals and calculated the share of pixels for each interval. However, these intervals are hard to describe with subjective color descriptions. Furthermore, we calculated the share of pixels that fall into cold (violet, blue, green) and warm (yellow, red, orange) colors.

3.2 Content Features

To analyze the content of the pictures, we used the Google Vision API. [4] The Google Vision API uses a deep neural network to analyze the pictures and assign tags ("description") with a confidence level ("score": $r \epsilon [0,1]$) to classify the content. For each picture in a picture-collection a JSON file was returned with tags and the confidence level (example given in Listing 1).

```
[{
        "score": 0.8734813,
        "mid": "/m/06__v",
        "description": "snowboard"
}, {
        "score": 0.8640924,
        "mid": "/m/01fklc",
        "description": "pink"
}, {
        "score": 0.81754106,
        "mid": "/m/0bpn3c2",
        "description": "skateboarding
            equipment and supplies"
}, {
        "score": 0.8131781,
        "mid": "/m/06_fw",
        "description": "skateboard"
}, {
        "score": 0.7329241,
        "mid": "/m/05y5lj",
        "description": "sports equipment"
}, {
        "score": 0.64866644,
        "mid": "/m/02nnq5",
        "description": "longboard"
}]
```

Listing 1: Example JSON file returned by the Google Vision API for one picture

[4]https://cloud.google.com/vision/

Using the Google Vision API, we were able to retrieve 4090 unique labels from the Instagram pictures. In order to create an initial clustering of the labels, we used a k-means clustering method that is applied to the vectors that represent the terms in the joint vector space. The vectors were generated with the doc2vec approach using a set of embeddings that are pre-trained on the English Wikipedia [5]. Using this method we collated the labels into 400 clusters. [6] After that, the output of the k-means was manually checked and the clusters were further (manually) collated into similar categories. This resulted into 17 categories representing:

(1) Architecture
(2) Body parts
(3) Clothing
(4) Music instruments
(5) Art
(6) Performances
(7) Botanical
(8) Cartoons
(9) Animals
(10) Foods
(11) Sports
(12) Vehicles
(13) Electronics
(14) Babies
(15) Leisure
(16) Jewelry
(17) Weapons

For each participant, we accumulated the number of category occurrences in their Instagram picture-collection. Since the number of Instagram pictures in each picture-collection is different, we normalized the number of category occurrences to represent a range of $r \epsilon [0,1]$. This to be able to compare users with differences in the total amount of pictures.

In addition to the Google Vision API, we counted the number of faces and the number of people in each picture. We used the standard Viola-Jones algorithm [36]. A manual inspection of the Viola-Jones face detector results revealed some false positives (e.g., a portrait within the picture) and false negatives (e.g., some rotated and tilted faces). However, in general the users who tended to take pictures of people (e.g., selfies) had a higher number of average number of faces/people per picture than those users who tended to take mostly still photographs.

4 PERSONALITY PREDICTION MODELS

We trained our predictive model with several classifiers in Weka, with a 10-fold cross-validation with 10 iterations. For each classifier we used, we report the root-mean-square error (RMSE) in Table 1, to indicate the root mean square difference between predicted and observed values. The RMSE of each personality trait relates to the [1,5] score scale (see Table 1).

A ZeroR classifier was used to create a baseline model. Three different classifiers were used and compared against the baseline model: M5' rules, random forest, and radial basis function network (RBF network). Each classifier was applied to the visual properties, content properties, and a combination of the two picture features (i.e., visual+content features).

We first started to train our predictive model with the M5' rules [37]. This is a classifier that has shown to be an effective classifier in

[5]https://github.com/jhlau/doc2vec
[6]The k-means clustering method allows for setting a parameter for the number of clusters to be forced. Different number of clusters were tried out. Setting the k-means to automatically define 400 clusters resulted in clusters with least errors in clustering the labels.

		RMSE		
Pers. Trait	**Classifier**	**Visual Prop.**	**Content Prop.**	**Comb. Prop.**
O	ZeroR	0.7619	0.7619	0.7619
	M5'Rules	0.7741	**0.7222**	0.7676
	Random Forest	**0.7318**	**0.7142**	**0.7513**
	RBF Network	**0.7231**	**0.7133**	**0.7141**
C	ZeroR	0.7201	0.7201	0.7201
	M5'Rules	**0.6277**	**0.6074**	0.7409
	Random Forest	**0.6542**	**0.6317**	**0.6546**
	RBF Network	**0.6175**	**0.6375**	**0.6275**
E	ZeroR	1.0539	1.0539	1.0539
	M5'Rules	**1.028**	**0.9525**	**0.9961**
	Random Forest	1.0622	1.0418	1.0592
	RBF Network	**0.9918**	**0.9777**	**0.9836**
A	ZeroR	0.6483	0.6483	0.6483
	M5'Rules	**0.6405**	**0.575**	**0.6177**
	Random Forest	**0.6025**	**0.5826**	**0.6201**
	RBF Network	**0.5971**	**0.6207**	**0.6108**
N	ZeroR	1.0122	1.0122	1.0122
	M5'Rules	**0.7907**	**0.8711**	**0.8766**
	Random Forest	**0.8819**	**0.8141**	**0.8923**
	RBF Network	**0.894**	**0.8978**	**0.8931**

Table 1: Different prediction models for each personality trait using only the visual properties, content properties, and a combination of both. ZeroR classifier represents the baseline. The boldfaced numbers indicate an out performance of the baseline. Root-mean-square error (RMSE) is reported ($r \in [1,5]$) to indicate prediction performance of the personality traits: (O)penness, (C)onscientiousness, (E)xtraversion, (A)greeableness, (N)euroticism.

previous work of Quercia et al. [29] on personality prediction from Twitter data. The M5' rules outperform the baseline model in predicting most of the personality traits (except for the openness trait using the visual features).

To further explore possible improvements by other classifiers, we tried out the random forests classifier. Random forests are known to have a reasonable performance when the features consist of high amounts of noise [20]. Compared to the M5' rules, the random forest classifier show slight improvements on half of the personality traits: openness to experience, agreeableness, and neuroticism (for the latter prediction only improved based on content features). For the other half of the personality traits M5' rules outperforms the random forest classifier.

As the M5' rules and random forest classifiers failed to outperform the baseline in all personality traits, we used the RBF network classifier. The RBF network is a neural network that has shown to work well on smaller datasets [22]. Applying the RBF network classifier we were able to gain an prediction improvement on all personality traits using the visual as well as the content features.

Since both the visual as well as the content features showed to be reliable predictors of personality traits, we also explored personality prediction by combining the two. However, combining visual and content features does not result in an improvement of the personality prediction. Instead, the RMSE values adjust towards the average of the visual and content features. Hence, although the visual and content features are good predictors on their own, they do not complement each other much.

Table 2 displays a comparison with prior research that use similar approaches to predict personality from SNS data. Compared to prior work of Ferwerda et al. [16] and Quercia et al. [29] we are able to outperform predictions in some traits. Whereas, visual and content properties do not complement each other in our study, Skowron et al. [31] found features that were able to improve prediction when being combined. Nevertheless, across all studies we found similar patterns and comparable results whereas most difficult traits to predict are consistently extraversion and neuroticism.

	RMSE			
Pers. traits	**Comb. Prop.**	**[16]**	**[31]**	**[29]**
O	0.71	0.68	0.51	0.69
C	0.62	0.66	0.67	0.73
E	0.98	0.90	0.71	0.96
A	0.61	0.69	0.50	0.78
N	0.89	0.95	0.73	0.97

Table 2: Comparison of personality prediction compared to prior work of Ferwerda et al. [16], Skowron et al. [31], and Quercia et al. [29]. Root-mean-square error (RMSE) is reported ($r \in [1,5]$) to indicate prediction performance of the personality traits: (O)penness, (C)onscientiousness, (E)xtraversion, (A)greeableness, (N)euroticism.

5 CONCLUSION

We explored the predictive value of different kind of features that can be extracted from pictures. Prior work of Ferwerda et al. [16] already showed that the visual features of Instagram consist of useful information to predict personality from. However, they did not explore other features that can be extracted from the pictures (i.e., content features). In this work we show that the visual features as well as the content features consist of information for personality prediction that attain similar results.

Although prior work [31] showed to be able to improve their personality predictor by combining information from SNSs, we were not able to achieve that. The visual and content features show to be good predictors on their own, but they do not seem to provide added value to each other when being combined. When combining the two features into one predictor, our results show that the RMSE adjust towards the average instead of showing an improvement. Hence, when personality prediction from Instagram picture is ought to be done, a focus on either visual features or content features will suffice to create a personality prediction model.

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