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Our Twitter Profiles, Our Selves: Predicting Personality with Twitter

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***Abstract*—Psychological personality has been shown to affect a variety of aspects: preferences for interaction styles in the digital world and for music genres, for example. Consequently, the design of personalized user interfaces and music recommender systems might benefit from understanding the relationship between personality and use of social media. Since there has not been a study between personality and use of Twitter at large, we set out to analyze the relationship between personality and different types of Twitter users, including popular users and influentials. For 335 users, we gather personality data, analyze it, and find that both popular users and influentials are extroverts and emotionally stable (low in the trait of *Neuroticism*). Interestingly, we also find that popular users are 'imaginative' (high in *Openness*), while influentials tend to be 'organized' (high in *Conscientiousness*). We then show a way of accurately predicting a user's personality simply based on three counts publicly available on profiles: following, followers, and listed counts. Knowing these three quantities about an active user, one can predict the user's five personality traits with a root-mean-squared error below 0.88 on a $[1, 5]$ scale. Based on these promising results, we argue that being able to predict user personality goes well beyond our initial goal of informing the design of new personalized applications as it, for example, expands current studies on privacy in social media.**

***Index Terms*—Web 2.0, Personality, Social Networks, Twitter**

I. Introduction

Personality has been found to significantly correlate with a number of real-world behaviors. It correlates with music taste: popular music tends to be significantly liked by extroverts, while people with a tendency to be less open to experience tend to prefer religious music and dislike rock music [32]. Personality also impacts the formation of social relations [36]: friends tend to be, to a very similar extent, open to experience and extrovert [35].

Personality also influences how people interact online. Previous work has shown this to be the case for Facebook users, but there has not been any analysis of Twitter users at scale (Section II). Since Twitter differs from Facebook, it would be beneficial to extend previous work to Twitter. To this end, we gather personality data for 335 Twitter users (Section III), and we then make two main contributions:

- We study the relationship between the big five personality traits and five types of Twitter users: *listeners* (those who follow many users), *popular* (those who are followed by many), *highly-read* (those who are often listed in others' reading lists), and two types of *influentials* (Section IV). We find that popular users and influentials are both extrovert and emotionally stable (low in the personality trait of *Neuroticism*). Also, popular users are high in *Openness* (they are 'imaginative'), while influentials tend to be high in *Conscientiousness* (they are 'organized').
- We predict a user's personality traits out of three numbers that are publicly available on any Twitter profile (Section V): the number of profiles the user follows (*following*), number of *followers*, and number of times the user has been *listed* in others' reading lists. We find that *Openness* is the easiest trait to predict, while *Extraversion* is the most difficult. Yet, the error (*RMSE*) for *Extraversion* is as low as 0.88 on a $[1, 5]$ scale.

These results not only provide insights on the personality of different Twitter users but also inform current research on privacy of social media users (Section VI) and suggest practical applications in a variety of areas, including marketing, user interface design, and recommender systems (Section VII).

Personality trait	High scorers	Low scorers
Openness	Imaginative	Conventional
Conscientiousness	Organized	Spontaneous
Extraversion	Outgoing	Solitary
Agreeableness	Trusting	Competitive
Neuroticism	Prone to stress and worry	Emotionally stable

TABLE I
THE BIG FIVE PERSONALITY TRAITS.

II. Background and Related Work

The relationship between real-world social networks and personality has been usually studied using a personality test called "The Big Five".

A. The Big Five Personality Test

The five-factor model of personality, or the big five, is the most comprehensive, reliable and useful set of personality concepts [7], [11]. An individual is associated with five scores that correspond to the five main personality traits and that form the acronym of *OCEAN* (Table I collates a brief explanation of each trait). Imaginative, spontaneous, and adventurous individuals are high in **O**peness. Ambitious, resourceful and persistent individuals are high in **C**onscientiousness. Individuals who are sociable and tend to seek excitement are

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high in **E**xtraversion [2], [5], [13], [34], [39]. Those high in **A**greeableness are trusting, altruistic, tender-minded, and are motivated to maintain positive relationships with others [15]. Finally, emotionally liable and impulsive individuals are high in **N**euroticism [18], [19].

B. Personality and Social Media

There has been few studies on how personality impacts interactions on social media. These studies have mainly analyzed the impact of personality on:

- *Using social media sites.* Extroverts tend to find social media easy to use and useful [33].
- *Selecting social contacts.* Users select contacts with similar *Agreeableness*, *Extraversion*, and *Openness*, and they generally tend to prefer people high in *Agreeableness* [35].
- *Keeping large number of contacts.* As one expects, the personality traits that correlates the most with number of social contacts is *Extraversion* [28], [36].

These preliminary studies have been recently expanded by Golbeck *et al.* [10]. The researchers analyzed the personality of 167 Facebook users and successfully predicted these users' five personality traits out of users' personal information and posts. More recently, Quercia *et al.* studied the relationship between sociometric popularity (number of Facebook contacts) and personality traits on a far larger number of subjects [29]. They concluded that popular Facebook users tend to have the same personality as people popular in the real world, suggesting that the nature of online interactions does not significantly differ from that of real world interactions. Also, they tested a widely held conjecture: that people who have many social contacts on Facebook are the ones who are able to adapt themselves to new forms of communication, present themselves in likable ways, and have propensity to maintain superficial relationships. They found no statistical evidence for such a conjecture.

There has not been any study on the personality of Twitter users, and Twitter differs from Facebook: people can use the two platforms in very different ways, if they choose to. Facebook is a social networking site that generally connects people who already know each other (e.g., friends, family and co-workers) - they very default is that two individuals need to be mutual friends on Facebook to fully share what they have been up to. Instead, Twitter is a social media site on which users can see just about anything about anybody, unless they protect their updates, which only a very tiny minority of active users do [24]. This important difference makes it possible to expand current discussions on privacy in social media by showing that one can accurately predict user personality not only from information on Facebook (whose accessed is generally restricted) but also from truly publicly available Twitter information.

III. Data Collection

To associate personality scores to Twitter users, we gather data from a Facebook application called *myPersonality*.

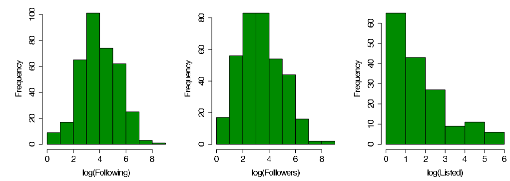


Fig. 2. Distributions of the logarithm of the number of *following*, *followers*, and times a user has been *listed*.

A. myPersonality

More than five million Facebook users have been able to take a variety of genuine personality and ability tests by installing *myPersonality* (Figure 1). Users are not paid and are solely motivated by the prospect of receiving reliable personality test results. The application ensures high test result validity by removing the protocols that may be a product of inattentive, language incompetent, or randomly responding individuals. The resulting quality of the responses is high: the scales' reliabilities are on average higher than reported in test manuals[1] and the discriminant validity (average $r = .16$) is better than one obtained using traditional samples (average $r = .20$ [16]).

myPersonality users can give their consent to share their personality scores and profile information, and around 40% of them choose to do so. Only few hundreds of those users have posted links to their Twitter accounts though. Twitter is a micro-blogging site on which users send and read short messages (up to 140 characters) called *tweets*. In general, tweets are publicly visible and are followed by subscribers called *followers*. Users of particular interest are kept in one's reading list. A profile's *listed* count is the number of users whose reading lists contain the profile's tweets. The distributions of following, followers, and listed are reported in Figure 2 and suggest that the users in our sample are more active than the users in the general Twitter population, that is, our users have higher numbers of following and followers.

B. Data Description

We consider *all* users who specified their twitter accounts on their Facebook profiles, verified the matching between Facebook and Twitter accounts, and end up having 335 Twitter users. We analyze the big five personality test results for those users. This group is composed of 171 women (52%) and 164 men (48%) and mirrors the gender distribution in Twitter: according to a study by the social media analytics company Sysomos in June 2009, women make up a slightly larger Twitter demographic than men (53% over 47% percent) [6]. Knowing the age of 165 users, we plot their age distribution in Figure 3(a) and estimate a geometric average of 22.7. As

[1] http://www.mypersonality.org/wiki/

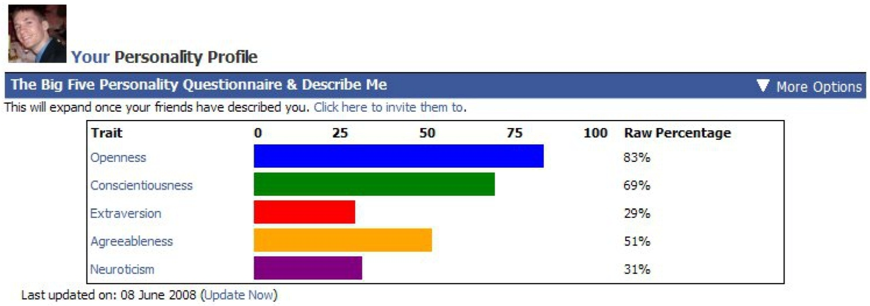


Fig. 1. Part of the myPersonality user interface.

we shall see in the next section, age is an important factor as it affects a user's activity. Figure 3(b) shows the logarithms of following, followers, and listed for users of increasing age (11 bins).

IV. Personality of Twitter Users

We identify four characteristics that define four distinct types of users. By considering the publicly available counts of (what Twitter calls) 'following', 'followers', and 'listed' counts, we identify three types of users first: *listeners* (those who follow many users), *popular* (those who are followed by many), and *highly-read* (those who are often listed in others' reading lists). We then identify *influential* users using two influence scores named '*Klout*' and '*TIME*' (detailed below).

We study the relationship between personality traits and the five user characteristics, that is, the logarithm of the number of followed users (following), followers, listings, and the two influence scores. We are interested in the logarithm because the corresponding distributions are not normal and their logarithm transformations (Figure 2) account for the violation of normality. We study the Pearson product-moment correlation between the logarithm of the five user characteristics and each of the (big) five personality traits, plus two additional attributes, namely age and sex. Pearson's correlation $r \in [-1, 1]$ is a measure of the linear relationship between two random variables.

We report the correlations in Table II[2], and then plot the relations between three types of users (popular, highly-read, and (*Klout*) influential) and the five personality traits at population-level in Figure 4.

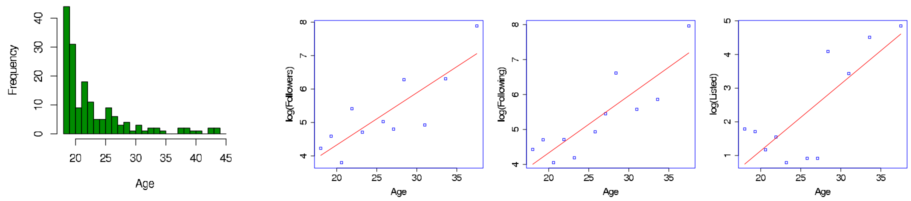
Listeners and Popular. Strongest and significant correlations are found with *Extraversion* (0.13 for listeners and 0.15 for popular users) and with *Neuroticism* (-0.17 for listeners and -0.19 for popular users). That is reasonable since *Extraversion* and *Neuroticism* are predictors for number of friends in the real world and number of social contacts on Facebook [10], [27], [39] - in both real life and Facebook, sociometrically popular individuals are extroverts (high in *Extraversion*) and emotionally stable (low in *Neuroticism*). Also, individuals high in *Extraversion* tend to maintain persistent communication with their friends [2], [5], [13], [34], while those high in *Neuroticism* withdraw from other during times of stress [22], [23] and generally report less satisfaction with the support received by their social networks [18], [19]. Listeners and popular users also tend to be older - the correlation with age is 0.28 for listeners and 0.37 for popular users. This indicates that older individuals tend to follow more users on Twitter than younger ones do. In Facebook, the opposite holds - the older a user, the fewer his/her social contacts [10]. The different age effects in the two social media sites could be explained by differences in: 1) *usage* - professionals tend to predominantly prefer Twitter over Facebook for work matters, and they are those who accumulate large numbers of followers [20]; 2) *age demographics* - in 2010, the fraction of users in the $[13-25]$ age band are 40% in Facebook and only 17% in Twitter [14].

Highly-read. Those who are saved in others' reading lists tend be high in *Openness*, with a correlation coefficient of 0.17. *Openness* is generally associated with descriptive terms such as imaginative, spontaneous, and adventurous and has been found to be positively associated with number of social relations in real life ($r = 0.23$) [38].

Influentials. To identify influentials, we now define two measures of influence. First, we use a well-established measure among social media analyst called '*Klout*' score (klout.com/). This score does not consider number of followers or tweets but, instead, considers whether a user's tweets are clicked, replied, and further propagated (retweeted) [21]. Second, we employ the measure used by TIME magazine to rank public figures such as Barack Obama, Oprah Winfrey, and Lady Gaga. The measure combines one's popularity on both Twitter and Facebook by computing $\frac{2 \cdot n_{followers} + n_{facebook}}{2}$ [37], where $n_{followers}$ is the number of Twitter followers, and $n_{facebook}$ is the number of Facebook social contacts.

The results reported in Table II are consistent between the two influence scores for *Extraversion* - this trait is positively correlated with both influence scores. In addition, *TIME* influentials are high in the trait of *Conscientiousness* (0.18). This trait is associated with descriptive terms such as ambitious,

[2]Consider that very low correlation coefficients can still be highly statistically significant: the correlation *Klout-N* of -0.03 is a case in point.



(a) Distributions of Age.

(b) User activity varies with age.

Fig. 3. Age distribution and effects on Twitter activity

Trait	Listeners *log(Following)*	Popular *log(Followers)*	Highly-read *log(Listed)*	Influential *Klout*	Influential *log(TIME)*
O	0.05	0.05	**0.17***	0.13	0.00
C	0.08	0.10	0.02	0.01	**0.18*****
E	**0.13***	**0.15****	0.09	**0.15***	**0.25*****
A	0.07	0.02	0.03	-0.17	0.06
N	**-0.17****	**-0.19*****	-0.03	**-0.03***	**-0.20*****
log(Age)	**0.28***	**0.37***	0.13	0.05	**0.39***
Male	-0.05	-0.05	-0.05	-0.04	0.01

TABLE II

CORRELATION COEFFICIENTS BETWEEN BIG FIVE PERSONALITY TRAITS AND FIVE QUANTITIES THAT CHARACTERIZE LISTENERS, POPULAR USERS, HIGHLY-READ USERS, AND (*Klout* & *TIME*) INFLUENTIALS. STATISTICALLY SIGNIFICANT CORRELATIONS ARE IN BOLD AND THEIR p-VALUES ARE EXPRESSED WITH *'S: $p < 0.001$ ($***$), $p < 0.01$ ($**$), AND $p < 0.05$ ($*$).

Trait	*RMSE*
O	0.69
C	0.76
E	0.88
A	0.79
N	0.85

TABLE III

PREDICTABILITY OF THE BIG FIVE TRAITS. THE ROOT-MEAN-SQUARE ERROR (*RMSE*) FOR PREDICTED PERSONALITY SCORES.

resourceful and persistent [26].

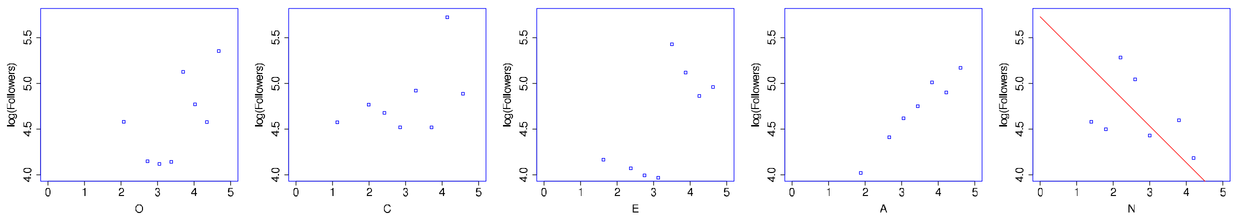
V. PREDICTING PERSONALITY

Given that correlations are significant, one may wonder whether it would be possible to predict personality scores of Twitter users, including of those who do not make their tweets publicly available. For privacy conscious users, we cannot access their tweets but we can access their basic network properties, that is, their following, followers, and listed counts. Thus, we turn to problem of predicting personality scores only on input of the three counts. To this end, for each personality trait, we perform a regression analysis with a 10-fold cross-validation with 10 iterations using *M5′ Rules* [42]. This algorithm generates decision trees with linear models at the leaves using the $M5'$ algorithm, which was introduced in Wang & Witten's work [40] and enhanced the original $M5$ algorithm by Quinlan [31]. We also measure the *root-mean-square error* (*RMSE*), which is the root mean squared differences between predicted values and observed values. On the $[1, 5]$ score scale, the maximum $RMSE$ is 0.88 (Table III). The error is low and, to see why, compare it to the error reduction needed to win in the $\$1M$ "Netflix prize". Netflix, an online DVD-rental service, launched an open competition for the best collaborative filtering algorithm to predict user ratings for films, based on previous ratings (ratings varied on the same scale - from 1 to 5) [25]. On 21 September 2009, the grand prize of \$1*M* was given to a team that achieved a test *RMSE* of 0.8567 [3]. Our results show that, based on three publicly available counts, we can accurately predict users' personality as well as state-of-the-art recommender systems predict user ratings for movies.

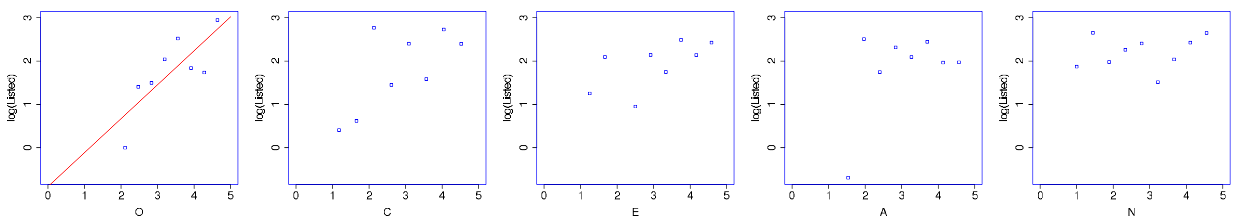
VI. DISCUSSION

Users of social media reveal a lot about themselves, but, depending on their privacy attitudes, they also choose not to share details they find sensitive. Few Facebook users purposely fake their personal information such as dates of birthday, and privacy-conscious mobile users have tools that allow them to fake their personal data (e.g., fake geographic locations) and then share it with mobile social-networking services [4], [30].

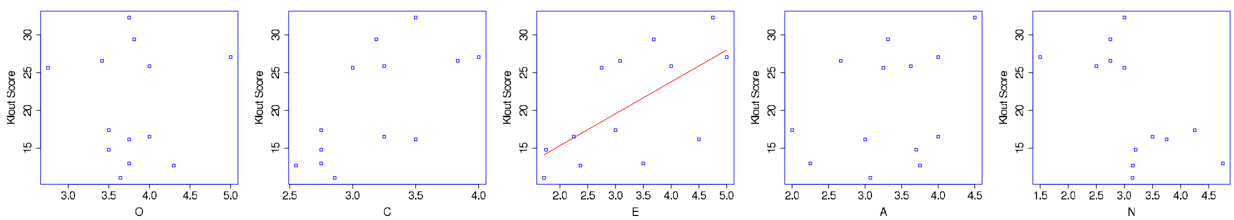
Users decide what to share and what not to based on reasonable expectations. The problem is that unexpected inferences can often be made from seemingly innocuous social media data. Crandall *et al.* showed that, from publicly available geo-referenced Flickr pictures, one is able to infer several coincidences (e.g., two people taking picture at the same place and at the same time). These coincidences, in turn, reveal "who befriends whom" [8]. The simple act of uploading few pictures on a social media site translates into implicitly and unknowingly disclosing one's private social contacts.



(a) Personality traits for popular users (*OCEAN* vs. *log(Followers)*).



(b) Personality traits for highly-read users (*OCEAN* vs. *log(Listed)*).



(c) Personality traits for influential users (*OCEAN* vs. *log(Klout)*).

Fig. 4. The five personality traits for popular, highly-read, and influential users at population level. For each user type, the trait with the highest correlation coefficient comes with regression line (red line).

This example illustrates that, although users' decisions on what to share might appear reasonable in the short term, they might well end up being unreasonable later on and, more worryingly, they might disrupt initial users' social expectations. Recent privacy failures are telling stories of disrupted social exceptions [9]. A few years ago, Facebook aggregated content in ways that made it more visible to users who could already access it. When a Facebook user switched to an "it's complicated" relationship, the user thought that only the few social contacts regularly visiting his profile would notice the change. Suddenly, that was not true anymore. A variety of contacts would learn the switch just from their streams of updates. This change caused a big outcry, but Facebook did not have to back off - the users did. Facebook founder Mark Zuckerberg recently contributed to the discussion and claimed that the rise of social networking online means that people no longer have an expectation of privacy, adding "we decided that these would be the social norms now and we just went for it" [17]. The result is that Facebook "users are now so hooked that they are unlikely to revolt against a gradual loosening of privacy safeguards" [1]. Another example comes from the site *pleaserobme.com* that combined data from Twitter and Foursquare (a service that lets people share their location so their social contacts can see where they are). This site publishes Foursquare location posts that appear on Twitter. The problem is that, when a user shares her location on Foursquare, the user thinks that only her social contacts on Foursquare or Twitter would notice it. But that changes with *pleaserobme.com* - the site exposes whether users are somewhere other than their home to the entire Internet community, including burglars. More generally, when sharing personal data (including location data), one does so in a specific social context and consequently has specific social expectations - one implicitly guesses who is more or less likely to come across that data. However, those exceptions are disrupted by inferring something unexpected: in the case of *pleaserobme.com*, whether someone is home or not. It now turns out that there is another piece of information that can be unexpectedly inferred from publicly available Twitter profiles: user personality traits. This insight not only raises awareness around privacy issues in social media but also calls for a rethinking of current privacy protection mechanisms.

VII. Conclusion

This study has produced two main insights. First, there are important personality similarities and differences among different types of Twitter users. All user types (listeners, popular, highly-read, and influential users) are emotionally stable (low in Neuroticism), and most of them are extrovert. These inferences have long been supported informally by intuition but have been difficult to make precise. Interestingly, popular users tend to be 'imaginative', while influential users tend to be 'organized'.

The second insight is that user personality can be easily and effectively predicted from public data, and that suggests future directions in a variety of areas, including : 1) *Marketing:* Since there is a relationship between marketing strategies and consumer personality [28], [41], one could select ads to which a user is likely to be most receptive; 2) *User Interface Design:* One could match not just content but also the basic "look and feel" of a social media site to personality traits (this idea has been previously called "web site morphing" [12]); and 3) *Recommender Systems:* Given the well-established relationship between personality and music taste [32], music recommender systems might improve their predictions by also considering user personality.

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