INVITED PAPER

Tracking the Digital Footprints of Personality

This paper reviews literature showing how pervasive records of digital footprints can be used to infer personality.

By Renaud Lambiotte and Michal Kosinski

ABSTRACT | A growing portion of offline and online human activities leave digital footprints in electronic databases. Resulting big social data offers unprecedented insights into population-wide patterns and detailed characteristics of the individuals. The goal of this paper is to review the literature showing how pervasive records of digital footprints, such as Facebook profile, or mobile device logs, can be used to infer personality, a major psychological framework describing differences in individual behavior. We briefly introduce personality and present a range of works focusing on predicting it from digital footprints and conclude with a discussion of the implications of these results in terms of privacy, data ownership, and opportunities for future research in computational social science.

KEYWORDS | Big data; personality; psychology; social networks

I. INTRODUCTION

In recent years, a growing portion of human activities such as social interactions and entertainment have become mediated by digital services and devices. The records of those activities, or "big social data," are changing the paradigm in the social sciences, as it undergoes a transition from small-scale studies, typically employing questionnaires or lab-based observations and experiments, to large-scale studies, in which researchers observe the behavior of thousands or millions of individuals and search for statistical regularities and underlying principles [1]–[6]. These works provide empirical observations at an unprecedented scale offering the potential to radically improve our understanding of the individuals and social systems.

One of the major insights offered by big social data research relates to the predictability of individuals' psychological traits from their digital footprint [3]. Ability to automatically assess psychological profiles opens the way for improved products and services as personalized search engines, recommender systems [7], and targeted online marketing [8]. On the other hand, however, it creates significant challenges in the areas of privacy [9], [10]. The main goal of this paper is to provide a review of the works investigating the potential of the big social data to predict a five-factor model of personality—the major set of psychological traits—supporting further studies of the relationship between personality and digital footprint and its implications for privacy and new products and services.

II. PERSONALITY

The most widespread and generally accepted model of personality is the five-factor model of personality (FFM; [11]). FFM was shown to subsume most known personality traits, and it is claimed to represent the basic structure underlying the variations in human behavior and preferences, providing a nomenclature and a conceptual framework that unifies much of the research findings in the psychology of individual differences. FFM includes the following traits.

1) Openness is related to imagination, creativity, curiosity, tolerance, political liberalism, and appreciation for culture. People scoring high on openness like change, appreciate new and unusual ideas, and have a good sense of aesthetics.

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2) Conscientiousness measures the preference for an organized approach to life in contrast to a spontaneous one. Conscientious people are more likely to be well organized, reliable, and consistent. They enjoy planning, seek achievements, and pursue long-term goals. Nonconscientious individuals are generally more easygoing, spontaneous, and creative. They tend to be more tolerant and less bound by rules and plans.
3) Extroversion measures a tendency to seek stimulation in the external world, the company of others, and to express positive emotions. Extroverts tend to be more outgoing, friendly, and socially active. They are usually energetic and talkative; they do not mind being at the center of attention and make new friends more easily. Introverts are more likely to be solitary or reserved and seek environments characterized by lower levels of external stimulation.
4) Agreeableness relates to a focus on maintaining positive social relations, being friendly, compassionate, and cooperative. Agreeable people tend to trust others and adapt to their needs. Disagreeable people are more focused on themselves, less likely to compromise, and may be less gullible. They also tend to be less bound by social expectations and conventions and are more assertive.
5) Emotional stability (opposite referred to as neuroticism) measures the tendency to experience mood swings and emotions, such as guilt, anger, anxiety, and depression. Emotionally unstable (neurotic) people are more likely to experience stress and nervousness, whereas emotionally stable people (low neuroticism) tend to be calmer and self-confident.

Research has shown that personality is correlated with many aspects of life, including job success [12], attractiveness [13], drug use [14], marital satisfaction [15], infidelity [16], and happiness [17]. The main limitations of classical personality studies are, however, the size of the samples, often too poor for statistical validation, and their strong bias toward white, educated, industrialized, rich, and democratic (WEIRD) people [18].

III. FROM OFFLINE TO ONLINE...

The increasingly prevalent access to digital media enables large-scale online projects aimed at collecting personality profiles and exploring their relations with digital footprints. Personality has been investigated through different types of online media, for instance, by focusing on website browsing logs [2], [19], contents of personal websites [20], music collections [21], or properties of Twitter profiles [22], [23].

The most complete online social environment is arguably Facebook, due to its popularity and rich social and semantic data stored on its users' profiles that can be conveniently recorded. It is important to note that Facebook profiles are increasingly becoming a channel through which to form impressions about others, for example, before dating [24] or before a job interview [25]. Moreover, research tends to show that a Facebook profile reflects the actual personality of an individual rather than an idealized role [26], and that personality can be successfully judged by the others based on Facebook profiles [27], [28]. These results suggest that personality is manifested not only in the offline, but also online behavior, and thus digital footprints can be used to predict it.

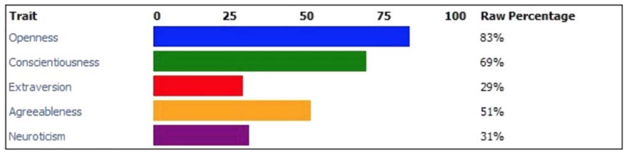

Fig. 1. *Snapshot of a personality profile generated by the myPersonality Facebook App, representing an individual that is liberal and open minded (high openness), well-organized (high conscientiousness), contemplative and happy with own company (low extroversion), of average competitiveness (average agreeableness), and laid back and relaxed (low neuroticism).*

The most popular data set used to study the relationship between personality and digital footprint comes from the myPersonality project. myPersonality was a Facebook application set up by David Stillwell in 2007 that offered participants access to 25 psychological tests and attracted over six million users. myPersonality users received immediate feedback (see Fig. 1) on their results and could donate their Facebook profile information to research resulting in a database that, after anonymization, is being shared with the academic community at mypersonality.org, allowing for the study of hitherto unanswered questions in a wide range of topics, such as geographical variations in personality ([29]; see Fig. 2), social networks [2], [22], [30], [31], privacy [32], language [6] (see Fig. 3), predicting individual traits [33], [3], computer science [34], happiness [35], music [36], and delayed discounting [37].

IV. SOCIAL NETWORK STRUCTURE

Social network structure is one of the major types of digital footprint left by the users, and a growing number of studies shows that it is predictive of often intimate personal traits. For instance, it is known that the location within a Facebook friendship network is predictive of sexual orientation [38]. Similarly, it is possible to accurately detect users' romantic partner by observing overlap in social circles [39].

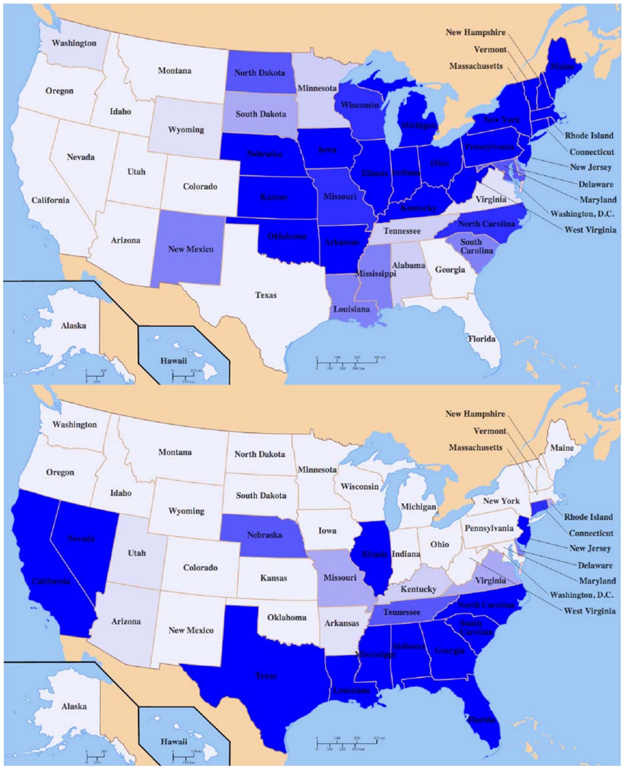

Fig. 2. ***Personality maps of U.S. states for neuroticism (upper) and extroversion (lower). Dark (light) blue indicates values higher (lower) than average. Figure based on myPersonality data.***

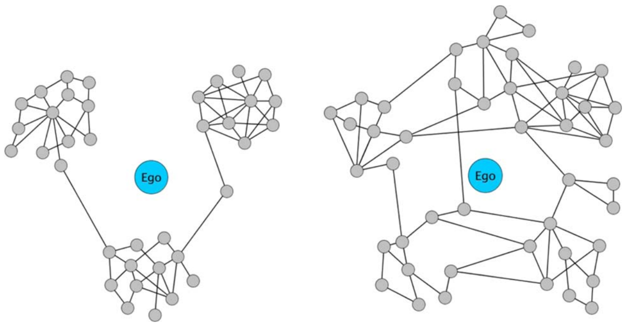

Fig. 4. ***Typical egocentric networks of introverts (left) and extroverts (right). Introverts tend to belong to fewer but larger and denser communities, while extroverts tend to act as bridges between more frequent, smaller, and overlapping communities. Connections between Ego and his friends have not been depicted for the sake of clarity.***

Personality is expected to affect people's social network surroundings as it affects the types and number of social ties formed by people. There are a number of studies exploring this relationship. Neuroticism is usually associated with negative social interactions, while extroversion positively correlates with the size of the network and greater social status [40], [41]. Results related to the remaining traits tend to be inconsistent, perhaps due to small sample sizes. More recently, Quercia *et al.* [31] used myPersonality data set to study the relation between sociometric popularity and personality traits, at a scale several orders of magnitudes larger than in the previous studies. They have shown that the strongest predictor for the number of friends is extroversion, while other personality traits do not play a significant role. On average, extreme extroverts tend to have twice as many friends as extreme introverts. A subsequent work [42] went one step further and, for the first time, quantitatively explained the way in which egocentric network topology is shaped by personality. It confirmed that extroversion plays a major role by showing that introverts are part of fewer but larger communities, whereas extroverts tend to act as bridges between more frequent but smaller communities (see Fig. 4).

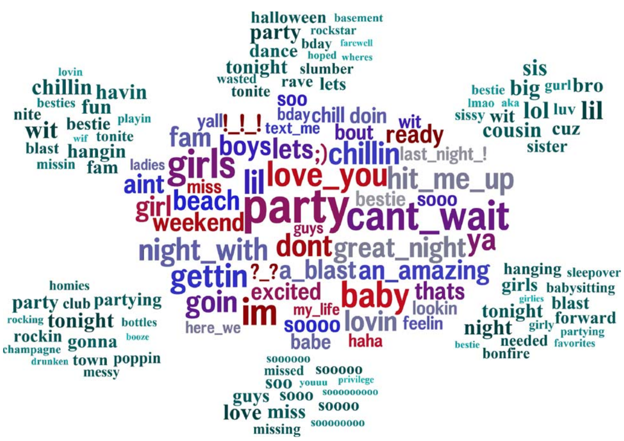

Fig. 3. ***Words, phrases, and topics most distinguishing extroversion from introversion. Source: [6].***

V. FACEBOOK LIKES

The Facebook profile of a user is not purely demographic, as it also contains robust records of digital footprints. In particular, Facebook likes exemplify a typical variety of digital footprint—a connection between the user and a content that is similar to other pervasive records such as playlists (see Fig. 5), website browsing logs, purchase records, or web search queries. A recent paper [3] based on the myPersonality database and using relatively straightforward methods (singular value decomposition and linear regression) showed that Facebook likes are highly predictive of personality and number of other psychodemographic traits, such as age, gender, intelligence, political and religious views, and sexual orientation (see Fig. 6). The paper provided examples of likes most strongly associated with given personality traits. For example, users who liked "Hello Kitty" brand tended to

Fig. 5. ***Dendrogram illustrating the structure of music tastes and its relationship to the personality trait of openness among myPersonality users. The structure was produced using hierarchical clustering of the most popular Facebook likes from musician/band category. The color scale represents the average openness of its subscribers, ranging from conservative (cyan) to liberal (magenta). The height of the nodes is proportional to the dissimilarity between individual likes or clusters at both ends. The shorter is the path between two musicians or bands, the larger overlap in audience. Source: [43].***

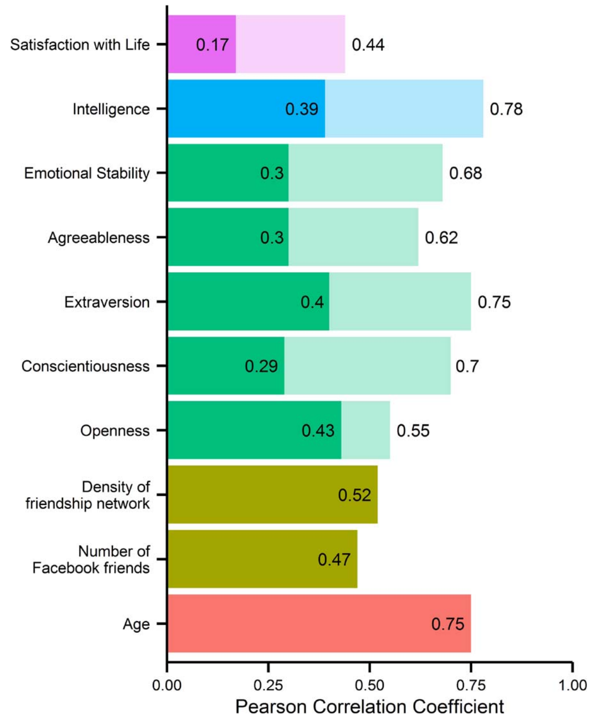

Fig. 6. ***Prediction accuracy of regression for numeric attributes and traits expressed by the Pearson correlation coefficient between predicted and actual attribute values; all correlations are significant at the $p < 0.001$ level. The red outline bars indicate the questionnaire's baseline accuracy, expressed in terms of test-retest reliability. Source: [3].***

have high openness, low conscientiousness, and low agreeableness.

VI. SEMANTIC ANALYSIS

Similar predictions can be based on the textual analysis of people's posts and other samples of text. There is a long tradition in using text to infer personality [44], [45], [46], however, never at the scale presented in [6]. This study applied differential language analysis to uncover features distinguishing demographic and psychological attributes to 700 million words, phrases, and topic instances collected by myPersonality from Facebook status updates of 75 000 participants. It showed a striking variations of language driven by personality, gender, and age. This work has not only confirmed existing observations (such as neurotic people's tendency to use the word "depressed"), but also posed new hypotheses (such as a relationship between physical activity and low neuroticism).

VII. . . . AND BACK FROM ONLINE TO OFFLINE

The proliferation of mobile-devices loaded with sensors means that offline human activities are also increasingly leaving digital footprint [47], [48]. For instance, physical states such as running or walking can be inferred from accelerometer data; colocation with other devices can be detected using Bluetooth; geolocation can be established using WiFi, Global Positioning System (GPS), or Global System for Mobile (GSM) triangulation; and social interactions can be measured by records of text messages and phone calls. These data can be recorded by dedicated apps, such as EmotionSense [49], which measures emotional states based on the speech patterns and matches it with physical activity, geolocation, and colocation with other users. In the last few years, call data records (CDRs) have been used to study the organization of social networks and human mobility [50], [51], [52].

Similarly to digital footprints left in the online environment, offline activities recorded with mobile devices' sensors reflect users' personality. A recent study combined CDRs with personality profiles of mobile device users and identified a number of mobility and social factors correlated with personality [53]. For instance, mobility indicators, such as distance traveled, significantly correlate with neuroticism, while social life indicators, such as the size of the social network, correlated with extroversion, in agreement with the previous results based on online digital footprints.

VIII. CONCLUSION

The main purpose of this paper was to review the evidence of the relationship between digital footprint and personality. We have shown that a wide range of pervasive and often publicly available digital footprints such as Facebook profiles or data from mobile devices can be used to infer personality. As our life is increasingly interwoven with digital services and devices, it is becoming critical to understand the consequences of the apparent ability to automatically and rapidly assess people's psychological traits.

Works cited in this paper indicate that the accuracy of the personality predictions is moderate, with typical correlation between the prediction and personality in the range of $r = 0.2$ and $r = 0.4$. It has to be noted, however, that the ground truth (i.e., personality scores) is also merely an approximation of the underlying latent traits. For example, the accuracy of the personality scales used in [3] expressed as a correlation between scores achieved by the same person in two points of time (test-retest reliability) ranged between $r = 0.55$ and $r = 0.75$. It is reasonable to expect that with, an increasing amount of data available and improved methods, assessment accuracy will improve.

Predicting users' personality can be used to improve numerous products and services. Digital systems and devices (such as online stores or cars) could be designed to adjust their behavior to best fit their users' inferred profiles [54]. For example, a car could adjust the parameters of the engine and the music to the personality and current mood of the driver. Also, the relevance of marketing and product recommendations could be improved by adding psychological dimensions to current user models. For example, online insurance advertisements might emphasize security when facing emotionally unstable (neurotic) users but stress potential threats when dealing with emotionally stable ones. Moreover, digital footprint may provide a convenient and reliable way to measure psychological traits at a low cost. Such automated assessment could prove to be more accurate and less prone to cheating and misrepresentation than traditional questionnaires.

Furthermore, it is likely that new insights into individual differences in human behavior offered by big social data will fuel the emergence of new, more accurate, robust models describing individuals and societies [5]. The translation of big social data into models and policies calls for a new wave of multidisciplinary collaborations between fields as diverse as psychology, social sciences, linguistics, computer science, and applied mathematics (perhaps under the banner of computational social psychology).

On the other hand, the results presented here may have considerable negative implications because it can easily be applied to large numbers of people without obtaining their individual consent and without them noticing. Commercial companies, governmental institutions, or even one's Facebook friends could use software to infer personality (and other attributes, such as intelligence or sexual orientation) that an individual may not have intended to share. There is a risk that the growing awareness of such digital exposure may decrease their trust in digital technologies, or even completely deter them from them. We hope that researchers, policy makers, and customers will find solutions to address those challenges and retain the balance between the promises and perils of the Digital Age. ■

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