Towards a Psychographic User Model From Mobile Phone Usage

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Abstract
Knowing the users' personality can be a strategic advantage for the design of adaptive and personalized user interfaces. In this paper, we present the results of a first trial conducted with the aim of inferring people's personality traits based on their mobile phone call behavior. Initial findings corroborate the efficacy of using call detail records (CDR) and Social Network Analysis (SNA) of the call graph to infer the Big Five personality factors. On-going work includes a large-scale study that shall refine the accuracy of the models with a reduced margin of error.

Keywords
psychographics, user modeling, personality, call detail record, big five, five factor model.

ACM Classification Keywords
H.1.2 Models and Principles: User/Machine Systems—Human factors.

General Terms
Experimentation, Human Factors, Measurement.

Introduction
The roots of personality assessment date from 460 BC with the Hippocratic school, but it was not until the First World War that psychologists fully engaged in studying models of personality assessment, with the goal of inferring people's personality profiles and hence better explain why we behave the way that we do. Personality Psychology has traditionally contributed to Social Psychology in behavior prediction [14, 4] providing empirical evidence that supports the study of personality to explain differences in human behavior. In

recent years, there has been an increased interest in the Computer Science community (and particularly HCI) on the importance of personality profiles: models of the users' personality traits and preferences can be used to adapt and personalize services. For example, Personality Psychology has provided evidence on the influence of different personality traits over leadership, performance and group interaction styles [3]. In addition, a range of HCI projects have leveraged personality models to design more persuasive e-commerce websites [11], enhance the user experience of robot's [7], model virtual agent emotions [6], design recommendation engines based on the users' personality facets [13] and implement mobile phone applications that encourage an active lifestyle [2].

Even though personality profiles have shown to be useful in a range of application domains, an important challenge that needs to be overcome is that of assessing the users' personality traits and sub-traits (facets). This task is usually achieved by either explicit or implicit methods. Explicit methods require the deployment of long surveys with up to 350 questions. In addition to the overhead of answering a few hundred questions before using an application [2], users may also feel uncomfortable with personality related surveys. Implicit methods aim at inferring personality from observed behavior. However, current implementations of the implicit approach usually require monitoring sensitive output channels, such as keyboard usage [15, 10] – from which passwords could be recorded – and snippets of daily conversations [12] – that could be used to reveal private and highly personal information.

In this paper, we propose to leverage mobile phone usage-derived variables to effectively infer the users' personality in an implicit manner. More specifically, we use information extracted from call detail records (CDRs), including variables obtained from social network analysis of the calls (SNA), to automatically infer the users' personality traits as defined by the Big Five personality model [8]. To the best of our knowledge, this is the first work that leverages mobile phone usage in order to infer personality traits. Note that with the proposed approach we only analyze aggregated and fully anonymized phone call usage-related data (e.g., duration and time of calls, number of SMS received/sent, etc.). Therefore, the data cannot be used in any way to reveal the users' identity or to obtain personal information from private conversations. Furthermore, the CDR-derived data could be also collected by mobile phone applications that would log similar variables. In fact, these types of applications will probably become increasingly pervasive with the wide adoption of mobile broadband – and associated services such as online application stores, online social networks, context-aware applications and recommendation engines. In this future, the automatic inference of the users' psychographic profile from their phone call usage behavior could be used to design interfaces and applications that would adapt to the user's personality profile.

Literature Review

As briefly mentioned before, previous work in the field of HCI has highlighted the importance of identifying the users' personality traits and preferences in order to build adaptive and personalized systems with an improved user experience. Lee and Nass [11] conducted a study with 72 students in which each participant accessed an e-commerce website and listened to five book descriptions via either an extrovert or an introvert synthetic voice. Their findings revealed that respondents felt stronger social presence when they heard a computer voice manifesting a personality similar to their own. Eckschlager et al. [6] created a model of agent emotion elicitation for various types of interfaces. They conducted a user study with 40 subjects and found six human emotions to be strongly correlated with the intensity of the personality traits (e.g. the more neurotic one is, the less joy he/she has in a given scenario). They leveraged these correlations to improve the model of non playable characters in 3D games. Similarly, Goetz and Kiesler [7] enhanced the user experience with robots by implementing versions with different personality traits. More recently, Arteaga et al. [2] have designed and implemented a mobile phone application to encourage long term adoption of physically active behaviors by: (1) recommending a list of games compatible with the user's personality traits; and (2) including a motivational agent whose spoken phrases are also chosen based on the user's traits.

However, a major disadvantage of all of the above-mentioned projects is that personality is explicitly assessed by means of long surveys. For instance, the copyrighted Five Factor Model (FFM) or Big Five – widely used in Computer Science [7, 6, 3, 13, 2] – requires participants to answer up to 350 questions. It structures the personality profile into five principal dimensions (or traits): E: Extroversion, A: Agreeableness, C: Conscientiousness, S: Emotional Stability, and O: Openness (hence the name of Big Five). Non-commercial alternatives to this questionnaire available on the International Personality Item Pool (IPIP) are also frequently used, mostly because of their public domain policy and good test-retest reliability [1]. However, managing these long questionnaires is generally time consuming and expensive to scale. In addition, some users could feel uncomfortable answering personality related questions.

Recently, scholars have tackled this problem by automatically inferring the Big Five personality traits from logged human behavior. For instance, Saati et al. [15] recorded the users' interaction with keyboard and mouse, and verified that some traits and sub-traits (facets) are strongly correlated with a number of actions and the speed between the actions. Likewise, Khan et al. [10] found strong correlations between the Big Five traits and specific keystrokes, mouse events, and standard deviation time between events. Other approaches to infer personality are based on human speech. For example, Mairesse and Walker [12] found that audio recorded from daily conversations can predict the Big Five personality traits. However, we believe that identifying alternative approaches to infer the users' personality without revealing private and sensitive information (e.g., private conversations, passwords, etc.) is of extreme relevance for the design of novel personalized interactive systems.

In this paper, we propose the use of anonymized mobile phone call usage data to automatically infer the users' personality (as characterized by the Big Five model) in a privacy-preserving manner. Our work is somewhat related to that of Butt and Phillips [4], in which they used personality traits to predict self-reported mobile phone usage from 112 subjects. However, our approach focuses on the inverse process (i.e., inferring personality traits from mobile phone usage) by extracting objective measures of mobile phone call behavior in order to create a scalable, robust and automatic personality assessment method.

We shall describe next the user study that we carried out to collect ground truth data, followed by the feature selection and machine learning models that we used to automatically infer the users' Big Five personality traits from the implicit mobile phone call data.

User Study

The user study presented herein was conducted in Mexico and we collected evidence that could help answer the following research questions:

RQ1 *Could the users' mobile phone behavior be used to automatically infer their Big Five personality traits?*
RQ2 *If so, could information derived from the users' social communication network – as captured by their mobile phone calls – be used to improve the accuracy of the models?*

The following sections describe the methodology used to shed some light on these research questions.

Participants
39 subjects (male: 24) living in Mexico answered a non-copyrighted Big Five online questionnaire. Their ages ranged between 18 and 34 years old ($\bar{x}$ = 26.2, s = 4.8) and they all belonged to the middle socio-economic class of their country (age range and socio-

economic class were constraints imposed to this study and therefore shall be taken into account when generalizing the main findings). Subjects were familiar with technology: the majority of participants reported using computers (92%) and the internet (85%) on a daily basis. Their level of education was also very satisfactory, given that all of them completed at least secondary school and the majority had either finished graduation (80%) or a technical career (15%). In terms of mobile phone use, 74% reported using it everyday, 21% several times a week and 5% only once a week.

Procedure

We used a public domain Big Five questionnaire available in the IPIP website to collect ground truth about the participants personality profile. The 50-item version [1] was chosen due to its balance between a low number of questions and a high level of internal consistency (Cronbach's alpha: .79 to .87). Given that Cupani [5] had recently translated and validated this questionnaire to Argentinean Spanish with satisfactory results, we reused his inventory and applied inverse translation to Mexican Spanish as described in [5].

Participants were recruited via email from an online panel with about 36,500 members living in Mexico. The sample considered in this paper corresponds to the initial pool of respondents that satisfied the demographic criteria (age and socio-economic class) and had a pre-paid mobile phone number with a certain mobile operator for at least the last six months (to ensure that there would be enough information from each participant's CDR data). All suitable participants were invited to fill out the Spanish online personality assessment survey. Participants rated their behavior/compliance with respect to each statement of the survey using a 7-point scale (1: almost never, 7: almost always). All participants provided consent to access their anonymized CDR data.

Questionnaire Analysis

The standard Big Five questionnaire presents one statement per personality trait at a time, with positive and negative scales intertwined between statements (please, refer to [1] for more detail). Therefore, we applied conventional rules for mirroring the rating scales and consequently calculate the *Trait Mean Score* (TMS) for every trait per participant, considering the corresponding 10 statements of each trait.

CDR Analysis

Call Detail Records (CDRs) are generated when a mobile phone connected to the network makes or receives a phone call or uses a service (SMS, MMS, etc.). In the process, the information regarding the connection is stored in the form of a Call Detail Record, which includes the originating/destination phone numbers, the time/date/length of the call, and the cell tower used for the communication. All phone numbers are encrypted to preserve privacy. Nevertheless, we did *not* use encrypted phone numbers, but only aggregated information such as number of calls, duration, time, etc. Hence, we extracted 474 variables from the CDRs, including total number – and duration for phone calls – of phone calls/SMS/MMS sent and/or received during the 6 months prior to the study and for each day of the week during different time slots (morning, afternoon, evening and night). Moreover, the user's social network was reconstructed from the CDRs, extracting nine additional SN-related variables, including the number and weight (measured by the number of reciprocal phone-calls or SMS) of contacts (degree of the nodes), number and social distance between relevant contacts, density of the subgraph from one's contacts, etc.

Feature Selection and Personality Inference

The goal of our models is to automatically infer – from the variables extracted from the CDRs and with maximum accuracy – the value (in a 7-point scale) of each of the 5 personality traits for each participant in the study. In this sense, we used the well known Support Vector Machines (SVM regression) [9] with a Gaussian kernel. We performed limited tuning of the *C* cost parameter and the σ Gaussian kernel hyper-parameter using a subset of the data. As a large number of variables was extracted from the CDR data

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(f_i - y_i)^2$$

where N is the number of data points, f_i the value returned by the model and y_i the actual value for data point i.

Figure 1. Mean Squared Error formula used to evaluate the user model.

(as previously described), we applied model selection using SVM Recursive Feature Elimination (SVM-RFE) [9]. The SVM-RFE algorithm returns a ranking of the features of a SVM learning problem. Features are eliminated recursively based on the impact they have on the SVM objective function. Based on this impact, a ranked list of features is returned and the variable with the least impact is eliminated in each step. We evaluated the SVM models on each participant's TMS variable using two approaches: (1) CDR variables only, and (2) CDR + SN variables. In both cases, feature selection and 10-fold cross-validation was performed and evaluated using the Mean Squared Error (MSE) measure for each TMS variable as shown by Figure 1.

Results and Discussion

The internal consistency of the questionnaire was satisfactory, with values of Cronbach's alpha ranging between .77 and .85 (α_E = .77, α_A =.83, α_C =.85, α_S =.82, and α_O =.83). These values are higher than those presented by Cupani (2009) [5] and indicate good reliability of our personality assessment inventory. Table 1 summarizes the main descriptive statistics regarding our participants' personality traits.

Table 1. Participants' personality traits based on their Trait Mean Score (7-point scale).

Personality traits	TMS avg	TMS std	TMS min	TMS max
Extroversion	4.4	1.1	2.0	6.9
Agreeableness	5.3	1.1	3.4	7.0
Conscientiousness	4.9	1.1	1.9	6.9
Emotional Stability	4.5	1.1	2.0	6.4
Openness	5.4	1.0	2.6	7.0

Twenty out of the 474 CDR variables were selected (see section on Feature Selection) as predictors of the TMS variable. Adding more variables did not significantly increase the model's performance. The selected variables were related to duration of received phone calls, number of received and placed phone calls, and the number of SMS and MMS sent/received at different times of the day. In addition, 4 out of the nine SN-related variables revealed a strong positive impact on the model's performance. These variables described the degree of the nodes (number of contacts), the density of the subgraph formed by the neighboring nodes, the number of strong contacts (defined as frequent calling partners) and the efficiency to reach nodes (reach divided by number of strong contacts).

Our findings reveal mean squared errors (MSE) between .73 and .86 for the five personality traits using the SVM regression models with CDR variables only (20 variables). These results are very satisfactory especially compared to a baseline predictor such as the mean, i.e. using the average TMS for the prediction (when using the TMS as a prediction value, the MSE values correspond to the variance). In addition, predictions using CDR + SN variables (16 CDR + 4 SN variables) revealed even lower MSE values ranging between .67 and .81. Significant improvements in performance were identified when including SN-related variables for the Extroversion, Agreeableness, and Openness traits (p<.05). Table 2 summarizes the main results.

Table 2. Regression MSE for 10-fold cross-validation results using SVM on the TMS variables (standard deviation values are included).

Personality traits	MSE using CDR only	MSE using CDR+SN	Baseline (MSE for TMS)
Extroversion	.863 ±.09	**.670 ±.07**	1.184
Agreeableness	.851 ±.08	**.650 ±.07**	1.049
Conscientiousness	.790 ±.07	.780 ±.09	1.390
Emotional Stability	.813 ±.08	.811 ±.08	1.277
Openness	.730 ±.07	**.615 ±.08**	0.903

These findings corroborate both of our research questions, highlighting the value that fully anonymized mobile phone call usage data – as captured by CDR aggregated variables – has on inferring the users' personality traits. Moreover, social network analysis of the call graph was shown to significantly improve the quality of the models. We expect future work to confirm these preliminary results and provide a more straight-forward approach for personality assessment than the usual time consuming questionnaire deployment.

Hence, solutions that require the users' personality profile to personalize their interfaces [2, 6, 7, 11, 13] shall become more popular in the next years.

Conclusions and future work

The findings presented herein suggest that variables derived from the users' mobile phone call behavior as captured by call detail records and social network analysis of the call graph can be used to automatically infer the users' personality traits as defined by the Big Five model. The proposed approach is privacy-preserving, easily scales to very large numbers of users, and uses aggregated measures that can be collected by today's mobile phone logging applications. We are currently deploying a large-scale survey in order to obtain enough ground truth data to learn models that would generalize to the entire population of the target country with a smaller margin of error.

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