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Assessing Personality through Objective Behavioral Sensing

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***Abstract*—Traditional personality assessment techniques often rely on subjective report obtained from questionnaires. This work complements traditional techniques by exploring objective measures of traits at the behavior level. We explored behavior features extracted from smartphone sensing data, and used selected features to predict the traits of the Five Factor Model. The specific dataset we explored was the StudentLife dataset. We found behavior features corresponding to each trait, and were able to predict the traits with varying degrees of accuracy. The best result of each trait are: Extraversion (91.2%), Agreeableness (67.6%), Conscientiousness (70.6%), Neuroticism (79.4%), Openness(73.5%). Our results suggest that behavioral measures extracted from smartphone sensing data has potential in the assessment of personality.**

1. Introduction

The study of personality has a long history in psychology. One of the most influential personality theories is the Five Factor Model, commonly referred to as the Big Five [1]. It describes personality under five major dimensions, namely Openness, Conscientiousness, Extraversion, Agreeable, and Neuroticism (OCEAN). The measurement of personality is a central research question in the field of personality psychology. The most common method is self-report instruments (essentially questionnaires). For example, the Big Five Inventory (BFI) [2] asks the extent to which you agree or disagree with statements about oneself such as “a reliable worker”, “outgoing, sociable” .

One drawback of such instruments is that self-report is inherently subjective. It is limited by people’s self-knowledge and colored by their self-perception. Another concern is that there is a gap between these broad abstract statements and specific behaviors grounded in everyday life. There is a lack of objective account at the behavior level. An alternative would be to assess personality in terms of specific, objectively measured behaviors such as whether a person shows up at meetings on time, how often does a person go out to socialize and so on. This alternative complements traditional personality assessment techniques by bridging the gap between subjective high-level abstraction of traits and the low-level embodiment of the traits in real-world behaviors, and therefore would enhance measurement techniques and also contribute to deeper understanding of personality in theory and in practice.

Research in personality has also been undertaken in the affective computing community [3]. Specifically research has looked at the recognition of personality from behavior, the perception of personality and the synthesis of behavior that suggests a virtual agent or robot has a particular personality.

The focus of this work is to explore a method of assessing personality through objectively measured behaviors. To that end, we have been exploring the use of smartphones as a means of deriving objective measures. Mobile devices have become indispensable in our daily life. Smartphones have various sensors, including accelerometer, light sensor, audio sensor, Bluetooth and GPS. The data recorded through those sensors contains information about our behaviors that reflects who we are and how we interact with others and the world around us [4]. For each personality trait there may be corresponding behavior characteristics and patterns that can potentially be inferred from data collected by those sensors. These patterns could then be used to predict traits.

Conversely, we can also view this work from a modeling and behavior prediction stance. If we know the correspondence between someone’s personality as measured by traditional instruments we can develop more accurate, more predictive models of their day-to-day behavior.

The specific dataset we looked at was the StudentLife dataset [5], which contains automated sensing data collected through smartphone and Big Five trait scores of a class of 48 Dartmouth students over a 10-week term. We extracted features about behavior characteristics for each of the Big Five personality trait, and selected the features most relevant to each trait using correlation coefficient. Based on those selected features, we classified subjects into high and low on each trait, and showed the classification accuracies.

2. Five Factor Model

The Five Factor Model has five primary factors - Openness, Conscientiousness, Extraversion, Agreeable, and Neuroticism (OCEAN). Extensive research effort has gone into developing inventories that measure these traits through self-report or peer-report. Commonly used inventories include

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NEO-FFI and NEO PI-R [6], and shorter ones such as Big Five Inventory (BFI) [2] and TIPI [7].

StudentLife used BFI to measure the traits. According to BFI, people who score high on extraversion assess themselves as more "outgoing, sociable, talkative, full of energy and enthusiasm". Agreeable people are "considerate and kind to almost everyone", and "like to cooperate with others". People who score high on conscientiousness are "reliable workers", and more likely to "make plans and follow through with them". People who score high on neuroticism "get easily upset", "worry a lot", and are less likely to "remain calm under tense situations". People with high openness score are more "curious about many different things", more "sophisticated in art, music, or literature" and prefer routine work less.

3. Dataset Description

StudentLife dataset contains comprehensive information about many aspects of students life, including automated sensing data as well as surveys on affect and mental well-being, ecological momentary assessment (EMA) [8] probing mood and stress, and personality survey. In this paper, the focus is on the relation between automated sensing data and personality survey data. Although previous studies on this dataset also analyzed the automated sensing data, their focus was on mental well-being and academic performance. Here we briefly describe the automated sensing data.

- **Wi-Fi Location:** Wi-Fi scanning logs contain the name of the buildings the participants were at while on campus, which is sampled every few seconds.
- **GPS:** GPS coordinates (latitude and longitude) of the participants were recorded every 20 minutes.
- **Bluetooth:** Bluetooth scans about every 10 minutes for surrounding devices, and records the MAC addresses of the detected devices.
- **Activity:** Four types of activity stationary, walking, running, unknown, were inferred from accelerometer stream. One activity label is generated every 2 or 3 seconds.
- **Audio and Conversation:** Audio data are labels of silence, voice, noise, or unknown inferred every 2 or 3 seconds from microphone. Conversation data contain the inferred start time and end time of each independent conversation that the participant is around based on the audio data [1]
- **Class schedule:** It contains the courses each participant was taking for the semester, including the scheduled times and locations.
- **Piazza:** Piazza, a web forum for classroom, was used in the common course the participants were taking. Piazza activity was recorded, including the number of posts they viewed, the number of questions they asked, and so on.

1. We refer readers to [5] for the details of how privacy concerns were addressed by the data collectors.

4. Approach

Our analyses only cover the participants who live on campus, which is 34 out of the total 48 subjects. The main reason for this is that the Wi-Fi data was missing for the commuters when they were off campus, thus limiting our analyses. We considered the possibility of using only the GPS data for the analysis of location, but GPS was collected too infrequently for us to obtain sequential information as well as other useful information such as the time the participants leave home for school, though we used the GPS data for other features. The commuting time also complicates the analyses of Bluetooth and activity data. We inferred whether the participant lives on campus or off campus through analyzing Wi-Fi location data at night.

4.1. Analysis of Trait Variables

We started with the analysis of trait variables. The descriptive statistics for the five traits are provided in Table 1. Agreeableness has a high negative skew. To address the it, agreeableness is log transformed by equation $y = log(K - y)$, where K is the largest score of agreeableness plus one.

Correlations of the traits are provided in Table 2. It shows there is a strong negative between neuroticism and extraversion. Studies have shown that extraversion and neuroticism predispose individuals towards positive and negative affect respectively [9], [10]. However, the relationship between positive and negative affect is complex. Some studies show they are independent [11], while others show they are correlated [12]. Different aspects of affect such as duration, intensity and frequency form the basis for this complexity [13].

TABLE 1. DESCRIPTIVE STATISTICS OF TRAITS

	Mean	Variance	Median	Min	Max	Skew
Extra	2.99	0.57	3.12	1.63	4.50	0.03
Agrbl	3.62	0.36	3.66	1.33	4.56	-1.39
Consc	3.41	0.45	3.44	1.89	4.78	-0.02
Neuro	2.95	0.46	2.88	1.76	4.50	0.25
Openn	3.56	0.26	3.5	2.30	4.60	-0.07

TABLE 2. CORRELATIONS OF TRAITS

	Extra	Agrbl	Consc	Neuro	Openn
Extra	1.0				
Agrbl	0.179	1.0			
Consc	0.057	-0.065	1.0		
Neuro	-0.488	-0.446	-0.305	1.0	
Openn	0.179	0.079	-0.154	0.112	1.0

4.2. Feature Extraction

Our feature extraction process is an exploration inspired and guided by the trait descriptions of the Five

Factor Model. We extracted the features from each source of the automated sensing data, and describe them as follows.

Wi-Fi Location: From Wi-Fi scanning logs, we can infer the sequences of locations each participant has been to every day. Based on the daily location sequences, we computed summary statistics such as the mean and the variance of the sequence length as features. Another feature we extracted from location sequence is based on edit distance or Levenshtein distance [14], which measures the difference between two strings by the minimum number of insertion, deletion or substitution that transform one to the other. We computed average pairwise edit distance of all the daily location sequences of each participant as feature. From daily location sequences we can also infer home location for each participant, which we consider to be the most frequent location they stayed at night. Based on home location, we were able to extract information such as the time each participant leave home for the day (start time) and the time they get home at night (end time). We computed the mean and variance of daily start time and daily end time as features. We additionally computed variance across the same weekdays since students usually have a weekly class schedule.

GPS: Participants GPS coordinates were collected every 20 minutes. Because of the high precision of GPS measurement, one location could correspond to a range of coordinates. We first convert the coordinates to location addresses. Based on the addresses, we can get a histogram or probability distribution of the places each participant visited. We consider the entropy of the distribution as an interesting feature. Entropy is a information theoretic measure of unpredictability. The more evenly distributed the probability, the higher the entropy. Additionally, we computed the area of the smallest rectangle that covers all the GPS coordinates of a participant each day, and use its mean and variance as features.

Bluetooth: Bluetooth scans for nearby devices every 10 minutes, which could belong to friends, family, classmates, or strangers. During the scanning, the unique Mac address (Bluetooth ID) of the each detected device is recorded. We computed the average number of Bluetooth devices detected per day, and per scanning. Since the same Bluetooth ID can appear in many scannings, the probability distribution of unique Bluetooth IDs for each participant is interesting. We computed the entropy of the distribution as a feature. We also computed the average number of unique Bluetooth IDs detected per day. For all those features, we computed them by daytime (9 am to 6 pm), evening (6 pm to 12 am) and night (12 am to 9 am) to have more fine-grained assessment, because different times of the day are usually associated with different activities, for instance, classes only happen at daytime [5].

Activity: The StudentLife dataset also contains inferences about participants physical activity status such as stationary, walking and running. The activity labels were inferred using a decision tree applied on accelerometer stream, and the accuracy of the inference was 94%, see [5]. Since activity inferences are continuously generated and recorded all the time, each participant should have about the same number of days with records, yet we found the number differed much among participants. A possible reason mentioned in [5] is that sometimes participants may leave their phones at home or forget to charge them, and data is removed from the dataset if detecting the phone is stationary or out of power the whole day. Based on this information, we also considered the number of days with recorded activity data as a feature. Additionally, instead of the number of stationary, walking and running labels, we computed the percentage of each activity as features.

Audio and Conversation: The StudentLife dataset also provided inferences about whether the ambient sound was human voice or noise derived by Hidden Markov model (HMM). Those inferences were in turn used as input to infer the start time and end time when a participant is around a conversation. According to the reports [15], [16], the accuracy of audio classifier ranged between 85% and 95%, and the accuracy of conversation detection was approximately 95%. We considered the total conversation duration and average daily conversation duration as features. We also computed the frequency of conversation in daytime, evening and night as features.

Class schedule: Based on the scheduled time and locations of the courses, as well as Wi-Fi location data, we can infer whether the participants actually went to their classes or not, and if they did, whether they were on time or late. Since participants have different classes, we computed the percentage of the missed classes and late arrival as features. We also consider the mean and variance of the late time as features.

Piazza: Piazza is a web forum where professors could post announcements and students ask questions. The topics are often about homework assignments and related resources. The information we interested in is the number of days the student logged in the class page, the number of posts viewed, the number of questions asked and the number of questions answered.

Frequent sequential patterns from Wi-Fi Location data: Among all the automated sensing data in the StudentLife dataset, Wi-Fi location data is especially interesting, since it contains sequential information that can be utilized by specialized algorithms that model frequently occurring ordered events or subsequences as patterns. Frequent location subsequences may differentiate behavior characteristics of people. For example, students who have higher frequency of the subsequence "classroom, library" may be more conscientious. We applied Generalized Sequential Pattern (GSP) algorithm [17] on Wi-FI location data to obtain frequent occurring location subsequences, and use their frequencies as features. We extracted 36 frequent subsequences as features.

All the features explored are summarized in Table 9 in the Appendix section.

4.3. Feature Selection

We extracted various behavior characteristics from the automated sensing data to use in the prediction of each trait. Due to the small sample size of the StudentLife dataset, we chose only the most relevant features for each trait to avoid overfitting. Also, by focusing on the features with significant correlations, we hoped to better illuminate the relationship between behavior characteristics and personality traits. Therefore, we apply feature selection as a preprocessing step before prediction. Feature selection methods can be grouped into three categories - filter method, wrapper method and embedded method [18]. We chose to use the filter method for it selects variables based on a generic measure regardless of the model. Commonly used measures include correlation coefficient and mutual information. Mutual information is more suitable for discrete or nominal variables [18], and requires more samples for accurate estimation. Therefore, we use Pearson correlation coefficient to select the features most relevant to each trait (p-value <0.05). We group the significant correlations by trait, as shown in Table 3 - 7. However, due to the post hoc nature of this analysis, these correlations are not being used here to test explicit hypotheses. Rather the goals are to provide a basis for selecting features for the classification of personality as discussed in Section 4.4, as well as suggest possible avenues of exploration for future testing of behavioral measures of personality.

TABLE 3. EXTRAVERSION

Feature	Correlation	p-value
Variance of daily location sequence length	0.466	0.005
Variance of location sequence length Monday	0.386	0.024
Average daily end time	-0.667	0.000
Variance of daily end time	0.503	0.002
Variance of end time Wednesday	0.450	0.008
Variance of end time Friday	0.354	0.040
Average edit dist of daily location sequence	0.425	0.012
Average daily GPS area	0.396	0.020
Average daily Bluetooth IDs daytime	0.377	0.031
Num of days with activity	-0.376	0.029
Frequence of pattern 53commons,sudikoff	0.341	0.048
Frequence of pattern occum	0.547	0.001

TABLE 4. AGREEABLE

Feature	Correlation	p-value
Variance of start time Monday	-0.339	0.050
Variance of end time Wednesday	0.331	0.056
Total Bluetooth IDs	-0.386	0.024
Average Bluetooth ID per scanning	-0.340	0.049

TABLE 5. CONSCIENTIOUSNESS

Feature	Correlation	p-value
Daily start time variance	-0.389	0.023
Bluetooth IDs entropy daytime	0.387	0.026
Piazza questions	0.375	0.029
Frequency of pattern baker-berry,kemeny	0.408	0.017
Frequency of pattern lsb,baker-berry,kemeny	0.402	0.018

TABLE 6. NEUROTICISM

Feature	Correlation	p-value
Variance of location sequence length Monday	-0.485	0.004
Variance of start time Monday	-0.346	0.045
Average daily end time	0.487	0.003
Variance of daily end time	-0.471	0.005
Varience of end time Wednesday	-0.569	0.000
Average edit distance of daily location sequence	-0.358	0.038
Average Daily Bluetooth IDs daytime	-0.429	0.013
Frequency of pattern 53commons,sudikoff	-0.391	0.022
Frequency of pattern occum	-0.480	0.004

TABLE 7. OPENNNESS

Feature	Correlation	p-value
Variance of location sequence length Thursday	-0.343	0.047
Average Daily Bluetooth IDs evening	-0.346	0.049
Frequency of pattern sport-venues	-0.407	0.017

In table 3, extraversion is shown to have strong positive correlation with the variance of daily location sequence length, as well as the mean and variance of daily end time. One possible interpretation is that extraverted people may go out more to different places for various activities. This interpretation is in line with the findings of Panonen et al [19] that extraversion is positively correlated with the self reported behavior of parties attended, dating variety, and sports participation. The positive correlation between average Bluetooth IDs in daytime and extraversion is also interesting, which suggests there were more people around the extroverts. A possible interpretation is extraverted people engage in more social activities than introverted people, as supported by many studies [20]–[22]. Although alternative explanations are possible for the larger average number of Bluetooth IDs. For example, they may stay in the library alone with many strangers nearby without socializing with them. In other words, we need to be cautious in drawing conclusions, especially because of the post hoc nature of the analysis.

In addition, there is a negative correlation between total Bluetooth IDs detected and agreeableness. Although we don't have an interpretation for it, Chittaranjan et al. also found the same negative correlation between Bluetooth IDs and agreeableness [23].

Conscientiousness is shown to be negatively correlated with the variance of daily start time. A likely explanation is that small variance of daily start time may be the result of a rigid schedule that requires high self-discipline, which is a facet of conscientiousness [2]. Additionally, the number of questions asked on Piazza has a positive correlation with conscientiousness. This correlation is not surprising, considering numerous studies has shown that conscientiousness is a strong predictor of academic performance such as grades [24]–[26], and class grade is positively correlated with Piazza usage in our dataset [5]. There were also studies show that conscientiousness is a predictor of punctuality [27], but no significant correlation was found between conscientiousness and the percentage of late arrival and missed classes in our dataset.

Most of the features significantly correlated with neuroticism are also significantly correlated with extraversion in the opposite direction. This may be explained by the fact that extraversion and neuroticism are negatively correlated in the dataset.

Only three features were found to be significantly correlated to openness. One possible reason is that openness has the smallest variance among all traits. Moreover, openness is associated with intellectual curiosity and artistic sophistication in BFI, and therefore is more likely to be reflected in cognitive patterns and only more indirectly through behavior patterns.

The results of frequent patterns are also interesting, especially after taking into consideration the function of the buildings using the Dartmouth Campus Map [28]. For example, extraversion is correlated with the frequent pattern “53commons;sudikoff” where “53commons” is the center of dining at Dartmouth and “sudikoff” is the lab of computer science department. Also, the frequent patterns correlated with conscientiousness all contain “baker-berry” along with other academic buildings. “baker-berry” is the library at Dartmouth.

4.4. Classification

After feature selection, we explored the prediction of traits using those features. In order to discriminate the higher and lower end of each trait, we defined a binary classification task by splitting the trait by median. Only features found to be significantly correlated with the trait were used in the model in order to avoid overfitting. Accuracy was evaluated by leave-one-subject-out cross-validation. Majority classification was used as baseline. We explored several classification algorithms, including logistic regression, Support Vector Machine (SVM), decision tree and boosting. For logistic regression, we experimented with L1 and L2 regularization. For SVM we experimented with different kernels including RBF, linear and polynomial. There wasn’t a classifier that performed best across all traits. SVM performed best on extraversion. SVM and logistic regression performed equally well on conscientiousness and neuroticism, while AdaBoosting classified openness and agreeableness best. Extraversion was classified with 91.2% accuracy, which was the highest of all traits. Neuroticism was classified with 79.4% accuracy, also outperforming baseline by a large margin. This is in line with past research that extraversion and neuroticism are better predicted than the other traits [29]. Agreeableness was classified with the lowest accuracy among all the traits.

TABLE 8. CLASSIFICATION RESULT

Trait	Baseline	Logistic Reg	SVM	AdaBoost
Extra	50.0%	82.4%	**91.2%**	85.3%
Agrbl	50.0%	64.7%	64.7%	**67.6%**
Consc	50.0%	**70.6%**	**70.6%**	67.6%
Neuro	50.0%	**79.4%**	**79.4%**	76.5%
Openn	52.9%	67.6%	70.6%	**73.5%**

5. Related Work

There has been several works that investigate the prediction of personality using smartphone data. Butt and Phillips conducted a study that asks participants questions about their smartphone usage, such as the average time they spend on phone calls and text messages [30]. In contrast, our work uses automated sensing to collect the data, which is more reliable than self report. Other work also used automated data collected through smartphones [23], [29], [31], [32]. In terms of the information collected, all the work used call logs and SMS logs. Staiano el al. extracted social network characteristics from Bluetooth logs [32]. Chittaranjan et al. [23] used Bluetooth logs as well as App logs.

We explored a rich dataset that has sensing data from Wi-Fi, GPS, Bluetooth, accelerometer as well as website data such as Piazza. Specifically, the use of Wi-Fi location data for personality prediction is unique to this study. Significant correlations were found between behavior features extracted from Wi-Fi location data and traits. For example, the mean and variance of daily end time both have a strong positive correlation with extraversion and a strong negative correlation with neuroticism. We also explored frequent sequential pattern mining algorithms on the Wi-Fi location sequences, and found interesting subsequence patterns that contributed to the prediction of the traits.

Considering the broader problem of predicting personality from behavioral measurements, there has been works that use data sources other than smartphones, including text, nonverbal communication, social media and computer games (see [3] for a comprehensive review). Studies that seek to predict personality using social media data such as Facebook likes [33], [34] and Twitter profiles [35], [36] had promising results.

Across all the related work, behavioral measurements extracted from various data sources show much potential in the assessment of personality.

6. Discussion

Our analysis identified behavior patterns correlated with each trait of the Five Factor Model. Notably, we found strong behavior features for extraversion, including the variance of daily location sequence length, the variance of daily end time, and the number of Bluetooth IDs detected during daytime. Using those features, extraversion was classified with 91.2% accuracy.

Nevertheless, there are limitations in the current work that need to be addressed. First, the sample size is small, and confined to students who chose the same computer science course. Dartmouth campus is located in Hanover, New Hampshire, a small town where students may not have many choices of activity. Considering these factors, the result of our study may not generalize to a larger population in a different setting. In addition, automated sensing can capture certain behavior patterns, but some aspects of personality traits like openness may be more reflected in cognitive patterns not easily measurable through behaviors, in contrast to extraversion which had many correlated behavior measures.

Going forward, we intend to address these limitations. To test the stableness and validity of the behavior features and the prediction model, we plan to collect more smartphone data on a larger sample in an urban setting using a more diverse population. We also plan to incorporate data from other sources such as social media increase the scope of behavior features.

Appendix

TABLE 9. FEATURES

Wi-Fi location data:
Average daily location sequence length
Average daily start time
Average daily end time
Variance of location sequence length (daily, and by each weekday)
Variance of start time (daily, and by each weekday)
Variance of end time (daily, and by each weekday)
Average edit distance of daily location sequence
Frequent sequential patterns
GPS:
Entropy of location distribution
Average daily GPS area
Bluetooth:
Average daily Bluetooth IDs (daytime, evening, night)
Average daily unique Bluetooth IDs (daytime, evening, night)
Entropy of Bluetooth ID distribution (daytime, evening, night)
Activity:
Percentage of stationary
Percentage of walking
Percentage of running
Number of days with activity
Conversation:
Total conversation duration
Average daily conversation duration
Conversation frequency (daytime, evening, night)
Class schedule:
Percentage of missed class
Percentage of late arrival of class
Average late time
Variance of late time
Piazza:
Number of days logged in the class page
Number of posts viewed
Number of questions asked
Number of questions answered

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