You are How You Behave in Your Group: Predicting Personality via Behaviors in a Co-located Group

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ABSTRACT

In co-located groups, common in most companies and organizations, members frequently interact with each other for better group performance and collaboration. Diversity in personality within a co-located group can both positively and negatively impact interactions between the group members. Therefore, to better understand the compositions of the group members' personality and utilize it, many companies and organizations operated by co-located groups utilize personality questionnaires. While self-assessment is widely used to detect personality, it is prone to bias due to self-reporting. Hence, automatic personality assessment (APA), which infers personality by analyzing a person's behavioral data, is on the rise. However, existing APA systems do not take into account the fact that a person's behaviors displayed in a group may differ from their behaviors outside the group. To fill this gap, we present a system that automatically detects the user's personality in a co-located group by analyzing their *group-specific behavioral data* both online and offline: user's online messenger and web/app usage, and offline location and movement. Using data from four co-located groups (n=32) collected for three weeks, our model predicts the Big Five personality traits up to 81.3%. We discuss the possible applications of utilizing the diversity among the detected personality in a co-located group along with the challenges.

KEYWORDS
Personality; APA; Co-located group

Research Area of Seoyoung Kim
Social computing, Computer-mediated communication, Human behavior data analysis

Online Messenger Usage Data

- Collected public channel logs excluding text content at all times
- Using a group messenger (Slack)

Online Web/App Usage Data

- Collected timestamp of access, time spent, and category of web/app on weekdays only inside the co-located space
- Using RescueTime

Offline Location Data

- Collected timestamp and location inside the lab in (x, y) on weekdays only inside the co-located space
- Using BLE beacons and smartwatch

Offline Movement Data

- Collected step counts and timestamps of detected steps on weekdays only inside the co-located space
- Using a smartwatch

Sidebar 1: Summary of collected data.

INTRODUCTION

Co-located groups, where all members work in the same physical location (e.g., workplaces and academic labs), have been prevalent for centuries. Sharing physical space provides an apposite environment for the group members to interact with each other. Diversity in personality plays an important role when members interact with each other. Differences in personality can enable the group members to complement each other, while similarity in personality can lead to concord in opinions. Understanding the similarities and differences in personality within a group can be helpful in resolving conflicts and understanding each other better. Therefore, to better understand the personality composition within the group, personality assessments are widely used in co-located group settings [9]. In fact, one of the biggest consumers of personality tests is organizations [2] and 88% of the Fortune 500 companies have utilized a personality test [3].

Two of the most widely used personality assessment methods are self-assessment and automatic personality assessment (APA). Self-assessment (e.g., Myers-Briggs, International Personality Item Pool (IPIP)) are widely used due to the ease of applicability and low cost of implementation. However, these questionnaires suffer from a self-report bias in the results, due to selective reporting or distorted recall of past events [8]. On the other hand, automatic personality assessment (APA) tries to overcome these shortcomings by predicting user's personality based on analysis of their behavioral data (e.g., mobile phone logs [4], social media profiles [5]). However, most existing APA systems rely on continuous tracking without considering the group context, even though personality results from APA systems that rely on group-specific behaviors—behaviors displayed within the group—can be different from systems which use behavioral data from non-group-specific contexts. For example, a person naturally gregarious, loud, and outgoing may not display these behaviors at work where these can be considered as inappropriate in some cultures.

To this end, we present a system that automatically detects personality of members in the group by analyzing various *group-specific behavioral data streams*. For more comprehensive personality detection, the system leverages both online and offline group-specific behaviors, i.e., user's online messenger usage, online web/app usage, offline location, and offline movement that are displayed in a group context, as earlier work suggests that people's behavior varies from online and offline environments [1, 7]. From the collected behavioral data, we extracted 41 behavioral features, which are utilized to predict the Big Five personality traits [6]. Our model can predict one's personality in the co-located group up to 81.3% of accuracy and 71.4% of F_1 macro score as shown in Figure 1, with 32 participants' IPIP personality test results as ground truth.

SYSTEM

In this section, we introduce an APA system that automatically detects personality by analyzing group-specific behavioral data. For more comprehensive personality detection, the system leverages both online and offline group-specific behaviors. Our system design involves two phases: data collection and model building. In the data collection phase, data is collected from four online and offline data streams: online messenger usage data, online web/app usage data, offline location data, and offline movement data as in Sidebar 1. We recruited 32 participants (19% female, mean age = 26.7, S.D. = 3.7) from four different research groups (consisting of five, seven, nine, and eleven participants respectively from each group) in the college of engineering at a large technical university in Korea for a three-week-long data collection for our system. Although the four groups were all academic labs in Korea, they varied in their culture, social dynamics, and space utilization. During three weeks, we collected total 2,690 online messenger activity logs (e.g., chats, reactions), and an average of 27.0 hours of online web/app usage with 47.8 hours of offline location and movement data per person. For the ground truth personality data, we also asked each participant to take IPIP [6] consisting of 100 short questions in the context of their lab to measure Big Five personality traits (i.e. openness, conscientiousness, extraversion, agreeableness, neuroticism) [2]. With the questionnaire result, we classified participants into three levels of each personality trait by defining the middle class as those defined with scores within one SD from the mean. This is done because bias in self-reporting can lead to small score difference within the same class.

In the model building phase, we extracted 19 online and 22 offline behavioral features from the collected data streams as shown in Table 2. We then post-processed all behavior features by standardizing each user's behavior relative to one's own group to prevent the difference in the group culture from influencing the users' detected personality. For instance, one group reacted a lot to others' messages in online messenger logs, while another group barely gave any reactions.

Finally, we built an APA model using the processed behavioral features to classify a user into one of the three levels of classes (i.e., low, medium, and high) for each of the Big Five Personality traits. We ran Leave-One-Out Cross-Validation and oversampled small-numbered-classes to balance out the classes with SMOTE algorithm. We oversampled using only the training dataset for every 10-fold cross validation. To prevent overfitting, we performed feature selection before oversampling the training set. Lastly, we selected the best model for each personality trait since each personality trait has different characteristics: we selected among a range of classification algorithms (Linear SVC, Gaussian Process Classifier, Decision Tree Classifier, Random Forest Classifier, and Gaussian NB). The best predicted personality trait is openness (accuracy: 81.3%, F_1 macro score: 71.4%) while the worst predicted personality trait is extraversion (accuracy: 81.3%, F_1 macro score: 46.4%) as in Figure 1.

Online Behaviors

- Using (1) social-related web/app, (2) group-specific-social web/app, and (3) Slack
- Accessing (1) social-related web/app and (2) group-specific-social web/app
- Initiating a conversation on (1) any Slack channel and (2) only Slack channels including everyone
- Sending / not sending a text message on (1) any Slack channel, (2) only Slack channels including everyone
- Replying to others on (1) any Slack channel, (2) only Slack channels including everyone
- Reacting to others on (1) any Slack channels, (2) only Slack channels including everyone

Offline Behaviors

- Staying / not staying at one's seat
- Staying in a common area
- Going to common area
- Staying together with other group members at other than one's own seat
- Staying together with other group members in a common area
- Arriving at the lab
- Walking / not walking

Sidebar 2: List of group-specific behaviors that were analyzed for predicting personality.

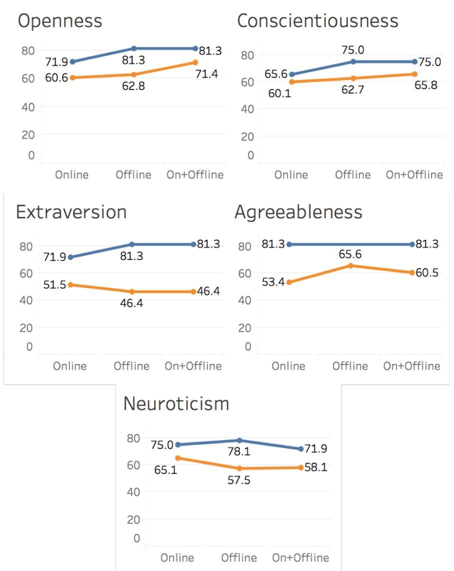

Figure 1: Personality prediction results of our system using online data only, offline data only, and both online and offline data. Blue line indicates accuracy, while orange line indicates F_1 macro score.

FUTURE WORK AND CHALLENGES IN UTILIZING DIVERSITY IN PERSONALITY

Diversity in personality can be beneficial when group members can complement each other. Groups formed with diverse personalities can compensate each others' weaknesses and increase balance in the group, thus improving productivity in the workplace. On the other hand, similarity in personality can be desirable in other times; homogeneous members can easily become intimate and avoid unwanted conflicts. Previous research has investigated the correlation between diversity in personality with various group factors (e.g., variance in extraversion leads to improved group performance) [2]. With the correlations, it is possible to algorithmically utilize the diversity in personality within a group. Team formations within the group can be algorithmically suggested considering the variance in extraversion for better group performance. Furthermore, integrated with group messengers, detected personality can be utilized to enhance informal communication: recommending extroverts to initiate a conversation with introverts or nudging introverts to actively participate in group chats. However, despite the possibilities of utilizing diversity in personality, there exist challenges in utilizing personality information of group members in practice. Even though personality influences a lot in how one behaves, there exists other variables determining one's future behavior. For example, one might not want to talk a lot due to their availability, current mood, and other social factors, despite being an extrovert. Therefore, for future work, a careful investigation is needed to understand how to utilize diversity in personality within a co-located group.

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