Detecting Personality Unobtrusively from Users' Online and Offline Workplace Behaviors

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Abstract
Personality affects various social behaviors of an individual, such as collaboration, group dynamics, and social relationships within the workplace. However, existing methods for assessing personality have shortcomings: self-assessed methods are cumbersome due to repeated assessment and erroneous due to a self-report bias. On the other hand, automatic, data-driven personality detection raises privacy concerns due to a need for excessive personal data. We present an unobtrusive method for detecting personality within the workplace that combines a user's online and offline behaviors. We report insights from analyzing data collected from four different workplaces with 37 participants, which shows that complementing online and offline data allows a more complete reflection of an individual's personality. We also present possible applications of unobtrusive personality detection in the workplace.

Author Keywords
Personality detection; Automatic personality assessment; Behavior observation; Large-scale data; Personality-based balancing

ACM Classification Keywords
H.5.m [Information interfaces and presentation (e.g., HCI)]: Miscellaneous

Extracted online components
Joined date
Message sent time
Reply
Reaction to message

Extracted offline components
Total time spent inside the lab
Total time spent at one's seat
Number of times visiting the common area
Number of times going in and out of the office

Table 1: Extracted online and offline components to calculate behavior features.

Introduction

Personality affects various workplace social behaviors of an individual. The presence of extroverted members enhances collaboration within a team, as extraversion is known to be a helping behavior in challenging conditions [8]. Personality also affects an individual's placement in a group: one's role within a team, interaction with the rest of the team, and agreeableness with team values [10]. Further, personality traits such as extraversion, sociability, and shyness affect the growth of peer networks [1].

However, detecting personality is often difficult. Self-assessed personality is prone to self-report biases arising from incorrect recall, estimation, or reports on self-behaviors [11]. Additionally, research suggests that an individual's personality changes over time [2], and updating personality data with periodic self-assessed measurements may burden users. Due to these shortcomings, ambient personality assessment based on automatic analysis of individual behaviors can be a promising way of assessing personality in the field. Pentland's Phone-based Metrics [4] is one example of ambient personality evaluation, in which personality was reliably predicted from standard mobile phone logs with up to 61% accuracy on three levels of extraversion. However, the main challenge in assessing personality through observing behaviors has been related to privacy [11]. Collecting personal behavior data from everyday life could be obtrusive. Therefore, we propose a new approach to detect an individual's personality by periodically analyzing one's activity patterns without the actual contents, gathered only inside the workplace without invading outside-work personal data.

Further, individuals of different personality types prefer online to offline channels and vice versa when interacting with others [5]. Detecting personality by analyzing behaviors from a single channel could be erroneous as the data may only partially reflect individual behaviors. Therefore, we analyze both online and offline behaviors to better detect individual's personality.

Extraversion, a dimension in the Big Five Personality traits [6], is positively related with being talkative, verbal, and sociable. Among several personality dimensions, extraversion is an indicative trait of collaboration within a workplace [8].

In this paper, we present an unobtrusive method of detecting personality, specifically extraversion, within the workplace from online and offline behavioral data: online messenger logs without message content, and location changes inside the workplace. We investigate several online and offline behavior features and present results of personality detection. We also present future applications of using detected personality in the workplace.

Using Online Data to Categorize Personality

Our analysis of online data is based on logs from Slack, an online messenger platform (https://slack.com). We collected chat logs in the workplace over 5 months from 4 different research groups at KAIST, consisting of total 37 users (72% male, mean age = 27.3, S.D. = 3.4). To capture the participants' natural usage of Slack, we have not given them any constraints or instructions while using Slack. We collected only the logs from public channels, excluding logs from private channels and direct messages, which are often used for more private conversations.

Moreover, even though there has been much work predicting personality based on written text content [7], we excluded the message content itself for privacy reasons as in Table 1. Instead, we found four different behaviors that can be extracted only from metadata of message logs as seen in Figure 1: initiating a conversation, replying to others, reacting to others, and sending a text message. We defined

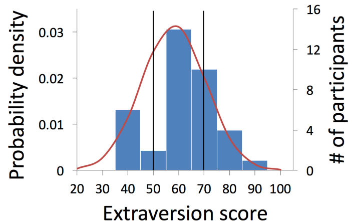

Figure 2: The distribution of participants' extraversion score. Two black vertical lines indicate thresholds for determining three classes of extraversion.

	Introvert	Ambivert	Extrovert
Introvert	4	4	0
Ambivert	2	18	2
Extrovert	0	4	3

Figure 3: Confusion matrix of personality detection using online behavior data. The ground truths are listed in the rows while the detected personality classes are listed in the columns.

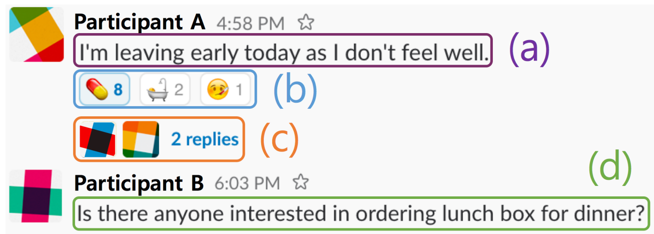

Figure 1: An example of 4 different social interaction behaviors found in Slack. (a), (c), (d): Sending a text message, (b): Reacting to others, (c): Replying to others, (d): Initiating a conversation

initiating a conversation as sending a new message in a public channel with no messages in the past 1 hour. For the behavior of replying and reacting to others, we utilized Slack's features of replying in a thread and adding reactions with emojis to others' messages, respectively. Lastly, we defined the behavior of sending a text message as sending a message or reply. This includes the behavior of initiating a conversation and replying to others, and also sending a message that is sent within 1 hour from a previous message. These behaviors, even without the message content itself, aligns with expressiveness among the Communication Styles Inventory factors, which show highest correlation with extraversion [9].

For each user, we extracted the number of times they exhibited these behaviors. Since each workplace has a different duration of Slack usage and users joining the group at different points in time, we calculated the frequency of exhibiting the behaviors by taking into account individual's tenure inside their Slack workplace. Although the Slack API does not provide individual's Slack usage period, we have calculated the amount of days they have spent after they have joined the group. In addition, since we did not constrain their usage of Slack in any way, every workplace had

	Initiating a conversation	Replying to others	Reacting to others	Sending a text message
Introvert	-0.284 (SD: 0.830)	-0.092 (SD: 1.017)	-0.355 (SD: 1.274)	-0.445 (SD: 0.761)
Ambivert	-0.129 (SD: 0.701)	0.095 (SD: 1.074)	-0.014 (SD: 0.795)	-0.147 (SD: 0.632)
Extrovert	0.730 (SD: 1.639)	-0.192 (SD: 0.817)	0.449 (SD: 1.221)	0.972 (SD: 1.576)

Figure 4: Average and standard deviation of z-scores for 4 different behaviors for each extraversion class

their own distinctive manner of using Slack. For example, in one of the workplaces that we have gathered data from, there was no case of adding reaction to messages, while in another workplace, users frequently added multiple emojis to a message. To prevent each workplace's custom Slack usage practice from influencing users' detected personality, we standardized each user behavior relative to one's own workplace so that every behavior feature in each workplace has a mean of 0 and standard deviation of 1.

To obtain ground truth scores of each user's personality, participants were asked to complete a self-assessment that measures extraversion. We used a validated 20-item set of IPIP Big-Five Factor Markers [6]. From this test, we were able to get participants' numerical value of extraversion ranging from 20 to 100. As shown in Figure 2, participants' personality scores followed a normal distribution (Anderson-Darling normality test: A = 0.494, p = 0.2030) which is consistent with previous research [4].

To identify the relationship between each behavior feature and one's personality, we chose to use support vector regression with a linear kernel with 10-fold cross validation. We then clustered the result into three classes. Through the generated personality categorization model, we were able to classify the users into three classes of extraversion with an accuracy of 67.5% as in Figure 3. According to the generated personality categorization model, initiating a conversation, reacting to others, and sending a text message to others were shown to have positive correlations with extraversion, while replying to others were shown to have a negative correlation, as in Figure 4. This aligns well with previous research of introverts being less expressive while they are communicating with others [9]. Introverts might prefer not to give unwanted notifications to channel members who are not in the same discussion and therefore reply in threads, whereas extroverts might care less about this feature and continue directly messaging in the channel.

Using Offline Data to Categorize Personality

Even though we were able to predict users' personality up to some degree only with online data, we wanted to improve the quality of personality detection by considering offline data as well, due to their complementary characteristics. As introverts relatively prefer online channels to offline channels for interacting with others than extroverts [5], analyzing online channel behaviors only can result in detecting an introvert to be expressive, which highly correlates with one being an extrovert [9]. Therefore, we analyze both online and offline channels to increase the detection accuracy. Although there have been other studies that utilized sensor tags [3] to record social interactions in a physical space, we investigated a novel way of detecting personality from users' movements inside an office, which is an indirect way of measuring social interactions. Among many different kinds of offline data, we assumed that from one's trace inside the workplace we can extract several behaviors that can give insights into deducing one's extraversion. From one's location inside a workplace, we are able to know whether the user goes to another colleague's seat or stays in common areas, which can signify social interaction. Frequent changes of location increase the opportunity to bump into other colleagues or give visual cues for others to easily initiate a conversation.

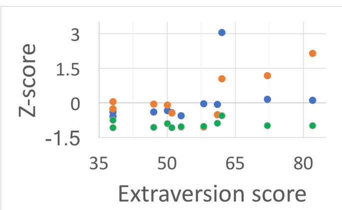

Figure 5: Distribution of extracted offline features, where orange instances indicate ratio of visiting common area, blue instances indicate ratio of passing workplace door, green instances indicate ratio of time spent at one's seat. It can be seen that visiting common area and passing workplace door have positive correlations with extraversion, whereas time spent at one's seat does not show significant correlation.

Before we collect the indoor location data in large scale, we first wanted to test our assumption that we can detect personality from movement traces inside the workplace. We video-recorded one research group's office space at KAIST with 12 members present during recording, who also participated in providing online data, for 4.5 hours on a day in January 2018. Nineteen people work in the 83.8m^2 space, with one common area with a couch and a table with a coffee machine. We also observed people using the table space right outside the office as a place to chat. From the video, we manually tagged each user's location over time. Extracted offline components are shown in Table 1. With the tagged data, we calculated the number of times each user visited the common area and the number of times each user entered and exited the office space relative to the amount of time the user stayed in the office. We also extracted the ratio of an individual's total time in one's seat over the time spent inside the office.

From the tagged data, we were able to confirm the possibility of detecting personality indirectly from one's movement. Extroverts tend to go to the common area and entered and exited the office more frequently, while the ratio of time spent at one's seat did not show correlations with extraversion as shown in Figure 5. Tagged data shows results that are complementary to the previous online results of categorizing extraversion. P6, an introvert who was misclassified as an ambivert through online data, showed to be less frequently moving around than others in the workplace (Z-score of passing workplace door ratio: -0.581, Z-score of visiting common area ratio: -0.248). On the contrary, P14, who was less active on Slack compared to those with similar extraversion scores, often roamed around the office visiting the common area (Z-score of passing workplace door ratio: 0.117, Z-score of visiting common area ratio: 2.160), increasing the chance of having a conversation with others.

However, there also were cases where offline data did not represent one's personality better than online data. P13, an introvert, had visited the common area often, relative to those with similar personality scores (Z-score of passing workplace door ratio: -0.384, Z-score of visiting common area ratio: 0.057). Despite the frequent visits, he interacted with others less, but this was not captured from the user's indoor location data. Instead, he was correctly classified as an introvert from online data analysis. In addition, since we have only analyzed offline data for a short time, we also encountered special cases. For example, P34 just came inside the office to collaborate with others and worked alone in a space outside on the recorded day, making his offline data features highly contributing to detected extraversion score (Z-score of passing workplace door ratio: 3.063, Z-score of visiting common area ratio: 1.052). We predict the data to be more reliable if it is collected in long-term.

In future studies, we will collect users' location data inside the workplace automatically by equipping the workplace with beacons. Using beacons, we can calculate users' indoor location using Bluetooth Low Energy (BLE) signals from their phone unobtrusively. With collected data, we will explore other psychologically relevant offline features as well. We also plan to collect data from other workplaces to confirm that the investigated offline features highly correlate with extraversion in workplaces with different customs. Further, we plan on addressing temporal and spatial dynamics of personality and its resulting behavior. As research suggests that an individual's personality changes over time [2], we plan on addressing this temporal dynamics of personality by conducting personality tests periodically to obtain updated ground truths and compare them with the change of personality test results over time. We plan on exploring the spatial dynamics of personality and possible organizational bias by collecting data from more organizations. With more large-scale and long-term offline and online data combined, we expect to develop a better detection model that yields accurate personality classification results.

Possible Applications

Automatically detected personality can be utilized in various ways in the workplace. We present some of the directions for future applications that could benefit from this technique.

Personality-aware mediator bot for managing informal communication: Personality can inform one's preference on communication styles [9]. Research shows introverts, compared to extroverts, feel that they are less able to express themselves offline than online [9]. With the detected personality from a team, an informal communication mediator may assist communication between team members with different communication styles. For example, the mediator bot could take into account different preferred channels for initiating communication or interacting, and suggest an online or offline channel of their preference to make communication less burdensome.

Assisting balanced workplace communication via real-time feedback: Introverts and extroverts have different communication styles, one of which suggests that introverts are less likely to initiate a conversation than extroverts [9]. With understandings of personalities within a team, we can naturally promote a balanced conversation within a team by suggesting an extrovert to initiate a conversation with an introvert with relatively less recent team communication. Likewise, knowledge of an individual's personality can allow real-time feedback between people of opposite personalities, mutually complementing different communication styles for enhanced communication in the workplace.

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