석 사 학 위 논 문
Master's Thesis

온라인 및 오프라인 행동 분석을 통한 직장 내 자동 성격 검출

Automatic Workplace Personality Detection
from Online and Offline Behavior Analysis

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한 국 과 학 기 술 원

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Automatic Workplace Personality Detection from Online and Offline Behavior Analysis

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Approved by

Juho Kim
Professor of School of Computing

The study was conducted in accordance with Code of Research Ethics[1].

[1] Declaration of Ethical Conduct in Research: I, as a graduate student of Korea Advanced Institute of Science and Technology, hereby declare that I have not committed any act that may damage the credibility of my research. This includes, but is not limited to, falsification, thesis written by someone else, distortion of research findings, and plagiarism. I confirm that my thesis contains honest conclusions based on my own careful research under the guidance of my advisor.

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초 록

그룹 내 개개인의 성격을 아는 것은 협업에 도움이 되고 불필요한 갈등을 피할 수 있다. 이러한 이유로 많은 기업들은 직원들을 트레이닝 하거나 특정 업무에 맞는 직원을 선별해내기 위해 성격 테스트를 활용한다. 그러나 널리 사용되는 자가 성격 평가 방법은 1) 자가 보고시 발생 가능한 편견 2) 사용자가 성격 검사를 수행하는데 있어서의 부담이 있어 제한적이다. 이에 따라 최근에 제시되는 사람의 행동이나 데이터를 분석하거나 관찰함으로써 성격을 탐지해내는 방법은 많은 양의 개인 데이터를 필요로하며, 이로 인해 개인 정보 문제가 야기되거나 사용자에게 특정 작업을 수행하도록 요구하여 평소의 행동을 분석하지 못 한다. 본 논문에서는 사생활 침해 문제를 고려하여 직장과 관련된 온라인 메신저 사용 데이터, 온라인 웹/앱 사용 데이터, 오프라인 위치 데이터 및 오프라인 움직임 데이터로 한정하여 분석하여 성격을 자동으로 탐지하는 시스템을 제시한다. 실험 결과 데이터 수집시 사생활이 고려되어도 정확도 87.1%, 거시 평균 F_1 점수 84.0% 까지 직장 내 성격이 탐지된다는 것을 보인다.

핵 심 낱 말 자동 성격 검출, 직장 내 성격, 직장 내 행동, 사생활, 빅데이터

Abstract

Knowing individual personalities within a group can be beneficial for collaboration and avoiding unnecessary conflicts. For this reason, companies utilize personality tests for evaluating best-fit candidates rather than going through resource-heavy evaluation procedures. However, widely used form of personality self-assessment methods are erroneous due to two reasons 1) self-reporting bias 2) burden of taking the personality test for users. Moreover, state-of-the-art methods of detecting personality through analyzing or observing the person's behavior or data require a vast amount of personal data, which can lead to privacy issues, or require users to do specific tasks which makes it hard to capture their natural behaviors. In this paper, we present a system that detects personality unobtrusively by analyzing workplace data, such as online messenger usage data, online web/app usage data, offline location data and offline movement behaviors inside workplace. Results shows that workplace personality can be predicted up to 87.1% with F_1 macro score of 84.0% even when privacy is preserved during the data collection.

Keywords Automatic personality assessment, privacy, workplace personality, workplace behaviors and large-scale data

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Chapter 1. Introduction

Personality has a deep impact in all aspects of human life that includes individual's emotions, his or her professional choices, workplace behavior, attitude, performance motivations and innovation [1, 2]. Research on personality assessment has been gaining momentum in recent years [11]. Personality assessments have made easier for the organization to operate efficiently in the areas like employee engagement, performance analysis, employee role identification and making collaborations which all can boost the productivity [3].

Traditionally, questionnaires on Big Five taxonomy of personality and Myers-Briggs Type Indicator (MBTI) have been used for personality assessments in various workplaces to ask each users to mark the items or adjectives that closely describe oneself [3]. 80% out of Fortune 500 and 89 out of Fortune 100 reported that they use Myers-Briggs Type Indicator personality test [4]. However, these self-assessed personality questionnaires suffer limitations such as: (i) self-report bias in the results due to selective reporting and distorted recall of past events, lack of awareness and social desirability [5], (ii) one has to go through the test again on temporal basis as his or her personality changes over time [6]. A more recent trend of assessing personality is automatic personality assessment (APA), such as analysis of mobile phone, social media or Internet browser usage of an individual [16] [17] [18]. These methods suggest that user's behavior data can indicate his or her personality. However, many studies of APA to date have focused on investigating either online or offline channel for personality detection, despite the difference in online to offline personality [7]. Further, many were inapplicable for field application due to privacy concerns arising from sharing excessive amount of personal data.

This paper complements and further extends these studies by analyzing both channels of online and offline behaviors at the same time, while collecting only workplace data to minimize privacy concerns. In order to automatically assess personality from online and offline data without being privacy-wise intrusive, we investigate the privacy issues by (i) carefully choosing data streams that would maintain behaviors that are correlated with personality as well as being less intrusive, (ii) exploring various measures while collecting data to let users feel less intrusive, (iii) weighing between the personality assessment accuracy and privacy-preservation.

We explore these issues focusing on extraversion, which is one of a personality trait among Big Five personality that is relevant to expressivity, social perceptiveness, affiliation and dominance of teamwork [3]. Extroverts can be characterized by one's outgoing, talkative, energetic behaviors, while introverts tends to perform reserved and solitary behaviors [8]. Therefore, to track all exhibited behaviors related to extraversion of an individual within a workplace, we subdivide the behaviors extracted from online and offline data streams each into social and solitary behaviors. An online social behavior within a workplace includes communication between workers via a messenger platform or emails whereas an online solitary activity consists of the general usage of one's computer or smart phone other than the primary purpose of interacting with others. On the other side, an offline social behavior is staying in common area with other colleagues, which implies that the individual is more willing to initiate a conversation with other colleagues than at a more solitary place, whereas an offline solitary behavior can be indirectly inferred by sedentary behaviors staying at one's own seat in the workplace. From a meta-analysis of these two channels, we devise an APA model for Big Five personality.

The contribution of this paper is a new APA model via analyzing individual's online and offline behaviors in the workplace. We collected online and offline data over 3 weeks from 4 different research groups at a large Korean technical university, consisting of total 32 users. During the data collection, we also investigate into privacy issues that could arise while users are sharing their real life data. Specifically, we collected online data consisting of chat logs in the workplace and use of electronic devices such as desktop and smart phones; and offline data consisting of position and movement inside the work space. From the collected data, we extract behaviors that are psychologically relevant and analyze their correlations and significance in indicating one's personality while weighing between privacy and accuracy of prediction. As of our knowledge, this is the first paper to assess workplace personality automatically.

The rest of the paper is organized as follows: we first discuss related work on APA models and analyzing online and offline social and solitary behaviors. Subsequently we introduces the design goals of an APA system based on the preliminary survey result. We then introduces our APA model designed based on the presented design goals. Finally we discuss the result of our APA system along with the discussion on each of the design goals.

Chapter 2. Related Work

Our system is inspired by previous research on analyzing correlation between user's behaviors and personality and automatically predicting personality. A thread of research have assessed personality using human artifacts gathered online. Shen et al. [25] has proposed a method to analyze email contents to infer user's personality. There have been several work on analyzing personality with social media logs: check-in behaviors in social media [26], Twitter profiles [33] [17]. Skowron et al. [24] has predicted personality from two different SNS, suggesting that mixing two different social media source could increase accuracy. Several work have also investigated the relevance of personality with messenger usages [30] [21] [31].

There has been another research stream where they predict personality from mobile or wearable devices. De Montjoye et al. [16] has automatically assessed personality using standard mobile phone logs. Staiano et al. [28] inferred personality with several features related to social network structures collected from mobile phone data. Olguin et al. [18] has shown that personality could be obtained by analyzing low-leveled sensor values collected from wearable devices.

In addition, researchers have also presented APA models with other data sources. Champa et al. [29] has proposed a method to predict personality from handwriting styles without human-intervention and Wright et al. [35] has analyzed free text to infer personality. Batrinca et al. [32] has assessed personality using features extracted from a short self-presentation task given to users. Lepri et al. [34] has investigated on predicting extraversion among Big Five personality from behaviors shown in small group meetings. Despite several attempts to automatically analyze personality from various sources, to best of our knowledge, there have been no work to specifically assess workplace personality.

Chapter 3. Preliminary Survey

To better design a workplace personality assessment system taking privacy into account and understand limitations in existing methods used to assess personality, we conducted a survey with full-time employees.

The scope of the survey was to first investigate user's behaviors in their workplace. Since the definition of personality is the enduring patterns in behaviors and thoughts resulting in a tendency for them to respond to certain ways in specific situations[3], to design a system to assess workplace personality we should first know their patterns in behaviors in the workplace. Despite previous work on difference in online social media personality and offline personality [7], we specifically questioned full-time employees' difference in online and offline workplace behaviors. Since in this paper, we are focusing on measuring their extraversion among personality traits, we asked their social and solitary behaviors performed each in online and offline workplace. In the next part, we asked their level of acceptability in sharing different streams of data that could include employees' social or sedentary behaviors. We also asked their perception in sharing data in different levels within the same data stream.

We launched web-based survey in an external commercial survey company, which allowed only the full-time employed panels to answer the survey. We also gathered responses through personal contacts and through posting in SNS. In order to gather responses from people working in a typical condition, we asked if the respondent is working in a workplace that is shared with other colleagues. We then excluded those who answered 'no' or 'not sure' to the question. We also disregarded those who spent less than 4 minutes completing our long survey in order to exclude those who answered randomly without reading the conditions. With these filtering conditions, out of 141 people, 121 people reported as working with colleagues in the shared workplace, and finally responses from total of 89 people (43.8% female, 33.7% aged 18∼29, 28.0% aged 30∼44, 24.7% aged 45∼60 and 13.5% aged more than 60) were taken into account who took more than 4 minutes to complete the survey.

3.1 Key Observations

3.1.1 Different workplace social behavior patterns shows in online and offline

Survey results showed that people spend different time online to offline on social interaction in workplace ($p = 0.03156$ with Wilcoxon signed-rank test, $z = -2.1535$). Interestingly, their choice on the channel of social interaction differed: 20 people out of 89 people spent more time on online than offline, 35 people favored offline to online and 34 people spent same time on online and offline.

In order to obtain more detailed information on how they differ, we asked how often they perform a certain social interaction behavior in their workplace online to offline. Even though respondents did

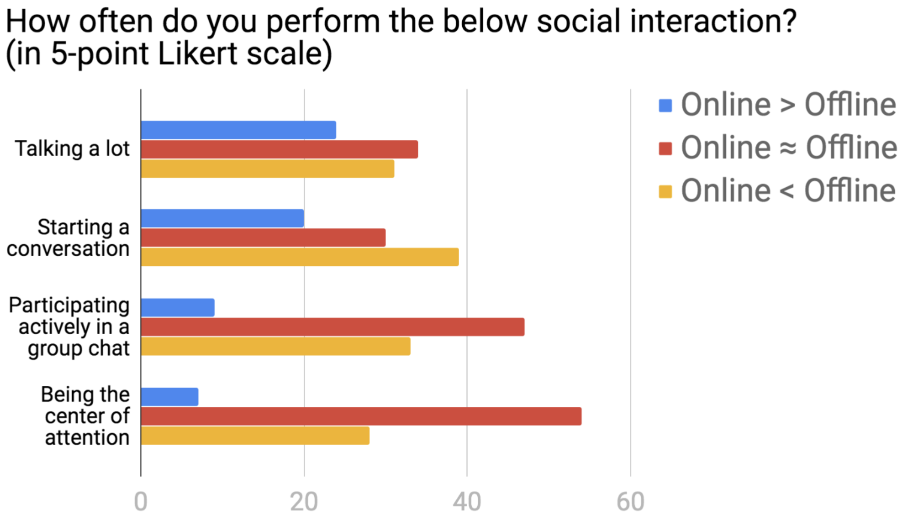

Figure 3.1: Users showed different patterns in performing social behavior.

not show significant difference of talking a lot online to offline (p = 0.4413 with Wilcoxon signed-rank test, z = -0.7747), they showed significant difference for starting a conversation online to offline (p = 0.00174 with Wilcoxon signed-rank test, z = -3.1324), participating actively in a group chat (p = 0.00038 with Wilcoxon signed-rank test, z = -3.5561) and being the center of attention online to offline (p = 0.0003 with Wilcoxon signed-rank test, z = -3.6116). Also, as can be seen from 3.1, respondents showed different patterns in performing social behavior in the workplace online to offline.

3.1.2 Different attitudes towards different levels of data sharing

Respondents were questioned on their level of acceptability in sharing data with their company or institute in 7-point Likert scale questions (1-unacceptable, 7-acceptable). We majorly wanted to know their perceptions on three different conditions of sharing data for different kinds of data streams: i) sharing workplace-related as well as non-workplace-related data of the given data stream when given no option to exclude any data instances ii) sharing workplace-related data of the given data stream when given no option to exclude any data instances iii) sharing workplace-related data of the given data stream when they have the control to exclude some of the data instances. We asked these questions in four different data streams: i) Online chatting logs ii) Online web or app usage logs iii) Offline position logs iv) Offline movement logs.

There existed a statistically significant difference in perceived acceptability depending on the three data sharing conditions for all data streams: i) online chatting logs ($\chi^2(2)$=37.4663 with Friedman test, significant at $p < 0.01$) ii) online web or app usage logs ($\chi^2(2)$=15.5225 with Friedman test, significant at $p < 0.01$) iii) offline position logs ($\chi^2(2)$=23.1742 with Friedman test, significant at $p < 0.01$) iv) offline movement logs ($\chi^2(2)$=12.1517 with Friedman test, significant at $p < 0.01$). Post-hoc analysis with Wilcoxon signed-rank test was conducted, resulting in a significance at $p < 0.05$ for condition (1) and (2)

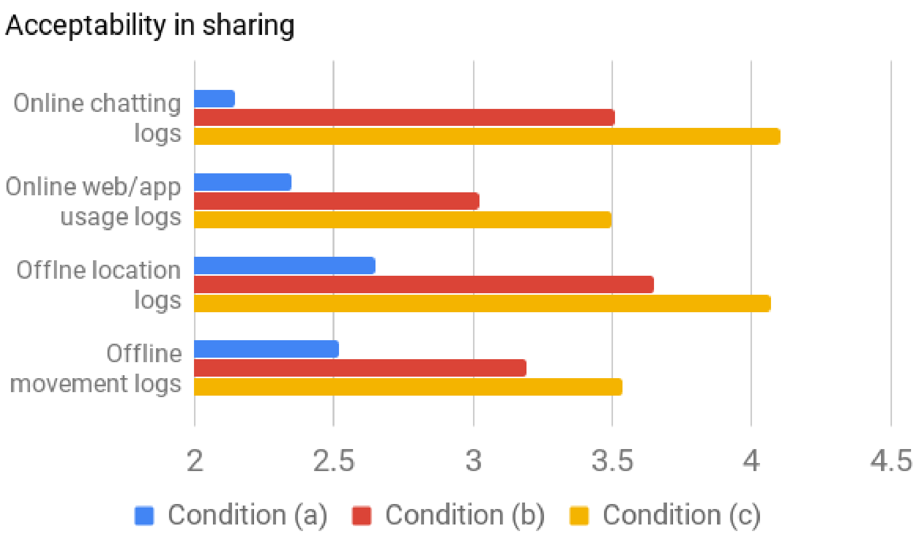

Figure 3.2: Users showed different acceptability in sharing with different data sharing conditions. (a): Sharing all data with no option to exclude, (b): Sharing only workplace-related data with no option to exclude, (c): Sharing only workplace-related data with control to exclude

Table 3.1: Difference in acceptability with different data sharing conditions

	Online chatting logs	**Online web/app usage logs**	**Offline location logs**	**Offline movement logs**
Condition (1)	2.1461	2.3483	2.6517	2.5169
Condition (2)	3.5056	3.0225	3.6517	3.191
Condition (3)	4.1011	3.4944	4.0674	3.5393

(i) Z = -5.2024, p = 0.000, ii) Z = -4.1866, p = 0.000, iii) Z = -4.9628, p = 0.000, iv) Z = -3.797, p = 0.00014). Condition (2) and (3) also showed significance at $p < 0.05$ (i) Z = -3.2602, p = 0.00112, ii) Z = -3.6132, p = 0.0003, iii) Z = -2.9833, p = 0.00288, iv) Z = -3.0301, p = 0.00244). Means of perceived acceptability for each condition are shown in 3.1 and 3.2. This indicates that people feel less intrusive when they only share workplace-related data compared to all data that includes private data, and when they can opt out some data logs that they do not want to share compared to sharing whole data.

3.1.3 Difference in perceived acceptability with different contextual information or scope of the same shared data stream

We also asked 7-point Likert scale questions to know whether there exists difference in perceived privacy level of sharing data with different levels of contextual information. For online chatting logs with data sharing condition (3), there was no significant difference between sharing text contents of the messages as well as meta-data such as time stamp of message, type of message or just meta-data (Z = -1.0955, p = 0.27134 with Wilcoxon signed-rank test). Moreover, we asked 22 respondents who have experience with Slack, an online messenger platform (https://slack.com), about their acceptability between sharing Direct Messages (DM), private channel and public channel. Public channel differs from DM or private channel, due to its characteristic of openness of all the logs to any members in the workspace. Indeed, perception between sharing different scope of online chatting logs differed significantly ($\chi^2(2)$=15.7045 with Friedman test, significant at $p < 0.01$). While there was not a significant difference between sharing DM and sharing private channel logs (Z = -0.2795, p = 0.77948 with Wilcoxon signed rank-test), there existed a significant difference between sharing DM and sharing public channel logs (Z = -2.1181, p = 0.034 with Wilcoxon signed rank-test) as well as between sharing private channel and sharing public channel logs (Z = -3.2881, p = 0.001 with Wilcoxon signed rank-test), with mean being each 2.772727, 2.863636 and 4.409091.

For online web or app usage data, we asked their perception in i) sharing specific pages of web or app, such as URL, ii) sharing domain information of web or name of the app and iii) sharing category of the web or app, such as whether it is social or non-social web/app. However, there was no significance in difference ($\chi^2(2)$=0.8764 with Friedman test, significant at p = 0.6452).

3.1.4 Different perceived acceptability for different data streams

We compared how employees feel towards sharing different data streams under data sharing condition (3). We compared that of i) online chatting logs ii) online web or app usage logs iii) offline location logs iv) offline movement logs v) audio recordings vi) video recordings. There existed significant difference among sharing these different data streams ($\chi^2(2)$=39.136 with Friedman test, significant at p = 0.0000). The result of post-hoc Wilcoxon signed rank-test for all pairs is shown in 3.2 with mean being 4.101123596, 3.494382022, 4.06741573, 3.539325843, 2.820224719 and 2.752808989 each. From the result, we could infer people feel significantly less intrusive when sharing online chatting logs, online web or app usage logs, offline location logs or offline movement logs than both audio recordings and video recordings.

Table 3.2: Difference in acceptability in sharing different data streams is shown as the result of post-hoc Wilcoxon signed rank-test for all pairs of data streams.

	Online chatting logs	**Online web or app usage logs**	**Offline location logs**	**Offline movement logs**	**Audio recordings**	**Video recordings**
Online chatting logs	N/A	0.007716 *	0.779133	0.023597 *	0.000004 *	0.000007 *
Online web or app usage logs	0.007716 *	N/A	0.017134	0.688684	0.052003 *	0.068316 *
Offline location logs	0.779133	0.017134 *	N/A	0.047348 *	0.000015*	0.000026 *
Offline movement logs	0.023597 *	0.688684	0.047348 *	N/A	0.019091 *	0.026178 *
Audio recordings	0.000004 *	0.052003 *	0.000015*	0.019091 *	N/A	0.904330
Video recordings	0.000007 *	0.068316 *	0.000026 *	0.026178 *	0.904330	N/A

Chapter 4. Design Goals

Based on the results of this preliminary study, design goals of our system are:

4.1 G1: For a complete personality assessment user online and offline behavior has to be combined

Our observation from the preliminary survey suggests that people engage differently in online to offline social activities. One might be socially active in online even though the person might be solitary. In this case, taking only one channel into account might mislead one's personality. Therefore, in order to make a robust system that capture one's personality more completely, the system should analyze both the online and offline channels.

4.2 G2: Privacy should be preserved during the data collection

As automatic personality assessment systems detect one's personality by analyzing one's artifacts, sharing personal logs or data is inevitable. However, as can be seen from the survey, users' acceptance of sharing their data differs a lot from data streams to data streams and even within the same data stream given different conditions. This can affect users' overall experience of an APA system. Especially in order to be applicable in workplaces in the field, privacy should be preserved during the data collection.

4.3 G3: The system should not alter user's natural behaviors and capture user's natural behaviors

Personality should be detected by analyzing user's natural behaviors. If the system changes their behaviors to behave in a specific way or perform a specific task, the APA system might collect unnatural behaviors of users and cannot assess one's true personality. Therefore, it is not desired to significantly change their natural behaviors nor give a specific task for them to perform. In fact, the system should collect the data that would include those user's natural behaviors.

Chapter 5. Methodology

5.1 Data collection

Based on the design goals presented, we first present how data is collected for our proposed novel Automatic Personality Assessment (APA) method to detect one's personality. We analyze social or energetic behaviors as well as solitary or sedentary behaviors that could be observed inside the workplace, as these behaviors are correlated with extraversion [11] [12]. Even though it is best to analyze one's video or audio data to extract the behaviors, it has privacy issues as our preliminary survey result presents. Therefore, we assess personality by collecting data streams that could indirectly represent one's behaviors. We analyze both online and offline channel since one's social behavior patterns might differ from online to offline as our survey result shows. We collected four data streams that include social or solitary behaviors: online messenger usage data and online web/app usage data, offline location data and offline movement data. While collecting the data, we preserved privacy by collecting with data sharing condition (3), to share only workplace-related data of the given data stream and to give users control to exclude some of the data instances. We describe each data stream in turn with more detail.

5.1.1 Online messenger usage data

Using messenger is one social behavior found in many workplaces for colleagues interacting with each other. Messenger logs contain various clues to infer one's personality [21] [22] [23]. However, from the preliminary survey, we discovered that users felt revealing message content as invading their privacy too much. Moreover, they felt that sharing personal messages outside the workplace are sensitive. Therefore, to be less invasive, we analyze only metadata of workplace messenger logs, excluding the content itself. We collected messenger logs of Slack (https://slack.com) that were used in the workplace. Among the logs, we only collected public channel logs as private channels and direct messages tend to be more personal as shown in the preliminary survey. To collect natural human behavior that could represent one's genuine personality, we did not give any constraints on them using Slack nor explicitly give users specific tasks. Therefore, collected logs contained various manners of Slack usage differing from workplace to workplace. For example, while logs from one workplace contained only few case of adding reaction to messages, there were lots of multiple reactions in messages in logs of another workplace.

5.1.2 Online web/app usage data

With the development of Internet, online web/app usage data contains a lot of information of oneself as it is an online trace of a person and captures various behaviors of a person. However, as we can collect a large amount of information from web/app history, collecting all of them could lead to privacy issues. Preliminary survey suggests that collecting only workplace-related web/app usage when giving users control to exclude some data that they do not want to share could lead to significant increase in acceptability of sharing the web/app history. Therefore, we confined the collected data to only workplace-related web/app usage data by only collecting the web/app usage logs when the person was physically inside the workplace only in the weekdays. Furthermore, in addition to giving them the authority to opt out some data instances, we also gave them the control to stop the logging with the RescueTime's feature of pausing the logging for certain amount of time. Even though there was no significant difference found with sharing different levels of web/app usage data from the preliminary survey, we only collected the domain information if the web/app is work-related social, as the participants answered in the pre-survey. Work-related social web/app included Slack, Hangout, Gmail, Facebook. Moreover, for other web/app usage, we collected only the category of web/app as either non-work-related social or non-social. We collected the web/app usage data using RescueTime. We also made a filtering program that would filter only the information level that we need and filter to collect only the web/app usage logs when the person was inside the workplace.

5.1.3 Offline Location Data

Location traces of a person can tell a lot about their personality. For example, it is shown that one's GPS logs of everyday life have correlations with personality [16]. However, many users felt too intrusive to share their location information for a whole day from the preliminary survey. Therefore, in this work, we collected user's location information inside a physical workplace as survey respondents felt collecting this data was less invasive. We limited the collection of data only to the weekdays. We also gave users the control to pause data collection by giving them the option to turn off our app by a switch and also to just turn off the watch as well as the control to exclude data instances. To collect offline location data, we developed an Android app for wearable devices, which calculates the user's indoor position inside the workplace with received Bluetooth Low Energy (BLE) signals from BLE beacons that we installed around the walls in each workplace. We deployed the app in ASUS ZenWatch 3 and collected user's indoor position in workplace. In order to not interfere in user's natural daily workplace behaviors, we did not give any constraints or requirements except for making them wear an off-the-shelf wearable watch.

5.1.4 Offline Movement Data

Movement of a user inside a workplace can imply their energetic or sedentary behaviors which are indicative of one's trait of extraversion [11] [12]. For example, if a person keeps sitting in one's own seat, it could indicate that a person is performing sedentary behavior. According to the survey result, in order to lessen the privacy concerns, we collected the movement information only within the workplace excluding on the weekends. Moreover, instead of collecting all kinds of movement such as whether the person is walking, running, sitting, and more, we only collected the movement information of steps. We added in the Android app that we installed in wearable watch the feature to collect the step counts and the time stamp when step was detected. Likewise, users had control to stop logging their movement.

5.2 Lab study

We collected data as presented in the previous section in 4 different research groups in a large Korean technical university. Each group was consisted of 5, 7, 9, 11 participants, total 32 participants (19% female, mean age = 26.7, S.D. = 3.7). Each participants received $30 for participation.

For data collection, we installed 11 or 12 Bluetooth Low Energy (BLE) beacons on the wall for each workplace. Each participant received a smart watch, which had an application installed which collects offline data when the user is inside one's own workplace. They were also asked to install RescueTime plugin and program on their desktop and application on their cell phone. Excluding this, we did not give any constraints nor restrictions on their workplace behaviors. We also instructed them how to pause logging for online web/app usage data collection and offline data collection and the possibility to exclude some data instances after the study. We deployed for three weeks in May, 2018. We collected average of 47.8 hours of offline data collected per person, total 2690 online messenger logs and average of 27.0 hours of online web/app usage data per person.

After the data collection period was over, each participant was asked to retrieve their online data by using the program given to filter out only necessary information that we are collecting. After looking at their online data, they retrieved the data. We then provided each individual with the summary of the data that was collected as 5.1. Before analyzing the data, we asked if there was any participant who wanted to take a closer look into their data or want to exclude some data. One participant (P26) asked to take a look at one's own data while nobody contacted to exclude any data. Moreover, we gathered 7 participants (P4, P6, P21, P23, P26, P28, P33) for an interview. During the interview, we showed their own collected data and asked their general opinions and thoughts regarding the design goals. Each interview session took about 30 minutes.

Table 5.1: Personality assessment result of 31 participants

	Self-assessed	**Peer-assessed**	**Self+Peer-assessed**
Introvert	4	3	6
Ambivert	21	22	21
Extrovert	6	6	4

In order to collect the ground truth of each participant's personality, each participant was asked to take International Personality Item Pool (IPIP) personality test for extraversion [14], consisting of 20 short questions. Even though self-assessment is widely used form of personality test, it has the problem of self-bias [15]. Therefore, for better ground truth, we asked participants to take the personality test in two forms: self-assessment and peer-assessment. Assessment from well-acquainted informants could be

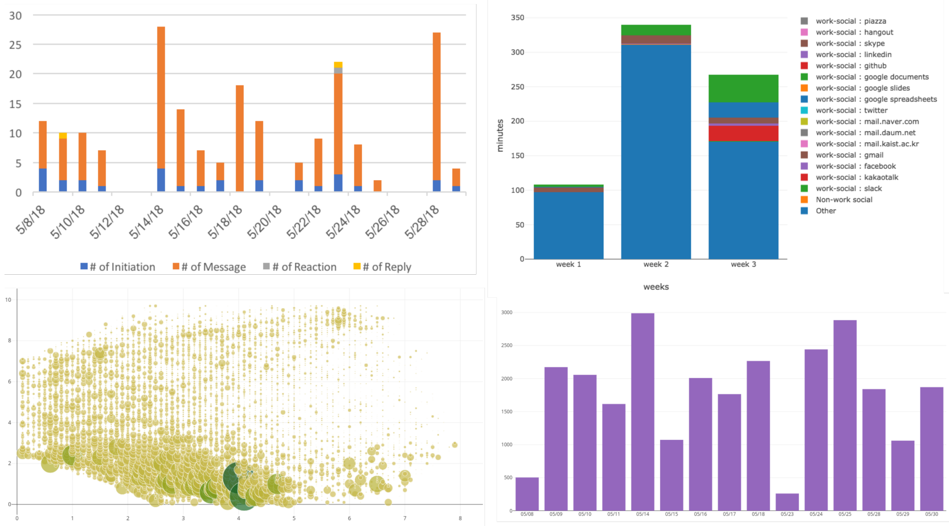

Figure 5.1: Example of individual summary of online messenger usage (Top left), online web/app usage (Top right), offline location changes (Bottom left) and offline movement changes (Bottom right)

supplement of self-rated personality since they are less selective since they do not have any motivation to protect ego [9]. Moreover, to minimize the impact of singular viewpoint and to get more consensus-based result of one's personality [9], we randomly asked 3 participants within the same workplace to assess other participants' personality. We averaged the result for the peer-assessment personality test and then averaged with self-assessment. For each of the ground truths, we divided into three classes of extraversion: extrovert, ambivert and introvert. In this way, we could get more stable personality, as determining extrovert and introvert is important than determining whose score is higher within the same class, as the score itself might vary even with retaking the test within a short span [13]. The result of personality using each method is shown in 5.1.

5.3 Building APA model

5.3.1 Behavior feature extraction and feature post-processing

From each of the collected data stream, we extracted 36 features of social or energetic behaviors and solitary or sedentary behaviors. We then post-processed each behavior features so that each features do not reflect the difference in each workplace's culture or customs. For example, there was one workplace which had lots of reactions put to other's messages in online messenger logs, while another workplace barely had reactions. To prevent each workplace's custom 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.

5.3.2 Model building

With the post-processed behavior features, we built an APA model to determine whether a person is an extrovert, ambivert or introvert. Since the three classes are imbalanced and the number of extroverted or introverted people were small, we did 10-fold cross validation and oversampled small-numbered-classes using SMOTE algorithm [10] to balance out the classes. We then selected features to prevent overfitting due to the large number of features. We compared several classification algorithms training different versions of personality score as in Table X. Our focus was on not only the high accuracy but with fair prediction of determining the extreme classes. Therefore, we mainly used two different performance metrics: accuracy and F_1 macro score. In addition, we made our own performance metric, to penalize the models that will detect the extreme cases totally opposite way: an introvert as extrovert and vice versa.

Chapter 6. Results

6.1 Feature Correlation

For each of the different ground truths, we listed top-seven features with high correlation with extraversion of three different ways: self-assessed, peer-assessed and self and peer-assessed extraversion in 6.1, 6.2, 6.3. Extraversion is the personality trait where the correlation between self-assessed and peer-assessed personality is high comparative to other personality traits in Big Five [13]. Here, we analyze what behavior features are the indicative of each ways of personality. This could be useful information when deciding how to supplement the peer-assessed result with self-assessed personality. As 6.1 suggests, self-rated personality is highly correlated with online behavior features, especially web/app usage behaviors, which are seldom noticeable by the colleagues in the workplace. Whereas for peer-assessed personality, more superficial social or solitary behaviors were correlated: behaviors shown in online messenger where they interact with other colleagues directly or workplace offline behaviors where they could directly observe when they share the work space. For the personality measured by supplementing self-assessed with peer-assessment, mixed result showed.

Table 6.1: Top-seven highly correlated behavior features with self-assessed personality

Correlation	Behavior Feature
0.3491	Number of times sending messages in general channels
0.3119	Ratio of number of times using social web/app over total time using any web/app
0.2896	Ratio of number of times using work-related social web/app over total time using any web/app
0.2850	Total time of not walking inside the workplace
0.2449	Total time using Slack
0.2247	Ratio of time using social web/app over time using any web/app
0.2173	Ratio of time using work-related social web/app over time using any web/app

Table 6.2: Top-seven highly correlated behavior features with peer-assessed personality

Correlation	Behavior Feature
0.2832	Total time of using Slack
0.2731	Number of steps detected
0.2681	Total number of steps
0.2558	Ratio of number of times sending message in Slack over number of times using Slack
0.2395	Average step count per one walking session
0.2319	Total time of not walking inside the workplace
0.2296	Number of times using Slack

Table 6.3: Top-seven highly correlated behavior features with self and peer-assessed personality

Correlation	Behavior Feature
0.408	Duration of not being at one's seat but inside the workplace
0.2735	Percentage of not being at one's seat but inside the workplace
0.2655	Total number of messages
0.2646	Total number of reply
0.2619	Number of times replying in general channels
0.2591	Total time outside the workplace
0.2395	Total time not walking inside the workplace

6.2 Model prediction

With the collected online and offline workplace behavior data and the ground truth personality of each participants, we built personality assessment models using several different machine learning algorithms. 6.4 shows the personality prediction result of each model. Among the models, model built by using Linear SVC showed the highest accuracy of 87.1% and F_1 macro score of 84.0% for self-assessed personality, while model built by using Random Forest showed highest accuracy of 74.2% and F_1 macro score of 66.3% for peer-assessed personality. Each prediction result as in confusion matrix is shown in 6.5 and 6.6, where no instance was found to predict one's personality radically different: an introvert as extrovert or an extrovert as introvert.

Table 6.4: Accuracy and F_1 macro score of predicted personality

	Decision Tree	**Random Forest**	**Linear SVC**	**RBF SVC**	**Gaussian NB**
Self-assessed Personality	0.806 (0.733)	0.871 (0.803)	0.871 (0.840)	0.710 (0.580)	0.806 (0.730)
Peer-assessed Personality	0.710 (0.624)	0.742 (0.663)	0.613 (0.561)	0.710 (0.435)	0.645 (0.599)

Table 6.5: Confusion matrix of predicted self-assessed personality

	Introvert	**Ambivert**	**Extrovert**
Introvert	4	0	0
Ambivert	1	19	1
Extrovert	0	2	4

Table 6.6: Confusion matrix of predicted peer-assessed personality

	Introvert	**Ambivert**	**Extrovert**
Introvert	2	1	0
Ambivert	1	15	6
Extrovert	0	3	3

Chapter 7. Discussion

Apart from the accuracy itself, participants agreed their overall experience was better than the traditional personality test that several had experiences with. P25 said: *"When you this type of test, you do it on a specific moment, you're under pressure. . . . You have 30 minutes you have to answer a lot of questions about yourself that you might have never asked to yourself. . . . I'm not sure I like that option."* P20 said: *"For assessing other's personality, I'm not sure about that since it might differ as up to how much they saw me. For assessing oneself, my whole lab agreed that the result will differ between the one that you took today with the one that you took yesterday according to their feelings. . . . Today I might feel cheerful that I might answer that I'm more sociable, but tomorrow I might be depressed. ... So I don't really trust it because it can result differently everyday. But when data is collected for a long time and assessed objectively by the data rather than marking myself subjectively, I think that personality is more reliable. And it was more convenient that I didn't have to think a lot."* P6 said: *"How I think about myself might be different from how I actually behave, . . . when I assess myself, I think I'm an introverted person, so I take personality test while thinking about that. But when the data is collected and analyzed, I think the result might be different. So I think if you analyze personality by the data along with taking a personality test, the result might give different patterns. I'm not sure if that would be meaningful, but assessing in various ways would be helpful."*

7.1 G1: For a complete personality assessment, user's online and offline behaviors both have to be analyzed

As can be seen from Figure X, combining online and offline behavior data resulted in a higher accuracy of personality assessment. This supports our observation from preliminary survey: different workplace social behavior patterns shows in online and offline.

This was also evident in the raw data itself. 7.1 shows that P10 spent a lot of percentage using social web/app. However, it shows that P7 spent significantly less proportion of time involving in social web/app than P10. With only web/app usage logs provided, P10 could seem as if is more of an extrovert than P7. However, given the offline location data as in 7.2, the result is different. From the offline location data we can infer that P10 spent a lot of time at a specific position of the workplace, which has a high probability of being P10's own seat in the workplace. This could indicate that P10 spent a lot of time performing sedentary behavior, which is a well-found behavior of an introvert [11] [12]. On the other hand, the position logs of P7 indicate that P7 moved around the workplace much more, showing energetic behavior. In this case, P7 is an extrovert and P10 is an introvert. As can be seen in this case, it is important to consider both online and offline channels since their behavior might differ thus considering only one channel might result in biased personality.

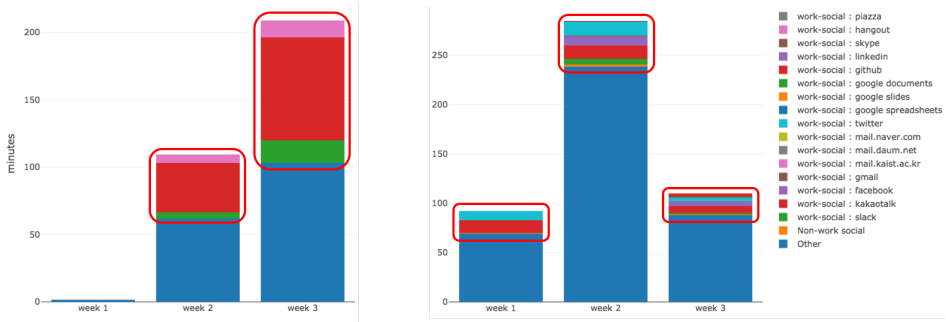

Figure 7.1: Online web/app usage logs of P10 (shown in left) and P7 (shown in right) for 3 weeks shown in average per each week, where social-related web/app usages are highlighted in red rectangles.

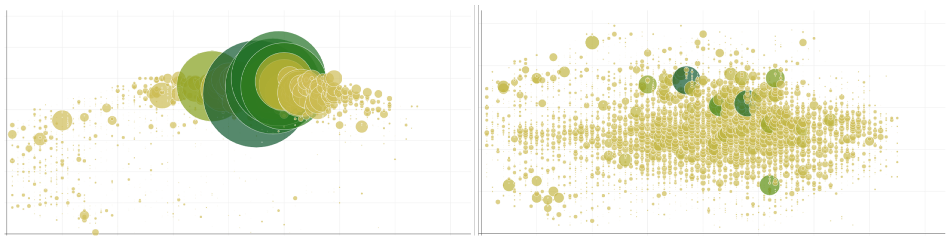

Figure 7.2: Offline position logs of P10 (shown in left) and P7 (shown in right) for 3 weeks shown in lab space coordinate, where the size and color intensity represents the amount of time spent at the position.

7.2 G2: Privacy should be preserved during the data collection

In order to determine whether privacy was well kept with our APA system, we interviewed 7 participants (P4, P6, P20, P22, P25, P27, P32) to know their thoughts regarding the privacy issues after the data was collected. We conducted a retrospective interview by showing each participant their own collected data as well as the summary data that we provided earlier and were asked to mention any privacy concerns that they would have. P25 said, *"Since the work space is a space that is open to the public, I always think that anybody could be watching what I'm doing at all times."* This is consistent with our preliminary survey observation, where people responded that they were significantly more acceptable in sharing workplace-related data compared to all data. Moreover, when asked if they want to exclude any data after showing them their own data, none responded that they want to. In addition, P22 said, *"Watch was good, since we could turn off, whereas for sensors on the door, it's like being watched all the time."* and P6 also mentioned that *"If we do not want to be logged (for specific web/app usage), we could stop the data collection."* This indicated that any option to exclude data to share or pause the data collection resulted in higher acceptability.

In addition, interviewees also said that limited contextual information or scope of collected data enabled them to feel acceptable to share those data. As in the preliminary survey, participants agreed that collecting messenger usage logs from only public channel made them more acceptable in sharing data: *"(Even though in this system text is excluded,) I do not even mind sharing text message contents since they are all public conversations."*(P4), *"Talking in the public channel is like broadcasting."* (P32) Even though in the preliminary survey respondents did not show significant difference between sharing text message contents or not, participants acknowledged differently: *"After excluding text, I have no privacy concerns."* (P20), "Even though I was notified that text content will not be collected, I kind of doubted that" (P6), *"No contents are included, it's just meta-data... It's hard to imagine any malicious thing that could be done."* (P22). Contrary to the survey result, participants addressed that sharing only the categories of the web/app used preserved privacy: *"Classification is clean..., not too many details."* (P25), *"Categories are broad enough...."* (P22). Participants also admitted that the scope of collected offline location data was acceptable: *"Since it doesn't say why the person stayed long, ..."* (P22), *"It is different from CCTV, since you cannot know what I did at that time at that position."* (P32). For offline movement data, P25 and P32 mentioned that sharing step was acceptable since being active is desirable in workplaces.

However, interviewees also raised some concerns on privacy. P32 said, *"(Since content is excluded,) I do not have any data to remove specifically, but by analyzing data you can guess what I did up to some sense."* Moreover, as asked to rank data streams in respect of privacy, all interviewees ranked online web/app usage data to be the most intrusive: *"(web/app data) is more personal than others."* (P25), *"You can know what I did right away while others don't."* (P20).

7.3 G3: The system should not alter user's natural behaviors and capture user's natural behaviors

In order to maintain user's natural behaviors, we did not give any constraints on their behaviors except asking participants to wear the watch and charge the watch. In order to further understand whether participants' natural behaviors were retained, we asked participants about any change in their behaviors except for wearing or charging the smart watch. P25 said: *"There was no change in any of the habits at all."* and P4 said: *"I behaved in a same way"*.

However, for online web/app data stream, some reported that *"For web/app I get the feeling that someone is watching me, so I got this sense that I should concentrate on work."* (P32), *"Since I can see the productive hours in RescueTime and they would send me daily report, I had this sense of guilt and did other things less than the usual, so my behavior changed at the beginning but later time on, it returned."* (P6). P20 also said, *"(For web/app,) at first, my behavior changed due to awareness of using RescueTime, ... , but later on I could feel that awareness of using it was getting low. So I doubt my earlier data is faulty."*. From the interview, we found that the change in user's natural behaviors were due to two reasons: privacy (P32) and self-recognition (P6, 20). In case of self-recognition, they all agreed that the effect of self-recognition decreased as time passed by, while for change in behaviors due to privacy, the effect was hard to decrease. Therefore, in order for an APA system to collect user's natural behaviors, privacy should be carefully considered.

7.4 Limitations

There are several possible causes of low accuracy of personality prediction result. First, data was collected from a small number of participants. Moreover, for the extreme case of extraversion of extrovert and introvert, the number of participants classified as those classes were even smaller. Therefore, training with the data could have resulted in overfitting of the model. Second, longer data collection is needed for better prediction. As personality is the enduring patterns in behaviors [3], it is only derivable from long span of data. If personality was predicted with short time span of the data, the participant might have been under a special circumstance that made the person to perform behaviors that are inconsistent with other times. Third reason could be on the hardware devices that we used, where even though we carefully selected off-the-shelf smart watch with long battery life and quick charging time, it still hampered participants from participating in data collection. In addition, we used beacons to track offline location data, where beacons are usually known to have about 1m of error. Although if the data is collected for a longer period, these error could have been buried, with the length of our data collection errors due to hardware devices could have remained. Lastly, low accuracy could have been due to the unreliability of ground truth. Even though we tried to minimize the unreliability by supplementing self-assessed personality with peer-assessment, it could have still existed. In fact, it is hard to retrieve the ground truth of one's personality. Therefore, our system could also be used to supplement in knowing one's workplace personality.

7.5 Future work

In this paper, we explored the privacy issue in data collection by investigating one's acceptability and sharing data. There still exists other dimensions of privacy in order for an APA to be used in the fields. For example, both P23 and P28 who participated in the retrospective interview said that trust is another factor that could affect the acceptability in sharing data along with what kind of data is being shared. P23 said, "Abuse case would be using it to enforce certain work styles.", and expressed his concern of data being used in another way that is not the purpose that was suggested in the first place.

Chapter 8. Conclusion

Despite the various effects personality can have on workplace, there exists limitations in existing methods of assessing of personality. Therefore an automatic personality assessment (APA) can provide another method of supplementing various methods to assess personality. This paper introduces several design goals that an APA system should follow based on the preliminary survey result. Moreover, this paper presents a new APA method that would assess workplace personality while keeping the design goals. To best of our knowledge, this is the first work that suggested an APA model that is specialized for measuring workplace personality instead of one's general personality. In addition, this paper presents results of the APA model as well as participants' experience with it.

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