Analyzing the Relationship between Cognitive Performance and Time to Find Intended Mobile App

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Abstract
Although mental illness is one of the most serious social problems, stress does not necessarily have a negative effect, on the contrary, an optimal amount of stress can result in individuals being able to perform better in tasks. While there have been several studies on estimating stress level from smartphone usage logs and several effective features were revealed as a result, there are few studies on estimating cognitive performance. Thus, in this paper, we explore several factors affecting the estimation of cognitive performance from smartphone logs. To conduct the analysis, we collected smartphone usage logs and Go/No-Go task data for 6 weeks from 39 participants in the wild. We found that the time to find intended app is related to cognitive performance. This result suggests that measuring the time to find intended app can be the effective feature of estimating cognitive performance from smartphone logs.

Author Keywords
Cognitive Performance, Go/No-Go task, Smartphone Log

ACM Classification Keywords
J.3. [Life and Medical Sciences]: Health; J.4. [Social and Behavioral Sciences]: Psychology

Introduction

Mental illness is one of the most serious social problems, with more than 300 million people suffering from depression[1]. To prevent mental disorders, it is important that an individual is able to perceive stress by themselves. However, stress does not necessarily have a negative impact on people. According to the Yerkes Dodson law [14], although the performance of a person is likely to decline in the case of an extremely high level of stress, an optimal level of stress can actually lead to performance enhancement. The Yerkes Dodson law states that the relationship between stress and performance is an inverted U shape. If we can measure both the stress level and cognitive attention (performance), we can figure out whether the stress level is optimal or not.

Recently, mobile mental health care, which passively senses people's behavior to estimate mental status through smartphone logs, has been attracting much attention [2]. The reason for this is that it is costly to directly and continuously assess stress levels although stress levels can be measured through self-assessment or physiological information. For example, self-assessment is time-consuming and the recording of physiological information requires special devices. Therefore, several studies have been conducted to estimate stress levels from passively sensed smartphone usage log, location data and wearable devices [3, 4, 10, 11, 12, 13]. On the other hand, cognitive performance can be measured through widely used psychological tests such as Go/No-Go (GNG) task [6] and Psychomotor Vigilance Task (PVT) [5]. However, it is also difficult to continuously assess the cognitive performance using psychological tests because these tests take a few minutes to conduct. While mental health estimation from smartphone logs has been well studied and explored, focusing on several effective features, cognitive performance estimation has been under explored, and to date, only a few studies [1, 8, 9] have been reported. Thus, it is not yet revealed which smartphone-related features are effective for estimation.

[1] http://www.who.int/mental_health/world-mental-health-day/2017/en/

In this paper, we investigate the relationship between cognitive performance and smartphone usage logs. We propose a hypothesis: people launch intended mobile apps quickly when their cognitive performance is high and when their performance is low, this launch is slow. To analyze the relationship between cognitive performance and smartphone usage logs, we first collected continuous GNG task data, which is widely used psychological test and smartphone usage logs in the wild for 42 days from 39 participants who are all office workers. To validate the hypothesis, we investigated the relationship between the time taken from turning on a smartphone to launching the target app and cognitive performance. We divided the data into high and low cognitive performance and the difference in the meantime to find intended app was statistically tested. The results show that there was a significant difference in the time taken, which suggests that the time to find intended app could be an effective feature for estimating cognitive performance from smartphone logs.

The contributions of this paper are as follows:

- We simultaneously collected both continuous GNG task and smartphone logs for 42 days from 39 participants.
- We explored effective features of estimating cognitive performance from smartphone logs and validated the hypothesis that there is a difference between time to find intended app in terms of high and low cognitive performance.

Related Work

Several studies have been conducted to estimate or measure cognitive performance using smartphone logs [1, 8].

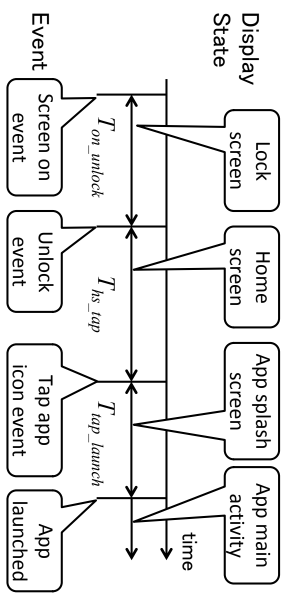

Figure 1: Definition of times.

Abdullah et al. [1] investigated the effect of smartphone usage (screen on/off events), sleep, chronotype and time-of-day for cognitive performance. They made a performance prediction model using PVT as ground truth. They reported that the model could predict response times with root mean square error of 80.64 ms and that the screen on/off event was an effective feature of estimating cognitive performance. Murnane et al. [8] also analyzed the relationship between smartphone app usage and cognitive performance, using PVT as a measure of the performance. They found a correlation between the pattern of app usage categorized into productivity (e.g. Evernote, OfficeSuite) and cognitive performance. In the work of Li et al. [7], they combined stress estimation and work performance (productivity) to distinguish between eustress and distress. They used heart rate, smartphone usage log and computer usage log to estimate stress type. Pielot et al. [9] proposed a method of detecting boredom, the opposite of measuring performance, from demographics and mobile phone usage. They used self-reported boredom feelings as ground truth.

To the best of our knowledge, no existing study has investigated the relationship between the time taken from turning on a smartphone to launching the first app and cognitive performance.

Data

Participants:We recruited participants from among the employees of the R&D division of NTT DOCOMO, INC. A total of 39 employees (34 males and 5 females, aged in their 20s to 50s) participated in the experiment. The data was collected between November 13th, 2017 and January 31st ,2018, with each subject participating for up to 42 days during this period. We created an Android application for collecting smartphone logs and performing GNG task, and asked the participants to install it on their phones. The study was approved by the ethics committee of the Graduate School of Medicine, part of the Faculty of Medicine at the University of Tokyo.

Go/No-Go Task: We asked the participants to perform GNG task three times a day. The time slots given were 9:30-10:30, 12:00-13:00 and 16:00-17:00. Eight types of characters were displayed on their smartphone. Six characters were set as ‘go” stimuli and the remaining two characters were set as ‘no-go” stimuli. To avoid character dependent effects, we randomized the “go” stimuli for of the each participant. We measured the following metrics: (1) commission error, (2) omission error, (3) correct rate and (4) reaction time.

Smartphone Usage Logs: Screen on/off (timestamp and event type) and app usage history (timestamp, activity name and event type) were recorded.

We collected a total of 926 records of both GNG task and smartphone logs from 25 participants.

Exploring the effective features for estimating cognitive performance

Definition

We define three types of smartphone usage time (T_{on_unlock}, T_{hs_tap}, and T_{tap_launch}) as shown in Figure 1. We define “time to find intended app” is $T_{on\_unlock} + T_{hs\_tap}$.

Method

In the work of Abdullah et al. [1], it was revealed that the screen on/off feature is one of the most effective features of estimating alertness from smartphone usage logs. Therefore, there is the possibility of estimating cognitive performance from other smartphone logs. If a person’s performance is high, it can be considered that the behavior of that person is efficient.

Therefore, in this study, we explored behavioral markers under the hypothesis that the efficiency of smartphone usage of an individual reflects their cognitive performance. Specifically, we hypothesized that individuals are able to unlock screen and launch an intended app quickly when their cognitive performance is high, On the other hand, individuals will take some time to do that when their cognitive performance is low as they are distracted by other things and cannot concentrate on finding intended app. Thus, we investigated the relationship between the time to find intended app and the cognitive performance to validate this hypothesis. We categorized the recorded data into high and low GNG performance and the difference in the meantime to find intended app was statistically tested. The specific procedure was as follows:

(1) The correct rate of GNG was calculated for each of the participants and time slots.

(2) The time to find intended app were computed using the corresponding smartphone logs for each of the participants and time slots. We extracted the events that met the following conditions: (1) the launched app was not the “home app”, and (2) the app launch log was next to screen on event, because it was supposed that there are two patterns of app launch as shown in Figure 2.

(3) The correct rate of a GNG task was labeled as relating to high or low cognitive performance based on whether a correct rate was over the average for the participants and time slots or not.

(4) The average time was calculated for each of the participants and time slots regarding high/low cognitive performance.

The correct rate was normalized for each of the participants and time slots as follows.

$$\frac{x_{u,s,i} - min_{u,s}}{max_{u,s} - min_{u,s}} \quad (1)$$

where x is Go/No-Go task indicator, u is participant, s is time slot and i indicates i-th sample. The cut-off time was set at 10 sec.

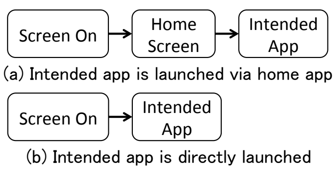

Figure 2: Illustration of the cases for app launch.

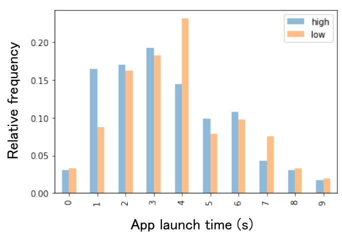

Figure 3: Comparison of the time taken from turning on a smartphone to launching first app.

Results and Discussion

Figure 3 shows the distribution of the average time to find intended app relating to high/low GNG task performance. The average time to find intended app for high performance is 3.756 sec and for low performance is 4.080 sec. We conducted statistical test (Welch’s t-test) on this distribution and as a result, the p-value was $0.049 < 0.05$. This result suggests that the time to find intended app can be used as an effective feature of estimating cognitive performance from smartphone logs. T_{on_unlock} and T_{hs_tap} are aggregated in this analysis, because both unlocking and finding intended apps require user’s attention for smartphone. However, T_{on_unlock} might decrease if biometric authentication (e.g., fingerprint) becomes popular. Thus, we would like to investigate each effect separately in future work.

Conclusion

We investigated the effectiveness of the time to find intended app for estimating cognitive performance from smartphone logs. To conduct the analysis, we collected smartphone logs and GNG task data for 6 weeks from 39 participants in the wild. Our analysis suggests that the time to find intended app can be used effectively to estimate cognitive performance from smartphone logs. Our work has a couple of limitations, as follows: (1) since the sample size is limited to 39, a larger scale study is needed. (2) only the difference in the app launch time distribution was evaluated, so a prediction model is required based on the time to find intended app.

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