
Towards Cognitive Awareness: A Mobile Context Modeling- and Notification-based Approach

Akhil Mathur

Nokia Bell Labs,
Cambridge, UK
akhil.mathur@nokia-bell-labs.com

Fahim Kawsar

Nokia Bell Labs
Cambridge, UK
fahim.kawsar@nokia-bell-labs.com

Abstract

Awareness about one's own cognitive state is a critical first step towards better physical, physiological, psychological, behavioral, and social health. When users are aware of their mental states – particularly those which might be detrimental to their health (e.g. high stress, low excitement) – they can take the necessary steps to either alter their behavior, or find ways to effectively cope with it. From a technology viewpoint, it is thus important to find ways to detect a user's cognitive state as unobtrusively as possible, and thereafter either inform or assist the users in coping with it. Through this position paper, we wish to discuss the potential of using mobile context data gathered from a user's smartphone to infer the user's cognitive state, and thereafter using mobile notifications to deliver timely intervention messages.

Author Keywords

Cognitive Awareness; EEG headsets; Context Modeling; Mobile Notifications; Intervention Design

ACM Classification Keywords

H.5.m. Information Interfaces and Presentation (e.g. HCI): Miscellaneous

Permission to make digital or hard copies of part or all of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. Copyrights for third-party components of this work must be honored. For all other uses, contact the Owner/Author.

UbiComp/ISWC'17 Adjunct , September 11–15, 2017, Maui, HI, USA
© 2017 Copyright is held by the owner/author(s).
ACM ISBN 978-1-4503-5190-4/17/09.
<https://doi.org/10.1145/3123024.3124565>



Figure 1: Emotiv Insight EEG Headset

Introduction

With the rapid advancements in consumer healthcare devices, we are now able to continuously measure various cognitive signals from a human body, and wirelessly stream them to a smartphone for real-time analysis. For example, off-the-shelf EEG headsets such as Emotiv Insight [2] (as shown in Figure 1) allow us to measure cognitive states of engagement, focus, stress, interest, or excitement based on the variations in brain waves. However, despite these advancements, such head-mounted devices are not yet widespread in the real world owing to their form factor, low social acceptance, and a rather high calibration time required for getting accurate EEG data. As a result, users are not able to realize the full potential of this technology in their everyday lives.

On the other hand, smartphones have become an integral part of our lives, and are now considered an effective indicator of our digital as well as physical interactions with the world (e.g. location, physical activity, face-to-face interactions [3]). In this work, we are investigating the possibility of modeling context information derived from a user's smartphone to infer his/her cognitive states. If this context modeling approach results in reasonably accurate inferences of a user's cognitive state (e.g. stress, excitement), it would enable a wide-variety of applications that require awareness of a user's cognitive state. For example, if attending long meetings in the morning lead to high stress for a user throughout the day, this awareness can be used by his/her Calendar application to avoid scheduling meetings in the morning.

Further, we are also exploring ways to effectively communicate this automatically detected cognitive-awareness back to the users. Our current investigations focus around the use of in-time smartphone

notifications to inform or alert the user about their cognitive state, and suggest possible ways for them to cope with it.

Proposed Methodology

Here we explain our methodology for building machine learning models to infer a user's cognitive states based on smartphone context data. It consists of two stages:

1) Small-scale EEG ground truth collection and modeling: As we discussed earlier, the EEG devices for measuring cognitive information are still not suitable for large-scale adoption primarily due to the challenges in calibrating them. However, in a small-scale controlled study, participants could be instructed to calibrate and wear them for a limited time. As such, our goal is to first develop machine learning classification models for various cognitive states (e.g. engagement, excitement, stress) based on ground truth collected from EEG headsets at a small-scale (50-100 users). Thereafter in the second stage, we will show how to deploy and fine-tune these models for individual user preferences in a large-scale setting.

For the small-scale study, we have developed an Android application called QuantApp [9], which runs as a background service on the users' phone and passively record all usage sessions on the device along with context information around them. This includes logging of screen events (screen on/off); call events (incoming/outgoing/missed); application events (foreground/background) and notification events, along with periodic recording of sensor data from the device. From this data, a list of features could be extracted for building machine learning models.

To collect cognitive state ground truth from the EEG headset, we use the Insight application provided by its

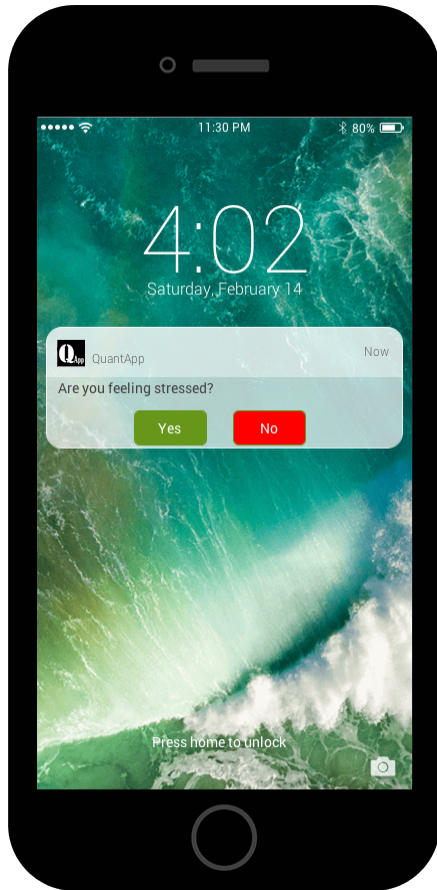


Figure 2: Wireframe of an Experience Sampling Question

manufacturer Emotiv on the Google Play Store [2]. The Insight application connects an Android smartphone to the EEG headset over Bluetooth Low Energy (BLE), and receives cognitive scores (e.g. stress levels, engagement score, excitement level) from the headset at the rate of 100Hz.

Finally, we input the features extracted from the smartphone context data along with the ground truth obtained from the EEG headsets into various off-the-shelf machine-learning classifiers such as SVM, Random Forests etc. to model the relationship between them.

At the time of writing this paper, we have trained a small-scale Random Forest model for 'Engagement Detection' with a F-value of 0.85 [9], which uses smartphone context features such as recency of communication, last-hour smartphone usage, battery levels and ambient noise levels to predict a user's Engagement state. The training of other models is a work-in-progress.

2) Model deployment and fine-tuning using experience sampling: In this stage, we will deploy the various cognitive state classifiers in-the-wild by embedding them inside QuantApp. However, as the classifiers are trained offline on a different user sample, their accuracy in-the-wild might be low. To address this, we propose using experience sampling as a way to fine-tune the classifier to each individual's behavior.

For this, QuantApp will send experience sampling questions by means of mobile notifications to the users at opportune moments as shown in Figure 2. For example, when QuantApp infers a user's cognitive state as 'High Stress', it will push an experience sampling question asking the user - "Are you feeling stressed?"

Based on the user's response, QuantApp will fine-tune the underlying Stress model embedded inside it.

Cognitive Awareness Using In-Time Mobile Notifications

Finally, we envision using mobile notifications as the modality for promoting cognitive awareness among users. For example, if the fine-tuned machine learning model for detecting 'Focus' outputs a 'low focus' score for a user, QuantApp will generate a notification alerting the user about it and recommending ways to alter their cognitive state based on their past behavior. For example, as shown in figure 3, the notification can warn the user that it has detected 'low focus in the task', and based on user's historical data, a 5-minute walk can help in regaining the focus.

Discussion

This research is currently a work-in-progress, with several challenges. At this point, it is unclear what kinds of cognitive metrics can be inferred from smartphone features. Our early explorations have shown that 'cognitive engagement' (i.e. how engaged does a user feel in a given task) has significant correlation with smartphone usage – similarly, we are now building models for other cognitive metrics at small-scale. Thereafter, we plan to deploy them in-the-wild and conduct a large-scale evaluation on their efficacy.

We would like to discuss the following aspects of cognitive awareness in the workshop:

- Apart from mobile notifications, what are other ways to make the users aware about their cognitive states?
- What are the possible intervention designs for motivating users to act on this cognitive awareness?

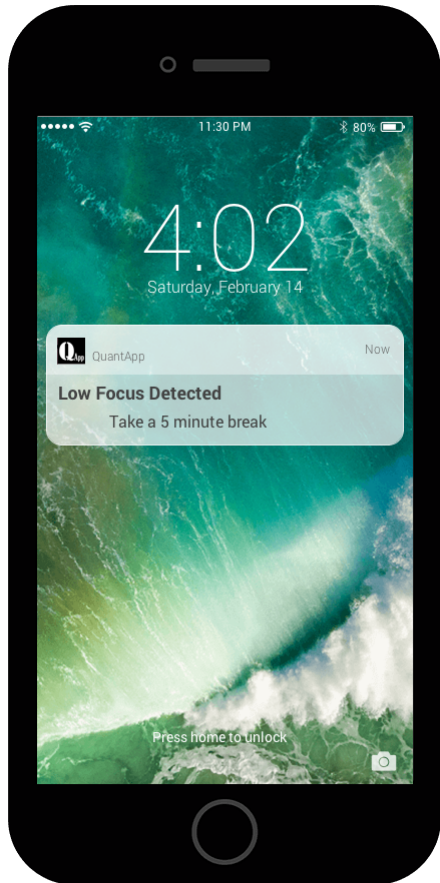


Figure 3: Cognitive Alert and Recommendation (wireframe)

For e.g., if the technology detects that a user is stressed in a given context, how can it motivate the user to avoid the stressor(s) in future?

- Which kinds of application scenarios could benefit from awareness about cognitive states of a user?
- We are also looking for feedback on our two-stage modeling methodology. Can it be extended to other sensor devices e.g., those which are currently very expensive for large-scale consumer use?

Related Work

In the field of Affective computing, systems have been developed that can detect and adapt themselves to users' affective states. Picard et al. [4] showed automatic recognition of eight affective states from sensed physiological signals with 80% accuracy. Bixler and D'Mello [7] proposed using keystrokes during writing tasks to detect affective states such as boredom and engagement. In the context of smartphones, Pielot et al. [5] showed that mobile phone features could infer boredom with an accuracy of up to 82.9%. Other works have found behavioral traits such as happiness [8], mood [6] to be correlated to mobile phone usage features and personality traits of an individual. Our investigation continues the tradition of past studies examining the mobile context features to understand cognitive states. Moreover, our focus is on taking these inventions outside the lab, by deploying these models in-the-wild, fine-tuning them to individual user's needs and then designing effective intervention plans to assist the users in their everyday lives.

Conclusion

In 2012, Campbell et al. [1] proposed the vision of a cognitive phone – a device much smarter than current smartphones, which can infer various cognitive states of the user. Currently, a major hurdle to this vision is

the difficulty in calibrating and using wearable devices that can measure cognitive signals (e.g., EEG headsets). In this position paper, we propose using features derived from smartphone context data to model various cognitive aspects (e.g. stress, engagement). Further, we proposed the idea of using mobile notifications to deliver timely intervention messages to the end-users to promote cognitive awareness. We hope that these ideas will provoke discussions in the UbiTention workshop regarding cognitive awareness, and lead to further research into this emerging area of HCI.

References

1. Campbell, Andrew, and Tanzeem Choudhury. "From smart to cognitive phones." *IEEE Pervasive Computing* 3.11 (2012): 7-11.
2. Emotiv Insight EEG headset. <https://www.emotiv.com/insight/>
3. Mashhadi A., Mathur A., Broeck M., Vanderhulst G., Kawsar F. Understanding the Impact of Personal Feedback on Face-to-Face Interactions in the Workplace. In Proceedings of ICMI '16.
4. Picard R., Vyzas E., and Healey J. Toward machine emotional intelligence: Analysis of affective physiological state. *Pattern Analysis and Machine Intelligence*, IEEE Transactions on 23, 10 (2001).
5. Pielot M et al. When attention is not scarce-detecting boredom from mobile phone usage. In Proceedings of UbiComp '15 . ACM.
6. LiKamWa R. et al. Moodscope: Building a mood sensor from smartphone usage patterns. In Proceeding of MobiSys '13 . ACM.
7. Bixler R., D'Mello S. Detecting boredom and engagement during writing with keystroke analysis, task appraisals, and stable traits. In Proceedings of UII '13.
8. Bogomolov A. et al. Happiness recognition from mobile phone data. In *Social Computing (SocialCom)*, 2013

9. Mathur, A., Lane, N.D. and Kawsar, F. Engagement-aware computing: Modelling user engagement from mobile contexts. In Proceedings of UbiComp '16. ACM.