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M.Sc. Thesis

Classifying brain activity using low-cost biosensors and automated time tracking

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Abstract

Add: Abstract

Contents

Notes & TODOs

1 Introduction

Add: Write introduction

2 Background

People spend more time than ever using computing devices. Work, entertainment, and services, have been steadily moving online over the last few decades and this trend is expected to continue. While several studies have been tracking how people spend time on their devices a wider study of how people's app usage is changing over time and how it varies with demographics, is not publicly available.

Furthermore, how different device activities affect the user behaviorally and neurologically is of interest for many areas of research, including:

- psychological well-being, such as depression and social anxiety [1][2], stress [3], self-esteem, life satisfaction, loneliness, and depression [4].
- the impact of screen time on children and adolescents [5].
- attention span among media multitasking adults [3].
- enhancing personal productivity [6].

Understanding device use and the underlying cognitive processes are essential when designing for motivation, engagement and wellbeing in digital experiences [7].

This becomes especially relevant for knowledge workers, such as software developers, who spend the majority of their working time on computing devices.

Add: Mention of Quantified Self movement, and the applicability/usefulness of EEG data to the cause

2.1 Automated time trackers

Automated time-trackers have been developed for computing devices, with various applications such as tracking productivity, managing excessive use of social networking sites (SNSs), and studying user behavior.

2.1.1 Commercial use

Companies like RescueTime [8], Hubstaff [9], and others offer automated time tracking as a service. These services let the user track their screen time by installing a program on their device which tracks the active application and sends the data to their servers for storage and analysis. The user can then view their data in a dashboard on the service's website. Some of these services, like RescueTime and Hubstaff, are marketed towards teams and professionals, who want to keep track of individual and team productivity.

However, these services have some issues for use by researchers and individuals alike. Notably, their collection of detailed and non-anonymized behavioral data into a centralized system bring significant privacy concerns, especially in cases where the data is shared with a team or an employer.

Other limitations of these services, such as low temporal resolution and limited event detail, cause additional issues for certain tasks that are timing-sensitive (such as ERPs), or preprocessing steps that can take advantage of high level of detail (like classifying activity).

2.1.2 Research use

Previous research has been published which used automated time trackers, such as TimeAware [6] and ScreenLife [10]. However, these previous contributions are — like the commercial services — not open source nor permissively licensed, and therefore not available for external research use nor further development.

2.1.3 ActivityWatch

The free and open source automated time tracker ActivityWatch [11] addresses aforementioned issues with other software around source availability/licensing, privacy, temporal resolution, event detail, and cross-platform support.

2.2 EEG and low-cost biosensors/functional brain imaging

Functional brain imaging methods such as fMRI, fNIRS, and EEG, have been used to study the relationship between cognitive or physical activity, and brain activity [12][13][14]. The more accurate methods such as fMRI are costly and inflexible/impractical for many uses.

However, the recent availability of low-cost biosensors such as EEG, HEG, and fNIRS, enables studying brain activity during real-life tasks. As an example it has been shown that it is possible to classify what task a participant is undertaking using fMRI [12], which has been replicated using EEG and low-cost biosensors [14].

But they are not without their limitations — among them a notably low signal-to-noise ratio [15] — yet visual evoked potentials (VEPs) have been shown to be sufficient for high-speed BCI applications [16].

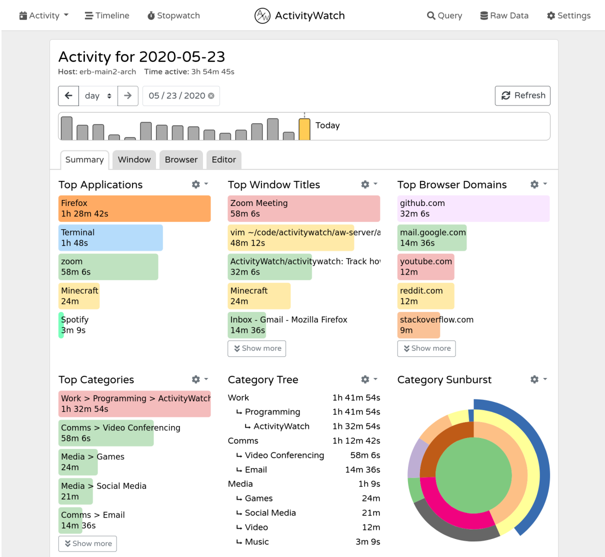

Figure 1: ActivityWatch activity dashboard. Showing top applications, window titles, browser domains, and categories.

To combat the low signal-to-noise ratio, machine learning methods have been employed with varying degrees of success. Examples from previous research include Convolutional Neural Networks (CNNs), which have been successful in classifying time series in general [17], and EEG data in particular [18]. As well as Hierarchical Convolutional Neural Networks (HCNNs), which have been used for EEG-based emotion recognition [19].

Add: Applications to software engineers

2.3 Aim of the thesis

The primary aim of the thesis is to improve upon previous attempts[14] to classify wether the user is reading code or prose using EEG data. This is to be achieved by using better EEG equipment and state of the art analysis methods such as Riemannian geometry. A secondary aim of the thesis is to investigate wether the ability of EEG analysis to classify code vs prode comprehension generalizes across more activities, such as the wide variety of tasks engaged in during organic device use.

Secondary aims of the thesis include:

1. Implementing a classifier for device activities from EEG data, during organic device use
2. Improving open-source tools for EEG analysis

Add: Insert stuff from goal document

2.4 Related work

It has previously been shown that fMRI [12] and EEG[14] provides enough information to classify wether a subject is reading prose or code. However, accuracy with single-channel EEG has been found to be poor, and notably outperformed by a heart rate variability (HRV) monitor.

Recently, it has been shown that the multiple demand (MD) system is typically recruited for code comprehension tasks, as opposed to the language system that is typically recruited during prose comprehension [20]. This sheds light on the significant differences in how the brain processes code vs prose.

Add: Insert mention of preprint that Fucci mentioned?

3 Methods

3.1 Collection of device activity data

All device activity is collected using the automated time tracker ActivityWatch [21]. The data from ActivityWatch is processed and categorized such that the resulting data has the 3 columns `start, end, category`. The category is determined by a regular expression that matches on window titles and URLs, such as `github.com`.

Add: Summary of ActivityWatch

3.2 Collection of EEG data

EEG data was collected during organic device use and under controlled conditions.

For both conditions, code from the open source eeg-notebooks [22] was used to record the raw EEG stream into a CSV file. For the Muse S, muse-lsl was used as the underlying software to handle the connection (which uses Lab Streaming Layer). For the OpenBCI and Neurosity devices, brainflow [23] was used to handle the connection.

3.2.1 During organic device use

For the organic device use conditions, we primarily used the Muse S EEG headband which features 4 channels with electrodes placed at TP9, AF7, AF8, and

TP10.[1] The Muse S was chosen mainly due the superior comfort and ease of use compared with the alternatives, making it especially suitable for long recordings.[2]

3.2.2 During code vs prose comprehension task

For the controlled condition, the hardware used was ....

decide on which hardware to use

We implemented the task in eeg-notebooks [22], which uses previously mentioned libraries for data collection as well as PsychoPy [24] to provide the experiment stimuli.

actually implement the task

actually perform controlled experiments

3.2.3 Devices

- Muse S
- OpenBCI Cyton (with Ultracortex headset)
- Neurosity Notion DK1
- Neurosity Notion 2 (preordered, arrives in spring)

3.3 Analysis

For classification and analysis, we used common open source Python libraries for data analysis, like numpy [25], pandas [26], and scikit-learn [27]. In addition, we used less common libraries tailored specifically for working with EEG data, such as MNE [28], pyriemann [29], and YASA [30].

3.3.1 Feature engineering

Bandpower features are simple and commonly used in EEG research for many tasks, including the paper by Fucci et al we seek to improve upon [14]. As a reference, we implemented classifiers which solely used bandpower features as input, to gain information of how much any improvement from classifier performance is likely due to better EEG equipment versys how much is due to from improved analysis methods.

To compute this feature, we utilized the bandpower function provided by YASA [30]. The implementation estimates the power spectral density using Welch's method for each channel, and bins them by their associated frequency band.

[1] According to the 1020-system.

[2] A wet electrode cap system was also considered, but ultimately not investigated due to being inconvenient to use.

3.3.2 Riemannian geometry

The state of the art in many EEG classification tasks involves the use of Riemannian geometry. For this, we used the open source pyriemann library by Alexandre Barachant[3].

Improve: according to whom?

Add: Explanation of riemannian geometry, from this tutorial we're working on

4 Results

Our classifier performance is...

5 Conclusions

Our results show...

6 Discussion

6.1 Ethical considerations

Add: Discuss ethics/privacy considerations of data collection, how it's dealt with in ActivityWatch, and implications of results on similar concerns apply to EEG data

Acknowledgements

- My advisor Markus Borg.
- My brother Johan Bjäreholt, for working with me on ActivityWatch all these years.
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- Andrew Jay Keller at Neurosity, for giving me a refurbished Notion DK1 to work with.
- Everyone who's contributed to the open source tools I've used.

[3] First author of the original paper to apply Riemannian geometry to EEG [31]

The Oxford English Dictionary defines 'thesis' as "a long essay or dissertation involving *personal research*, written by a candidate for a university degree". I can't think of more "personal research" than research in quantified self with personal data.

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