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# Detecting stress level through computer usage pattern

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## Abstract

Stress is inevitable. Sometimes people fall back to their old habits or perform a series of actions that can be directly linked to their stressful states. Identifying stress is important but the approach scales poorly when invasive sensors have to be used or the method relies on induced stress in a timed lab experiment. Our solution aims to identify stressful states based on continuous logging of keystroke dynamics, mouse patterns, and foreground application usage. We propose a privacy-aware system, E-stress detector, that logs participants' computer activities alongside their stress self report. After extracting relevant features, our top classifiers provide 85 to 95 % accuracy for predicting user stress level.

## 1. Introduction

As we know, overstress undermines our productivity, and more seriously, it might bring harm to our health, even cause mental diseases. However, sometimes we tend to feel exhausted and stressed, but unaware of what cause us to feel stressed exactly. Therefore, it is crucial to find out the sources of stress, and at some appropriate time, give users some reminders that you are overstressed and you should take a break and relax yourself right away.

When people are under stress, their behaviors tend to change accordingly. In particular, we have observed that peoples computer using patterns, the way they type, click, browse webs change with regard to their stress, or anxiousness level. For example, when people feel stressed, they click the mouses with higher

frequency; they tend to have more typos, and thus the frequency of doing error correction raises; the frequency of switching between different web pages also increases; they might check their phones more frequently but unconsciously, etc. We suppose these are good indicators to users stress level, and by analyzing users baseline stress level and detecting abnormal stress level, we will be able to understand whether they are overstressed and give proper reminders.

Since the computing age has encouraged working on personal computers, stress detection correlated to usage of these electronic devices could lead to insightful results. This research aims to discover which computer activities, if any, correlate with individual stress levels. Can ones typing pattern, duration on a browser, rate of mouse clicking or overall computer usage be linked to their stress level? Insightful results could have multiple applications such as personalized health recommendation systems for handling stress, timely interventions for detecting stress at an individuals peak, holistic feedback for doctors during diagnosis, among other health driven and personal purposes.

## 2. Related Work

Computer activities such as keystroke dynamics and mouse click patterns have been used in detecting user emotional and stress states. Related works can be broadly grouped into three major categories: Affective Computing, Keystroke Dynamics, and Mouse Usage.

### 2.1. Affective Computing

Epp Clayton et al, arguably did the first major work connecting keystroke dynamics and emotional states. This research measured 15 emotional states of users using periodical self report and keystroke features throughout the day (Epp et al., 2011). Hong proposed StressSense, which can detect human stress by focusing on paralinguistic features instead of actual vocal

contents (Lu et al., 2012). StudentLife utilized SurveyMonkey and mobileEMA to measure participants stress as ground truth (Wang et al., 2014). Similarly, we will use the same approach as our ground truth. Instead of 15 emotional states, our research primarily focuses on user’s level of stress.

## 2.2. Keystroke Dynamics

Hernandez, Javier, et al in Under Pressure use a pressure sensitive keyboard and capacitive mouse to discriminate between stressful and relaxed states in a lab setting (Hernandez et al., 2014). To allow our application to scale easily, we do not rely on using custom hardware.

## 2.3. Mouse Usage

Early work done by Ark Wendy S. et al in The Emotion Mouse relate the mouse touch to the emotion attached to a computer task. GSR and chest sensors were used to collect heart rate, temperature, galvanic skin response (GSR), and somatic movement, which were measured against the six Ekmans facial emotions (Ark et al., 1999). In more recent work, Sun, David et al in MouStress proposed an approach to detect stress from mouse motion, but from a physiological perspective – a model of the arm (Sun et al., 2014). Our approach is less intrusive as we do not propose an external sensor; rather, we focus on non-invasive continuous mouse tracking activities such as click rate and coordinates.

## 2.4. Computer Applications

Karpathy on his blog shows how he measures computer activities for self tracking. However, this is done with the idea of quantified self but without linking user stress state. Some of the ideas used in our project design were inspired by work on Karpathy’s system (Karpathy).

## 3. Methodology

The experiment involves stress self-report and data collection of keystrokes, mouse activities, together with computer applications used.

### 3.1. Experience Sampling of Keystrokes

Emotional states were collected using PAM and EMA.

### 3.2. Data Collection Software

Using our custom applications, we will install our background scripts on the participants computers.

Ideally, our background programs will record the keys users type, but the corresponding values will be randomized due to privacy sensitivity, and the frequency of mouse clicking as well. Data for Web browsing and application usage will be collected through available python APIs. All the data will be stored as txt/csv files, awaiting further analysis.

## 3.3. Feature Extraction

For training and testing, 15 keyboard features were used, which include typing speed per minute, etc;

## 3.4. Classification

Figure 1 shows the performance when all keyboard features were used.

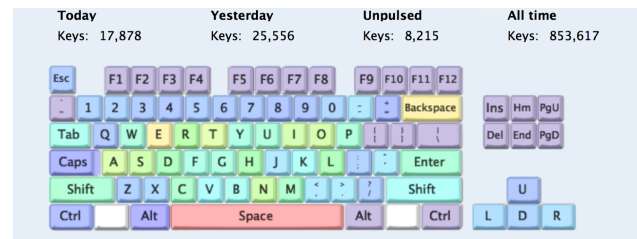


Figure 1. Heatmap for keyboard

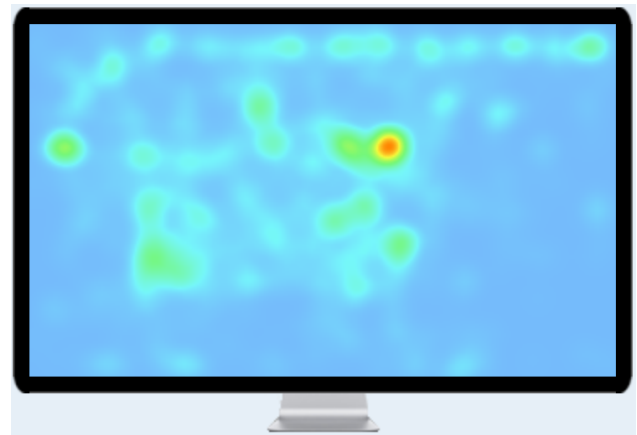


Figure 2. Mouse movement

## 4. Discussion

PAM and EMA were used in other to reduce the chances of false report. For instance, a user who picks an ‘angry’ picture and goes on to select ‘not stressed at all’, ‘very energetic’, ‘very pleasant’, will have two differing results, thereby nullifying the input.



Figure 3. Photographic Affect Meter (PAM)

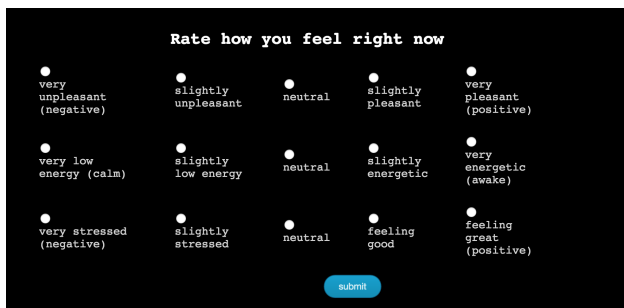


Figure 4. Ecological Momentary Assessment (EMA)

#### 4.1. Limitations

Since recruited participants were PhD students, our prediction model performance cannot be generalized to a broader audience. Since self-report surveys are subject, the definition of stress for different participants will have varying likert scale values.

Survey popping up periodically can become annoying to users thereby making reducing performance over time. Since emotional states are short-lived and a user can have multiple emotions in a short time, the surveys cannot fully capture the end user's entire emotional states but only a fraction of it.

## 5. Future Work

In order to improve multimodal sensing, future work will involve external sensors for measuring HR, BP, EEG. The current application focuses on batch learning of data already amassed so for next iteration will

involve online learning especially for making efficient recommendation systems. Participants for this experiment were PhD students recruited from a research lab familiar with some of the measuring tools used; more insightful applications might involve workers in industries especially end users oblivious of the methods of the current research.

## Acknowledgments

Special thanks to Prof Daniel Cosley, students of INFO 6010, reviewers of Advanced Machine Learning course (Spring 2015), members of the PAC lab at Cornell University Information Science, and Prof Tanzeem Choudhury, whose guidance was instrumental in this project.

### 5.1. Citations and References

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Alphabetize references by the surnames of the first authors, with single author entries preceding multiple author entries. Order references for the same authors by year of publication, with the earliest first. Make sure that each reference includes all relevant information (e.g., page numbers).

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