DEPARTMENT OF INFORMATICS

TECHNISCHE UNIVERSITÄT MÜNCHEN

Master's Thesis in Informatics

Detection and Dialog-Based Self-Reporting of Stress for Eating Behavior Prediction

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Erkennen und dialogbasiertes Self-Reporting von Stress zur Vorhersage des Essverhaltens

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I confirm that this master's thesis in informatics is my own work and I have documented all sources and material used.

Munich, 15.05.2020 Wenjian Li

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Abstract

Contents

1 Introduction

Eating is an activity that people perform on a daily basis. It is the essential source of ingredients for us humans. Our nutrition intake, in turn, affects our health. However, people's choice of food cannot be simply regulated in terms of time and ingredients to make the best health effect out of it, because it is a highly emotional behavior (Gardner et al. 2014). According to Gardner et al., both positive and negative moods affect food choices. Especially, having negative moods often leads one to pick indulgent food instead of healthy food to cope with the emotion.

Stress is a common reaction to the environment that is often linked to negative emotions. In fact, Du et al. (2018) suggests that there is a significant positive correlation between the level of stress one has and the degree of negative emotions one experiences. Combining the results from both studies, it is therefore highly likely that food choices could be affected by stress.

A study by Mental Health Foundation (2018) suggests that a majority of the population in the United Kingdom may have been overwhelmed with stress at some time within the year 2018. This suggests that many of the health problems resulted from unhealthy eating behaviors could be linked to stress. However, regulating eating behavior often requires a deep understanding of nutrition and diet, which is not the possession of non-experts. There are professionals who are out there to offer counseling services on people's diet, but this is understandably not always accessible by the general public, given the pervasiveness of stress among them. Moreover, the specific eating behaviors resulted from stress differ among individuals (Torres and Nowson 2007). For example, the same level of stress can lead to overeating for one person, but undereating for another. It is, therefore, crucial to work out an individual's eating behavior under the influence of stress without professional medical intervention. This information can be helpful in building food recommendation systems that can detect stress, and recommend healthy food based on the user's eating patterns. The prerequisite of such is to build another (predictive) system so that given a specific user and his/her stress level, it can predict what the user is likely to eat, especially whether he/she is likely to eat more or less than usual. This thesis focuses on establishing a method to build such a system.

The first step is to collect user data. Specifically, data on users' stress and eating behavior, as well as the relations between them. One way of doing this is to use a chatbot. Compared with more explicit ways of acquiring data, such as questionnaires or interviews, a chatbot is obviously less intrusive and offers the possibility to collect data in a real-world setting instead of in laboratories. On the other hand, users are likely to be more adherent to chatbots compared to other types of cognitive-behavioral therapeutic (CBT) apps such as self-help web-based therapy (Barak et al. 2008) given their conversational and human-like nature, which is crucial in the context of this research (Fitzpatrick et al. 2017).

This thesis presents the design, implementation, and testing of a chatbot which collects data on the users' stress information and food consumed whilst being stressed, and presents a method to build a connection between the two on a per-user basis, i.e. building a stress-eating profile for a potential user. The following chapters will provide details regarding the design, realization, and evaluation of such a system. Chapter 2 formalizes the goal and requirements of the project. It will put the terms "stress detection", "dialogue-based self-reporting of stress" and "eating behaviors" into the context of this work. Chapter 3 summarizes previous works related to the topic of this research, which focused on the effect of emotion on eating, chatbots as dietary advisors, and stress detection utilizing data collected by smartphones and wearable smart devices. Chapter 4 offers the details of the system design, focusing on the framework used for building the chatbot, the detection and self-reporting of stress, the collection and processing of eating behavior data, the design of states in the conversation flow, and how data is persisted for processing and analysis. Chapter 5 presents how the chatbot was tested among pilot users, including the recruitment process, the process of data collection, and the methods for evaluation of such experiment. This will be followed by chapter 6 which explains the data gathered, including the data size and content, as well as how the data is trained to result in predictive models. Chapter 7 demonstrates the result of both the data processing and the feedback from the participants.

There are certain limitations of this research which are discussed in chapter 8. Since this study aims at building a foundation for more sophisticated systems related to stress eating, e.g. food recommendation systems, chapter 9 is going to give suggestions to future work. Finally, chapter 10 will conclude this thesis.

1.1 Section

1.1.1 Subsection

See Table 1.1, Figure 1.1, Figure 1.2, Figure 1.3.

Table 1.1: An example for a simple table.

A	B	C	D
1	2	1	2
2	3	2	3

$$
\begin{tikzcd}
R_1 \arrow[r, dash] \arrow[d, dash] & R_2 \arrow[r, dash] \arrow[d, dash] & R_5 \\
R_3 \arrow[r, dash] & R_4 &
\end{tikzcd}
$$

Figure 1.1: An example for a simple drawing.

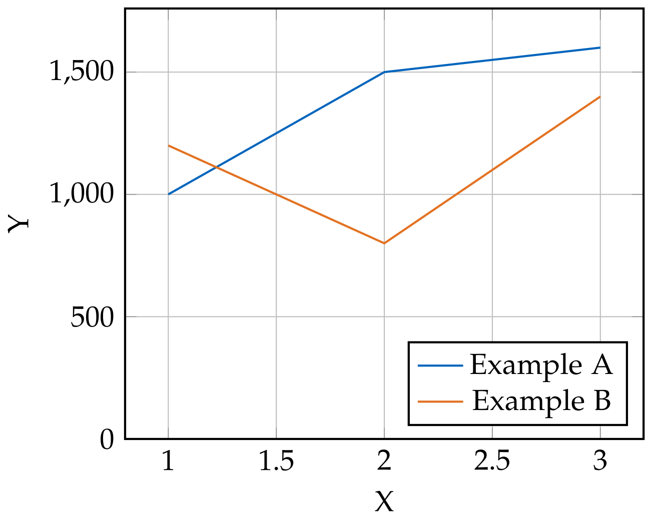


Figure 1.2: An example for a simple plot.

```sql
SELECT * FROM tbl WHERE tbl.str = "str"
```

Figure 1.3: An example for a source code listing.

2 Goal and Scope

Developing a system to serve the purposes as introduced in the previous chapter is a complicated task that covers a wide area of knowledge and various domains. Therefore, it is essential to define the scope of the study, i.e. the goal it aims to achieve, and the scope which the key terms of it is supposed to cover.

2.1 Goal

The goal of this study is to find a method to create a stress-eating profile for a random individual, based on his/her stress and eating data. More specifically, it tries to build a pipeline along which the following data can be collected via a conversational agent (which in this project was a chatbot) that interacts with its user on a daily basis:

- Data on the individual's level of stress at the time of measure, which is either detected by the conversational agent or reported by the individual through conversations
- Data on the individual's level of stress during the days for a measurement period of more than 2 weeks
- Data on the individual's food consumed when he/she was stressed at the time of measure, as self-reported by the individual to the conversational agent
- Data on the individual's amount of food consumed during the days for a measurement period of more than 2 weeks

after which it builds a classification model for the individual based on the data collected that predicts whether the individual is likely to eat more or less under the influence of stress.

Furthermore, it is expected that the method can be applied to more users over a longer period of time, and ultimately provide insights and input for other applications, such as a dietary adviser or a food recommendation system.

The following sections will define the scope of this project.

2.2 Scope of Stress Detection

Some of the most predominant research works on stress detection (Zhai and Barreto 2006; Sun et al. 2012; Melillo et al. 2011) all rely on sensor data. Sensors, especially those embedded in smart devices such as smartwatches and smart armbands, have the advantage of accessing health data including heart rate, sleep, and physical exercises, which is, on the one hand, non-intrusive, and on the other, hardly available by other forms of non-intrusive daily-used data-providers such as smartphone apps. Some smartphones are also equipped with such sensors but their data quality is relatively poor, considering that users are not carrying the phone all the time. However, for this study, we choose not to utilize wearable smart devices because the data qualities provided by different smart devices vary, while this factor has to be controlled to obtain an accurate and unbiased prediction of stress across users.

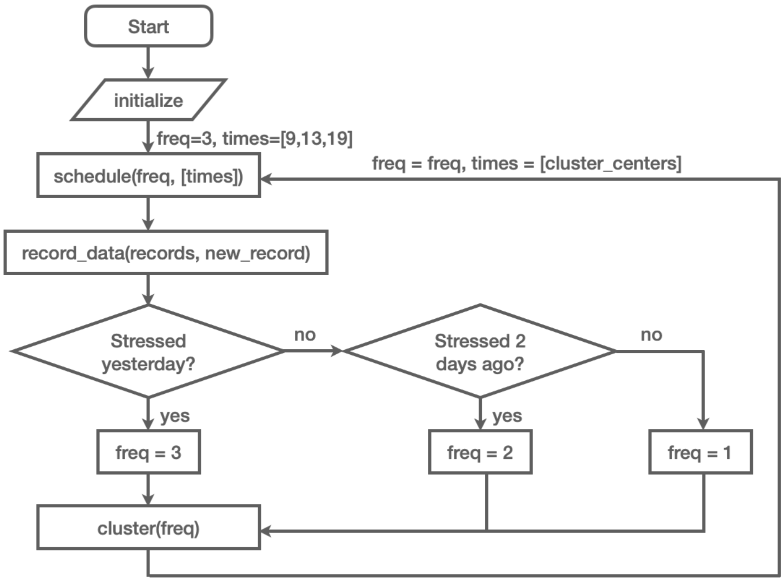
Furthermore, no contextual information such as GPS data and social activities being performed by the participants is utilized, for the chatbot platform (Rasa) (Rasa 2020) and API (Telegram Bot API) (Telegram 2020) chosen to be used do not support the gathering of such data in the background, making it intrusive to try to get these contexts (for example, in order to get the social activity a user is performing, the bot has to ask explicitly for where he/she is, whom he/she is with, and what exactly is he/she doing). More information on the choice of the framework can be found in chapter 4.

Instead, stress detection is done with a two-step process solely relying on simple conversations between the chatbot and the user. First, stress is sampled three times per day at fixed hours for every participant, i.e, the chatbot decides to ask about the user's level of stress at these timestamps. Second, based on the answers collected from the users in the first two weeks, a weighted clustering algorithm is performed on the timestamps to determine the scheduled time of the coming day of stress detection. The number of clusters is determined by the stress states of the user in the past two days. If the user was stressed the day before, stress is going to be sampled three times the day after, hence three clusters. If the user was not stressed the day before but was two days before, two clusters will be trained, leading to asking for stress in twice in the coming day. Otherwise, only one cluster is going to be trained. Figure 2.1 illustrates the way this adaptive stress-sampling works.

2.3 Scope of Stress Self-Reporting

Users of the system have the option to actively report stress in the form of a conversation with the chatbot. The self-reporting uses natural language, and specifically in this

Figure 2.1: The adaptive stress-sampling process



project, English, as a natural language understanding (NLU) module in English is trained in this project. No other forms of interaction are involved.

2.4 Definition of Eating Behaviors

In this research, the so-called "eating behaviors" refer to patterns in food consumption. The scope of such patterns differs in two scenarios, under one of which is the data the system collects which is related to eating. This data is used as input to a supervised learning scheme which builds predictive models. Under the other scenario, i.e. when such models are put into use, "eating behaviors" refer to food consumption patterns of the participants and future users that the models try to predict.

In the first scenario, the chatbot collects both descriptive and categorical data. It asks the participants to describe the food consumed, in natural language, at the time when they are stressed, or at the end of the day. In addition, it invites the participants to reflect the amount of food consumed during the day, and in case the participants have been stressed during the day, to compare this amount with the amount they are likely to eat when they are not stressed.

In the second scenario, the models try to predict only the categorical data related to food consumption, i.e. the amount of food likely to be consumed by a user given his/her stress level. In addition, it tries to predict whether the user is likely to eat any comfort food, which is defined in the coming section.

3 Related Work

4 System Design

5 Experiment

6 Data Analysis

7 Result

8 Limitations

9 Future Work

10 Conclusion

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Bibliography

Barak, A., L. Hen, M. Boniel-Nissim, and N. Shapira (2008). "A Comprehensive Review and a Meta-Analysis of the Effectiveness of Internet-Based Psychotherapeutic Interventions." In: *Journal of Technology in Human Services* 26.2-4, pp. 109–160. DOI: 10.1080/15228830802094429. eprint: https://doi.org/10.1080/15228830802094429.

Du, J., J. Huang, Y. An, and W. Xu (Jan. 2018). "The Relationship between stress and negative emotion: The Mediating role of rumination." In: *Clinical Research and Trials* 4. DOI: 10.15761/CRT.1000208.

Fitzpatrick, K. K., A. Darcy, and M. Vierhile (June 2017). "Delivering Cognitive Behavior Therapy to Young Adults With Symptoms of Depression and Anxiety Using a Fully Automated Conversational Agent (Woebot): A Randomized Controlled Trial." In: *JMIR Ment Health* 4.2, e19. ISSN: 2368-7959. DOI: 10.2196/mental.7785.

Gardner, M. P., B. Wansink, J. Kim, and S.-B. Park (2014). "Better moods for better eating?: How mood influences food choice." In: *Journal of Consumer Psychology* 24.3, pp. 320–335. DOI: 10.1016/j.jcps.2014.01.002. eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1016/j.jcps.2014.01.002.

Melillo, P., M. Bracale, and L. Pecchia (2011). "Nonlinear Heart Rate Variability features for real-life stress detection. Case study: students under stress due to university examination." In: *BioMed Eng OnLine* 10.96. DOI: 10.1186/1475-925X-10-96.

Mental Health Foundation (2018). *Mental health statistics: stress*. URL: https://www.mentalhealth.org.uk/statistics/mental-health-statistics-stress (visited on 04/09/2020).

Rasa (2020). *Rasa: Open source conversational AI*. URL: https://rasa.com/ (visited on 04/15/2020).

Sun, F.-T., C. Kuo, H.-T. Cheng, S. Buthpitiya, P. Collins, and M. Griss (2012). "Activity-Aware Mental Stress Detection Using Physiological Sensors." In: *Mobile Computing, Applications, and Services*. Ed. by M. Gris and G. Yang. Berlin, Heidelberg: Springer Berlin Heidelberg, pp. 282–301. ISBN: 978-3-642-29336-8.

Telegram (2020). *Telegram Bot API*. URL: https://core.telegram.org/bots/api (visited on 04/15/2020).

Torres, S. J. and C. A. Nowson (2007). "Relationship between stress, eating behavior, and obesity." In: *Nutrition* 23.11, pp. 887–894. ISSN: 0899-9007. DOI: https://doi.org/10.1016/j.nut.2007.08.008.

Zhai, J. and A. Barreto (2006). "Stress Detection in Computer Users Based on Digital Signal Processing of Noninvasive Physiological Variables." In: *2006 International Conference of the IEEE Engineering in Medicine and Biology Society*, pp. 1355–1358.