Remotion

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1 Introduction

Recommender systems filter content information for users to predict their most preferred products. In the world of modern television, these systems provide user oriented suggestion to reduce the vast amount of different movies and shows to a small manageable number to choose from. Currently most recommender systems are based on ratings and user profiles build from data all around their viewing habits. However different studies show, that emotions and personality play a major role in the decision making process [3]. Therefore, we propose a model that adds more dimensions to the classical approaches, by considering personality and current emotion of the user.

2 Data generation

A first obstacle to our approach is to model emotion and personality of a given user. Different sources of data input are needed to approximately model the needed features. To represent personality, we decided to make use of information provided by social media activities. These activities in form of shared content, liked pages, etc... has been exploited by machine learning models before[4, 5] to infer personality traits [2]. Unfortunately, we are unable to collect this kind of data and are also unable to get access to a respective dataset. Hence, this data can be collected from user of the later product upon their agreement.

Regarding the emotion part of the data, we plan on collecting current vital data of user through smart devices and match the data with possible emotional states of the user. For the scope of this project, we were only able to collect heart-rate data of every member of our team over a short period of time using an apple watch. The calculated heart-rate variability(HRV) can be used as an indicator of stress or physical activity[8, 1], which are important features to understand emotions, however many more vital data could be collected from different devices to further understand the emotional state of a person. For example a lower HRV could indicate a higher stress level. Furthermore, data collected from the environment like weather or location data can be an important factor. To derive the emotional state of a user, we believe, that it is important to use the collected data of a short period of time (12-24h).

3 Model

Due to a lack of data, we were unable to build a complete machine learning model. However, we provide a conceptual pipeline on how this model might look like. This pipeline is build upon a model build by Polignano et al.[7], which already uses personality data in the form of Social Media data to build a recommendation system for songs and might therefore solve a very similar task to movie recommendation. In the pipeline, we added the additional data collected by smart devices and environmental data.

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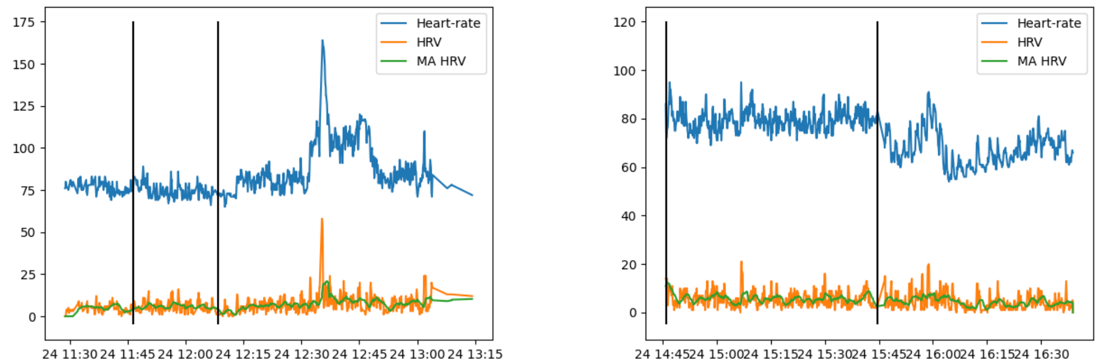

Figure 1: Heart-Rate and HRV of our team members at different times (the vertical lines indicate that a different person used the watch). The green line indicates the moving average of the HRV for better visualization.

4 Conclusion and further use cases

Emotions play an inevitable role in product appreciation. Recommender systems should leverage this opportunity by suggesting personalized content by detecting the user's emotions. With our concept, user's can receive content recommendations that not only satisfy their needs but can also help them in many ways. From past smokers not receiving any triggering smoking scenes to depressive users being encouraged to watch mood elevating content. In several studies, movies and shows have proven themselves to have an effect on user's well-being and emotions.[6, 11]

While we understand that emotions and personality are complex constructs that are not easy to fully grasp with data, we recognise the potential for further research and studies. We also identify the need for sensitive treatment of such social data, as it poses a risk of unfair treatment, discrimination and bias. It is therefore particularly important to build transparent recommender systems that allow decisions to be scrutinized and thus avoid unfavorable consequences.

However, if multi-dimensional data on emotions and personality can be collected with user consent and in their best interest, the foundation for promising machine learning models can be established. Many authors have paved the way for emotion-aware TV recommendations with their research and have been able to show already that the inclusion of above-mentioned factors has a positive effect on user satisfaction and recommendation accuracy [10, 9]. In the context of the START Hack Sunrise-UPC case, we hope to provide a framework that, in a similar way, will set the foundation for the development of emotion-aware TV recommendations.

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