Remotion

Emotion-aware TV recommendations

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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 suggestions to reduce the vast variety of movies and show a small manageable number to choose from. At the moment, 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 [4]. Therefore, we propose a model that adds more dimensions to the classical approaches, by incorporating personality and current emotion of the user.

2 Data generation

A first obstacle to our approach is to model personality and emotions of a given user. Different sources of data inputs are necessary to approximately model such 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... have been exploited by machine learning models before[6, 7, 9] to infer personality traits [3]. Unfortunately, we are unable to collect this kind of data and get access to a respective dataset at this point in time. However, upon further investigation we came to the conclusion that such data can be collected from users quite easily and hence monitoring a users social-media behavior seems to be a feasible approach to attain individual personality specific features.

Regarding user emotions, or a users "assertive state" as we refer to it, we plan on collecting live vital data via 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 mental stress or physical activity[10, 1], which are important features in order to understand emotions. In general the HRV and the stress level are negatively correlated, i.e. the lower the HRV the higher the stress level. As you can see in Fig 1, the third person that used the Apple Watch had a higher average HRV which suggest a lower stress level compared to all other test participants. This also correlates with the fact, that the third person was the most physically active, which tends to lower the mental stress level in a high stress setting like a Hackathon.

Despite so far only addressing heart-rate as a potentially impactful feature to specify certain assertive states, many more vital indicators such as body temperature or blood pressure could be collected from different devices to further understand and validate a users emotions. Additionally, data gathered from the users environment, like weather, location or political situation can influence their assertive state.

We believe, that the systematic and continuous collection of several specific data points is particularly effective when monitoring longer periods of time (12 -24h), especially capturing activities that are not directly related to media consumption, but which may affect a user's assertive state and correlate with their choice of preferred media content.

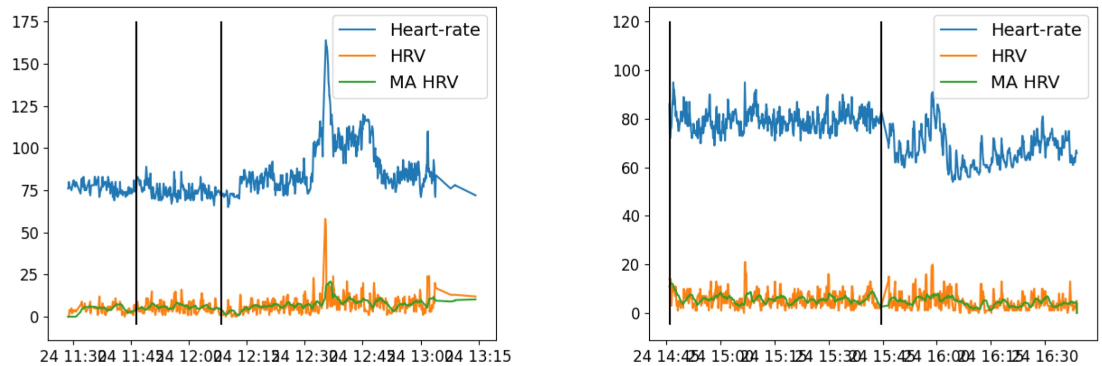

Figure 1: Heart-Rate and HRV of our team members at different times (the vertical lines indicate that a different person used the watch). The green line indicates the moving average of the HRV for better visualization.

3 Model

Due to the 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. As previously claimed, the input of our model consists of multiple different streams, including the movie and environment data from the Sunrise database, the user data from social media and other online contents and the vital data from different digital devices.

The main preprocessing steps consist of cleaning the input data, imputing missing values where necessary, feature scaling and finally outlier detection and handling. We believe, that especially outlier processing plays a crucial role in being able to differentiate between even the slightest variations of assertive states on the one hand and in being able to filter uncommon and misleading online and media consumption behaviour on the other.

In general, there are two approaches to produce meaningful user recommendations, namely through collaborative filtering[5], which focuses on extracting features based on the similarity of user behaviours compared to the target user, and through content-based filtering[15], which aims to narrow down the recommendation space of the target user by incorporating knowledge about only their own past behaviour in media consumption. Due to our two additional input streams, we can stand out from the classic approaches, by being able to let short- and long-term behavioral and emotional aspects of a user flow both into the content-based and collaborative filtering process. Firstly, similar assertive reactions to the same media content (measured with smart device), as well as similar interests on social media by multiple users, could enable to generate meaningful clusters of different emotion profiles to feed the recommendation system. Secondly, monitoring the assertive state of an individual user before, while and after media consumption could reveal behavioral patterns. Combining this knowledge with specific environment and media related data points of the user, we are able to generate deep situational insights into a users media content behaviour and needs.

Both collaborative and content-based filtering individually can be seen as powerful approaches to extract media recommendations. We see huge potential in combining both methods to grasp local as well as global influences on a users media consumption behaviour, to maximize user satisfaction. While many strictly collaborative or strictly content-based machine learning models in areas like deep learning[14] and reinforcement learning[2] are used successfully today, we envision the additional input parameters of social-media and vital data and their influence on a users assertive state, to give the necessary edge to be able to create an impactful bridge between both filtering approaches and generate tailor-made user recommendations at any time, place and in any emotional situation.

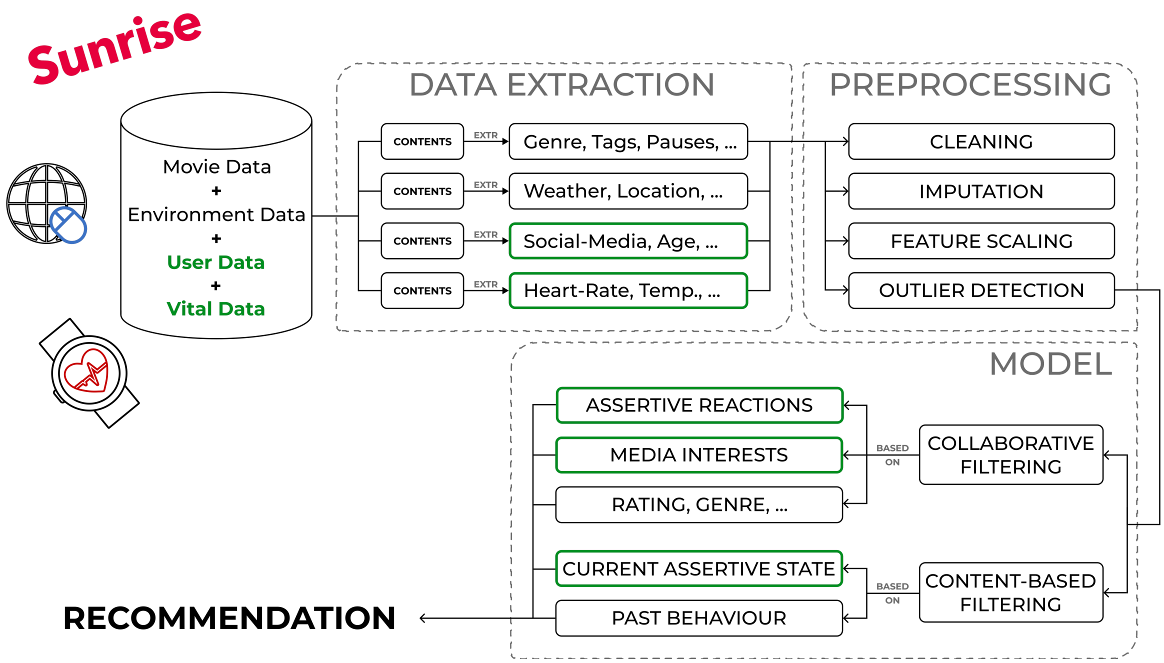

Figure 2: Pipeline of the proposed model

4 IPFS Challenge

To fully utilize the fast access to content which is already cached by nearby computers, we decided to use the IPFS network for storing important movie/tv metadata. This metadata includes genres, a short description of the movie, its runtime and its IMDB rating.
As an example we used Pinata[1] to pin the metadata for the movie "Scarface" (1983). This way the metadata for Scarface can now be accessed threw this CID[2] instead of by querying the Sunrise server. Especially when some computer nearby has already cached this metadata file, the speedup for accessing it should be significant.

5 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, users 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.[8, 13]

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 [12, 11]. 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 for Sunrise-UPC.

[1] https://pinata.cloud
[2] CID: QmWLoPjqJjvYY4mzeFvLP1GjFP3d4FbiPMfWV6LbZZ5GCX

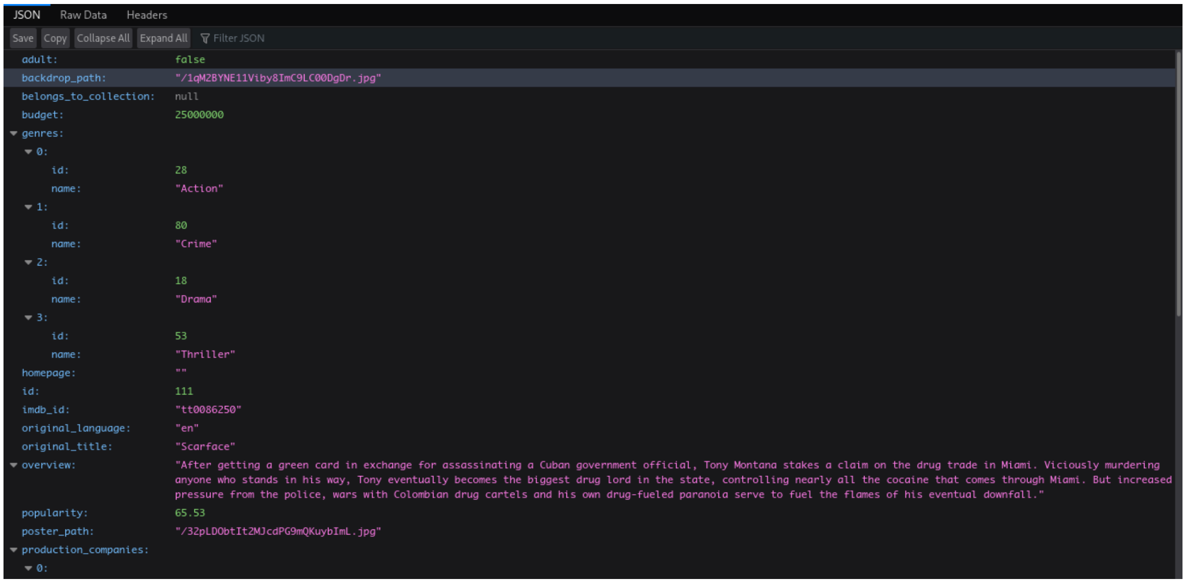

Figure 3: Metadata for the movie Scarface on IPFS. Link to access: https://ipfs.io/ipfs/QmWLoPjqJjvYY4mzeFvLP1GjFP3d4FbiPMfWV6LbZZ5GCX

References

[1] How to Analyze Stress from Heart Rate Heart Rate Variability: A Review of Physiology. Accessed: March 25, 2022.

[2] Mohammad Mehdi Afsar, Trafford Crump, and Behrouz H. Far. Reinforcement learning based recommender systems: A survey. *CoRR*, abs/2101.06286, 2021.

[3] Mitja D. Back, Juliane M. Stopfer, Simine Vazire, Sam Gaddis, Stefan C. Schmukle, Boris Egloff, and Samuel D. Gosling. Facebook profiles reflect actual personality, not self-idealization. *Psychological Science*, 21(3):372–374, 2010. PMID: 20424071.

[4] Kahneman D. Thinking, fast and slow. *New York: Farrar, Straus and Giroux*, 2013.

[5] Soyeon Caren Han, Taejun Lim, Siqu Long, Bernd Burgstaller, and Josiah Poon. Glocal-k: Global and local kernels for recommender systems. *CoRR*, abs/2108.12184, 2021.

[6] Gabriella Kazai, Iskander Yusof, and Daoud Clarke. Personalised news and blog recommendations based on user location, facebook and twitter user profiling. In *Proceedings of the 39th International ACM SIGIR Conference on Research and Development in Information Retrieval*, SIGIR '16, page 1129–1132, New York, NY, USA, 2016. Association for Computing Machinery.

[7] Chao Ma, Chen Zhu, Yanjie Fu, Hengshu Zhu, Guiquan Liu, and Enhong Chen. Social user profiling: A social-aware topic modeling perspective. In Selçuk Candan, Lei Chen, Torben Bach Pedersen, Lijun Chang, and Wen Hua, editors, *Database Systems for Advanced Applications*, pages 610–622, Cham, 2017. Springer International Publishing.

[8] Ante Odic, Marko Tkalcic, Jurij F Tasic, and Andrej Kosir. Personality and social context: Impact on emotion induction from movies. In *UMAP workshops*, page 72, 2013.

[9] Marco Polignano, Fedelucio Narducci, Marco de Gemmis, and Giovanni Semeraro. Towards emotion-aware recommender systems: an affective coherence model based on emotion-driven behaviors. *Expert Systems with Applications*, 170:114382, 2021.

[10] Fredric Shaffer and Jp Ginsberg. An overview of heart rate variability metrics and norms. *Frontiers in Public Health*, 5:258, 09 2017.

[11] Marko Tkalčič. Emotions and personality in recommender systems: Tutorial. In *Proceedings of the 12th ACM Conference on Recommender Systems*, pages 535–536, 2018.

[12] Marko Tkalcic, Andrej Kosir, and Jurij Tasic. Affective recommender systems: the role of emotions in recommender systems. In *Proc. The RecSys 2011 Workshop on Human Decision Making in Recommender Systems*, pages 9–13. Citeseer, 2011.

[13] Valentijn T Visch, Ed S Tan, and Dylan Molenaar. The emotional and cognitive effect of immersion in film viewing. *Cognition and Emotion*, 24(8):1439–1445, 2010.

[14] Shuai Zhang, Lina Yao, and Aixin Sun. Deep learning based recommender system: A survey and new perspectives. *CoRR*, abs/1707.07435, 2017.

[15] Charilaos Zisopoulos, Savvas Karagiannidis, Georgios Demirtsoglou, and Stefanos Antaris. Content-based recommendation systems. 11 2008.