Theory-driven Recommendations: Modeling Hedonic and Eudaimonic Movie Preferences

Marko Tkalcic\textsuperscript{1} and Bruce Ferwerda\textsuperscript{2}

\textsuperscript{1} Faculty of Computer Science, Free University of Bozen-Bolzano, Piazza Domenicani 3, I-39100, Bozen-Bolzano, Italy  
marko.tkalcic@unibz.it  

\textsuperscript{2} Department of Computer Science and Informatics, School of Engineering, Jönköping University, P.O. Box 1026, SE-551 11, Jönköping, Sweden  
bruce.ferwerda@ju.se

Abstract. Most of the research in recommender systems focuses on data-driven approaches. In this paper we present our vision for complementing data-driven approaches with model-driven ones. We present a preliminary experimental set-up and we expose our research plan. In the experimental set-up we acquired eudaimonic characteristics of movies and user preferences. Furthermore, we performed a preliminary analysis of the acquired data.

Keywords: recommender systems · personality · hedonic emotions · eudaimonic emotions

1 Introduction

Mainstream research in recommender systems is data-driven. Logs of user behaviour, such as clicks, ratings, purchases, are used in a variety of algorithms, such as collaborative and feature-based approaches to generate recommendations \cite{6}. In recent years we have worked on complementing these bottom-up, data-driven approaches with top-down, model-driven approaches to recommendations.

We view recommender systems as tools for helping users make better decisions \cite{7}. Psychology research has shown that human decisions are influence by diverse factors, among others by personality and emotions \cite{3}. In our past work we focused mainly on these two models \cite{8, 2, 10}. In this paper we present the preliminary results of introducing a known psychological model, that of eudaimonia in user modeling and recommender systems. The experience of consumption of an item (listening to a song, watching a movie) does not have only hedonic qualities (fun, enjoyment, relaxation) but also eudaimonic qualities, which are related to meaning and purpose \cite{4}.

2 Eudaimonic Modeling and Related Work

We assume that users differ in their need for eudaimonic experiences, i.e. some people prefer to just have fun, while other people may prefer to spend their time
contemplating meaning and purpose. Similarly, we observe that movies differ in the experience quality they induce. For example, the movies *The Hangover* and *La vita e ’bella* are both comedies. But while the former is a shallow comedy with a series of simple jokes the latter deals with deeper issues, such as the holocaust.

In positive psychology, happiness is often described through two opposite concepts: hedonism and eudaimonism [1]: the hedonic view equates happiness with pleasure, comfort, and enjoyment, whereas the eudaimonic view equates happiness with the human ability to pursue complex goals which are meaningful to the individual and society. Oliver and Raney [5] have carried out research to identify whether there are distinct eudaimonic and hedonic motivations for consuming entertainment. Through a series of studies they devised an instrument for measuring the eudaimonic and hedonic qualities of entertainment experiences. They showed that in addition to viewing movies for purposes of fun and pleasure, individuals also turn to entertainment for purposes of greater insight and meaningfulness. Wirth et al. [11] further extended Oliver’s work by analyzing what are the hedonic and eudaimonic qualities of movies with good and bad endings and found significant differences.

3 Work Plan

In order to devise personalization approaches using eudaimonia there are a lot of steps to make, since it is an unexplored area. We foresee the following steps need to be taken:

1. unobtrusive inference of eudaimonic and hedonic user preferences
2. automatic labeling of movies’ eudaimonic and hedonic qualities
3. a personalized recommender system that takes advantage of eudaimonic and hedonic features

4 Data acquisition

We performed a user study to acquire data. We let the subjects choose movies from a pool of popular movies. For the hypothetical context of choosing a movie to watch alone on a Saturday evening, each subject had to choose the most appropriate movie (the liked movie) and the least appropriate movie (the disliked movie). The subjects were then asked to describe, for each of the two movies, their viewing experience in terms of hedonic and eudaimonic experience using an adaptation of the scale developed by [5]. After answering the movie-related questions, the subjects filled in the ten-items personality questionnaire (TIPI).

We hand-picked the movies in order to have a mix of hedonic and eudaimonic movies.

We ran the study through Amazon Mechanical Turk. After removing subjects who did not pass a control question and removing outliers using the Mahalanobis distance we had the answers of 84 subjects (*M* = 34.2 years, *SD* = 9.5 years, 29 females).
Table 1. Excerpt of movie titles used in the experiment. The eudaimonic and hedonic qualities are our subjective assessments.

<table>
<thead>
<tr>
<th>Title</th>
<th>Eudaimonic</th>
<th>Hedonic</th>
</tr>
</thead>
<tbody>
<tr>
<td>Manchester by the sea</td>
<td>Y</td>
<td>N</td>
</tr>
<tr>
<td>Bad Moms</td>
<td>N</td>
<td>Y</td>
</tr>
<tr>
<td>Mad Max: Fury Road</td>
<td>N</td>
<td>Y</td>
</tr>
<tr>
<td>The Shawshank Redemption</td>
<td>Y</td>
<td>N</td>
</tr>
<tr>
<td>Inside Out</td>
<td>Y</td>
<td>Y</td>
</tr>
</tbody>
</table>

5 Results

A deeper analysis of the data acquired is going to be presented at the UMAP 2018 conference [9]. Here we pick two specific aspects: (i) bimodal distribution of eudaimonic reasoning and (ii) movie characteristics.

Users divided themselves into two clusters in terms of the eudaimonic qualities of the liked movies (see Fig. 1): some users liked movies with high eudaimonic qualities (scores > 3) while some users liked movies with low eudaimonic qualities (scores < 3), which is reflected in the bimodal shape of the histogram in Fig. 1. We conjecture that this bi-modal shape is due to user being either pleasure-seekers or meaning-seekers.

We clustered the movies into three categories: hedonic-only, eudaimonic-only and mixed. We performed the Wilcoxon rank sum test in order to test the hypothesis of the mean reported hedonic and eudaimonic quality being equal. Examples from all three clusters are reported in Tab. 2.

Table 2. Examples from clusters of movies. The left column shows movies that have a stronger eudaimonic quality, the right column shows movies with a stronger hedonic quality and the mid column shows movies that are equally hedonic and eudaimonic.

<table>
<thead>
<tr>
<th>Eudaimonic</th>
<th>Mixed</th>
<th>Hedonic</th>
</tr>
</thead>
<tbody>
<tr>
<td>Arrival</td>
<td>La La Land</td>
<td>Deadpool</td>
</tr>
<tr>
<td>Passengers</td>
<td>Hidden Figures</td>
<td>Mad Max: Fury Road</td>
</tr>
<tr>
<td>The Girl on the Train</td>
<td>Bad Moms</td>
<td></td>
</tr>
<tr>
<td>Fifty Shades of Gray</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

6 Future Work

The results of our study indicate that eudaimonic characteristics are useful for accounting variance in user preferences and for characterizing movies.

We plan to proceed the with the three steps: (i) unobtrusive inference of eudaimonic/hedonic preferences, (ii) automatic labeling of movies and (iii) personalized recommendations of movies.
I liked the movie because it challenged my way of seeing the world.

**Fig. 1.** Distribution of eudaimonic qualities of liked movies. The variable reported in this figure is the agreement with the statement *I liked this movie because it challenged my way of seeing the world.*

For the unobtrusive inference we are designing an experiment. In addition to the variables acquired in the experiment reported above, we will collect also the users’ social media data. We plan to ask for Facebook likes, twitter activity and Instagram activity. Using features extracted from social media activity we plan to do a predictor of the user preferences for movies in the hedonic/eudaimonic space. The recent scandal with Facebook data integrity may pose a further problem in devising such a method.

For the automatic labeling of movies we plan to use movie subtitles for feature generation. We foresee the usage of NLP techniques and generate features using TF-IDF and embeddings. In order to get ground truth movie labels we plan to crowd-source the labeling of a pool of movies.

For the personalized recommendation part we plan to use content-based recommendation methods that take advantage of the eudaimonic and hedonic features.

**References**


