Intended Movie Experience: Linking Elicited Emotions to Eudaimonic and Hedonic Characteristics

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Abstract

This study investigates the relationship between movies' elicited emotions and their eudaimonic (meaningful) and hedonic (pleasurable) characteristics. We use emotional signatures derived from movie reviews, which have been previously shown to capture these elicited emotions. We examine correlations with both the movies' eudaimonic and hedonic characteristics and the users' eudaimonic and hedonic orientations, calculated based on their highly rated movies. We demonstrate the predictive power of emotional signatures in determining both movies' and users' experiential qualities and assess how genre clusters differ in their eudaimonic and hedonic characteristics based on these signatures. To the best of our knowledge, this is the first study to explore these connections. Ultimately, our findings aim to enhance personalized recommender systems by aligning recommendations with users' emotional needs and desired experiences.

Keywords

Movie Recommender Systems, Emotional signature, Eudaimonia, Hedonia, Emotional experience

1. Introduction

Recommender systems in the movies domain aim to assist users with the movie selection decision-making process [1]. The conventional approach involves predicting a calculated utility for a movie for each user based on user-specific signals, either explicit (e.g., ratings) or implicit, behavior-based (e.g., play, stop, purchase) [1]. However, research has shown that the utility of the movie for a user is multi-faceted [2], and that current algorithms limit the coverage of users' tastes [3]. One of the fundamental facets in movie consumption is the often overlooked emotional aspect [4]. The primary intention of movies is to elicit emotions, generating an "ongoing, genuine emotional response" [5], that audiences are attracted to [6]. Bartsch [7] showed that users consume movies and TV shows for emotional gratification. Yet, the sought after emotional experience is complex, as movies are made to elicit a range of experiences, and also complex, as audiences seek various emotional experiences [8, 9, 5, 10] .

Emotions and the intended emotional experience play an important role in the decision-making process [11, 12, 13, 14]. Lerner et al. [15] suggest, in their decision-making model, that the current and expected emotions influence a decision. Emotions as factors in decision-making are specifically important in the movie domain, as movies are made with the intent of eliciting emotions [16, 5]. The choice of movie is based on the expected experience [17]. Furthermore, "effect elicitation, triggered by emotions, was found to be a powerful reason for box office success" [18]. Additionally, Mokryn et al. [19] showed that movies' elicited emotional experience relates to success factors such as ratings and box office earnings. Similarly, emotional regulation appears to be the main motive for consuming music [20] and other media, such as video games and books [21].

Recently, positive psychology researchers argued that people expect both pleasure and meaning when choosing a movie [8]. These expectations are described by the concepts of hedonia and eudaimonia [8],

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which refer to two distinct experiences. A *hedonic experience* refers to movie consumption characterized by pleasure and amusement. In contrast, a *eudaimonic experience* relates to life's meaning and purpose [8]. For example, *The Hangover (2009)* is considered a movie that induces a hedonic experience, while *Manchester by the Sea (2016)* induces a eudaimonic experience.

In this work, we explore the relationship between the emotions elicited by movies and their eudaimonic and hedonic characteristics. To identify a movie's elicited emotions we build on the work of Mokryn et al. [19], who showed that the emotions evoked in viewers when watching a movie can be inferred from the movie's reviews. They termed the inferred vector of basic emotions as the *emotional signature* of a movie. Using movies' emotional signatures and eudaimonic or hedonic characteristics, as found by Tkalčič and Ferwerda [17], we address here the following three research questions (RQs):

- RQ1: What are the correlations between movie emotional signatures and eudaimonic and hedonic characteristics?
  RQ1.1: What are the correlations between movies' emotional signatures and their respective eudaimonic or hedonic characteristics?
  RQ1.2: What are the correlations between the users' eudaimonic or hedonic orientation characteristics and the emotional signatures of the movies they liked?
- RQ2: Can the experience of a movie, either hedonic or eudaimonic, be predicted from its emotional signature?
  RQ2.1: Can we predict movies' eudaimonic or hedonic characteristics from their emotional signatures?
  RQ2.2: Can we predict the users' eudaimonic or hedonic orientation from the emotional signatures of the movies they liked?
- RQ3: When movie genres are clustered based on the emotional signatures of the movies within them, are there any statistical differences between these clusters in terms of their eudaimonic or hedonic characteristics?

Our final goal is to use these findings to inform the design of better personalized recommender systems. As people are choosing movies with the intent of receiving a specific meaningful emotional experience [7, 5, 17], understanding the type of sought-after experience and the emotions associated with it can help in the creation of personalized recommendations that can cater to the user's various moods. While this work focuses on the movie domain, similar studies can be conducted in other media types, such as TV shows, music, video games, or books.

2. Related Work

We discuss here the importance of emotions, hedonia, and eudaimonia for decision-making supported by recommender systems.

Emotions and the expected emotional experience are a fundamental part of choice-based decision-making [11, 12, 13, 14]. In particular, the implied emotional effect of a decision is pivotal in the construction of personal preferences [12, 13, 2].

Tan [5] describes movies as "emotion machines ... created with the intention of eliciting a wide range of emotions". Smith [16] describes a movie as an "invitation to feel". Yet, it is impossible to infer from the movie the emotions it will elicit in its audience, and the success of a movie lies in the gap between the directors' intent in this suggested invitation and the emotions experienced by the audience, which can be assessed only after they have seen the movie [16, 22].

Mokryn et al. [19] showed rigorously that the emotions evoked by movies could be extracted from movie reviews. When people write reviews for movies, they also share the emotions the movie elicited in them [23]. To validate their hypothesis, [19] extracted values for each of Plutchik's eight basic emotions [24] from IMDb reviews, forming an "emotional signature" for each movie as a vector of these eight emotions. Their analysis confirmed that these emotional signatures align with the normative emotional experiences elicited by the films, demonstrated through a series of experiments. They established convergent validity by correlating the emotional signatures with manually measured evoked emotions. Face validity was supported through various experiments, including visualizing the emotional signatures and conducting genre analysis by calculating average emotional signatures for movies within specific genres. Additionally, criterion-related validity was shown through experiments that revealed a movie's emotional signature could predict its genre and partially explain its success, as indicated by ratings and box office revenue. They also observed that sequels tend to have emotional signatures significantly more similar to each other than to randomly selected movies or movies within the same genre.

In their seminal work, Oliver and Raney [8] explained the paradox that users often enjoy consuming entertainment content that does not necessarily induce happiness. The inclination to be attracted to other types of experiences, such as sadness, is explained by the fact that people have different needs. One such need is the need to experience pleasure and positive aspects in general, referred to as hedonic experience. The other is the need to engage in contemplation about truth, meaning, and purpose, known as eudaimonic experience. Tkalčič and Ferwerda [17] demonstrated that in the movie domain, there is a large variance in user preferences for eudaimonic or hedonic experiences, with some users preferring one over the other, while many prefer to consume both, at different times.

In general, the quality of the experience, whether eudaimonic or hedonic, can be broken down into two parts: the item and the user counterpart. In our case, the item is a movie. To have, for example, a eudaimonic experience, (i) the user needs to be inclined to have it, and (ii) the movie should have the potential (or being perceived as having the potential) to elicit it. We refer to the former as the eudaimonic (or hedonic) *orientation of the user* and to the latter as the eudaimonic (or hedonic) *perception of the movie*. Further research on eudaimonia and hedonia in relation to recommender systems has shown that item perception can be predicted from various signals, such as song lyrics [25], movie subtitles [26] or movies' audio and visual features [27]. The user orientation part can be predicted from user interactions with recommender systems [28, 29].

Both emotions and eudaimonia/hedonia have been shown to contribute to the performance of recommender systems. Zheng et al. [30] has successfully used emotions as contextual variables to improve the accuracy of recommender systems. In a recommender system for images, the target emotion proved to be the most important predictor of image ratings [31]. Motamedi et al. [32] have shown in a real-world application that the relevance of music videos can be predicted from eudaimonic and hedonic qualities.

Although both emotions and eudaimonia/hedonia have received considerable attention in research, no work so far has attempted to connect these two constructs. In this work we aim at filling this gap in knowledge by showing how these two constructs are related.

3. Experiments

Our goal is to identify potential relationships between movies' elicited emotions and their hedonic and eudaimonic characteristics at both the movie and genre levels, as well as the user's identified hedonic and eudaimonic orientation. In our experiments, we define the following variables:

- Movie's *emotional signature*: a vector describing the emotions a movie elicits.
- Genre's *emotional signature*: a vector describing the expected emotions when watching films in that genre.
- Movie's *eudaimonic and hedonic perception (EP, HP)*. Two numerical values representing how users perceive the potential of a movie to generate a eudaimonic or hedonic experience.
- User's *eudaimonic and hedonic orientation (EO, HO)*. Two numerical values describing the inclination of the user to seek eudaimonic or hedonic experiences.

To address the three research questions we ran three studies: (i) a correlational analysis to establish relationships between the observed variables, (ii) predictive models trained to predict movies' EP and HP, and users' EH, and HO from emotional signatures, and (iii) a genre-based comparison of the genres' movies' mean EP and EP.

3.1. Datasets

We merged two datasets, the emotional signatures dataset [19] and the eudaimonia/hedonia (E/H) dataset [29]. For genre clustering, we additionally used the GenreData dataset as explained below. The data acquisitions for (i) the emotional signatures dataset and (ii) the eudaimonia/hedonia (E/H) dataset, were carried out in their respective works, (i) Mokryn et al. [19] and (ii) Motamedi et al. [29]. For completeness, we will summarize the data acquisition of these two datasets below.

For the emotional signatures dataset, we collected reviews and additional movie data for 20,514 movies from the IMDb database spanning 2021 and 2022. The emotional signatures were generated according to the method described in [33, 19, 10]. The final dataset includes the following details for each movie: name and ID, director(s), cast, genres, rating, synopsis, plot, release year, and the emotional signature extracted from the reviews [19].

Specifically, the emotional signatures were derived as follows. We aggregated the reviews for each movie into a single document and created a Bag of Words (BoW) per document. This involved tokenizing, normalizing, and stemming the text, while omitting stop words. Using the NRC lexicon [34], we annotated the words in the BoW for each of the Plutchik's eight basic emotions. Then, for each movie, the frequency of each emotion was calculated based on occurrences in the annotations. Following a normalization phase, the resulting set of emotion values forms the vector termed the emotional signature of a movie. This is an eight-dimensional vector, with each dimension representing the strength of the corresponding basic emotion, namely anger, anticipation, disgust, fear, joy, sadness, surprise, and trust.

The additional dataset used for genre calcualtions, GenreData, includes 2937 movies that were assigned various genre labels by their distributors. There were 21 genres in total, and most movies (89.4%) had more than one genre label. The majority of movies were tagged as belonging to 2, 3, or 4 genres (27.4%, 33.2%, 19.8%, respectively).

The E/H dataset was collected through a user study. A total of 350 participants were asked to annotate[1] how they perceived the eudaimonic and hedonic quality of several movies. On average each movie was annotated by five users. These multiple annotations were than aggregated into the mean movie eudaimonic perception (EP) and the mean movie hedonic perception (HP). Additionally, the participants in the user study provided ratings for the movies. On average, each user provided ratings for 10 movies. Each participant also filled in a questionnaire on their inclinations to prefer hedonic and eudaimonic content. This yielded, for each user, their user eudaimonic orientation (EO) and user hedonic orientation (HO) scores.

We merged the two datasets by the title and year fields. In total we had 410 movies with both emotional signatures and E/H annotations. Table 2 shows an excerpt from the merged dataset while the descriptive statistics are provided in Tab. 1.

	Ratings	Users	Movies
Merged Dataset	2408	350	410
Dataset used for user profile analysis	1562	240	370
Dataset used for movie profile analysis	1946	345	225

Table 1
Dataset Summary

3.2. Correlational Analysis

We analyzed the correlations between emotional signatures and eudaimonic and hedonic variables from two perspectives: (i) movie-centric and (ii) user-centric.

In the first correlational analysis we compute correlations between the basic emotions elicited by a movie according to its emotional signature and its average eudaimonic and hedonic perceptions.

[1]The annotations were in the range from 1 to 7 and derived using the questionnaire detailed in Motamedi et al. [29].

User ID	Movie ID	Anger	Anticipation	Disgust	Fear	Joy	Sadness	Surprise	Trust	EP	HP	EO	HO	Rating
63	tt043440	0.09	0.11	0.05	0.13	0.09	0.06	0.06	0.18	4.7	6.0	4.0	4.0	3
313	tt185372	0.10	0.13	0.06	0.12	0.11	0.08	0.06	0.13	5.3	6.7	4.5	5.5	5

Table 2
Excerpt of the dataset used. Each data point contains the userID, movieID, a set of emotions from the emotional signature of that movie, the movie's eudaimonic perception and hedonic perception, the user's eudaimonic orientation and hedonic orientation, and finally the rating the user has given to this movie.

To make sure that we have enough variability when calculating the average EP and HP of movies, we included only movies with at least 5 scores for eudaimonic and hedonic perceptions from users. We had a total of 225 such movies (ref. Table 1), which we used in this analysis. Table 3 shows the results of the analysis. The movies' eudaimonic and hedonic perceptions are strongly correlated with several basic emotions. Specifically, we find that movies with high hedonic perception tend to have above-average positive emotions, i.e., high anticipation, and joy. They are also correlated with low values in some of the negative emotions, i.e., low fear and sadness. Surprisingly, they also correlate with high surprise. Movies with high eudaimonic perception, on the other hand, seem to not elicit strong emotional responses, and have average or below average values for the emotions anticipation, disgust, joy, and surprise.

	Movie Eudaimonic Perception (EP)	Movie Hedonic Perception (HP)
EP	1.0***	-0.4***
HP	-0.4***	1.0***
Anger	-0.09	-0.08
Anticipation	-0.15*	0.31***
Disgust	-0.19**	-0.04
Fear	0.02	-0.21**
Joy	-0.18**	0.41***
Sadness	0.05	-0.22**
Surprise	-0.27***	0.31***
Trust	0.07	0.02

Table 3
Correlations between movies' elicited basic emotions as identified in their emotional signatures and movies' eudaimonic and hedonic characteristics.

In the second analysis we consider users. We examine the correlation between a user's eudaimonic and hedonic orientation and emotional signatures of the movies the user liked, i.e., those they rated with 4 or 5 stars. To ensure that we had enough variability in emotional signatures per user, we included only users who rated at least five movies with 4 or 5 stars. We had a total of 240 such users (ref. Table 1), which we used for this analysis.

The correlation results, shown in Tab. 4, are weak. Generally, users with a high eudaimonic orientation prefer movies with a wide range of anger, as indicated by the high standard deviation of anger in their liked movies. The movies they prefer tend to have lower levels of anticipation, and joy, and higher levels of sadness. In contrast, movies liked by users with a high hedonic orientation typically display average levels of all emotions, except for high anticipation and a significant variance in anger.

	User Eudaimonic Orientation (EO)	User Hedonic Orientation (HO)		User Eudaimonic Orientation (EO)	User Hedonic Orientation (HO)
EO	1.0***	-0,04	HO	-0,04	1.0***
Anger (mean)	0.13*	-0,1	Anger (stdev)	0.17**	-0.13*
Anticipation (mean)	-0.14*	0.16*	Anticipation (stdev)	0,01	0,09
Disgust (mean)	0,1	0	Disgust (stdev)	0,09	0,06
Fear (mean)	0,1	0,01	Fear (stdev)	0,11	-0,07
Joy (mean)	-0.19**	0,05	Joy (stdev)	-0,08	0
Sadness (mean)	0.23***	-0,1	Sadness (stdev)	0.2**	-0,11
Surprise (mean)	-0,03	0,02	Surprise (stdev)	0,1	-0,08
Trust (mean)	-0,1	-0,04	Trust (stdev)	-0,06	-0,05

Table 4
Correlation between the user eudaimonic and hedonic orientations, and the emotional signatures of the movies the user liked, i.e. rated as 4 or 5.

3.3. Predictions

Here we also look at our problem from two perspectives, movies and users. We aim at answering:

- Can we predict movies' eudaimonic perception and hedonic perception from their emotional signatures?
- Can we predict the users' eudaimonic orientation and hedonic orientation from the emotional signatures of the movies they liked?

To predict the movie EP and HP we used the movie emotions in the emotional signatures as features. We evaluated only two simple models – linear regression and random forest – to gain an initial understanding of the predictive potential of these features, as this is early work. The baseline method was the mean predictor of the target variable. We tuned the hyperparameters of the models utilizing grid search, and evaluated the models through five-fold cross-validation. RMSE and MAE were chosen as metrics because the target variables were ordinal continuous.

In the second prediction task, predicting users' eudaimonic and hedonic orientation, we used as features the emotions from the emotional signatures of movies the users liked by filtering only movies with a rating of 4 or 5. The other details (models, hyperparameter tuning and splitting) are the same as for the first prediction task.

The results in Tab. 5 show that, except for the prediction of the user hedonic orientation, all predictors beat the mean baseline. In the case of the prediction of movies' eudaimonic perception the difference in RMSE is statistically significant at $p < 0.05$ using a paired t-test. This calls for further prediction experimentation with larger datasets and more complex and optimized models. In summary, the emotional signatures of movies can predict their eudaimonic and hedonic perception, and the emotional signatures of movies rated highly by users can predict the users' orientation, either eudaimonic or hedonic.

3.4. Between-cluster Comparison

Here, we wanted to investigate the relationship between movies' emotional signatures, their eudaimonic and hedonic experiences, and movie genres. Mokryn *et al.* [33] explored the emotional signatures of genres and showed that movies' emotional signatures can predict the genre of a movie, when the movie has one genre label. Here, we continue to see whether genres that have "close" emotional signatures also have similar quality, either hedonic or eudaimonic. To that end, we cluster the genres based on their emotional signatures and observe the differences in the values of the eudaimonic perception and hedonic perception between clusters of movies.

Prediction	Method	RMSE	MAE	R^2
Movies' EP	Mean Baseline	1.0266	0.8443	-0.0172
	Linear Regression	0.9852	0.8102	0.0531
	Random Forest	**0.9603***	**0.7863**	**0.1094**
Movies' HP	Mean Baseline	0.6645	0.5480	0.0418
	Linear Regression	**0.5790**	**0.4542**	**0.1992**
	Random Forest	0.5799	0.4602	0.2005
Users' EO	Mean Baseline	1.0635	1.0635	-0.0537
	Linear Regression	1.0984	0.8719	-0.1283
	Random Forest	**1.0549**	**0.8324**	**-0.0384**
Users' HO	**Mean Baseline**	**1.2730**	**1.0135**	**-0.0929**
	Linear Regression	1.3838	1.0736	-0.2882
	Random Forest	1.2910	1.0283	-0.1208

Table 5
Results from our predictive modelling of movies eudaimonic and hedonic perceptions (EP, HP), as well as users's eudaimonic and hedonic orientations (EO, HO). The best-performing models are marked in bold. Statistically significant results are marked with *. All prediction targets (EP, HP, EO, HO) are in the range from 1 to 7.

To cluster genres together according to their emotional signatures we used the GenreData dataset (described in Section 3.1) and performed k-means clustering on the emotional signatures of genres. Similar to the emotional signatures of movies (as described for movies in Section 3), and following the process in [19], we calculated a genre's emotional signature by aggregating the reviews of all movies belonging to a specific genre into a single document and computing the emotional signature of that document.

The k-means clustering was performed with $k = 3$ clusters[2]. All genres but one (horror) were divided into the clusters *Comedy, Action.* At this stage we assigned movies to one of the clusters according to their genres. As most movies (89%) have multiple genre labels, we mapped a movie to the cluster that contained most of its genres. For example, a movie with the genres Comedy (Comedy), Romance (Comedy), Family (Comedy), and Mystery (Action), was placed in Comedy. Horror movies were placed only in the Horror cluster. We excluded movies for which the genre tie could not be broken, e.g., a movie with the genres Comedy (Comedy), Romance (Comedy), Action (Action), and Mystery (Action). We then calculated for each cluster of *Comedy, Action* and *Horror* its emotional signature and its cluster HP and EP values. Given the ordinal nature of the the within-cluster movies EP and HP variables, we used the Mann-Whitney U test for testing the difference of means of EP and HP between the clusters.

The results, summarized in Tab. 6, show that the differences between clusters in terms of eudaimonic perception and hedonic perception are almost always statistically significant. The average within-cluster movie EP is the highest in the action cluster and lowest in the horror cluster, which is to be expected. Although the comedy cluster has a lower EP than the action cluster, the difference is not significant. With regards to the movies HP, the comedy cluster has it higher and statistically significant than the other two clusters, whose values are almost the same.

4. Discussion

Getting back to our research questions, we have shown that emotional signatures, movies' eudaimonic perception and hedonic perception, and users' eudaimonic orientation and hedonic orientation are correlated. This is important when we think that all these constructs are well-supported in psychology

[2]We tested different values for k, in the range of 2 to 15, and chose $k = 3$ using the elbow method.

Cluster	Genres	Avg. EP within cluster	Avg. HP within cluster	U-Test
C1: Comedy	Comedy, Romance, Family, Animation, Musical, Sport, Music	3.680	5.139	Diff. C1 and C2: EP p<0.001; HP p<0.001;
C2: Action	Crime, Sci-Fi, Adventure, Fantasy, Western, Mystery, War, Documentary, Biography, Thriller, Action, Drama, History	4.297	4.601	Diff. C1 and C3: EP p>0.5; HP p<0.01;
C3: Horror	Horror	3.432	4.473	Diff. C2 and C3: EP p<0.01; HP p>0.05;

Table 6
Summary of cluster analysis. The average movie eudaimonic perception (EP) and hedonic perception (HP) of each of the three clusters are reported. In the last column are the p–values of the Mann-Whitney U test of the current cluster compared to the other two clusters.

research, valid, and have numerous measurement instruments.

Not only have we shown that there are correlations between the constructs, we also demonstrated that this correlation can be used to perform predictions from one set of constructs to the other.

Finally, we have also shown that movie genres, which stem from the movie making process, have substantially different emotional signatures and eudaimonic/hedonic characteristics.

4.1. Where do we go from here?

There is always room for expanding our understanding of the topic by running larger studies, collecting more data and using more complex models.

However, the potential, we believe, lies in the knowledge bound to these constructs that stems mostly from psychology but also from other domains, such as movie making. For example, screen-writers and directors aim at eliciting certain emotions in viewers.

The most important challenge in the future is how to take advantage of this knowledge to improve recommender systems. There are several ways one could go about it. The most obvious is using these features to improve rating predictions. Another option is to use these constructs to cluster the movies and adjust the ranking according to the clusters. As these constructs describe the elicited experience, which is a sought experience, a connection with intent-based recommendations is a viable way of investigation. One could also investigate how context influences the users' eudaimonic and hedonic orientations. For example, a user may be generally inclined to have eudaimonic experiences, but if she's really tired in the evening, she might prefer to pursue a hedonic experience to chill out. Hence, an interesting question would also to tie these orientations to user's moods, and how to match a recommendation to changing users' moods.

Additionally, we see explainable recommender systems having a strong potential with the constructs of emotions and eudaimonia/hedonia experiences. Recommender systems algorithms, especially those based on latent features, are hard to explain. However, the constructs we propose are not just interpretable features but have also a strong background knowledge in psychology that can be leveraged for generating explanations. As Miller [35] stated in his seminal work, *"explanations are social — they are a transfer of knowledge, presented as part of a conversation or interaction, and are thus presented relative to the explainer's beliefs about the explainee's beliefs."* The general familiarity of these constructs and the possibility of increasing this familiarity with knowledge from psychology opens new possibilities for explainable recommender system.

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