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Master's thesis
(Magistrsko delo)

Recognition of eudaemonic and hedonic qualities from song lyrics

(Razpoznava hedoničnih in eudaimoničnih lastnosti na podlagi besedil pesmi)

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Izvleček:
To diplomsko delo obravnava raziskovalno vprašanje, kako z uporabo metod strojnega učenja razviti računalniški model, s katerim je mogoče na podlagi besedil pesmi napovedati hedonične in evdemonične lastnosti pesmi. Izvedli smo raziskavo na 1991 uporabnikih (1904F, 87M) s povprečno starostjo 28 let (SD = 9 let), v kateri smo zbrali demografske podatke, test osebnosti velikih pet, eudaemonske in hedonske težnje pesmi, splošno glasbeno zahtevnost in podatke za razvrščanje pesmi. Nato smo z iskanjem po spletu zbrali besedila pesmi. Besedila pesmi so bila normalizirana, tokenizirana, lemmatizirana in stemmed, vsaki besedi v pesmi pa je bila dodeljena ocena TFIDF. Zbrani podatki so bili preoblikovani v smiselne podatke in posredovani modelom strojnega učenja. Uporabili smo klasifikacijske in regresijske modele strojnega učenja. Uporabljeni klasifikacijski modeli so kNN, logistična regresija, naključni gozd, bagging, SVC in ridge, uporabljena regresijska modela pa sta naključni gozd in XGBoost. Ustvarili smo dva modela, enega hedoničnega in enega evdemoničnega. Najboljša modela sta bila dosežena s klasifikatorji bagging za oba modela strojnega učenja, medtem ko je regresor naključni gozd dal najboljše rezultate med regresorji. Rezultati kažejo, da obstaja povezava med hedoničnostjo in evdemoničnostjo ter besedili pesmi in da lahko z ustvarjenima modeloma razvrstimo pesmi na zelo hedonične ali zelo evdemonične. Ta študija je pokazala tudi, da obstaja razlika med eudaemoničnimi in hedoničnimi težnjami med spoloma ter da obstaja močna povezava med čustvi in eudaemonijo.

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Abstract:
This thesis addresses the research question of how to use machine learning methods in order to develop a computational model which is able to predict the hedonic and eudaemonic qualities of songs from song lyrics. We conducted a survey on 1991 users (1904F, 87M) with an average age of 28 years (SD = 9 years), where we gathered demographics, big five personality test, eudaemonic and hedonic song tendencies, overall music sophistication and data for song classification. After that we gathered song lyrics by web scraping. Song lyrics were normalized, tokenized, lemmatized and stemmed, and a TF-IDF scored was assigned to each word in a song. The collected data was transformed into meaningful data and fed to machine learning models. We used classification and regression machine learning models. The classification models that were used are kNN, logistic regression, random forest, bagging, SVC and ridge, while the regressor models that were used are random forest and XGBoost. We created two models, one hedonic and one eudaemonic. The best models were achieved with bagging classifiers for both machine learning models, while the random forest regressor gave the best results out of the regressors. The results show that there exists a connection between hedonia and eudaemonia and song lyrics, and that we can classify songs into highly hedonic or highly eudaemonic, with the created models. This study also showed that there exists a difference between eudaemonic and hedonic tendencies between genders, as well as that there exists a strong connection between emotions and eudaemonia.

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List of Abbreviations

i.e.	that is
e.g.	for example
NLP	natural language processing
PCA	principal component analysis
SVM	support vector machine
$TF-IDF$	term frequency–inverse document frequency
kNN	k-nearest neighbors
SVM	support vector machines
SVC	c-support vector classification
$RMSE$	root-mean-square deviation
MSE	mean squared error
MAE	mean absolute error
STD	standard deviation

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1 INTRODUCTION

1.1 MOTIVATION

Music surrounds us - whether we listen to it in private or hear it at a shopping mall, while walking next to a coffee shop or even in an elevator - it is becoming almost an unavoidable aspect of our lives. In a study by Roberts D.F. et al., it was shown that some young people consider music as an element that defines their identity and their course through life [23]. The respondents of this study even went as far as to compare music to oxygen and water. Elif T.G. has shown in her research that the main reasons for listening to music are enjoyment, emotional mood, peer group, and family [28]. The study has also shown that the majority of the respondents listen to music between two to nine hours per day [28].

Thomas Schäfer and Peter Sedlmeier have shown that the liking for a particular kind of music depends on the functions which are fulfilled for the listener [27]. In their study, they have shown that cognitive functions, such as communication and self-reflection, have the strongest influence on music preference, while emotional functions had less impact compared to the other functions [27].

There have been many studies conducted on emotion recognition based on different combinations of data features, such as the work done by Dan Yang [31], as well as some other works which were solely based on music lyrics [11].

This brings up a question as to why is music so often categorized by emotions if emotional functions have less impact than some other functions such as self-reflection.

Eudaemonia is based on a self-determination motivational concept of pursuing intrinsic values such as personal growth, relationships and health rather than extrinsic values such as wealth, popularity and power [25]. Hedonia and eudaemonia are juxtaposed as opposing perspectives on human wellness, with hedonia involving the seeking of happiness and life satisfaction, and reducing negative affect [8].

Music is often classified by the emotion it conveys, but what happens if we dig deeper and look further than just at the specific emotion a certain song gives. We have seen that eudaemonia and hedonia have shown to be useful for user modeling and recommendations, as shown by Tkalcic et al. [29]. In their study the results show that eudaimonic user profiling effectively divides users into pleasure-seekers and meaning-seekers. Therefore we can explore this idea further by looking for hedonic and eudaemonic qualities within songs by using song lyrics instead of movies. Eudaemonia equates happiness with the human ability to pursue personal and societal meaningful values, while hedonia equates happiness with pleasure, enjoyment and comfort [3].

Searching for hedonic and eudaemonic qualities within songs by human annotation would be time consuming. This is why a method for the automatic recognition should be devised. A model which will be able to take in the song lyrics and as an output give us a hedonic and eudaemonic quality of the given song. The main purpose of this study is to devise a model for the automatic recognition of the hedonic and eudaemonic qualities of songs from their lyrics. Therefore, the goal is to create a model which will be able to differentiate between eudaemonia and hedonia in song lyrics and as a result show us how eudaemonic or hedonic a certain song is.

The research questions that we will be answering in this study include whether a connection between eudaemonic and hedonic qualities in song lyrics exists, and if so, can songs be characterised as hedonic, eudaemonic or both. Could a classification algorithm based on song lyrics be able to extract valuable features from song lyrics and be able to classify songs by hedonic and eudaemonic characteristics? Whether we can find a connection between the overall music sophistication and eudaemonic/hedonic tendencies of respondents or not.

1.2 STRUCTURE OF THE THESIS

In Chapter 2, we introduce the related work which has dealt with emotion recognition in music, from song lyrics to audio signals. We also explore works of eudaemonia and hedonia, and their connection to user profiling.

In Chapter 3, we talk about preliminaries which need to be introduced beforehand. We introduce the definitions of hedonism and eudaemonia and their connection, as well as the big five personality test and the five personality traits that its made out.

In Chapter 4, we talk about the methodology of this research. We start with explaining the data collection process, data cleaning process as well as the feature engineering. In this part we describe how we transformed the survey results into meaningful features which are going to be fed to the machine learning model afterwards. In this section we also talk about natural language processing techniques which are going to be used on the song lyrics.

In Chapter 5 we report the results of our experiments and compare the models. The results are interpreted in Chapter 6, where we discuss the findings and limitations to the study.

The research is concluded in Chapter 7 where we discuss the future work and give an overview of all of the findings from this study.

2 RELATED WORK

A current problem, that this thesis will be dealing with, is the lack of methods for automatic recognition of hedonic and eudaemonic qualities in songs. There have been many studies that dealt with music recognition from song lyrics before, as shown by Malheiro et al. [11], but none of them went as far as to explore the hedonic and eudaemonic qualities of song lyrics.

Computational research in music emotions has been an interesting field for quite some time. The music industry is growing rapidly and streaming websites are competing with each other, trying to showcase the best recommendation systems they can. In current music streaming sites and online music services, there is a use of some kind of a recommendation system in order to create a better experience for the users. Jannach et al. has described different types of music recommendations that can be found in practice and discussed the specific challenges of the domain [9]. Music genres are predefined and selected by artists when their albums or singles are submitted. But genres are not enough in order to recommend a good song choice, because there are artists that have both upbeat and ballad songs. This is why making a good recommendation system, that is going to look deeper into the song itself, is a very important task.

There have also been studies that explored the music recommendation systems which are driven by listener feelings and emotions with the purpose of helping people with music selection for many different life situations, such as dealing with mental and physical conditions as shown by Rumiantcev et al. [24].

Recognition of music emotion has been going around for two decades. Music emotion can be extracted from songs in many ways, such as from song lyrics, speech audio signals [14] etc. In his phd thesis, Renato P. writes about emotion-based analysis and classification of audio music using audio signals, which explores the typical approaches of emotion recognition [18]. Most of the emotion recognition approaches start with a data set, usually composed of songs and emotion ratings collected from listeners. From here on, the data is processed by computational algorithms which extract and summarize the data characteristics. In her paper, Shamila N. writes about widely used feature selection and feature extraction techniques and their effectiveness when it comes to the performance of learning algorithms [16]. As mentioned, all of the work is focused on deriving emotion characteristics from songs through different channels. But what if we could try to derive and classify songs not only based on emotions, but on other factors as well. People have different pathways to happiness, and these pathways can be described as hedonia and eudaemonia, which are both important aspects of well-being [7]. Eudaemonia and hedonia have been shown to be useful for user modeling and recommendations. Tkalcic et al. have shown that there exists an eudaemonic user profiling which divides users into pleasure-seekers and meaning-seekers [29]. In their study, they performed a characterization of users in terms of eudaimonic and hedonic preferences. Although, this profiling was used in movies, we believe it can also be transfered to songs.

Therefore, that drives a question: do song lyrics contain eudaemonic and hedonic elements, and if so, can songs be classified as eudaemonic and hedonic?

So far, several works have shown that personality is related to user preferences when it comes to entertainment content, not only movies but music as well [6] [22]. The Big Five factor model is the most widely used model of personality, organizing personality traits in five basic dimensions which are Neuroticisn, Conscientiousness, Extraversion, Agreeableness, and Openness to Experience [12]. Therefore, the Big Five factor model can be used in order to further explore the connection between personality and user preferences.

A current problem that this thesis will be dealing with, is the lack of methods for automatic recognition of hedonic and eudaemonic qualities in songs. Therefore the goal is to create a model which will be able to differentiate between eudaemonia and hedonism in song lyrics, and as a result give us a score on how eudaemonic or hedonic a certain song is. This could drive the recommendation systems in a completely different direction, which would allow them to target their audience, by expanding it from emotion to different pathways to happiness - eudaemonia and hedonia.

3 PRELIMINARIES

3.1 HEDONISM AND EUDAEMONIA

3.1.1 HEDONISM

There are many definitions of hedonism, such as: ”Pursuit of or devotion to pleasure, especially to the pleasures of the senses.”, or ”Pursuit of or devotion to pleasure, especially to the pleasures of the senses.”, or ”The definition of hedonism is the relentless pursuit of pleasure”. We can see that most of these definitions resolve around pleasure, and this is because the word Hedonism comes from the Attic-Greek word hedone, meaning simply “pleasure” [8]. Hedonism is a theory which states that pleasure and pain are the only factors in a human life [1]. There are many different kinds of hedonism, such as prudential hedonism [30], but mostly hedonism is represented as a pursuit to pleasure. Just like the other hedonistic values which resolve around the pursuit of pleasure and avoidance of pain, prudential hedonism also resolves around the idea that the only pleasure is good for us in itself and only pain is bad for us in itself [4].

Hedonism is the pursuit of pleasure and a sensual self-indulgence. In philosophy it is an ethical theory that states that pleasure is the highest good and proper aim of human life. There are many hedonic theories but most of them revolve around pleasure playing the main role in one’s life.

3.1.2 EUDAEMONIA

Eudaemonia is a Greek word which is most commonly translated as ’happiness’. Eudaemonia appears in aristotelianism and is described as a life of activity governed by reason. Eudaemonia is all about states and pursuits which are associated with developing the best in yourself. Eudaemonia is also a term which is used in religion, and it is mostly referred to as conception of what it means to be a better person.

Eudaemonia revolves around human flourishing or living well. It is an orientation towards a better good [8].

Hedonia and eudaemonia relate to different experiences, as described above. People that pursue both eudaemonia and hedonia, have a better picture of well-being compared to people that pursue one or another. Hedonia is related to carefreeness, positive affects and very low negative affects, while eudaemonia is related to meaning and elevation. Most people have both, eudaemonic and hedonic needs, but for the purpose of this study, we will be doing an oversimplification regarding separating people with hedonic tendencies and people with eudaemonic tendencies [8]. People that tend to have better eudaemonic tendencies, tend to seek for a deeper meaning in most of the things in their lives, while people with hedonic tendencies tend to seek pleasure and fun in life – without a deeper meaning included.
Based on the definitions of hedonism and eudaemonia we are going to propose a definition of eudaemonia and hedonism in song lyrics.
Songs that have a deeper meaning, or that make someone question everything on a deeper level are going to be categorized as eudaemonic songs.
Songs that don't have a deeper meaning, but are rather based on different pleasures, enjoying life, and not digging deep for a different meaning are going to be categorized as hedonic songs.

3.2 BIG FIVE PERSONALITY TRAITS

The 'Big Five' is a personality trait model which consists of five factors which are openness, conscientiousness, extraversion agreeableness and neuroticism. [2] This model is a result of applying the principles of the psycholexical approach to personality [21]. Each factor in this model represents a continuum between two extreme ends, for example extreme extraversion and extreme introversion. Most people lie in between of these two extremes of each dimension. In order to better understand what these factors mean, we are going to look at each one of them separately.

3.2.1 OPENNESS

People with high openness are expected to be more creative, open to try new things and focused to take on new challenges, while people with low openness usually dislike change, do not enjoy new things and ideas, and are not very imaginative.

3.2.2 CONSCIENTIOUSNESS

People with high conscientiousness spend more time preparing themselves, they tend to finish important tasks right away and pay attention to detail, while people with low conscientiousness dislike schedules, are messy, procrastinate and fail to complete assigned tasks.

3.2.3 EXTRAVERSION

People with high extraversion enjoy being the center of attention, they are communicative, enjoy meeting new people, find it easy to make new friends and say things before thinking about them, while people with low extraversion prefer solitude, feel exhausted when they need to socialize, find it difficult to start new conversations and dislike being the center of attention.

3.2.4 AGREEABLENESS

People with high agreeableness care about other people, feel empathy, enjoy helping and contributing, while people with low agreeableness take little interest in others, don't care about other people's feelings, and manipulate others to get what they want.

3.2.5 NEUROTICISM

People with a high neuroticism score experience a lot of stress, worry about things, and get upset very easily, they feel anxious and experience dramatic shifts in their mood, while people with low neuroticism are emotionally stable, deal better with stress, don't worry too much and are usually very relaxed.

4 METHODOLOGY

In order to devise a model which will be able to differentiate between eudaemonia and hedonism in song lyrics and tell us how eudaemonic or hedonic a certain song is, we need to collect song lyrics and the weighted eudaemonic/hedonic scores for each song. We are going to acquire the song lyrics by web scraping, and the weighted eudaemonic/hedonic scores by a survey, where respondents will answer questions about songs, and these questions will be transformed into hedonic and eudaemonic scores. In order to explore the topic further, we are going to be collecting some additional data as well.

4.1 DATA COLLECTION

Data collection for this study was done in three parts. The first part was done by collecting pre studies results through google forms. After the data collection, we moved on to the second part which was done by collecting the song lyrics by web scraping. The third part was done using the 1ka platform. This platform allows us to export the data results and do further data analysis on them. It is also a very powerful website which does the data analysis for us, but for the purpose of this study, the platform was only used to conduct a survey and export the results in a comma-separated values (CSV) form, where the further data processing and analysis will be done in python.

4.1.1 PRE-STUDIES

For the purpose of this study, which is to create a model that will be able to do automatic recognition of hedonic and eudemonic qualities in songs, we need to choose songs that are going to give us meaningful information. To avoid bias and in fact collect songs that are going to be meaningful for this study, we ran a pre study with 17 respondents. Our sample consisted of 17 students, 16F and 1M, with an average age of 25 years (SD=4 years). The respondents were given definitions of eudaemonia and hedonism and were asked to give their favorite songs for each category. At the end of this pre study, we collected 100 songs for each category, respectively.
After the songs were collected, a second pre study test took place, where the collected songs from the first pre study were put in a list and the same respondents were asked to vote for the songs which they deem to fit the given category. For eudaemonia, they were

given a list of 100 songs that were collected in the first pre study, and they were asked to choose the ones they think fit the eudaemonic category. The same process was done for the hedonic category of songs. After we collected responses from the respondents, we were left with a list of songs and a certain weight assigned to them. This weight is represented by a score, derived from respondents' votes. Since respondents were able to choose or not to choose a song for each of the two categories, the final score represents a percentage of how many respondents picked the song over the overall number of respondents included in the pre study. The songs that were deemed to fit the given category by the most respondents were the songs that were later included in the main study.

It is important to note that at this point of the study the hedonic/eudaemonic weight to each song does not have any influence on the main study. Since each user will get to rate a set of songs later, we needed a pre study which allowed us to give each user a mix of hedonic and eudaemonic songs and not just either one or the other.

4.1.2 OBTAINING SONG LYRICS

After we collected the responses from the pre studies, we decided to choose 65 songs out of 100 from each category and move forward with the study. The number of songs chosen for the main study is arbitrary. This gives us a data set of 130 songs to work with. The reason that we chose 65 songs is in order to create 13 different groups, each containing 10 songs out of which 5 were deemed as hedonic and 5 as eudaemonic by the pre study that we ran. By choosing this number of songs with the highest eudaemonic and hedonic scores from the pre-study we get a data set of 130 songs which contain a better balance of both hedonia and eudaemonia, compared to as if we were to choose 130 songs randomly. Now, we finally have a song data set we can work with and from which we can extract features and which we can use for the main survey.

In order to create a machine learning model which will be able to recognize hedonic and eudaemonic qualities of songs from song lyrics, we need to obtain the song lyrics as well. The song lyrics were obtained using python and beautiful soup, regular expressions, and requests packages. We created our own model for obtaining song lyrics from the web. This model consists of a function which scrapes a website, taking the lyrics of a given song and saves the lyrics of that song to a dictionary. The first step was to inspect the elements of the website that we wanted to scrape and decide which ones are needed to acquire the song lyrics. After that we created a short program which takes in two lists as its input parameters. The first list contains the names of the singers and the second list contains the names of the songs. After the function takes in these two parameters, it scrapes the lyrics and writes it in the predefined dictionary. It appends the song name as the dictionary key and song lyrics as the dictionary value.

At the end of this step, we are left with a dictionary that consists of song names and song lyrics in a dictionary form, which need some further natural language processing in order to be useful and to give us correct machine learning model results.

4.1.3 MAIN STUDY

The main study consisted of collecting data with a 7-part survey. The survey was collected using an 1ka platform, while the respondents were reached via social media platforms. Each part of the survey collected meaningful data which was used for further data analysis. The first five parts of the survey are used in order to model a relationship between respondents' personality traits, music sophistication and their eudaemonic and hedonic qualities, while the last two parts of the survey are used for modeling a machine learning algorithm.

4.1.3.1 DEMOGRAPHICS

In this section of the survey, we collected the gender (M or F), age and level of education of the respondents.

4.1.3.2 MUSIC GENRE PREFERENCES

This part of the survey consisted of a 5-points Likert scale with 18 music genres as the questions. The respondents were asked how often they listen to each genre of music. The 5-points Likert scale included:

Table 1: 5-points Likert scale for music genre preferences

Never	Seldom	Sometimes	Often	Almost Always
1	2	3	4	5

The given genres are presented in Table 2 and were chosen from a study performed by Tkalcic et al. [6].

4.1.3.3 BIG FIVE PERSONALITY TEST

Since there are five core personality traits, or in other words five factors of personality, a big five personality test could be used to explore a possible correlation between personality traits and hedonic/eudaemonic preference. In order to explore this relation further, we need to collect data about the respondent's personality. The best way to do so is by conducting a Big Five Personality test on our sample size. The Big Five

Table 2: Music genres

Alternative	New Age
Blues	Pop
Classical	Punk
Country	RB
Easy Listen	Rap
Electronic	Reggae
Folk	Rock
Jazz	Vocal
World	

Personality test consisted of 44 questions where the respondents were asked how much they agree with the given statements about them on a 5-points Likert scale:

Table 3: 5-points Likert scale for Big Five personality test

Never	Seldom	Sometimes	Often	Almost Always
1	2	3	4	5

The Big Five personality test that was used is a test from John Fell's paper on Big Five Inventory (BFI) [5].

4.1.3.4 EUDAEMONIC AND HEDONIC MUSIC ORIENTATION

In order to explore the connection between the big five personality test and the eudaemonic and hedonic music orientation, we need to collect data about the eudaemonic and hedonic music orientation of each respondent. The eudaemonic and hedonic movie orientation scale was developed by Oliver and Raney in 2011 [17]. This part of the survey consists of 10 questions (5 related to hedonism and 5 related to eudaemonia) and is done with a 7-points Likert scale:

The respondents were asked to answer questions about their song preferences, such as whether they like songs that challenge their view of the world, or simple songs with no important context.

Table 4: 7-points Likert Scale for eudaemonic and hedonic music orientation

Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
1	2	3	4	5	6	7

4.1.3.5 INDEX OF OVERALL MUSIC SOPHISTICATION

This part of the study consists of 12 questions about the index of overall music sophistication of the respondents. In 2014 Müllensiefen et al. [15] created an index for assessing musical sophistication in the general population. This index was shortened from six factors to three factors, used in this study. Based on these 12 questions we can easily extract the activity (alpha: 0.87), perceptual abilities (alpha: 0.87) and emotions (alpha:0.79) score. This score can be used to check the connection between the overall music sophistication and eudaemonic/hedonic tendencies of respondents. The collection of data for this part of the survey was done using a 5-points Likert scale:

Table 5: 5-points Likert Scale for the index of overall music sophistication

Never	Seldom	Sometimes	Often	Almost Always
1	2	3	4	5

4.1.3.6 SONG LIKERT SCALE

In this part of the survey the respondents were randomly assigned 1 out of 13 sets of songs, containing 10 songs each. The songs were selected based on the results from the second pre-study where we selected 65 songs with the highest eudaemonic score and 65 songs with the highest hedonic score. Each set of songs contains 5 songs from each preliminary group of songs (hedonic and eudaemonic). The respondents were asked how much they like a certain song on a 6-points Likert scale:

The 6-points Likert scale will later be scaled down to a 5-points Likert scale, excluding the “I didn’t listen to this song” option, in order to get a consistent “Song Liking” score which matches the previous survey questions which are also conducted using a 5-points Likert scale.

Table 6: 6-points Likert Scale for song liking

Didn't listen to this song	Not at all	Not really	Undecided	Somewhat	Very much
1	2	3	4	5	6

4.1.3.7 EUDAEMONIC AND HEDONIC PERCEPTIONS OF SONGS

In the last part of the survey the respondents are asked to respond to 10 questions about each song from the previous section of the survey with a 7-points Likert scale:

Table 7: 7-points Likert Scale for eudaemonic and hedonic Perceptions of Songs

Strongly disagree	Disagree	Somewhat disagree	Neither nor disagree	Somewhat agree	Agree	Strongly agree
1	2	3	4	5	6	7

The first 5 questions are used in order to get a hedonic and eudaemonic score for each song. This score will be used in pair with the song lyrics in order to create a model that will be able to do automatic recognition of hedonic and eudemonic qualities in songs.

4.2 DATA CLEANING

In order to get meaningful results from our data set we need to first prepare it and clean it. Before the data cleaning process our data set consisted of 8447 respondents. This includes the respondents that have unanswered questions, that skipped questions, dropped out of the survey midway, and left the survey blank. We could either replace the missing values or remove the participants that have missing values. Because of the high number of participants, for the first step of data cleaning we decided to remove the participants that have unanswered questions, that skipped questions, dropped out of the survey midway, or left the survey blank. The second step of data cleaning was to filter out users by demographics. Users that did not have a male or a female gender (1 or 2 respectively) were removed from the study, as well as the users that had an education level outside of the given border (1 – 6). Users were also filtered by age, where everyone under 1 years old was removed from the study, as well as everyone that is older than 99 years of age. After the first part of the age filtering, the second part consisted of the age data exploration. There were no participants younger than 12 years old or older than 60 years old.

The third step of data cleaning consisted of removing the participants that had repetitive answers for music genre preferences, big five personality test, eudaemonic and hedonic music orientation, index of overall music sophistication, song Likert scale and eudaemonic and hedonic perceptions of songs. This data cleaning step included searching for patterns in answers (such as 1-2-3-4-5 or 1-1-1-1-1 etc.) All of the respondents with these patterns were removed from the study as well. Our sample ended up consisting of 1991 users (1904F, 87M) with an average age of 28 years (SD = 9 years). The level of education of the respondents is described in the Table 8. 7

4.3 FEATURE ENGINEERING

4.3.1 BIG FIVE PERSONALITY TEST

Our survey collected data about the respondent's personality traits. These traits were collected in a form of 44 questions. As mentioned earlier the test used to acquire the results is a test from John Fell's paper on Big Five Inventory (BFI) [5]. All of the questions explored the respondent's personality traits. The collected data is hard to interpret because it consists of 44 questions and a 5-points Likert scale. In order to get meaningful results which can be compared, we need to transform the results into scores that are going to tell us more about respondent's personality traits. This can easily be done by calculating the big five personality factors:

- Extraversion (alpha: 0.88)
- Agreeableness (alpha: 0.81)
- Conscientiousness (alpha: 0.77)
- Neuroticism (alpha: 0.84)
- Openness (alpha: 0.81)

In order to transform the 44 questions into these five factors, we need to do some further data manipulation. Since the big five personality test consisted of questions that are negatively keyed, as well as the questions that were positively keyed, we needed to do further data manipulation on these scores by transforming the negatively keyed scores into positively keyed scores.

For example in order to calculate the extraversion score we take into the account answers to these two statements: "I am expressive" and "I am self-contained and reserved". Both of these affect the extraversion score, but in different ways. Answer to the first question can be added to the extraversion score, but the answer to the second question needs to be re-scaled. If a person has given a low score for "I am self-contained and reserved" it means that they are not self-contained and reserved but rather expressive and open, which adds a value to the extraversion score. By changing a score 2 to a score 4 which is the opposite on the 5-points Likert scale, we are transforming the negatively keyed score into a positively keyed score. This is done for all the negatively keyed values for all five factors.

The answers to each of the 44 questions were then averaged with respect to their belonging factors, and as the result we got a score for each of the five personality factors. The factors can now easily be interpreted. Higher the extraversion score, more extraverted you are, lower the extraversion score, more introverted you are etc.

4.3.2 EUDAEMONIC AND HEDONIC MUSIC ORIENTATION

In one of the parts of our survey, we also collected data about eudaemonic and hedonic music orientations of the respondents. The respondents were asked 10 questions, from which 5 were related to hedonism and 5 to eudaemonia. The questions were then averaged, with respect to hedonism and eudaemonia and as a result we obtained a score for the respondents hedonic and eudaemonic music preferences, with alpha values, or in other word significance values being equal to 0.80 and 0.90, respectively. The hedonic score was calculated by averaging the answers to the hedonic questions, while the eudaemonic score was calculated by averaging the responses to eudaemonic questions.

4.3.3 INDEX OF OVERALL MUSIC SOPHISTICATION

The respondents were asked to answer 12 questions related to their overall music sophistication. The overall music sophistication can be described through three factors: activity, perceptual abilities, and emotions. The activity score resembles the respondents' interest in music, the perceptual abilities is self-explanatory as it resembles the respondents' perceptual abilities when it comes to songs, while the emotions score describes the emotional song interest of the respondent. The survey questions were used to assign the weight to 3 different factors: activity (alpha: 0.87), perceptual abilities (alpha: 0.87) and emotions (alpha:0.79) score. We can see that the significance levels are relatively high for all of the factors, with the emotions factor being a bit lower than the other two. Out of the 12 questions, 4 questions were carrying an activity score weight, 4 questions were carrying the perceptual abilities weight and 4 questions were carrying an emotions weight. The averages of these four questions, respectively, gave us a final activity, perceptual abilities and emotions scores.

4.3.4 SONG LIKERT SCALE

The respondents were asked to rate how much they like songs that were randomly assigned to them. Since this Likert scale was different than the previous ones, because it also contained an extra option for when the user does not know the song, it needs to be manipulated in order to match the Likert scale of other questions. Since the purpose of this part of the analysis is to see how acquainted respondents were with the songs they were randomly assigned, we subtracted 1 from the final score, which gave us the same results but on a 5-points Likert scale instead of a 6-points Likert scale. With this, we also removed all the respondents which didn't know the song, from having influence on the final score of each song. At the end of this data manipulation step, we obtained an average score of each song which tells us how familiar this song is, by only taking into account the people that actually knew the song.

4.3.5 EUDAEMONIC AND HEDONIC PERCEPTIONS OF SONGS

In this part of the survey, we asked the users how much they like the songs they were randomly assigned, and to answer 10 questions about each of the 10 songs. An average of 153 respondents responded to questions about each song. Out of the 10 questions that were asked, 5 were related to hedonic (alpha: 0.80) and 5 to eudaemonic (alpha: 0.90) tendencies of the song. These answers were transformed into a hedonic and eudaemonic score for each song, similar to eudaemonic and hedonic music orientation score calculation.- In order to achieve a hedonic and eudaemonic score for each song, first we needed to combine the hedonic and eudaemonic score for each song from each user. Since each user has answered 10 questions about each song, 5 of which were related to hedonia and 5 to eudaemonia, we first calculated the hedonic and eudaemonic score of the song by each user independently. Then we averaged the hedonic and eudaemonic scores from each user to get the final hedonic and eudaemonic score for each song. The final result is two columns, hedonia and eudaemonia respectively, which carry a value of how hedonic/eudaemonic a song is based on user ratings. Now our data set contains two new columns hedonia and eudaemonia which carry percentage scores of how eudaemonic and hedonic a certain song is. Since these percentages are between 0 and a 100, we are going to normalize them in order to get scores between 0 and 1 - which is going to prepare our data set for regression analysis. On another hand, in order to perform classification models on our data set we need to transform our data into two groups. These groups are going to be "Low Hedonic" or "High Hedonic" and "Low Eudaemonic" and "High Eudaemonic". These scores are going to be represented as 0's for low scores and 1's for high scores. Since we have a data set which has songs as rows and hedonic and eudaemonic scores as columns, we are going to simply take the median values of these columns and assign a "High Hedonic" score to songs which have a hedonic score higher than the median, and "Low Hedonic" score to songs which have a hedonic score lower than the median. This same process is done on the eudaemonic scores as well. As a result we obtain a data set which contains classes as hedonic and eudaemonic columns, and songs as rows.

4.3.6 NATURAL LANGUAGE PROCESSING

Natural language processing (NLP) is defined as a subfield of linguistics, computer science and artificial intelligence [10]. NLP is processing of natural languages by machines (computers). NLP is very important because it easily processes and analyzes large amounts of natural language data. NLP techniques are used in order for a computer to understand the natural language better. Natural language processing is a very sparse topic but in order to understand what we are going to be doing in this research, we will be going through some of the most basic and important aspects of NLP.

After obtaining the song lyrics, we are left with a dictionary which contains song names as keys and song lyrics as values. In order to get meaningful information from the song lyrics, we need to implement some natural language processing techniques on the obtained dictionary. This will prepare our data for a machine learning model which will look for connections between the hedonism/eudaemonia score and the song lyrics.

4.3.6.1 NORMALIZATION

Normalization is a process in NLP that takes in a list of words and creates a more uniform sequence. Normalization is a very important pre-processing step because a machine needs simple and readable data to work with, in order to give the best results. Some of the normalization functions include converting all words to lowercase. This simplifies the searching process because all words are lowercase, and it also improves the text matching process. Normalization should be done when the text you are normalizing does not carry any important information in it's original form, i.e. capital letters. A basic example of normalization would be mapping of near identical words, i.e. "stopwords", "stop-words" and "stop words" to "stopwords". Since our data set does not carry any information in the uppercase letter, we are doing a normalization of the song lyrics.

4.3.6.2 STOP WORDS

With regards to the previous example in normalization, stop words are a set of commonly used words in a language. Some basic examples of stopwords in English are "a", "is", "are", "the" and etc. Stop words are a very important part in text mining and NLP. By removing stopwords we are eliminating words that are commonly used. Commonly used words carry little to no useful information, and since the purpose is to extract useful information from text using NLP tehniques, we need to get rid of the words that carry little to no useful information. English stop words are usually predefined, and it is relatively easy to use NLP techniques to get rid of stop words. A small example of removing stop words would be the removal of "what", "is" and "a" from the following sentence: "what is a stop word?".

4.3.6.3 TOKENIZATION

Tokenization is a process of segmenting text into sentences and words. If we have a sentence: "What is tokenization?", the tokenization process will tokenize it into the following tokens: "what", "is", "tokenization", "?". Tokenization makes the text easier to process, and therefore it is easier to remove unnecessary tokens such as "?", which again carry no necessary information.

4.3.6.4 STEMMING

Stemming is a process of reducing the words to their root form. The main purpose of stemming is to reduce the number of words, by taking the stem of each word. An example of good stemming with be the words "connection", "connected" and "connecting" being stemmed down to a common word "connect".

There are many stemming algorithms, especially when it comes to English language but the most famous ones are Porter Stemmer [19] and Snowball Stemmer [20].

Stemming is a crude heuristic process which chops off the end of each word, but sometimes it creates words that are not actual words.

There are two common errors in stemming: over-stemming and under-stemming. Over-stemming is when a much larger part of a word is chopped off and as a result the word is reduced to the same root as some other word which is not connected. A most basic example of over-stemming would be the stemming of words "university" and "universe" to a common word "univers". On the other hand, under-stemming happens when two words which are related to eachother get stemmed down to two different roots. An example of this would be the words "data" and "datum" being stemmed to "dat" and "datu, respectively. Snowball stemmer is an improvement to the Porter stemmer, and it has shown to create more accurate stems.

4.3.6.5 LEMMATIZATION

Compared to stemming, which reduces the word to its stem, lemmatization reduces the word to its base word. A root word in the lemmatization process is called a lemma. Lemmatization process can be improved by parts-of-speach, also known as POS tagging. POS tagging identifies the grammatical group of a word which is being lemmatized by looking at the context. It looks whether the word is an adjective, verb, noun etc. POS tagging is known to improve the accuracy. A basic example of POS tagging could be shown with a word "leaves". If we didn't have a POS tag the world "leaves" would get lemmatized to "leaf", but with a POS tag equal to a verb, it would be lemmatized to "leave".

4.3.6.6 TF-IDF

These NLP techniques are very useful when it comes to natural language processing because they allow us to take only the necessary information from our textual data and feed it to the machine learning model. At this step we acquire a document-term matrix version of our song lyrics where each column is a word, and each row is a song. The values are the number of times a word appears in the song. In order to feed this data into our machine learning model, we need to transform our data a bit further. We have a data set with song names as rows, words as columns, and our data is how many times a certain word appears in each song, or in other words the frequency of appearance of a word in a song. Term Frequency — Inverse Document Frequency, allows us to assign a weight to each word based on its appearance in the song. It takes the frequency of a word appearing in a song and transforms it into a score between 0 and a 1 which is easier to interpret than a random number such as "12" or "4".

4.3.7 FINAL DATA SET

After applying TF-IDF to our song lyrics data set, we are going to merge it with our hedonic / eudaemonic scores of songs data set. We are going to do so, by taking the hedonic score from our eudaemonic and hedonic perceptions of songs data set and add it to the final song lyrics data set. We are going to do the same with the eudaemonic score. Since we are creating two models, one for hedonia and one for eudaemonia, we need two data sets which we are going to feed to our machine learning model. We can see the hedonic classification data set in Figure 1, and the eudaemonic classification data set in Figure 2.

When it comes to the regression we can see the final data set in Figure 3 and Figure 4, for hedonic and eudaemonic scores of songs, respectively.

4.4 EXPERIMENTAL EVALUATION

In this section we are going to be talking about the techniques, models and metrics used in our machine learning models.

We are using a nested cross validation, with an outer loop splitting the data set into 5 folds, repeating it 4 times. The nested 5-fold cross validation works in a way that it splits the data set into 5 folds, and each time one fold is the test set, while the remainder of the data is the train set. Data are randomly split into 5 folds, and in

	...	hard	head	heart	hey	...	just	know	life	look	love	...	HEDONIC
24kmagic	...	0.0192	0.0897	0.0000	0.0201	...	0.0220	0.0319	0.0000	0.0760	0.0000	...	1
7rings	...	0.0000	0.0000	0.0000	0.0000	...	0.0864	0.0167	0.0000	0.0479	0.0000	...	1
aintyourmama	...	0.0000	0.0000	0.0000	0.0747	...	0.0204	0.0000	0.0000	0.0000	0.0214	...	0
allofme	...	0.0483	0.1802	0.0439	0.0000	...	0.0000	0.0267	0.0000	0.0000	0.1740	...	0
anaconda	...	0.0000	0.0000	0.0000	0.0512	...	0.0000	0.0000	0.0000	0.3219	0.0293	...	1
animals	...	0.0000	0.0175	0.0000	0.0000	...	0.1073	0.0000	0.0000	0.0000	0.0113	...	1
areyouwithme	...	0.0000	0.0000	0.0000	0.0000	...	0.0000	0.0000	0.0000	0.0000	0.0000	...	0
aslongasyouloveme	...	0.0000	0.0000	0.0209	0.0481	...	0.0262	0.0760	0.0000	0.0000	0.3860	...	0
backtoblack	...	0.0000	0.0412	0.0000	0.0000	...	0.0000	0.0000	0.0418	0.0000	0.0796	...	0
badromance	...	0.0000	0.0000	0.0000	0.0000	...	0.0000	0.0256	0.0000	0.0000	0.1185	...	0
bangbang	...	0.0000	0.0000	0.0445	0.0128	...	0.0070	0.0607	0.0000	0.0000	0.0000	...	1
beautifulpeople	...	0.0000	0.0353	0.0000	0.0000	...	0.0648	0.0627	0.0000	0.0898	0.0227	...	1
becauseofyou	...	0.1166	0.0000	0.0530	0.0000	...	0.0333	0.0322	0.0551	0.0000	0.0000	...	0
believer	...	0.0000	0.0239	0.0000	0.0000	...	0.0000	0.0000	0.0726	0.0202	0.0461	...	0
biggirlsdontcry	...	0.0000	0.0000	0.0000	0.0000	...	0.0000	0.1221	0.1046	0.0000	0.0000	...	1
billiejean	...	0.0000	0.0194	0.0756	0.0000	...	0.0712	0.0115	0.0000	0.0329	0.0125	...	1
blurredlines	...	0.0000	0.0000	0.0000	0.0000	...	0.0452	0.2621	0.0000	0.0000	0.0000	...	0
bodakyellow	...	0.0183	0.0000	0.0000	0.0000	...	0.0942	0.0709	0.0000	0.0725	0.0000	...	0
bohemianrhapsody	...	0.0000	0.0306	0.0000	0.0000	...	0.1496	0.0000	0.0930	0.0259	0.0394	...	1
boomboompow	...	0.0000	0.0000	0.0000	0.0000	...	0.0000	0.0000	0.0000	0.0000	0.0000	...	0
booty	...	0.0000	0.0000	0.0000	0.0000	...	0.0076	0.0222	0.0127	0.0106	0.0241	...	1
bootylicious	...	0.0120	0.0000	0.0000	0.0252	...	0.0000	0.0000	0.0000	0.0190	0.0000	...	1
...	...	...	...	...	...	...	...	...	...	...	...	...	...

Figure 1: Document Term Matrix with TF-IDF scores and a classification hedonic score for each song

	...	hard	head	heart	hey	...	just	know	life	look	love	...	EUDAEMONIC
24kmagic	...	0.0192	0.0897	0.0000	0.0201	...	0.0220	0.0319	0.0000	0.0760	0.0000	...	0
7rings	...	0.0000	0.0000	0.0000	0.0000	...	0.0864	0.0167	0.0000	0.0479	0.0000	...	0
aintyourmama	...	0.0000	0.0000	0.0000	0.0747	...	0.0204	0.0000	0.0000	0.0000	0.0214	...	1
allofme	...	0.0483	0.1802	0.0439	0.0000	...	0.0000	0.0267	0.0000	0.0000	0.1740	...	1
anaconda	...	0.0000	0.0000	0.0000	0.0512	...	0.0000	0.0000	0.0000	0.3219	0.0293	...	0
animals	...	0.0000	0.0175	0.0000	0.0000	...	0.1073	0.0000	0.0000	0.0000	0.0113	...	0
areyouwithme	...	0.0000	0.0000	0.0000	0.0000	...	0.0000	0.0000	0.0000	0.0000	0.0000	...	1
aslongasyouloveme	...	0.0000	0.0000	0.0209	0.0481	...	0.0262	0.0760	0.0000	0.0000	0.3860	...	1
backtoblack	...	0.0000	0.0412	0.0000	0.0000	...	0.0000	0.0000	0.0418	0.0000	0.0796	...	0
badromance	...	0.0000	0.0000	0.0000	0.0000	...	0.0000	0.0256	0.0000	0.0000	0.1185	...	1
bangbang	...	0.0000	0.0000	0.0445	0.0128	...	0.0070	0.0607	0.0000	0.0000	0.0000	...	0
beautifulpeople	...	0.0000	0.0353	0.0000	0.0000	...	0.0648	0.0627	0.0000	0.0898	0.0227	...	0
becauseofyou	...	0.1166	0.0000	0.0530	0.0000	...	0.0333	0.0322	0.0551	0.0000	0.0000	...	1
believer	...	0.0000	0.0239	0.0000	0.0000	...	0.0000	0.0000	0.0726	0.0202	0.0461	...	1
biggirlsdontcry	...	0.0000	0.0000	0.0000	0.0000	...	0.0000	0.1221	0.1046	0.0000	0.0000	...	0
billiejean	...	0.0000	0.0194	0.0756	0.0000	...	0.0712	0.0115	0.0000	0.0329	0.0125	...	1
blurredlines	...	0.0000	0.0000	0.0000	0.0000	...	0.0452	0.2621	0.0000	0.0000	0.0000	...	1
bodakyellow	...	0.0183	0.0000	0.0000	0.0000	...	0.0942	0.0709	0.0000	0.0725	0.0000	...	1
bohemianrhapsody	...	0.0000	0.0306	0.0000	0.0000	...	0.1496	0.0000	0.0930	0.0259	0.0394	...	1
boomboompow	...	0.0000	0.0000	0.0000	0.0000	...	0.0000	0.0000	0.0000	0.0000	0.0000	...	1
booty	...	0.0000	0.0000	0.0000	0.0000	...	0.0076	0.0222	0.0127	0.0106	0.0241	...	0
bootylicious	...	0.0120	0.0000	0.0000	0.0252	...	0.0000	0.0000	0.0000	0.0190	0.0000	...	0
...	...	...	...	...	...	...	...	...	...	...	...	...	...

Figure 2: Document Term Matrix with TF-IDF scores and a classification eudaemonic score for each song

each iteration we have a test set and a validation set. The model works in a way that it trains each proposed parameter set on the train data, evaluates it on the validation data and keeps track of the accuracy for classification models, and RMSE, MSE and MAE for regression. After looking at the average score for each set of the parameters, it chooses the best ones and trains a model based on that set of parameters.

We are also applying PCA on our data set. We are using a 70% for the number of components parameter. This means that the scikit-learn will choose the minimum number of principal components, such that 70% of the variance is retained.

	...	hard	head	heart	hey	...	just	know	life	look	love	...	HEDONIC
24kmagic	...	0.0192	0.0897	0.0000	0.0201	...	0.0220	0.0319	0.0000	0.0760	0.0000	...	0.6765
7rings	...	0.0000	0.0000	0.0000	0.0000	...	0.0864	0.0167	0.0000	0.0479	0.0000	...	0.6861
aintyourmama	...	0.0000	0.0000	0.0000	0.0747	...	0.0204	0.0000	0.0000	0.0000	0.0214	...	0.4693
allofme	...	0.0483	0.1802	0.0439	0.0000	...	0.0000	0.0267	0.0000	0.0000	0.1740	...	0.4875
anaconda	...	0.0000	0.0000	0.0000	0.0512	...	0.0000	0.0000	0.0000	0.3219	0.0293	...	0.6305
animals	...	0.0000	0.0175	0.0000	0.0000	...	0.1073	0.0000	0.0000	0.0000	0.0113	...	0.6818
areyouwithme	...	0.0000	0.0000	0.0000	0.0000	...	0.0000	0.0000	0.0000	0.0000	0.0000	...	0.6032
aslongasyouloveme	...	0.0000	0.0000	0.0209	0.0481	...	0.0262	0.0760	0.0000	0.0000	0.3860	...	0.5955
backtoblack	...	0.0000	0.0412	0.0000	0.0000	...	0.0000	0.0000	0.0418	0.0000	0.0796	...	0.5659
badromance	...	0.0000	0.0000	0.0000	0.0000	...	0.0000	0.0256	0.0000	0.0000	0.1185	...	0.5296
bangbang	...	0.0000	0.0000	0.0445	0.0128	...	0.0070	0.0607	0.0000	0.0000	0.0000	...	0.7393
beautifulpeople	...	0.0000	0.0353	0.0000	0.0000	...	0.0648	0.0627	0.0000	0.0898	0.0227	...	0.7130
becauseofyou	...	0.1166	0.0000	0.0530	0.0000	...	0.0333	0.0322	0.0551	0.0000	0.0000	...	0.5612
believer	...	0.0000	0.0239	0.0000	0.0000	...	0.0000	0.0000	0.0726	0.0202	0.0461	...	0.4919
biggirlsdontcry	...	0.0000	0.0000	0.0000	0.0000	...	0.0000	0.1221	0.1046	0.0000	0.0000	...	0.7176
billiejean	...	0.0000	0.0194	0.0756	0.0000	...	0.0712	0.0115	0.0000	0.0329	0.0125	...	0.6459
blurredlines	...	0.0000	0.0000	0.0000	0.0000	...	0.0452	0.2621	0.0000	0.0000	0.0000	...	0.5780
bodakyellow	...	0.0183	0.0000	0.0000	0.0000	...	0.0942	0.0709	0.0000	0.0725	0.0000	...	0.5878
bohemianrhapsody	...	0.0000	0.0306	0.0000	0.0000	...	0.1496	0.0000	0.0930	0.0259	0.0394	...	0.6107
boomboompow	...	0.0000	0.0000	0.0000	0.0000	...	0.0000	0.0000	0.0000	0.0000	0.0000	...	0.5358
booty	...	0.0000	0.0000	0.0000	0.0000	...	0.0076	0.0222	0.0127	0.0106	0.0241	...	0.7187
bootylicious	...	0.0120	0.0000	0.0000	0.0252	...	0.0000	0.0000	0.0000	0.0190	0.0000	...	0.7338
...	...	...	...	...	...	...	...	...	...	...	...	...	...

Figure 3: Document Term Matrix with TF-IDF scores and a hedonic score for each song

	...	hard	head	heart	hey	...	just	know	life	look	love	...	EUDAEMONIC
24kmagic	...	0.0192	0.0897	0.0000	0.0201	...	0.0220	0.0319	0.0000	0.0760	0.0000	...	0.4525
7rings	...	0.0000	0.0000	0.0000	0.0000	...	0.0864	0.0167	0.0000	0.0479	0.0000	...	0.3710
aintyourmama	...	0.0000	0.0000	0.0000	0.0747	...	0.0204	0.0000	0.0000	0.0000	0.0214	...	0.7199
allofme	...	0.0483	0.1802	0.0439	0.0000	...	0.0000	0.0267	0.0000	0.0000	0.1740	...	0.6659
anaconda	...	0.0000	0.0000	0.0000	0.0512	...	0.0000	0.0000	0.0000	0.3219	0.0293	...	0.3890
animals	...	0.0000	0.0175	0.0000	0.0000	...	0.1073	0.0000	0.0000	0.0000	0.0113	...	0.3192
areyouwithme	...	0.0000	0.0000	0.0000	0.0000	...	0.0000	0.0000	0.0000	0.0000	0.0000	...	0.5887
aslongasyouloveme	...	0.0000	0.0000	0.0209	0.0481	...	0.0262	0.0760	0.0000	0.0000	0.3860	...	0.5574
backtoblack	...	0.0000	0.0412	0.0000	0.0000	...	0.0000	0.0000	0.0418	0.0000	0.0796	...	0.4429
badromance	...	0.0000	0.0000	0.0000	0.0000	...	0.0000	0.0256	0.0000	0.0000	0.1185	...	0.6481
bangbang	...	0.0000	0.0000	0.0445	0.0128	...	0.0070	0.0607	0.0000	0.0000	0.0000	...	0.4413
beautifulpeople	...	0.0000	0.0353	0.0000	0.0000	...	0.0648	0.0627	0.0000	0.0898	0.0227	...	0.4567
becauseofyou	...	0.1166	0.0000	0.0530	0.0000	...	0.0333	0.0322	0.0551	0.0000	0.0000	...	0.6906
believer	...	0.0000	0.0239	0.0000	0.0000	...	0.0000	0.0000	0.0726	0.0202	0.0461	...	0.6652
biggirlsdontcry	...	0.0000	0.0000	0.0000	0.0000	...	0.0000	0.1221	0.1046	0.0000	0.0000	...	0.3881
billiejean	...	0.0000	0.0194	0.0756	0.0000	...	0.0712	0.0115	0.0000	0.0329	0.0125	...	0.5791
blurredlines	...	0.0000	0.0000	0.0000	0.0000	...	0.0452	0.2621	0.0000	0.0000	0.0000	...	0.5690
bodakyellow	...	0.0183	0.0000	0.0000	0.0000	...	0.0942	0.0709	0.0000	0.0725	0.0000	...	0.5032
bohemianrhapsody	...	0.0000	0.0306	0.0000	0.0000	...	0.1496	0.0000	0.0930	0.0259	0.0394	...	0.5250
boomboompow	...	0.0000	0.0000	0.0000	0.0000	...	0.0000	0.0000	0.0000	0.0000	0.0000	...	0.7789
booty	...	0.0000	0.0000	0.0000	0.0000	...	0.0076	0.0222	0.0127	0.0106	0.0241	...	0.4248
bootylicious	...	0.0120	0.0000	0.0000	0.0252	...	0.0000	0.0000	0.0000	0.0190	0.0000	...	0.3818
...	...	...	...	...	...	...	...	...	...	...	...	...	...

Figure 4: Document Term Matrix with TF-IDF scores and a eudaemonic score for each song

PCA of 70% was used in all of the models except the Bagging classifier hedonic model, where we used a PCA of 50%. We are going to be testing our model by classification and regression techniques. For classification models we are going to be using the following list of classifiers: Random Forest Classifier, KNN Classifier, SVC Classifier, Logistic Regression Classifier , Ridge Classifier and a Bagging Classifier and we are going to be comparing the accuracy and standard deviation results of these models to the baseline model. We are also going to be using a Random Forest Regressor and compare the results to the baseline results. The metrics we are going to be comparing are Accuracy and Standard Deviation for the classification models and RMSE, MSE and MAE for our regression model. We are using Random Search and Grid Search in order to find the best parameters. We are first using a Random Search outside of the algorithm and selecting the hyperparameters which are going to be used for the Grid Search inside the model itself. The following list shows the hyperparameters which are used as a part of the Grid Search in our models:

1. Random Forest Classifier
   - number of estimators = (10, 100, 500)
   - max features = (2, 4, 6, 8, 10, 12)
2. Logistic Regression:
   - solver = ('newton-cg', 'lbfgs', 'liblinear')
   - penalty = ('l2')
   - C = (100, 10, 1.0, 0.1, 0.01)
3. Ridge Classifier:
   - alpha = (0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1.0)
4. K Neighbours Classifier:
   - number of neighbours = range(1, 21, 2)
   - weights = ('uniform, distance)
   - metric = ('euclidean', 'manhattan', 'minkowski')
5. Bagging Classifier:
   - number of estimators = (10, 100, 1000)
6. SVC Classifier:
   - C = (100, 150, 200, 250, 300, 500, 1000)
   - Gamma = (1, 0.1, 0.01, 0.02, 0.03, 0.04, 0.05, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9)
   - Kernel = ('rbf')

For the regression we are using the following hyperparameters:

- splitter = ["best", "random"];
- max depth = [1, 3, 5, 7, 9, 11, 12];
- min samples leaf = [1, 2, 3, 4, 5, 6, 7, 8, 9, 10];
- min weight fraction leaf = [0, 0.5];
- max features = ["auto", "log2", "sqrt", None];
- max leaf nodes = [None, 10, 20, 30, 40, 50, 60, 70, 80, 90]

As the model is ran 5 times, we are taking the average of the Accuracy, RMSE, MSE and MAE and comparing it to the baseline results. For the regression we are using 4-Fold cross validation for the inner and the outer loop.

The results of the classification and regression algorithms are compared to the baseline results achieved by a dummy classifier/regression model. The baseline classifier was calculated by using the "most frequent strategy" which takes in the most frequent class from the two and assigns it as the predicted value. The baseline regression model uses a "mean strategy", where it takes the average of the actual values and uses it as the predicted value.

5 RESULTS

Our sample consists of 1991 users (1904F, 87M) with an average age of 28 years (SD = 9 years). The level of education of the respondents is described in Table 8.

Table 8: Level of education of survey respondents

Level of Education	Number of Respondents
High School	870
Bachelor's Degree	655
Master's Degree	358
Elementary School	63
Doctorate Degree	26
Unfinished Elementary School	19

5.1 CORRELATIONAL ANALYSIS

The Figure 5 shows a correlation matrix, with Bonferroni correction, between different aspects of personality, demographics, eudaemonia/hedonia and music sophistication.

The Figure 6 shows a correlation matrix, with Bonferroni correction, between music genres.

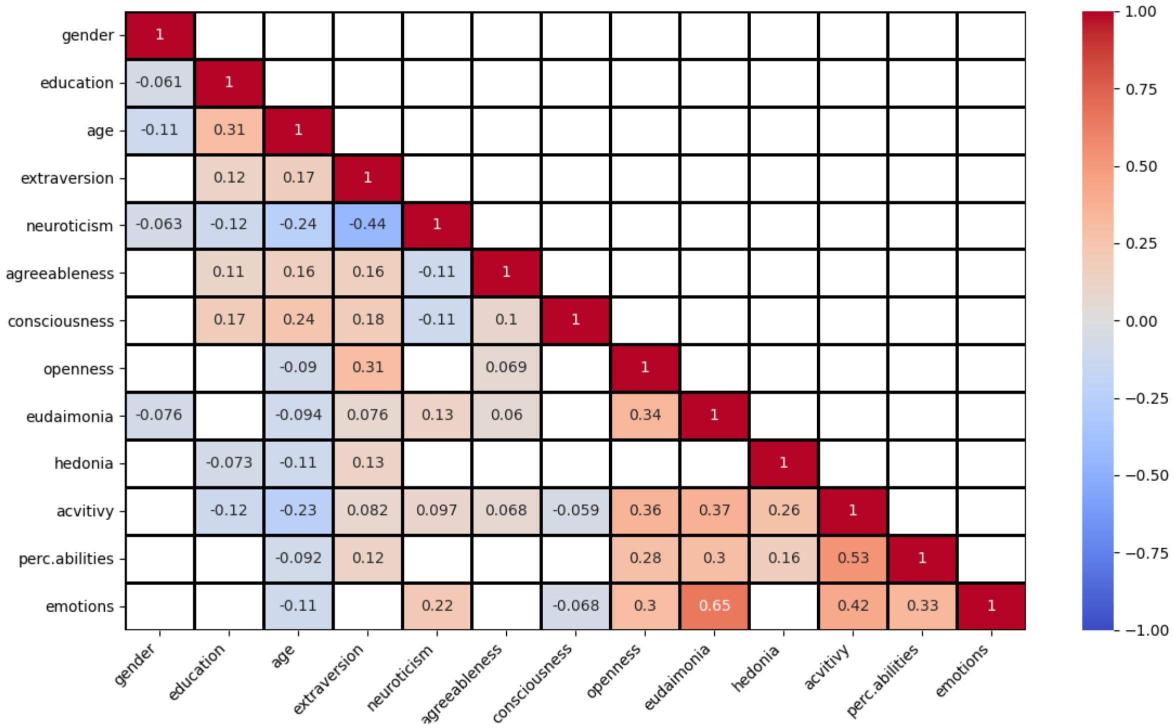

Figure 5: Personality correlation plot

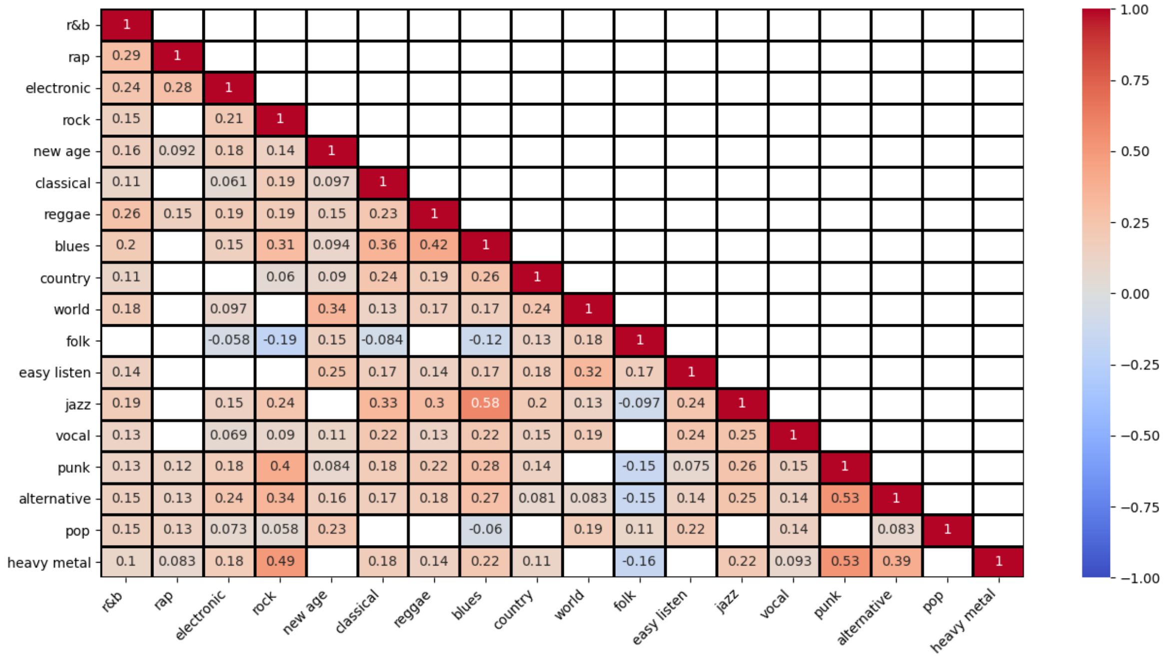

Figure 6: Music genre correlation plot

5.2 GENDER AND HEDONIA/EUDAEMONIA

While conducting the study, we wanted to see whether there exists a statistically significant difference between hedonic and eudaemonic tendencies between genders. We can see the average scores of eudaemonia and hedonia based on genders in Table 9.

Comparing the eudaemonic and Hedonic scores and genders:

Table 9: Differences of Eudaemonic and Hedonic means between Genders

gender	eudaemonia	hedonia
female	5.113	5.115
male	4.696	4.836

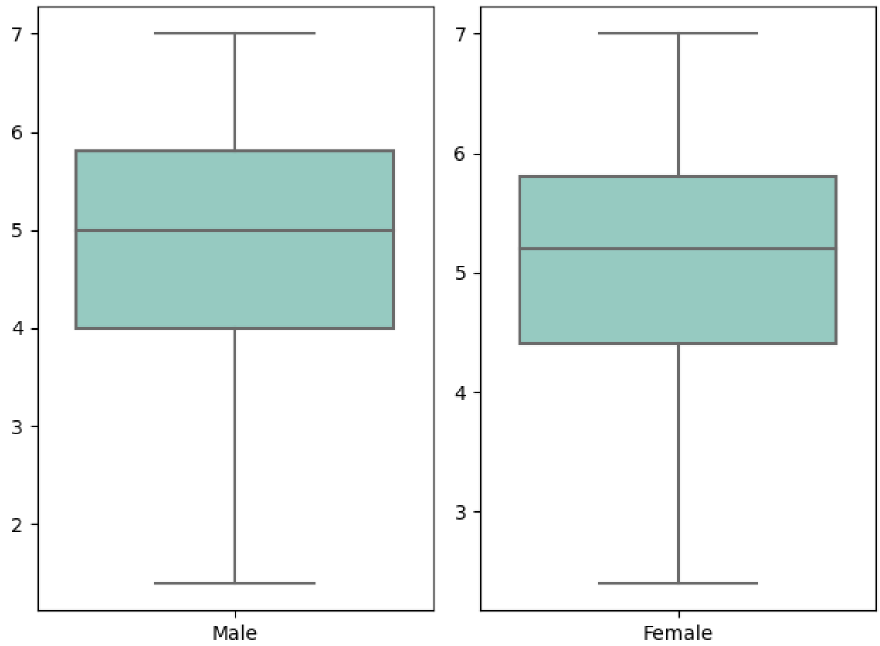

Figure 7: Hedonic tendencies box plot between genders

Before doing any further tests we need to see whether our data comes from the same distribution. H_0 hypothesis states that the data comes from the same distribution. After running a mannwhitney test, we see that our data actually comes from the same distribution with a $p = 0.051$ which is bigger than $alpha = 0.05$. After running a two sample t test we get the $p = 0.012$, with the H_0 hypothesis stating that there is no difference between means. The results show that there exists a statistical significance between hedonic tendencies in songs between males and females. We are comparing if there exists a statistical significance between eudaemonic scores of males and females. After running the same mannwhitney test to see whether our eudaemonic data comes from the same distribution, we get a $p = 0.001$ which means that our data does not come from the same distribution, therefore we reject the H_0 hypothesis. We are running a two sample t test which gives us a $p = 0.001$ which shows that there exists a statistical significance between eudaemonic tendencies in songs between males and females. Therefore we reject the H_0 hypothesis once again.

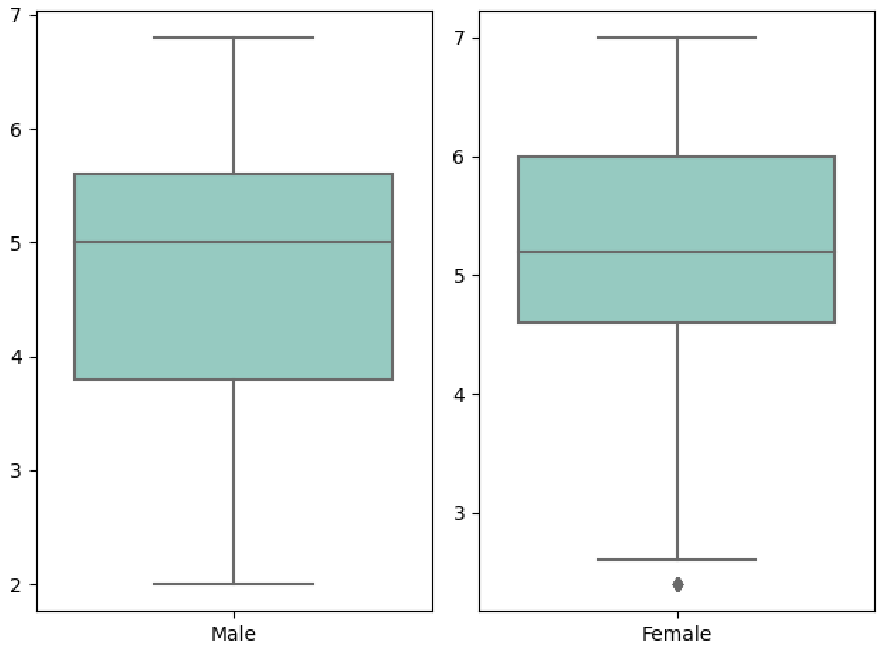

Figure 8: Hedonic tendencies box plot between genders

5.3 PREDICTION RESULTS

Comparing the results from binary classification using random forest, knn, logistic regression, bagging, svc and ridge classifiers we get the following results:

Table 10: Eudaemonic machine learning model accuracy and standard deviation results for classifiers and the baseline

MODEL	ACCURACY	STD
Random Forest	0.515	0.099
KNN	0.523	0.052
SVC	0.515	0.062
Logistic Regression	0.531	0.057
Ridge	0.531	0.045
Bagging	0.538	0.054
Baseline	0.423	0.069

Table 11: Hedonic machine learning model accuracy and standard deviation results for classifiers and the baseline

MODEL	ACCURACY	STD
Random Forest	0.485	0.093
KNN	0.523	0.099
SVC	0.500	0.047
Logistic Regression	0.423	0.081
Ridge	0.485	0.105
Bagging	0.546	0.057
Baseline	0.408	0.031

Table 12: Eudaemonic machine learning model MAE, MSE and RMSE results for regressors and the baseline

	SCORE	SCORE STD	BASELINE	BASELINE STD
MAE	0.115	0.011	0.115	0.010
MSE	0.018	0.003	0.018	0.002
RMSE	0.132	0.012	0.132	0.010

Table 13: Hedonic machine learning model MAE, MSE and RMSE results for regressors and the baseline

	SCORE	SCORE STD	BASELINE	BASELINE STD
MAE	0.064	0.010	0.064	0.007
MSE	0.006	0.002	0.006	0.002
RMSE	0.076	0.012	0.078	0.008

6 DISCUSSION

6.1 INTERPRETATION OF THE RESULTS

Comparing the results from our models and the baseline model results we can see that best classifiers from our eudaemonic and hedonic models perform better than the baseline. The best accuracy from the eudaemonic model is 0.54, with a standard deviation of 0.054, compared to the baseline model of 0.42, with a standard deviation of 0.069. This accuracy score comes from a Bagging classifier. Some other classifiers that were almost as good as the bagging are Ridge and Logistic regression, while the classifier that performed the worst on the eudaemonic model are SVC and Random Forest - which still performed better than the baseline classifier.
The best performance regarding our hedonic model comes from Bagging classifier as well which gives us the accuracy of 0.55. Compared to the baseline model of 0.41 we see that our model performs much better with a 0.14 accuracy increase. The classifiers which gave us the best results for the hedonic model are Bagging and kNN, while the ones with the lowest accuracy scores are Logistic Regression, Ridge and Random Forest classifiers.

When it comes to the regressors, neither the hedonic nor eudaemonic regression model gives us satisfying results compared to the baseline model. The RMSE of the eudaemonic model is equal to 0.132, compared to the baseline of 0.132 we see no improvement in the performance. On another note, we see that the hedonic model performs slightly better than the baseline model with the RMSE score of 0.076 compared to the baseline model of 0.078.

We can see that there exists a correlation between song lyrics and hedonia and eudaemonia, and our models successfuly classify songs into high hedonic and high eudaemonic or low hedonic and low eudaemonic songs.

The best classifiers from each of the two models give us a better result compared to the baseline model, but the average of eudaemonic models is higher than the average of hedonic models.

The possible problem could be the small song data set. If we were to have a data set of 500 songs instead of 130, we would have more data for the splitting, therefore the model results accuracy could possibly improve.

6.2 LIMITATIONS AND FUTURE WORK

Some of the limitations that this study has come across are the number of female respondents and the number of male respondents. The difference is drastically huge with having 1904 female respondents and 87 male respondents. Since we have seen that there exists a difference between eudaemonic and hedonic tendencies between genders, this raises the question whether the eudaemonic and hedonic scores of songs would have changed if we had more of a balanced gender test group. Another limitation could possible be the way the study was conducted. This specific study was conducted by a survey on an online source, therefore the respondents were only able to see a certain part of lyrics (mainly the introduction and the chorus). It would be interesting to conduct this study in person where we can make sure that the respondent has understood the song lyrics more, therefore we might change the outcome results of hedonic and eudaemonic scores for each song. Another consideration for the future work is to add more songs in the study. While building models we came accross an issue of splitting the data into testing, validating and training sets with K-fold cross validation because of the small amount of songs included in the study.

7 CONCLUSION

Songs can be classified into hedonic and eudaemonic by human annotiation, but now we see that it can also be done by machine learning models. In this thesis we addressed a research question of how to use machine learning methods in order to develop a computational model which will be able to predict the hedonic and eudaemonic qualities of songs from song lyrics. After collecting survey results from 1991 users (1904F, 87M) with an average age of 28 years (SD = 9 years), where we gathered demographics, big five personality test, eudaemonic and hedonic song tendencies, overall music sophistication and data for song classification, we successfully created a model which classifies songs into highly eudaemonic and highly hedonic, based on the features we extracted from song lyrics. Out of the two classification models, the hedonic model does not perform as well as the eudaemonic one, even though both models perform better than the baseline. On the other hand, the regression model created was not able to perform better than the baseline. The created classification models are able to classify songs with a higher accuracy than a baseline model, which opens new possibilities of modeling song user recommendation based on hedonia and eudaemonia with the application of given limitations to this study.

8 DALJŠI POVZETEK V SLOVENSKEM JEZIKU

V magistrskem delu sem naslovil problem prepoznave eudaimoničnih in hedoničnih lastnosti pesmi iz njihovih besedil.

Koncepta eudaimoničnosti in hedoničnosti sta znana iz področja pozitivne psihologije. Hedoničnost je izkušnja, kjer prevladuje zadovoljstvo, udobnost, eudaimoničnost pa izkušnja, kjer prevladujejo spraševanja o pomenu posameznika in samouresničitev. Raziskave so pokazale, da uporabniki pri porabi multimedijskih vsebin, še posebej pri filmih, doživljajo tako hedonično kot eudaimonično izkušnjo. Nekateri filmi ponujajo izrazito hedonično izkušnjo (npr. komedije), nekateri izrazito eudaimonično (npr. drame), nekateri pa oboje (tak primer je film Roberta Benignija Življenje je lepo). Na področju glasbenih vsebin podobnih raziskav še ni bilo.

V tem delu sem se posvetil raziskovalnemu vprašanju kako z metodami računalniških družbenih ved razviti računski model, ki lahko napove hedonično in eudaimonično kvaliteto pesmi iz besedila.

Besedila pesmi so se v preteklosti uporabljala za prepoznavo raznih lastnosti pesmi, na primer žanra [26] in emocij [13]. V teh primerih so avtorji raziskav dobili značilke za prepoznavo iz besedil s pomočjo tehnik obdelave naravnega jezika, npr. TF-IDF ali vektorskih vložitev besed. S pomočjo teh značilk so avtorji razvili napovedne modele s pomočjo tehnik strojnega učenja. Hedoničnosti in eudaimoničnosti pesmi še nihče ni napovedoval.

Ker gre za novo raziskovalno področje, ustrezni podatki niso bili na razpolago. Zato sem najprej zbral podatke. Zbiranje podatkov je potekalo v treh fazah: dve predštudiji in glavna študija. V prvi predštudiji sem razvil vprašalnik, kjer 17 udeležencev, zbranih preko družbenih omrežij, podalo naslove pesmi, za katere so menili da imajo tipično hedonične ali eudaimonične lastnosti. V drugi predštudiji so isti udeleženci ocenili hedoničnost in eudaimoničnost pesmi. Tako kategorizirane pesmi smo uporabili v glavni študiji, kjer je vsak udeleženec moral oceniti nekaj pesmi, poleg tega pa je vsak udeleženec odgovoril še na vprašalnike o eudaimoničnosti in hedoničnosti pesmi, o glasbeni sofisticiranosti ter o osebnosti po modelu velikih pet. Ocene udeležencev o eudaimoničnosti in hedoničnosti pesmi sem povprečil in tako dobil vrednosti napovedovanih spremenljivk. Po čiščenju podatkov sem v glavni študiji zbral odgovore 1991 udeležencev.

Besedila pesmi sem pridobil s pomočjo krajšega programa, ki je preko programskega vmesnika storitve Musicmatch prenesel sama besedila. Besedila sem nato obdelal s pomočjo tehnik obdelave naravnega jezika in pridobil značilke, potrebne za korak strojnega učenja. Uporabil sem postopke normalizacije (odstranitev nepotrebnih besed, lematizacija) in metodo TF-IDF. Nato sem uporabil metodo PCA za zmanjšanje števila značilk.

Na tako oblikovani bazi podatkov, ki je vsebovala značilke, pridobljene z metodami naravnega jezika, ter napovedani spremenljivki hedoničnosti in eudaimoničnosti, sem nato poganjal eksperimente z metodami strojnega učenja. Napovedoval sem tako s pomočjo regresijskih metod kot s pomočjo klasifikacije, kjer sem uporabil metodo medianske razpolovitve za označevanje ciljnih razredov. Pri evalvaciji sem uporabil dvojno križno validacijo, kjer sem najprej poiskal optimalne hiperparametre za dani algoritem in nato evalviral uspešnost algoritma na testnem delu podatkov.

Rezultati so pokazali, da besedila pesmi vsebujejo informacije potrebne za pravilno napoved eudaimoničnosti in hedoničnosti. Predlagane metode napovedi so bile bolj uspešne od osnovne metode klasifikacije najbolj pogostega razreda ter napovedi povprečne vrednosti pri regresiji.

Rezultati so tudi pokazali značilne korelacije med spremenljivkami zajetimi v vprašalniku. Na primer, eudaimonično nagnjenje uporabnikov je značilno korelirano z emotivno glasbeno sofisticiranostjo uporabnika.

Pričujoče delo je pokazalo na uspešnost napovedi hedoničnosti in eudaimoničnosti. V prihodnje se da to delo razviti še naprej. Potrebno bi bilo zbrati podatke za širši nabor pesmi, imeti ocene udeležencev, ki bi bile bolj uravnotežene po spolu in preveriti ali druge metode pridobivanja značilk lahko izboljšajo uspešnost napovedi.

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Appendices

APPENDIX A Questions Included in the Survey

A.1 DEMOGRAPHICS

Question 1: Gender

- Female
- Male

Question 2: Level of Education

- Unfinished Elementary School
- Elementary School
- High School
- Bachelor's Degree
- Master's Degree
- Doctorate Degree

Question 3: Age

A.2 MUSIC GENRE PREFERENCES

Question 4: How Often do you listen to different genres of music? (See Table 2)

- RB
- Rap
- Electronic

- Rock
- New Age
- Classical
- Reggae
- Blues
- Country
- World
- Folk
- Easy Listening
- Jazz
- Vocal (a cappella)
- Punk
- Alternative
- Pop
- Heavy Metal

A.3 PERSONALITY TEST

Question 5: How much do you agree about these statements about you? (See Table 3)

- I am expressive
- I often look for mistakes in other people
- I am a perfectionist
- I am depressed
- I am original and always have new ideas
- I am self-contained and reserved

- I am selfless and I always help others
- I am unpredictable
- I am relaxed and laid-back
- I am interested in different things
- I have a lot of energy
- I am argumentative and confrontational
- I am a hard worker
- I get tense easily
- I am comprehensible and I think a lot
- I am enthusiastic
- I quickly forgive others
- I am messy
- I am always worried about something
- I have a big imagination
- I am calm and quiet
- I trust people easily
- I am lazy
- I am emotionally stable and don't get upset easily
- I am resourceful
- I am confident
- I am cold and sublime
- I don't give up until I am done
- I am erratic and impulsive
- I appreciate art and aesthetics
- I am easily frightened

- I am considerate and kind
- I effectively finish most of my work
- I stay calm in stressful situations
- I prefer routines
- I am friendly and like to be amongst people
- I am sometimes rude to others
- I like to plan everything and stick to it
- I easily become nervous
- I like to think and play with different ideas
- I don't have many artistic interests
- I like to work with others
- I easily get distracted and confused
- I am interested in art, music and literature

A.4 EUDAEMONIC AND HEDONIC MUSIC ORIENTATION

Question 6: How true are these statements about you? (See Table 4)

- I like songs that challenge my view of the world
- I like songs which encourage me to think about myself
- My favorite songs are the ones that encourage me to carefully listen to the lyrics and think in general
- I like songs that focus on real life situations and problems
- I like songs that have a deeper meaning
- It's important for me to have fun while listening to a song
- My favorite songs are the ones that make me want to dance and party
- If they're fun or have a good beat, I also enjoy simpler songs with no important context

- I like songs even if they're classified as "absurd" and "meaningless"
- My favorite songs are fun and positive

A.5 MUSIC SOPHISTICATION

Question 7: How true are these statements about you? (See Table 5)

- I enjoy listening to music
- I often read or search the internet for things related to songs or activities associated with singers
- I am interested in new music genres
- I am addicted to music, I can't live without it
- I can easily say if a singer is good or bad
- When I listen to a song, I can easily guess the genre
- I know who sings which songs
- I am a music expert
- I often choose songs to listen to that have a deeper meaning
- Sometimes I listen to songs that make me cringe
- I often listen to songs that address more serious topics
- Songs often arouse my emotions

A.6 SONG LIKERT SCALE

Question 8: How much do you like this song? (See Table 6)

A.6.1 SONG GROUP 1

- Lady Gaga - Bad Romance
- Ke$ha - Tik Tok
- Adele - Someone Like You
- Celine Dion - My Heart Will Go On
- Ariana Grande - Breakup With Your Girlfriend
- LMFAO - Sorry For Party Rocking
- Michael Jackson - Billie Jean
- One Direction - Drag Me Down
- Lil Nas X - Montero
- Harry Styles - Sign Of The Times

A.6.2 SONG GROUP 2

- Rihanna - Don't Stop The Music
- Rihanna - SM
- Adele - Rolling In The Deep
- Whitney Houston - I Will Always Love You
- Christina Aguilera, Lil Kim, MYA, PINK - Lady Marmalade
- PINK - So What
- G-Eazy and Halsey - Him And I
- Justin Bieber - As Long As You Love Me
- Olivia Rodrigo - Deja Vu
- Michael Jackson - Earth Song

A.6.3 SONG GROUP 3

- Harry Styles - Watermelon Sugar
- 50 Cent - Candy Shop
- Adele - Hello
- John Legend - All Of Me
- Nelly Furtado - Maneater
- The Rolling Stones - Sympathy For The Devil
- Eminem - Lose Yourself
- Katy Perry - Part Of Me
- Lady Gaga, Ariana Grande - Rain On Me
- Backstreet Boys - I Want It That Way

A.6.4 SONG GROUP 4

- Ariana Grande - Side To Side
- Cardi B - WAP
- SIA - Elastic Heart
- Beyonce - Halo
- Little Mix - Wasabi
- Justin Bieber - Yummy
- Scorpions - Wind Of Change
- Taylor Swift - You Belong With Me
- Dua Lipa - Levitating
- Ariana Grande - Into You

A.6.5 SONG GROUP 5

- Ariana Grande - 7 Rings
- Lady Gaga - Just Dance
- Linkin Park - Numb
- SIA - Chandelier
- Chris Brown - Strip
- Jennifer Lopez - Ain't Your Mama
- Halsey - Colors
- Ed Sheeran - Shape Of You
- Doja Cat - Kiss Me More
- Justin Timberlake - What Goes Around Comes Around

A.6.6 SONG GROUP 6

- Beyonce - Single Ladies
- Kelis - Milkshake
- Queen - Bohemian Rhapsody
- Justin Timberlake - Cry Me A River
- Christina Aguilera - Genie In A Bottle
- Ke$ha - We R Who We R
- Halsey - Castle
- Maroon 5 - One More Night
- Bruno Mars - 24K Magic
- Zayn - Pillowtalk

A.6.7 SONG GROUP 7

- The Weeknd - Can't Feel My Face
- Fergie - Fergalicious
- PINK - Just Give Me A Reason
- Kelly Clarkson - Because Of You
- Britney Spears - Circus
- The Black Eyed Peas - Boom Boom Pow
- Jessie J - Nobody's Perfect
- ZAYN - Dusk Till Dawn
- Katy Perry - I Kissed A Girl
- Mario - Let Me Love You

A.6.8 SONG GROUP 8

- Miley Cyrus - Party In The USA
- Pharell Williams - Blurred Lines
- Ed Sheeran - Thinking Out Loud
- Rihanna - Diamonds
- Bruno Mars - Versace On The Floor
- Meghan Trainor - Me Too
- Frank Sinatra - Can't Take My Eyes Off You
- Toni Braxton - Un-break My Heart
- Jessie J, Ariana Grande and Nicki Minaj - BANG BANG
- SIA - Never Give Up

A.6.9 SONG GROUP 9

- David Guetta - Se*y Bit*h
- Selena Gomez - Hands To Myself
- James Arthur - Impossible
- Imagine Dragons - Believer
- Ludacris - Move Bit*h
- Pitbull - Timber
- Billie Eilish - Your Power
- Ellie Goulding - Burn
- Ricky Martin - Livin La Vida Loca
- Shawn Mendes - Treat You Better

A.6.10 SONG GROUP 10

- The Black Eyed Peas - Pump It
- Beyonce - Naughty Girl
- Ed Sheeran - Beautiful People
- Taylor Swift - I Knew You Were Trouble
- Ariana Grande - God Is A Woman
- Jennifer Lopez - Booty
- Billie Eilish - Lovely
- Zombie - The Cranberries
- Nicki Minaj - Anaconda
- Charlie Puth - We Don't Talk Anymore

A.6.11 SONG GROUP 11

- Britney Spears - Toxic
- Nicki Minaj - Hey Mama
- Ed Sheeran - Perfect
- Jordin Spark, Chris Brown - No Air
- Destiny's Child - Bootylicious
- LMFAO - Sexy And I Know It
- Amy Winehouse - Back To Black
- No Doubt - Don't Speak
- Rihanna - Rude Boy
- Taylor Swift - Wildest Dreams

A.6.12 SONG GROUP 12

- Alexandra Stan - Mr. Saxobeat
- The Black Eyed Peas - My Humps
- Billie Eilish – Everything I Wanted
- Justin Timberlake - Mirrors
- Pitbull – Hotel Room
- Lady Gaga – Love Game
- Fergie – Big Girls Don't Cry
- Lost Frequencies – Are You With Me
- Maroon 5 - Animals
- Rihanna – Hate That I Love You

A.6.13 SONG GROUP 13

- Lady Gaga - Telephone
- Justin Timberlake - Sexyback
- Wiz Khalifa – See You Again
- One Direction – Story Of My Life
- Katy Perry – California Girls
- Cardi B – Bodak Yellow
- Jessie J – Who You Are
- Katy Perry – The One That Got Away
- Gwen Stefani – Rich Girl
- Pussycat Dolls – I Hate This Part

A.7 EUDAEMONIC AND HEDONIC PERCEPTIONS OF SONGS

Question 8: Answer the following questions about each song from the given group: (See Table 7)

- The song challenged my view of the world
- The song made me think about myself
- The song made me carefully listen to the lyrics
- It seemed to me that the song focused on important issues
- It seemed to me that the song has a deeper meaning
- I had fun while listening to the song
- This song made me want to dance and party
- It seemed like the song was very simple and without an important context
- I like the song even though the lyrics seemed a bit “absurd” and “meaningless”
- The song was very fun and positive