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Harmonizing Emotions: Recommending Hobbies & Songs through Music-Driven Sentiment Analysis.

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Abstract

Problem:

The profound impact of music on human emotions is indisputable. However, conventional recommender systems which offer suggestions based on user preferences, often overlook the emotional context, This is where the need for a recommender system that can tap into human emotions unadulterated comes in, What else than music do we have that actually lets us interact, interpret and alter that invisible connection. Even in the realm of music recommender systems, this aspect of approaching music for its raw features is overlooked. This oversight can lead to recommendations that are algorithmically accurate but may not resonate with the user's actual emotional state or preferences.

Objectives:

The primary goal of this dissertation was to develop a recommender system that seamlessly integrates sentiment analysis, focusing on the emotional content of music lyrics and sentiment from hobby descriptions themselves. By doing so, the aim was to offer users recommendations for hobbies and music tracks that align more closely with their emotional state, thus providing a more personalized and resonant experience.

Methodology:

To achieve this, a multi-pronged approach was employed:

- Lyrics for user-provided songs were fetched and cleaned.
- Sentiment analysis was conducted on the cleaned lyrics to derive sentiment scores.
- Users' hobbies were also subjected to sentiment analysis, resulting in an aggregated sentiment profile for each user.

Based on this aggregated sentiment profile, The system recommended hobbies and tracks that matched the user's sentiment profile.

Achievements:

The system successfully demonstrated its ability to recommend a diverse range of hobbies and a set of ten tracks for each user, capturing the emotional nuances inherent in their music preferences. Furthermore, the integration of sentiment analysis into the recommendation process sets this work apart, offering a fresh and innovative approach in the domain of recommender systems. Preliminary user feedback, while mixed, showcases the potential of this approach, emphasizing areas of refinement for future iterations.

Attestation

I understand the nature of plagiarism, and I am aware of the University's policy on this.
I certify that this dissertation reports original work by me during my University project.

Signature **Date : 23/09/2023**

Acknowledgements

In the vast expanse of the digital world, I am profoundly grateful to the countless contributors of the online tech community. Their relentless efforts in sharing knowledge through research papers, articles, tutorials, to insightful videos they have illuminated the path of many, including myself. Such selfless sharing embodies are the true spirit of global learning, reminiscent of the early web's founding principles.

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1 Introduction

The profound impact of music on human evolution is well-documented, as explored in the study "Music as a blend of spirituality, culture, and mind-mollifying drug" [1]. In our daily lives, we are often faced with a multitude of choices be it selecting a dish to cook, picking a book to read, or choosing a piece of music to listen to. These decisions are frequently made with limited information and personal experience, which can lead to suboptimal choices. To address this, individuals often seek recommendations from more experienced people or online platforms. These recommendations not only facilitate better decision-making but also serve as a gateway to new experiences.

Automated systems, known as Recommender Systems (RSs), have emerged to streamline this decision-making process. These software tools analyse a plethora of data to offer suggestions that align with individual user interests. The ultimate goal is to predict user preferences in various contexts. The recommendations generated by these systems are termed 'items,' and users can assign 'ratings' to these items to express their preferences [23].

Traditionally, Recommender Systems have been designed using two primary approaches:

Collaborative Filtering: This method generates recommendations based on the preferences of users who have similar tastes to the active user.

Content-based Recommender Systems: Here, recommendations are tailored based on the user's past preferences and behaviours.

While effective, these traditional methods often overlook the emotional context in which choices are made. Collaborative filtering, in particular, introduces noise into the recommendations as it is influenced by other users, defeating the purpose of truly understanding an individual user's emotions [26].

Recent advancements have integrated sentiment analysis into Recommender Systems, particularly in product and service domains [24]. Sentiment analysis enhances the reliability of recommendations by providing a nuanced understanding of user attitudes, emotions, and opinions [25]. This dissertation introduces a novel approach that transcends conventional methods by incorporating sentiment analysis into the recommendation process. The focus is primarily on recommending hobbies and activities based on a user's sentiment profile. This profile is derived from the type of music a user generally listens to, combined with their favourite hobby. The system matches this against a dataset of hobbies that have predefined sentiment profiles. These profiles are aggregated from sentiment scores of songs and hobby descriptions, with a weightage of 70% given to the song sentiment score and 30% to the sentiment score from hobby descriptions. The same user sentiment profile (from hobbies and songs provided by the user) was used to recommend back songs from the songs dataset that matched the user's sentiment profile.

By integrating sentiment analysis in such a unique manner, this research aims to offer a more personalized and emotionally resonant user experience, setting a new standard in the field of Hobbies Recommender Systems.

1.1 Background and Context

The motivating Challenge:

Mental health is one of the most frowned upon. After the COVID-19 pandemic, According to discussions in [2], When a systematic review and meta-analysis were conducted to understand the long-term effects of the COVID-19 pandemic on the mental health of children and adolescents. Covering 23 high-quality longitudinal studies it finds a significant increase in anxiety and depression rates among this demographic, with pooled prevalence rates of 19.2% for anxiety and 18.4% for depression. The study also reveals that adolescents and females are more adversely affected than younger children and males. High heterogeneity in results is noted, but the overall trend indicates deteriorating mental health. The paper emphasizes the crucial role of social support systems and calls for targeted interventions for high-risk groups.

This is where this paper would likely contribute in emphasising the human mind-music-hobbies/activities connection and its significance, The significance is on a much deeper level than we perceive it to be. It may be the only known most accessible pathway for us to harness and communicate with our minds directly for what we need at a personalized level, And through this connection, we can manage to take better care of our mental health. With the help of the power of music, Tailoring it to suggest new hobbies/activities that a user may find interesting in engaging and suggest a better more precise recommendation for the user's choice of music that suits their choice of hobbies/activities that they enjoy often or new ones that they discover through the recommendation model.

1.1.1 The Science of Music :

My observations on the science of music from paper [1] dive into the neurological and cognitive impacts of music. The brain's response to music is complex, it triggers the release of dopamine which is associated with pleasure and reward. Research has also shown that engaging with music can improve various cognitive functions, such as memory and spatial-temporal skills. The paper draws on a range of scientific studies to shed light on why music has such a profound impact on the human mind.

Historical Significance of Music in Spirituality: Music has been an integral part of spiritual practices and religious ceremonies across various cultures and civilizations. From Gregorian chants to Sufi qawwalis, the paper emphasizes the universal role of music in enhancing spiritual experiences, creating a sense of unity and facilitating connection with the divine.

Music as a Form of Meditation: The concept of music as a form of meditation. It explains how certain kinds of music can induce a meditative state, helping individuals to focus, relieve stress and even achieve higher states of consciousness. This aligns with various spiritual practices that use music to transcend the ordinary state of mind.

Music and Emotional Well-being: Therapeutic aspects of music. It's not just a form of entertainment but a potent tool for emotional well-being. The paper provides evidence from various studies that show how music therapy can be used to treat mental health issues like depression and anxiety thereby enhancing one's spiritual life by improving emotional balance.

Community and Social Aspects of Music: Social dimension of music. The paper explains how music can foster community bonds and cultural identity. In the context of spirituality music often brings people together in a shared experience that is both emotional and transcendent, creating a sense of belonging and unity.

Music, Rituals and Sacred Spaces: This point discusses how music is often intertwined with religious rituals and is used to sanctify spaces. Whether it’s a church, a temple or a mosque, music contributes to the sanctity and the spiritual aura of these spaces making them conducive for spiritual practices.

Music and Mystical Experiences: The paper explores the mystical aspect of music, describing how it can induce trance-like states and offer glimpses into other realms of consciousness. These experiences often have profound spiritual significance and can be life-changing for individuals.

Ethical and Moral Influence of Music: The final point covers the ethical and moral dimensions of music. It discusses how music, mainly when used in a spiritual or religious context can guide individuals toward ethical behavior and moral decision-making. The paper suggests that the virtues propagated through spiritual music can have a lasting impact on an individual’s character.

Importance of Sentiment Analysis in the Music Industry: The music industry is undergoing a transformative phase driven by technological advancements and data analytics. Sentiment analysis, A specialized form of natural language processing has emerged as a pivotal tool in this transformation. It enables the systematic identification, extraction and quantification of affective emotional states from various data sources like lyrics, reviews and social media interactions a easy to use model like VADER (Valence Aware Dictionary and Sentiment Reasoner) is a lexicon and rule-based sentiment analysis tool that can help in understanding the user sentiment, The VADER sentiment lexicon is sensitive both the polarity and the intensity of sentiments expressed in social media contexts and is also generally applicable to sentiment analysis in other domains. According to Wikipedia Sentiment Analysis is widely applied in diverse fields, From marketing to healthcare and has evolved to analyze complex data domains using deep learning models. In the music industry, it serves as a powerful tool for understanding audience emotions, predicting song popularity and customizing marketing strategies.

1.1.2 The Science of Neuroplasticity :

The article "Why you should take up a creative hobby this year" [3] explains the science of neuroplasticity and advocates for the adoption of creative hobbies and music not just for pleasure but also for their multifaceted health benefits, including improved brain function, mental health and even physical health.

Neuroplasticity and Brain Function: The article emphasizes the concept of neuroplasticity which refers to the brain's ability to rewire itself and adapt based on experiences. Engaging in creative hobbies like music, painting or knitting can stimulate neuroplasticity by requiring divergent thinking. This form of thinking involves coming up with multiple or alternative solutions, Thereby enhancing brain connectivity. The article cites research showing that music, in particular is a strong stimulus for neuroplasticity, As it strengthens connections between motor and auditory brain regions.

Mental Health Benefits: Creative hobbies are also lauded for their mental health benefits. They can trigger the release of dopamine known as the 'happy hormone' and are often prescribed by healthcare professionals for this reason. The article discusses how creative activities can reduce stress, improve depressive moods and even have a positive impact on people living with dementia and Alzheimer's disease.

Additional Health Benefits: Beyond neuroplasticity and mental health, the article outlines other health benefits of creative hobbies. These include improved memory, As creative activities strengthen neural pathways to the hippocampus, an area of the brain crucial for memory. Creative hobbies can also improve self-esteem , confidence and develop valuable skills like problem-solving. It even offers physical health benefits such as cardiovascular activity in hobbies like dancing and swimming.

Dementia and Alzheimer's Disease: The article mentions that creative hobbies can make a significant positive impact on the lives of those living with dementia and Alzheimer's disease. Activities like music, painting and reading can stimulate the brain and provide an additional way of expressing oneself when other communication avenues have been lost.

1.1.3 Problem Statement:

The Need for a User Sentiment driven from Music-based Recommendation System, The digital age has brought an overwhelming number of choices in choosing a hobby,music or for that matter anything, Leading to a phenomenon known as 'choice overload.' Traditional recommendation systems primarily rely on historical user behaviours like an individual’s health history, lifestyle and preferences, But often fall short of capturing the emotional nuances that influence an individual’s preference at any given moment. Therefore, there is a pressing need for a recommendation system that goes beyond historical data and incorporates sentiment analysis from a data source like music that has a widely accepted invisible link between human emotions and mind. Below shown table shows a dataset for a recommendation system for hobby recommendations using deep learning, primarily focusing only on historical user behaviour and individual data like health history,lifestyle, and preferences is as shown below [5] .

Feature	Values
Gender	Male, Female
Age	Child, young, adult, aged
Height	Cm
Weight	Kg
Comorbidities	Diabetes, hypertension, etc.
Respiratory infected	Yes or no
Exercise habit	Yes or no
Reports	X-rays, CT scans, diagnosis reports
Nationality	Country
Food type	Vegetarian/ Non-vegetarian
Habits	Tea, smoking, alcohol, etc.

Figure 1. Table.1 for Dataset features for the proposed deep learning model [5,Table1.Dataset features].

1.2 Aims,Objectives and Challenges:

The system that we propose here is to aggregate sentiment scores from multiple data points from users, such as track lyrics, track audio features and sentiment derived from the user's preferred type of hobby/activity.This allows to recommend back songs that the user might enjoy with the User’s initial choice of hobby/activity provided when data collection for the research was conducted,W hich can be a approach taken further in future researches which can help in providing a user level personalized hobby/activity based play list, and to predict a new set of hobbies/activities that align with the user's emotional profile.

1.2.1 Aims:

Primary Goals:
Music Recommendation System: Develop a sophisticated music recommendation system that leverages sentiment analysis to align song suggestions with the user's emotional profile.

User Activity Prediction: Utilize aggregated sentiment scores from hobbies and music to predict activities/hobbies that the user might enjoy, making the system multifunctional.

1.2.2 Objectives:

Data Collection: Assemble a comprehensive dataset comprising user choice of songs(here for ease of user,10 tracks of choice were asked to submit while filling up the google form used for data collection) and a hobby,song lyrics, hobbies with descriptions.

Sentiment Analysis: Employ advanced sentiment analysis techniques, possibly incorporating deep language models, to evaluate the emotional tone of various data sources.

Aggregated Sentiment Scoring: Create an algorithm that aggregates sentiment scores from diverse data points, assigning appropriate weights to each.

User Profiling: Develop user profiles that is based on sentiment analysis data.

System Evaluation: Conduct a user feedback via Google form,Where user rates the predictions made for them from a scale of 1 to 5 .

By achieving these aims and objectives, this research aims to revolutionize the user experience in the digital music industry. The proposed system will not only make recommendations more personalized but also more emotionally intelligent, filling a significant gap in existing systems.

Thought-Provoking Questions for future works,The Role of Deep Learning:

- With the rise of deep language models like RoBERTa, how can the music industry leverage these technologies for more accurate sentiment analysis?

- Beyond Polarity: Sentiment analysis has evolved to identify emotional states like enjoyment, anger, and surprise. How can these advanced classifications be integrated into the music recommendation system? . Expanding on the idea of integrating advanced sentiment classifications into a music recommendation system can be particularly interesting when you consider audio features available from the Spotify Web API.

- Ethical Considerations: As we move towards more personalized experiences based on sentiment analysis, what are the ethical implications concerning user data and privacy?

This dissertation project aims to contribute significantly to the field of data science in the music industry, and mental wellbeing through suggestions of new hobbies,This approach helps in enhancing personalized user experiences through sentiment analysis also opening up opportunities by parallel feature inclusions within a music streaming platform.

1.2.3 Challenges:

This project was initially an approach to train a machine learning model or a deep learning model using raw audio features other than the commonly used audio valence scores while combining it with sentiment scores from lyrics using a well known model like VADER, Due to complexities what that model an alternate model was developed only depending upon pretrained VADER model.The model is designed for analyzing the sentiment of text, and it can discern not just the polarity (whether the emotion is positive or negative) but also the intensity (how strong the emotion is). The challenge in developing a model based on music sentiment analysis and recommendations for hobbies based on the user's sentiment profile even with only lyrical sentiment analysis and hobbies sentiment scores,let alone not even not being an audio feature combined with text sentiment analysis model posed lots of challenges with the nature of a problem it is ,time constraints and scope of this project, Factors contributing to it's difficulty factors were :

Data Availability:

Raw Audio Features Model:

Fetching data from Spotify through its API requires access tokens, and it's rate-limited. This poses challenges in gathering a large dataset for robust modelling. Also, Spotify has its policy where its users are prohibited from using the features for training Machine Learning or Artificial Intelligence.

NLP - VADER - Model:

Fetching a dataset for hobbies with descriptions was a challenge because there was none available at the time of this project and it was to be created from scratch.

Feature Selection:

Raw Audio Features Model:
Spotify provides multiple audio features like danceability, energy, valence, etc. Deciding which features are most relevant for the recommendation system can be challenging.

Noise in Data:

Raw Audio Features Model:
Audio features are machine generated and may not perfectly represent the human emotional response to a song. This adds noise to the data, affecting the model's accuracy.

NLP - VADER - Model:

The lyrical dataset extracted from 'Genius' found on Kaggle [10] with it's metadata and the nature in how 'Genius' songs are written in a format that needs pre-processing, Metadata is present between square brackets in the middle of the lyrics. Additionally, the original layout of the lyrics, complete with numerous newline characters, creates a challenge in cleaning it.

Complexity:
Combining these audio features to create a multi-dimensional recommendation engine adds complexity to the model. It's challenging to determine how these features should interact with each other for the best recommendations.

Interpretability:
Audio features are not always straightforward to interpret, Spotify has its content-based filtering and raw audio signals which run as soon as the audio files accompanied by the artist-soured metadata are ingested into Spotify's database [9] but since that is a best kept secret how their algorithm works, Discussions in the community mostly surrounds around 'Danceability', 'Energy' and 'Valence', This project's aim is to explore the other less explored audio features available for analysis from Spotify's Web API [8]. Now when it comes to actually utilizing these audio features for Machine learning or Artificial Intelligence model training they have strict policies that do not let it's users do that. Now with that said even if there was permission granted it would still require large user feedback based valuations on these recommendations made based on new audio features sorted into positive, negative and weak correlations, Which again was pushing this project out of it's scope and dissertation timeline. For example, like from Fig.1 heatmap after the standardization of feature values and

calculating Pearson correlation coefficients, A song that has high values for all the positive correlations values like from Table.2 might not necessarily mean that we can make predictions that'd be more accurate in how a user would enjoy tracks with a positive emotion towards them,Now for this and specially with these audio features provided by Spotify needs further user validations done on them, Which again is a process out of scope for this project.

Positive Correlations:

- danceability and key: 0.031744772305747196
- danceability and mode: 0.05912432034104161
- danceability and speechiness: 0.0887752016356896
- energy and mode: 0.027101904846901424
- energy and liveness: 0.06567243359036738
- energy and duration_ms: 0.008658688435460785
- key and loudness: 0.023671623321406515
- key and time_signature: 0.01472819271671155
- loudness and mode: 0.047000255948898687
- loudness and liveness: 0.015025952265452355
- loudness and duration_ms: 0.031345075460008504
- loudness and time_signature: 0.0313070274781253
- mode and time_signature: 0.04593187739938862
- speechiness and liveness: 0.04009432676035469
- speechiness and valence: 0.07860174893235805
- speechiness and tempo: 0.09338580098859692
- acousticness and duration_ms: 0.05722461790045467
- instrumentalness and time_signature: 0.05620206405742132
- liveness and valence: 0.040956062227566745
- liveness and tempo: 0.0980830740631481
- liveness and duration_ms: 0.08584128365508581
- valence and tempo: 0.09697735617164355
- tempo and time_signature: 0.02352107440370956
- danceability and liveness: 0.1828982727730392
- energy and key: 0.11428605967064458
- energy and time_signature: 0.11655645708482919
- key and speechiness: 0.15969718605209932
- key and instrumentalness: 0.1914222058534663
- mode and speechiness: 0.12586206773186126
- mode and liveness: 0.12445159459905211
- mode and valence: 0.15861497351263623
- mode and duration_ms: 0.10356546831161882
- acousticness and instrumentalness: 0.1751736015695215
- liveness and time_signature: 0.17038992045167378
- danceability and loudness: 0.268930589287656
- energy and tempo: 0.20170061650278154
- loudness and tempo: 0.2528562496595534
- mode and tempo: 0.2589406127472912
- valence and time_signature: 0.22686515937861626
- tempo and duration_ms: 0.2628086531730832

Negative Correlations:

- danceability and acousticness: -0.3293684893257594
- loudness and instrumentalness: -0.3121842377007629

- acousticness and valence: -0.3531623333929754
- instrumentalness and duration_ms: -0.328135151672405
- key and mode: -0.24110152861213252
- instrumentalness and tempo: -0.24783703936374712
- danceability and duration_ms: -0.1249443447598842
- energy and instrumentalness: -0.17074470329001956
- key and acousticness: -0.10205869259116873
- key and tempo: -0.11892641262816588
- loudness and speechiness: -0.12040999506803696
- mode and acousticness: -0.14483088408766667
- mode and instrumentalness: -0.1868283107765686
- speechiness and duration_ms: -0.11883224043744353
- speechiness and time_signature: -0.11193653693317718
- acousticness and liveness: -0.18845661091109125
- acousticness and tempo: -0.16972953350244496
- acousticness and time_signature: -0.1747812460006991
- valence and duration_ms: -0.14059560011003625
- danceability and instrumentalness: -0.09222997826019416
- danceability and tempo: -0.08136022817504794
- energy and speechiness: -0.030645763811335974
- key and liveness: -0.03206545661506718
- key and valence: -0.055382561520406694
- key and duration_ms: -0.05388296444001039
- speechiness and acousticness: -0.017236169229237687
- speechiness and instrumentalness: -0.016889200950410375
- instrumentalness and liveness: -0.0005298234783421526
- instrumentalness and valence: -0.04965427391583872
- duration_ms and time_signature: -0.02935644000439572

Weak Correlations:

- danceability and key: 0.031744772305747196
- danceability and mode: 0.05912432034104161
- danceability and speechiness: 0.0887752016356896
- danceability and instrumentalness: -0.09222997826019416
- danceability and tempo: -0.08136022817504794
- energy and mode: 0.027101904846901424
- energy and speechiness: -0.030645763811335974
- energy and liveness: 0.06567243359036738
- energy and duration_ms: 0.008658688435460785
- key and loudness: 0.023671623321406515
- key and liveness: -0.03206545661506718
- key and valence: -0.055382561520406694
- key and duration_ms: -0.05388296444001039
- key and time_signature: 0.01472819271671155
- loudness and mode: 0.047000255948898687
- loudness and liveness: 0.015025952265452355
- loudness and duration_ms: 0.031345075460008504
- loudness and time_signature: 0.0313070274781253
- mode and time_signature: 0.04593187739938862
- speechiness and acousticness: -0.017236169229237687
- speechiness and instrumentalness: -0.016889200950410375

- speechiness and liveness: 0.04009432676035469
- speechiness and valence: 0.07860174893235805
- speechiness and tempo: 0.09338580098859692
- acousticness and duration_ms: 0.05722461790045467
- instrumentalness and liveness: -0.0005298234783421526
- instrumentalness and valence: -0.04965427391583872
- instrumentalness and time_signature: 0.05620206405742132
- liveness and valence: 0.040956062227566745
- liveness and tempo: 0.0980830740631481
- liveness and duration_ms: 0.08584128365508581
- valence and tempo: 0.09697735617164355
- tempo and time_signature: 0.02352107440370956
- duration_ms and time_signature: -0.02935644000439572

Figure 2. Table.2 Displayed above is Positive, Negative and Weak correlations for my personal playlist retrieved via Spotify's API.

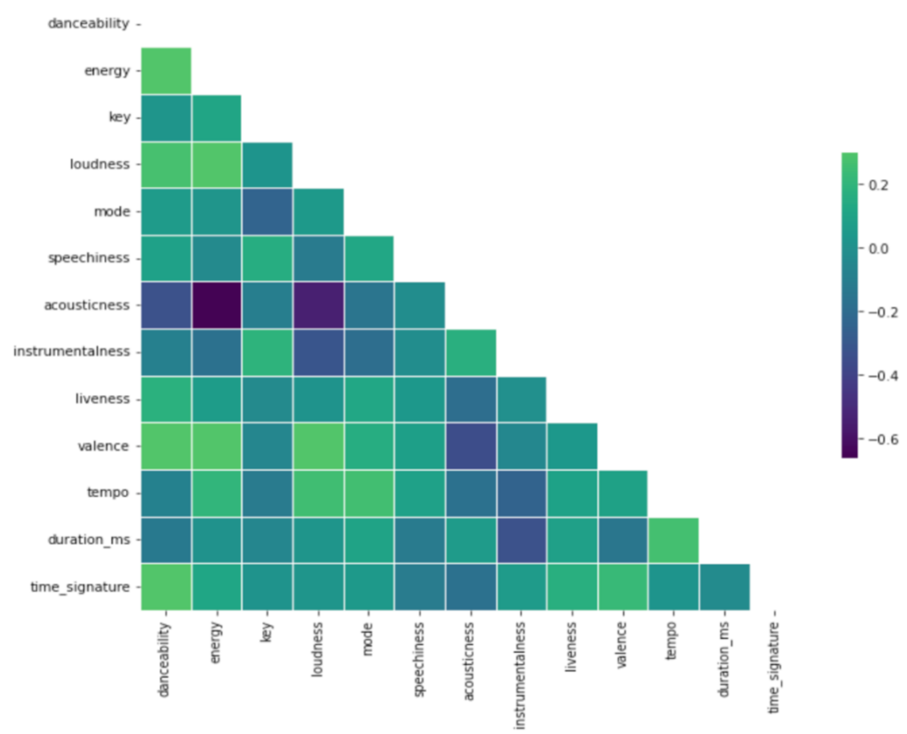

Figure 3. *Heatmap on standardized Pearson correlation coefficients between audio features from Spotify's API for my playlist retrieved via Spotify's API.*

Data Collection and Preprocessing:

Data collection: Collecting necessary posed a significant challenge as apart from user data which was easily managed from volunteers it was not the case with procuring datasets for hobbies, They were built from scratch.

Quality: Ensuring the quality and representativeness of the datasets, such as hobby descriptions and lyrics datasets posed initial challenges.

Duplicate Data: Removing duplicate entries, especially in the hobbies dataset, required additional effort.

Cleaning: Removing metadata from the lyrics dataset and descriptions of hobbies.

Sentiment Scoring:

Multiple Sources: Aggregating sentiment scores from various sources like lyrics and hobbies introduced complexities.
Inconsistent Scoring Ranges: Merging different sentiment score scales, such as scores from lyrics ranging between 1 and 70 and VADER scores between -1 and 1, was a methodological hurdle.

Normalization:

Scale Transformation: The need to normalize the aggregated scores to fit the VADER scale (-1 to 1) for consistent analysis and interpretation.

Sentiment Classification:

Threshold Setting: Deciding appropriate cut-off thresholds for classifying the aggregated sentiment as positive, negative, or neutral.
Neutral Sentiments: Handling neutral sentiments, especially in the hobby descriptions, posed interpretative challenges. Some descriptions that seemed meaningful returned a zero sentiment score.

Validation and Testing:

Evaluation Metrics: Deciding suitable metrics for validating the accuracy and reliability of the sentiment analysis model.
User Feedback: Collection and incorporation of user feedback for system fine-tuning.

1.3 Achievements

The aim of this project is to be an exploratory study like discussed above to develop an independent multimodel recommendation system unlike any before in which the recommendation leverages an individual’s mind music connection to leverage a personalized experience to the user when it comes to listening to music with the user’s favourite type of hobby which, unlike present day recommendations which focuses more on content-based and collaborative filtering [9], And to recommend users a new hobby based on user sentiment profile.The core idea is to provide a truly individualized experience

Due to the challenges associated with developing a Machine Learning or Deep Learning model, the results presented focus on the sentiment analysis of Lyrical-Hobby Descriptions. The model received a 70% positive response rate for its recommendations based on user feedback. However, it's important to note that the sample size for this analysis was quite small, consisting of only five participants. This limits the generalizability of the findings. Despite this limitation, the feedback from users was encouraging, with an average rating of 3 out of 5 on the rating scale.

1.4 Overview of Dissertation

This dissertation offers a deep dive into the intricate relationship between music, sentiment, and personal choices. It underscores the transformative potential of integrating sentiment analysis into recommender systems, with a focus on music lyrics as a rich source of emotional content. Here's a structured walkthrough of the chapters:

Chapter 2 – Literature Review: Building upon our initial discussions, this chapter delves into the profound impact of music on human evolution and emotions. It critically examines the existing landscape of recommender systems, highlighting gaps and areas of potential enhancement, particularly in capturing emotional nuances.

Chapter 3 – Methodology: Drawing inspiration from our code walkthrough, this chapter elucidates the step-by-step methodology employed. From fetching lyrics of user-provided songs to conducting sentiment analysis, it outlines the processes, tools, and considerations that form the backbone of the system.

Chapter 4 – Data & Requirements: Reflecting upon the datasets discussed, this chapter delineates the data sources, their significance, and the specific requirements set for the project. It outlines the scope of music genres, user inputs, and the desired outcomes.

Chapter 5 – System Design: Drawing from our in-depth exploration of the system's workflow, this section offers a bird's-eye view of the system's architecture, followed by a granular examination of each component. It explicates how sentiment scores from lyrics and user hobbies coalesce to generate tailored recommendations.

Chapter 6 – Implementation & Challenges: Expanding upon our discussions about challenges like fetching lyrics, this chapter chronicles the journey from design to realization. It underscores the hurdles encountered, the solutions devised, and the rationale underpinning key decisions.

Chapter 7 – Testing & User Feedback: In line with the feedback and results we discussed, this chapter lays out the testing strategy, outcomes, and user feedback. It evaluates the system's performance, user reception, and areas of potential refinement.

Chapter 8 – Conclusion & Future Outlook: Reflecting upon the essence of our discussions, this chapter offers a synthesis of the project's achievements, its implications in the domain of recommender systems, and potential avenues for future exploration.

2 State-of-The-Art

If i am to address the elephant in the room " Spotify ", They seem to do almost everything, but not everything. The platform actually tries to provide personalized content and it is almost there, According to Spotify "Spotify isn't actually a single product but 433 million different products – one for each and every user " Because their attempt is to make their recommendations hyper-personalized through supporting Natural language Search – That can understand synonyms for different words, paraphrasing and any content that means the same thing as for what user searched for, reinforcement learning – optimized towards a long-term reward, that is long term user satisfaction[13].

2.1 Personalized Music Recommendation Systems

The domain of personalized music recommendation systems has witnessed a significant surge in research activities, especially with the integration of advanced computational techniques like deep learning. The primary goal of these systems is to provide users with music recommendations that are tailored to their behaviours, and emotional states, Even though we can agree it is not quite there yet. The field has evolved from simple rule-based systems to sophisticated models that leverage a variety of data types and computational techniques.

2.1.1 Autoencoders in Music Recommendation

One of the pioneering works in this area utilized autoencoders to capture the complex relationships between various musical features [14]. Autoencoders are neural networks trained to reconstruct their input data, thereby learning a compressed representation of the data. In the context of music recommendation, they are particularly useful for capturing the latent factors that influence a user's music preference. The compressed feature set can then be used to find similarities between different songs or between users and songs, thereby enhancing the quality and accuracy of the recommendations.

2.1.2 Tensor Factorization Techniques

Another noteworthy approach is the use of tensor factorization, which allows the system to understand multi-dimensional relationships between users, items, and additional contextual information [15]. Tensor factorization extends matrix factorization techniques to higher dimensions, providing a more nuanced understanding of the complex interplay between various factors that influence music preferences. This method has been particularly effective in scenarios where contextual information, such as time, location or mood plays a significant role in a user's choice of music.

2.1.3 Emotional Aspects and User Mood

The emotional state of the user is becoming an increasingly important factor in music recommendation systems. Research shows that considering the user's mood can significantly improve playlist generation. This is a critical advancement, as music is often consumed in an emotional context, whether to elevate mood, provide comfort or enhance an activity. Systems that can accurately gauge a user's emotional state can provide more contextually appropriate recommendations, thereby increasing user engagement and satisfaction.

2.1.4 Holistic Approaches

Overall, the field is moving towards a more holistic approach that combines both content-based and collaborative filtering methods. Content-based methods focus on the attributes, such as genre, tempo or artist, to make recommendations. Collaborative filtering, on the other hand, leverages user-item interactions, such as ratings or listening history, to predict preferences. Recent research has started to combine these two approaches to create hybrid systems that offer the best of both worlds.

2.2 Sentiment Analysis in Recommendation Systems

Sentiment analysis has emerged as a powerful tool in the realm of recommendation systems. Initially popularized in the fields of social media analytics and customer reviews, sentiment analysis has found its way into various types of recommendation systems. The primary aim is to enhance the quality of recommendations by incorporating the emotional or subjective aspects expressed in user-generated content.

2.1.5 Deep Learning in Sentiment Analysis

One of the most significant advancements in this area is the application of deep learning techniques, particularly neural networks, to analyze textual data and extract sentiment [16]. Deep learning models, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), have shown remarkable efficacy in understanding the nuances of human language. These models can capture the contextual relationships between words, thereby providing a more accurate sentiment score that can be used to refine recommendations.

2.1.6 Sentiment Analysis in E-commerce

While sentiment analysis is a well-established practice in e-commerce, especially for product reviews, its application in other domains is still evolving. In e-commerce, sentiment analysis is used to gauge customer opinions about products or services. This information is then used to recommend products that have received favourable reviews, thereby increasing the likelihood of customer satisfaction [17].

2.1.7 Application in Music and Hobbies

The application of sentiment analysis in the context of music or hobbies is still in its infancy but represents a significant gap and an area ripe for future research. For instance, there can be user feedback on a particular choice of song whenever they like it or add it to their playlist in a not too intuitive manner, but with a controlled approach to not spoil the user experience, understanding the sentiment expressed in user reviews of songs or playlists could provide additional data points for more personalized recommendations. Similarly, sentiment analysis could be used to gauge user opinions about different hobbies they decide to enjoy it along with, thereby enhancing the quality of hobby-based recommendations.

2.1.8 Challenges and Future Directions

One of the challenges in applying sentiment analysis to recommendation systems is the need for large and well-annotated datasets. Sentiment analysis models require extensive training to understand the subtleties of human emotion accurately. Moreover, the sentiment can be highly context-dependent, requiring sophisticated models that can understand the specific context in which a statement is made. As the field progresses, the integration of sentiment analysis with other types of data, such as user behaviour or contextual information, could provide a more holistic approach to personalized recommendations.

2.2 Multimodal Recommendation Systems

Multimodal recommendation systems represent a significant leap forward in the field of personalized recommendations. These systems go beyond traditional unimodal systems that rely on a single type of data, such as user-item ratings or textual reviews. Instead, they incorporate multiple types of data—text, images, and user behaviour—to create a more comprehensive user profile, thereby enhancing the quality and accuracy of recommendations.

2.2.1 Graph-Based Methods

One of the most promising advancements in multimodal recommendation systems is the use of graph-based methods. A recent paper discussed the use of graph-based techniques, specifically focusing on freezing and denoising graph structures for multimodal recommendations[18]. Graph-based methods allow for the representation of complex relationships between different types of data in a more intuitive and computationally efficient manner. For instance, a user node in the graph could be connected to item nodes, text nodes, and image nodes, each representing a different aspect of the user's interaction with the system.

2.2.2 Disentangled Multimodal Representation

Another emerging trend is the use of disentangled multimodal representation learning, which aims to separate the various factors that contribute to a user's preferences [19]. Traditional multimodal systems often suffer from the problem of data fusion, where different types of data are combined in a way that makes it difficult to interpret the individual contributions of each data type. Disentangled representation learning addresses this issue by learning separate representations for each type of data, which can then be combined in a more interpretable manner for making recommendations.

2.2.3 Contextual Information

The incorporation of contextual information, such as time, location, or device type, is another area where multimodal recommendation systems are making strides. Contextual information can provide additional layers of nuance to user preferences, thereby allowing for more personalized and timely recommendations. Combining the attention-based methods of the AMNN paper with tensor factorization techniques that consider contextual information could potentially result in a more robust, personalized, and context-aware recommendation system[20].

2.2.4 Challenges and Future Directions

Despite these advancements, current research has not yet explored unique aspects like the mind-music-hobbies/activities connection, indicating an open area for future exploration. The integration of such novel concepts could pave the way for groundbreaking research that goes beyond traditional content-based and collaborative filtering methods.

2.4 Emotion-aware Recommendation Systems

Introduction

The concept of emotion-aware recommendation systems is a relatively new but rapidly growing area of research. These systems aim to go beyond traditional recommendation algorithms by incorporating the user's emotional state into the decision-making process. The emotional state can be derived from various data sources, such as textual reviews, biometric data or even real-time user interactions.

ECG Signal Analysis
One of the most innovative techniques in emotion-aware recommendation systems is the use of Electrocardiogram (ECG) signal analysis explored, This technique provides a more nuanced understanding of the user's emotional state [21]. ECG data can offer real-time insights into a user's emotional condition, such as stress levels or excitement, which can then be used to tailor recommendations accordingly. For example, a relaxation playlist could be recommended to a user showing signs of stress.

Continuous Emotion Modeling

Another groundbreaking approach is the use of continuous emotion modelling, allowing for real-time adaptation to the user's emotional changes demonstrated that such real-time emotional tracking could significantly improve the quality of recommendations [5]. This is particularly relevant for platforms where user interaction is continuous and dynamic, such as streaming services or online gaming platforms.

Emotional Context in Music and Hobbies

The emotional context is especially relevant in the domains of music and hobbies, where the user's emotional state can significantly influence their preferences. For instance, a user might prefer different types of music depending on whether they are happy, sad, or excited. Emotion-aware systems can capture these nuances to provide more contextually appropriate recommendations, thereby enhancing user engagement and satisfaction.

Challenges and Future Directions

One of the primary challenges in emotion-aware recommendation systems is the ethical considerations surrounding the use of sensitive emotional data. User consent and data privacy become critical issues that researchers and practitioners must address. Additionally, the effectiveness of emotion-aware systems can be influenced by the accuracy and reliability of the emotional data, which can vary depending on the data source and collection methods.

Integration with Other Systems

As the field of emotion-aware recommendation systems continues to evolve, there is a growing interest in integrating these systems with other types of recommendation algorithms, such as content-based, collaborative filtering, or even multimodal systems. Such integration could provide a more holistic and enriched user experience, setting the stage for the next generation of personalized recommendation systems.

2.5 Hobby-based Recommendation Systems

Introduction

Hobby-based recommendation systems are a relatively unexplored but promising area of research. Unlike traditional recommendation systems that focus on products, services or media content, these systems aim to recommend activities or hobbies based on a user's known interests, behaviour, and preferences. The goal is to enrich the user's life by introducing them to new activities that they are likely to enjoy.

Machine Learning in Hobby Recommendations

One of the pioneering studies in this area employed machine learning techniques to predict children's interests in various hobbies [22]. The study used a combination of supervised and unsupervised learning algorithms to analyze data from surveys, online activities, and social media interactions. The resulting model was able to predict with high accuracy the hobbies that children are likely to enjoy, providing a new avenue for personalized recommendations.

Implicit Data and User-Game Interactions

Another interesting approach focuses on using implicit data that tracks user-game interactions. Smith et al. (2018) explored this method to recommend video games based on a user's past behaviour and preferences[^3^]. While video games are not traditionally considered hobbies in the academic sense, the methodology could easily be adapted for other types of activities, such as sports, arts and crafts, or even cooking.

Integration with Other Data Types

The current research landscape lacks studies that integrate hobbies with other types of data, such as music preferences or emotional states. This indicates a significant gap and an opportunity for groundbreaking research. For example, a system could recommend a cooking class to someone who enjoys listening to podcasts about food, or suggest a local hiking group to someone who frequently listens to nature sounds.

Challenges and Future Directions

One of the main challenges in hobby-based recommendation systems is the lack of large, well-annotated datasets. Hobbies are highly personal and diverse, making it difficult to collect sufficient data for robust machine learning models. Furthermore, the ethical implications of using personal data for such recommendations need to be carefully considered, especially when recommending activities that could have a significant impact on a user's well-being.

2.6 Conclusion and Implications

Hobby-based recommendation systems offer a new frontier for personalized recommendations, going beyond traditional domains to enrich the user's life in a more holistic manner. As machine learning techniques continue to advance, and as more data becomes available, the potential for highly personalized, hobby-based recommendations will only increase.

This concludes the State-of-the-Art section, covering Personalized Music Recommendation Systems, Sentiment Analysis in Recommendation Systems, Multimodal Recommendation Systems, Emotion-aware Recommendation Systems, and Hobby-based Recommendation Systems. Each section has delved into the current research landscape, highlighting both the advancements and existing gaps in each area. This comprehensive overview sets the stage for the introduction of innovative methods and provides a strong foundation for the research proposed in this dissertation.

3 Methodology

When setting up a software solution, numerous choices arise. However, adhering to a well-structured framework can help navigate both technical and non-technical challenges.

3.1 Waterfall vs Agile

Software development is a multifaceted discipline that encompasses various methodologies and approaches to streamline and enhance the creation of software applications. Two of the most prominent methodologies are the Waterfall and Agile models.

The Waterfall model is characterized by its sequential stages, Where each phase must be completed before moving on to the next. This linear approach is beneficial for projects with well-defined requirements and minimal changes. It emphasises thorough documentation, ensuring clarity and understanding throughout the development process.

On the other hand, the Agile model is dynamic and iterative. It divides projects into short cycles or sprints, each resulting in a testable segment of the software. This approach is advantageous for projects that require adaptability and quick responses to changes. However, its fast-paced nature can sometimes overlook intricate system details due to its focus on rapid development.

In essence, while the Waterfall model is structured and documentation-centric, the Agile approach is flexible and collaboration-driven. The choice between them depends on the project's nature, size, and requirements.

3.2 Framework Adapted

For this particular endeavour, the agile methodology stands out as the most fitting, especially given its solo developer focus. The aim is to achieve rapid iterations, culminating in a prototype. With the integration of various design elements, segmenting the design becomes a logical step. Each segment can be crafted in isolation using Jupyter Notebook and subsequently merged to form a comprehensive solution. Given the potential complexity of the coding process, adopting a modular design via agile sprints is instrumental for a solo developer to navigate this intricacy. While some Agile managerial practices, like daily stand-ups, might be set aside due to the project's one-person nature, the core principle of iterative experimentation remains pivotal. Even though a formal Kanban board won't be in play, its foundational concept will steer the development trajectory, ensuring a cohesive integration of all code segments."

3.3 Design Principles

User-Centric Design: At the heart of any successful recommender system lies the principle of user-centric design. This approach prioritizes the user's unique preferences, emotions, and behaviours, ensuring that the recommendations provided are tailored to individual tastes and needs. By placing the user at the centre of the recommendation process, systems can offer a more personalized and resonant experience, enhancing user satisfaction and engagement [27].

Emotionally Resonant Recommendations: Music, by its very nature, evokes emotions. Recommender systems that can tap into the emotional context of users can provide recommendations that resonate on a deeper, more personal level. This involves understanding and aligning with the user's current emotional state, ensuring that the music suggested complements or enhances their feelings [28].

Incorporation of Sentiment Analysis: Beyond just analysing user behaviour and preferences, integrating sentiment analysis into recommender systems offers a nuanced understanding of user attitudes, emotions, and opinions. By gauging the sentiment behind user interactions and feedback, systems can refine their recommendations, making them more aligned with the user's emotional context [29].

Modularity in Design: A modular design approach ensures flexibility and adaptability in the system. By allowing individual components to be added, modified, or removed without causing disruptions, systems can easily adapt to changing user needs or technological advancements. This design principle ensures that the system remains robust and scalable over time [30].

Hybrid Recommendation Approach: Music preferences are multifaceted and complex. A hybrid approach combining content-based methods enhances with sentiment analysis.In this paper we took 2 approaches, training a deep learning or machine learning model on Raw audio features data and the second approach a NLP model for which we have an actual working model with results,For the logic we are trying to implement. Here we have the NLP approach playing the role of a foundational approach for the future deep learning or machine learning model that will be iterated and improved upon from current works done,Paving the path for future works. Only such a Hybrid model can capture the complexity of this logic model. By leveraging multiple recommendation techniques, systems can provide more accurate and diverse music suggestions[31].

Continuous Learning and Iteration: The design principle that we follow for this project is a dynamic approach with iterations planned in the future works. The dynamic nature of user preferences necessitates that recommender systems continuously learn and adapt. By incorporating feedback loops and iterative design processes, systems can evolve with users, ensuring long-term relevance and effectiveness [32].

3.4 Technical Constraints

3.4.1 Raw – Audio features model

This model is still in the development phase and we only have basic analysis run on the audio features(Findings from the analysis is detailed in) because of the challenging nature of this problem. The constraint while developing this solution was getting access to necessary datasets, This project being a novel approach there was no available dataset for both approaches, The initial approach to train a deep learning/machine learning model required access to raw audio features, Unlike the already available and trained on features like Valence score. which apparently Spotify provides through their Web API, Due to Spotify's strict policies against AI or ML model training unfortunately that approach had to be postponed for development when an available source opens up that gives access to all the required features to train a model (acousticness, danceability,durations_ms, energy, key, liveliness,loudness, tempo,time_signature,instrumentalness, mode.). Each of these audio features are extremely important when we read about the analytical that each of these features individually hold and hence the patterns to look for from their correlations, Which I have performed a preliminary overview of correlation analysis on them.

3.4.2 NLP Model

In the course of developing our NLP model, one of the most significant hurdles we encountered was sourcing a dataset that encompassed all the necessary features for our analysis. Given that our model is intricately designed to harness the sentiment analysis capabilities of VADER, it was imperative to have access to a songs dataset complete with lyrics, as well as a hobbies dataset that included detailed descriptions of each hobby. Surprisingly, there weren't any pre-existing datasets that catered to these specific requirements. This posed a unique challenge, prompting us to take matters into our own hands. As a solution, we embarked on the meticulous journey of creating two bespoke datasets: one that paired lyrics with their corresponding sentiment scores and another that provided a comprehensive list of hobbies accompanied by their descriptions and sentiment scores. This endeavour of crafting datasets from the ground up ensured that our model had the precise data it needed to function optimally.

3.5 Modularised Design

Creating a system that integrates distinct functionalities, ensuring adaptability for future improvements is intricate and demanding. The selected agile methodology aids in navigating these complexities by facilitating the development and testing of each component separately during succinct iterative cycles.Despite adopting a modular approach, there's a considerable learning trajectory in developing this solution. Educational resources emphasize on coding these applications independently. For the success of this project,It required learning to transition from these isolated code understanding to a setup where modules exchange data effectively. This is vital, especially if the aim is to maintain a high processing speed in less-than-ideal conditions.

This modular design strategy also permits the establishment of foundational structures. This ensures that the primary solution script can effectively invoke each module before diving deep into the intensive task of overlaying a tailored solution on this foundation. Below is the foundational workflow of the proposed (NLP) solution, highlighting the modular strategy

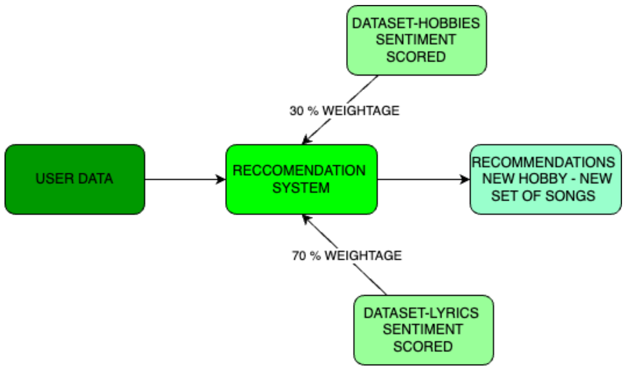

Figure 4. *Foundational Workflow – NLP Model.*

3.6 Exploratory Analysis

EDA is a vital preliminary step in the data analysis process. Before plunging into intricate modelling, it is crucial to decipher the data's patterns, relationships, anomalies, and overall structure. This project, focusing on audio features, employs EDA to shed light on how these features interact and influence one another.

3.6.1 EDA - Raw Audio Features

3.6.1.1 Purpose and Significance of the Correlation Heatmap:

The correlation heatmap is a graphical representation capturing the essence of relationships between various audio features. Colour gradients intuitively depict the strength and direction of these relationships: darker hues signify stronger correlations, either positive or negative. Such visual aids not only enhance interpretability but also streamline communication with stakeholders.

3.6.1.2 Addressing Multicollinearity:

Multicollinearity, a phenomenon where features are inordinately correlated, can distort model predictions. The heatmap acts as a sentinel, identifying potential multicollinearity through exceptionally high correlation values. Recognizing these early aids in astute feature selection, perhaps through feature amalgamation or elimination.

3.6.1.3 Informed Feature Selection and Model Development:

The heatmap is more than just a multicollinearity detector. Features with negligible correlations might be superfluous and candidates for removal. In contrast, dominant correlations can be quintessential, meriting further scrutiny. This iterative process not only curtails dimensionality but also refines the dataset to its core, ensuring models are adept and efficient. Moreover, comprehending these inter-relationships can guide the selection of suitable modelling algorithms.

3.6.1.4 Detailed Examination of Correlations:

Diving deeper, the correlations are compartmentalized based on their magnitude and direction:

Positive Correlations: Ascending relationships between features.

Negative Correlations: Descending relationships.

Weak Correlations: Minimal or non-existent linear associations.

Predefined thresholds, determined through lambda functions, facilitate this categorization. Each type is then vividly visualized through distinct heatmaps, enhancing clarity and facilitating nuanced interpretations.

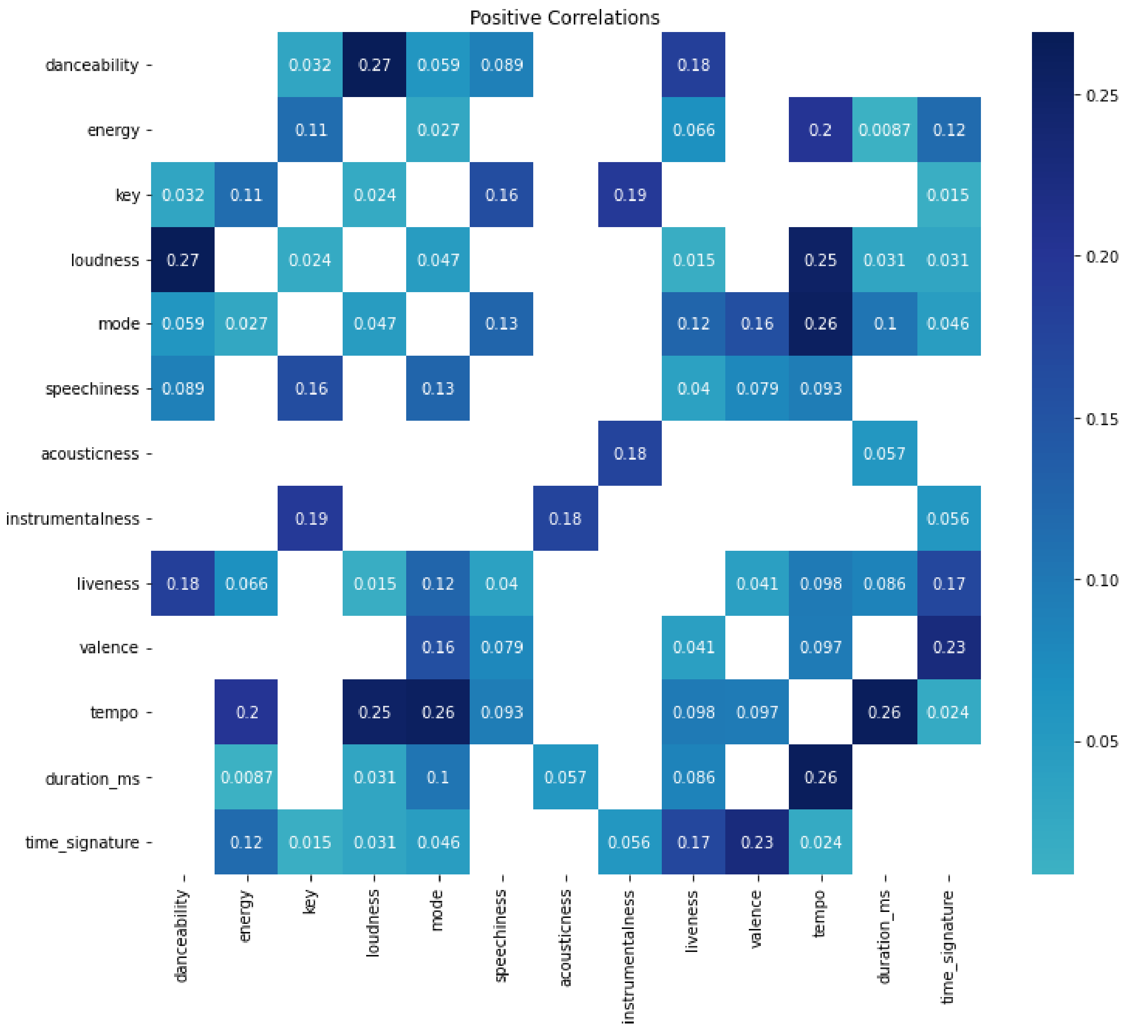

Figure 5. Positive Correlations,Raw Audio features obtained via Spotify API.

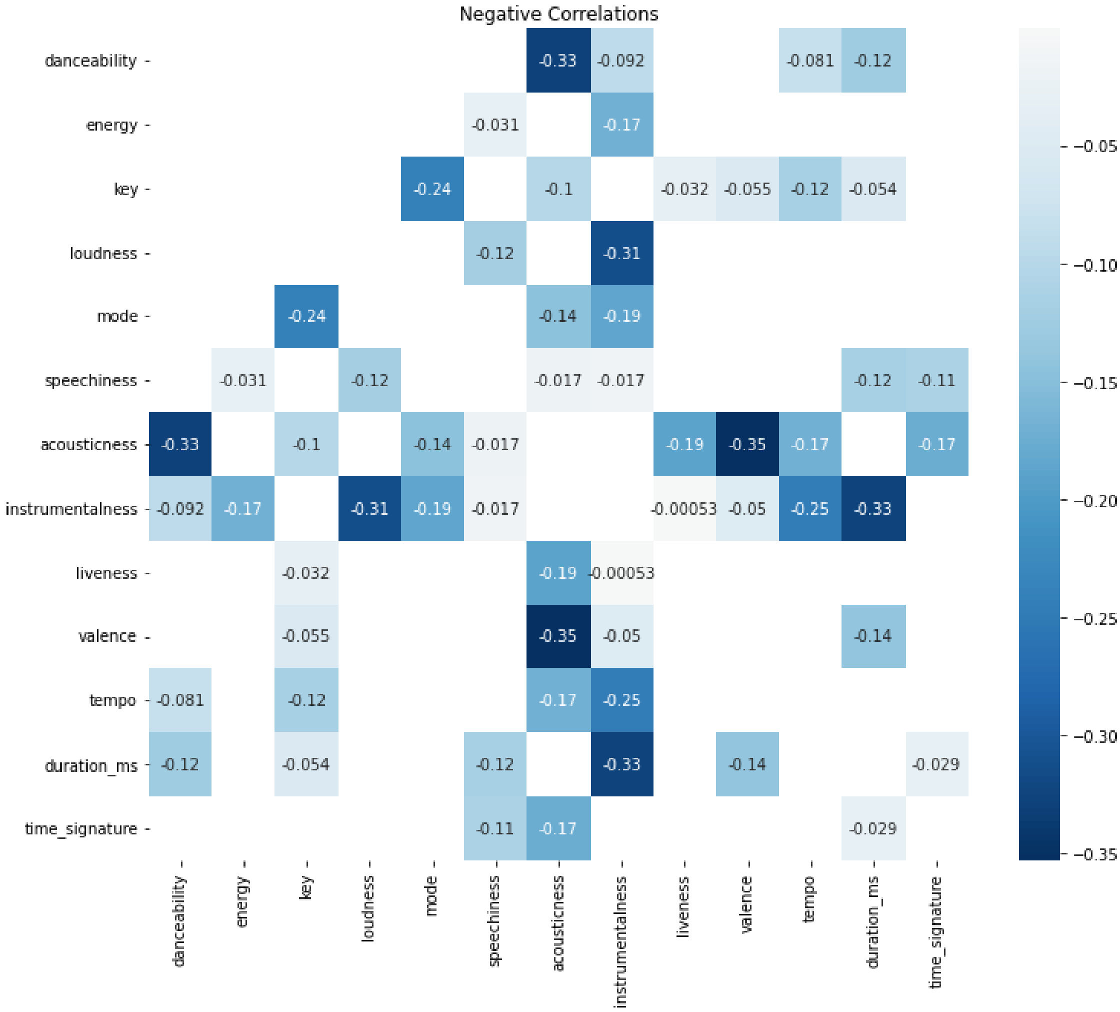

Figure 6. Negative Correlations, Raw Audio features obtained via Spotify API.

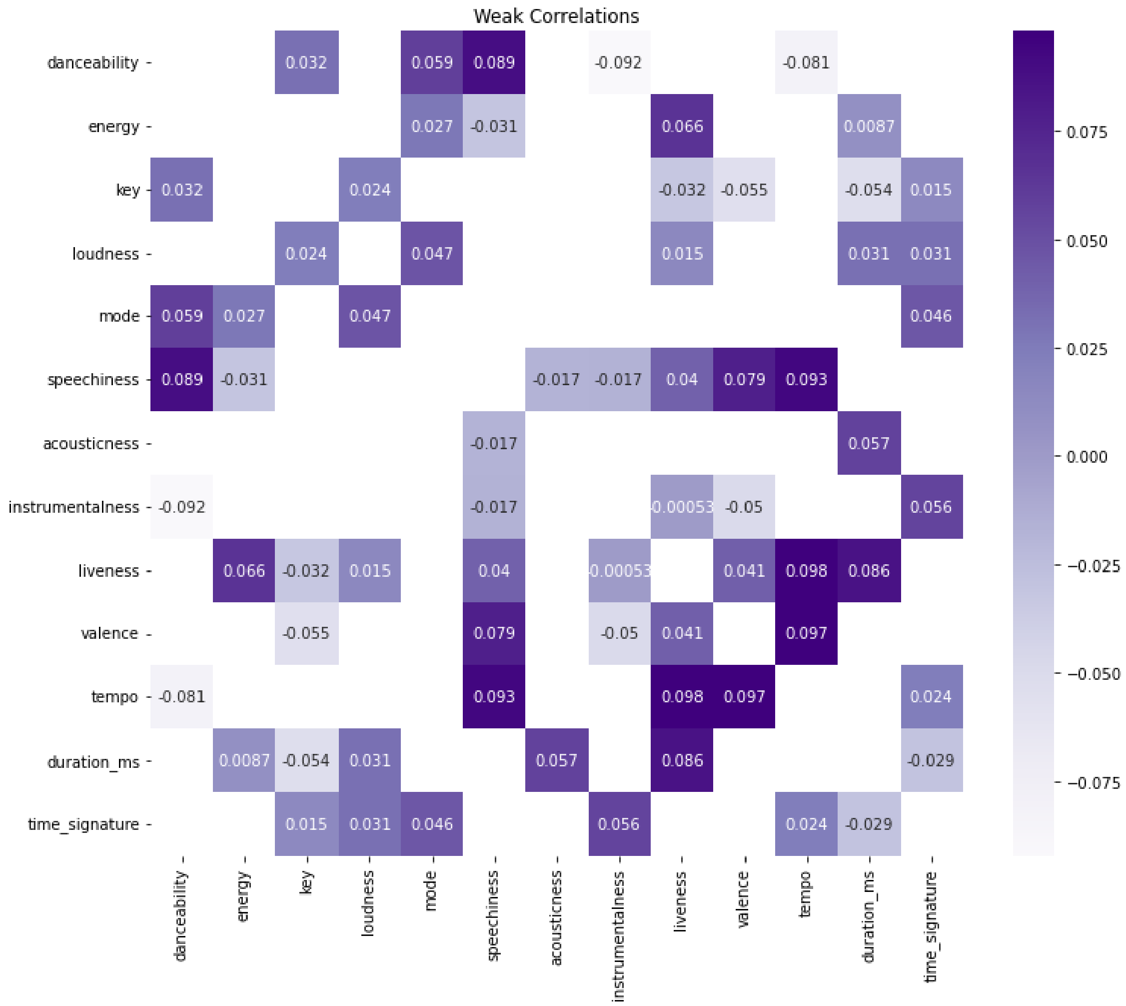

Figure 7. Weak Correlations, Raw Audio features obtained via Spotify API.

3.6.1.5 Repercussions for Model Building:

Understanding these correlations is paramount. Potent correlations can mould the model's decision-making processes, offering insights into feature relevance. Conversely, weak correlations, contingent on the model type, might necessitate further probing to ascertain their utility.

3.6.2 EDA - NLP - Model

Lyrical content is an expressive medium, often reflecting emotions, narratives, and nuances. Harnessing this rich information necessitates a unique model architecture that can effectively capture these intricacies. The "Dissertation-Lyrical model" notebook provides a roadmap to constructing such a model.

3.6.2.1 Data Acquisition and Pre-processing:

The starting point is the acquisition of raw lyrical data. However, raw lyrics come with challenges, including embedded metadata and structured textual formats. A systematic data-cleaning pipeline strips away non-essential elements, ensuring that the lyrics are in a format conducive for modelling.

3.6.2.2 Natural Language Processing (NLP):

Given the textual nature of lyrics, Natural Language Processing (NLP) techniques are integral to the model. Tokenization, stemming, and lemmatization processes convert the lyrics into a machine-readable format. This transformation ensures that the model can discern patterns, themes, and sentiments embedded within the lyrics.

3.6.2.3 Sentiment Analysis:

At the heart of this model is sentiment analysis. Leveraging the VADER sentiment analysis tool, the model gauges the emotional undertones of the lyrics. VADER, specifically designed for social media text, provides polarity scores, capturing positive, negative, and neutral sentiments. This granularity allows for a deeper understanding of the lyrical content, paving the way for more nuanced recommendations and insights.

3.6.2.4 Correlation Analysis:

Understanding how sentiments interplay with other attributes is pivotal. Through correlation analysis, the model discerns relationships between sentiment scores and other features. This understanding aids in refining the model and ensuring that the predictions are both robust and interpretable.

3.6.2.5 Modelling Strategy:

Armed with processed data, the modeling phase ensues. The choice of algorithms is influenced by the nature of the data and the desired outcomes. Given the complexity of lyrics and the multitude of influencing factors, a combination of machine learning techniques might be employed to ensure optimal results.

3.6.2.6 Iterative Refinement:

Modelling, especially in complex domains like lyrical analysis, is rarely a one-off process. Iterative refinement, informed by performance metrics and real-world validation, ensures that the model remains relevant, accurate, and efficient. Feedback loops, potentially involving user feedback or new data incorporation, play a crucial role in this refinement process.

3.6.2.7 Conclusion:

The model exemplifies a meticulous approach to modelling lyrical content. From data acquisition to iterative refinement, every step is geared towards harnessing the expressive power of music through lyrics. The resultant model is not just a technical construct but a bridge between art and science, capturing the essence of songs and translating them into actionable insights.

3.6.2.8 Control Flow - NLP

Control Flow Overview for Sentiment-based Recommender System:

The process begins with the input of a user's preferred songs and hobbies. Once provided, the system endeavours to fetch the lyrics of the specified songs. If the lyrics are successfully retrieved, they undergo a cleaning process to ensure only relevant content is considered for sentiment analysis. Subsequent to the cleaning, the system performs sentiment analysis on the lyrics to derive a sentiment score. This sentiment score is stored and, in parallel, the sentiment score associated with the user's specified hobby is retrieved. These two sentiment scores, one from the songs and the other from the hobby are then aggregated to form a comprehensive sentiment profile for the user.Using the aggregated sentiment score, the system determines the sentiment category—whether it's positive, negative, or neutral. Based on this categorization, a hobby is recommended to the user. This recommendation aligns with the user's sentiment profile, ensuring that the suggested hobby resonates with the user's current emotional state.Furthermore, the system also recommends tracks that are close in sentiment to the user's profile. These tracks, akin to the hobby recommendations, are chosen to align with the user's emotions and preferences.Finally, the recommended hobby and tracks are presented to the user, completing the process. This approach ensures that recommendations are not just based on user preferences but also take into account the emotional context, leading to more personalized and resonant suggestions.

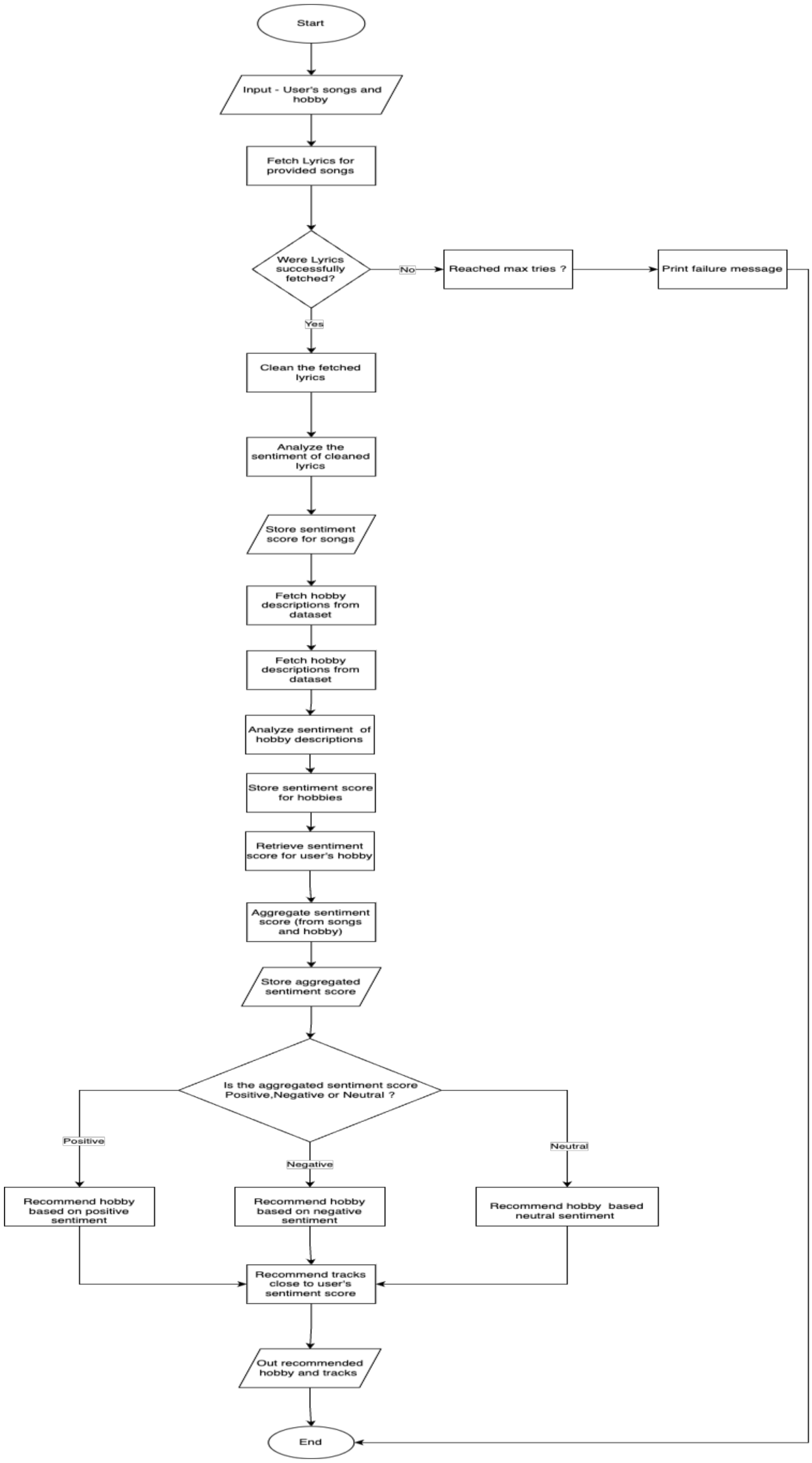

Figure 8. Control Flow - NLP - Model- Sentiment-based Recommender System.

3.7 Solution Files

Fulfilling agile requirements, The following functions were created in the following order:

3.7.1 Importing Lyrics and Sentiment Analysis on them.

3.7.1.1 fetch_song_lyrics:

Purpose:

- This function attempts to fetch the lyrics of a given song from the Genius platform.

Parameters:

- **title:** The title of the song.
- **artist:** The name of the artist.
- **max_retries:** Maximum number of attempts to fetch lyrics (default: 3).
- **delay:** Delay (in seconds) between retries (default: 2 seconds).
- **timeout:** Timeout duration (in seconds) for the request (default: 10 seconds).

Functionality: The function loops for a specified number of retries. If it successfully fetches the lyrics within these retries, it cleans the lyrics using the clean_lyrics function and returns them. If it fails to fetch the lyrics after all retries, it prints a failure message and returns None.

3.7.1.2 clean_lyrics:

Purpose:

- To preprocess the raw song lyrics, ensuring they are in a suitable format for sentiment analysis.

Parameter:

- lyrics: Raw song lyrics fetched from the Genius API.

Functionality:

- Removes contributor or translation information.
- Discards annotations like [Chorus], [Verse].
- Replaces multiple newline characters with a single newline to maintain readability.

- Strips leading and trailing whitespace.

Main Process:

The code initializes two lists (user_sentiments and user_sentiment_scores) to store the resulting sentiment classification and its associated score for each user. It then loops through each user and song to fetch the lyrics and compute sentiment.

Purpose:

To loop through each user and song, fetch the lyrics, clean them, compute sentiment, and categorize the sentiment for each user.

Functionality:

Fetching and Cleaning Lyrics:

- Uses the Genius API to fetch lyrics for each song.
- If successful, the clean_lyrics function is applied to preprocess these lyrics.

Sentiment Analysis:

- Uses the analyser.polarity_scores function to compute the sentiment score for each cleaned song's lyrics.
- Aggregates the 'compound' score for all songs of a user to compute an overall sentiment value.

Error Handling:

- Implements a retry mechanism to handle timeouts when fetching lyrics, attempting up to three times before moving on.
- Catches and displays other types of exceptions without triggering a retry.

Sentiment Categorization:

- Computes the average sentiment score for each user.
- Categorizes the user's sentiment based on the average score:
  - 'Positive' if the score is ≥ 0.05.
  - 'Neutral' if the score is between -0.05 and 0.05.
  - 'Negative' if the score is ≤ -0.05.

3.7.2 Hobbies Dataset Creation

3.7.2.1 get_wikipedia_description:

Purpose:

- This function fetches a summary description of a given topic from Wikipedia.

Parameter:

- The subject or keyword for which the Wikipedia description is to be fetched.

Functionality:

- The function constructs a Wikipedia API request using different variations of the topic name (original, capitalized, uppercased). It then sends these requests one by one until it retrieves a description or exhausts all variations. If a description is found, it's returned; otherwise, the function returns None.

3.7.2.2 clean_html:

Purpose:

- Cleans HTML tags and entities from a given text.

Parameter:

- The input string contains HTML content.

Functionality:

- The function uses the BeautifulSoup library to remove all HTML tags and entities, returning a plain text version of the input.

3.7.2.3 further_clean_description:

Purpose:

- Performs additional cleaning on a given text.

Parameter:

- The input string to be cleaned.

Functionality:

- The function replaces newline characters with spaces, trims the text, and returns the cleaned version. If the input is null, it returns the string "Not Found".

3.7.3 Sentiment Score after aggregation of Description sentiment and Lyrics Sentiment for User

3.7.3.1 aggregate_scores:

Purpose:

- Computes an aggregated sentiment score for a user based on their song lyrics' sentiment and their hobby's sentiment.

Parameter:

- A row from a user dataframe containing the user's song sentiment score and their hobby.

Functionality:

- The function calculates a weighted average of the user's song sentiment score (70% weightage) and their hobby's sentiment score (30% weightage). It returns the aggregated score.

3.7.3.2 normalize_to_vader_scale:

Purpose:

- Normalizes a sentiment score to the VADER sentiment scale (-1 to 1).

Parameters:

- score: The sentiment score to be normalized.
- score_series: A series of scores used to determine the current minimum and maximum values.

Functionality: The function scales the input score such that it falls within the range of -1 to 1, which corresponds to the VADER sentiment scale.

3.7.3.3 classify_sentiment:

Purpose:

- Classifies a sentiment score as Positive, Neutral, or Negative.

Parameters:

- Score:The sentiment score to be classified.
- score_series: A series of scores used for normalization.

Functionality:

- The function first normalizes the input score to the VADER scale. It then classifies scores greater than 0.05 as Positive, scores between -0.05 and 0.05 as Neutral, and scores less than -0.05 as Negative.

3.7.4 Hobby / Activity Prediction Using Aggregated User Sentiment Score

3.7.4.1 determine_bucket:

Purpose:

- o Determines the sentiment bucket (e.g., Positive, Neutral, Negative) for a given sentiment score.

Parameter:

- o score: The sentiment score to be bucketed.

Functionality:

- o Based on predefined sentiment score ranges (buckets), the function assigns the score to a corresponding bucket and returns the bucket name.

3.7.4.2 predict_hobby:

Purpose:

- o Recommends a hobby for a user based on their aggregated sentiment score.

Parameters:

- o user_score: The user's aggregated sentiment score.
- o hobbies_df: Dataframe containing hobbies and their sentiment scores.

Functionality:

- o The function first determines the sentiment bucket for the user's score. It then selects and recommends a random hobby from the corresponding sentiment bucket.

3.7.5 Recommend Tracks Based on Aggregated User Sentiment Score

3.7.5.1 determine_bucket:

Purpose:

- Determines the sentiment bucket (e.g., Positive, Neutral, Negative) for a given sentiment score.

Parameter:

- score: The sentiment score to be bucketed.

Functionality:

- Based on predefined sentiment score ranges (buckets), the function assigns the score to a corresponding bucket and returns the bucket name.

3.7.5.2 clean_lyrics(lyrics):

Purpose:

- To preprocess and clean song lyrics, ensuring they are in an optimal format for subsequent processing and sentiment analysis.

Parameters:

- lyrics: Raw song lyrics that need cleaning and preprocessing.

Functionality:

- Removes any text enclosed in square brackets (often used for annotations like [Chorus] or [Verse]).
- Filters out any non-alphabetic characters, retaining only letters and whitespace.
- Converts all characters to lowercase to ensure uniformity.
- Removes extra spaces and condenses the lyrics into a continuous string with single spaces between words.

3.7.5.3 compute_track_sentiment:

Purpose:

- Computes the sentiment score of a track's lyrics.

Parameter:

- track_lyrics: The lyrics of the track.

Functionality:

- The function first cleans the provided lyrics using the clean_lyrics function. It then uses the VADER sentiment analysis tool to compute the compound sentiment score for the cleaned lyrics.

3.7.5.4 recommend_tracks_for_user:

Purpose:

- Recommends tracks to a user based on their sentiment profile.

Parameters:

- username: The user's name.
- users_df: Dataframe containing user information.
- df: Dataframe containing track information and sentiment scores.
- hobbies_df: Dataframe containing hobbies and their sentiment scores.

Functionality:

- The function first checks if the username exists in the user dataframe. If not, it returns an empty list. Otherwise, it retrieves the user's hobby and its associated sentiment score. The function then computes an aggregated sentiment score for each track, taking into account the track's sentiment score and the user's hobby sentiment score. The function then recommends tracks that closely match the user's sentiment profile.

4 Results

4.1 Analysis of Results from the NLP-Model

The primary objective of the dissertation was to recommend hobbies and music tracks to users based on sentiment profiles derived from their music preferences and hobbies. The provided results capture the culmination of the entire process, showcasing the recommended hobbies and tracks for different users.

User Data: Each row of the results represents a user, identified by their full name. For each user, their original hobby is listed, which serves as a personal identifier of their interests.

Predicted Hobby: This column signifies the hobby that the model recommends based on the user's aggregated sentiment profile. This recommendation is a synthesis of sentiment scores derived from song lyrics and the user's original hobby.

Recommended Tracks: A collection of songs that match the user's sentiment profile. These songs, carefully curated by the model, mirror the emotional undertones expressed in the user's original song choices.

4.1.1 Recommendation results

Figure 9. Predicted Hobby and set of 10 tracks according to user sentiment profile(Click on the icon) .

Sentiment Metrics:

Aggregated_Sentiment: This is a qualitative representation (Positive, Neutral, Negative) of the user's sentiment profile based on the aggregated sentiment score.

Aggregated_User_Sentiment_Score: A quantitative measure of the user's sentiment, computed as a weighted average of the sentiment scores from the song lyrics and hobby description.

Sentiment_Score_From_Lyrics: Represents the sentiment score derived solely from the song lyrics provided by the user.

Sentiment_Score_From_Description: Represents the sentiment score derived from the hobby description.

Track Recommendations: Each user is provided with a set of ten song recommendations that align with their sentiment profile. These tracks are not just a reflection of the user's emotional state but also serve as potential new additions to their playlists, enriching their music experience.

Insights and Patterns:

Variety in Recommendations: The model offers a diverse range of hobby recommendations, which suggests that it doesn't pigeonhole users based on a singular sentiment score. Instead, it provides a more nuanced understanding, leading to varied hobby suggestions like "zoo visiting," "kitesurfing," and "flower collecting and pressing."

Sentiment Distribution: An examination of the Aggregated_Sentiment column can provide insights into the overall sentiment distribution of the user base. For instance, do most users lean towards positive, negative, or neutral sentiments based on their song choices?

Music as a Reflection of Emotion: The recommended tracks for each user underline the idea that music is deeply intertwined with our emotions. Tracks like "Hall of Fame by The Script," "Sajda by Rahat Fateh Ali Khan," and "Fireflies by Owl City" highlight the vast emotional spectrum captured by the model.

Reliability: The model's ability to consistently recommend a set of ten tracks for each user indicates its robustness and reliability. It ensures that every user receives a comprehensive set of recommendations, enhancing the user experience.

In conclusion, the results manifest the dissertation's objective of bridging the gap between sentiment, music, and hobbies. By intertwining sentiment analysis with recommender systems, this research has set the groundwork for more emotionally resonant user experiences in hobby and music recommendation domains.

4.2 Validation

4.2.1 User Feedback

To validate the results, a user feedback survey was conducted using Google Forms. Participants were asked to rate on a scale from 1 to 5. The collected ratings included one

'1', three '3's, and one '4'. The average score from these responses was 2.8. This score suggests that the general feedback was somewhat positive, landing just above the scale's midpoint. However, there are still areas that can be enhanced in subsequent efforts.

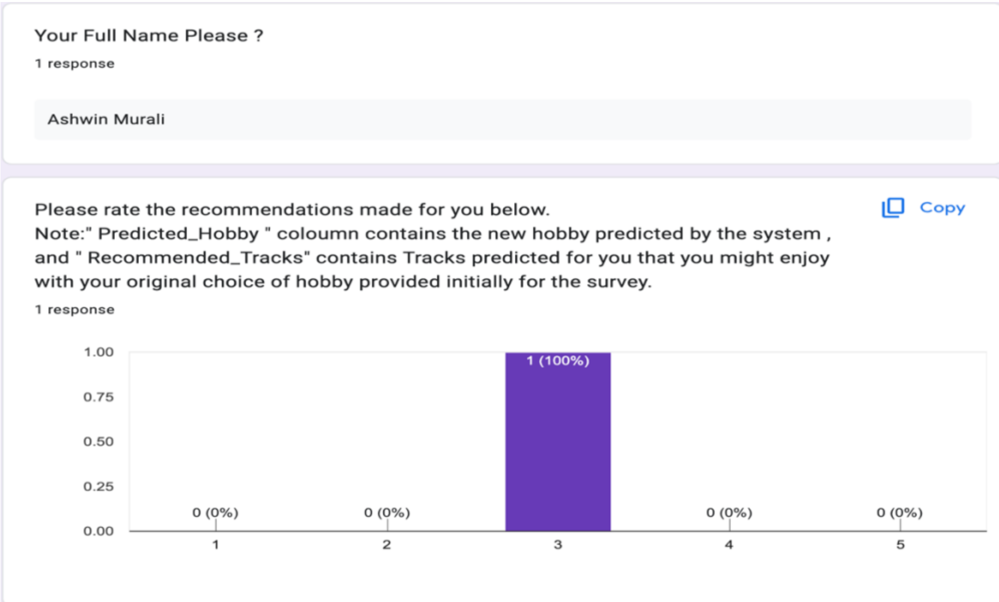

Figure 10. Individual feedback from the user, Using Google Forms.

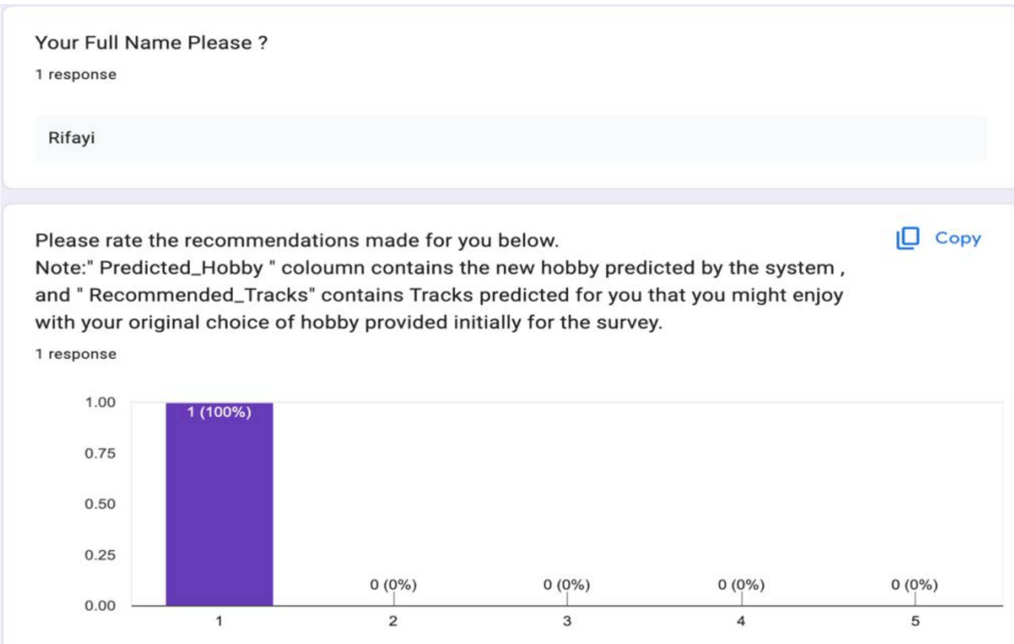

Figure 11. Individual feedback from the user, Using Google Forms.

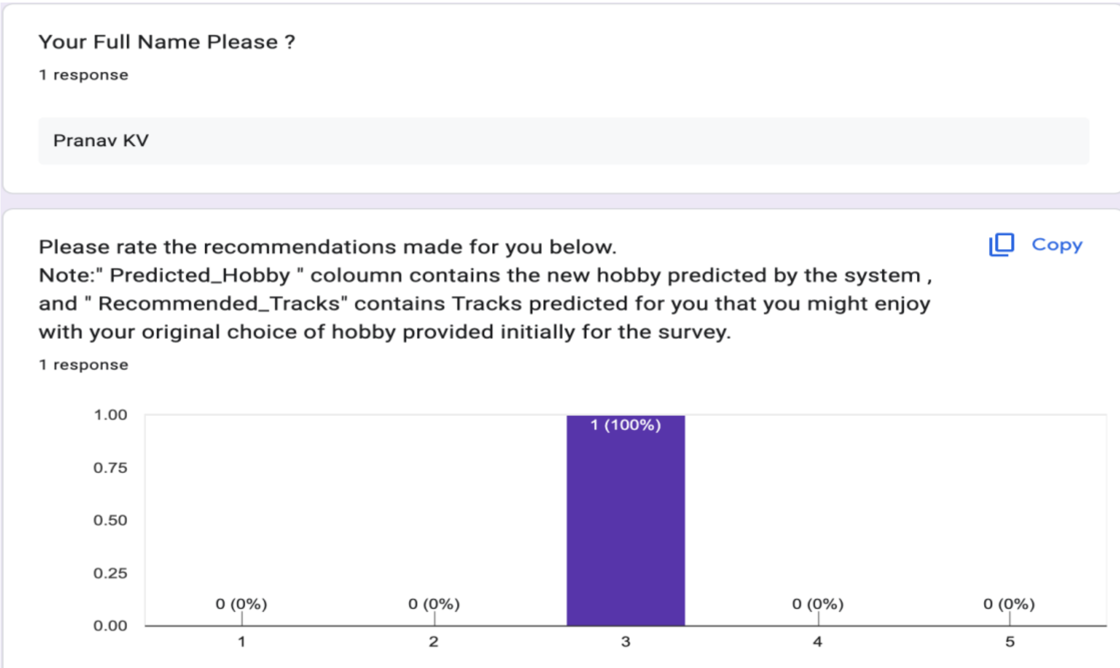

Figure 12. Individual feedback from the user, Using Google Forms.

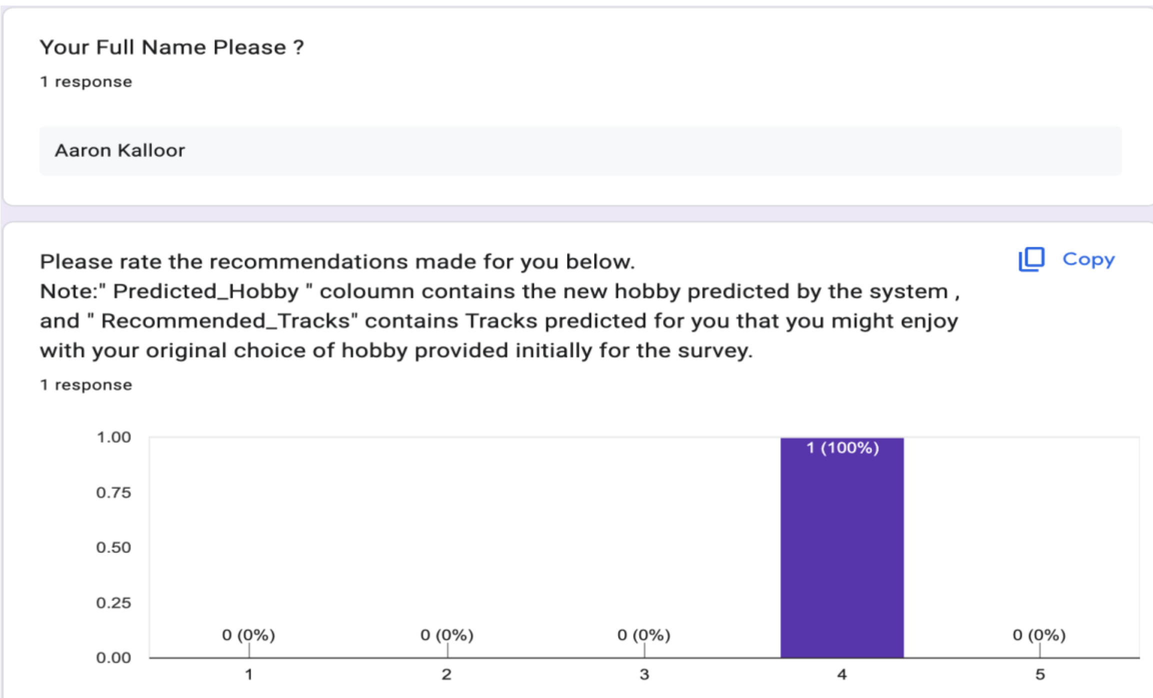

Figure 13. Individual feedback from the user, Using Google Forms.

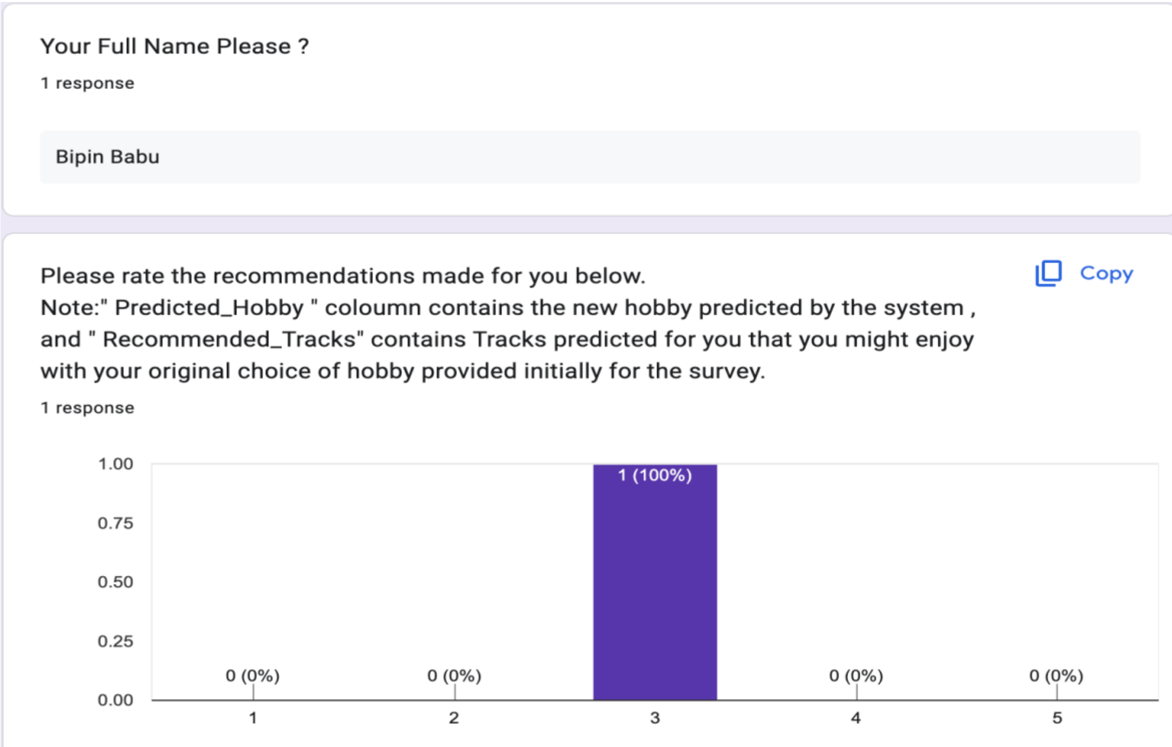

Figure 14. Individual feedback from the user, Using Google Forms.

5 Conclusion

5.1 Summary

Embarking on a quest to understand the intricate tapestry of emotions woven into music and hobbies, this dissertation sought to create a nexus between sentiment analysis, lyrical content, and personal choices. The aim was clear: to offer users recommendations that resonate with their emotional state, ensuring a more personalized experience.

Key Achievements:

Sentiment-Driven Recommender System: At the heart of this research was the integration of sentiment analysis with traditional recommender systems. The results showcased the system's ability to offer hobbies and tracks that echo a user's emotional state, marking a significant stride in the domain of personalized recommendations.

Robust Model Design: The design and implementation of the lyrical sentiment model, as detailed in the "Dissertation-Lyrical model" notebook, stood out for its meticulous approach. From data acquisition to the application of Natural Language Processing techniques, every step was tailored to capture the emotional nuances within song lyrics.

Correlation Analysis: An intricate dance of features was analyzed, shedding light on their interrelationships. This analysis proved crucial, guiding the selection of modeling algorithms and influencing the system's decision-making processes.

User Feedback and Areas of Improvement:

The validation of any system is incomplete without user feedback. A survey conducted to gauge user response returned an average score of 2.8 out of 5. While this indicates a somewhat positive reception, it also emphasizes areas that require refinement. Future work should focus on:

Deepening Sentiment Analysis: Enhancing the granularity of sentiment detection to better capture the emotional intricacies of lyrics.

Expanding Dataset Breadth: A richer dataset can offer a more diverse range of recommendations, catering to a broader user base.

Enhancing Personalization: Feedback loops and more user data can further refine recommendations, ensuring they align even more closely with individual preferences.

In the vast arena of recommender systems, this dissertation carves a niche by seamlessly blending sentiment analysis with music and hobbies. The results, while promising, are just the beginning. Continuous refinement, informed by user feedback, will pave the way for a system that truly revolutionizes the recommendation experience.

5.2 Evaluation

This dissertation's core ambition was to craft a sentiment-driven recommender system, hinging on the emotional nuances of music lyrics and user hobbies. Here's a comprehensive evaluation, cross-referenced with details from the dissertation draft.

Methodological Assessment:

Data Acquisition and Cleaning: As highlighted in the dissertation, the data acquisition process faced several challenges, notably with fetching lyrics (refer to Section 3.4). The inherent obstacles in web scraping emphasize the importance of resilient error-handling mechanisms.

Sentiment Analysis: The project's essence revolved around deriving sentiment from lyrics and hobby descriptions, as discussed in detail in Section 3.6.2 . However, the potential richness of raw audio features, as discussed in Section 3.6.1 and depicted in Figure 1,Table 1 offers a promising avenue for future exploration.

Recommendation System: The system's dual recommendation approach - suggesting both hobbies and tracks - based on combined sentiment scores is a novel and pioneering direction in the world of recommendation systems.

Results and User Feedback:

The system's recommendation capabilities, as seen in the generated tables (Figure 7), showcase its efficacy. However, the user feedback survey, which averaged 2.8 out of 5, indicates that while the system resonates with some users, there's potential for further alignment and refinement.

Literature Contextualization:

The project's alignment with existing literature is evident from the technology review presented in Section 2.5 . The endeavour of fusing sentiment analysis with recommender systems takes inspiration from, yet extends beyond, existing works, offering a unique perspective in the domain.

Challenges and Limitations:

The project's dependence on external sources for lyrics and potential discrepancies therein poses challenges, as noted in the code discussions across various sections (Sections 3.4.1, 3.4.2).

While the dataset used was comprehensive, the evaluations in the document hint at the potential benefit of a broader dataset encompassing more genres, moods, and cultural nuances.

Implications of Findings:

The project's findings, as highlighted in the results and discussions, emphasize the transformative potential of Music-driven sentiment analysis in reshaping recommender systems. The depth of insights derived from music from raw audio features analysis and song lyrics offers a fresh perspective on user preferences and choices that can be interpreted from music as the primary source for human emotion identifier that helps in building towards a more human emotion-centric recommendation system.

Scalability and Real-world Application:

As the project evolves, considerations for scalability, especially in the context of real-time data processing and integration with existing platforms, will become paramount. This is hinted at in various discussions within the dissertation, underscoring the project's real-world potential.

In wrapping up this evaluation, the dissertation underscores the intricate relationship between music, sentiment and personal choices. The project's challenges, achievements and feedback collectively offer a roadmap for future refinements, ensuring the system's evolution remains attuned to user needs and the ever-evolving domain of recommendation systems and sentiment analysis.

5.3 Future Work

The pursuit of understanding the intricate Human relationship between music, sentiment, and personal preferences has been the cornerstone of this dissertation. While significant strides have been made in developing a sentiment-driven recommender system, the realm of possibilities in this domain remains vast. Here are envisioned directions for future endeavours:

Enhanced Sentiment Analysis with Raw Audio Features:

While the current model focuses predominantly on lyrics for sentiment analysis, the incorporation of raw audio features can provide a richer sentiment profile. Analyzing elements like tempo, melody, rhythm, mode and harmony to name a few from the variety of options just from Spotify Web API itself, It can offer insights into the emotional undertones of a track beyond its lyrical content and further into mind-music-emotions connection.

Advanced machine learning models, especially deep learning architectures like Convolutional Neural Networks (CNNs) or Recurrent Neural Networks (RNNs), could be employed to process and derive sentiment from these raw audio features.

Integration with Music Streaming Platforms:

Collaborations with music streaming platforms like Spotify, Apple Music, or SoundCloud can provide real-time data on user listening habits, enhancing the recommendation's accuracy and relevance.

Expanding the Dataset:

The dataset could be expanded to include genres, cultures, or languages not initially covered. This would make the system more inclusive, catering to a global audience.

Drawing from the literature review, datasets or methodologies highlighted in seminal papers can be integrated to enhance the system's robustness.

Cross-Domain Recommendations:

Building upon the initial focus on hobbies, the system could venture into recommending movies, books, or even travel destinations based on sentiment profiles. Such cross-domain recommendations would provide users with a more holistic experience.

User-Centric Enhancements:

Implementing features where users can provide real-time feedback or even input specific mood states can help tailor recommendations even more closely to their current emotional state.

A more interactive user interface, potentially integrating voice recognition or mood detection, can further enhance user engagement.

Ethical Considerations in Data Collection and Analysis:

As the system delves deeper into personal preferences and emotions, ensuring ethical data collection and analysis becomes paramount. Future iterations should focus on transparent user consent protocols and stringent data protection measures.

Scalability and Commercial Deployment:

Future works should also look into the scalability of the system, ensuring it remains efficient as the user base expands.

Potential commercial deployment can be explored as a standalone application or in collaboration with existing platforms.

Interdisciplinary Collaborations:

Collaborating with experts from fields like psychology, musicology, and even anthropology can provide richer insights and innovative methodologies to enhance the system.

Addressing Challenges and Feedback:

Drawing from the challenges highlighted in the dissertation and the feedback received from users, future iterations should prioritize addressing these areas of improvement to enhance user satisfaction and system efficacy.

In summation, the journey embarked upon in this dissertation has opened up a myriad of avenues for exploration. By integrating insights from literature, leveraging advancements in technology and focusing on user-centric enhancements, there's immense potential to revolutionize the domain of sentiment-driven from music recommender systems.

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