# PROJECT REQUIREMENTS SPECIFICATION

## Music Recommender System with Sentiment Analysis

### UE20CS390A – Project Phase – 1

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# 1. Introduction

This document details the project plan for the development of a music recommender system that uses sentiment analysis. It is intended for developers, designers, and testers working on the project as well as project investors.

This plan will include a summary of:

- How the product will function
- The scope of the project from the development viewpoint
- The technology used to develop the project
- The metrics used to determine the project's progress
- Overall Description

Recommender systems are always in need of more personalisation, especially for objects that require a user's sentiment to be considered. Music falls under this category and is something most people listen to on a daily basis and a music recommendation should incorporate more personalized recommendations on it, which is where this project comes into play.

## 1.1. Project Scope and Motivation

Recommendation systems have high value in the music domain. They help users find music & tracks worth their while and enjoyment. While the availability of electronic devices and browser music services has made accessing a vast selection of music easier, it has also made selecting the right music for a specific situation or mood more challenging. Current applications do not provide music selection based on sentiment. Currently, there is not much research on recommending songs based on users' moods or their personality traits. This project aims to provide a music recommendation system that fits a listener's profile and mood in terms of emotional, music universe and familiarity, making it personalized based on the data collected from their social media activity.

# 2. Literature Survey

1.. *A qualitative and quantitative comparison between Web scraping and API methods for Twitter credibility analysis*

A comparative evaluation is performed on the extraction techniques, identifies which has a better credibility value and analyzes the Twitter API performance from different locations. The attributes and credibility measures retrieved by Web scraping methods are less than the ones from Twitter API. After normalizing the text obtained by the extraction methods produce identical credibility results. Language or the type of text has no impact on the credibility but followers may have minor changes as they grow constantly in real time.

Web Scraping is more flexible and faster but constant changes in the webpage affects the data as they do not follow the current HTML tags and the network speed affects data. API's are independent of the information displayed on the website and they also provide many attributes related to tweet, user, location but the access to data is restricted and is not free and the response time is dependent on the location. The comparison shows that the total of retrieved tweets with the Twitter API is always less than with the Twitter Scrapy. However, all of them are Twitter API dependent, which is now restricted, and most of them are no longer available.

2.. *Latent Personality Traits Assessment From Social Network Activity Using Contextual Language Embedding*

Each personality trait is characterized by particular behavioral patterns observed on social media platforms. The proposed linguostylistic personality traits classification framework uses up to 50 tweets per user, with URLs and Twitter mentions filtered out. The preprocessed text is then converted into real-valued vector representations using TF-IDF, distributed word embedding techniques (GloVe), and Universal Sentence Encoder.

The combination of GloVe and USE representations are used as input to the ensemble personality assessment model, with the features reduced using a GA. The framework estimates the extent to which a personality trait is exhibited by a user on a scale. The developed personality traits were further augmented on classification models with a set of stylistic features, which have shown to be effective in content-based prediction and user identification tasks.

TF-IDF + GloVe + USE exhibits the best performance among all other language-based input representations, with the highest accuracy of 81.3% for the N-S dimension on the TwitterMBTI dataset and the lowest RMSE of 0.121.

3. *A Hybrid Deep Learning Technique for Personality Trait Classification From Text*

The proposed method for personality trait classification from social media text involves three modules: data acquisition, data pre-processing, and implementation of a deep neural network. The pre-processed social media reviews are transformed into a machine-readable format using a deep neural network with CNN and LSTM models as hidden layers. The CNN model extracts important features, while the LSTM model learns long-term information to efficiently classify the user reviews into different personality classes.

After feature extraction through a convolutional layer, down-sampling through the pooling layer, and learning long-term information through the LSTM layer, the classification of the learned features is performed at the output layer. They performed experiments to evaluate the efficiency of the proposed CNN+LSTM model that utilizes word embedding compared to machine learning classifiers that use the classical feature representation scheme, Bag-of-Words.

The proposed CNN+LSTM model outperformed machine learning classifiers with the classical Bag of words representation approach, as well as deep neural network techniques. It was concluded that the proposed model outperformed machine learning methods due to their limitations.

4. *Employing BERT-DCNN with sentic knowledge base for social media sentiment analysis*

This paper used BERT and dilated convolution neural networks for sentiment analysis. BERT is a deep bidirectional transformer model for language representation which is capable of jointly learning relationships in both left and right context. SenticNet, a knowledge base, offers a set of sentics, semantics, and polarity associated with over 200k natural language concepts.

The basic CNN model does not have the ability to handle long-term dependencies and capture the semantic features. Therefore, another model, the dilated CNN model was proposed which handles information loss due to the down-sampling method in primary pooling operations. DCNN also extends the receptive field size exponentially without including any extra attributes. Hence, it becomes easier for DCNN to handle long-term semantics.

The BERT language model which was used to generate word representation from social media reviews was combined with the DCNN model which was used to fine-tune the model. It considered three layers of the dilated convolutional network in parallel instead of sequentially stacking multiple layers for processing the word vectors.

The accuracy, precision and recall were observed to be 87.1%, 0.87 and 0.86 respectively.

5. *An emotion-aware music recommender system: bridging the user's interaction and music recommendation*

This paper uses pattern of users interactions with input devices to classify the emotion and recommend the music.It creates an interaction vector considering this four features that are the number of keystrokes,mouse clicks and average time spent on that.It uses the moving average model and gives the higher weight to the recent interaction vector and recommend the music by calculating the cosine similarity between the users and corresponding to that it takes the music rating to recommend the music.

Advantages of this approach is the music is recommended directly, without labeling the user's emotion, so that the error of estimating the user's emotion does not negatively affect the recommendation accuracy,Does not require additional hardware (such as sensors, camera, or microphone) to identify the emotion; It collects data only based on user's regular interactions.

Disadvantages of this approach are that it needs to maintain an interaction vector for every t- time interval which increases the storage space and calculating the similarity between the vectors stored in the rs table is time consuming nad the music rating table can be sparse.

## 3. Product Perspective

A music recommendation system using sentiment analysis on Twitter data involves analyzing the emotional tone of tweets and using this information to suggest songs that match the user's personality and mood. By leveraging social media data, this system can provide personalized music recommendations based on the user's personality or current emotional state.

The origin of this product can be traced back to the rise of big data and machine learning technologies in the music industry. As streaming services like Spotify and Apple Music became more popular, they started collecting vast amounts of data on their users' listening habits, including what songs they liked, skipped, and added to their playlists. With this data, they could develop algorithms that would recommend new music to users based on their preferences.

However, simply recommending music based on a user's listening history was not always enough. Users often listen to music to match their current mood and their music taste largely varies based on their personal tastes. To address this, we are building a music recommendation system using sentiment analysis of a user's social media.

### 3.1. Product Features

Twitter Data Collection: The product collects data from Twitter and analyzes different tweets of the specified user..

Sentiment Analysis: The product uses machine learning algorithms to analyze the emotional tone of tweets, determining whether they are positive, negative, or neutral.

Music Recommendations: Based on the sentiment analysis of tweets, the product recommends songs that match the emotional tone of the tweets.

Personalization: Technique that involves analyzing a person's personality and emotions to make personalized music recommendations. Personalization in music recommendation using sentiment analysis can enhance the user experience and increase engagement with music streaming services by providing personalized music recommendations that align with a person's emotional state.

### 3.2. User Classes and Characteristics

Various user classes that may use this product include:

- *Music Enthusiasts:* This user class is likely to use the system to discover new music and get personalized recommendations based on their emotional state. They may be avid music listeners and use the system to explore new genres or artists that align with their preferences.
- *Mood-based listeners:* This user class is likely to use the system to find music that matches their mood or emotional state. They may use the system to find music that calms them down when they are feeling anxious or music that pumps them up when they are feeling low.

- *Music Event Organizers:* This user class is likely to use the system to curate playlists and recommend music for events. They may use the system to recommend music that matches the event's theme or helps create a particular ambiance.
- *Music therapists:* This user class is likely to use the system to recommend music for therapeutic purposes based on the emotional state of their clients. They may use the system to recommend music that helps their clients relax, focus or manage their emotions.

User classes can be distinguished based on different characteristics including:

- *Frequency of use:* Users may use the system frequently - on a daily basis while others may only use it occasionally. The frequency of use may impact the level of personalization required for each user and the amount of data that can be collected to improve recommendations.
- *Functionality:* Different user classes may require different levels of functionality from the system. For example, fitness enthusiasts may require features like workout tracking and integration with fitness apps, while music event organizers may need features for creating playlists and recommending music for specific events.
- *Technical capability:* Some users may be more tech savvy than others and may require more advanced features or customization options. For example, music therapists may need more fine-grained control over the types of music recommended to their clients, while casual listeners may prefer a simpler user interface.
- *Security:* Some users may have higher security needs, such as music event organizers who may require the system to have strong data privacy and protection features to keep attendee information secure.

### 3.3. Operating Environment

Hardware platform: 8 GB RAM,  above i4 processor

Operating system and versions: Windows 10, macOS

Software platform: Python, Google Colab

### 3.4. General Constraints, Assumptions and Dependencies

- Regulatory Policies: Music recommendation systems need to comply with various regulations, such as copyright laws and data privacy regulations. These policies may limit the types of data that can be used to train the sentiment analysis models or the sources of music data that can be used for recommendations.
- Hardware Limitations: The performance of sentiment analysis models and the speed of music recommendation algorithms can be limited by the hardware capabilities of the system. If real-time music recommendations are required, the system may need to meet certain signal timing requirements, which can limit the hardware choices available to the developers.

- Limitations of Simulation Programs: Simulation programs used to test the performance of the sentiment analysis models and music recommendation algorithms. However, these programs may not accurately simulate real-world scenarios, which can limit the choices available to developers in terms of testing and refining the system.
- Interfaces with Other Applications: Music recommendation systems need to interface with other applications, like social media sites, to access user data or to produce recommendations. These interfaces may be limited by integration options provided by these applications, which can impact the design and functionality of the music recommendation system.
- Criticality of Application: The criticality of the music recommendation system can also limit the choices available to developers. If the system is used in safety-critical applications such as healthcare, certain performance or reliability requirements may need to be met, which can impact the design and implementation of the system.
- Safety and Security Considerations: Sentiment analysis models and music recommendation systems need to be designed with safety and security considerations in mind. The system needs to protect user data or prevent the recommendation of inappropriate or offensive content. These considerations can limit the types of data that can be used for training or the sources of music data that can be used for recommendations.

### 3.5. Risks

There are several risks associated with resource requirements and functionality in a music recommendation system that uses sentiment analysis on tweets:

- Scalability: The system may not be able to handle large volumes of data, leading to slower response times or even system failures.
- Accuracy: Sentiment analysis is not 100% accurate, and incorrect analysis could lead to inaccurate recommendations. The system must continuously monitor and improve the accuracy of its analysis.
- Bias: The sentiment analysis algorithm may have biases due to the training data used, leading to recommendations that are skewed towards certain demographics or genres of music.

## 4. Functional Requirements

- Validity Tests on Inputs: The system should perform validity tests on the input data obtained from Twitter, including checks for missing data, invalid characters, and spam or irrelevant tweets. The system should also ensure that the input data meets any necessary formatting requirements.

- Sequence of Operations: The system should be designed to perform the required operations in the correct sequence to generate accurate and timely music recommendations. The sentiment analysis should be performed before user and music classification to ensure that the recommended music matches the sentiment of the tweets.
- Error Handling and Recovery: The system should have robust error handling and recovery mechanisms in place to handle any unexpected errors or failures. For example, if the sentiment analysis model fails to analyze a tweet, the system should have a fallback mechanism to ensure that the tweet is not ignored and that the recommendation process continues.
- Consequences of Parameters: The system should consider the consequences of the parameters used in the sentiment analysis and music recommendation algorithms. For example, the weight given to positive versus negative sentiment in the recommendation algorithm may impact the overall recommendations generated by the system.
- Relationship of Outputs to Inputs: The system should ensure that the music recommendations generated are relevant and consistent with the sentiment of the tweets. The relationship between the inputs (tweets) and the outputs (music recommendations) should be transparent and understandable to the user, to build trust and confidence in the system.

## 5. External Interface Requirements

### 5.1. User Interfaces

- Required screen formats with GUI standards : The screen format should be simple and straightforward. The interface should be designed using standard GUI styles and will include features such as buttons and text fields.
- Screen layout and standard functions: The screen layout should be organized and easy to navigate. Standard functions such as help should be provided to assist users in using the system effectively.
- Relative timing of inputs and outputs: The system will be responsive and provide timely outputs to user inputs. The time taken to process user inputs and provide recommendations should be minimal to ensure a positive user experience.
- Availability of some form of programmable function key: Programmable function keys will be provided to allow users to customize the interface based on their preferences.
- Error messages: The system will provide clear and concise error messages to help users understand what went wrong and how to fix it. The error messages should be displayed in a prominent location on the screen to ensure users do not miss them.

### 5.2. Hardware Requirements

- Memory: Around 8 GB of RAM.
- Network: High-speed internet connection with minimum bandwidth of 20 Mbps.
- Processor: A multi-core processor with a clock speed of 2.0 GHz or higher.

### 5.3. Software Requirements

For each required product the following shall be provided,

- The software is developed for all devices running on web servers on devices which are able to connect to the internet.
- The application makes use of some third -party resources, such as required data from Kaggle.
- The application also extracts the user's social media (tweets) from their account.
- The application will also make use of a Database to handle the backend, where the data in relation to the music as well as sentiment analysis will be stored. The database will be a SQL database.
- Operating Systems on which this can be used are Windows 10 and above, macOS
- Tools and libraries used will include scraping tools like Snscrape and Tweepy, Apify, tensorflow, keras

### 5.4. Communication Interfaces

The communication interfaces for the application will be:

- Any queries can be e-mailed to the address provided in the help and feedback section of the application.
- A live chat session can be incorporated for users who have issues which need to be resolved with immediate effect.
- The application will need the user to be connected to the internet for installation of updates over 50 MB.
- A helpline number can also be provided for attending to queries and feedback.

## 6. Non-Functional Requirements

### 6.1. Performance Requirements

- Accuracy: The system should have a reasonable level of accuracy in recommending music based on the sentiment analysis of tweets. It should be able to accurately classify the preferences of the user based on their tweets and recommend appropriate music.
- Speed: The system should be able to recommend music quickly and efficiently. Users should not have to wait for a long time to receive recommendations.

- Scalability: The system should be able to handle a large volume of users and tweets. As the number of users and tweets increases, the system should be able to handle the load without any decrease in performance.
- Reliability: The system should be reliable and consistent in its recommendations. It should not recommend inappropriate music or fail to recommend music altogether.
- Robustness: The system should be able to handle unexpected inputs, errors, and exceptions gracefully. It should be able to recover from errors and continue functioning without any significant impact on performance.
- Availability: The system should be available to users at all times. It should have a high level of uptime and should be able to handle high levels of traffic without any downtime.

### 6.2. Safety Requirements

- Ethical considerations: The system should ensure that the recommendations made are ethical and do not promote offensive or discriminatory content.
- User safety: The system should ensure the user's safety and prevent the spread of harmful malware or inappropriate content. This can include using secure data storage practices and filtering out offensive language.
- User consent: The system should obtain user consent before capturing and analyzing their tweets. Users should be informed about the purpose of the system and the data that will be collected and used.

### 6.3. Security Requirements

- Data privacy: The system should ensure that user data is kept private and confidential. It should not share or expose user data to unauthorized persons or entities.
- Authentication: The system should require user authentication to prevent unauthorized access. Users should be required to provide valid credentials, such as usernames and passwords, to access the system.
- Secure Data Storage: Store data in a secure manner to prevent data breaches and cyber attacks.

## 7. Other Requirements

- Scalability: The system should be able to handle a large volume of users and tweets. As the number of users and tweets increases, the system should be able to handle the load without any decrease in performance.
- Monitoring and reporting: The system should be monitored regularly for any security breaches or safety concerns. If any safety concerns are identified, they should be reported immediately to relevant stakeholders.
- Portability: We are building a web application so it can be accessed anywhere on any device connected to the internet.

## Appendix A: Definitions, Acronyms and Abbreviations

- API: Application Programming Interface
- BERT: Bidirectional Encoder Representations from Transformers- pre-trained natural language processing model
- CNN: Convolutional Neural Network - deep learning neural network sketched for processing structured arrays of data such as portrayals.
- DCNN: Dilated Convolution Neural Networks - deep learning models that use a convolution operation with increased gaps between the input feature maps to increase the receptive field without increasing the number of parameters
- GB: GigaBytes
- MB: MegaBytes
- GloVe: Global Vectors for Word Representation - an unsupervised learning algorithm for obtaining vector representations for words.
- LSTM: Long Short-Term Memory networks - a variety of recurrent neural networks that are capable of learning long-term dependencies.
- RAM: Random-access memory
- SQL: Structured Query Language - used to access and manipulate databases
- TF-IDF: Term Frequency-Inverse Document Frequency - a measure that can quantify the importance or relevance of string representations in a document amongst a collection of documents
- USE: Universal Sentence Encoder - encodes text into high dimensional vectors that can be used for text classification, semantic similarity, clustering, and other natural language tasks

## Appendix B: References


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