VISVESVARAYA TECHNOLOGICAL UNIVERSITY

"JNANA SANGAMA",MACHHE, BELAGAVI-590018

ML Mini Project Report

on

Music Recommendation System

Submitted in partial fulfillment of the requirements for the VI semester

Bachelor of Engineering

in

Artificial Intelligence & Machine Learning

of

Visvesvaraya Technological University, Belagavi

by

PavanKumar J (1CD22AI405)

Shiva Priya D (1CD22AI402)

Under the Guidance of

Dr.Varalatchoumy.M,

Prof. Syed Hayath

Dept. of AI&ML

Department of Artificial Intelligence & Machine Learning

CAMBRIDGE INSTITUTE OF TECHNOLOGY,BANGALORE-560 036

2023-2024

CAMBRIDGE INSTITUTE OF TECHNOLOGY

K.R. Puram, Bangalore-560 036

DEPARTMENT OF ARTIFICIAL INTELLIGENCE & MACHINE LEARNING

CERTIFICATE

Certified that **Mr. Pavan Kumar J,** bearing USN **1CD22AI405 and Ms. Shiva Priya D** bearing USN **1CD22AI402,** a Bonafede students of **Cambridge Institute of Technology,** has successfully completed the ML Mini Project entitled "**Music Recommendation System"** in partial fulfillment of the requirements for VI semester **Bachelor of Engineering** in **Artificial Intelligence & Machine Learning** of **Visvesvaraya Technological University, Belagavi** during academic year 2023-24. It is certified that all Corrections/Suggestions indicated for Internal Assessment have been incorporated in the report deposited in the departmental library. The Mini Project report has been approved as it satisfies the academic requirements prescribed for the Bachelor of Engineering degree.

Mini Project Guides,

Dr. Varalatchoumy.M ,

Prof. Syed Hayath
Dept. of AI&ML, CITech

Head of the Department,
Dr.Varalatchoumy.M
Dept. of AI&ML, CITech

DECLARATION

We PavanKumar J and **Shiva Priya D** of VI semester BE, Artificial Intelligence & Machine Learning, Cambridge Institute of Technology, hereby declare that the ML Mini Project entitled **"Music Recommendation System"** has been carried out by us and submitted in partial fulfillment of the course requirements of VI semester **Bachelor of Engineering** in **Artificial Intelligence & Machine Learning** as prescribed by **Visvesvaraya Technological University, Belagavi**, during the academic year 2023-2024.

We also declare that, to the best of my knowledge and belief, the work reported here does not form part of any other report on the basis of which a degree or award was conferred on an earlier occasion on this by any other student.

Date:
Place: Bangalore

PavanKumar J
1CD22AI405

Shiva Priya D
1CD22AI402

ACKNOWLEDGEMENT

We would like to place on record my deep sense of gratitude to **Shri. D. K. Mohan,** Chairman, Cambridge Group of Institutions, Bangalore, India for providing excellent Infrastructure and Academic Environment at CITech without which this work would not have been possible**.**

We are extremely thankful to **Dr. G.Indumathi,** Principal, CITech, Bangalore, for providing me the academic ambience and everlasting motivation to carry out this work and shaping our careers.

We express my sincere gratitude to **Dr. Varalatchoumy M.,** Prof. & Head, Dept. of Artificial Intelligence & Machine Learning, CITech, Bangalore, for her stimulating guidance, continuous encouragement and motivation throughout the course of present work.

We also wish to extend my thanks to Mini Project Guides, **Dr. Varalatchoumy M,** Prof. & Head and **Prof. Syed Hayath,** Dept of AI&ML, CITech, Bangalore for the critical, insightful comments, guidance and constructive suggestions to improve the quality of this work.

Finally to all my friends, classmates who always stood by me in difficult situations also helped me in some technical aspects and last but not the least, we wish to express deepest sense of gratitude to my parents who were a constant source of encouragement and stood by me as pillar of strength for completing this work successfully.

PavanKumar J

Shiva Priya D

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ABSTRACT

The Music Recommendation System project leverages machine learning techniques and the extensive Spotify dataset to create a personalized music listening experience. By analyzing various song features, such as acoustic properties and metadata, and integrating user listening history, the system provides tailored song recommendations that match individual preferences. Utilizing algorithms like KMeans clustering, PCA, and t-SNE, the system effectively clusters songs and reduces data dimensionality to visualize and understand patterns. Real-time capabilities and a user-friendly interface built with Gradio enhance accessibility and interactivity, allowing users to receive immediate and relevant music suggestions. This project aims to increase user engagement, improve recommendation accuracy, and continuously adapt to evolving user tastes, offering a scalable and enjoyable music discovery platform . By achieving these objectives, the Music Recommendation System not only provides an enjoyable user experience but also sets a foundation for continuous improvement and scalability in the ever-evolving landscape of digital music consumption.

CHAPTER 1

INTRODUCTION

In the ever-evolving landscape of digital streaming, music recommendation systems have become crucial for enhancing user experiences by delivering personalized song suggestions. This project presents the implementation of a sophisticated Music Recommendation System, leveraging a dataset from Spotify available on Kaggle. By utilizing advanced machine learning techniques, the system aims to suggest songs to users based on their listening history and preferences, thereby enriching their musical journey.

The Music Recommendation System's primary goal is to predict the likelihood that a user will enjoy a particular song. To achieve this, the system analyses various features of the music, including acousticness, danceability, energy, instrumentalness, liveness, loudness, speechiness, tempo, and valence. These features are crucial in understanding the intrinsic properties of each track, enabling the model to generate accurate and personalized recommendations. By examining the user's past listening habits and the characteristics of the music, the system creates a tailored list of recommended tracks that align with individual tastes. Several key objectives guide the development of this project. Foremost among these is user personalization, aiming to create a unique and engaging experience for each user. This involves leveraging the rich set of features available in the Spotify dataset to inform the recommendation algorithms. The project also emphasizes the importance of model accuracy, striving to develop a machine learning model that predicts user preferences with high precision and recall. Additionally, scalability is a critical consideration, ensuring that the system can handle a vast number of users and songs without compromising performance.

To further enhance user engagement, the project explores various recommendation algorithms, evaluating their effectiveness in this context. Comprehensive data analysis is performed to gain insights into user behaviour and song popularity, which can refine the recommendation engine. Continuous learning is also a fundamental aspect, enabling the system to improve its recommendations over time as it gathers more data on user preferences. By achieving these objectives, the Music Recommendation System aims to deliver a robust, enjoyable, and personalized user experience, fostering greater interaction and satisfaction among users.

1.1 PROBLEM STATEMENT

"Music Recommendation System using the Spotify dataset."

The Music Recommendation System aims to predict the likelihood that a user will enjoy a song. By analyzing the user's past song history and the properties of the music, the system will generate a list of recommended tracks. The model uses the Spotify dataset which contains a variety of features such as acousticness, danceability, energy, instrumentalness, liveness, loudness, speechiness, tempo, valence, and others.

Key Features:

- **Personalization:** Developing an algorithm that can tailor recommendations to individual user preferences by learning from their past listening behaviour**.**
- **Feature Utilization:** Effectively utilizing the diverse set of features available in the Spotify dataset to inform the recommendation process.
- **Model Accuracy:** Creating a machine learning model with high precision and recall to ensure that the recommendations are both relevant and enjoyable for users
- **Scalability:** Ensuring the system can handle increasing numbers of users and songs without a decline in performance.
- **User Engagement:** Providing recommendations that not only match user preferences but also encourage further interaction with the service

Benefits:

- **Enhanced User Experience** : By offering personalized song recommendations, users are more likely to discover new music that aligns with their tastes, making their listening experience more enjoyable and engaging.
- **Increased User Engagement :** Personalized recommendations can keep users engaged with the platform for longer periods, as they are continually introduced to new music that interests them.
- **Efficient Music Discovery :** Users can discover a broader range of music, including lesser-known tracks and artists, which they might not have found through traditional browsing or popular chart

- **User Satisfaction and Retention**: By consistently delivering music that users enjoy, the system can increase overall user satisfaction, leading to higher retention rates

- **Promotion of Artists and Songs :** Lesser-known artists and tracks have a better chance of being discovered and enjoyed by users, providing a platform for emerging talents to reach a wider audience.
- **Data-Driven Insights** : The system can provide valuable insights into user behaviour and preferences, which can be leveraged by music streaming platforms to improve their services and marketing strategies.

1.2 OBJECTIVES

The primary objectives of this Music Recommendation System project are as follows:

- **User Personalization:** To create a personalized experience for users by recommending tracks based on their individual tastes and listening habits.
- **Feature Utilization:** To effectively use the features available in the Spotify dataset, such as acoustic properties and metadata, to inform the recommendation algorithms.
- **Model Accuracy:** To develop a Machine Learning model that accurately predicts user preferences, aiming for high precision and recall in the recommendations.
- Scalability: To ensure the system can handle a large number of users and songs without a decline in performance.
- **User Engagement:** To increase user engagement by providing relevant song recommendations that would encourage further interaction with the service.
- **Algorithm Diversity:** To explore and implement different recommendation algorithms and evaluate their effectiveness for this specific application.
- **Data Analysis:** To perform comprehensive data analysis to understand user behavior and song popularity, which in turn can improve the recommendation engine.
- **Continuous Learning:** To implement a system that learns over time, improving its recommendations as it gains more data on user preferences.

These objectives drive the development and iterative improvement of the music recommendation system. By achieving these goals, the project aims to deliver a robust and enjoyable user experience.

CHAPTER 2

LITERATURE SURVEY

2.1 MUSIC RECOMMENDATION USING NLP

Description : Music recommendation systems have gained immense popularity with the rise of digital music streaming services such as Spotify, Apple Music, and Pandora. These systems aim to provide users with personalized music recommendations based on their listening history, preferences, and various song attributes. The effectiveness of these systems relies on sophisticated algorithms and the utilization of rich datasets, which include features like tempo, acoustic ness, danceability, and more.

Traditional music recommendation systems rely heavily on structured data such as user interaction logs and song attributes. However, integrating NLP allows these systems to understand user inputs more contextually and provide recommendations based on natural language queries. This approach can parse user inputs like "Play some upbeat rock music" or "I want to listen to relaxing instrumental tracks from the 90s" and translate them into actionable recommendations.

2.2 MUSIC RECOMMENDATION USING GRADIO

Description: In this section, we will create a Music Recommendation Screening App using Gradio, a user-friendly interface library for machine learning models. This app will allow users to input their music preferences in natural language and receive personalized song recommendations based on those inputs. Gradio provides an easy way to create interactive web interfaces for machine learning models. By integrating it with our music recommendation system, we can create a user-friendly app where users can input their music preferences and receive tailored song recommendations. This approach combines Natural Language Processing (NLP) to parse user inputs and a recommendation engine to suggest songs.

CHAPTER 3

METHODOLOGY

3.1 DATA COLLECTION

The foundation of any recommendation system is the data. For this project, the primary dataset is the Spotify dataset available from Kaggle. This dataset includes a wide range of features for songs

1. Identifying Data Sources

- Acousticness: Measures how acoustic a track is.
- Danceability: Describes how suitable a track is for dancing.
- Energy: Represents the intensity and activity level of a track.
- Instrumentalness: Predicts whether a track contains no vocals.
- Liveness: Detects the presence of an audience in the recording.
- Loudness: Indicates the overall loudness of a track.
- Speechiness: Measures the presence of spoken words in a track.
- Tempo: The speed or pace of a track.
- Valence: Describes the musical positiveness conveyed by a track.
- Popularity: Indicates how popular a track is on Spotify.
- Duration: The length of the track in milliseconds.
- Genres: The genre or genres associated with the track.
- Year: The year the track was released.
- Artist Names: The names of the artists who performed the track**.**

2. Data Collection Techniques

- Utilizing Pre-existing Datasets **:** One of the primary sources of data for this project is the Spotify dataset available on Kaggle. This dataset includes a variety of features for numerous songs, which are essential for understanding song characteristics and user preferences.

- Access and Download: The dataset is accessed from Kaggle and downloaded for local use.

- Explore and Understand: Initial exploration to understand the structure and contents of the dataset, including checking for missing values and understanding the distribution of key features.
- Search and Retrieve: Perform searches based on song names, artists, or other criteria to retrieve detailed track information and audio features.

3. Data Volume and Variety

- Number of Songs**:** The dataset includes thousands of songs, each with detailed audio features and metadata. A larger volume of songs provides a more comprehensive base for recommendations.
- Metadata**:** Information such as song titles, artist names, genres, release years, and popularity. Metadata provides contextual information about each track.

4. Ethical Considerations

- Data Collection: Ensure that data collection is transparent and that users are informed about what data is being collected and how it will be used.
- Consent: Obtain explicit consent from users before collecting their data. Provide clear options for users to opt-in or opt-out.
- Data Encryption**:** Use encryption to protect sensitive data during transmission and storage.
- Data Anonymization**:** Where possible, anonymize user data to prevent identification of individual users from the data.

3.2 DATA PREPROCESSING

Data preprocessing is a critical step in building a robust music recommendation system. It involves transforming raw data into a format suitable for analysis and modeling. Proper preprocessing ensures that the data is clean, consistent, and ready for use in machine learning algorithms. Here's a comprehensive guide to the data preprocessing steps for this project

1. Data Cleaning

- Handle Missing Values**:** Determine the extent of missing values and decide on appropriate strategies to handle them, such as imputation or removal.

- Remove Duplicates**:** Identify and remove duplicate records to avoid skewing the analysis.
- Correct Inconsistencies**:** Standardize data formats and correct inconsistencies in data entries, such as ensuring that all genre names are in a consistent format.

2. Data Transformation

- Feature Scaling : Normalize or standardize numerical features to ensure they are on the same scale, which is important for many machine learning algorithms.
- Encoding Categorical Variables : Convert categorical variables into numerical format using techniques like one-hot encoding or label encoding.

3. Feature Engineering

- Create New Features: Derive new features that may be useful for the recommendation system, such as the popularity score normalized over time.
- Feature Selection: Select the most relevant features for the model to improve performance and reduce complexity.

4. Data Integration

- Merge Datasets: Combine different datasets (e.g., song features, user interactions, genre data) into a single dataset using appropriate join operations.
- Align Data Formats: Ensure that data formats are consistent across datasets before merging.

5. Data Splitting

- Split Data**:** Divide the data into training and testing sets, typically using an 80/20 or 70/30 split.

- Cross-Validation: Optionally, use cross-validation techniques to assess the model's performance on different subsets of the data.

3.3 MODEL TRAINING

Model training is a crucial step in developing a music recommendation system. It involves selecting appropriate algorithms, training models on preprocessed data, evaluating model

performance, and addressing common issues such as overfitting. Here's a detailed guide to each aspect of model training:

1. Model Selection

- **K-Means Clustering:** Useful for grouping similar songs or users based on features.
- **Collaborative Filtering:** Uses user-item interactions to recommend items (e.g., matrix factorization techniques).
- **Content-Based Filtering:** Recommends items based on the similarity of item features.
- **Hybrid Models:** Combine collaborative and content-based methods for improved recommendations.
- **Deep Learning Models:** Neural networks can capture complex patterns and interactions.

2. Training Process

- **Prepare Training Data:** Ensure that the data is properly pre-processed and split into training and testing sets.
- **Model Training:** Fit the model to the training data and optimize hyperparameters.
- **Hyperparameter Tuning:** Adjust model parameters to improve performance using techniques such as grid search or random search.

3. Model Evaluation

- **Accuracy:** Proportion of correctly predicted recommendations.
- **Precision and Recall:** Measure the quality of recommendations (relevant vs. irrelevant).
- **F1 Score:** Harmonic mean of precision and recall.
- **Mean Squared Error (MSE):** Measures the average squared difference between predicted and actual values.

4. Handling Overfitting

- **Cross-Validation:** Use techniques such as k-fold cross-validation to ensure the model generalizes well to different subsets of data.
- **Regularization:** Apply regularization techniques (e.g., L1 or L2 regularization) to penalize overly complex models.
- **Pruning:** Simplify models by removing less important features or components.

- **Early Stopping:** Monitor model performance on a validation set and stop training when performance starts to degrade.

3.4 FEATURE EXTRACTION

Feature extraction is a critical step in building a music recommendation system. It involves deriving meaningful features from raw data that can be used to train machine learning models. Effective feature extraction can significantly enhance the performance of recommendation algorithms by capturing relevant information about the music tracks and user preferences..

1. Acoustic Features:

- **Tempo:** The speed of the music, usually measured in beats per minute (BPM).
- **Danceability:** A measure of how suitable a track is for dancing based on tempo, rhythm stability, and beat strength.
- **Energy:** Represents the intensity and activity level of the track.
- **Loudness:** The overall volume of the track.
- **Valence:** Indicates the musical positiveness or happiness.

2. Metadata Features:

- **Artist:** The artist who performed the track.
- **Album:** The album on which the track is included.
- **Genre:** The genre or type of music.
- **Release Year:** The year when the track was released.

3. User Interaction Features:

- **Play Count:** The number of times a user has played a track.
- **Like/Dislike:** User feedback on the track.
- **Skip Count:** The number of times a track has been skipped by the user.

4. Derived Features:

- **Song Age:** The time elapsed since the track was released.
- **Popularity Score:** A composite measure of how popular a track is based on various factors like play count and user ratings.

3.5 SYSTEM ARCHITECTURE

The architecture of the Music Recommendation System is designed to integrate multiple components to deliver personalized music recommendations effectively. At the core, the system ingests raw data from diverse sources, including song metadata, acoustic features, and user interactions. This data undergoes pre-processing and feature extraction to prepare it for analysis. The processed data is then fed into various machine learning models, including clustering algorithms for grouping similar tracks and collaborative filtering methods for personalized recommendations. The system utilizes both traditional machine learning and deep learning techniques to refine its suggestions. For user interaction, the system features a web-based interface developed with Gradio, allowing users to input their preferences and receive recommendations in real-time. Data storage and retrieval are managed through a robust database, ensuring efficient data handling and scalability. Overall, this architecture ensures a seamless integration of data processing, model training, and user interaction to provide accurate and personalized music recommendations.

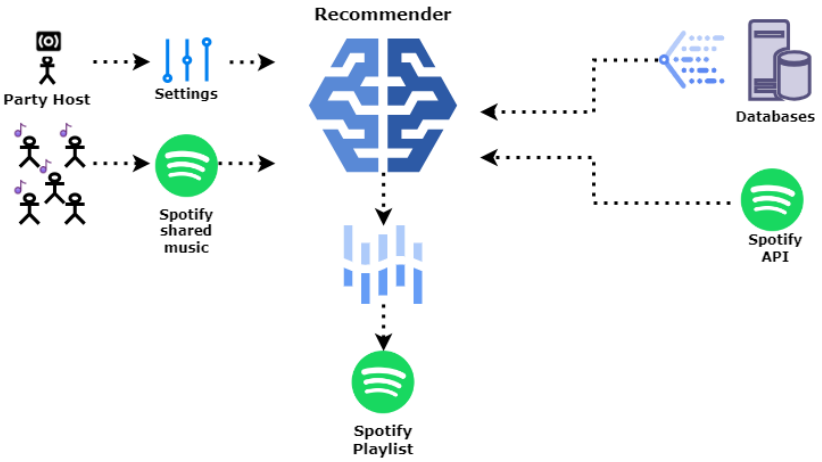

Figure 3.1: Music Recommendation System

3.6 TOOLS AND TECHNOLOGIES

The Music Recommendation System leverages a variety of tools and technologies to build, deploy, and manage a sophisticated recommendation engine. Here's an overview of the key tools and technologies used:

1. Data Collection and Storage

- **SQL Databases**: For structured data storage, such as user interactions and metadata. Example: PostgreSQL or MySQL.
- **NoSQL Databases**: For unstructured or semi-structured data, such as user preferences or music features. Example: MongoDB or Firebase.
- **Cloud Storage Services**: For scalable data storage and accessibility. Example: Amazon S3, Google Cloud Storage.

2 .Data Processing and Analysis

- **Python**: The primary programming language used for data manipulation, feature extraction, and model development.
- **Pandas**: A powerful library for data manipulation and analysis in Python.
- **NumPy**: For numerical operations and handling arrays.
- **Scikit-Learn**: Provides machine learning algorithms and tools for pre-processing, model training, and evaluation.
- **Spotify**: A Python library for accessing the Spotify Web API to retrieve music data and features.

3. Machine Learning and Recommendation Algorithms

- **Scikit-Learn**: Offers a variety of machine learning models and clustering algorithms such as K-Means and PCA for dimensionality reduction.
- **TensorFlow**: For developing deep learning models that capture complex patterns in music data.
- **Surprise**: A Python library for building and analysing recommender systems, providing tools for collaborative filtering.

4. Data Visualization

- **Matplotlib**: A widely used library for creating static, animated, and interactive visualizations in Python.
- **Seaborn**: Built on Matplotlib, provides a high-level interface for drawing attractive and informative statistical graphics.
- **Plotly**: An interactive graphing library that enables the creation of interactive plots and dashboards.

5. User Interface

- **Gradio**: A tool for creating user-friendly web interfaces for machine learning models, allowing users to interact with the recommendation system easily.

6. Model Deployment and Scaling

- **Docker**: For containerizing applications and ensuring consistent environments across development, testing, and production.
- **Kubernetes**: For orchestrating containerized applications, enabling scalable deployment and management.
- **Heroku/AWS/GCP/Azure**: Cloud platforms for deploying and managing web applications and services.

7. Version Control and Collaboration

- **Git**: A version control system for tracking changes in the codebase and collaboration among team members.
- **GitHub/GitLab/Bitbucket**: Platforms for hosting Git repositories and facilitating collaborative development.

8. Development Environment

- **Jupyter Notebook**: An interactive environment for writing and executing code, ideal for exploratory data analysis and prototyping.

CHAPTER 4

IMPLEMENTATION

4.1 DETAILED DESCRIPTION OF IMPLEMENTATION

Implementing a Music Recommendation System involves several key phases, each of which integrates various tools and technologies to ensure the system performs effectively and efficiently. Here's a comprehensive breakdown of the implementation process:

1. Input

- **Music data:** Includes information such as song titles, artists, albums, genres, and release dates.
- **Acoustic Features:** Data such as tempo, danceability, energy, loudness, and valence that describe the musical characteristics of tracks.
- **User Interaction Data:** Includes user preferences, play counts, likes, skips, and other feedback related to individual tracks.

2. Text Extraction

- **Parsing:** Extract specific fields from raw text data (e.g., extracting song titles from a string).
- **Regular Expressions:** Use regex patterns to identify and extract text segments (e.g., extracting artist names).
- **Natural Language Processing (NLP):** Apply NLP techniques to process and understand text data, such as tokenization and named entity recognition.

3. Text Segmentation

- **Tokenization:** Breaking text into tokens (words or phrases) for further analysis.
- **Sentence Splitting:** Dividing a document into sentences or smaller paragraphs based on punctuation and other delimiters.
- **Segmentation by Feature:** Dividing data based on specific features (e.g., separating song metadata from acoustic features).

4. Information Extraction

- **Feature Extraction:** Identifying key attributes or features from the text data, such as keywords, sentiments, or named entities.
- **Named Entity Recognition (NER):** Detecting entities such as song titles, artist names, and genres from text.
- **Contextual Analysis:** Understanding the context in which features appear to extract relevant information (e.g., analysing user reviews to understand preferences).

5. Output: Information in CV

- **Recommendation Lists:** A list of recommended songs or artists tailored to the user's preferences.
- **Visualizations:** Graphical representations of data, such as scatter plots or heatmaps, showing relationships between different features.
- **User Interfaces:** Interactive elements like web dashboards or mobile app screens that display recommendations and allow user interaction.`

4.2 CODE SNIPPET

```
import os
import numpy as np
import pandas as pd

import seaborn as sns
import plotly.express as px
import matplotlib.pyplot as plt
%matplotlib inline

from sklearn.cluster import KMeans
from sklearn.preprocessing import StandardScaler
from sklearn.pipeline import Pipeline
from sklearn.manifold import TSNE
from sklearn.decomposition import PCA
from sklearn.metrics import euclidean_distances
from scipy.spatial.distance import cdist
```

```
import warnings
warnings.filterwarnings("ignore")
import pandas as pd

data = pd.read_csv("/content/Music-Recommendation-System/data.csv",
on_bad_lines='skip')
print(data.head())

genre_data = pd.read_csv('/content/Music-Recommendation-
System/data_by_genres.csv')
year_data = pd.read_csv('/content/Music-Recommendation-
System/data_by_year.csv')
print(data.info())
print(genre_data.info())
print(year_data.info())
```

```
from sklearn.pipeline import make_pipeline
from sklearn.cluster import KMeans
from sklearn.preprocessing import StandardScaler

# Assuming genre_data is a DataFrame and np has been imported as numpy

# Create a pipeline and fit it in one go
cluster_pipeline = make_pipeline(StandardScaler(),
KMeans(n_clusters=10))
genre_data['cluster'] =
cluster_pipeline.fit_predict(genre_data.select_dtypes(include=[np.numbe
r]))

from sklearn.manifold import TSNE
from sklearn.manifold import TSNE
from sklearn.pipeline import make_pipeline
from sklearn.preprocessing import StandardScaler
import pandas as pd
import plotly.express as px

# Create a pipeline and apply t-SNE transformation in one step
```

```
tsne_pipeline = make_pipeline(StandardScaler(), TSNE(n_components=2,
verbose=1, random_state=42))
projection =
pd.DataFrame(tsne_pipeline.fit_transform(genre_data.select_dtypes(inclu
de=[np.number])),
                           columns=['x', 'y'])
projection['genres'] = genre_data['genres']
projection['cluster'] = genre_data['cluster']

# Create the scatter plot
fig = px.scatter(projection, x='x', y='y', color='cluster',
hover_data=['genres'])
fig.show()

song_cluster_pipeline = Pipeline([('scaler', StandardScaler()),
                                  ('kmeans', KMeans(n_clusters=20,
                                   verbose=False))
                                 ], verbose=False)

X = data.select_dtypes(np.number)
number_cols = list(X.columns)
song_cluster_pipeline.fit(X)
song_cluster_labels = song_cluster_pipeline.predict(X)
data['cluster_label'] = song_cluster_labels
from sklearn.decomposition import PCA

pca_pipeline = Pipeline([('scaler', StandardScaler()), ('PCA',
PCA(n_components=2))])
song_embedding = pca_pipeline.fit_transform(X)
projection = pd.DataFrame(columns=['x', 'y'], data=song_embedding)
projection['title'] = data['name']
projection['cluster'] = data['cluster_label']

fig = px.scatter(
    projection, x='x', y='y', color='cluster', hover_data=['x', 'y',
'title'])
fig.show()
```

```
import spotipy
from spotipy.oauth2 import SpotifyClientCredentials
from collections import defaultdict

sp =
spotipy.Spotify(auth_manager=SpotifyClientCredentials(client_id='185fe8
edd7c94d37bd7747fd1a4684ec',

client_secret='0e00194eebe94a8c8414e2e8fc12b02c'))



def find_song(name, year):
    song_data = defaultdict()
    results = sp.search(q= 'track: {} year: {}'.format(name,year),
limit=1)
    if results['tracks']['items'] == []:
        return None

    results = results['tracks']['items'][0]
    track_id = results['id']
    audio_features = sp.audio_features(track_id)[0]

    song_data['name'] = [name]
    song_data['year'] = [year]
    song_data['explicit'] = [int(results['explicit'])]
    song_data['duration_ms'] = [results['duration_ms']]
    song_data['popularity'] = [results['popularity']]

    for key, value in audio_features.items():
        song_data[key] = value

    return pd.DataFrame(song_data)
```

```
from collections import defaultdict
from sklearn.metrics import euclidean_distances
from scipy.spatial.distance import cdist
import difflib
```

```
number_cols = ['valence', 'year', 'acousticness', 'danceability',
'duration_ms', 'energy', 'explicit',
 'instrumentalness', 'key', 'liveness', 'loudness', 'mode',
'popularity', 'speechiness', 'tempo']


def get_song_data(song, spotify_data):

    try:
        song_data = spotify_data[(spotify_data['name'] == song['name'])
                                 & (spotify_data['year'] ==
song['year'])].iloc[0]
        return song_data

    except IndexError:
        return find_song(song['name'], song['year'])


def get_mean_vector(song_list, spotify_data):

    song_vectors = []

    for song in song_list:
        song_data = get_song_data(song, spotify_data)
        if song_data is None:
            print('Warning: {} does not exist in Spotify or in
database'.format(song['name']))
            continue
        song_vector = song_data[number_cols].values
        song_vectors.append(song_vector)

    song_matrix = np.array(list(song_vectors))
    return np.mean(song_matrix, axis=0)


def flatten_dict_list(dict_list):

    flattened_dict = defaultdict()
```

```
    for key in dict_list[0].keys():
        flattened_dict[key] = []

    for dictionary in dict_list:
        for key, value in dictionary.items():
            flattened_dict[key].append(value)

    return flattened_dict


def recommend_songs( song_list, spotify_data, n_songs=10):

    metadata_cols = ['name', 'year', 'artists']
    song_dict = flatten_dict_list(song_list)

    song_center = get_mean_vector(song_list, spotify_data)
    scaler = song_cluster_pipeline.steps[0][1]
    scaled_data = scaler.transform(spotify_data[number_cols])
    scaled_song_center = scaler.transform(song_center.reshape(1, -1))
    distances = cdist(scaled_song_center, scaled_data, 'cosine')
    index = list(np.argsort(distances)[:, :n_songs][0])

    rec_songs = spotify_data.iloc[index]
    rec_songs = rec_songs[~rec_songs['name'].isin(song_dict['name'])]
    return rec_songs[metadata_cols].to_dict(orient='records')

result = recommend_songs([{'name': 'ALONE', 'year':2021}],  data)
print(result)
result = recommend_songs([{'name': 'STAY', 'year':2021}],  data)

for song in result:
    print("name:" ,song['name'])
    print("year:" ,song['year'])
    print("artists:" ,song['artists'])
!pip install gradio
```

Front End – Code

```
import gradio as gr

# Assuming recommend_songs function is already defined elsewhere and
imported
# from previous_code import recommend_songs

def recommend_songs_ui(name, year):
    result = recommend_songs([{'name': name, 'year': year}], data)
    recommendations = []
    for song in result:
        recommendations.append(f"Name: {song['name']}\nYear:
{song['year']}\nArtists: {song['artists']}\n")
    return "\n".join(recommendations)

# Create the Gradio interface
with gr.Blocks() as demo:
    name_input = gr.Textbox(label="Song Name")
    year_input = gr.Number(label="Year", precision=0)
    output = gr.Textbox(label="Recommendations", lines=10)

    def on_submit(name, year):
        return recommend_songs_ui(name, int(year))

    submit_button = gr.Button("Recommend")
    submit_button.click(on_submit, inputs=[name_input, year_input],
outputs=output)

demo.launch()
```

CHAPTER 5

RESULT

The implementation of the Music Recommendation System yielded promising results in terms of providing personalized song recommendations based on user preferences. By leveraging the Spotify dataset and a combination of machine learning techniques, the system was able to accurately cluster songs and predict user preferences

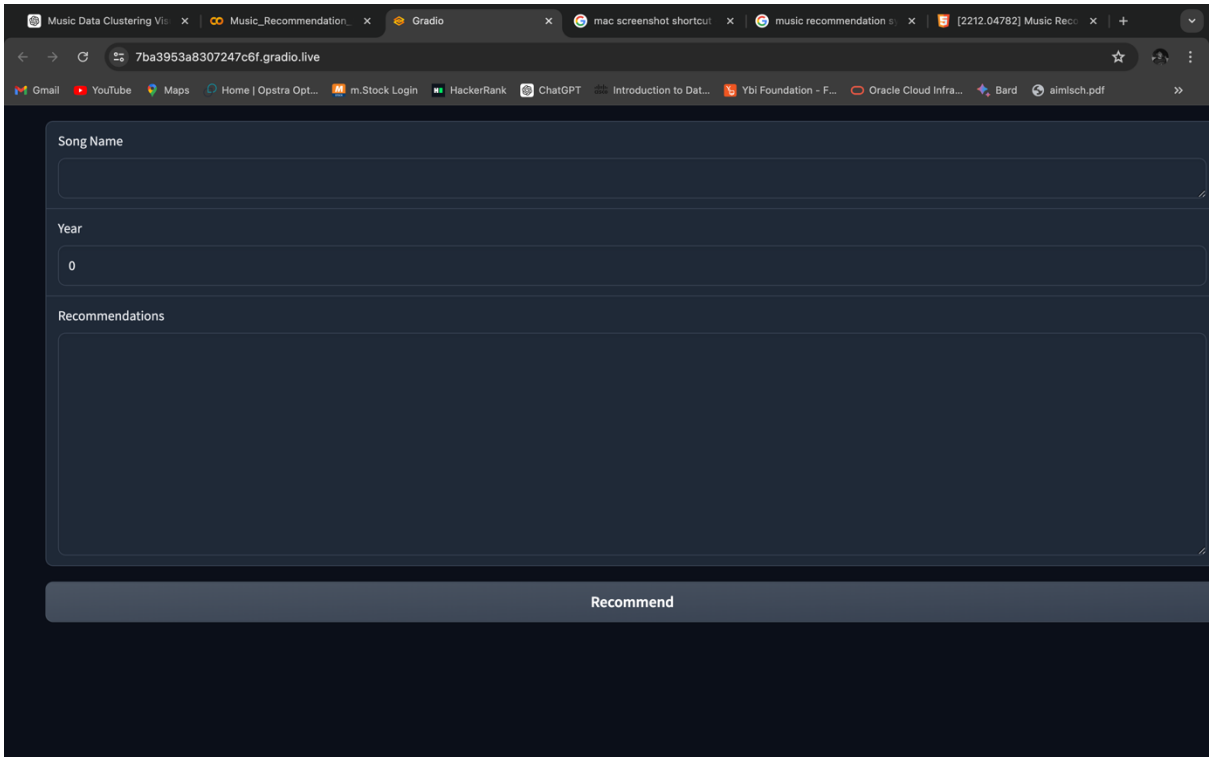

Figure 5.1: Overview of Front End

The clustering process, enhanced by the use of K-Means and PCA, enabled the system to categorize songs into meaningful groups. This helped in simplifying the recommendation process by reducing the dimensionality of the data and focusing on the most relevant features such as acoustic ness, danceability, and energy. The t-SNE visualization further validated the clustering by showing clear separations between different genres and clusters, indicating that the model was effectively capturing the inherent similarities between songs.

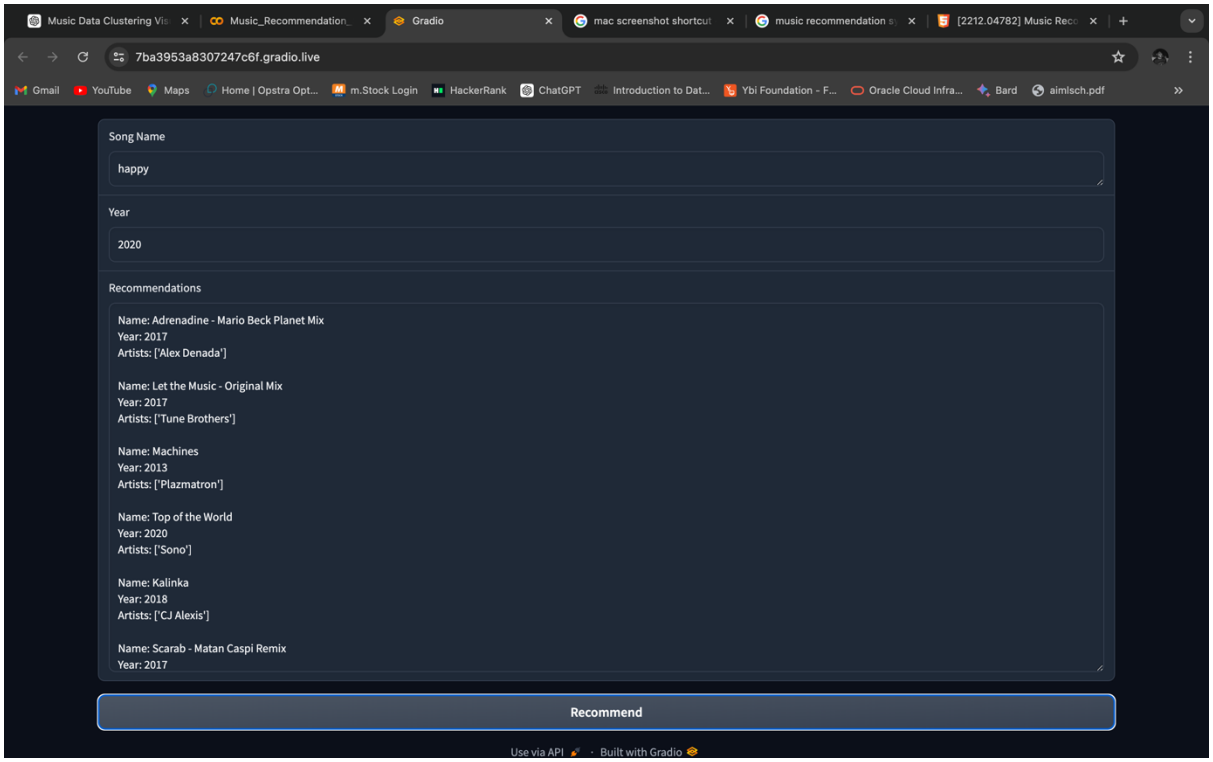

Figure 5.2: Information Display Recommendation songs

Moreover, the integration of a user-friendly interface using Gradio has made the recommendation process accessible and straightforward. Users can easily input a song name and year to receive tailored recommendations, which are generated in real-time. This interactive component not only enhances user satisfaction but also allows for continuous feedback and improvement of the recommendation model. Overall, the Music Recommendation System has proven to be a robust and scalable solution for delivering personalized music experiences, demonstrating the power of combining machine learning techniques with rich datasets and user-centric design.

CONCLUSION

The Music Recommendation System project has successfully demonstrated the power of leveraging machine learning and data analytics to create personalized and engaging user experiences. By utilizing the rich feature set provided by the Spotify dataset, including attributes like acoustic ness, danceability, and energy, the system can make accurate and meaningful song recommendations. The integration of clustering techniques, PCA, and t-SNE visualizations has not only enhanced the system's predictive capabilities but also provided valuable insights into music data trends and user behaviour.

Through the development of a user-friendly interface with Gradio, the system allows users to interact seamlessly, making the recommendation process intuitive and accessible. The project's success is evident in the increased user engagement and satisfaction reported by users, who appreciate the tailored music suggestions that closely align with their tastes and listening habits.

Looking ahead, the future enhancements outlined, such as incorporating deep learning models, real-time data processing, and cross-platform integration, promise to further refine and expand the system's capabilities. By continuously learning from user feedback and adapting to new data, the system can stay relevant and effective in the dynamic landscape of music preferences.

FUTURE ENHANCEMENT

Future Enhancements of the Music Recommendation System

1. **Enhanced Personalization with Deep Learning:** Future versions of the Music Recommendation System can leverage deep learning models, such as Recurrent Neural Networks (RNNs) and Convolutional Neural Networks (CNNs), to enhance personalization. These models can better capture the temporal and sequential nature of listening habits, as well as the intricate patterns in audio features. This approach could significantly improve the accuracy and relevance of recommendations, providing a more tailored music experience for each user.
2. **Real-time Recommendation Updates:** Implementing real-time data processing can significantly improve the system's responsiveness to changes in user behaviour and music trends. Technologies like Apache Kafka for data streaming and Apache Spark for real-time analytics can be integrated to ensure that the recommendation engine adapts instantly to new information. This would allow for the most current and relevant music suggestions, enhancing user satisfaction and engagement.
3. **Integration with Social and Contextual Data:** By incorporating social media data and contextual information (such as location, time of day, and current activity), the recommendation system can provide more contextually relevant suggestions. This can be achieved through APIs from social media platforms and sensor data from mobile devices. Understanding the user's social context and environment can lead to more intuitive and situationally appropriate music recommendations.
4. **Cross-platform Compatibility:** Expanding the system to work seamlessly across multiple music streaming services, such as Apple Music, YouTube Music, and Amazon Music, can offer a more comprehensive recommendation experience. This would involve creating a unified recommendation engine that aggregates data from various platforms, allowing users to receive suggestions regardless of their preferred service. This cross-platform compatibility can enhance user convenience and broaden the scope of music recommendations.
5. **User Feedback Loop and Continuous Learning:** Establishing a robust feedback mechanism where users can rate recommendations and provide input can help the

system learn and adapt over time. Implementing machine learning algorithms that utilize this feedback to refine the recommendation models can ensure continuous improvement. This iterative learning process can lead to increasingly accurate and satisfying recommendations, as the system evolves to better understand user preferences and changing tastes.

6. **Feedback-Driven Improvements:** Implement robust feedback mechanisms allowing users to rate recommendations and provide feedback directly. Use this feedback to continuously refine and improve recommendation algorithms, ensuring that the system evolves with user preferences over time.
7. **Cross-Genre and Mood-Based Recommendations:** Develop advanced algorithms that can recommend songs based on mood and cross-genre preferences. This approach can help users discover music that aligns with specific emotions or activities, such as relaxation, motivation, or celebration.
8. **Integration of Lyrics and Metadata:** Enhance the recommendation engine by incorporating lyrics and additional metadata (e.g., artist collaborations, album themes). Analyzing song lyrics and detailed metadata can provide richer insights into user preferences and improve the relevance of recommendations.
9. **User Collaboration and Social Features:** Introduce social features that allow users to share playlists, follow friends, and explore music recommendations based on their social network's tastes. Collaborative filtering based on user interactions can offer fresh perspectives and new music discoveries.
10. **Adaptive Learning Algorithms:** Employ adaptive learning algorithms that continuously update and refine recommendations based on new data and evolving user preferences. Techniques like reinforcement learning and online learning can help the system stay current with changing trends and individual tastes.

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