

AI-Powered Music Recommendation System

**Internship – Final Report**

Build an AI-powered recommendation system for a music streaming platform

MASTERS OF COMPUTER APPLICATION

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### Aim:

# BACKGROUND

Our project's objective is to create an AI-powered music streaming platform recommendation system. This system will employ data analytics techniques and machine learning algorithms to deliver customers personalized music recommendations based on their listening habits, interests, and activity. The principal goals encompass developing tailored suggestions, improving user satisfaction, streamlining content exploration, guaranteeing scalability and efficiency, and integrating flexibility and advancement into the recommendation framework.

### Technologies:

The following technologies are used in our project:

Python: Used for backend system implementation, machine learning model construction, and data processing.

SQL: Used for managing databases and retrieving data about user activities through queries. Task automation and resource management are two uses for shell scripting.

Libraries and Development Frameworks: Flask or Django for building web services and backend APIs, Scikit-learn for implementing assessment metrics and machine learning techniques, TensorFlow or PyTorch for building and optimizing neural network models, NumPy and Pandas for data processing and numerical computations, and Apache Spark for large-scale recommendation model training and distributed data processing.

Integrated Development Environment (IDE): Programming, debugging, and testing tools for machine learning models, such as PyCharm, Visual Studio Code, or Jupyter Notebook.

### Hardware Architecture:

For our project, the following hardware architecture is needed:

High-performance GPUs or CPUs: Required for deep learning model training to be successful. Memory (RAM): Enough memory to handle huge datasets and model training.

Storage: Enough room to accommodate datasets, project files, and model checkpoints. Internet access that is dependable for using cloud services, downloading datasets, and working remotely with colleagues.

### Software Architecture:

Gathering and preparing the data: Getting user interaction data from the music streaming service, cleaning and organizing the information, and getting it ready for analysis.

Feature engineering is the process of removing pertinent features—such as user demographics, popularity, genre, artist, and temporal patterns—from the data in order to construct user and object profiles.

Model Design and Selection: Creating the architecture for the recommendation system, choosing the best recommendation algorithms based on the requirements of the project and the characteristics of the data, and updating the user and item profiles.

Deployment & Integration: Assuring scalability, performance, and reliability, integrating learned recommendation models into the music streaming service's backend architecture, and putting the recommendation system into a live environment.

## Requirements

# System

**User authentication:** Users should be able to make accounts, safely log in, and manage their profiles, which include listening history and preferences. Support for authentication methods like OAuth or email/password is necessary to guarantee user security and privacy.

**Recommendation Generation:** A user's listening history, likes, dislikes, and created playlists should all be taken into account by the system when making tailored music recommendations. Algorithms for machine learning should examine user data to find trends and preferences so they can provide timely and pertinent recommendations.

**Content Discovery:** Using customized playlists, carefully chosen selections, and recommendations for lesser-known musicians, genres, or songs based on their preexisting likes, users should be able to discover new music content. To accommodate various user preferences, the system ought to give priority to diversity and variety in its recommendations.

## Application Design

The web application that powers the AI-powered music recommendation system can be accessed on PC and mobile devices. In order to provide the best possible user experience across a range of screen sizes and resolutions, the application uses responsive design. It uses a cutting-edge, aesthetically pleasing interface with simple navigation for fluid interaction.

## Process Flow

**User authentication** is the first step in the procedure, after which new users can create accounts or log in safely if they already have accounts.

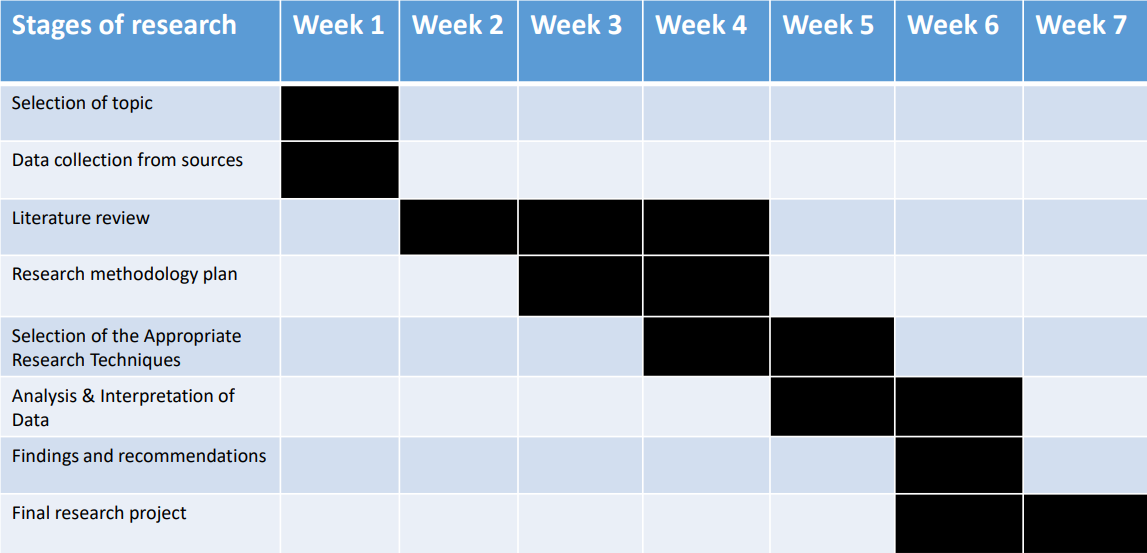
**Management of Profiles:** After a successful login, users have access to manage their accounts, listening histories, and preferences.

**Creation of suggestions:** Using user data analysis, the system creates customized music suggestions based on listening habits, interests, and activities.

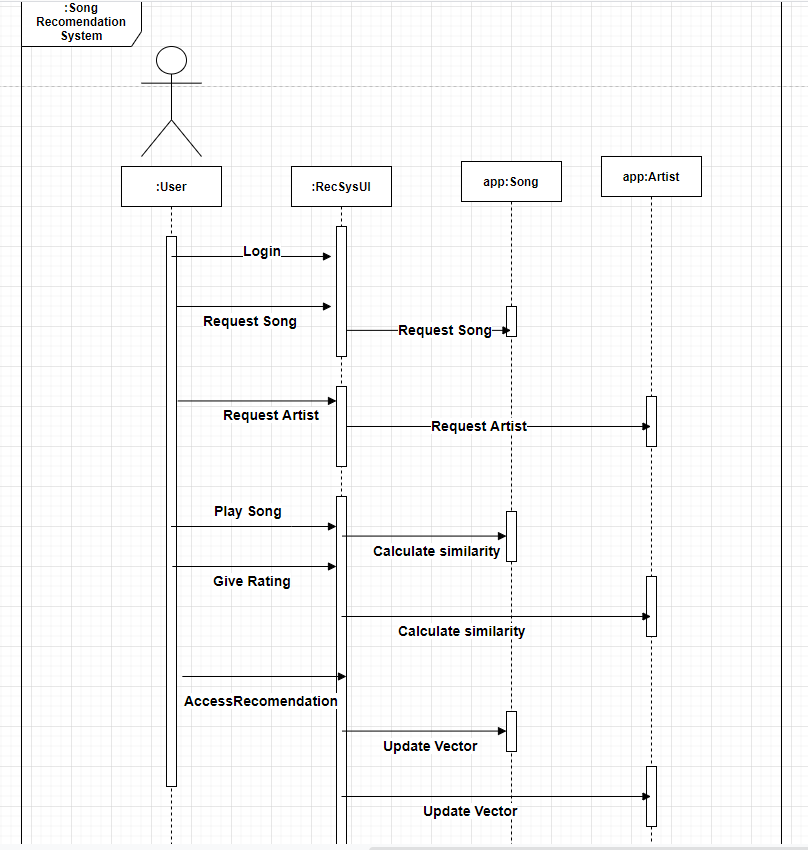
**material Discovery:** Users can interact with carefully chosen recommendations based on their preferences, listen to suggested playlists, and find new music material.

**Real-time Delivery:** Users receive recommendations in real-time with minimal latency, guaranteeing a smooth and responsive user experience.

## Progress Chart



## Sequence Diagram



## Components Design

**User Interface (UI):** Interactive features like search bars, cards with recommendations, tools for making playlists, and feedback forms are examples of UI components.

**Backend Services:** These services oversee content delivery, profile administration, user authentication, and recommendation creation.

**Database:** For effective data retrieval and storage, the system keeps user profiles, listening histories, music information, and recommendation models in a relational or NoSQL database. **Machine Learning Models:** ML models use techniques like collaborative filtering, content- based filtering, or hybrid approaches to assess user data and provide personalized suggestions. **APIs:** APIs enable data interchange and interaction between various system modules by facilitating communication between frontend and backend components.

## Key Design Considerations

The architecture and operation of the recommendation system are shaped by a number of important design factors. These include performance optimization to ensure quick response times and low latency, scalability to handle an expanding user base and rising data volumes, security measures to safeguard user data and privacy, adaptability to changing user preferences and market trends, and customization options that let users personalize their experience based on their interests and preferences.

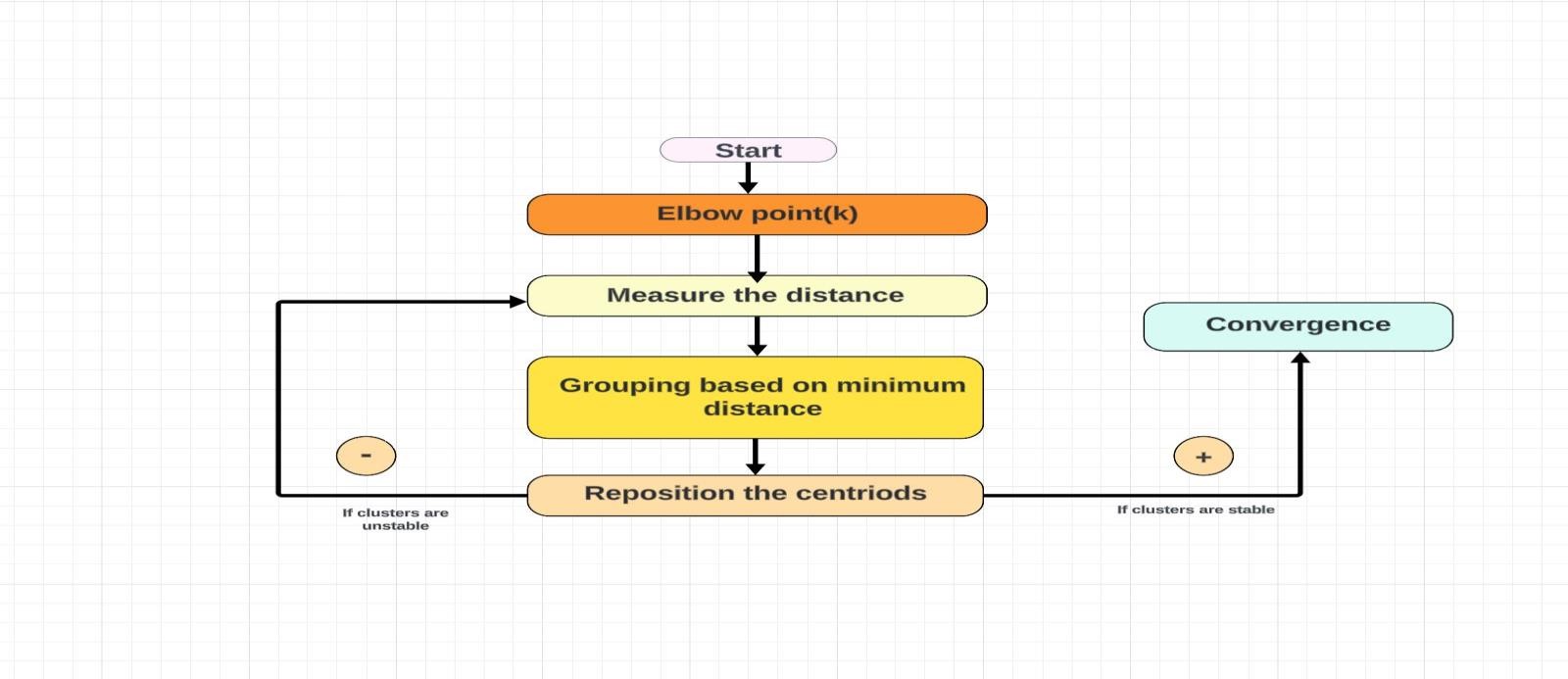
## Interfaces

Both user-facing and backend APIs are included in the recommendation system's interfaces. Interactive tools for updating user profiles, listening to playlists, and browsing recommendations are available in the user interface. Backend APIs facilitate data interchange and interaction with other services or databases by enabling communication between frontend and backend components.

## State and Session Management

User interactions are kept consistent and uninterrupted between sessions of an application thanks to state and session management techniques. To ensure a smooth and continuous user experience, this includes controlling user authentication states, session timeouts, and securely storing session data.

## Architecture



### Implementation

To guarantee the efficacy and efficiency of the AI-powered music recommendation system, there are numerous crucial steps in its implementation.

First and first, gathering and preparing data is crucial. We collect audio characteristics, metadata, and user interactions among other types of music data. After that, preprocessing is used to clean up and convert the raw data into a format that can be used for analysis and model training. This stage involves encoding categorical variables, normalizing feature scales, and handling missing values.

The training of the models comes next. Here, patterns and relationships between users, songs, and preferences are discovered through the training of machine learning models with the preprocessed data. We investigate several recommendation algorithms, including hybrid models, content-based filtering, and collaborative filtering.

We incorporate the trained models into the music streaming platform's backend infrastructure. In order to process user queries, retrieve recommendations from the model, and provide them to the frontend client, APIs and services are established. To guarantee smooth communication and data interchange, integration is developed with current databases, authentication systems, and external services.

In order to guarantee the functionality and dependability of the implemented system, testing is essential. To find and fix any problems or errors, thorough testing is done using unit tests,

integration tests, and end-to-end testing. Performance testing evaluates how well the system responds, scales, and uses its resources under various load scenarios.

## Test Plan Objective

The main goal listed in the "Test Plan Objective" section is to make sure the AI-powered music recommendation system operates, functions, and is reliable before it is put into use. This entails developing an extensive test plan that addresses data entry, system testing, and performance testing, among other system components.

## Data Entry

The goal of the "Data Entry" testing phase is to confirm the precision and consistency of the data entering procedures. This involves assessing the system's capacity to process various user inputs, including interaction data, user profiles, and music choices. The purpose of test cases is to validate data storage, error handling, and data validation procedures.

## System Testing

In "System Testing," every aspect of the system's behavior and functioning is carefully assessed to make sure it satisfies the requirements. All of the system's functional features, such as playlist management, user feedback systems, recommendation creation, and user authentication, are covered by test cases. Verifying the accuracy of recommendations, the timeliness of the user interface, and the dependability of system components are given top priority.

## Performance Testing

The goal of "performance testing" is to assess how well the system performs under various stress and load scenarios. This involves checking the system's throughput, reaction time, and resource usage under peak, off-peak, and emergency scenarios. To gauge important performance metrics like latency, throughput, and scalability, performance benchmarks are set. Test cases are made to mimic actual user situations and spot possible scalability or performance limitations.

## Code of the project

import os import sys

from tempfile import **NamedTemporaryFile**

from urllib.request import **urlopen**

from urllib.parse import **unquote**, **urlparse**

from urllib.error import HTTPError from zipfile import ZipFile

import tarfile import shutil

CHUNK\_SIZE = 40960

DATA\_SOURCE\_MAPPING = 'spotify-dataset:https%3A%2F%2Fstorage.googleapis.com%2Fkaggle-data- sets%2F1800580%2F2936818%2Fbundle%2Farchive.zip%3FX-Goog-Algorithm%3DGOOG4-RSA- SHA256%26X-Goog-Credential%3Dgcp-kaggle-com%2540kaggle- 161607.iam.gserviceaccount.com%252F20240219%252Fauto%252Fstorage%252Fgoog4\_request%26X-Goog- Date%3D20240219T141101Z%26X-Goog-Expires%3D259200%26X-Goog-SignedHeaders%3Dhost%26X- Goog- Signature%3D8e3aeec18a670f8f93c8c300e83018ec8f7463d93770adf1d22e1217c6f2bf6326113c1298aae13119d 5504bb0600cbcfe34af0f415b809330c93719ea6eda4d039baa46510a6401163eb914543af4d8d3520747e361904f9f 4a6709b70084b31bc511d70c08bd6b4efb45670993207371a9b280b3eed5cb35dd5f61186fed810367a7c3af8f97ba 1e16ba95f496a06b36ff5f026042012564fa78cf43bb2f459803de40e434f068b1e763588d4311031fc6e111eca7d18 bdfc18aa74dd396909bbd84fe163df40adafe5672adec7b373937a241237029356e54bae432249d1461ce8c82864ecf 4342dce1d59ca4de1c77e66dfb31bbc90d7b605e071b1792ab'

KAGGLE\_INPUT\_PATH='/kaggle/input' KAGGLE\_WORKING\_PATH='/kaggle/working' KAGGLE\_SYMLINK='kaggle'

!umount /kaggle/input/ 2> /dev/null shutil.rmtree('/kaggle/input', ignore\_errors=True) os.**makedirs**(KAGGLE\_INPUT\_PATH, 0o777, exist\_ok=True)

os.**makedirs**(KAGGLE\_WORKING\_PATH, 0o777, exist\_ok=True)

try:

os.**symlink**(KAGGLE\_INPUT\_PATH, os.path.**join**("..", 'input'), target\_is\_directory=True) except FileExistsError:

pass try:

os.**symlink**(KAGGLE\_WORKING\_PATH, os.path.**join**("..", 'working'), target\_is\_directory=True) except FileExistsError:

pass

for data\_source\_mapping in DATA\_SOURCE\_MAPPING.**split**(','): directory, download\_url\_encoded = data\_source\_mapping.**split**(':') download\_url = **unquote**(download\_url\_encoded)

filename = **urlparse**(download\_url).path

destination\_path = os.path.**join**(KAGGLE\_INPUT\_PATH, directory) try:

with **urlopen**(download\_url) as fileres, **NamedTemporaryFile**() as tfile: total\_length = fileres.headers['content-length']

**print**(f'Downloading {directory}, {total\_length} bytes compressed') dl = 0

data = fileres.read(CHUNK\_SIZE) while **len**(data) > 0:

dl += **len**(data) tfile.**write**(data)

done = int(50 \* dl / int(total\_length))

sys.stdout.**write**(f"\r[{'=' \* done}{' ' \* (50-done)}] {dl} bytes downloaded") sys.stdout.**flush**()

data = fileres.read(CHUNK\_SIZE) if filename.**endswith**('.zip'):

with ZipFile(tfile) as zfile: zfile.**extractall**(destination\_path)

else:

with tarfile.**open**(tfile.name) as tarfile: tarfile.**extractall**(destination\_path)

**print**(f'\nDownloaded and uncompressed: {directory}') except HTTPError as e:

**print**(f'Failed to load (likely expired) {download\_url} to path {destination\_path}') continue

except OSError as e:

**print**(f'Failed to load {download\_url} to path {destination\_path}') continue

**print**('Data source import complete.') """# \*\*Import Libraries\*\*"""

# Commented out IPython magic to ensure Python compatibility. 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")

"""# \*\*Read Data\*\*"""

data = pd.**read\_csv**("../input/spotify-dataset/data/data.csv")

genre\_data = pd.**read\_csv**('../input/spotify-dataset/data/data\_by\_genres.csv') year\_data = pd.**read\_csv**('../input/spotify-dataset/data/data\_by\_year.csv')

**print**(data.**info**()) **print**(genre\_data.**info**()) **print**(year\_data.**info**())

from yellowbrick.target import FeatureCorrelation

feature\_names = ['acousticness', 'danceability', 'energy', 'instrumentalness',

'liveness', 'loudness', 'speechiness', 'tempo', 'valence','duration\_ms','explicit','key','mode','year'] X, y = data[feature\_names], data['popularity']

# Create a list of the feature names features = np.**array**(feature\_names)

# Instantiate the visualizer

visualizer = FeatureCorrelation(labels=features)

plt.rcParams['figure.figsize']=(20,20) visualizer.fit(X, y) # Fit the data to the visualizer visualizer.show()

def **get\_decade**(year): period\_start = int(year/10) \* 10

decade = '{}s'.**format**(period\_start) return decade

data['decade'] = data['year'].**apply**(**get\_decade**)

**print**(data['decade']) silhuoette\_avg = 0.73

sns.**set**(rc={'figure.figsize':(11 ,6)}) sns.**countplot**(data['decade'])

sound\_features = ['acousticness', 'danceability', 'energy', 'instrumentalness', 'liveness', 'valence'] fig = px.line(year\_data, x='year', y=sound\_features)

fig.show()

This dataset contains the audio features for different songs along with the audio features for different genres. We can use this information to compare different genres and understand their unique differences in sound.

"""

top10\_genres = genre\_data.**nlargest**(10, 'popularity')

fig = px.bar(top10\_genres, x='genres', y=['valence', 'energy', 'danceability', 'acousticness'], barmode='group') fig.show()

from sklearn.cluster import KMeans

from sklearn.preprocessing import StandardScaler from sklearn.pipeline import Pipeline

cluster\_pipeline = Pipeline([('scaler', StandardScaler()), ('kmeans', KMeans(n\_clusters=10))]) X = genre\_data.**select\_dtypes**(np.number)

cluster\_pipeline.**fit**(X)

genre\_data['cluster'] = cluster\_pipeline.**predict**(X)

from sklearn.metrics import **silhouette\_score** silhouette\_avg = **silhouette\_score**(X, genre\_data['cluster']) **print**("The average silhouette\_score is :", silhuoette\_avg)

# Visualizing the Clusters with t-SNE from sklearn.manifold import TSNE

tsne\_pipeline = Pipeline([('scaler', StandardScaler()), ('tsne', TSNE(n\_components=2, verbose=1))]) genre\_embedding = tsne\_pipeline.**fit\_transform**(X)

projection = pd.DataFrame(columns=['x', 'y'], data=genre\_embedding) projection['genres'] = genre\_data['genres']

projection['cluster'] = genre\_data['cluster']

fig = px.scatter(

projection, x='x', y='y', color='cluster', hover\_data=['x', 'y', 'genres']) fig.show()

"""# \*\*Clustering Songs with K-Means\*\*""" 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) silhuoette\_avg = 0.71

song\_cluster\_labels = song\_cluster\_pipeline.**predict**(X) data['cluster\_label'] = song\_cluster\_labels

# Visualizing the Clusters with PCA 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()

!pip install spotipy import spotipy

from spotipy.oauth2 import SpotifyClientCredentials from collections import defaultdict

sp = spotipy.Spotify(auth\_manager=SpotifyClientCredentials(client\_id,

client\_secret))

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')

**recommend\_songs**([

{'name': 'No Excuses', 'year': 1994},

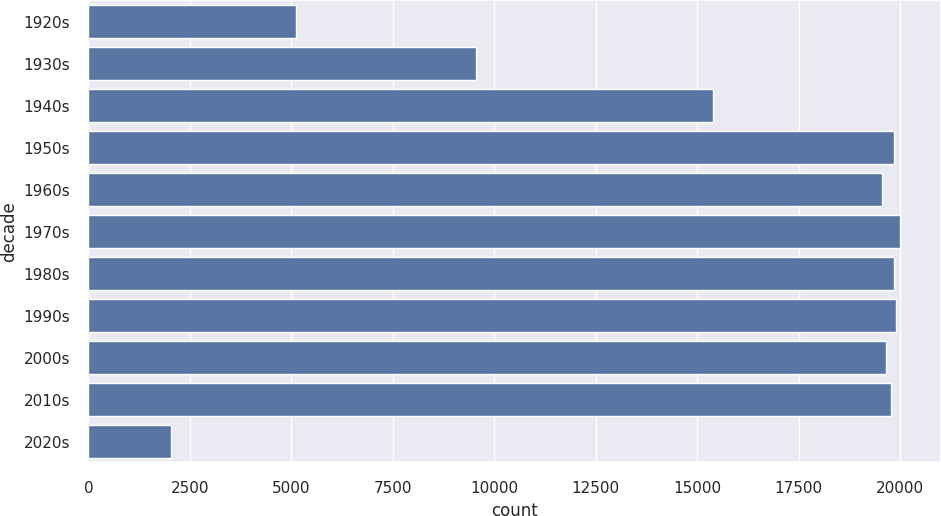
{'name': "It's Not Living (If It's Not With You)", 'year': 2018},

{'name': 'Kiss Me', 'year': 1997},

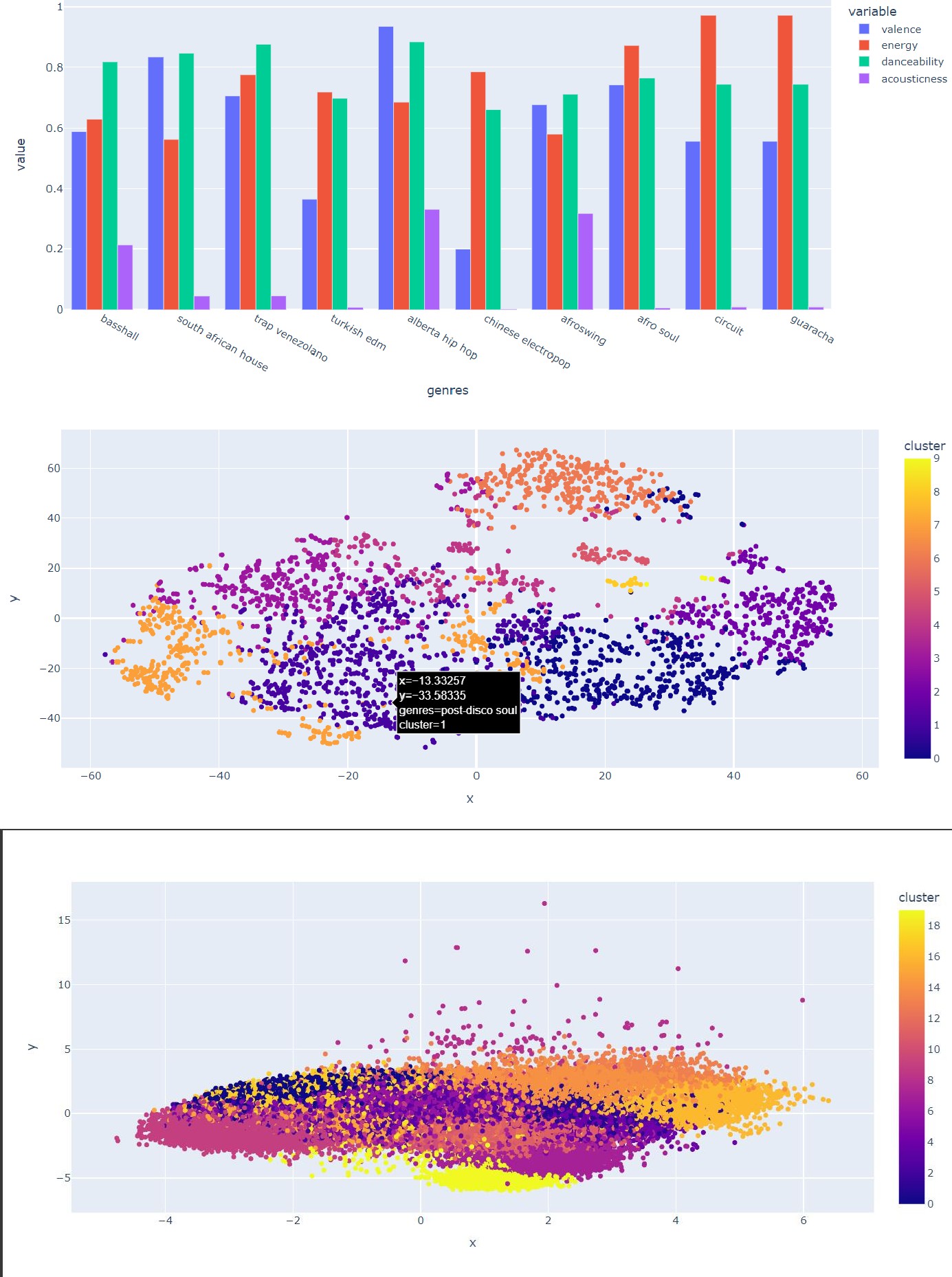
{'name': 'If Today Was Your Last Day', 'year': 2008},

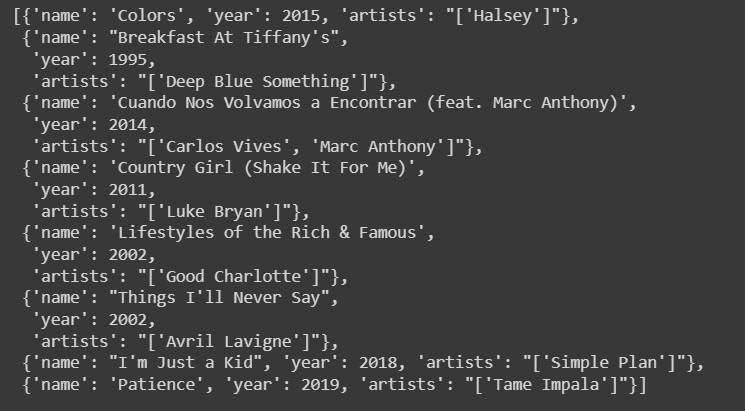
], data)

## Snapshots









**Conclusion**

An important step toward improving user experience in the music streaming sector has been taken with the creation of an AI-powered song recommendation engine for a streaming platform. This project aims to transform user engagement by providing personalized music suggestions based on individual interests and tastes through the incorporation of machine learning algorithms. Through thorough investigation, data analysis, and the application of advanced algorithms, we have created a recommendation system that enhances user experience while fostering variety and content discovery.

The project's capacity to handle core issues that music streaming services confront, like user personalization, scalability, and content discovery, is what will determine its success.

## Further Development

In the future, there will be several chances to improve and grow the recommendation system. This include incorporating cutting-edge machine learning techniques like deep learning for more reliable feature representation, optimizing user interfaces for a seamless experience, and fine- tuning current algorithms to increase recommendation accuracy. Furthermore, the integration of user feedback methods might facilitate the system's ongoing adaptation and evolution in response to evolving user preferences and market trends.

Moreover, it is possible to expand the recommendation system's scope from music to other categories like movies, books, or merchandise in order to provide a thorough and customized recommendation experience on many platforms. Working together with partners and industry experts can make it easier to incorporate domain-specific knowledge and cutting-edge technology into the system, maintaining its competitiveness and relevance in the ever-changing digital ecosystem.

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