UPES
UNIVERSITY OF TOMORROW

AI-Powered Music Recommendation System

Internship – Final Report

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

MASTERS OF COMPUTER APPLICATION

SUBMITTED BY:

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BACKGROUND

Aim:

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.

System

Requirements

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.

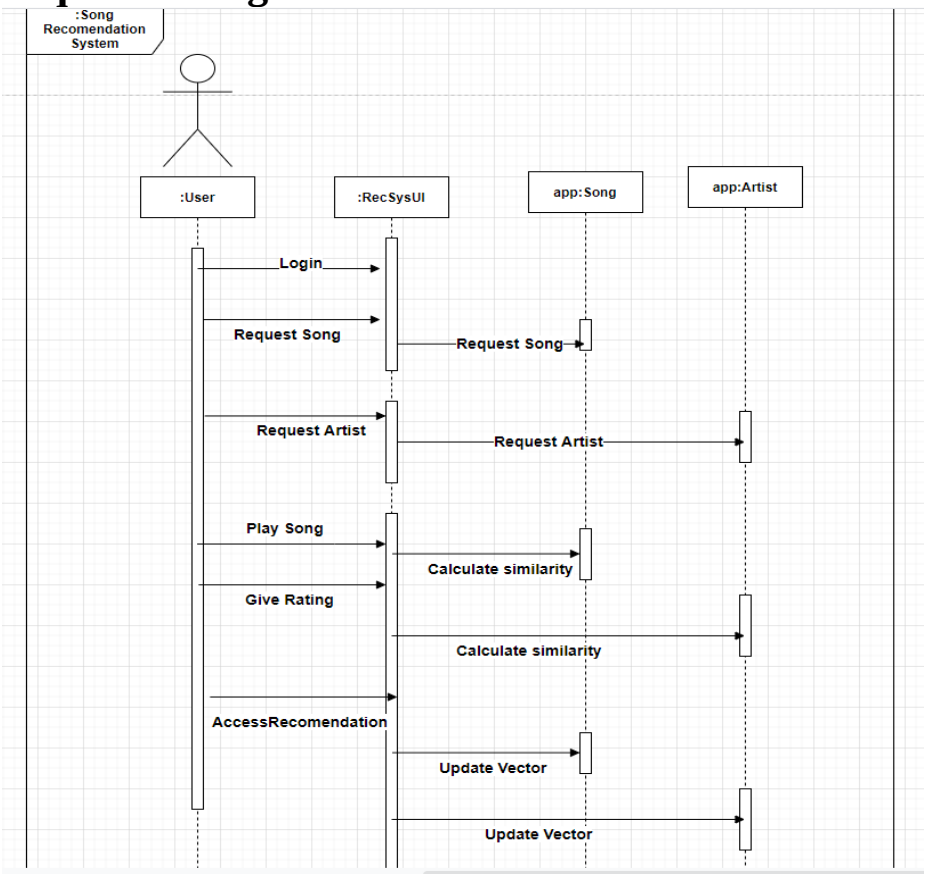
Process Flow

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

Stages of research	Week 1	Week 2	Week 3	Week 4	Week 5	Week 6	Week 7
Selection of topic							
Data collection from sources							
Literature review							
Research methodology plan							
Selection of the Appropriate Research Techniques							
Analysis & Interpretation of Data							
Findings and recommendations							
Final research project							

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.

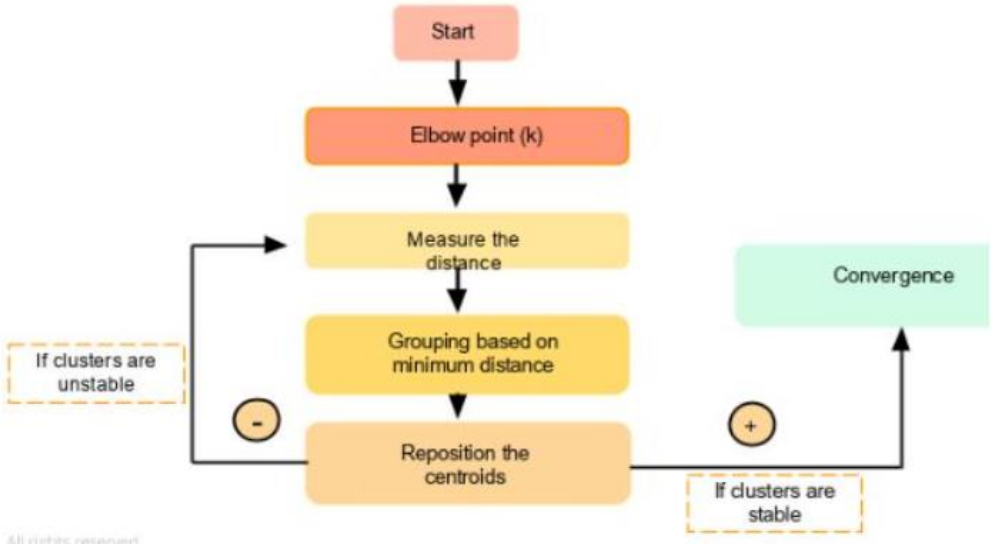
Interfaces

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%3D8e3aeec18a670f8f93c8c300e83018ec8f7463d93770adf1d22e1217c6f2bf6326113c1298aae13119d5504bb0600cbcfe34af0f415b809330c93719ea6eda4d039baa46510a6401163eb914543af4d8d3520747e361904f9f4a6709b70084b31bc511d70c08bd6b4efb45670993207371a9b280b3eed5cb35dd5f61186fed810367a7c3af8f97ba1e16ba95f496a06b36ff5f026042012564fa78cf43bb2f459803de40e434f068b1e763588d4311031fc6e111eca7d18bdfc18aa74dd396909bbd84fe163df40adafe5672adec7b373937a241237029356e54bae432249d1461ce8c82864ecf4342dce1d59ca4de1c77e66dfb31bbc90d7b605e071b1792ab'

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())
```

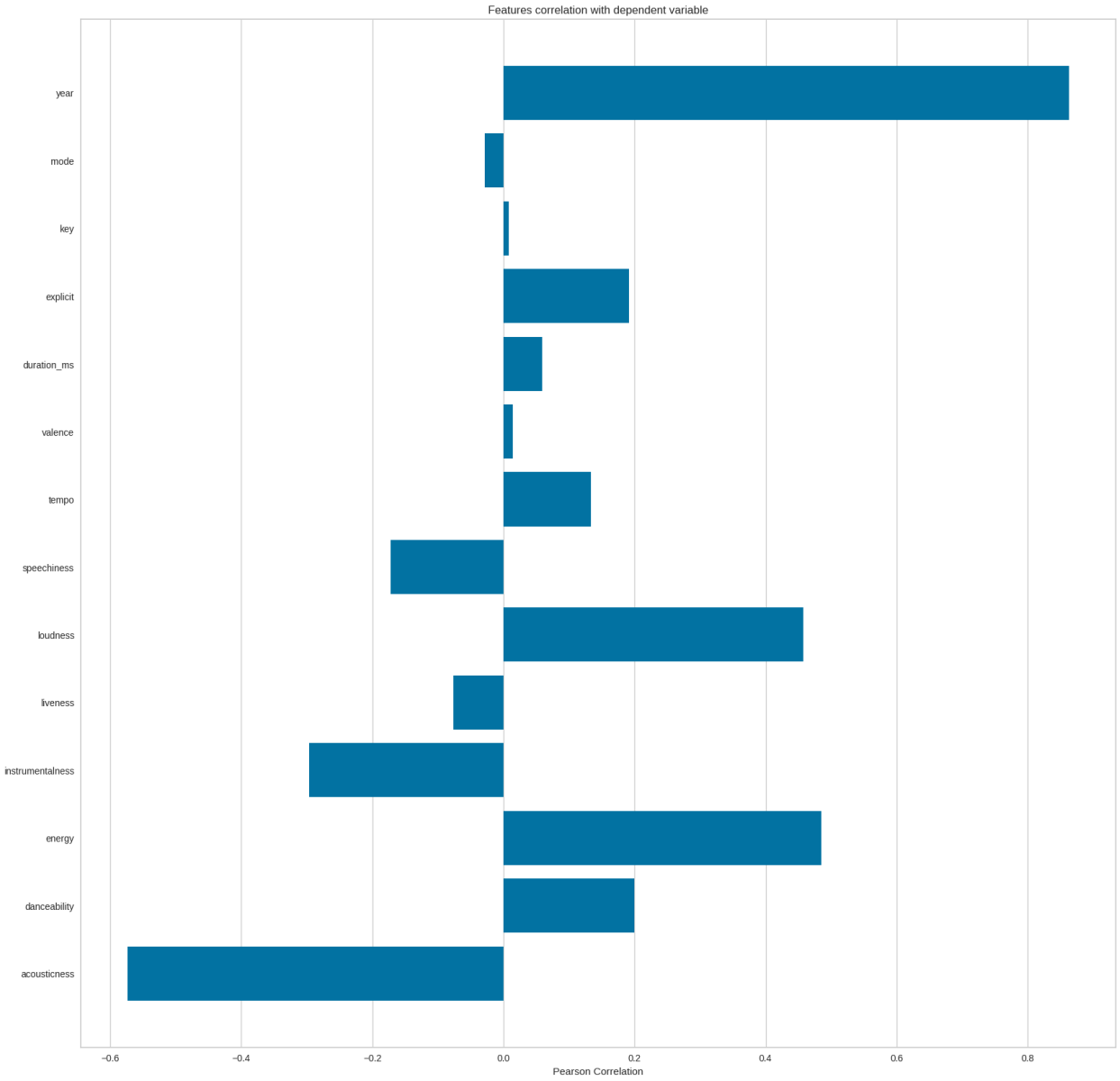
```
from yellowbrick.target import FeatureCorrelation

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


Features correlation with dependent variable
year
mode
key
explicit
duration_ms
valence
tempo
speechiness
loudness
liveness
instrumentalness
energy
danceability
acousticness
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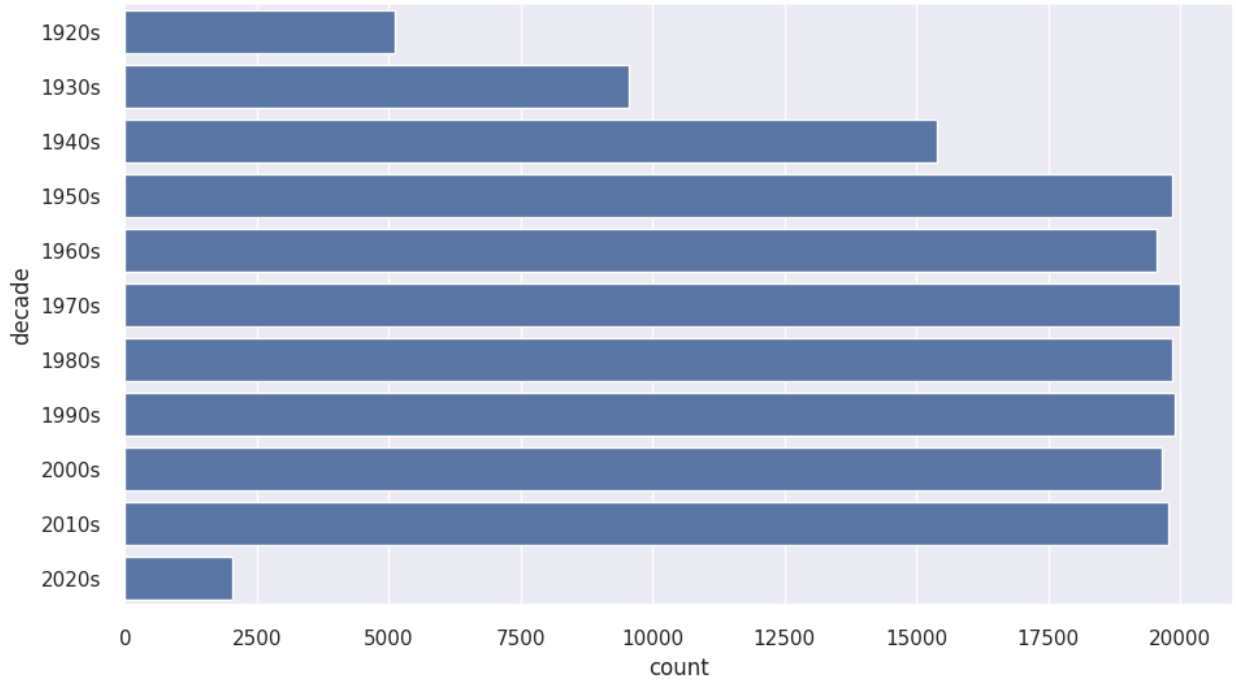
−0.4
−0.2
0.0
0.2
0.4
0.6
0.8
Pearson Correlation


1920s
1930s
1940s
1950s
1960s
1970s
1980s
1990s
2000s
2010s
2020s
decade
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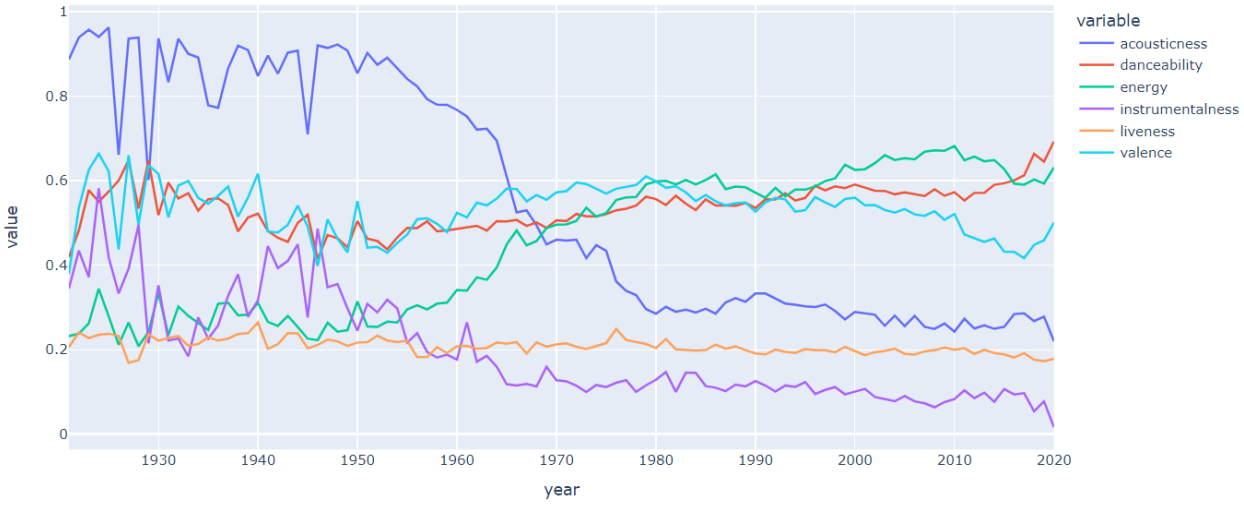
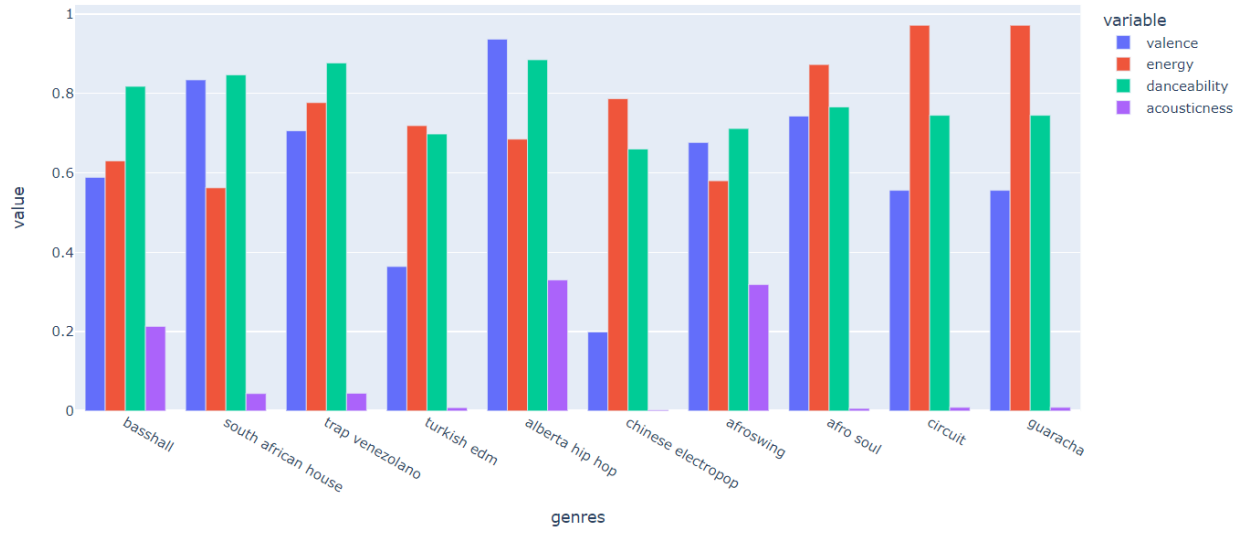
5000
7500
10000
12500
15000
17500
20000
count


1
0.8
0.6
0.4
0.2
0
value
1930
1940
1950
1960
1970
1980
1990
2000
2010
2020
year
variable
acousticness
danceability
energy
instrumentalness
liveness
valence


variable
valence
energy
danceability
acousticness
value
genres
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chinese electropop
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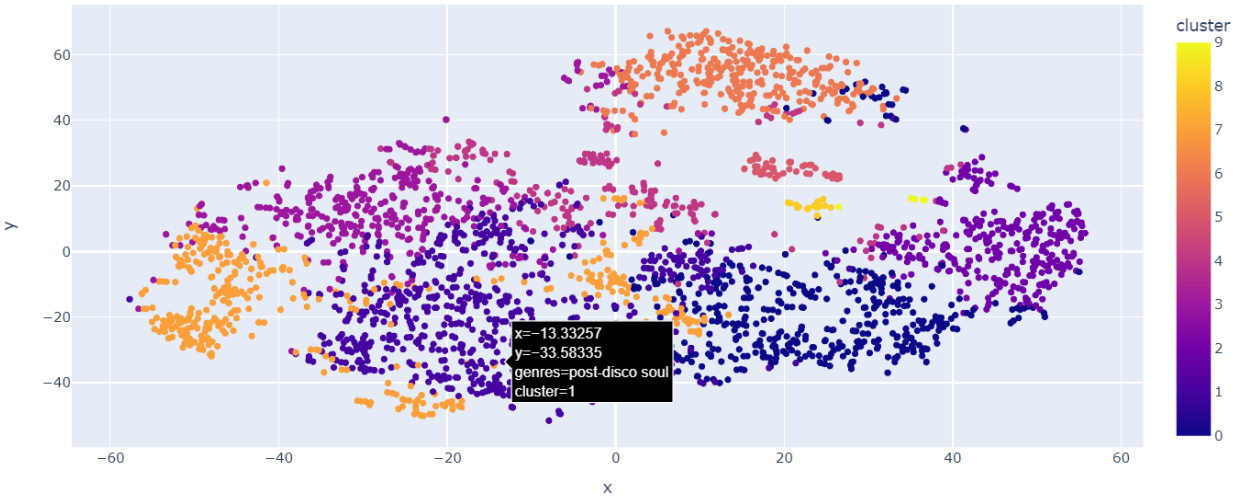
afro soul
circuit
guaracha


cluster
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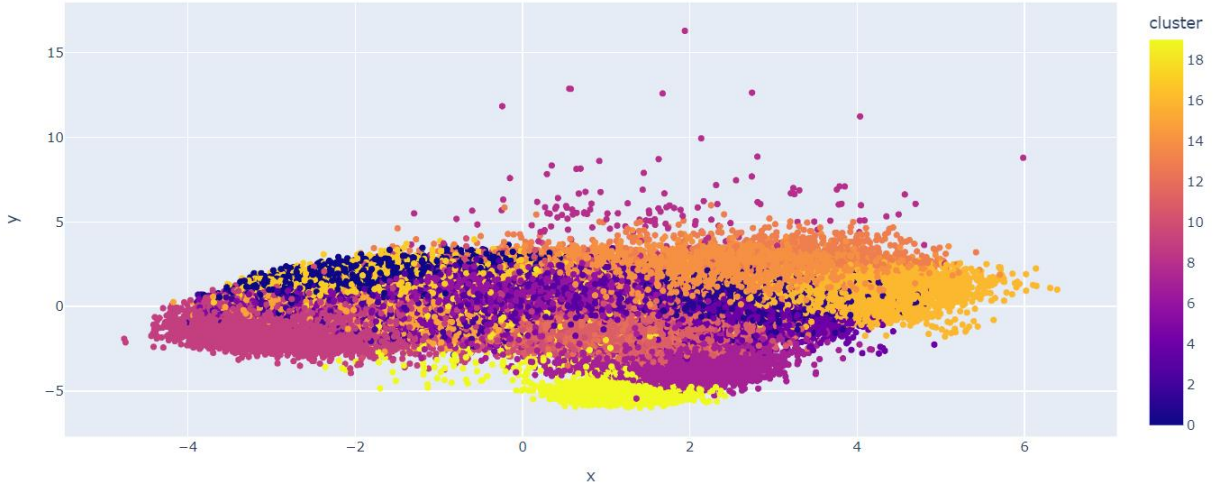
y=-33.58335
genres=post-disco soul
cluster=1
x
y


cluster
x
y

```
[{'name': 'Colors', 'year': 2015, 'artists': "['Halsey']"},
 {'name': "Breakfast At Tiffany's",
  'year': 1995,
  'artists': "['Deep Blue Something']"},
 {'name': 'Cuando Nos Volvamos a Encontrar (feat. Marc Anthony)',
  'year': 2014,
  'artists': "['Carlos Vives', 'Marc Anthony']"},
 {'name': 'Country Girl (Shake It For Me)',
  'year': 2011,
  'artists': "['Luke Bryan']"},
 {'name': 'Lifestyles of the Rich & Famous',
  'year': 2002,
  'artists': "['Good Charlotte']"},
 {'name': "Things I'll Never Say",
  'year': 2002,
  'artists': "['Avril Lavigne']"},
 {'name': "I'm Just a Kid", 'year': 2018, 'artists': "['Simple Plan']"},
 {'name': 'Patience', 'year': 2019, 'artists': "['Tame Impala']"}]
```

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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