Music Recommendation System

PROBLEM STATEMENT:

To Develop a music recommendation system using machine learning to suggest personalized music tracks based on user preferences and listening history.

DESCRIPTION:

This mini project aims to develop a personalized music recommendation system using machine learning techniques. The system will analyze user preferences and listening habits to suggest relevant and enjoyable music tracks. By leveraging machine learning algorithms, such as collaborative filtering and content-based filtering, the system will be able to provide accurate and tailored recommendations. The project will involve collecting and preprocessing music data, designing and training the recommendation model, and implementing a user-friendly interface for users to interact with the system.

The music recommendation system will enhance user experience by offering curated playlists and song suggestions, thereby increasing user engagement and satisfaction. Additionally, the project will explore the integration of various features such as genre preferences, mood detection, and contextual information to further improve the quality of recommendations. Through this project, we aim to demonstrate the practical application of machine learning in the field of music recommendation, benefiting both music enthusiasts and streaming platforms alike._

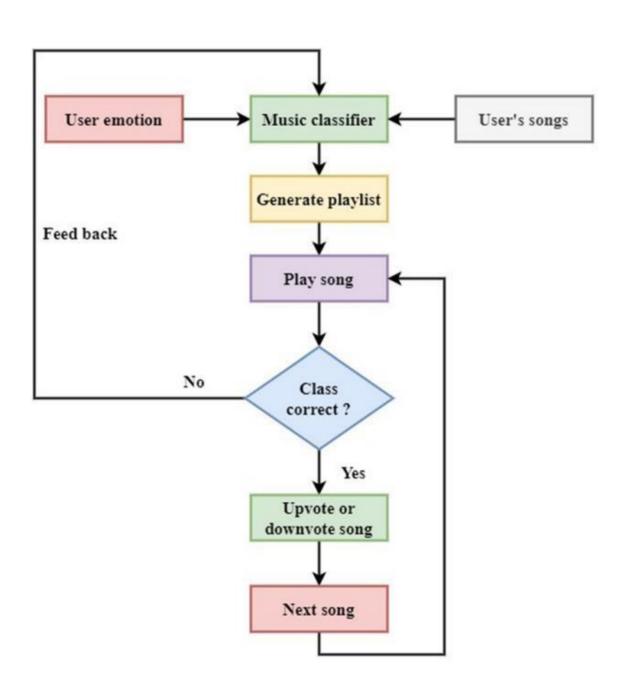
APPLICATIONS:

- Personalized Music Streaming: Tailor music suggestions to each user's taste, boosting engagement.
- Playlist Curation: Create playlists based on mood, activity, or genre preferences, simplifying music selection.
- Music Discovery: Introduce users to new tracks, encouraging exploration and diversity in music.
- Improved User Retention: Keep users engaged with relevant music suggestions, increasing platform loyalty.
- **Targeted Marketing:** Use listening insights to tailor music promotions, enhancing marketing effectiveness.

SOFTWARE REQUIREMENTS:

- Database Management System
- Machine Learning Libraries
- Web Development Framework
- User Interface Design Tools

FLOW-CHART:



CODING:

Main.pv:

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-datasets%2F1800580%2F2936818%2Fbundle%2Farchive.zip%3FX-Goog-Algorithm%3DGOOG4-RSA-SHA256%26X-Goog-Credential%3Dgcp-kaggle-com%2540kaggle-

Signature % 3D2174d140 aab12ea 64a 650 fe 99043d1 fe 618e3993f25cf3 be e9bdca 00 ee 436d24fd 2f0df8ddf058ac47c8ea 3036be38cf882f25e4124eb1cee7a 3704a 25e9d8797b89d856b0543655 232a 5629ab5453f46171e523e58f28da3b531c0a74f1bb48bd35621b93d357cf884b52b5060a4 a86b38289718ad321a 20837ca1de998f545b79a 22beb38616ca5e28e88c8eca5c2da538cb1fc33 10573a051dd5a9b93438537d9bc5ba9d557166eedf1ec5313b59d5c33cb7954e60e466dc41e1f7a8fb777bb1cb4916f4f89bc511aef3a780a109092ce09e8054b2ea41b920046d3d89e72aa21a84eeee082b9013a8eba859bda33e67d838d7aa1a98b6d039015a5021903,-spotify-tracks-

dataset:https%3A%2F%2Fstorage.googleapis.com%2Fkaggle-data-

Algorithm % 3DGOOG4-RSA-SHA256% 26X-Goog-Credential% 3Dgcp-kagglecom% 2540 kaggle-

 $161607.iam.gservice account.com \% 252F20240316\% 252Fauto\% 252Fstorage\% 252Fgoog4_re~quest\% 26X-Goog-Date\% 3D20240316T102818Z\% 26X-Goog-Expires\% 3D259200\% 26X-Goog-Signed Headers\% 3Dhost\% 26X-Goog-$

Signature % 3D0dc 032c 3787baf 0c 0c 05f 67fa69a 326a 629b 01b 37fd 2d9529d79c 00ba67eb fa4be 228c 45e85b 8249cd 6806090a 592c 468e 3705c 63880c f49a 178dc f01d1aebc 2b445b fec 9f 681386 f95c f48b 437e 761a 68640eba 21be 3416a 177ea 0b4cdd 397e 86845ce 2eabbafdac 761b 41f 60cac 3e 904ed 8774741db 4d87e 6f b6743727201eabba429c 6781fb 73b 10c 10647cdc 9f 08d2a 7bd 1fe4ccb 0f 918fb 199ed 37ea 5e0 9e 84a 733a 4603a 6e 894a 8553e 89a 6ac 0f 1d5060104f 179f 362697db 592b 70f 7b0 1045d 66ecf 590716096f 11719f 632939c060e 25e 327de 34108379783fb 69fed 0222e 179f 36abccd 0786c 91017e 84e 1b2511dbd 0162112e 11aee 2f 2c 3ecf 3d0c'

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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}')
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continue
  except OSError as e:
    print(f'Failed to load {download_url} to path {destination_path}')
    continue
print('Data source import complete.')
import pandas as pd
import numpy as np
from sklearn.preprocessing import MinMaxScaler
from sklearn.metrics.pairwise import cosine_similarity
import warnings
warnings.filterwarnings('ignore')
#Main Raw Dataframe
df = pd.read_csv("/kaggle/input/-spotify-tracks-dataset/dataset.csv")
df.drop(columns='Unnamed: 0',inplace=True)
#Dataframe for getting year feature of songs
dfYear = pd.read_csv("/kaggle/input/spotify-dataset/data/data.csv")
dfYear = dfYear[['id', 'year']]
dfYear['track_id'] = dfYear['id']
dfYear.drop(columns='id',inplace=True)
#Merge 2 Dataframe
df = pd.merge(df,dfYear,on='track_id')
display(df.info(),df.head())
# Duplicate Check
df[df.duplicated('track_id')==True]
df[df['track_id']=='6Vc5wAMmXdKIAM7WUoEb7N']
# Crosstab Genre and Song
xtab_song = pd.crosstab(
  df['track_id'],
  df['track_genre']
)
xtab\_song = xtab\_song*2
display(xtab_song.head(),len(xtab_song))
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# Concatenate the encoded genre columns with the original dataframe
dfDistinct = df.drop_duplicates('track_id')
dfDistinct = dfDistinct.sort_values('track_id')
dfDistinct = dfDistinct.reset_index(drop=True)
xtab_song.reset_index(inplace=True)
data encoded = pd.concat([dfDistinct, xtab song], axis=1)
display(data encoded.head(),len(data encoded))
numerical_features = ['explicit', 'danceability', 'energy', 'loudness', 'speechiness',
'acousticness', 'instrumentalness', 'liveness', 'valence', 'year']
scaler = MinMaxScaler()
data encoded[numerical features] = scaler.fit transform(data encoded[numerical features])
# Select the relevant columns for computing item similarities
calculatied features = numerical features +
list(xtab_song.drop(columns='track_id').columns)
cosine_sim = cosine_similarity(data_encoded[calculatied_features],
data_encoded[calculatied_features])
def get_recommendations(title, N=5):
  indices = pd.Series(data_encoded.index,
index=data encoded['track name']).drop duplicates()
  try:
    idx = indices[title]
     try:
       len(idx)
       temp = 2
     except:
       temp = 1
  except KeyError:
     return "Song not found in the dataset."
  if temp == 2:
     idx = indices[title][0]
  else:
     idx = indices[title]
  sim_scores = list(enumerate(cosine_sim[idx]))
  sim scores = sorted(sim scores, key=lambda x: x[1], reverse=True)
  sim\_scores = sim\_scores[1:N+1]
  song\_indices = [i[0] for i in sim\_scores]
  recommended_songs = data_encoded[['track_name', 'artists',
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'album_name']].iloc[song_indices]
  sim_scores_list = [i[1] for i in sim_scores]
  recommended_list = recommended_songs.to_dict(orient='records')
  for i, song in enumerate(recommended_list):
    song['similarity_score'] = sim_scores_list[i]
  return recommended_list
# Get the recommendations
recommended_songs = get_recommendations("Time", N=5)
if isinstance(recommended_songs, str):
  print(recommended_songs)
else:
  print("Recommended Songs:")
  for song in recommended_songs:
    print(f"Title: {song['track_name']}")
    print(f"Artist: {song['artists']}")
    print(f"Album: {song['album_name']}")
    print(f"Similarity Score: {song['similarity_score']:.2f}")
    print()
```

SAMPLE OUTPUT:

Recommended Songs:

Title: Suite: Judy Blue Eyes - 2005 Remaster

Artist: Crosby, Stills & Nash Album: Crosby, Stills & Nash

Similarity Score: 1.00

Title: Red House

Artist: Jimi Hendrix

Album: Are You Experienced

Similarity Score: 1.00

Title: Heroes And Villains - Remastered 2001

Artist: The Beach Boys

Album: Smiley Smile (Remastered)

Similarity Score: 1.00

Title: The Wind Cries Mary

Artist: Jimi Hendrix

Album: Are You Experienced Similarity Score: 0.99

Title: The Trial
Artist: Pink Floyd
Album: The Wall

Similarity Score: 0.99