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Report On Project of Music Recommendation System Using Python

INT-254

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Introduction

A recommendation system plays a major role in providing a good user experience in an application by recommending the most suitable and personalized services for each user.

Recommendation system uses **Collaborative filtering** to recommend songs and podcasts to users. Collaborative filtering recommends products or services by finding similarities between users and the products or services to provide a better user experience.

Dataset Used

I will be using a dataset that has been collected from Spotify. The dataset contains over 175,000 songs with over 19 features grouped by artist, year and genre.

Libraries Used

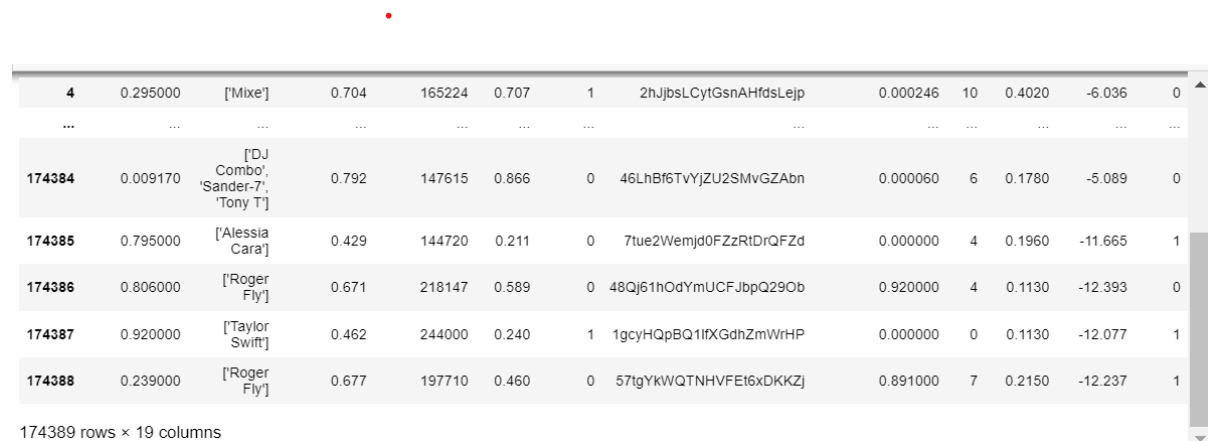
- **NumPy**: - NumPy is a library for the Python programming language, adding support for large, multi-dimensional arrays and matrices, along with a large collection of high-level mathematical functions to operate on these arrays.
- **Pandas**: Pandas is a Python package providing fast, flexible, and expressive data structures designed to make working with “relational” or “labelled” data both easy and intuitive. It aims to be the fundamental high-level building block for doing practical, real-world data analysis in Python.
- **Matplotlib**: It is a comprehensive library for creating static, animated, and interactive visualizations in Python. Matplotlib makes easy things easy and hard things possible.
- **Seaborn**: Seaborn is a Python data visualization library based on . It provides a high-level interface for drawing attractive and informative statistical graphics.
- **TQDM**: tqdm is a library in Python which is **used for creating Progress Meters or Progress Bars**. tqdm got its name from the Arabic name taqaddum which means ‘pro’

Import :-

```
import warnings
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from tqdm import tqdm
sns.set()
```

```
data = pd.read_csv("spotify.csv")
```

data



4	0.295000	['Mixe']	0.704	165224	0.707	1	2hJbsLCytGsnAHfdsLejp	0.000246	10	0.4020	-6.036	0
...
174384	0.009170	['DJ Combo', 'Sander-7', 'Tony T']	0.792	147615	0.866	0	46LhBf6TvYjZU2SMvGZAbn	0.000060	6	0.1780	-5.089	0
174385	0.795000	['Alessia Cara']	0.429	144720	0.211	0	7tue2Wemjd0FZzRtDrQFZd	0.000000	4	0.1960	-11.665	1
174386	0.806000	['Roger Fly']	0.671	218147	0.589	0	48Qj61hOdYmUCFJbpQ29Ob	0.920000	4	0.1130	-12.393	0
174387	0.920000	['Taylor Swift']	0.462	244000	0.240	1	1gcyHQpBQ1lftXGdhZmWrHP	0.000000	0	0.1130	-12.077	1
174388	0.239000	['Roger Fly']	0.677	197710	0.460	0	57lgYkKWQTNHVFEt6xDKKZj	0.891000	7	0.2150	-12.237	1

174389 rows × 19 columns

data.head()

	acousticness	artists	danceability	duration_ms	energy	explicit	id	instrumentalness	key	liveness	loudness	mode	name
0	0.991000	['Mamie Smith']	0.598	168333	0.224	0	0cS0A1fUEUd1EW3FcF8AEI	0.000522	5	0.3790	-12.628	0	Keep A Song In Your Soul
1	0.643000	['Screamin' Jay Hawkins']	0.852	150200	0.517	0	0hbkKFIJm7Z05H8ZI9w30f	0.026400	5	0.0809	-7.261	0	I Put A Spell On You
2	0.993000	['Mamie Smith']	0.647	163827	0.186	0	11m7laMUgmOKql3oYzuhne	0.000018	0	0.5190	-12.098	1	Golfing Papa
3	0.000173	['Oscar Velazquez']	0.730	422087	0.798	0	19Lc5SfJJ5O1oaxY0fpwfh	0.801000	2	0.1280	-7.311	1	True House Music - Xavier Santos & Carlos Gomi...
4	0.295000	['Mixe']	0.704	165224	0.707	1	2hJbsLCytGsnAHfdsLejp	0.000246	10	0.4020	-6.036	0	Xuniverxe

data.shape

Output :- (174389, 19)

data.info()

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 174389 entries, 0 to 174388
Data columns (total 19 columns):
#   Column                Non-Null Count  Dtype
---  -
0   acousticness          174389 non-null float64
1   artists               174389 non-null object
2   danceability          174389 non-null float64
3   duration_ms          174389 non-null int64
4   energy               174389 non-null float64
5   explicit             174389 non-null int64
6   id                   174389 non-null object
7   instrumentalness      174389 non-null float64
8   key                  174389 non-null int64
9   liveness             174389 non-null float64
10  loudness             174389 non-null float64
11  mode                 174389 non-null int64
12  name                 174389 non-null object
13  popularity            174389 non-null int64
14  release_date         174389 non-null object
15  speechiness          174389 non-null float64
16  tempo                174389 non-null float64
17  valence              174389 non-null float64
18  year                 174389 non-null int64
dtypes: float64(9), int64(6), object(4)
memory usage: 25.3+ MB
```

data.isnull().sum()

```
acousticness      0
artists           0
danceability       0
duration_ms       0
energy            0
explicit          0
id                0
instrumentalness   0
key               0
liveness          0
loudness          0
mode              0
name              0
popularity        0
release_date      0
speechiness       0
tempo             0
valence           0
year              0
dtype: int64
```

df = data.drop(columns=['id', 'name', 'artists', 'release_date', 'year'])

df.corr()

corr():-this function to find the correlation among the columns in the Dataframe using the 'Pearson' method.

	acousticness	danceability	duration_ms	energy	explicit	instrumentalness	key	liveness	loudness	mode	popularity	speech
acousticness	1.000000	-0.263217	-0.089169	-0.750852	-0.208176	0.221956	-0.028028	-0.029654	-0.546639	0.064633	-0.396744	-0.002437
danceability	-0.263217	1.000000	-0.100757	0.204838	0.200842	-0.215589	0.026266	-0.110033	0.249541	-0.048358	0.123746	0.239962
duration_ms	-0.089169	-0.100757	1.000000	0.060516	-0.033808	0.103621	0.002020	0.028942	0.019791	-0.046849	0.024717	-0.097838
energy	-0.750852	0.204838	0.060516	1.000000	0.102561	-0.177750	0.035780	0.134815	0.779267	-0.056160	0.328939	-0.112616
explicit	-0.208176	0.200842	-0.033808	0.102561	1.000000	-0.130609	0.005282	0.037288	0.106249	-0.062503	0.152545	0.353872
instrumentalness	0.221956	-0.215589	0.103621	-0.177750	-0.130609	1.000000	-0.004619	-0.047941	-0.317562	-0.056731	-0.300625	-0.133966
key	-0.028028	0.026266	0.002020	0.035780	0.005282	-0.004619	1.000000	-0.003368	0.025227	-0.127397	0.001951	0.009648
liveness	-0.029654	-0.110033	0.028942	0.134815	0.037288	-0.047941	-0.003368	1.000000	0.062695	0.001677	-0.078959	0.122034
loudness	-0.546639	0.249541	0.019791	0.779267	0.106249	-0.317562	0.025227	0.062695	1.000000	-0.019250	0.337194	-0.213504
mode	0.064633	-0.048358	-0.046849	-0.056160	-0.062503	-0.056731	-0.127397	0.001677	-0.019250	1.000000	0.007652	-0.040711
popularity	-0.396744	0.123746	0.024717	0.328939	0.152545	-0.300625	0.001951	-0.078959	0.337194	0.007652	1.000000	-0.195329
speechiness	-0.022437	0.239962	-0.097838	-0.112616	0.353872	-0.133966	0.009648	0.122034	-0.213504	-0.040711	-0.195329	1.000000
tempo	-0.223840	0.005479	-0.008182	0.266448	0.008075	-0.068656	0.005009	0.008586	0.217914	0.002438	0.094985	-0.002437
valence	-0.166968	0.536713	-0.183199	0.326418	-0.009275	-0.219188	0.025592	-0.005781	0.302520	0.021592	0.063471	0.002437

```
from sklearn.preprocessing import MinMaxScaler
```

```
datatypes = ['int16', 'int32', 'int64', 'float16', 'float32', 'float64']
```

```
normalization = data.select_dtypes(include=datatypes)
```

```
for col in normalization.columns:
```

```
    MinMaxScaler(col)
```

Created a class:-

```
class Spotify_Recommendation():
```

```
    def __init__(self, dataset):
```

```
        self.dataset = dataset
```

```
    def recommend(self, songs, amount=1):
```

```
        distance = []
```

```
        song = self.dataset[(self.dataset.name.str.lower() ==
                               songs.lower())].head(1).values[0]
```

```
        rec = self.dataset[self.dataset.name.str.lower() != songs.lower()]
```

```
        for songs in tqdm(rec.values):
```

```
            d = 0
```

```
            for col in np.arange(len(rec.columns)):
```

Conclusion and Future Scope

Recommendation is about extending listeners music universe beyond what they know and like. It empowers listeners once they have exhausted all their songs/artists search capabilities with further navigation celerity. Music services, even before the digital revolution, have been relying on several points of entry in the music catalogue: filter by genres, decades, selections of hits, of new releases/what's trending, by curators/influencers, playlists by context (moods/activities), and provided means for sharing content and playlists.

A song is a 3 minute experience, and the question of what to listen next keeps coming back, contrary to other creative contents (movies, books,...). Hence the historic format of the album, which provides a minimum acceptable duration, along its artistic intention.

People in their day to day life encounter many situations where music can be listened to while doing something else: in transport (cars, traveling,...), while eating, doing sport...or with other people (party,...). In those situations their sight and hands may be busy doing another activity, their hearing is available to listen to music. Music can also be more functional and directly stimulate the activity (dance, yoga, cheering up,...).

The digital revolution provides listeners with devices, apps and algorithms that allow to better capture those listening situation opportunities, and to adapt to each context: rich UI on PC, simplified UI on mobile phones and in cars, voice control in the car and smart speakers.

Even during situations where interaction with screens is limited, listeners can enjoy rich navigation, to the point of inviting designers to create a zero interface where no interaction is possible. Digital brings higher granularity (the possibility to provide multiple types of playlists, similar artists and songs), higher frequency of updates of selections, a much deeper dive in the catalogue, and personalization (personalized recommendations/playlists/UI to each listener).

Project Github Link :-

<https://github.com/gopi76/Music-Recommendation-System->