



ILS Z604: Music Data Mining

# A Mood-Based Music Generator System

*Team Zimmer*

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# Introduction

Music is the art form that is seen to have a stronger connection to a person's emotions. It has the innate power to raise one's mood. In the subject of musical preferences, the emotional expression of a song and, more importantly, its emotional influence on the listener is sometimes disregarded, even though the genre of music is vitally important in forming and showing social identity. Convolutional Neural Network(CNN) models for facial emotion recognition and artificial neural networks (ANN) for music categorization are needed to handle the challenging issue of emotion identification.



Link to the blog: <https://medium.com/@vishwasdesai.info/a-mood-based-music-generator-system-c22586aa2233>



# Literature Review

# Paper 1: *Song Playlist Generator System Based on Facial Expression and Song Mood*

*K. Patel and R. K. Gupta, 2021 International Conference on Artificial Intelligence and Machine Vision (AIMV)*

- This paper proposes a Deep Learning based approach for the playlist generation based on human current mood with the help of user's history of song selection.
- The authors mention that the model for the music playlist generator was based on small datasets and scaling this model to larger dataset will have its own set of issues.

Factors considered for the project include

- What the person (user) is doing ?
- Time recorder while data logging
- Weather affecting the mood of the person
- what community the user belongs to ?



## Paper 2: *Music recommendation system based on facial emotion recognition*

*Samuvel, D. J., Perumal, B., & Elangovan, M. (2020)*

- This paper uses facial recognition technology which the authors say has an “***enormous application value***”
- Facial recognition as a tool is being used in specific fields like security systems to detect intruders (IDS), digital video processing amongst others.
- Compared to other existing algorithms for facial recognition to detect emotions, the proposed algorithm is claimed to be “proficient enough” to rival **large pose variations\***

*Pose variations lead to a special phenomenon that (a) two faces of different persons under a similar viewpoint are smaller than (b) that of the same person under different viewpoints*





# Datasets

## Datasets/data sources recommended for this InfoPack include:

- Spotify Web API

Based on simple REST principles, the Spotify Web API endpoints return JSON metadata about music artists, albums, and tracks, directly from the Spotify Data Catalogue.

- YouTube Music API

YT music API supports nearly all content interactions in the YouTube Music web app like browsing, exploring music, library management, playlist management etc.

- Million Song Dataset

- Face Detection Dataset

The **Face Detection Dataset and Benchmark (FDDB)** dataset is a collection of labeled faces from Faces in the Wild dataset. It contains a total of 5171 face annotations, where images are also of various resolution



# Creating a dataset using the Spotify API

## Using Spotipy

*Spotipy is a lightweight Python library for the Spotify Web API. With Spotipy you get full access to all the music data provided by the Spotify platform.*

```
!pip install spotipy
```

```
[2] import spotipy
    from spotipy.oauth2 import SpotifyClientCredentials
    client_id = "1a93a39ccdef4989afbda65e9662b3c0"
    client_secret = "6b41fe63cd364e2598750deb4e633c67"
    client_credentials_manager = SpotifyClientCredentials(client_id=client_id, client_secret=client_secret)
    data = spotipy.Spotify(client_credentials_manager=client_credentials_manager)
```

```
name = ["The Weeknd", "Rihanna", "Amit Trivedi"]
result = data.search(name)
result['tracks']['items'][1]['artists']
```





*Using the Spotify web API we can collect and organize our dataset based on the artiste.*

```
import pandas as pd
dataframe = pd.DataFrame.from_dict(dic_df)
dataframe
```

	album	track_number	id	name	uri	acousticness	danceability	energy	instrumentalness	liveness	loudness	speechiness	tempo	valence	popularity
0	Dawn FM (Alternate World)	1	3gj1hwku4JaoamJVqlll	Dawn FM	spotify:track:3gj1hwku4JaoamJVqlll	0.674000	0.280	0.478	0.000058	0.4830	-8.755	0.0370	111.650	0.0807	54
1	Dawn FM (Alternate World)	2	6Uj2XaahYXK2WeD7GGwBY	Gasoline	spotify:track:6Uj2XaahYXK2WeD7GGwBY	0.000582	0.728	0.741	0.002060	0.3300	-7.075	0.0473	123.006	0.3100	55
2	Dawn FM (Alternate World)	3	3kOIREqmcGaEA2KhqIFnw	How Do I Make You Love Me?	spotify:track:3kOIREqmcGaEA2KhqIFnw	0.020300	0.805	0.498	0.000024	0.0850	-7.927	0.0737	121.006	0.6360	54
3	Dawn FM (Alternate World)	4	3WXYy2PxX88kpBIB0GH61w	Take My Breath	spotify:track:3WXYy2PxX88kpBIB0GH61w	0.012800	0.698	0.769	0.001660	0.2380	-7.154	0.0368	121.020	0.3540	54
4	Dawn FM (Alternate World)	5	0xa4hvXeYHRRNhA7wBfUar	Sacrifice	spotify:track:0xa4hvXeYHRRNhA7wBfUar	0.029600	0.735	0.795	0.000032	0.0678	-6.523	0.1130	122.000	0.9050	54
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
321	Beauty Behind The Madness	10	3MaQvpdNb4Vv7J7K9jYw1t	In The Night	spotify:track:3MaQvpdNb4Vv7J7K9jYw1t	0.079600	0.505	0.680	0.000000	0.0465	-4.990	0.0713	168.021	0.5390	40
322	Beauty Behind The Madness	11	6MkumkB800lwJXGOln4Th	As You Are	spotify:track:6MkumkB800lwJXGOln4Th	0.131000	0.371	0.329	0.006250	0.2790	-9.667	0.0574	173.661	0.0539	26
323	Beauty Behind The Madness	12	41oeGHskl8UfgwEbyRuP8	Dark Times	spotify:track:41oeGHskl8UfgwEbyRuP8	0.114000	0.501	0.403	0.000011	0.1240	-9.607	0.0752	132.608	0.2700	26
324	Beauty Behind The Madness	13	3dkeFXyOIKg0THR22hxsv	Prisoner	spotify:track:3dkeFXyOIKg0THR22hxsv	0.441000	0.550	0.404	0.000220	0.1100	-12.755	0.0398	135.016	0.3290	26
325	Beauty Behind The Madness	14	3Df2uB1b5XD6JAlu2xOHvH	Angel	spotify:track:3Df2uB1b5XD6JAlu2xOHvH	0.105000	0.626	0.583	0.000000	0.1150	-7.574	0.0435	127.956	0.3350	26

326 rows × 15 columns



An example dataframe of last 5 albums of the artiste “The Weeknd” with other columns in the dataframe like acosticness, danceability, liveliness loudness etc.

```
dataframe.head()
```

	album	track_number	id	name	uri	acousticness	danceability	energy	instrumentalness	liveness	loudness	speechiness	tempo	valence	popularity
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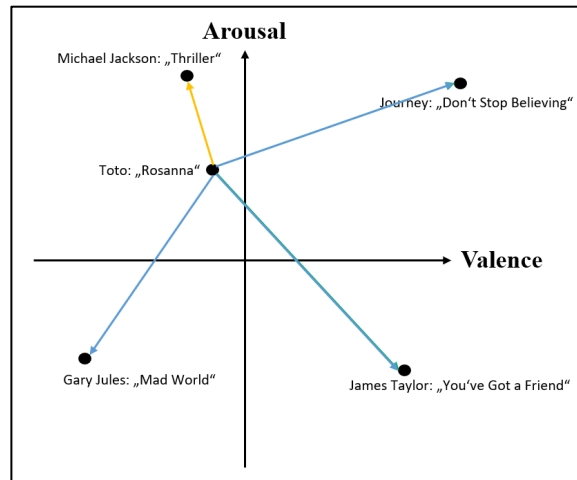




# Case Study

## Case Study: Building a mood-based music recommendation system using Spotify API

- Here a dataset is built using the Spotify API. The recommendation system is based on the vector distance between arousal and valence values for a song.
- A recommendation algorithm is then built which recommends the user a song based on the valence — arousal ratio.



Distance on the Valence-Arousal plane



## Case Study: Building a mood-based music recommendation system using Spotify API

### *Key Takeaways from the Case study*

- The authors have built a music recommendation system that uses an adaptation of the “Valence-Arousal Plane” alongside vector-distance measurements to match tracks that convey a similar type of emotion/mood.*
- This approach is fundamentally different from collaborative filtering methods since it attempts to extract the inner qualities of a song without relying on user data.*
- This is particularly helpful, free and a good learning curve for those who do not operate a large music platform and have billions of relevant user data points.*



**Thank You**



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