Musical Moods

The Problem: The aim of our website was to help users analyze and categorize songs. The categorization was made based on the emotion the songs invoke instead by their frequency and tempo instead of the Genres or Labels they had been tagged by the producers.

The Solution: We designed and developed a website which used the Spotify API to visually distribute and categorize the songs to help the user make a better choice about the mood of the songs they prefer to hear.

The link to our website is here:

<link>

The Project Overview

Most of the music application use popular labelling to categorize the songs into Happy Songs or Sad Songs or Party Songs. What they miss out is a scientific reasoning to that categorization and usually the categories are very wide. Happy Songs category doesn’t tell you how happy, or if its more Exciting than Happy. On the subjective interpretation of the person who was Labelling the Song, it was Labelled as a Happy Song and put into the Happy Songs category.

We have designed a website which uses factors which have Scientific backing for categorization of all Music. Helping the user to select songs based on the emotion and the intensity of that emotion using a Scatter plot, and allowing them to view a song and the emotion it invokes in a Radial graph to distinctly see whether a song is more Happy than Exciting, along with comparing multiple songs in that manner.

Tools:

* Jetbrains Webstorm 2016.3.2
* XAMPP
* Github Desktop Application

Methods/Technology:

* Sketching
* Balsamiq
* HTML/CSS
* Jquery
* D3
* NVD3

My Role:

* Researching the appropriate solution for our problem
* Creating the low fidelity(Sketches) of our idea
* Development using HTML/CSS/Jquery + D3

Method

We researched on papers and articles ranging from mid 1900s to 2016. Research on why music affects the mood was vast and inconclusive. The latest research stated that the main components of music that affects the mood are:

Valence (Spectrum of emotions in music): A measure from 0.0 to 1.0 describing the emotional positivity conveyed by a track. Tracks with high valence are more positive (e.g. happy, cheerful, euphoric), while tracks with low valence are more negative (e.g. sad, depressed, angry).

Energy/Arousal (Intensity and energy in music):Energy is a measure from 0.0 to 1.0 and represents a perceptual measure of intensity and activity. Typically, energetic tracks feel fast, loud, and noisy. For example, death metal has high energy, while a Bach prelude scores low on the Energy. Perceptual features contributing to this attribute include dynamic range, perceived loudness, timbre, onset rate, and general entropy.

Depth is defined as the “intellect and sophistication in music”

We also considered many other components of music which, on review, do not contribute to the mood solely directly, such as:

* Frequency
* Key
* Chords
* Acousticness
* Danceability
* Mode
* Loudness

Dataset

We created our own database of songs from ten different genres’: classic rock, alternative rock, classical music, jazz, soul, country, techno/electronic, heavy metal, pop, and rap. Each genre had ten songs totaling 100 different songs. Each song was unique, and no artist or musician was used twice. Songs also ranged from the 1940’s to 2016.

Along with the songs mentioned above, we integrated our system with Spotify API to allow the user to search any track or albums.

Features of the Website:

Spotify API

Using a scatterplot, song distribution based on their valence and energy.

**Insight**: Each song influences a mood based on the valence and energy.

Recognition of a set of songs based on mood using hover function on the smiley of that mood. If that smiley is clicked, the songs remain highlighted.

Hover and click interactions to get more details about a song in the scatterplot.

Tooltip for each song in the scatterplot. (Minor glitch: If the tooltips do not appear, please refresh and try again)

A radar graph for each song to give details and reasoning about the placement of the song on the scatterplot.

Ability to compare multiple songs in the scatterplot and radar graph.

A legend to help identify songs in the radar graph.

A radar graph goes from 0-100% on each of the axis.

**Insight**: For any individual song, the opposite moods are not necessarily complementary, that is if a song is 60% happy, it doesn’t make the song 40% sad. But, it can also never happen that a song is a great % happy and sad at the same time.

**Insight**: Different songs of extreme position in the scatterplot show very distinct radar graph thus satisfying the co-relation between the two graphs.

Dataset of 100 popular songs, each from a different artist, genre and time preloaded and interactive to give a head start for the user.

Ability to search a track using Spotify API, and extract the song and play it.

Once the song is extracted, so are its components (valence and energy) and hence it is placed on the scatterplot accordingly. This provides the user with the information about the mood of the song and the freedom to create and compare the radar graph of this specific song that the user searched.

The new song is placed on the scatterplot in a different color to distinguish it from the rest, along with a tooltip of itself.

Ability to search for an entire album and once selected, the songs of the album are placed on the scatterplot for the user to analyze the entire album using the scatterplot or each song individually using the radar graph.

**Insight**: Most albums exhibit the trend such as all songs being high in energy or all songs high in valence.

Ability to select from a set of suggestions from the search bar.

A set of 4 visualizations of the song based on its frequency while the song is playing. Unfortunately, Spotify doesn’t allow us to play the complete song unless it’s a paid account.

Frequencies are generated after a Fast Fourier Transform (FFT) approximately 192,000 times/sec, but to avoid graphic overload, most frames are dropped, thus we get an array where ith element represents a frequency range and value of the ith element represents the decibel level in that frequency range. This array is generated multiple times a second, depending on the processing capacity of the client’s system.

Ability to play and pause a song.

Ability to choose another song.

Information provided to the user in the documentation page of the website about the how the valence and energy values influence moods in form of a graph. This is provided for the user’s reference and further analysis if he wants to conduct one.

Things we were planning to include:

* Compare multiple albums by the same artists or different artists
* Ability to create a playlist by selection of songs using the scatterplot, aiding the user to listen to the songs of the similar emotions.
* Searching and compare songs by an artist.
* Searching and compare songs by a genre.
* More detailed visualizations of the song when its playing.
* Refining the current visualizations.

Limitations of our project:

* Understanding which component of the songs affects the mood took up all of the research time as we kept hitting dead ends.
* Spotify API was very complex and understanding it took a big chunk of our time
* Data regarding valence and energy received from Spotify was in a different format from the theory of our research. Converting this data into the other format created complications for the scatterplot and the radar graph.
* Using a separate d3 library using NVD3.
* Extremely subjective dataset and hence hard to find scientific reasons for any claims regarding mood and what affected the mood.

Other research we have:

Research on various ways of extracting the following of a song.

* frequency,
* keys
* chords,
* tempo,
* melody
* genre
* Musicovery API
* Sonic API
* Music Mood API

We did not include the above features since we do not have any research on how these are related to emotions. We have working code for all the above.