Music Analysis & Recommendation Engine (M.A.R.S.)

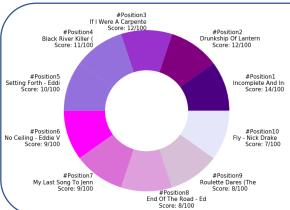
Simon Fraser University, Big Data Programming II

Kashish Kohli Kanksha Masrani

Problem & Approach

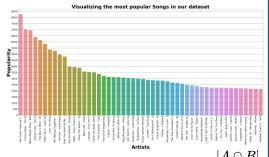
- In 2018, the global music industry was worth USD 130 Bn + and is estimated to grow faster than ever fueled by the rise of paid streaming services.
- Numerous advantages vs challenges.
- We developed a Popularity Based Recommender and a User Similarity based Collaborative Filtering Model.
- Song popularity prediction using 6+ ML algorithms.
- Music Sentiment Analysis by region.





Recommendation Engine

Million Songs Dataset with 2 million songs and 75,000 user profiles.

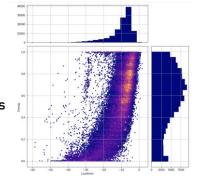


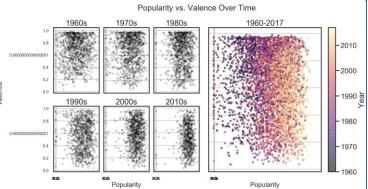
- Recommendations for the User Similarity model by using Jaccard Index to plot the Cooccurrence matrix.
- Included dual functionality of suggesting songs based on history of the user as well as based on a single song alone.



Song Popularity Prediction

- Amalgamation of Spotify and MSD Dataset with 120,000 records of music features and metadata.
- Analyzed trends to map success of music in the present and future

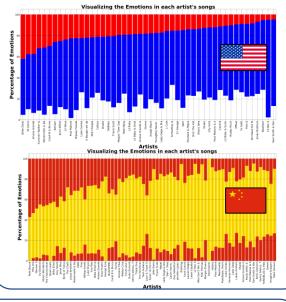


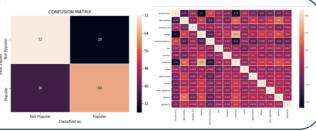


- Machine Learning Models using Gridsearch for Model Tuning:
 - KNN Clustering: 62%
 - Support Vector Classifier : 65%
 - Adaptive Boosting: 65.5%
 - Logistic Regression : 66%
 - Convolutional Neural Network : 67.5%
 - Random Forest: 70%

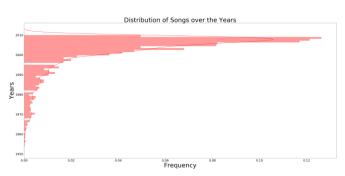
Global Sentiment Analysis

- Extracted data from iTunes RSS Feed Generator to get top 100 hit songs for multiple countries.
- Calculated the Lexical Richness of each country's top songs and performed sentiment analysis using NLTK Sentiment Vader, GoogleTrans and GoSlate.





Recommendation System



Popularity Based Recommender

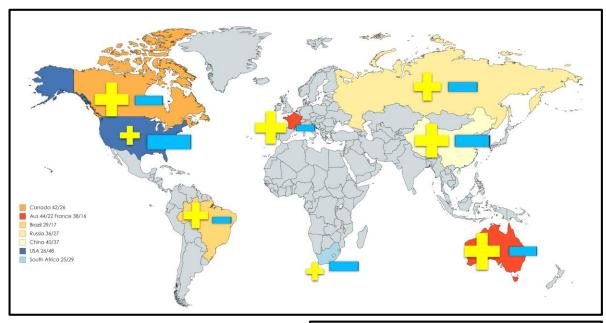
| | Song Name | Similarity Score | Position |
|------|--|------------------|----------|
| 2309 | Me Gusta Todo de Tí - Luis Alfonso Lizárraga | 34 | 1.0 |
| 66 | A Puro Dolor - Son By Four | 26 | 2.0 |
| 657 | Cheap Trick - The Flame | 23 | 3.0 |
| 3975 | Use Somebody - Kings Of Leon | 23 | 4.0 |
| 2818 | Poker Face - Lady Gaga | 22 | 5.0 |
| 3576 | The Boy Is Mine - Brandy Norwood | 21 | 6.0 |
| 3702 | The Scientist - Coldplay | 21 | 7.0 |
| 476 | Boom Boom Pow - Will.I.Am Fergie | 19 | 8.0 |
| 1605 | How You Remind Me - Nickleback | 19 | 9.0 |
| 2218 | Low - Flo Rida | 18 | 10.0 |

User Similarity based Collaborative Filtering Model

| | Song Suggestions | Similarity Score | Position |
|---|--|------------------|----------|
| 0 | Isolation - Joy Division | 0.030351 | 1 |
| 1 | Transmission - Joy Division | 0.029383 | 2 |
| 2 | Shadowplay - Joy Division | 0.029157 | 3 |
| 3 | Digital - Joy Division | 0.027941 | 4 |
| 4 | The Stranger Song - Leonard Cohen | 0.021234 | 5 |
| 5 | Dead Souls [Re-mastered] - Joy Division | 0.020127 | 6 |
| 6 | The Killing Moon - Echo And The Bunnymen | 0.016971 | 7 |
| 7 | Damaged Goods - Gang Of Four | 0.016238 | 8 |
| 8 | Friction (LP Version) - Television | 0.014653 | 9 |
| 9 | This Charming Man - The Smiths | 0.014265 | 10 |

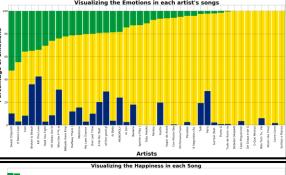
Global Music Sentiment Analysis

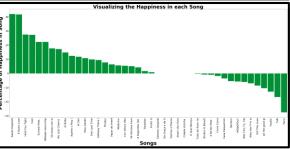




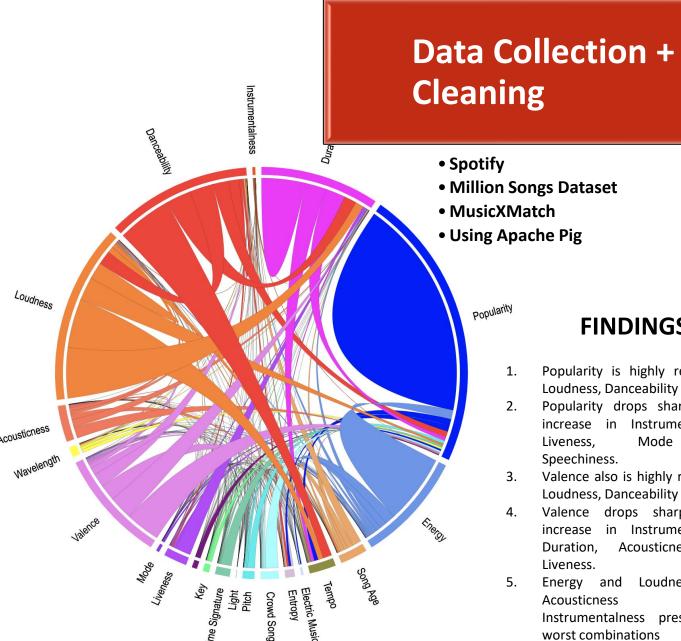
Workflow

- 1. Fetch JSON format data from iTunes RSS Feed Generator
- 2. Fetch lyrics of these songs from Genius.com using Pypi wrappers
- 3. Analyze unique wordcount to calculate lexical richness.
- 4. Translate the song (if required) using GoogleTrans/GoSlate/Pypi wrappers
- 5. Perform lyrical sentiment analysis using NLTK Sentiment Vader and calculate the percent of positive/neutral/negative lyrics to ascertain song trends in each country.
- 6. Plot the positive/negative percentage of songs heard in the country.









Exploratory Data Analysis

Data Manipulation

- Detecting Outliers
- Plotting Correlations

- One Hot Encoding
- Categorization into popularity classes

FINDINGS

- Popularity is highly related to Loudness, Danceability & Energy
- Popularity drops sharply with increase in Instrumentalness, Mode Liveness, and Speechiness.
- Valence also is highly related to Loudness, Danceability & Energy
- Valence drops sharply with increase in Instrumentalness, Duration, Acousticness and Liveness.
 - Loudness with Energy and Acousticness and Instrumentalness present the worst combinations

| acousticness - | 1 | -0.35 | 0.028 | -0.7 | 0.26 | -0.017 | -0.098 | -0.59 | 0.064 | -0.11 | -0.21 | -0.16 | -0.17 | -0.1 |
|--------------------|--------|--------|----------|--------|---------|----------|---------|--------|---------|---------|---------|--------|--------|---------|
| danceability - | -0.35 | 1 | -0.12 | 0.27 | -0.3 | 0.019 | -0.14 | 0.42 | -0.055 | 0.24 | 0.077 | 0.21 | 0.46 | 0.13 |
| duration_ms - | 0.028 | -0.12 | 1 | -0.018 | 0.026 | -0.00084 | -0.0032 | -0.016 | 0.0075 | -0.092 | -0.0082 | 0.02 | -0.14 | -0.0094 |
| energy - | -0.7 | 0.27 | -0.018 | 1 | -0.29 | 0.037 | 0.21 | 0.76 | -0.065 | 0.1 | 0.23 | 0.16 | 0.31 | 0.12 |
| instrumentalness - | 0.26 | -0.3 | 0.026 | -0.29 | 1 | -0.025 | -0.054 | -0.51 | -0.0056 | -0.22 | -0.086 | -0.087 | -0.24 | -0.21 |
| key - | -0.017 | 0.019 | -0.00084 | 0.037 | -0.025 | 1 | 0.0073 | 0.026 | -0.18 | 0.0075 | 0.005 | 0.0077 | 0.041 | 0.0027 |
| liveness - | -0.098 | -0.14 | -0.0032 | 0.21 | -0.054 | 0.0073 | 1 | 0.061 | -0.0031 | 0.1 | -0.014 | -0.02 | -0.012 | -0.028 |
| loudness - | -0.59 | 0.42 | -0.016 | 0.76 | -0.51 | 0.026 | 0.061 | 1 | -0.032 | 0.075 | 0.22 | 0.18 | 0.31 | 0.24 |
| mode - | 0.064 | -0.055 | 0.0075 | -0.065 | -0.0056 | -0.18 | -0.0031 | -0.032 | 1 | -0.055 | 0.0018 | -0.038 | 0.017 | -0.012 |
| speechiness - | -0.11 | 0.24 | -0.092 | 0.1 | -0.22 | 0.0075 | 0.1 | 0.075 | -0.055 | 1 | 0.052 | 0.054 | 0.12 | -0.0013 |
| tempo - | -0.21 | 0.077 | -0.0082 | 0.23 | -0.086 | 0.005 | -0.014 | 0.22 | 0.0018 | 0.052 | 1 | 0.085 | 0.1 | 0.036 |
| time_signature - | -0.16 | 0.21 | 0.02 | 0.16 | -0.087 | 0.0077 | -0.02 | 0.18 | -0.038 | 0.054 | 0.085 | 1 | 0.07 | 0.06 |
| valence - | -0.17 | 0.46 | -0.14 | 0.31 | -0.24 | 0.041 | -0.012 | 0.31 | 0.017 | 0.12 | 0.1 | 0.07 | 1 | 0.036 |
| popularity - | -0.1 | 0.13 | -0.0094 | 0.12 | -0.21 | 0.0027 | -0.028 | 0.24 | -0.012 | -0.0013 | 0.036 | 0.06 | 0.036 | 1 |
| | - v | , , | - 5 | , - y | - '2 | , Y | 10 | , s | ė. | - v | - 0 | به | - u | - h |

Split Data

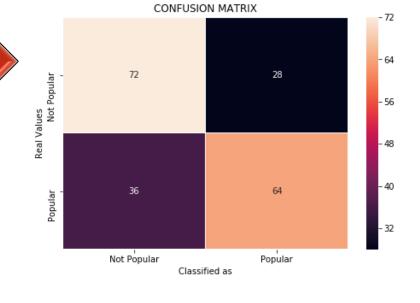
With & without Outliers

Design & Test Models

Test Results

- Train test Split
- 80% Training Data vs 20% Test Data
- 64000 vs 16000

- Confusion Matrix
- Classification Report
- ROC Curve



KNN Clustering

- •Accuracy 0.63
- •With Cross Validation 0.62

Adaptive Boosting

•Accuracy 0.65

Support Vector Classifier

- Used Gridsearch to get optimum parameters
- Accuracy 0.65

Convolution al Neural Networks

- •Used Gridsearch
- •Accuracy 0.67

Random Forest

- Used Gridsearch
- Accuracy 0.7

