Music Recommender and Genre Classification System

(CSCI 5502)

Team Overview

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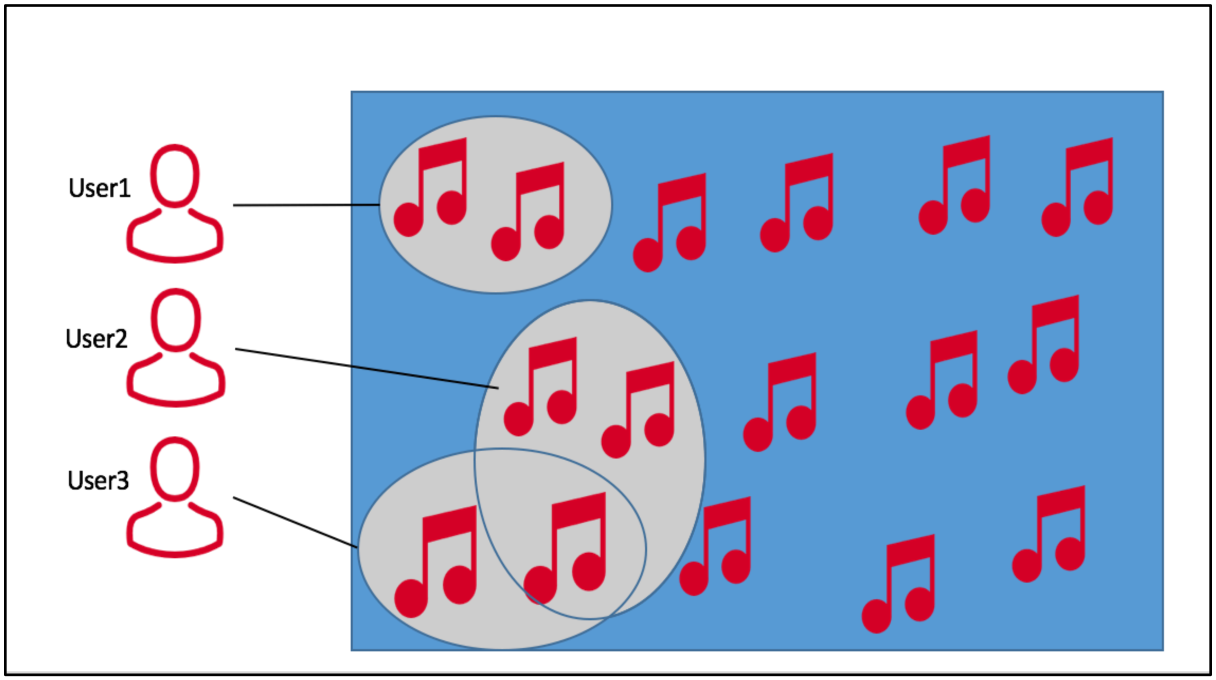
Problem

How to recommend music to Users ?

Given

- Set of Songs
- Set Users
- User profile



Previous Works

- Recommendation Systems produce recommendation in two ways - through collaborative or content-based filtering.

Collaborative filtering

- Depends on Community of Users
- Based on User Similarity
- “Cold Start” Problem

Content Based filtering

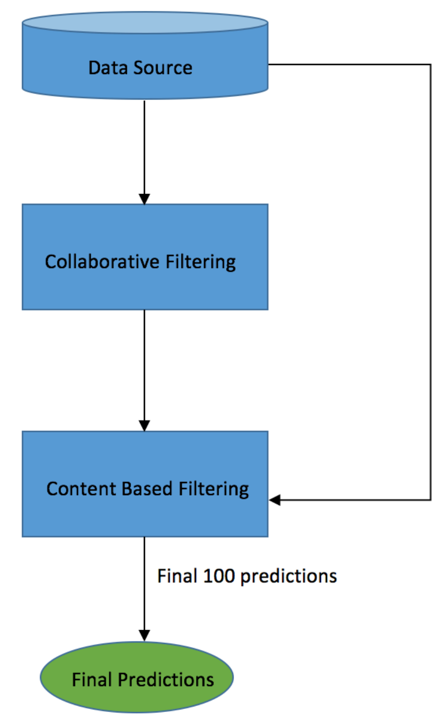
- Based on Song Similarity
- Depends on Song Features

Collaborative

Content Based

Proposed Work

- Combine the advantages of collaborative filter and content-based filter to form a hybrid recommendation system
- Genre Classification to categorize music
- Recommendation based on time of the day and User mood



Hybrid Model for Recommendation

Libraries / Frameworks Used

- Python
- Apache Spark
- Sklearn
- Theano
- Tensorflow google
- Numpy
- Pandas

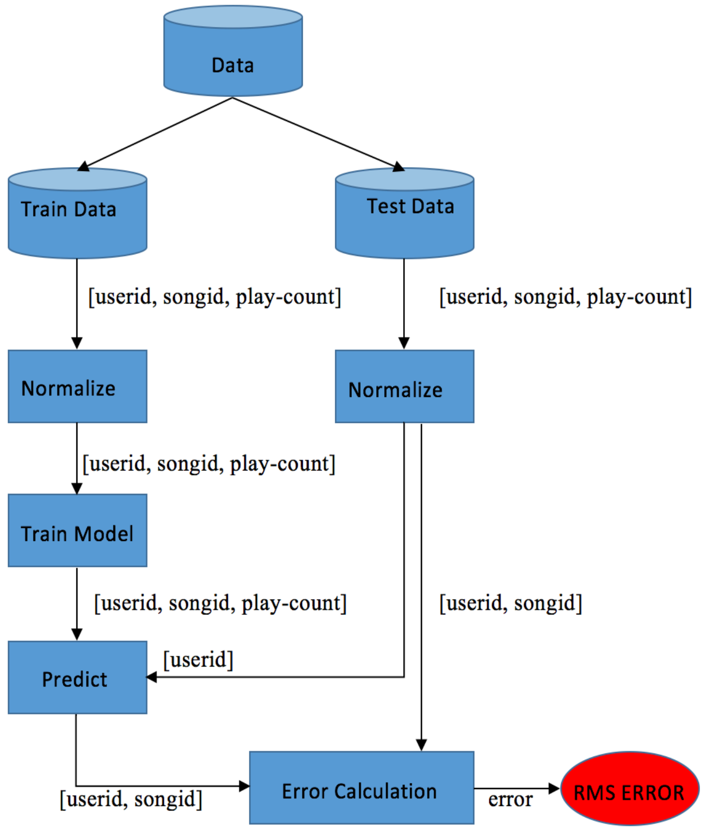
Datasets

- Million Song dataset (http://labrosa.ee.columbia.edu/millionsong/) - Open Source
- Available Datasets
  - SecondHandSongs dataset -> cover songs
  - musiXmatch dataset -> lyrics
  - Last.fm dataset -> song-level tags and similarity
  - Taste Profile subset -> user data
  - thisismyjam-to-MSD mapping -> more user data
  - tagtraum genre annotations -> genre labels
  - Top MAGD dataset -> more genre labels

- The raw data consists of listening history of a million users in HD5 format.
- Only a subset (1 million entries) of the data is used for testing.
- Full dataset (46 million entries) – AWS (~4hr) Collaborative Filtering
- K-Fold Cross-Validation (4:1)

Collaborative Filter(CF)

- Memory based CF:
  - Based on user rating to compute the similarity between the users
  - Performance decreases as the data gets sparse
- Model Based CF:
  - Based on machine learning algorithms to find patterns on training data
  - The users and items are a small set of latent factors used to predict missing entries
  - Performance is better in case of sparse data and is scalable
  - Used Alternating Least square algorithm to learn the latent factors
  - Play count of a song is used as rating

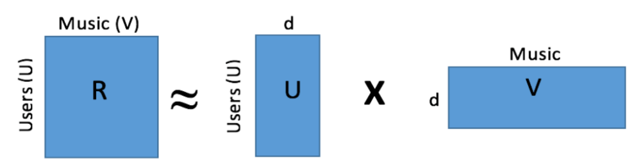


Collaborative Filter(CF)

- Used Apache Spark's Mlib - Model based collaborative – Uses Alternating Least square Algorithm.

Algorithm 1 ALS Algorithm

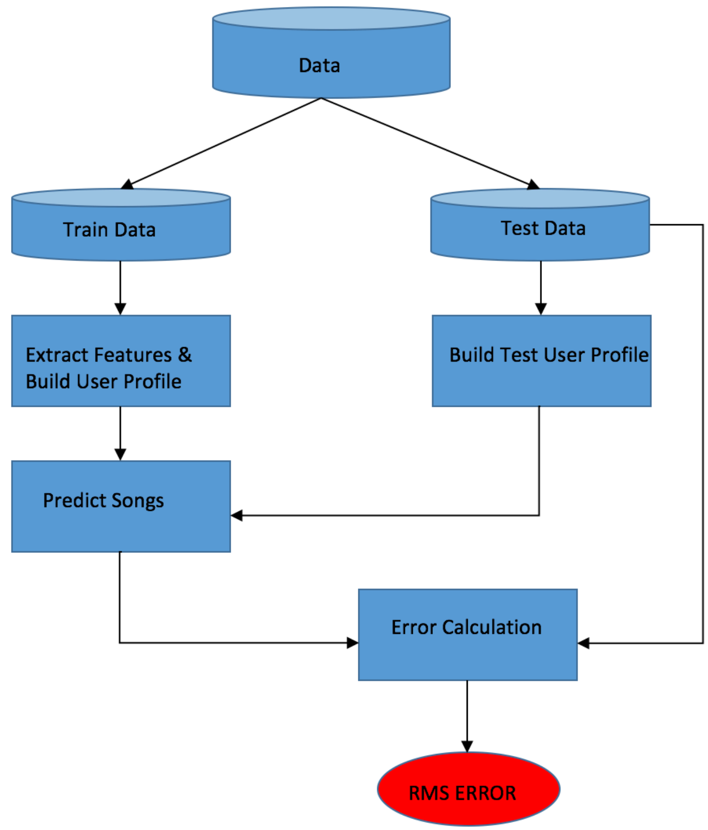
```
Set up vectors yUsers, yItems, xq, and xp
Initialize μ, a_i, b_u, y_ui
while MSE not converged and iteration ≠ max limit do
    Create q_i vectors
    Solve for p_u vectors
    Create p_u vectors
    Solve for q_i vectors
    Rescale each p_u and q_i vector
    Update μ, a_i, b_u, y_ui
    Find MSE
end while
```



Low Rank Matrix Factorization

Proposed Work – Content-Based Filtering

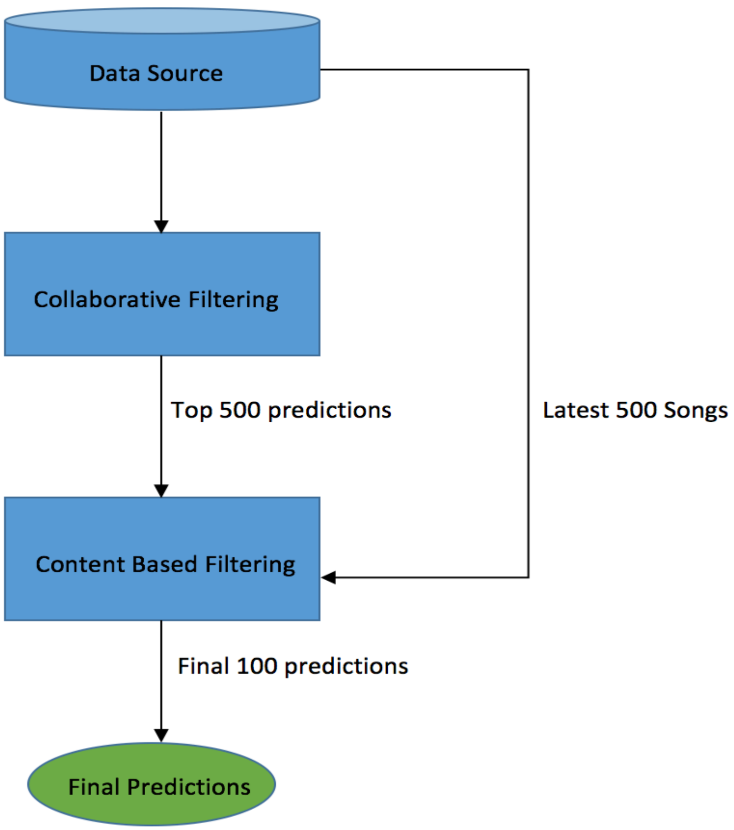
- Depends on the attributes and features of the songs
- Song attributes considered include danceability, tempo, energy, timbre, key, loudness
- User profile is based on a weighted vector of songs This weights denote importance of each feature.
- Machine learning algorithms like Bayesian Classifiers, cluster analysis, decision trees, artificial neural networks, etc., were used



Hybrid Model = Collaborative Filter + Content-based Filter

Two approaches are pipelined – Output of Collaborative Filtering is fed as input for Content based Filtering

Feed latest songs for content based filtering to recommend the latest songs also – to overcome the disadvantage of Collaborative Filtering.



Genre Classifier

- Automatic Genre Classification – Categorize music based on genre
- Data mining techniques and Machine learning algorithms on existing data.
- Feature vector include
  - Loudness,
  - Tempo
  - Danceability
  - Key
  - Energy
  - Duration
  - Artist Name etc
- Model is constructed using above feature vector to predict genre.
- Modelling techniques –
  - Support Vector Machines (SVM), Nearest-Neighbor (NN) classifiers
  - Gaussian Mixture Models, Linear Discriminant Analysis (LDA), Random Forest

Completed Tasks

- **Collaborative Filtering**
  - Apache Spark model-based collaborative filter using Alternating Least Squares (ALS) algorithm.
- **Content Based Filtering**
  - Logistic Regression from Apache Spark
  - SVM
- **Hybrid Model**
- **Genre classifier:**
  - Constructed feature vector using attributes like “Loudness", “Tempo", “Time-Signature", “Mode", “Key", “Average Timbre", “Duration" and “Variable Timbre”.
  - Logistic Regression
  - Naïve Bayes
  - Random Forest
  - Decision Tree
- **Evaluation Metrics**

Performance Evaluation

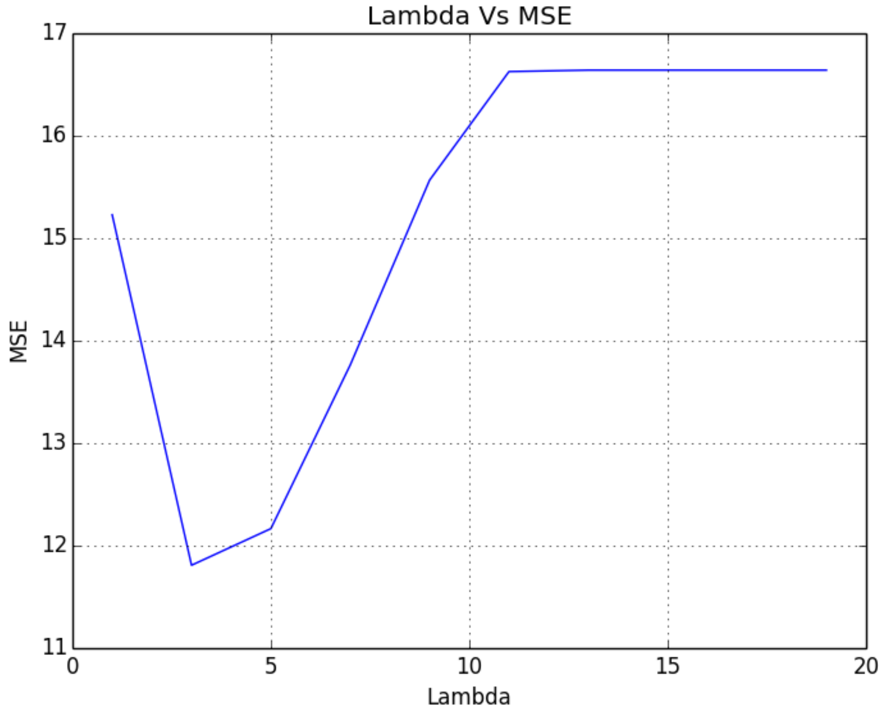
- Mean Squared Error and Root Mean Squared Error.
- Precision and recall or DCG to assess the quality of the recommendation system.
- K Fold Cross Validation in the ratio of 4:1 (Split the input data into training set and test set)
- RMSE formula :

$$RMSE = \sqrt{\frac{1}{n}\sum_{p,q}|P_{u,v} - R_{u,v}|^2}$$

- Evaluation of Genre Classifier – Predicted genre for songs of known genre and compare the predicted genre with the actual genre of the song.

Key Results

- Collaborative Filtering Results



Rank = 8 Number of Iterations = 10

Lambda – Regularization Parameter	Mean Squared Error
1	15.23
3	11.80
5	12.16
7	13.76
9	15.56
11	16.62
13	16.64
:	:
20	16.64

Key Results

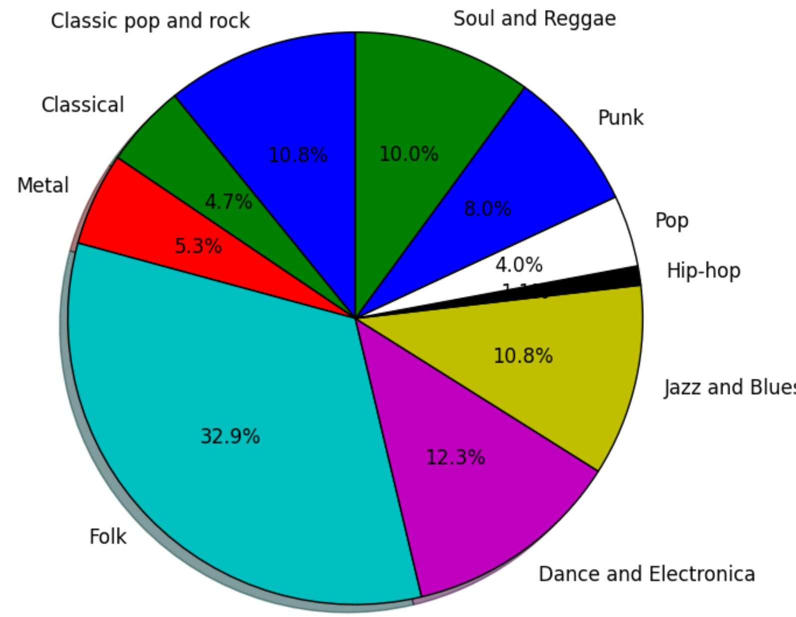
- Content Based Filtering Results

Key Results

- Genre Classifier

Classifier	Accuracy
Logistic Regression	53.76
Decision Tree	47.58
Naïve Bayes	24.52
Random Forest	58.37
SVM	41.73
SVM + Boosting	49.64

Classifier Vs Accuracy

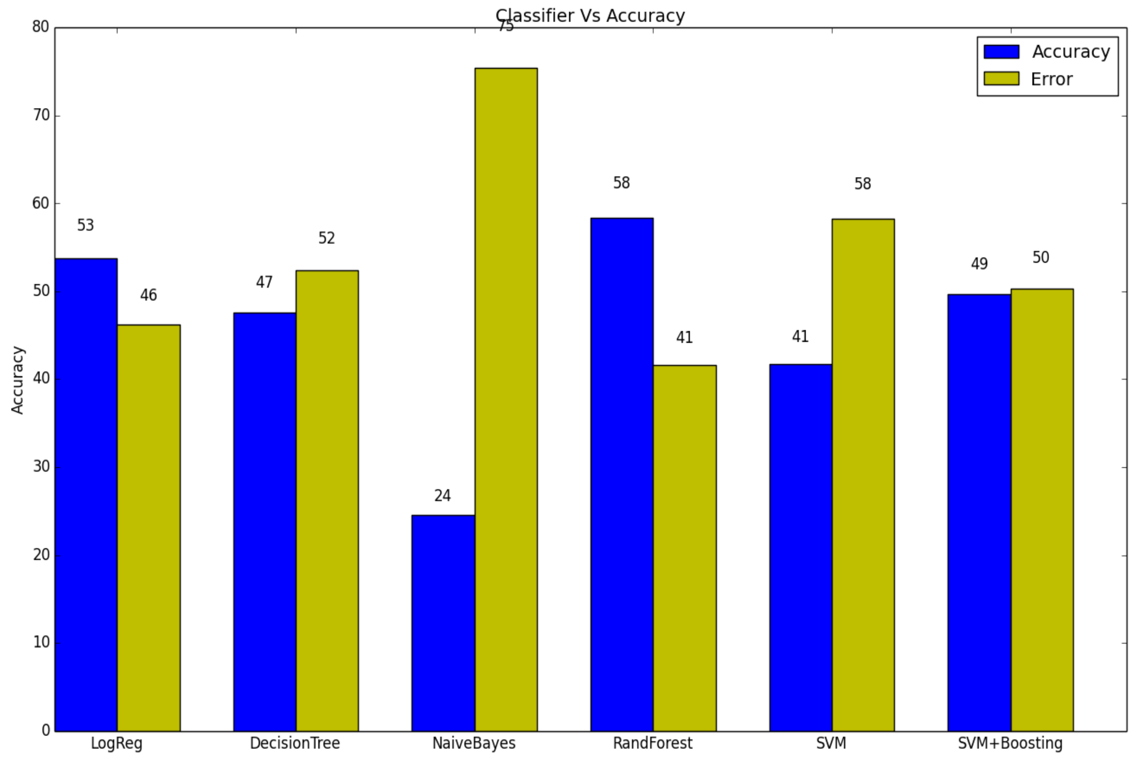


Distribution of Genre

Key Results

Genre Classifier

- Random Forest – Highest Accuracy – Ensemble method



Showing Top 20 rows in Genre Classification using Random Forest

genre	track_id	features	indexedLabel	rawPrediction	probability	prediction	predictedLabel
classic pop and rock	TRAAAGR128F425B14B	[-7.322,123.989,4...	0.0	[0.30337078651685...	[0.15168539325842...	2.0	dance and electro...
classic pop and rock	TRAACPE128F421C1B9	[-11.939,110.189,...	0.0	[0.87855449075979...	[0.43927724537989...	0.0	classic pop and rock
classic pop and rock	TRAACQW128F428854F	[-7.032,47.271,4....	0.0	[0.98946869070208...	[0.49473434535104...	0.0	classic pop and rock
classic pop and rock	TRAAGJV128F1464090	[-9.091,129.122,1...	0.0	[0.90697350069735...	[0.45348675034867...	0.0	classic pop and rock
classic pop and rock	TRAAGNL128F4299BF1	[-11.335,137.29,4...	0.0	[1.09313479623824...	[0.54656739811912...	0.0	classic pop and rock
classic pop and rock	TRAAIAN12903CFF16D	[-11.479,151.911,...	0.0	[0.96922310797627...	[0.48461155398813...	0.0	classic pop and rock
classic pop and rock	TRAAMUY128F4283222	[-7.947,108.94,4....	0.0	[0.57220342053330...	[0.28610171026665...	1.0	folk
classic pop and rock	TRAAOAU12903D0154B	[-15.146,77.27,4....	0.0	[0.88663745892661...	[0.44331872946330...	0.0	classic pop and rock
classic pop and rock	TRAAUSW128F426646E	[-10.173,102.055,...	0.0	[0.84805175267037...	[0.42402587633518...	0.0	classic pop and rock
classic pop and rock	TRAAXRS128F932F05D	[-14.26,121.93,4....	0.0	[1.38208708930594...	[0.69104354465297...	0.0	classic pop and rock
classic pop and rock	TRABEKP128E078C123	[-17.772,116.267,...	0.0	[0.64463445530220...	[0.32231722765110...	1.0	folk
classic pop and rock	TRABJYG128F92EB8DC	[-8.482,120.809,4...	0.0	[1.28955547736335...	[0.64477773868167...	0.0	classic pop and rock
classic pop and rock	TRABLSO128F14A4707	[-13.134,152.434,...	0.0	[0.31194968553459...	[0.15597484276729...	1.0	folk
classic pop and rock	TRABMTM12903D083D2	[-4.942,92.014,1....	0.0	[1.15726233421274...	[0.57863116710637...	0.0	classic pop and rock
classic pop and rock	TRABTFI128F14905F6	[-18.264,151.477,...	0.0	[1.00660429279031...	[0.50330214639515...	0.0	classic pop and rock
classic pop and rock	TRABTYR128F9304934	[-16.172,127.207,...	0.0	[0.93363338820870...	[0.46681669410435...	0.0	classic pop and rock
classic pop and rock	TRABWPT128F42B06CC	[-10.548,89.966,4...	0.0	[0.57273482959268...	[0.28636741479634...	1.0	folk
classic pop and rock	TRABXHU128F147EDE9	[-14.369,157.219,...	0.0	[0.93995765275257...	[0.46997882637628...	0.0	classic pop and rock
classic pop and rock	TRACRBQ128F4263964	[-14.293,111.492,...	0.0	[0.96624803767660...	[0.48312401883830...	0.0	classic pop and rock
classic pop and rock	TRACTIQ128F4288A7C	[-8.45,130.031,4....	0.0	[1.18783945428682...	[0.59391972714341...	0.0	classic pop and rock

Future Scope

- Use Deep learning techniques.
- Use Probabilistic Topic Modelling with Collaborative Filtering
- Recommend songs based on time of the day (Morning,Noon,Evening).
- Recommendation based on mood tags sad, happy, joyful, romantic, etc.
- Integration with Spotify/I-tunes etc