# Data Mining Final Project

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# Song Recommendation System

## Introduction

The project is about a model producing a new playlist for the user depending on his music taste. The idea is based on commonly used frameworks such as Spotify and YouTube. The user types a song and its respective artist, and a playlist of recommendations is created. As with the platforms mentioned before, the system does not recommend a single song, but a whole playlist from which the user can pick his preference, or listen to the whole playlist.

Every individual has a unique music taste and making accurate propositions based on a single input song, he or she likes is tricky. For example, if two people love a particular song, there is a big possibility that a single song proposed by the system, closer to their desired choice, might not be as likable to both users. For this reason, to evade the problem of false positives, the model will create a playlist instead of a single recommendation.

As a result, the probability of recommending songs, that would be liked by the user, is raised. Moreover, when users pick new songs out of the proposed playlist, more data about this user's likes is acquired. Making accurate propositions based on more information about the targeted user would highly increase the performance of the model.

The approach the proposed model uses is a hybrid method. A combination of both content-based and collaborative filtering. This approach was selected to hide the limitations of both methods. Moreover, song similarity can be counted by comparing both metadata, such as music genres and attributes, in addition to counting the number of times, particular users listened to these songs. If many people streamed a song a high number of times and these same users listened to another song as many times, there is a big possibility these two songs are much alike. However, both approaches aren't perfect. Users often have completely different music likes and dislike,and songs that have similar metadata, arent as close as data suggest they are. As a result,a combination of both methods was selected.

## Datasets Used

As far a the content-based method is concerned, ..Firstly,a data frame including 10.000 Artists and 4 unique descriptive tags for each, was scraped from the web.LastFm is a website with a huge collection of music data and offers free access to developers, to get an API key and download information about artists or songs. Scraping code along with the scraped dataset, are included

Out[48]:

| | Artist | Tags |
|---|---|---|
| **0** | Kanye West | Rap,Rnb,HipHop |
| **1** | Billie Eilish | Indie,Electronica,Pop |
| **2** | Post Malone | Rap,Trap,CloudRap,HipHop |
| **3** | Ariana Grande | Pop,Rnb,FemaleVocalists |
| **4** | Coldplay | Alternative,Rock,Pop,Uk |
| **...** | ... | ... |
| **13995** | Kronos Quartet | Classical,Instrumental,Contemporary |
| **13996** | Wim Mertens | Classical,Contemporary,Minimal,Piano |
| **13997** | The Seeds | 60S,Rock,Psychedelic,Garage |
| **13998** | The Appleseed Cast | Indie,Rock,Emo,PostRock |
| **13999** | Brand Nubian | Underground,Rap,HipHop |

10000 rows × 2 columns

(Dataset’s final form.)

When the data frame was downloaded, it had over 2100 tags in total. A number that would create many sparse issues and bad recommendations. To begin with, some of them only appeared less than 4 times. These tags were removed since, in a dataset of 10.000 observations, it would be highly unlikely to take advantage of these tags and use them for making accurate recommendations. As a result, they were treated as noise and got removed.

Secondly, a number of tags were the same, but with a single character being different. For example, PopRock and Pop_Rock are exactly the same. These tags were identified and only a single version of them was kept. To do that, Levenshtein distance between tags was measured, and tags whose distance was less than 3 characters were examined, to identify these similarities.

What is more, association analysis was applied so more insights could be discovered. Different approaches with different support and confidence thresholds were used. One very interesting discovery was the existence of some tags that were a merge of two others. For example, PopRock or SpanishMetal, and AlternativeRock. These tags were split, and the total number of tags was reduced. Moreover, the respective weights of the two tags, created after the split, were raised and, as a result, more accurate predictions could be made. Furthermore, some tags had the same meaning but were defined differently. These tags were examined and altered as well.

In addition, text mining and TF-iDF were also applied to check the importance of some tags to their respective bands. The conclusion of this approach was that tags were following a hierarchical structure. Specific tags such as Rock, Indie, HipHop, and Electronic had a total weight of over 450. This is because they were some kind of “superclass” and most tags contained one of them. Moreover, tags with weights over 50 and less than 450 were second in the hierarchy while “less important” tags that were pretty descriptive were last.

The main idea was to split more tags, so the weights of the tags in the second class would be raised. This was mainly because, these tags would be the tags that would be decisive and define the high similarity scores between artists. Furthermore, after considering the results of the apriori algorithm, superclass tags were added to most artists, so a certain number of similarities between them was built. Lastly, tags with a very small weight sum were removed. The last approach, which was used to lower the number of tags, was human knowledge. Tags were examined one by one and the unnecessary ones were removed, while the ones with the same meaning were merged.

The number of tags after these methods was reduced to 432. Pretty good to be used for comparing similarities between artists.

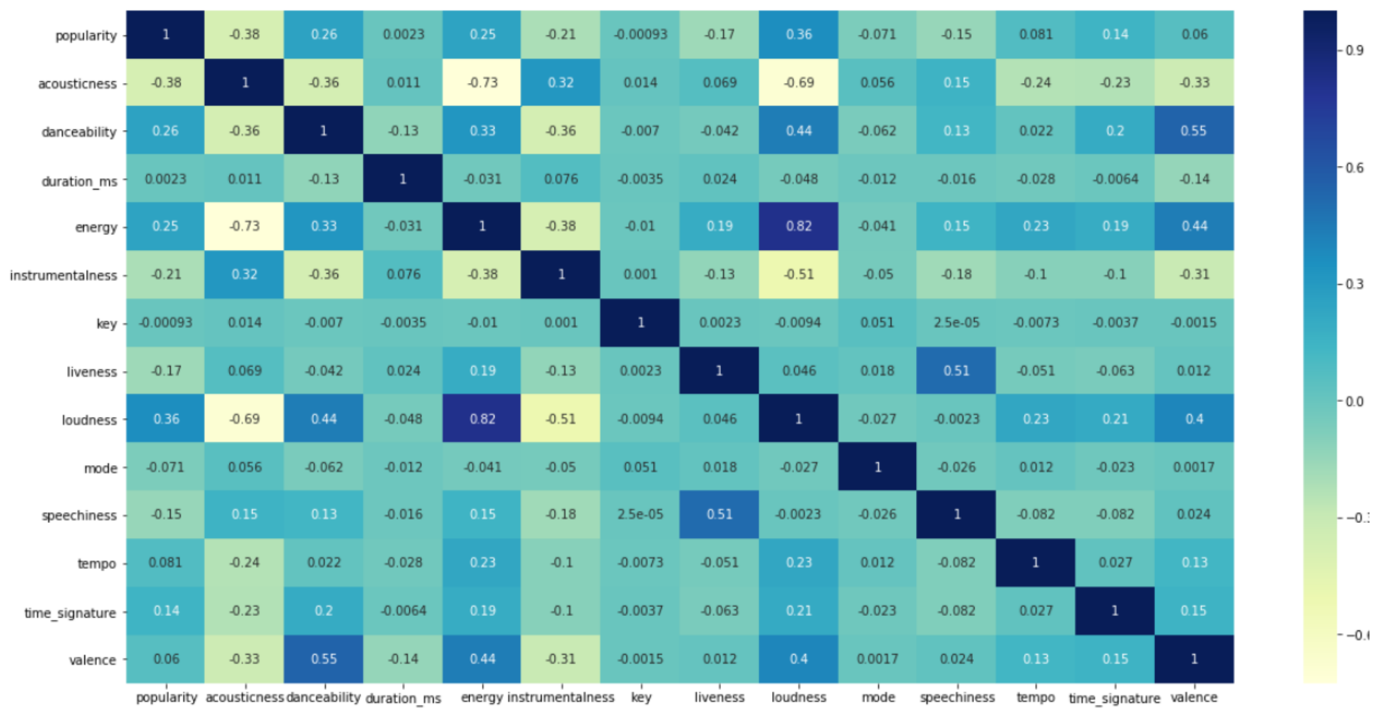
The second dataframe used for the content-based approach had its focus entirely on songs, not artists. Over 232.000 songs, from different music types, were included and each song had over 12 features. These features were continuous values that were describing a specific metric of each song. These metrics included loudness in decibels, valence, which described the musical positiveness of a track, energy, and others. A detailed explanation of what each feature describes is included later on.

Link: https://www.kaggle.com/zaheenhamidani/ultimate-spotify-tracks-db

Out[50]:

| | Genre | Artist | Song | popularity | acousticness | danceability | duration_ms | energy | instrumentalness | key | liveness | loudness | mode | speechi |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | Movie | HENRI SALVADOR | c'est beau de faire un show | 0 | 0.61100 | 0.389 | 99373 | 0.910 | 0.000000 | C# | 0.3460 | -1.828 | Major | 0.( |
| **1** | Movie | MARTIN & LES FÉES | perdu d'avance (par gad elmaleh) | 1 | 0.24600 | 0.590 | 137373 | 0.737 | 0.000000 | F# | 0.1510 | -5.559 | Minor | 0.( |
| **2** | Movie | JOSEPH WILLIAMS | don't let me be lonely tonight | 3 | 0.95200 | 0.663 | 170267 | 0.131 | 0.000000 | C | 0.1030 | -13.879 | Minor | 0.( |
| **3** | Movie | HENRI SALVADOR | dis-moi monsieur gordon cooper | 0 | 0.70300 | 0.240 | 152427 | 0.326 | 0.000000 | C# | 0.0985 | -12.178 | Major | 0.( |
| **4** | Movie | FABIEN NATAF | ouverture | 4 | 0.95000 | 0.331 | 82625 | 0.225 | 0.123000 | F | 0.2020 | -21.150 | Major | 0.( |
| **...** | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | |
| [illegible] | [illegible] | [illegible] | son of | [illegible] | [illegible] | [illegible] | [illegible] | [illegible] | [illegible] | [illegible] | [illegible] | [illegible] | [illegible] | [illegible] |

This particular dataset was ready to be used, with only slight alterations needed. However, in order to further understand similarities between songs, some exploratory analysis was implemented. First of all, correlations between each feature were explored. The very low correlated feature would later be removed. Higher correlated ones were further examined.




(correlation heatmap)

High correlations were spotted between loudness and energy, valence and danceability, and between speeches and loudness. On the other hand, negative correlations can be seen between energy and instrumentalness, valence and instrumentalness, and loudness and accousticness. In addition, features such as key and major had very small correlation scores with the other metrics and were later removed.

At first loudness and energy were merged into a single feature, using their mean value. This was due to their high correlation in comparison to the other attributes. However, since by definition, these features are different, and after examining the results of the recommendation system, with and without merging them, the final model uses them individually and not merged.

What is more, data was normalized so everything is under the same scale and the selection of the features took place. Features such as key and major were removed, in addition to time_stamp, duration as they wouldn't play a significant role in my recommendation system. Lastly, the music genre will also not be included since the dataset described before is more descriptive. The features contained in the final dataset:

- Accousticness: A measure for high acoustic is each song, the higher the value the more acoustic.

- Danceability: How suitable is a song for dancing. Higher values for more danceable songs.
- Energy: A measure of intensity and activity. Fast, loud and noisy tracks have high energy values.
- Instrumentalnes: How non-vocal each track is. High values stand for a song that has a small number of vocals and is more acoustic.
- Liveness: Detects the presence of an audience in the recording. Higher liveness values represent an increased probability that the track was performed live.
- Loudness: Overall loudness in decibels
- Speachness: The presence of spoken words in a track. Values over 0.66 represent songs that are primarily made of spoken words, while values between 0.33 and 0.66 stand for a song that has some balance between music and speech.
- Valence: Musical positiveness of a track. High valence songs are positive songs.

With reference to:
[https://developer.spotify.com/documentation/web-api/reference/tracks/get-several-audio-features/](https://developer.spotify.com/documentation/web-api/reference/tracks/get-several-audio-features/)

| | Artist | Song | Genre | popularity | acousticness | danceability | energy | instrumentalness | liveness | loudness | speechiness | tempo | valence |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **36510** | !!! | Get That Rhythm Right | Electronic | 39 | 0.03820 | 0.832 | 0.798 | 0.10400 | 0.0980 | -0.7418 | 0.0475 | 0.120022 | 0.961 |
| **36675** | !!! | Except Death | Electronic | 37 | 0.00996 | 0.812 | 0.776 | 0.07060 | 0.0737 | -0.7223 | 0.0386 | 0.118021 | 0.912 |
| **99191** | !!! | Even When The Water'S Cold | Children's Music | 61 | 0.10800 | 0.709 | 0.831 | 0.00128 | 0.1590 | -0.6847 | 0.0391 | 0.104971 | 0.866 |
| **23712** | !!! | Lucy Mongoosey | Electronic | 48 | 0.01940 | 0.872 | 0.584 | 0.00085 | 0.1130 | -0.7412 | 0.0788 | 0.109987 | 0.212 |
| **36523** | !!! | Funk | Electronic | 35 | 0.01620 | 0.932 | 0.546 | 0.49400 | 0.0891 | -0.8462 | 0.1750 | 0.116016 | 0.440 |

Finally, the dataset that will be used for the collaborative filtering method, is taken from Kaggle.It contains 76,353 unique user IDs and how many times they have streamed one out of the 10.000 different songs. The initial data downloaded from Kaggle contained two different datasets. The first one, had information, such as the Artists name and song's Release date, while the second one, had the user's IDs and the stream counts. Both datasets had a unique song ID in order to merge them.
Link: [https://www.kaggle.com/anuragbanerjee/million-song-data-set-subset](https://www.kaggle.com/anuragbanerjee/million-song-data-set-subset)

| | Song | Artist | user | play_count | song_id |
|---|---|---|---|---|---|
| **0** | Anyone Else But You | Michael Cera & Ellen Page | d6589314c0a9bcbca4fee0c93b14bc402363afea | 6 | SOSZNRJ12A8AE46E38 |
| **1** | Anyone Else But You | Michael Cera & Ellen Page | 484b69dd013df1ec0cfd504886d4f647cb32b08f | 1 | SOSZNRJ12A8AE46E38 |
| **2** | Anyone Else But You | Michael Cera & Ellen Page | 3f9ed694a79835c921ef6d94acd28f876c1d901e | 4 | SOSZNRJ12A8AE46E38 |
| **3** | Anyone Else But You | Michael Cera & Ellen Page | b882a5b0dbd1a80533e40745be976f19d1fad5b0 | 1 | SOSZNRJ12A8AE46E38 |
| **4** | Anyone Else But You | Michael Cera & Ellen Page | 2bcef2a30bd8913405971761a0e6c292d771c086 | 1 | SOSZNRJ12A8AE46E38 |
| **...** | ... | ... | ... | ... | ... |
| **2086941** | The Outer Banks | The Album Leaf | 37781fff15682ccd92aface63f66d3f525e2f88f | 1 | SOBPQCK12AF72A2FD5 |
| **2086942** | The Outer Banks | The Album Leaf | 49e66adb87d5d39781add88c202aa9802010e848 | 3 | SOBPQCK12AF72A2FD5 |
| **2086943** | The Outer Banks | The Album Leaf | 9d659bb73b93384297f240a4adadccf4d81bd681 | 1 | SOBPQCK12AF72A2FD5 |
| **2086944** | The Outer Banks | The Album Leaf | c65a346ab8f41fb56926b503ece810f358b0d241 | 1 | SOBPQCK12AF72A2FD5 |
| **2086945** | The Outer Banks | The Album Leaf | 84e72d86fab784be544a8e2fe2826c73530165fd | 1 | SOBPQCK12AF72A2FD5 |

2054534 rows × 5 columns

This is the form of the dataset after merging these two dataframes.
It will be an item-based approach and the similarity between songs based on people's likes will be counted.

## Merging the DataSets.

After preprocessing each dataset individually the next step was to merge all of them, in order to check how many similar artists and songs are contained in all three datasets. Merging the second and the third dataset would be on both artists and Songs. One major setback was that some artist's and songs' names were spelled differently, in these two datasets. To fix this issue, I converted the letter size and stripped all special characters and words inside brackets.

Despite, that the length of the merged dataset was pretty small, compared to the length of the two initial ones. The idea to fix that problem was to calculate the Levenshtein distance between artists' names on these two datasets. The main focus was on the Artists and not the names of the songs because this technique would get really complex on so many song titles, in addition to each artist having many different songs, raises the number of identical songs that would be on both dataframes. Calculating Levenshtein distance was a time-consuming but effective technique since the total number of the common Artists was raised. A total number of over 20.000 different songs is a relatively good sample size.

## Recommendation System Architecture.

Combining the three approaches into the hybrid model was a tricky task to optimize. However, after considering that most people prefer to stick to a certain music type at each specific moment, a hierarchical approach was implemented. A person who loves rock music and chooses a rock song as an input song would prefer to get a rock playlist, instead of a playlist with mixed electronic, rock, and hip hop music. Similarly, a user who loves Hip Hop music won't be interested in a black metal recommendation, just because a hip hop and a black metal song might have similar features.

The first step's focus would be on the artist's dataset. A list of the artists who have tags "closer" to the user's preferred artist, is produced. These artists play the same music type and share the most common tags with the user's pick. What is more, all of the songs of these proposed artists would be gathered, and they would be "filtered" through the second content-based dataset, which contains song features. With this approach, all songs that are totally unfamiliar with the user's preferred song would be removed.
For example, a user that picked an acoustic, sad, song from a Rock Artist would most likely prefer a calm, acoustic, low-on valence playlist. Filtering the songs of the Rock artist through this dataset would only keep this kind of song. Similarly, if a person chooses an energetic, danceable, pop song, the model will extract the danceable energetic songs from pop artists.

Last but not least, item-based collaborative filtering will be used and out of the songs produced by the second method, a playlist of songs that were most liked by users, who liked the input song, will be produced. Another reason for choosing collaborative filtering as the last method is its high sparsity. Getting slow recommendations would be a major setback. Preparing recommendations from a "smaller" UT matrix would highly improve the calculation time. In addition, it is a powerful method that finds the "closer" songs from a list of, close to the initial user input, songs.

## Model's step-by-step algorithm description.

First of all, the user would be asked to enter a song he or she likes and its respective artists. The proposed model will convert the letter size of the two inputs and will search the first content-based dataset, for the artist the user picked. If the Artist is found, the procedure will keep going. Otherwise, the user will be asked to type another artist's name. When the artist's name has been matched, the model will search in both the two other datasets for the song's name. If the input song is found on both of them, the recommendation function will be implemented. If not, songs of the given artist, which are contained in the merged dataframe, will be presented so users can pick one of these existing songs.

```
recommandation('hardwire','metallica')
```

```
Artist Match
Oops
Song Not Found
Try Again If you like one of the following songs by: METALLICA
['One' 'Fight Fire With Fire' 'Enter Sandman' 'Fade To Black'
 'Eye Of The Beholder' 'Of Wolf And Man' 'Welcome Home'
 'The Thing That Should Not Be' 'Until It Sleeps'
 'The Day That Never Comes' 'Master Of Puppets' 'The Four Horsemen']
```

If and only if, both the artist name and the song's name have been found, the unsupervised NearestNeighbors algorithms will be used to find the 100 closest artists. The metric the model uses is Pearson's correlation because it produced more accurate results than cosine similarity. The number of closest artists was picked after testing many different size numbers. It is a balanced number, considering the total number of artists, that is 10.000, that produced approximately 500 songs for the two other algorithms to work with.

Afterward, NearestNeighbors, Pearson similarity will be used again. The selected neighbor's number was 300. The number was picked, so the completely irrelevant songs would get removed in the second step and the clear selection of the song to be included in the playlist is performed in the final step. If the first step produced more songs for the selected artists, the number would be higher. The second step is more like a filtering step that reduces the number of songs, by cutting of songs that are not similar to the user's initial choice in order for the collaborative filtering to be used.

Finally, in the third step, the proposed playlist is being produced. A utility matrix is used, where every row contains a song's ID, every column a unique user, and each data point is how many times a song was streamed by a user. Cosine similarity metric was used, due to the better results, and the 20 "closest" songs are being recommended to the user. What is more, inspired by Spotify's recommendation system, the ten closest to the user's input artists are also recommended by considering the first dataset regarding artists tags.

## Algorithms Performance

To measure the performance of the algorithm different input songs were used and different users were asked to give their feedback. The algorithm excelled in pop and Hip Hop music and produced some pretty good recommendations. On the other hand, as far as rock music is concerned, because of the many “subclasses” of rock music and their big music collection, some questionable recommendations were given.

The small number of common artists in all three datasets in comparison to the individual number each one contained, is worth mentioning. Having many songs from specific artists and not songs from a variety of them, was the main reason the model underachieved on specific rock recommendations. Not containing a suitable amount of artists for some specific rock subgenres, resulted in recommendations being rather general than specialized.

Despite the approaches made to increase the number of common artists, the results were still not perfect. In some future work, the same hybrid method will be used, but datasets would be acquired from the same source, so artists’ names will be similar. As a result, a larger collection of songs will be available to be proposed and the recommendations will be more accurate.

In conclusion, the proposed music recommendation system, combined a collaborative filtering item-based approach, with two content-based ones, in order to recommend songs based on a single input. Artists’ tags along with songs features and other user’s streams were used, so a playlist “close” to the initial input was produced. A 3-steps hierarchical approach was implemented to reduce the sparsity of the data and take advantage of all three datasets. Despite some limitations based on the different data sources, used to acquire the data, the results were pretty encouraging. In the future, the model will be further improved.

Some Recommendation results:

## Pop Recommendations:

```
recommandation('Take A Bow','rihanna')
```

```
Artist Match

Song Matched

 Preparing Recommandations for:
Take A Bow , by , RIHANNA
..................................
All My Life  by  K-CI & JOJO
Halo  by  BEYONCÉ
U Smile  by  JUSTIN BIEBER
We Belong Together  by  MARIAH CAREY
Stuck In The Moment  by  JUSTIN BIEBER
The Climb  by  MILEY CYRUS
There Goes My Baby  by  USHER
Ride For You  by  DANITY KANE
Nice & Slow  by  USHER
How It Feels To Fly  by  ALICIA KEYS
Through The Rain  by  MARIAH CAREY
Ego  by  BEYONCÉ
That Should Be Me  by  JUSTIN BIEBER
Naughty Girl  by  BEYONCÉ
..................................

Recommended Artists:
['RIHANNA', 'BEYONCÉ', 'MILEY CYRUS', 'BRITNEY SPEARS', 'JUSTIN BIEBER', 'JUSTIN TIMBERLAKE', 'USHER', 'LADY GAGA', 'FERGIE',
'ASHANTI']
```

```
recommandation('Boys Boys Boys','LADY GAGA')
```

```
Artist Match

Song Matched

 Preparing Recommandations for:
Boys Boys Boys , by , LADY GAGA
..................................
Toxic  by  BRITNEY SPEARS
Wind It Up  by  GWEN STEFANI
We Ride  by  RIHANNA
Party In The U.S.A.  by  MILEY CYRUS
Take A Bow  by  RIHANNA
Bulletproof  by  LA ROUX
Rehab  by  RIHANNA
Good Girl Gone Bad  by  RIHANNA
Ray Of Light  by  MADONNA
Fuck The Pain Away  by  PEACHES
Breakin' Dishes  by  RIHANNA
2 Become 1  by  SPICE GIRLS
Hoedown Throwdown  by  MILEY CYRUS
See You Again  by  MILEY CYRUS
Hollaback Girl  by  GWEN STEFANI
Luxurious  by  GWEN STEFANI
Te Amo  by  RIHANNA
East Northumberland High  by  MILEY CYRUS
Unwritten  by  NATASHA BEDINGFIELD
..................................

Recommended Artists:
['LADY GAGA', 'CARRIE UNDERWOOD', 'LA ROUX', 'RIHANNA', 'DAFT PUNK', 'MILEY CYRUS', 'BRITNEY SPEARS', 'M.I.A.', 'THE PUSSYCAT D
OLLS', 'LILY ALLEN']
```

```
recommandation('Party In The U.S.A.','MILEY CYRUS')
```

```
Artist Match

Song Matched

 Preparing Recommandations for:
Party In The U.S.A. , by , MILEY CYRUS
...................................
Toxic  by  BRITNEY SPEARS
Miss Independent  by  KELLY CLARKSON
Halo  by  BEYONCÉ
My Life Would Suck Without You  by  KELLY CLARKSON
Already Gone  by  KELLY CLARKSON
Irreplaceable  by  BEYONCÉ
The Trouble With Love Is  by  KELLY CLARKSON
Naturally  by  SELENA GOMEZ & THE SCENE
A Perfectly Good Heart  by  TAYLOR SWIFT
Alejandro  by  LADY GAGA
Magic  by  SELENA GOMEZ
Breakin' Dishes  by  RIHANNA
You Belong With Me  by  TAYLOR SWIFT
When I Grow Up  by  THE PUSSYCAT DOLLS
Love Story  by  TAYLOR SWIFT
Touch My Body  by  MARIAH CAREY
Candyman  by  CHRISTINA AGUILERA
Walk Away  by  KELLY CLARKSON
...................................

Recommended Artists:
['MILEY CYRUS', 'KELLY CLARKSON', 'RIHANNA', 'TAYLOR SWIFT', 'SELENA GOMEZ & THE SCENE', 'BEYONCÉ', 'LADY GAGA', 'BRITNEY SPEAR
S', 'MARIAH CAREY', 'DEMI LOVATO']
```

## Hip Hop Recommendations

```
recommandation('Roses','KANYE WEST')
```

```
Artist Match

Song Matched

 Preparing Recommandations for:
Roses , by , KANYE WEST
...................................
Cooler Than Me  by  MIKE POSNER
Breathe  by  FABOLOUS
As The World Turns  by  EMINEM
Locked Up  by  AKON
Money On My Mind  by  LIL WAYNE
'97 Bonnie & Clyde  by  EMINEM
Deception  by  BLACKALICIOUS
Criminal  by  EMINEM
Rollout  by  LUDACRIS
Ice Box  by  OMARION
Cyclone  by  BABY BASH
Ms. Fat Booty  by  MOS DEF
My Name Is  by  EMINEM
If I Had  by  EMINEM
Cum On Everybody  by  EMINEM
Money Folder  by  MADVILLAIN
Mass Appeal  by  GANG STARR
Runnin'  by  THE PHARCYDE
Method Man  by  WU-TANG CLAN
...................................

Recommended Artists:
['KANYE WEST', 'EMINEM', 'DJ KHALED', 'LUPE FIASCO', 'COMMON', 'GANG STARR', 'MADVILLAIN', '50 CENT', 'MIKE POSNER', 'OUTKAST']
```

```
recommandation('My Name Is','eminem')
```

```
Artist Match

Song Matched

 Preparing Recommandations for:
My Name Is , by , EMINEM
..................................
Tha Crossroads  by  BONE THUGS-N-HARMONY
Roses  by  KANYE WEST
Stronger  by  KANYE WEST
Ms. Jackson  by  OUTKAST
Like A Boss  by  THE LONELY ISLAND
Opposite Of Adults  by  CHIDDY BANG
Rollout  by  LUDACRIS
Up Up & Away  by  KID CUDI
The Glory  by  KANYE WEST
Be With You  by  AKON
Cyclone  by  BABY BASH
O.P.P.  by  NAUGHTY BY NATURE
E.I.  by  NELLY
P.I.M.P.  by  50 CENT
Hey Mama  by  KANYE WEST
Homecoming  by  KANYE WEST
Day 'N' Nite  by  KID CUDI
Jump Around  by  HOUSE OF PAIN
Big Brother  by  KANYE WEST
..................................

Recommended Artists:
['EMINEM', 'KID CUDI', 'KANYE WEST', 'DJ KHALED', '50 CENT', 'THE LONELY ISLAND', 'LIL WAYNE', 'NAUGHTY BY NATURE', 'TALIB KWEL
I', 'DMX']
```

# Rock Recommendations:

# Punk Rock:

```
recommandation('Bob','nofx')
```

```
Artist Match

Song Matched

 Preparing Recommandations for:
Bob , by , NOFX
..................................
Time Bomb  by  RANCID
Online Songs  by  BLINK-182
Going Away To College  by  BLINK-182
Move Along  by  THE ALL-AMERICAN REJECTS
Pepper  by  BUTTHOLE SURFERS
Dysentery Gary  by  BLINK-182
Every Time I Look For You  by  BLINK-182
Savior  by  RISE AGAINST
My Own Worst Enemy  by  LIT
Ruby Soho  by  RANCID
Gonna Find You  by  OPERATION IVY
Feeling This  by  BLINK-182
Having A Blast  by  GREEN DAY
Bouncing Off The Walls  by  SUGARCULT
Kabuki Girl  by  DESCENDENTS
Want You Bad  by  THE OFFSPRING
Mutt  by  BLINK-182
Audience Of One  by  RISE AGAINST
..................................

Recommended Artists:
['NOFX', 'DEAD KENNEDYS', 'RANCID', 'STREETLIGHT MANIFESTO', 'OPERATION IVY', 'BILLY TALENT', 'THE CLASH', 'RISE AGAINST', 'PAN
```

# Post Rock:

```
recommandation('Burn','THE CURE')
```

```
Artist Match

Song Matched

 Preparing Recommandations for:
Burn , by , THE CURE
...................................
Prelude 12/21  by  AFI
Always Something There To Remind Me  by  NAKED EYES
Smooth Criminal  by  ALIEN ANT FARM
Temptation  by  NEW ORDER
Slave To Love  by  BRYAN FERRY
Relax  by  FRANKIE GOES TO HOLLYWOOD
Road To Nowhere  by  TALKING HEADS
Smalltown Boy  by  BRONSKI BEAT
Eyes Without A Face  by  BILLY IDOL
Dance Hall Days  by  WANG CHUNG
Sowing The Seeds Of Love  by  TEARS FOR FEARS
I Melt With You  by  MODERN ENGLISH
One Step Beyond  by  MADNESS
Do You Really Want To Hurt Me  by  CULTURE CLUB
Rio  by  DURAN DURAN
Too Shy  by  KAJAGOOGOO
Safety Dance  by  MEN WITHOUT HATS
Mad World  by  TEARS FOR FEARS
...................................

Recommended Artists:
['THE CURE', 'CULTURE CLUB', 'KAJAGOOGOO', 'TEARS FOR FEARS', 'INTERPOL', 'DEAD OR ALIVE', 'DURAN DURAN', 'THE JESUS AND MARY C
HAIN', 'TELEVISION', 'DIVINYLS']
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# Classic Rock:

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recommandation('Under Pressure','QUEEN')
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Artist Match

Song Matched

 Preparing Recommandations for:
Under Pressure , by , QUEEN
...................................
Eye Of The Tiger  by  SURVIVOR
Wind Of Change  by  SCORPIONS
Love Walks In  by  VAN HALEN
Breakdown  by  TOM PETTY AND THE HEARTBREAKERS
These Dreams  by  HEART
The Joker  by  STEVE MILLER BAND
St. Elmos Fire  by  JOHN PARR
Dreams  by  VAN HALEN
Yer So Bad  by  TOM PETTY
Magic Man  by  HEART
Missing You  by  JOHN WAITE
Crazy On You  by  HEART
Square One  by  TOM PETTY
Dream On  by  AEROSMITH
Magic Carpet Ride  by  STEPPENWOLF
Radar Love  by  GOLDEN EARRING
You Got Lucky  by  TOM PETTY AND THE HEARTBREAKERS
We Belong  by  PAT BENATAR
...................................

Recommended Artists:
['QUEEN', 'DIO', 'RAM JAM', 'TOM PETTY AND THE HEARTBREAKERS', 'BRYAN ADAMS', 'AEROSMITH', 'FREE', 'PAT BENATAR', 'MÖTLEY CRÜ
E', 'CHEAP TRICK']
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# Metal:

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recommandation('Before I Forget','slipknot')
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Artist Match

Song Matched

 Preparing Recommandations for:
Before I Forget , by , SLIPKNOT
..................................
One  by  METALLICA
I-E-A-I-A-I-O  by  SYSTEM OF A DOWN
Bleed It Out  by  LINKIN PARK
Beautiful  by  10 YEARS
Awake  by  GODSMACK
Crawling  by  LINKIN PARK
Du Hast  by  RAMMSTEIN
Lotion  by  DEFTONES
Just Stop  by  DISTURBED
Caught In A Mosh  by  ANTHRAX
The Day That Never Comes  by  METALLICA
Land Of Confusion  by  DISTURBED
Radio/Video  by  SYSTEM OF A DOWN
Too Many Puppies  by  PRIMUS
Bark At The Moon  by  OZZY OSBOURNE
Decadence  by  DISTURBED
Rollin'  by  LIMP BIZKIT
The Fight Song  by  MARILYN MANSON
..................................

Recommended Artists:
['SLIPKNOT', 'LINKIN PARK', 'IN FLAMES', 'DISTURBED', 'DEFTONES', 'RAMMSTEIN', 'SYSTEM OF A DOWN', 'METALLICA', 'PANTERA', 'SEP
ULTURA']
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recommandation('Angel Of Death','SLAYER')
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Artist Match

Song Matched

 Preparing Recommandations for:
Angel Of Death , by , SLAYER
..................................
Fight Fire With Fire  by  METALLICA
Wait And Bleed  by  SLIPKNOT
Are You Dead Yet  by  CHILDREN OF BODOM
Purity  by  SLIPKNOT
Davidian  by  MACHINE HEAD
The Heretic Anthem  by  SLIPKNOT
Tommy The Cat  by  PRIMUS
Strength Of The World  by  AVENGED SEVENFOLD
Floods  by  PANTERA
Fade To Black  by  METALLICA
Lotion  by  DEFTONES
Surfacing  by  SLIPKNOT
Everything Ends  by  SLIPKNOT
Caught In A Mosh  by  ANTHRAX
My Plague  by  SLIPKNOT
Disasterpiece  by  SLIPKNOT
Almost Easy  by  AVENGED SEVENFOLD
Eyeless  by  SLIPKNOT
..................................

Recommended Artists:
['SLAYER', 'SEPULTURA', 'MASTODON', 'ANTHRAX', 'PANTERA', 'MUDVAYNE', 'LAMB OF GOD', 'MARILYN MANSON', 'AVENGED SEVENFOLD', 'AR
CH ENEMY']
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