Data Mining Project: Recommendation system

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Song Recommendation System

Music Recommended System

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Music Recommended System

Introduction:

As with most Music Recommendation Platforms

- User will type an input song and its respective artists
- A playlist of Songs close to the user preference will be produced

First Limitation:

The unique music taste of people.

Unique Music Taste: Playlist instead of a single song

Since every individual person has a unique music taste,proposing a single song is very tricky.A common problem:

- Fil and Chara like a particular song
- Model proposes a song “close” to their preference
- Fil likes the song,Chara does not.

As a result,model will propose a playlist of 20songs:

1. User can choose which one he likes,or listen the whole playlist
2. “Force” the user to pick more and more songs out of the proposed playlists, so more data about his preferences can be gathered.

Model Approach: Hybrid

An approach that would combine the advantages of both content based and collaborative filtering :

1. “Hide” limitations of both approaches -> popularity + counting music similarity based on metadata
2. Propose songs based on both similar metadata, such as music attributes and music genres , in addition to songs that got streamed a lot, by people with similar music taste.

Eventually,the results from the two approaches will be combined and the “closest” songs will be proposed.

Datasets Used: Content Based

Artists Dataset.

- 10.000 unique Artists
- 4 tags for every Artist

Similarity between Artists is counted

based on their tags.

Dataset was scrapped from LastFm

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

Artists Dataset:

When the Dataset was scrapped it contained over 2100 unique tags.

Problems:

1. Sparsity
2. Insignificant tags
3. Few similar tags within artists

Results:

Bad and slow recommendations.

```
print(len(vect.get_feature_names()),'\n')
print(vect.get_feature_names() )
```

```
2107

['00S', '070', '112', '1970SSoul', '19ThCentury', '2010S', '2019', '20ThCenturyClassical', '24Kgoldn', '2Ne1', '2Step',
S', '40S', '4Ad', '50S', '5Stars', '60', '60S', '60SGirls', '60SPsychedelic', '70S', '80', '80S', '8Bit', '90S', '98Degre
'ABoogieWitDaHoodie', 'ACapella', 'ACappella', 'ACappellaMetal', 'AHa', 'Aanheid', 'Absofacto', 'Abstract', 'AbstractHip
'Acapella', 'Accoustic', 'Ace', 'Acid', 'AcidHouse', 'AcidJazz', 'Acousic', 'Acousmatic', 'Acoustic', 'AcousticPop', 'Ac
cPunk', 'AcousticRock', 'AcrossTheUniverse', 'Actor', 'Actors', 'Actress', 'AdamLevine', 'AdultContemporary', 'Africa',
cainFrancais', 'African', 'Afrikaans', 'AfroDisco', 'AfroHouse', 'AfroTrap', 'Afrobeat', 'Afrobeats', 'Afroswing', 'Afte
l', 'Aggressive', 'Aggrotech', 'Aiesec', 'Alabama', 'AlanJackson', 'Alberta', 'Algerian', 'Algorithm', 'Alkopoligamia',
l', 'AllThingsAnnoyingInTheWorldPutTogetherIntoOneStupidBitch', 'AltCountry', 'Alternative', 'AlternativeCountry', 'Alte
veDance', 'AlternativeHipHop', 'AlternativeIndie', 'AlternativeMetal', 'AlternativePop', 'AlternativeRap', 'AlternativeR
'AlternativeRock', 'Alternativo', 'Amazing', 'Ambidjent', 'Ambient', 'AmbientBlackMetal', 'AmbientPop', 'AmbientTechno',
rica', 'American', 'AmericanIdol', 'Americana', 'Amsterdam', 'AnaGabriel', 'AnadoluRock', 'AnarchistBlackMetal', 'Anarch
k', 'AnatolianRock', 'AndesStep', 'AndreRieu', 'AndreaBocelli', 'AngeschwolleneEier', 'Anime', 'Anjunabeats', 'Anjunadee
'AntennaMusic', 'AnthonyGreen', 'AntiFolk', 'Antifa', 'AntiguaAndBarbuda', 'Aor', 'ApocalypticFolk', 'Arabic', 'Aracy',
ngel', 'Argentina', 'Argentinian', 'ArianaGrande', 'Arijit', 'Arizona', 'Arkansas', 'Armenian', 'Arrocha', 'ArtPop', 'Ar
k', 'ArtRap', 'ArtRock', 'AsfaltRecords', 'AshleyTisdale', 'Asian', 'AternativeRock', 'Atlanta', 'Atmospheric', 'Atmosph
lackMetal', 'AtmosphericDeathMetal', 'AussieHipHop', 'Austin', 'AustinMahone', 'Australia', 'Australian', 'Austrian', 'A
pop', 'Autotune', 'AvantFolk', 'AvantGarde', 'AvantGardeBlackMetal', 'AvantGardeJazz', 'AvantGardeMetal', 'AvantProg',
me', 'Axe', 'Ayo', 'AyoAndTeo', 'Azerbaijan', 'B0Ss', 'B2St', 'Bachata', 'Background', 'BackstreetBoys', 'Bahia', 'Baile
```

Artists DataSet Cleaning.

First Approach: Noise Removal.

Over 1370 tags appeared less than 4 times.

In a dataset of 10.000 observations it would be unlikeable to find these tags many times and take advantage of them.

They were treated as noise and removed.

```
Mean value of Sums:  25.51922164214523

Max:  2516

Min:  1

Values that appear once:  693
Values that appear once or twice:  1217
Values that appear less than 4 times:  1370
```

Artists DataSet Cleaning.

Second Approach: Similar names.

Many tags had the same name but a character being different(whitespace,special characters or typing errors)

-> Hip Hop and HipHop

-> PostRock and Post_Rock

->French and France

Finding and merging this kind of tags was necessary.

Artists DataSet Cleaning.

A distance matrix between the tags was calculated using Levenshtein distance.

- Threshold value was 3

Tags below the threshold were examined.

Similar tags were merged.

	40S	50S	60	60S	70S	80	80S	8Bit	90S	ACappella	...
40S	0.0	1.0	2.0	1.0	1.0	2.0	1.0	4.0	1.0	9.0	...
50S	1.0	0.0	2.0	1.0	1.0	2.0	1.0	4.0	1.0	9.0	...
60	2.0	2.0	0.0	1.0	2.0	1.0	2.0	4.0	2.0	9.0	...
60S	1.0	1.0	1.0	0.0	1.0	2.0	1.0	4.0	1.0	9.0	...
70S	1.0	1.0	2.0	1.0	0.0	2.0	1.0	4.0	1.0	9.0	...
...	...	...	...	...	...	...	...	...	...	...	...
WuTang	6.0	6.0	6.0	6.0	6.0	6.0	6.0	6.0	6.0	9.0	...
XFactor	7.0	7.0	7.0	7.0	7.0	7.0	7.0	6.0	7.0	8.0	...
Youngstar	9.0	9.0	9.0	9.0	9.0	9.0	9.0	8.0	9.0	9.0	...
Youtube	7.0	7.0	7.0	7.0	7.0	7.0	7.0	6.0	7.0	9.0	...
nan	3.0	3.0	3.0	3.0	3.0	3.0	3.0	4.0	3.0	8.0	...

Artists DataSet Cleaning.

Third Approach: Apriori

Different approaches with different minsup and minconf thresholds was used.

Some of the most important insights:

- {Kpop,Korean} -> {Pop} (Compound words)
- General trend: {“subclasses”} -> {“Superclass”}

(ig {IndustrialRock,Industrial} -> {Rock}

Artists DataSet Cleaning.

1. Many tags contained their language and/or their music genre in a compound word. These tags were Splitted (ig KPop -> Korean + Pop)
2. Some tags were the consequent in many association rules. These classes were considered SuperClasses and the antecedents of the rules were considered Subclasses.

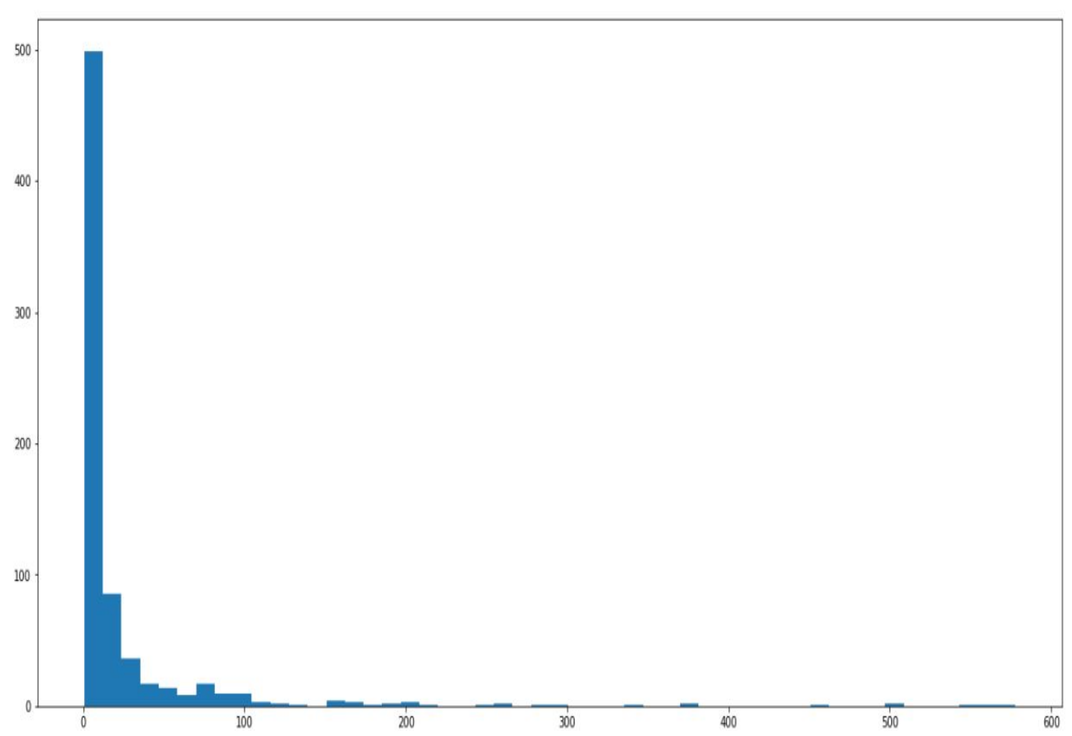
To validate this subclass-superclass assumption tf-idf was used on the tags.

Artists DataSet Cleaning.

Three observations on the histogram of the “sum of the weights of each tags.”

1. Superclass: weight>450
2. First subclass: [50,450]
3. Second subclass : [0,50]

First subclass will be the most important class,so raising their occurrence number was major



Artists DataSet Cleaning.

Consider tags such as PostRock and AlternativeElectronic.

- These two tags contain a superclass -> Rock and Electronic
- They also contain a first-subclass tag: Post, Alternative

Splitted all tags that follow this pattern.

Added the superclass of every artist, on every tag (after considering apriori)

Artists DataSet Cleaning.

Last Approach : My Experience.

- After examining the remaining tags I removed the insignificant ones and replaced some tags that had the same meaning.
- Used tf-idf again on the tags. Removed tags with summed weight below a threshold value

The final number of total tags was reduced to 430.

Second Dataset:

Song Metrics:

Metadata for every song.

Artist	Song	popularity	acousticness	danceability	duration_ms	energy	instrumentalness	key	liveness	loudness	mode	speechir
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	0.0
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	0.0
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	0.0
HENRI SALVADOR	dis-moi monsieur gordon cooper	0	0.70300	0.240	152427	0.326	0.000000	C#	0.0985	-12.178	Major	0.0
FABIEN NATAF	ouverture	4	0.95000	0.331	82625	0.225	0.123000	F	0.2020	-21.150	Major	0.0
...	...	...	...	...	...	...	...	...	...	...	...	
[illegible]	son of	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

Taken from :

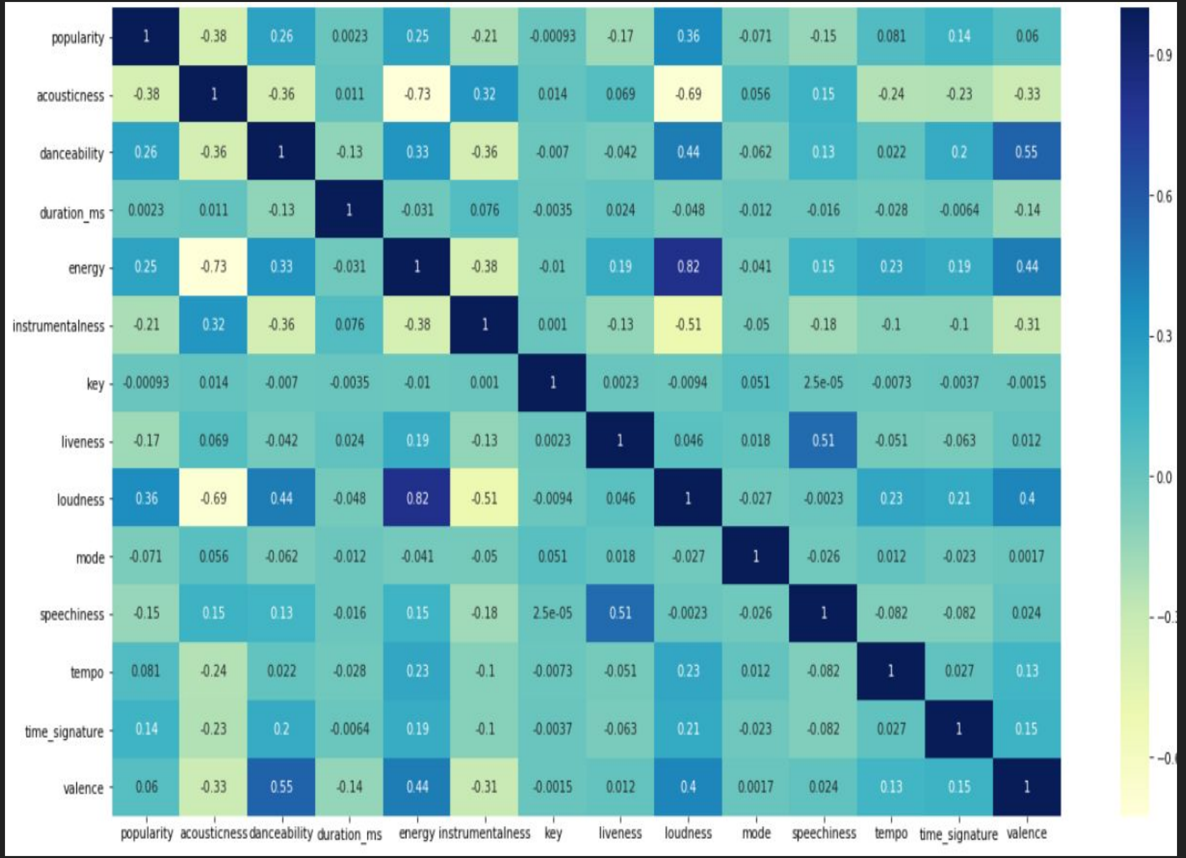
https://www.kaggle.com/zaheenhamidani/ultimate-spotify-tracks-db

Exploring the DataSet:

Correlation between features:

Interesting correlations:

- Loudness-Energy
- Valence-Danceability
- Speachness-loudness
- Energy-instrumentalness
- Valence-instrumentalness



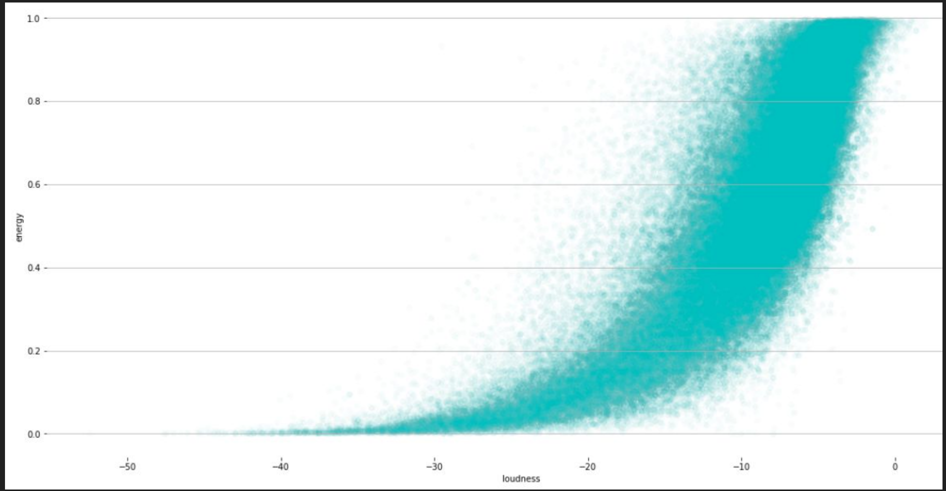
Analysis:

Highest correlation : Loudness + Energy -> 0.82

At first these values were merged into a single features due to their high correlations. Because they regard a different song feature and after considering the results with and without merging them, I kept them splitted.Moreover,despite getting the trend,MSE was high.

Low correlation features:

1. key
2. major
3. time_stamp
4. duration



Feature Selection:

Totally irrelevant tags such as key,major,time_stamp and duration were removed.

Final Form:

Out[88]:

	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

Third Dataset Collaborative Filtering:

	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

Taken from : https://www.kaggle.com/anuragbanerjee/million-song-data-set-subset

Third dataset:

Dataset contains:

- Over 76.000 unique user IDs
- Over 10.000 different songs
- Stream count of users
- Song title and artist

Limitation :

- Different songs in comparison with the previous dataset for same artists
- Artists and songs names spelled differently

Model Approach: Hybrid

Model combines the features from the three datasets and takes advantage of both collaborative filtering and content based methods.

A hybrid approach

To build the hybrid method many approaches were taken:

1. Average similarity distance to user’s input
2. Hierarchical Approach with different hierarchies

Model Architecture:

After considering that most people prefer to stick to the specific music genre they choose at specific times:

First step would be to find the Artists closer to the input Artist.

A person who loves metal music wouldn't want to get a HipHop song that was voted highly from other metal lovers or share similar music attributes.

As a result,the first hierarchical step would be to collect the artists closer to the initial choice. Artists with the most similar tags(similar music genres) will be picked.

Model’s Architecture:

Songs of the selected Artists will be gathered.

A limitation mentioned before was the small number of common artists and songs in the two datasets,with regards to their total individual size.

This limitation was a result of :

1. Misspelled names
2. Different songs for same artists

Merged Dataframe’s size

To try and fix this limitation:

- Capitilized the letters on Artists names
- Removed Special Characters and whitespaces
- Removed text from parenthesis
- Calculated Levenshtein distance between Artists names

The size of the merged dataframe was raised.

Model’s Architecture:

The selected songs of the chosen Artists were gathered.

The second step on the hierarchical approach was to filter out the totally irrelevant songs.

Music Features:

- Chara chooses an acoustic sad song from a Rock Artist.
- She probably is sad and wants to relax
- She wants acoustic sad songs.

Model’s Architecture:

Metrics content based Dataset can identify these song’s features.

Out of all the songs selected in the first step:

- Model will choose those that have similar music features.

Filtering out the irrelevant songs was fundamental in making accurate predictions

Model’s Architecture:

Lastly, model’s recommended playlist would be produced based on Item-Based collaborative filtering.

- Similarity between songs(item based),based on user reviews,will be counted and the closest 20 songs will be produced.
- Another reason for choosing this method as my last step,was to avoid the big calculation time based on the high sparsity of this last dataset.

Slow recommendations are considered bad recommendations.

Model’s Algorithm

- After user entered a song and its artists, a search on all three datasets would take place. If the entered Artists is matched,then the song would be searched.
- In case the Artist is not found,recommendation wont take place. If the specific song is not found,all existing songs of the entered Artists would be proposed.

```
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']
```

Model’s Algorithm:

First hierarchical approach used K-NN with pearson correlation to find the 100 closest artists.

Number 100 was chosen:

- It is a balanced number considering the total length of 10.000 Artists
- Will create many songs for the other two models

Model’s Algorithm:

Approximately, 500-600 songs were generated from the first dataset.

Out of these songs:

- 200 songs would filtered out
- K-NN will be used with pearson correlation again.
- 300 closest songs will be kept for the final step

In the final Step,out of 300 songs a playlist of top 20 would be selected.

Despite having a few songs,the big number of artists(features) resulted in good recommendations.Moreover,A list of the closest artists would also be produced,by using the first Artists dataset

Results: Pop Music

```
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']
```

Results: Pop Music

```
: 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']
```

Results: HipHop Music

```
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']
```

Results: PunkRock

```
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
```

Results: Metal

```
recommandation('Before I Forget','slipknot')
```

```
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']
```

Results: Classic Rock

```
recommandation('Under Pressure','QUEEN')
```

```
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']
```

Results Analysis:

Different input songs and different people were asked to give feedback to the model.

Algorithm excelled on Pop and HipHop music Genre.

As far as rock music is concerned,same major limitations were spotted

Limitations

Because of the many subgenres of Rock music and its big collection:

- The small number of common artists and songs on specific music genres gave general and not specialized suggestions
- Having a small number of artists with many songs,rather than many artists,resulted in recommendations being the same for many rock genres

Despite the approaches to raise the number of common Artists and Songs,some recommendations were still questionable.

In some future work,the same model will be used with data being collected from the same source so names would be identical.