



Music Recommendation System

Recommendation with continuous/objective values



Why?

- The majority of recommendation system are based on user-ratings to provide recommendations to users.
- I wanted to see if it would be viable to utilize objective measures of sound to provide a similar experience, taking the user out of the equation
- This is an experiment, which ultimately did not turn out how I had hoped
- Despite this, it was a good exercise in recommendation systems and understanding why user-based collaborative filtering leads the field at the moment



The Data

- The dataset contains 170,000 songs from spotify, ranging from 1920-2020
- The measures included in the dataset are an attempt at an objective measure of the sound itself including:
 - Energy
 - Loudness
 - Acoustic-ness
 - Dance-ability
 - Loudness (dB)



Initial Findings from EDA

- There were a few correlations in the dataset that were interesting, mainly because they spoke both about the objective measures and the history of music itself



Everything is Quiet

When songs are created, they are very quiet.

It is the responsibility of audio engineers to level these tracks out, and bring the volume up to an industry standard.



What is 'Loudness?'

Loudness is the objective measure of volume in decibels (db)

When songs are created, they usually sit around -12 to -24 dB in volume or 'loudness'

For reference, this is very quiet.



What you hear on Spotify

When songs are brought up to that industry standard volume, they are pushed as close as possible to 0db

0dB is the threshold, as anything louder than 0 dB is considered to be 'peaking'

Peaking is that scratchy sound you hear when things get too loud!



A War? With Loudness?

During the 80's, audio engineers figured out an interesting correlation that led to all music becoming progressively louder over the years



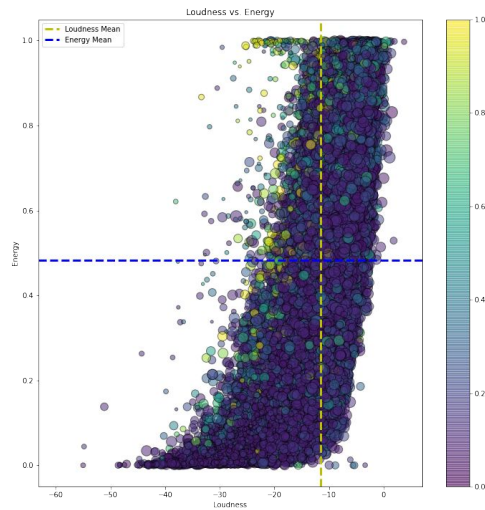
Energy and Loudness

Energy could be considered a somewhat subjective measure of volume.

It's felt, not heard.

Engineers found that as music gets louder, the perceived level of energy grows with it

Energy compared to Loudness



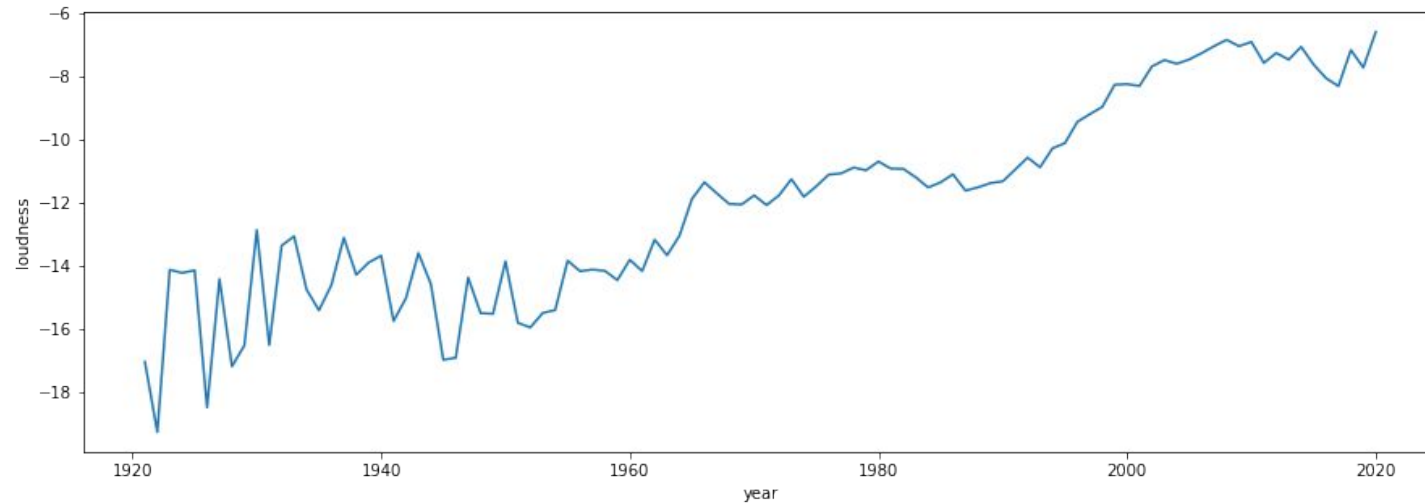


The Correlation Leads To...

Once the correlation between loudness and energy became clear, audio engineers began to push their tracks louder and louder - beyond the capabilities of the equipment available at the time



Average Volume Of Music Over Time





Modeling

The recommendations were calculated a few different ways

1. Calculate cosine similarity to group 'similar' tracks together
2. K-Nearest Neighbors

These models performed equally as well, there was very little difference between the results of the two.



Recommendation System Findings

- The model is big fan of rap music
 - It really knows the distinguishing features that are found within the measures pertaining to rap
 - It performed best on this type of music than any other
 - It was hard to trick the model into getting something else



Where it failed

- Ultimately, the model failed where lines between these measures get blurry
- A good example of this is dance-ability
 - If you think about it, Rock music could be considered low in 'dance-ability', but so could soft, acoustic music - Recommendations start to get bad around here.
 - Similarly, Rock music could rate high in energy, but so will EDM. This produced results that were less than ideal, because it would blend many genres of music together

Example of Recommendations

Good:

1 recommend_artist('Bring Me The Horizon', 2)	
Bring Me The Horizon	1.000000
A Day To Remember	0.987807
Trivium	0.983088
Bullet For My Valentine	0.982074
Bad Wolves	0.979866
Andy Mineo	0.977085
Five Finger Death Punch	0.975015
Alison Wonderland	0.973705
Of Mice & Men	0.972341
Evans Blue	0.972041
Foo Fighters	0.971632
Attack Attack!	0.970140
Linkin Park	0.969872
Killswitch Engage	0.969451
Atreyu	0.969222
dtype: float64	

Song Referenced:
Sleepwalking

1 recommend_artist('Gunna', 1)	
Gunna	1.000000
Sheff G	0.980424
Lil Baby, Moneybagg Yo	0.979180
Lil Skies	0.975615
Yo Gotti	0.974938
Duckwrth	0.974671
Bhad Bhabie, Kodak Black	0.973527
Young Dolph	0.972903
Flo Milli	0.970787
Jack Harlow, jetsonmade	0.970739
Josh A, Iamjakehill	0.970136
Bad Bunny	0.969864
Lizzo, Missy Elliott	0.969853
Five Finger Death Punch	0.969832
Ty Dolla \$ign, E-40	0.969667
dtype: float64	

Song Referenced:
Who You Foolin



Examples of Recommendations

Bad

```
1 recommend_artist('Bring Me The Horizon', 1)
```

Bring Me The Horizon	1.000000
Calvin Harris, John Newman	0.987953
Alison Wonderland	0.981160
Chevelle	0.976773
One Direction	0.971795
Rihanna	0.971090
Jory Boy, Bad Bunny	0.971080
Stereophonics	0.970913
Rihanna	0.970903
K/DA, Madison Beer, (G)I-DLE, Lexie Liu, Jaira Burns, Seraphine, League of Legends	0.970775
EXO	0.970318
Bad Wolves	0.969700
Jason Aldean	0.969397
Justin Bieber, Big Sean	0.968851
Bring Me The Horizon	0.968655

dtype: float64

Song Referenced:
Throne

EDM, Rock, Hardcore, and RNB all in one!

Examples of Recommendations

Bad

```
1 recommend_artist('Mumford & Sons', 2)
```

Mumford & Sons	1.000000
Pierce The Veil	0.981555
Moderatto	0.975989
ZAYN, Zhavia Ward	0.973609
Hillsong Worship	0.970897
Julie Roberts	0.969972
LeAnn Rimes	0.969792
Lorde	0.968064
Vince Staples	0.967429
Lorde	0.967256
Taylor Swift	0.965110
ZAYN, Taylor Swift	0.965075
Taylor Swift	0.962409
Faith Hill	0.961677
Pentatonix	0.961104

dtype: float64

Song Referenced:
Awake My Soul

These results are bad, ultimately because there is quite a bit of cross-genre recommendation occurring. Within these genres, they may have similarities on a song by song basis, but not artist to artist

Recommendations by Song

Good

```
Song Chosen: Picture To Burn
By: Taylor Swift
```

```
Recommended:
```

```
16846      Our Song
16874      Teardrops On My Guitar - Radio Single Remix
16885      Picture To Burn
16904      Tim McGraw
16932      Should've Said No
```

```
...
138465     Silent Night
138467     White Christmas
140553     It's Nice To Have A Friend
153303     You Belong With Me
168573     Drops Of Jupiter - Live/2011
Name: name, Length: 207, dtype: object
```

```
By: Taylor Swift
```

```
Song Chosen: Who You Foolin
By: Gunna
```

```
Recommended:
```

```
57143      Isis
75110      Isis (feat. Logic)
Name: name, dtype: object
```

```
By: Joyner Lucas, Logic
```

```
19424      BOP
19459      Suge
19496      VIBEZ
38375      Goin Baby
38447      Brother's Keeper
38460      Gucci Peacoat
38494      Shanyah
38499      More Money More Problems
74693      21
74850      INTRO
108299     Next Song
108324     Walker Texas Ranger
124647     OFF THE RIP
155362     XXL
170105     Today - Intro
170425     Taking It Out
Name: name, dtype: object
```

```
By: DaBaby
```



Recommendations by Song

Bad

```
Song Chosen: Throne
By: Bring Me The Horizon
```

```
Recommended:
```

```
18570    Blame (feat. John Newman)
Name: name, dtype: object
```

```
By: Calvin Harris, John Newman
```

```
17422    Little Lion Man
17435    The Cave
17570    Awake My Soul
18042    I Will Wait
36366    White Blank Page
36440    Winter Winds
```

Again, we see problems where those lines between measures begin to blur.

Here we have a heavy rock song giving back EDM, and Folk music



Future Improvements

As you can see the idea did not turn out in an ideal way

User-Based Collaborative filtering is the most ideal version of recommendation systems available

For future improvements

1. Find what best defines certain genres. Maybe we won't take dance-ability into account in relation to folk music, and only acoustic-ness, and return songs that have a high similarity between measures that are chosen by genre.