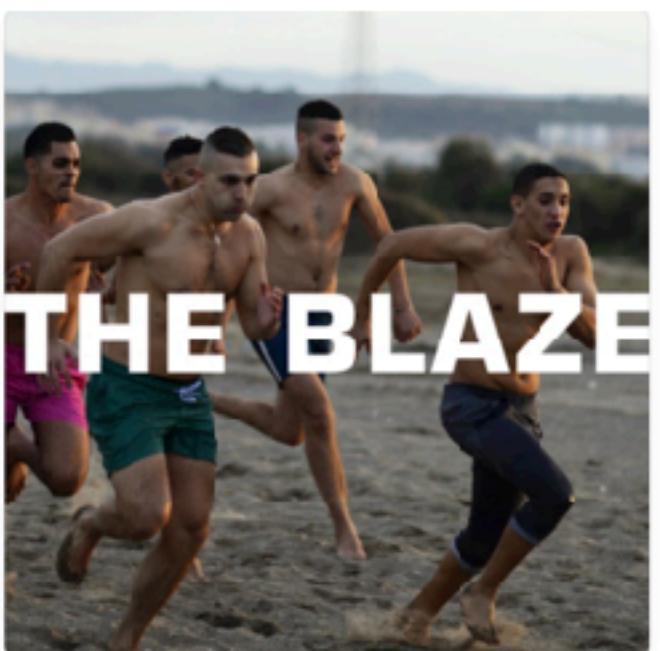
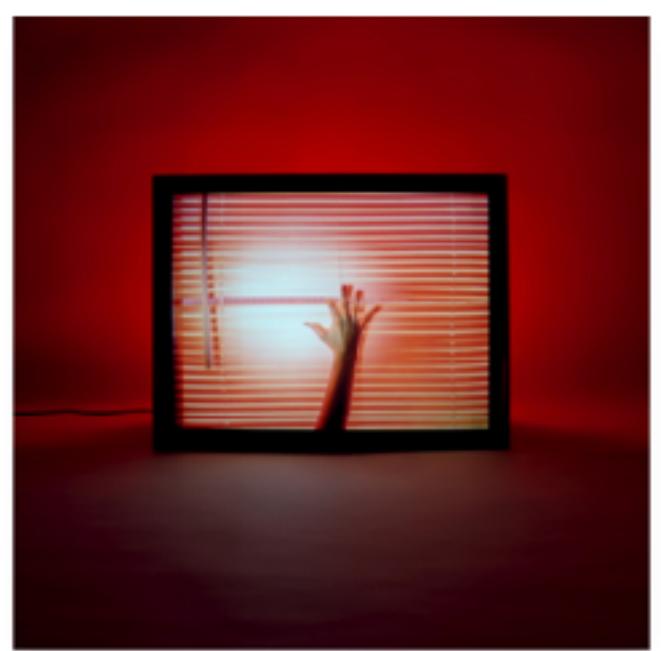




I Forget Where We Were
Ben Howard



Territory - EP
The Blaze



Screen Violence
CHVRCHES



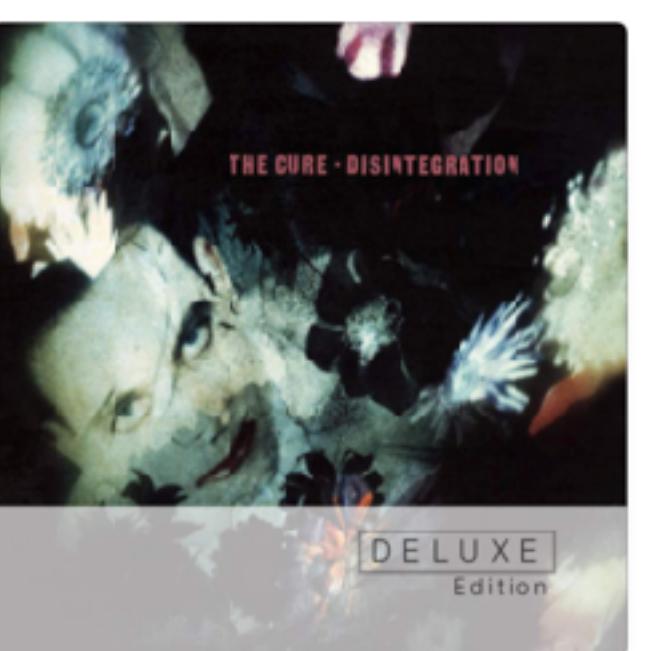
E
Bootstraps
Bootstraps



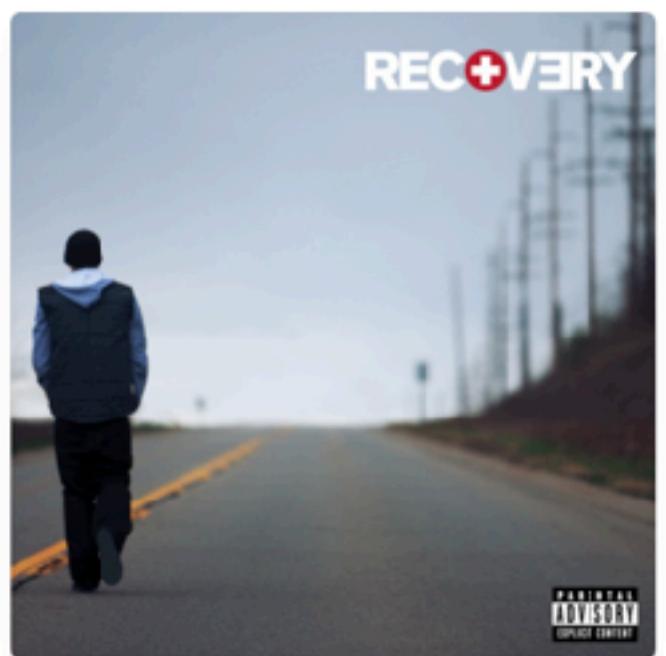
Chaleur Humaine (Deluxe Edition)
Christine and the Queens



Life for Rent
Dido



Disintegration (Deluxe Edition)
The Cure



Recovery
Eminem



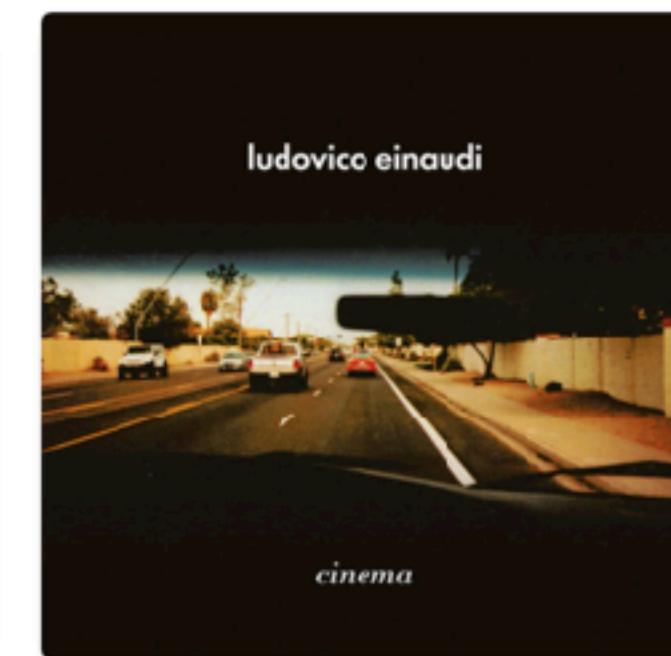
DAMN.
Kendrick Lamar



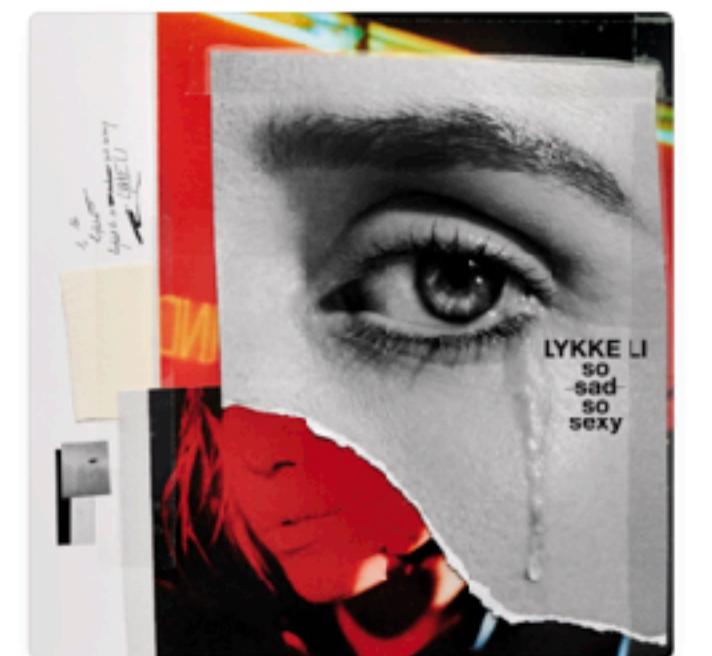
E
Minutes to Midnight
LINKIN PARK



If You Wait
London Grammar



Cinema
Ludovico Einaudi



so sad so sexy
Lykke Li



808s & Heartbreak
Kanye West



18
Moby



7
Paul Kalkbrenner



Alla mia età
Tiziano Ferro



Achtung Baby
U2



Astral Weeks
Van Morrison



The 1975
The 1975



Sotto la Pioggia
Antonello Venditti

Recommended Frequencies

A Music Recommendation Engine
by Lucas Chizzali



Listen to music



Analyse music

Recommended Frequencies

What?

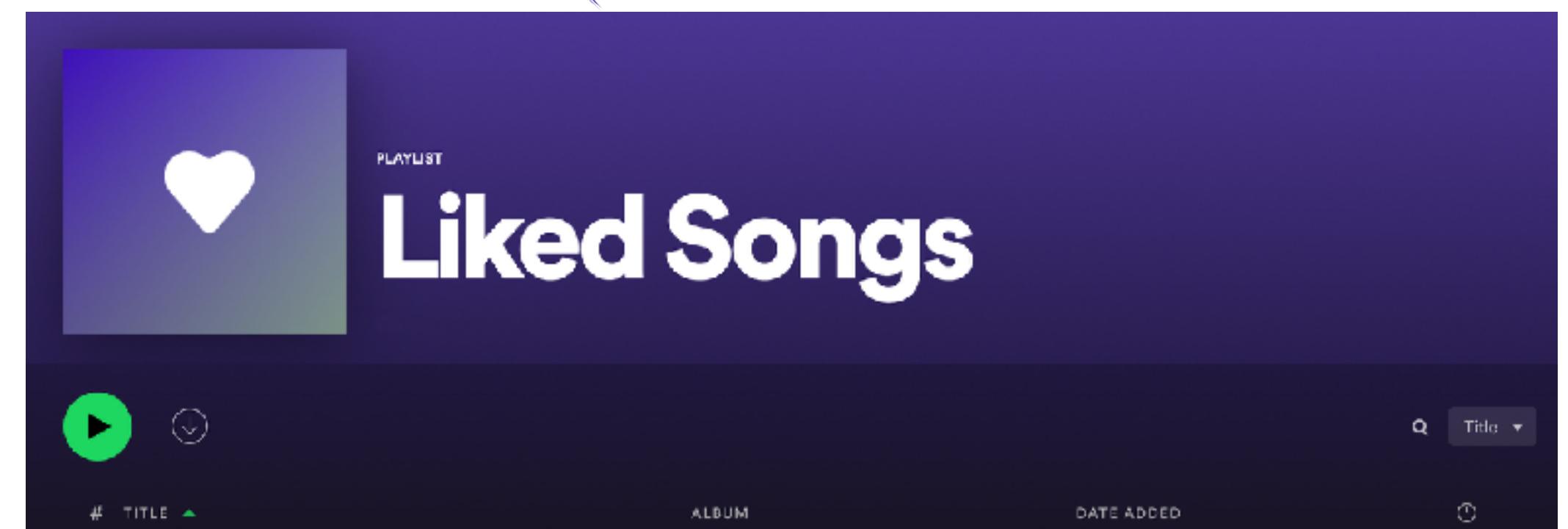
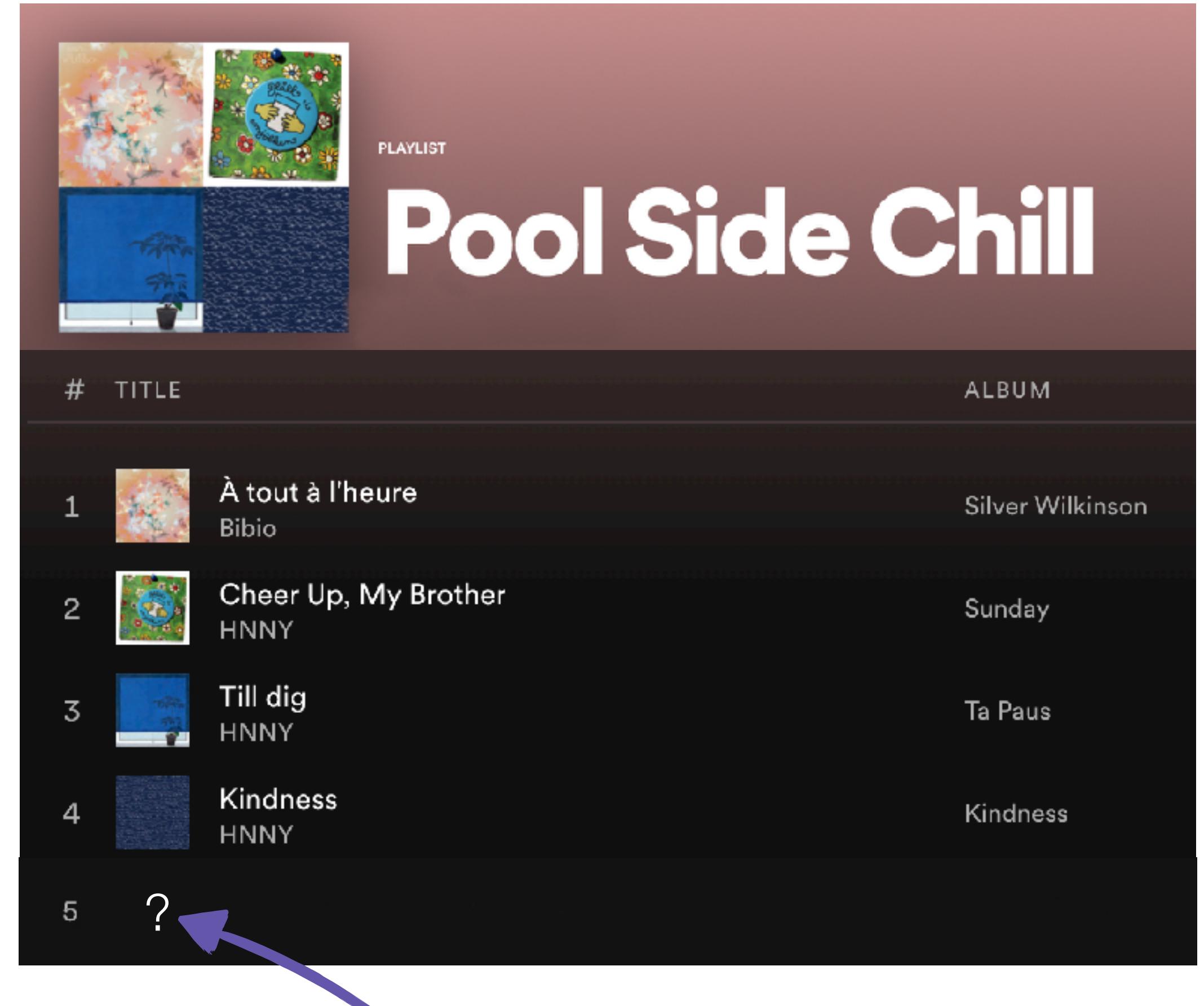
Help manage playlists

→ Identify songs in a person's music library that may fit well into a chosen, existing playlist

Multifaceted and difficult task since music is subjective

Specifically, a playlist may represent

- Mood (Summertime 🍉)
- Memory (High School 🎓)
- Genre (Synthwave 💡)
- Era (80s 🎵)
- etc.

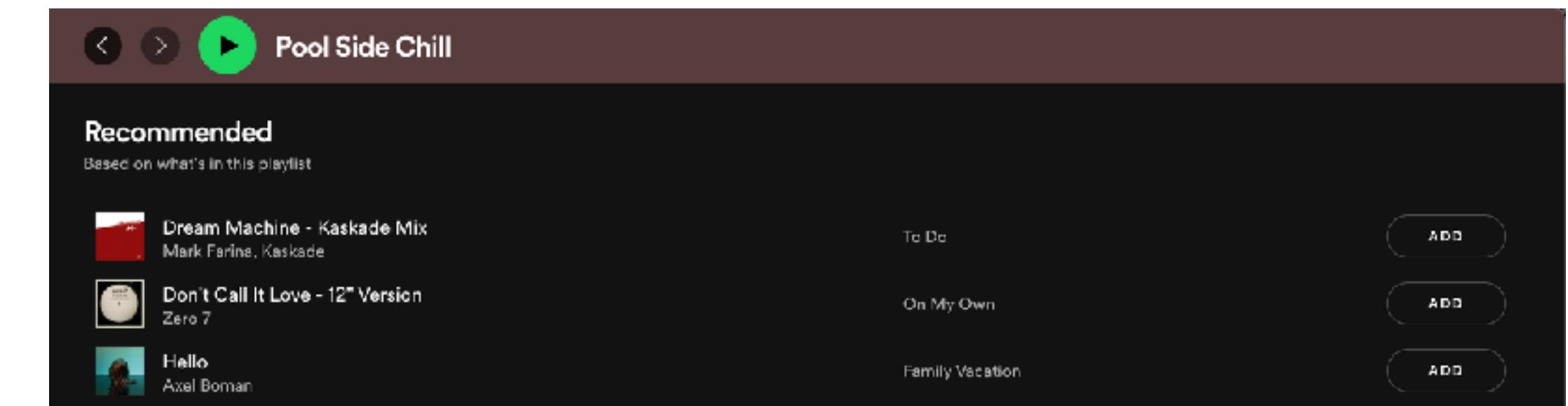


Recommended Frequencies

Why?

Playlists are an integral means to enjoying music

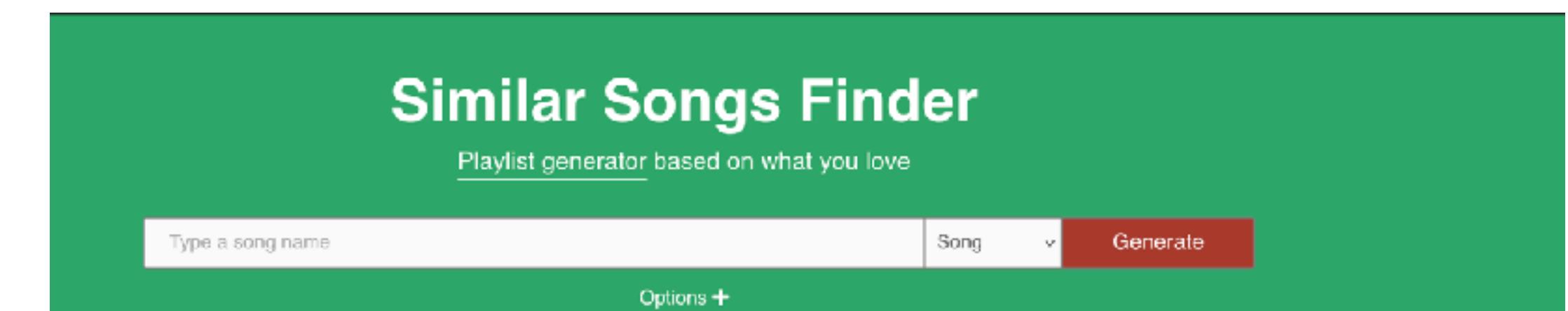
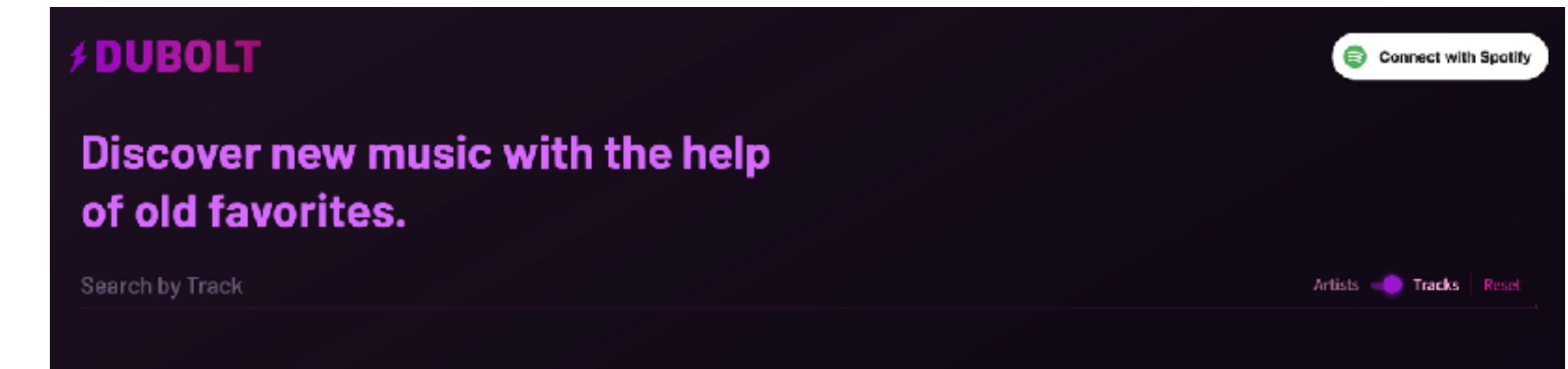
- Anecdotal evidence
- 4 bn playlists vs 350 m users on Spotify*



Music recommendation is nothing new

Nevertheless

- DIY is fun
- Re-discovering your own music



Let's research the



Verified Artist

State of Sound the Art

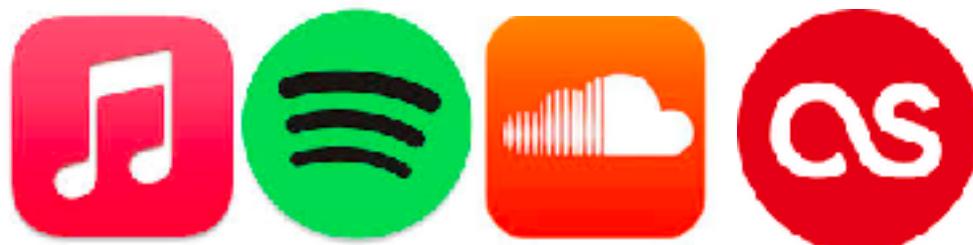
222,704 monthly listeners



Music Recommendation

How?

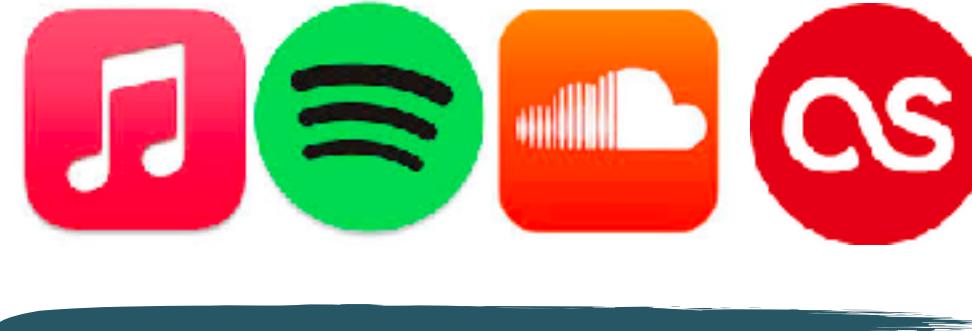
- Popular researched domain
- Competitive edge for streaming services
- Usage **vs** content data

	Usage data	Content data
Approaches	Recommender Systems	Music Information Retrieval
Example of technique	Collaborative filtering [1]	Deep Learning [2]
Example of datasource		Million Song Dataset

[1] Song, Yading, Simon Dixon, and Marcus Pearce. "A survey of music recommendation systems and future perspectives." In 9th international symposium on computer music modeling and retrieval, 2012.

[2] Van den Oord, Aaron, Sander Dieleman, and Benjamin Schrauwen. "Deep content-based music recommendation." Advances in neural information processing systems 26 (2013)

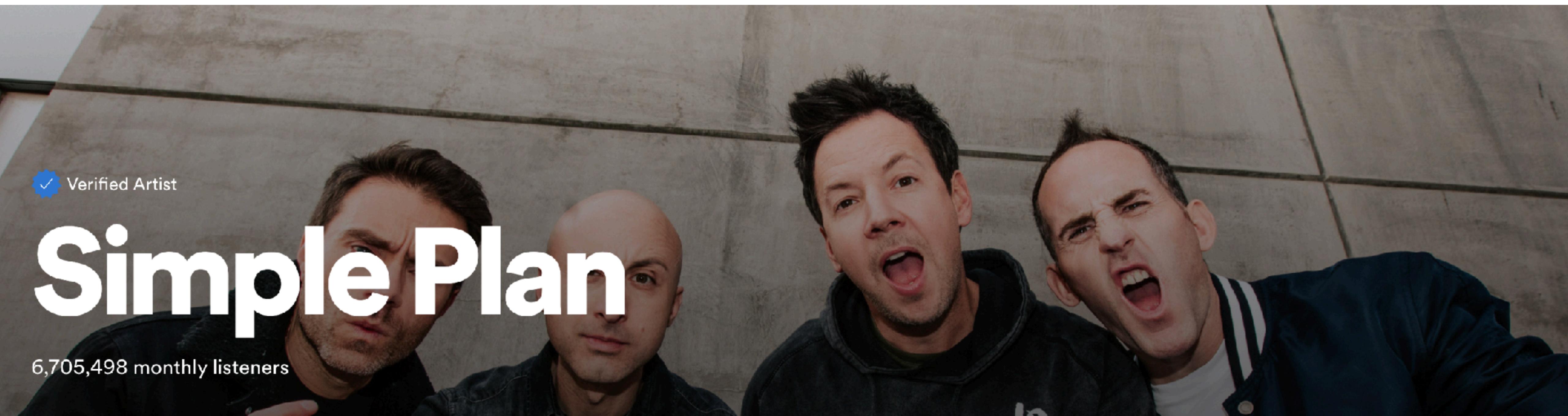
Music Recommendation Implications

	Usage data	Content data
Approaches	Recommender Systems	Music Information Retrieval
Example of technique	Collaborative filtering [1]	Deep Learning [2]
Example of datasource	 A row of four circular icons representing different music platforms: Apple Music (red square with white note), Spotify (green circle with three horizontal lines), SoundCloud (orange square with white cloud), and Last.fm (red circle with white 'AS' logo). A dark blue brushstroke underline is positioned below the icons.	 A dark blue brushstroke underline is positioned below the text.

- Not easy to come by
- Proprietary / limited access to the public
- Large amounts of data

- Limited number of songs available
- Pre-trained models for audio → features
- Audio not straightforward to come by (e.g. copyright)

For now, let's devise a



Simple Plan

6,705,498 monthly listeners



Simple Plan

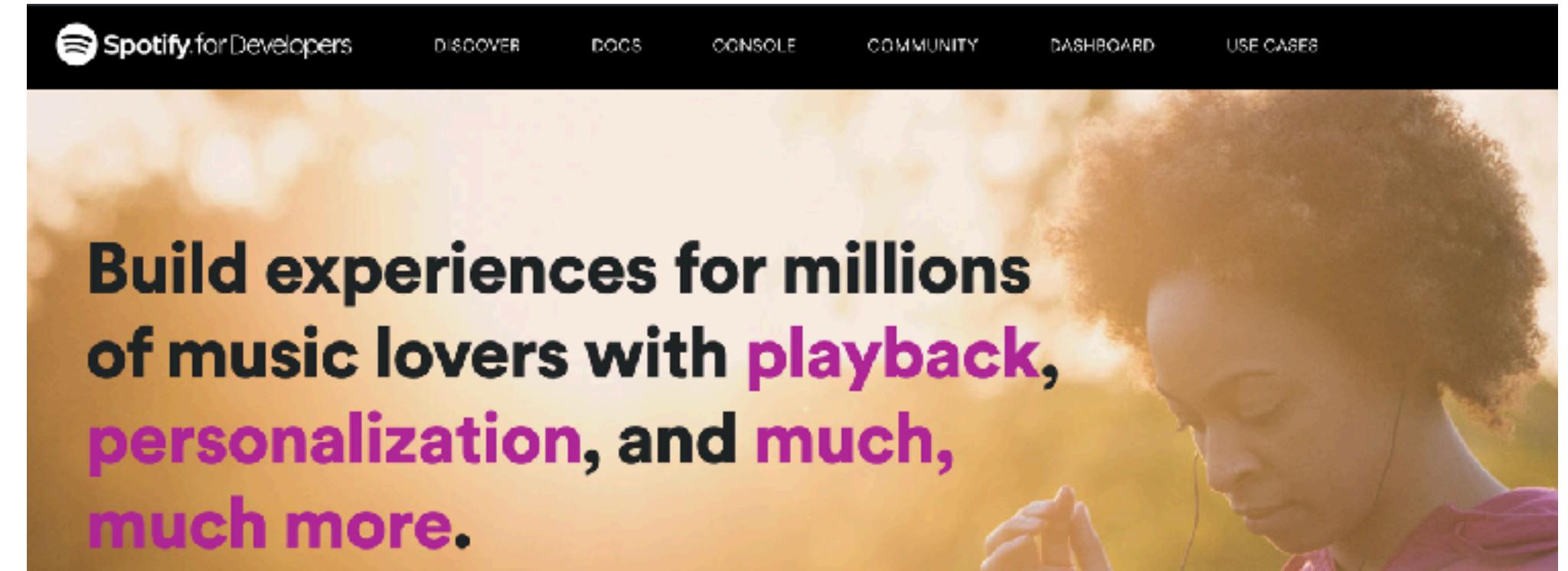
6,705,498 monthly listeners

- Only use information relating to a person's music library
- Work with readily available audio features
- Quickly build an easy-to-use tool to consume recommendations

Recommended Frequencies

How?

Use readily available audio features



Spotify API

- Free
- Popular
- Audio features + metadata
- Python library

A screenshot of the Spotify API documentation website. On the left is a sidebar with the title "spipy" and version "2.19.0". It includes a search bar and a list of topics: Welcome to Spotify!, Features, Installation, Getting Started, Authorization Code Flow, Client Credentials Flow, IDs URIs and URLs, Customized token caching, Examples, API Reference, and client Module. The main content area has a heading "Welcome to Spotify!" and a subtext explaining that Spipy is a lightweight Python library for the Spotify Web API. To the right is a photo of a person holding a smartphone displaying the Spotify app.

Build a dashboard for interacting with results

Streamlit

- “The fastest way to build and share data apps”

A screenshot showing Streamlit in action. On the left, a code editor window titled "MyApp.py" contains Python code for a Streamlit application. The code imports streamlit and pandas, writes a "Hello world!" message, and creates a line chart from a CSV file. On the right, a browser window titled "My App + Streamlit" shows the resulting "My first app" interface with the "Hello world!" message and the line chart.

Data, or should I say...



Verified Artist

JSON Derulo

34,123,266 monthly listeners



Spotify API

Audio Features

▼ Body

✓ **audio_features** array of objects

acousticness number<float>

A confidence measure from 0.0 to 1.0 of whether the track is acoustic. 1.0 represents high confidence the track is acoustic.
>= 0 <= 1

danceability number<float>

Danceability describes how suitable a track is for dancing based on a combination of musical elements including tempo, rhythm stability, beat strength, and overall regularity. A value of 0.0 is least danceable and 1.0 is most danceable.

energy number<float>

Energy is a measure from 0.0 to 1.0 and represents a perceptual measure of intensity and activity. Typically, energetic tracks feel fast, loud, and noisy. For example, death metal has high energy, while a Bach prelude scores low on the scale. Perceptual features contributing to this attribute include dynamic range, perceived loudness, timbre, onset rate, and general entropy.

instrumentalness number<float>

Predicts whether a track contains no vocals. "Ooh" and "aah" sounds are treated as instrumental in this context. Rap or spoken word tracks are clearly "vocal". The closer the instrumentalness value is to 1.0, the greater likelihood the track contains no vocal content. Values above 0.5 are intended to represent instrumental tracks, but confidence is higher as the value approaches 1.0.

application/json

required

liveness number<float>

Detects the presence of an audience in the recording. Higher liveness values represent an increased probability that the track was performed live. A value above 0.8 provides strong likelihood that the track is live.

loudness number<float>

The overall loudness of a track in decibels (dB). Loudness values are averaged across the entire track and are useful for comparing relative loudness of tracks. Loudness is the quality of a sound that is the primary psychological correlate of physical strength (amplitude). Values typically range between -60 and 0 db.

speechiness number<float>

Speechiness detects the presence of spoken words in a track. The more exclusively speech-like the recording (e.g. talk show, audio book, poetry), the closer to 1.0 the attribute value. Values above 0.66 describe tracks that are probably made entirely of spoken words. Values between 0.33 and 0.66 describe tracks that may contain both music and speech, either in sections or layered, including such cases as rap music. Values below 0.33 most likely represent music and other non-speech-like tracks.

tempo number<float>

The overall estimated tempo of a track in beats per minute (BPM). In musical terminology, tempo is the speed or pace of a given piece and derives directly from the average beat duration.

valence number<float>

A measure from 0.0 to 1.0 describing the musical positiveness conveyed by a track. Tracks with high valence sound more positive (e.g. happy, cheerful, euphoric), while tracks with low valence sound more negative (e.g. sad, depressed, angry).

>= 0 <= 1

Spotify API Song Metadata

release_date string

required

The date the album was first released.

genres array of strings

A list of the genres the artist is associated with. If not yet classified, the array is empty.

A lot of genres exist (>5k)!

global genres
local genres
random genres
any genre

finnish metal
pop house
reggae en espanol
christian alternative rock
pop argentino
banda carnavalera
haryani pop
turkish pop
norwegian indie
art pop
christian indie
german techno
cubaton
circuit
chinese drama ost
hindi hip hop
canadian underground hip hop
cologne hip hop
new romantic
dutch hip hop

afripop
atmospheric
background
blues
brazil
children
christian
classical
comedy
country
edm
electronic
folk
france
hip hop
india
indie
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jazz
latin
metal
mexican
oldies
pop
punk
r&b
reggae
rock
soul
soundtrack
slovene

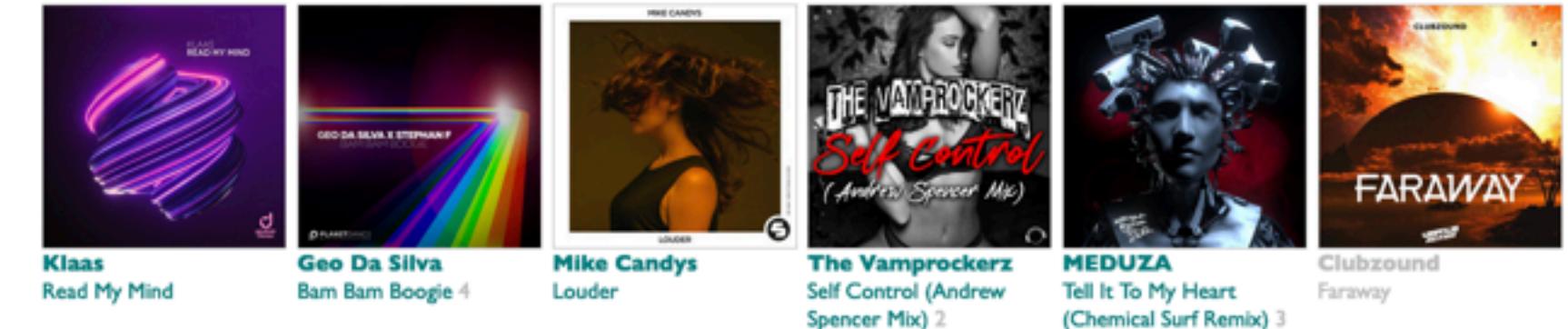
world folk
world hip hop
world pop
world punk
world rock

21st century classical
432hz
5th wave emo
8-bit
8d
a cappella
a3
aberdeen indie
abstract
abstract beats
abstract hip hop

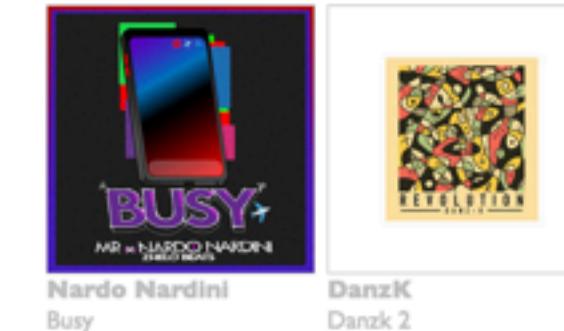
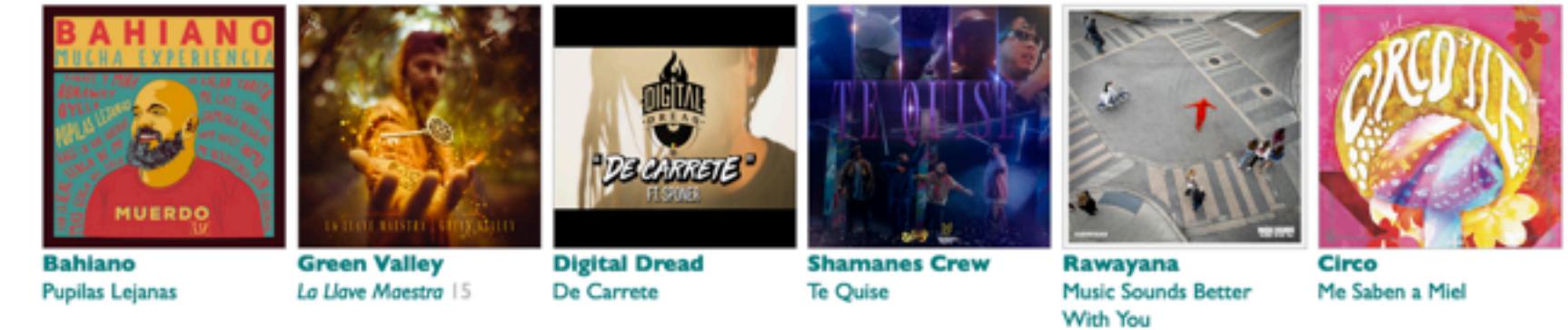
finnish metal 6



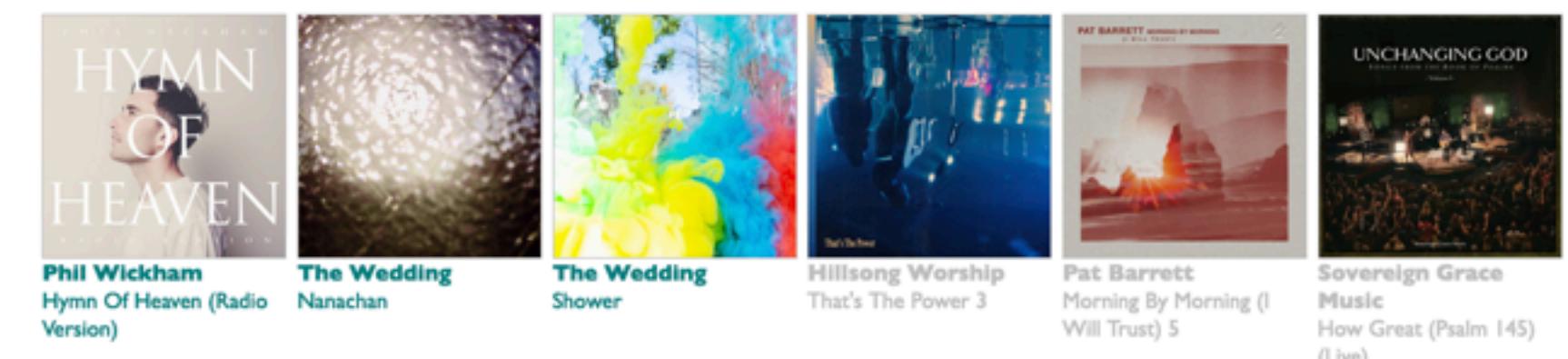
pop house 6



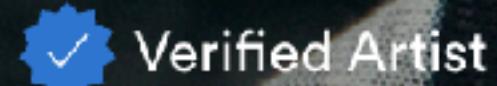
reggae en espanol 14



christian alternative rock 11



Methodology, a.k.a



Machine Gun Kelly → Learning

18,242,348 monthly listeners

Audio Feature Similarity

Weighted Euclidean distance

$$d(\mathbf{P}, \mathbf{s}) = \sqrt{\sum_i^d \log\left(\frac{1}{\sigma(\mathbf{P}_i)}\right) (\mu(\mathbf{P}_i) - \mathbf{s}_i)^2}$$

where

- feature vector of a song $\mathbf{s} \in \mathbb{R}^d$

$$\mathbf{P} = \begin{bmatrix} \mathbf{s}_1 \\ \vdots \\ \mathbf{s}_n \end{bmatrix} \in \mathbb{R}^{n \times d}$$

- $d = 9$ audio features + release date

Average of feature across songs in playlist

Weigh each feature by its standard deviation across songs in the playlist

- Inverse: more uniform \rightarrow more important
- Log: limit influence of highly uniform features



Look at this graph...

... every time it makes me laugh

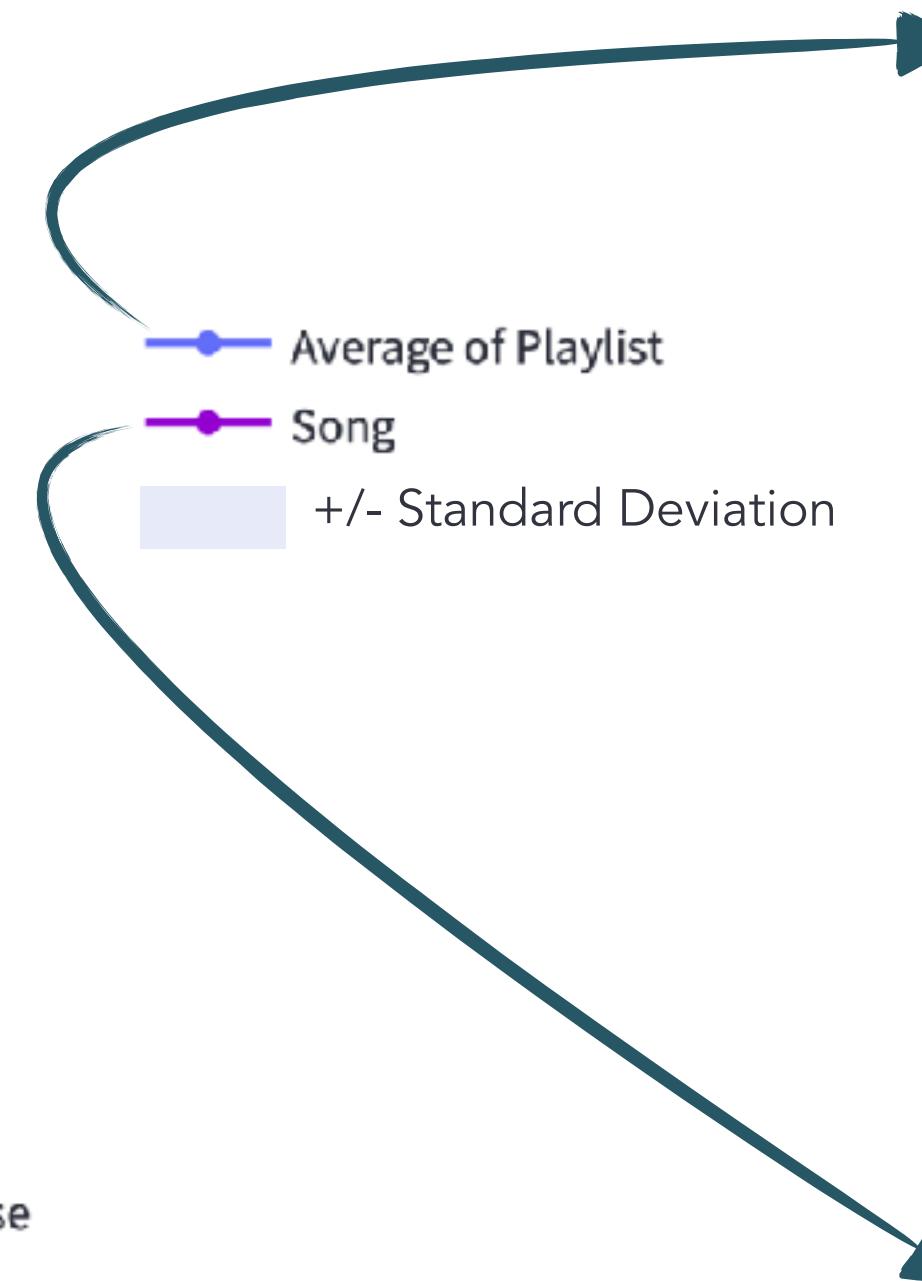
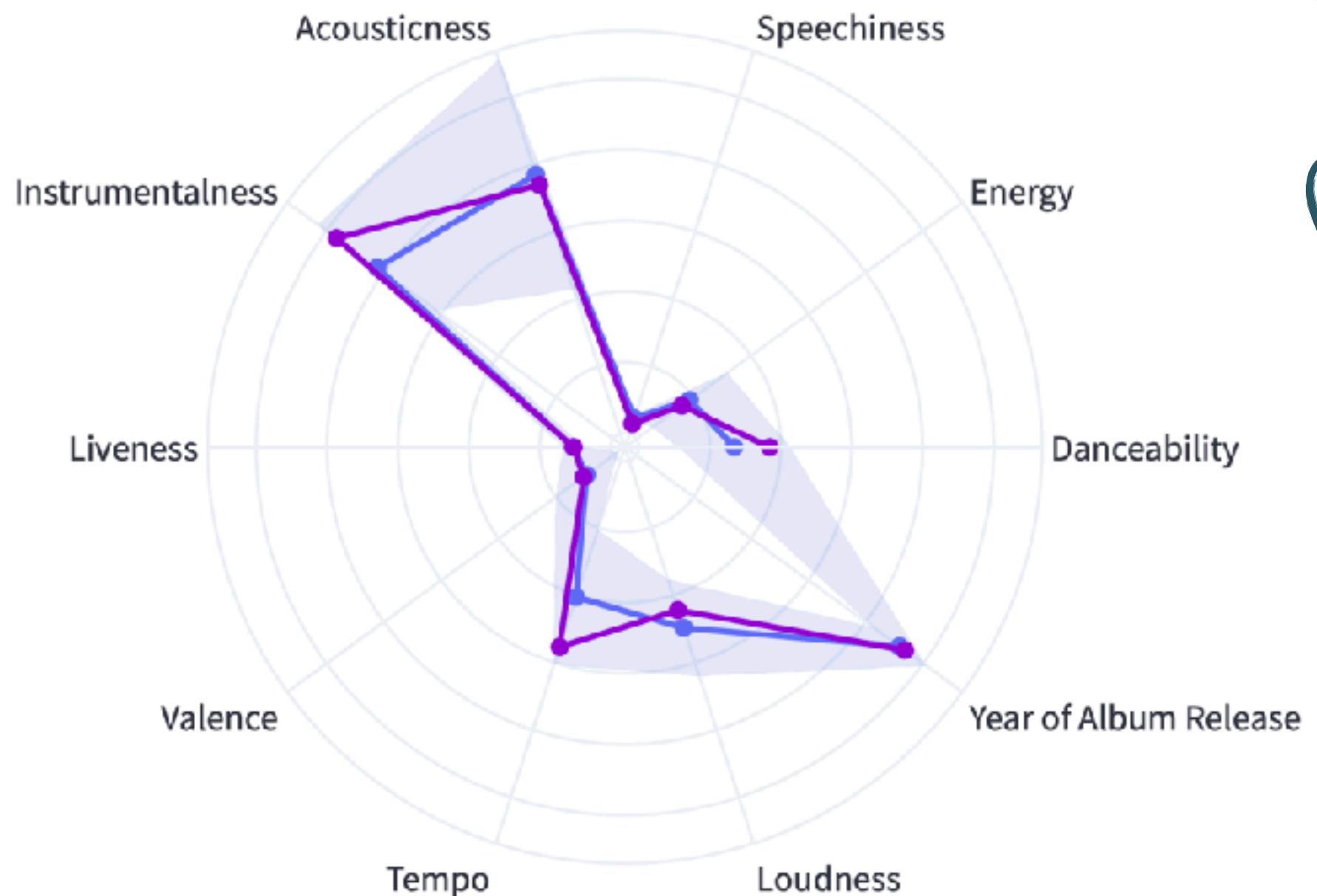
Audio Feature Similarity Visualisation



Similarity for this feature is more important since majority of songs share the same attribute

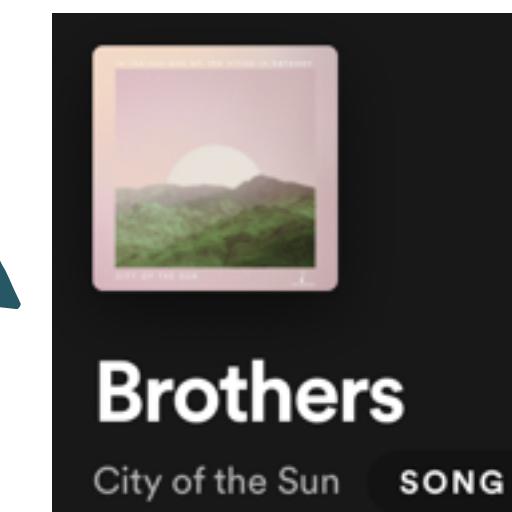
Similarity for this feature is less important since few songs share the same attribute

Audio Feature Similarity Limitations



The Spotify interface shows a playlist titled "Classico - Adagio". The playlist contains four tracks: "Berlin Song" by Ludovico Einaudi, "Two Trees" by Ludovico Einaudi, "Experience" by Ludovico Einaudi, Daniel Hope, I Virtuosi Italiani, and "Fly - Reimagined by Mercan Dede and Dexter Crowe" by Ludovico Einaudi, Mercan Dede, Dexter Crowe. All tracks were added on Jul 27, 2021.

#	Title	Album	Date Added
1	Berlin Song Ludovico Einaudi	Nightbook (Exclusive)	Jul 27, 2021
2	Two Trees Ludovico Einaudi	In A Time Lapse (Deluxe Edition)	Jul 27, 2021
3	Experience Ludovico Einaudi, Daniel Hope, I Virtuosi Italiani	In A Time Lapse	Jul 27, 2021
4	Fly - Reimagined by Mercan Dede and Dexter Crowe Ludovico Einaudi, Mercan Dede, Dexter Crowe	Reimagined, Volume 1, Chapter 1	Jul 27, 2021



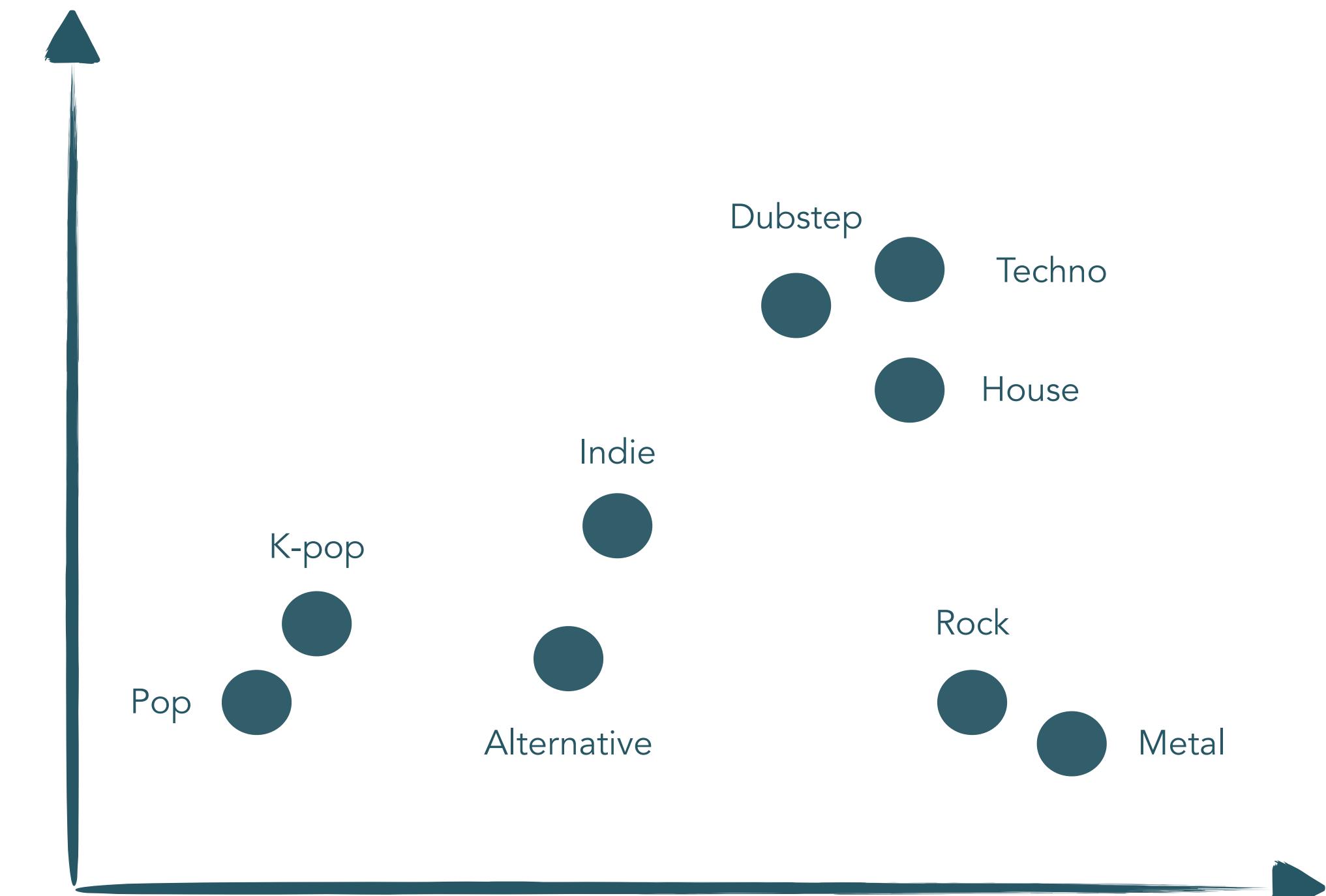
Genre Similarity

Many options

1. Set similarity
2. Co-occurrence
3. Word2Vec embedding
4. “Every Noise at Once” embedding

and more

Similar genres should be close together

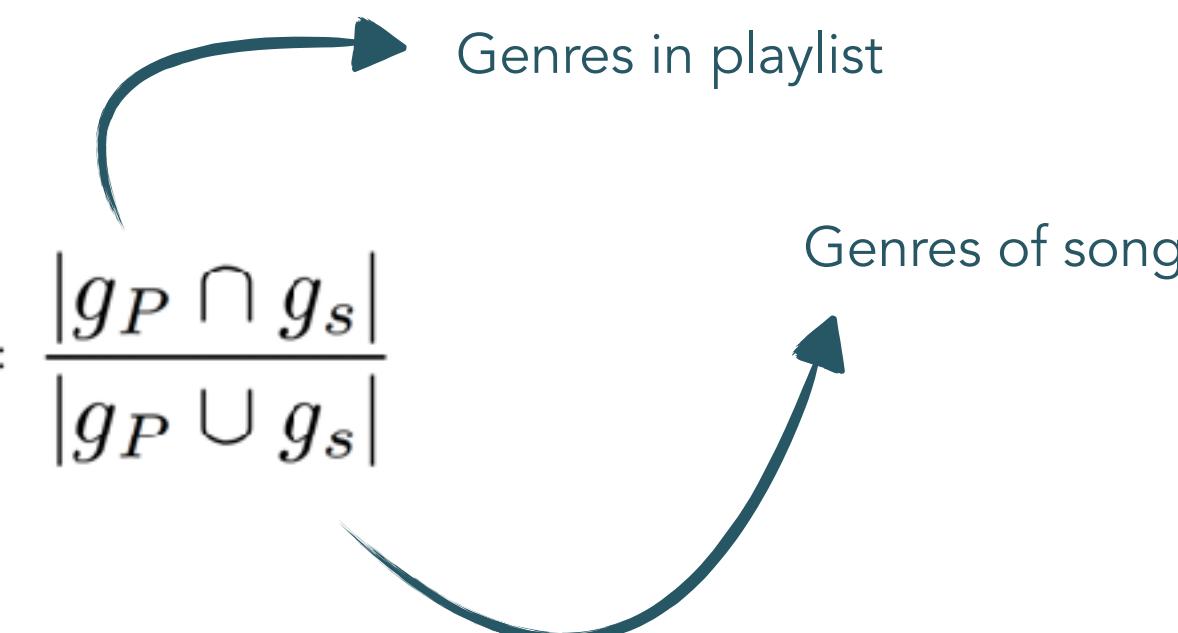


Illustration

Genre Similarity

Jaccard index & co-occurrence

Jaccard index

$$\text{sim}(g_P, g_s) = \frac{|g_P \cap g_s|}{|g_P \cup g_s|}$$


Co-occurrence

$$\text{co-occurrence}(g_1, g_2) = \sum_i f(g_1, g_2, P_i)$$

$$\text{where } f(g_1, g_2, P_i) = \begin{cases} 1, & \text{if } (g_1 \in P_i) \cap (g_2 \in P_i) \\ 0, & \text{otherwise} \end{cases}$$



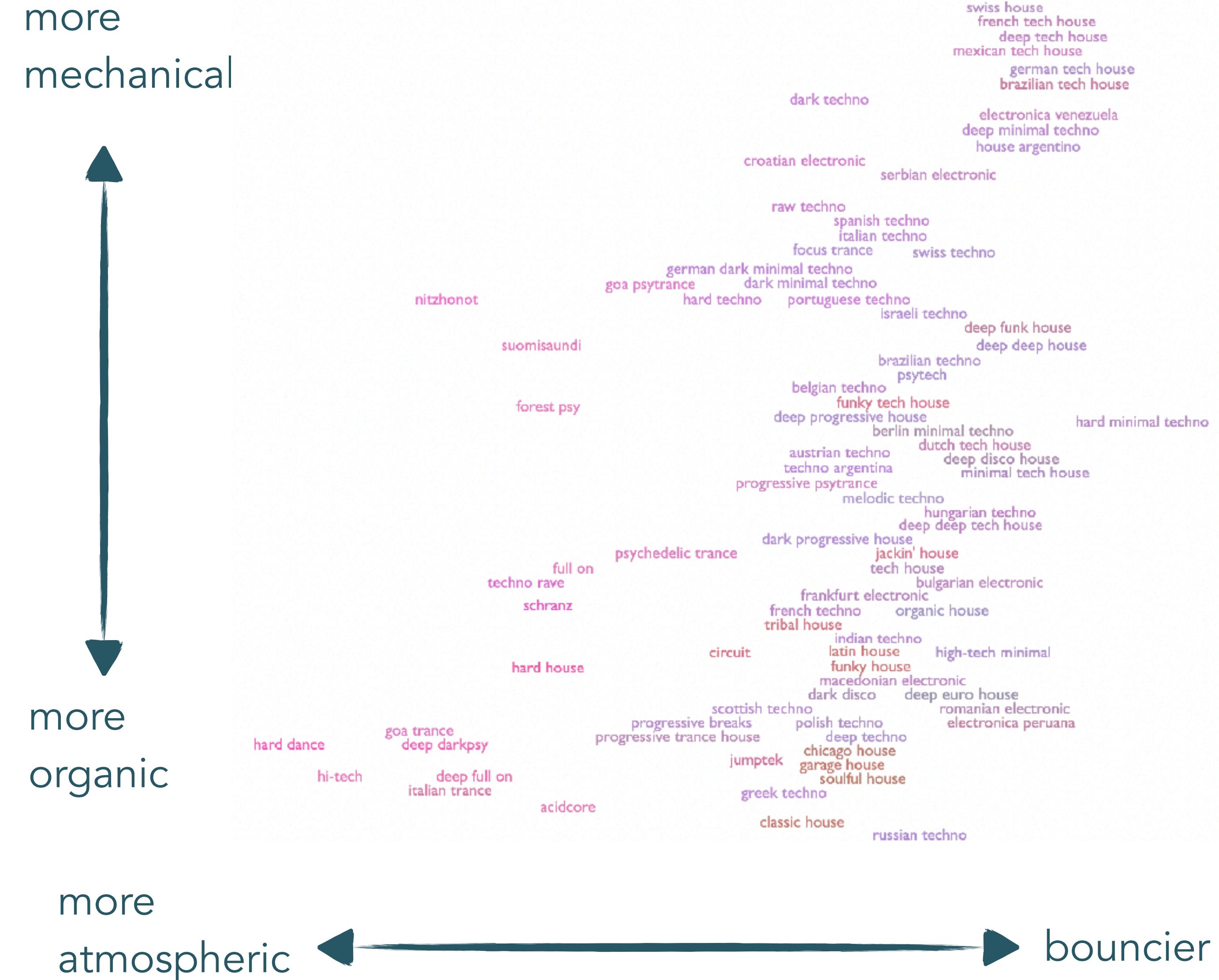
Genre Similarity

Every Noise at Once

- everynoise.com provides an “algorithmically-generated [...] scatter-plot of the musical genre-space” of Spotify
 - Embedding equals (x, y) coordinates of genre in plot

```
><div id="item2627" preview_url="https://p.scdn.co/mp3-preview/8f54913108882af589270d12840b087ae33adf0" class="genre scanme" scan="true" style="color: #0382c9; top: 0px; left: 1427px; font-size: 101%" onclick="playx('5K7Dmv4712ml7tbzvljdTA', "latin tech house", this); title="e.g. Hector Couto "Salimo"">...</div>
```

- Song genre embedding equals (\bar{x}, \bar{y}) , i.e. centroid of all associated genres
 - Use Euclidean distance as similarity metric



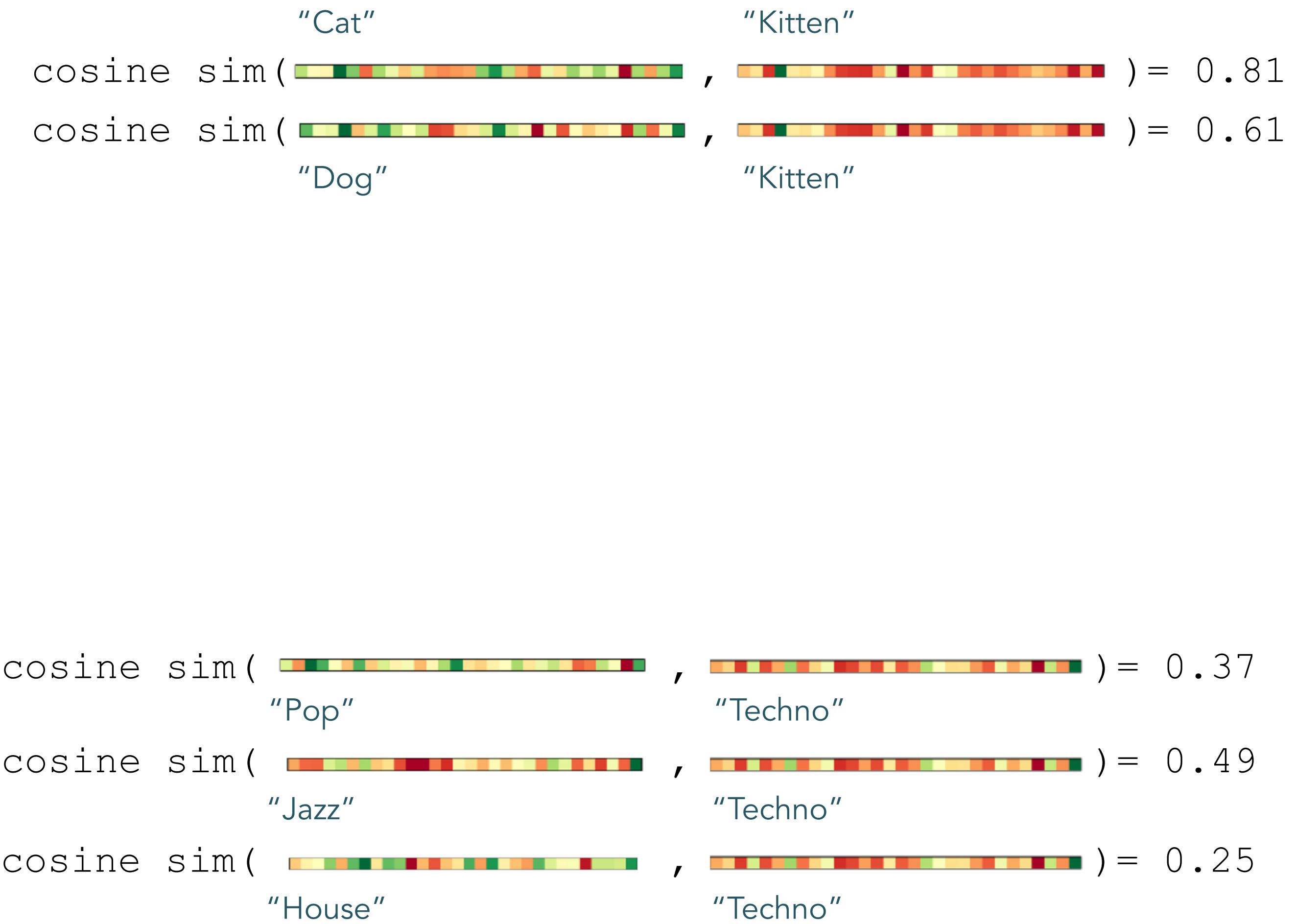
Genre Similarity

Word2Vec

1. Treat genre as any other word in a natural language, in this case English
2. Apply a pre-trained Word2Vec model to get word embeddings
3. Use cosine similarity as similarity metric

Is this a reasonable approach?

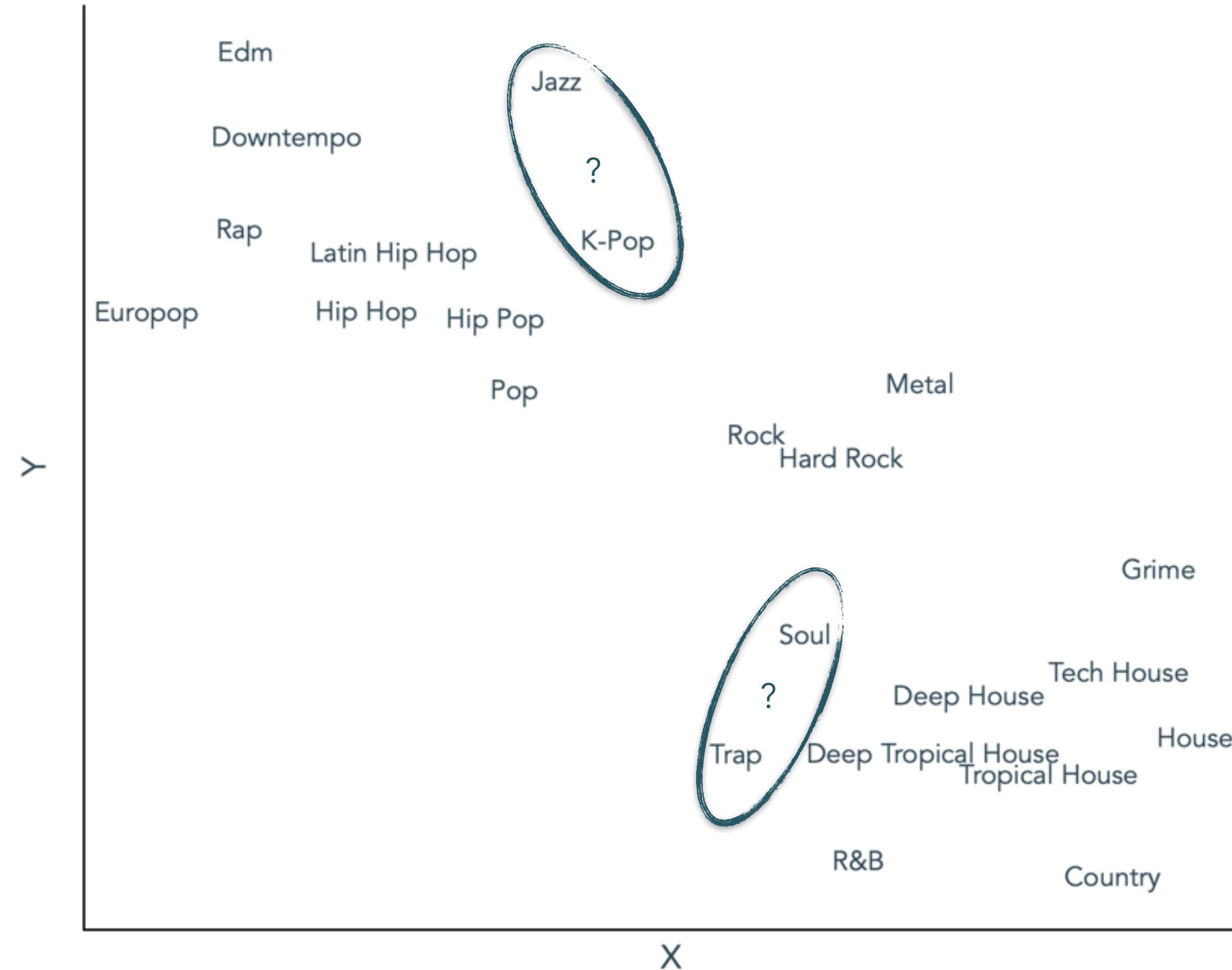
Subjective or not, Jazz is not more similar to Techno than House



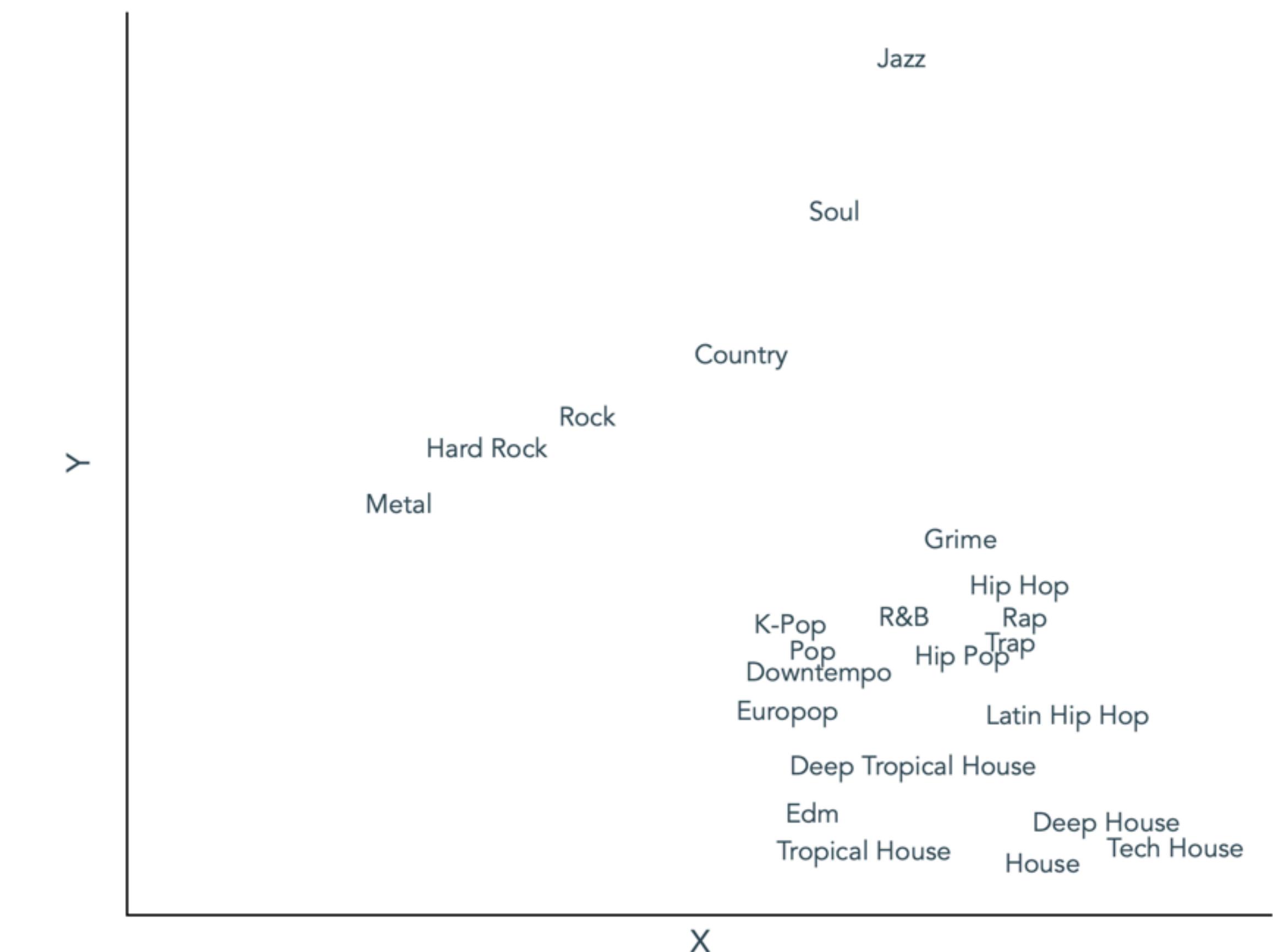
Genre Similarity

Every Noise at Once vs Word2Vec for selected genres

Word2Vec Embedding Space Projected in 2D Using t-SNE



Every Noise At Once Embedding Space



Word2Vec embeddings seem to lead to strange genre similarities

Genre Similarity

Every Noise at Once vs Word2Vec

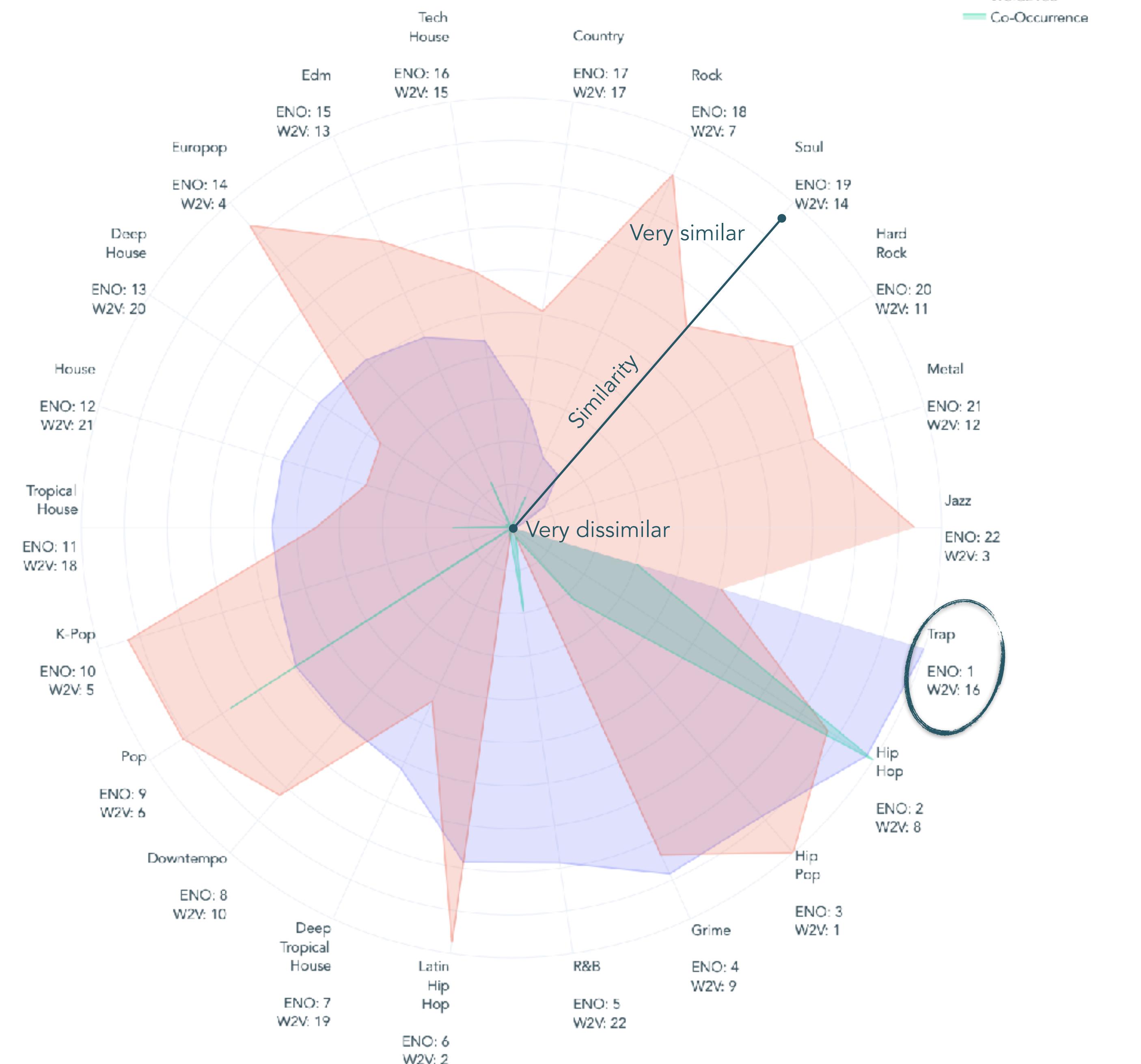
t-SNE introduces distortions

- Difficult to deduce nearest neighbours

Measure genre similarity in original space

Compare similarity ranks for a given genre

- Choose Rap
- Trap is most similar to Rap according to "Every Noise at Once"
- Word2Vec ranks Trap only 16th in terms of similarity
- The difference in rank is 15, i.e. the two approaches disagree quite considerably



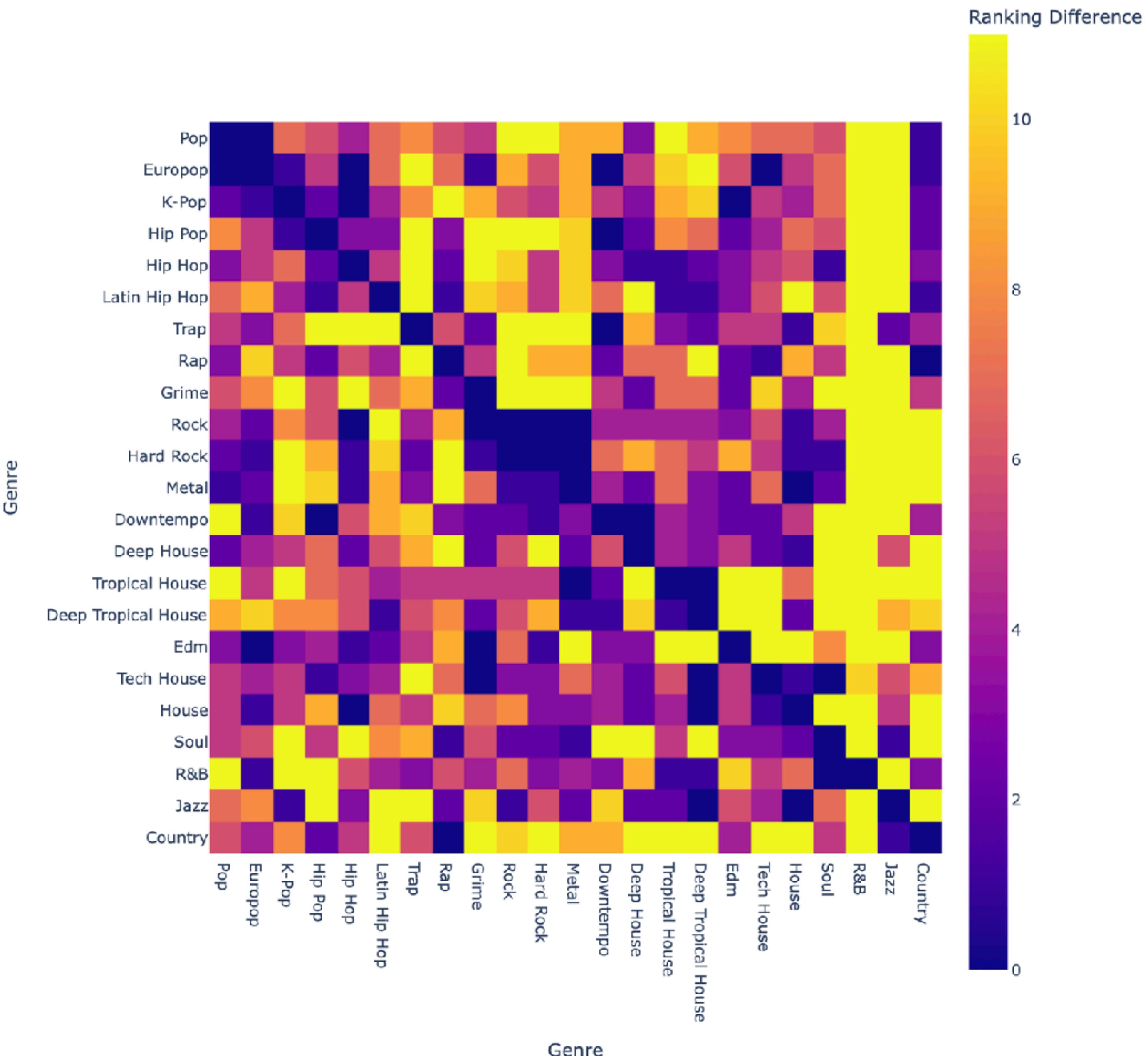
Genre Similarity

Every Noise at Once vs Word2Vec

- Visualise the (dis)agreement between the two methods for all genres at once
- Generally, there is a lot of disagreement (high difference in ranking)
- This is especially the case for R&B and Jazz

Take-away

- Word2vec does not lead to same similarities as Every Noise at Once
- The latter can subjectively be considered as the better embedding approach



YOU BROKE
ME FIRST



Dash Berlin board

1,356,807 monthly listeners



Recommended Frequencies: A Recommendation System For Playlists

This app allows users to identify songs in their library that may fit well into a selected playlist

Page Settings

+

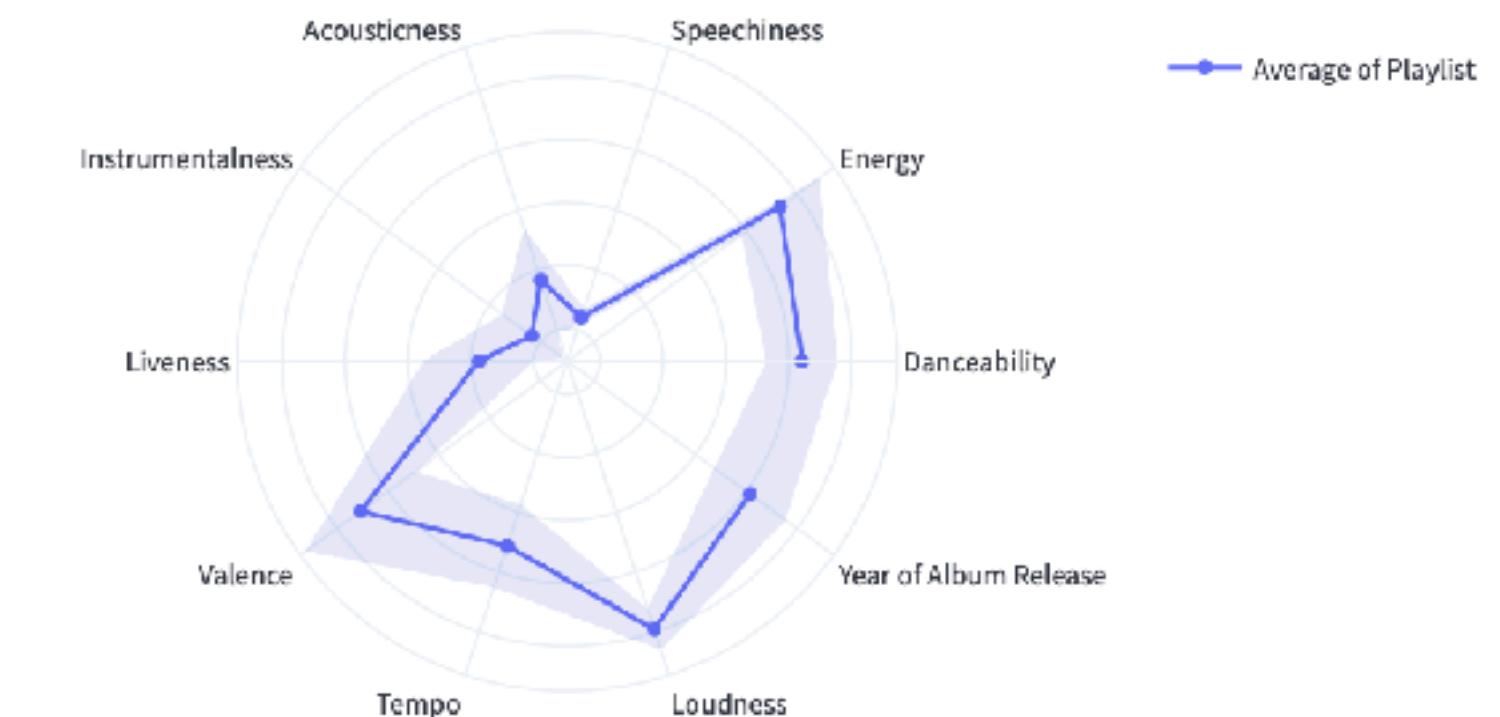
1. Choose a playlist

80's Retro

Examples of songs in playlist «80's Retro»

	SongName	Artist	ID
0	Sledgehammer	Peter Gabriel	029NqmlySn1kOY305AAhxT
1	200度	Sally Yeh	0CYelmjEps63DAuqLV9b6J
2	Stella Stai	Umberto Tozzi	0NUyAEi7WIhF0SJGVavUG
3	Tainted Love	Soft Cell	0cGG2EouYCEEC3xfa0tDFV
4	The Rhythm of the Night	Corona	0afMkl3jzmGCElAOgOLeo3
5	Just Can't Get Enough	Depeche Mode	0qi4b1l0eT3jpzeNHeFXDT
6	I'm So Excited	The Pointer Sisters	1ot6jEe4w4hYnsOPjd3xKQ
7	Like a Prayer	Madonna	1z3ugFmUKaCzGsl6jdY4Ci
8	Two Tickets to Paradise	Eddie Money	22CIOfLZB9z8He7WgHYAgH
9	Tarzan Boy	Baltimora	273uCXd7NPrinaiNqtkOrA

Song attributes for playlist «80's Retro»



2. Find similar songs

Similarity Settings

Similarity Features

Numeric Song Attributes + Genre

Genre Similarity Metric

everynoise

Genre Weight

0.00 0.30 1.00

Nr of Suggestions

5 10 20

Most similar songs to playlist «80's Retro»

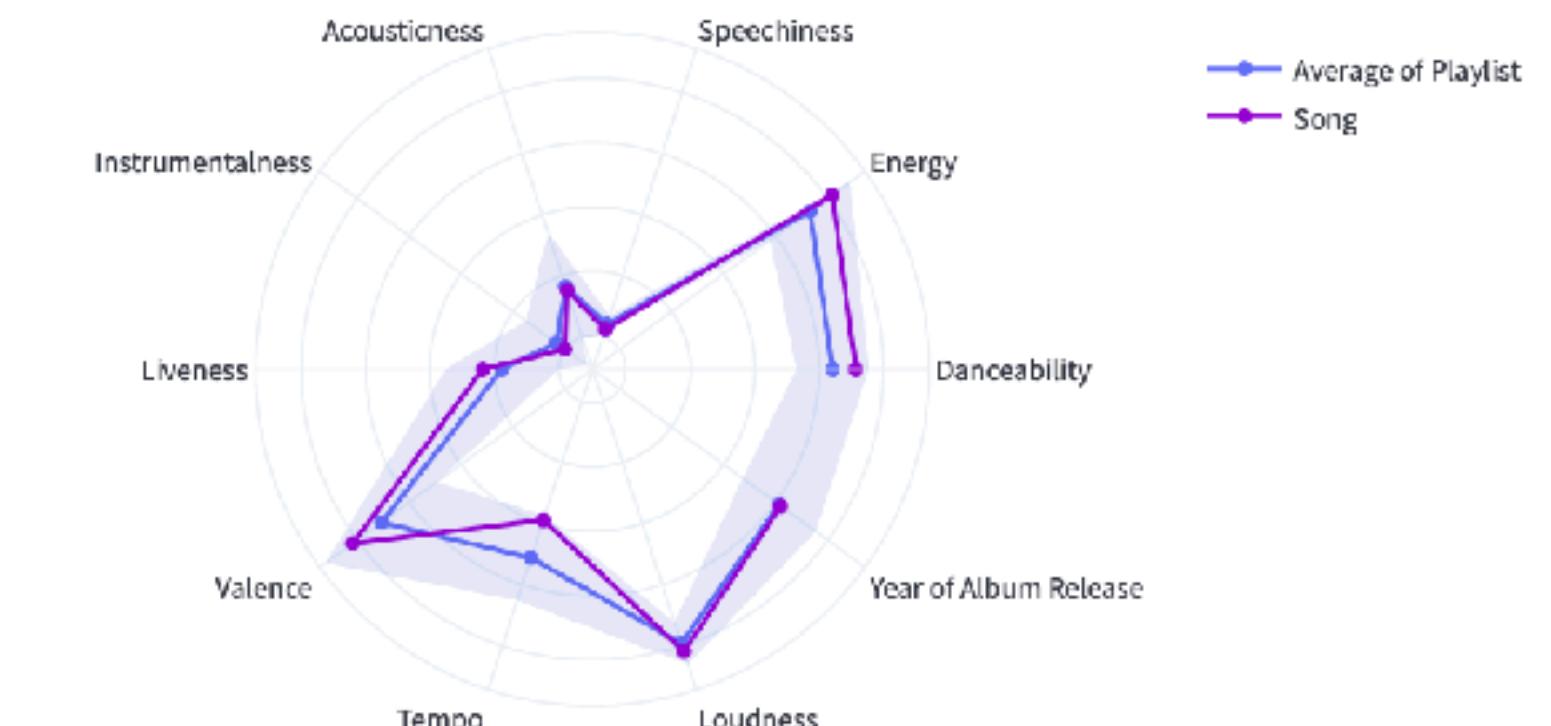
	SongName	Artist	ID
0	Stars	Simply Red	75CgD6l7K4qMzZrn4CbZqz
1	The Best	Tina Turner	6pPWRBubXOBAHnjl5ZIujB
2	How Bizarre	OMC	46q5BtHso0ECuTKeq70ZhW
3	Fairground	Simply Red	3lghqWELEWj9yEPvme7c4W
4	You Get What You Give	New Radicals	1Cwsd5xI8CajJz795oy4XF
5	Save Tonight	Eagle-Eye Cherry	0smyCrJiibi2uwCiq5R1vj
6	Breakfast At Tiffany's	Deep Blue Something	1uzWOoJdADfstQuFtQFTUn
7	If You Love Somebody Set Them Free	Sting	5Xhqe9xu6bKR5qLj1mS1SB
8	Wouldn't It Be Good	Nik Kershaw	00FDHurakzVEiPutdUxXXq
9	In These Shoes?	Kirsty MacColl	6K2exMTxOTgErtQlp5BRMp

Visualise similarity of proposed song

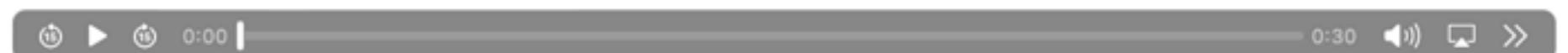
Spotify song ID to visualise

75CgD6l7K4qMzZrn4CbZqz

Song: Stars by Simply Red
Playlist: 80's Retro



Listen to proposed song



Let's deep dive into some results



ALBUM

Results May Vary



Limp Bizkit • 2003 • 18 songs, 1 hr 8 min

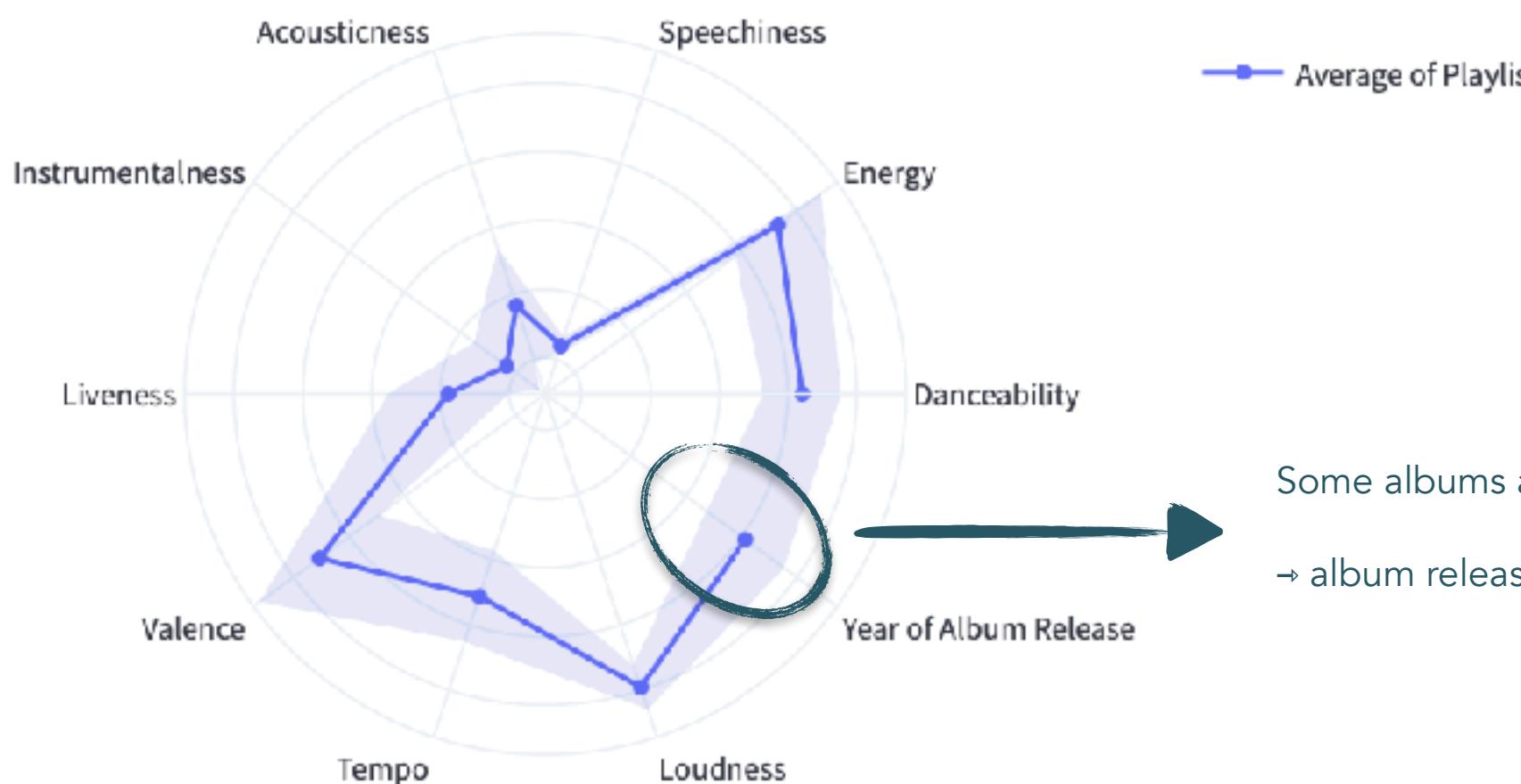
«80's Retro»

for that 80's feeling



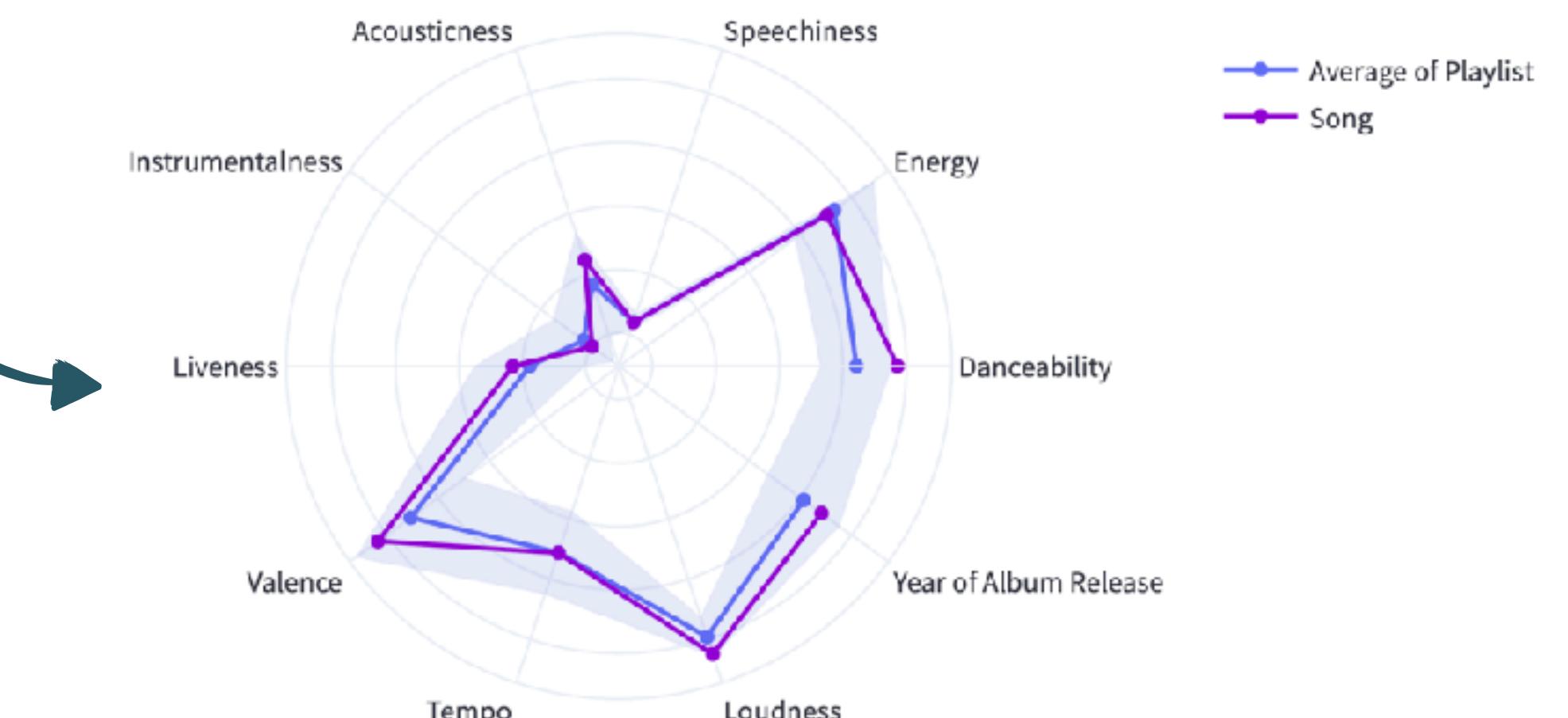
Example of songs in the playlist

Sledgehammer	Peter Gabriel
200度	Sally Yeh
Stella Stai	Umberto Tozzi
Tainted Love	Soft Cell
The Rhythm of the Night	Corona
Just Can't Get Enough	Depeche Mode
I'm So Excited	The Pointer Sisters
Like a Prayer	Madonna
Two Tickets to Paradise	Eddie Money
Tarzan Boy	Baltimora



Top recommendations

👍 Stars	Simply Red
👌 The Best	Tina Turner
👎 How Bizarre	OMC
👍 Fairground	Simply Red
👎 You Get What You Give	New Radicals
👎 Save Tonight	Eagle-Eye Cherry
👎 Breakfast At Tiffany's	Deep Blue Something
🤔 If You Love Somebody Set Them Free	Sting
👌 Wouldn't It Be Good	Nik Kershaw
👎 In These Shoes?	Kirsty MacColl





Song

Takeaway

The Chainsmokers

- Works decently well for playlists based on acoustic characteristics
- Faces limitations when it comes to playlists based on concepts

Some possible improvements for the



- Include language of songs to filter on
- Address issue with remastered albums by getting oldest release
- Allow specific filters (e.g. acceptable interval of valence)
 - Useful for playlists capturing certain mood

The End

