I Forget Where We Were
Ben Howard

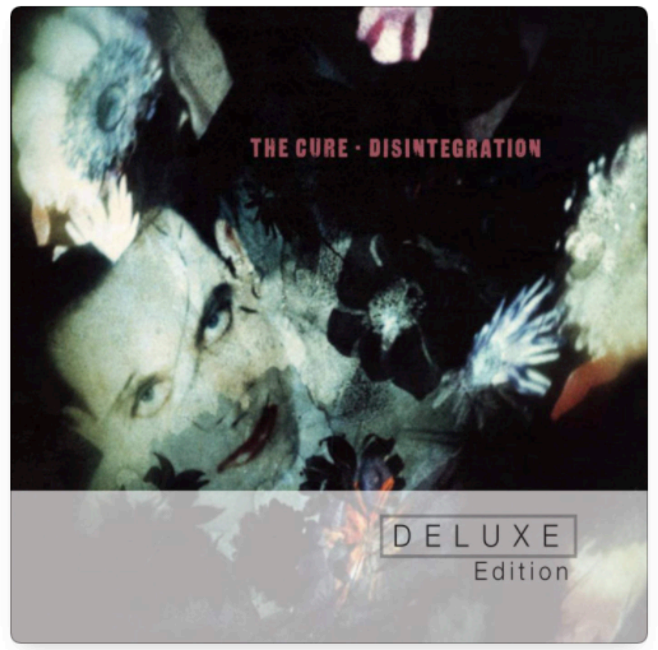
Territory - EP
The Blaze

Screen Violence
CHVRCHES

Bootstraps
Bootstraps

Chaleur Humaine (Deluxe Edition)
Christine and the Queens

Life for Rent
Dido



Disintegration (Deluxe Edition)
The Cure

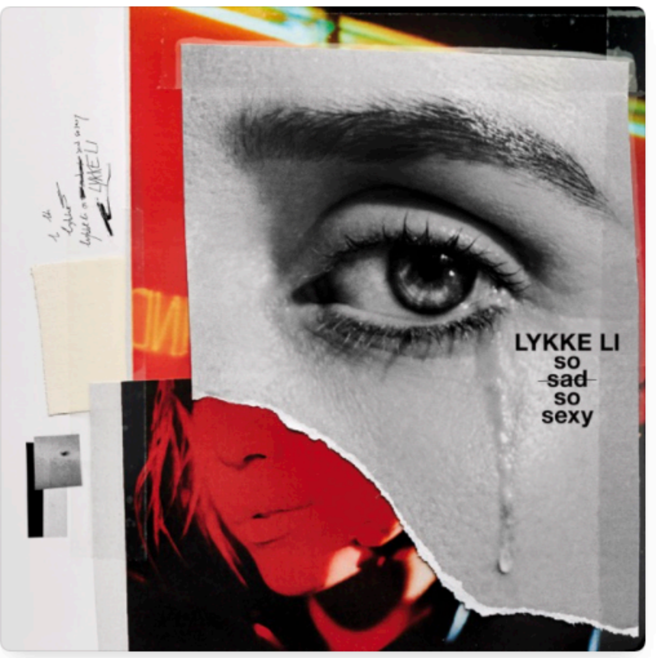
Recovery
Eminem

DAMN.
Kendrick Lamar

Minutes to Midnight
LINKIN PARK

If You Wait
London Grammar

Cinema
Ludovico Einaudi



so sad so sexy
Lykke Li

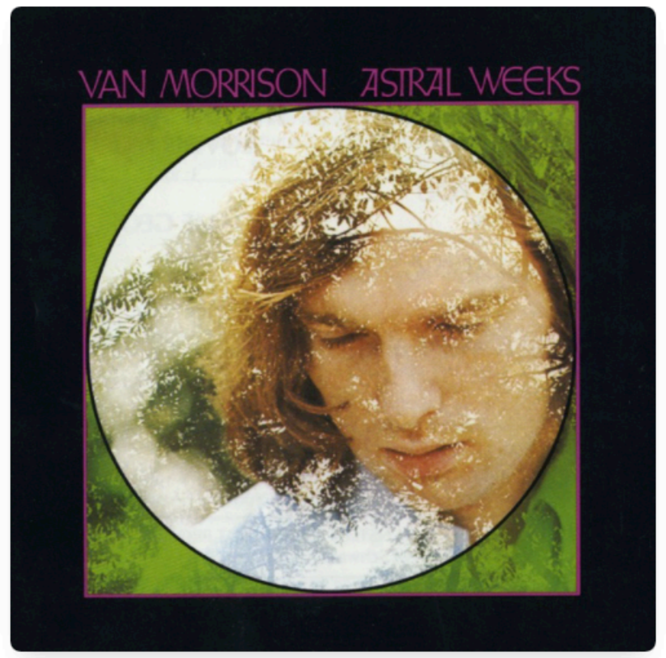
808s & Heartbreak
Kanye West

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?

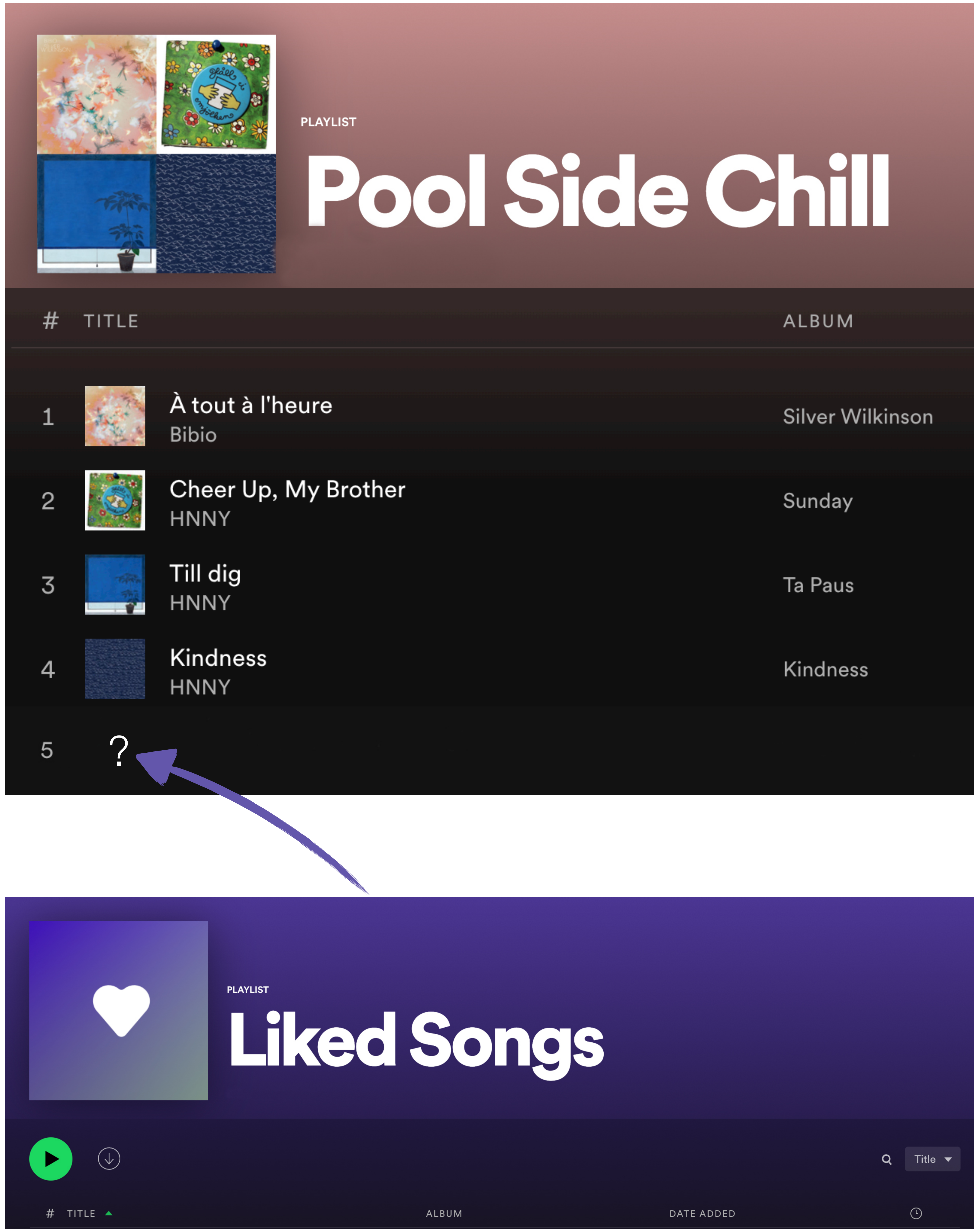
Help manage playlists

→ Identify songs in a person's music library that may fit well into a selected 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?

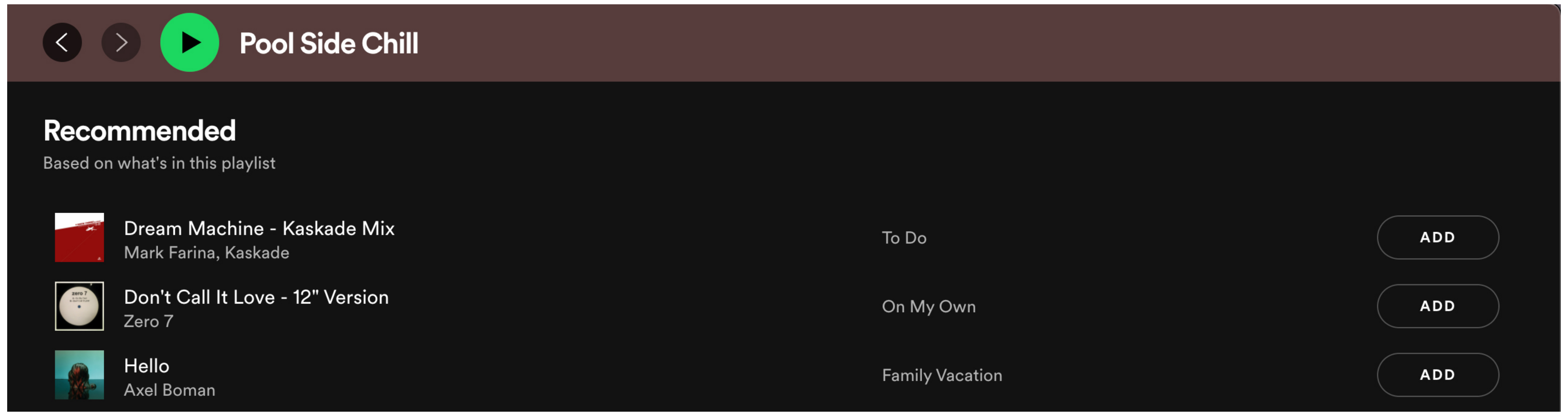
Playlists are an integral means to enjoying music

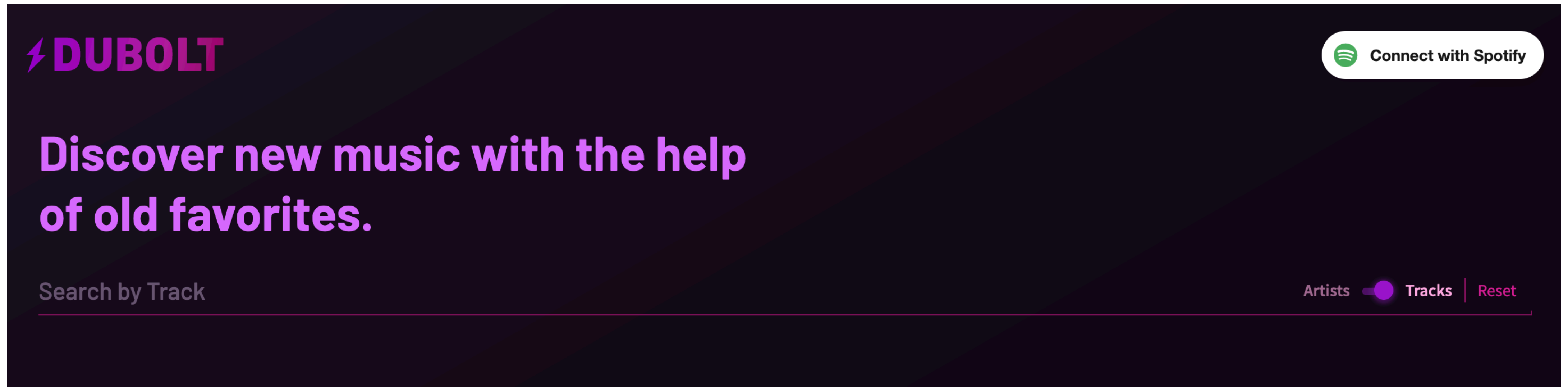
- Anecdotal evidence
- 4 bn playlists vs 350 m users on Spotify*

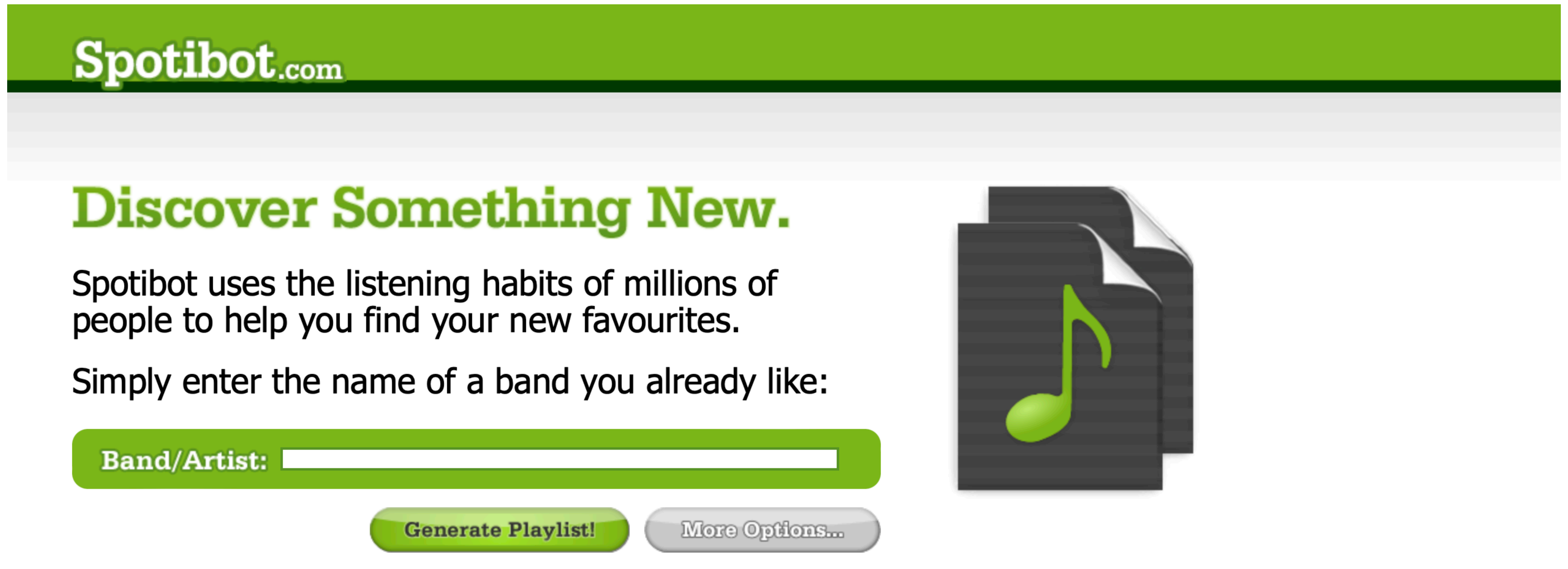
Music recommendation is nothing new

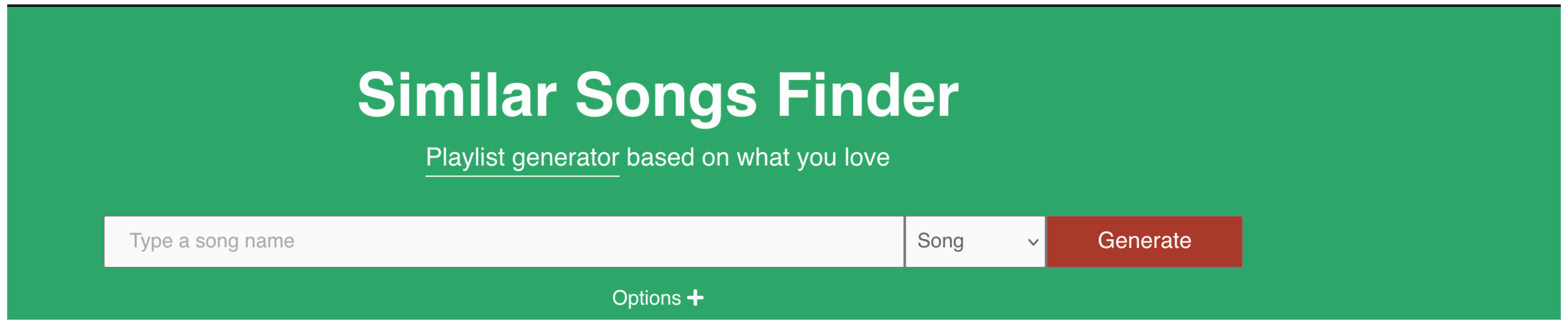
Nevertheless

- DIY is fun
- Re-discovering your own music









*https://soundplate.com/how-many-playlists-are-there-on-spotify-and-other-spotify-stats/

Let's research the

Music Recommendation
How?

- Popular research 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		Million Song Dataset

Usage data:

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

Content 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

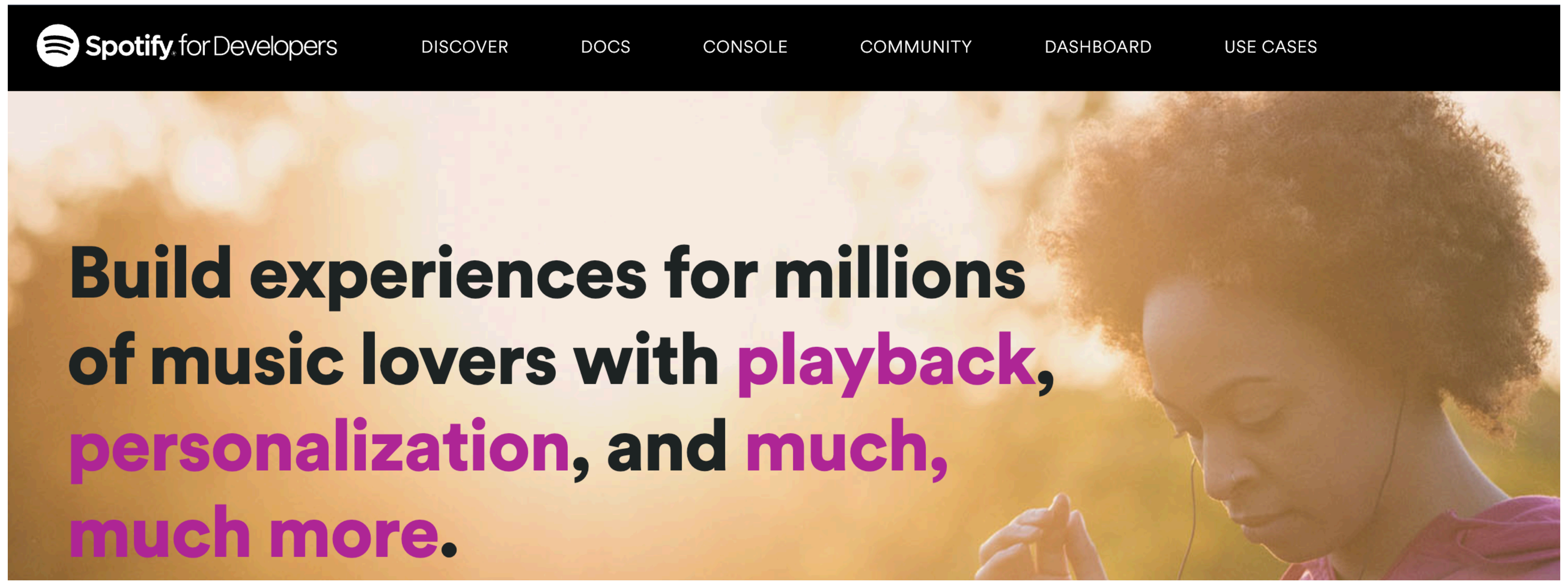
- Only use information relating to a person’s music library
- Work with readily available audio features
- Quickly build an easy-to-use tool to consume recommendations

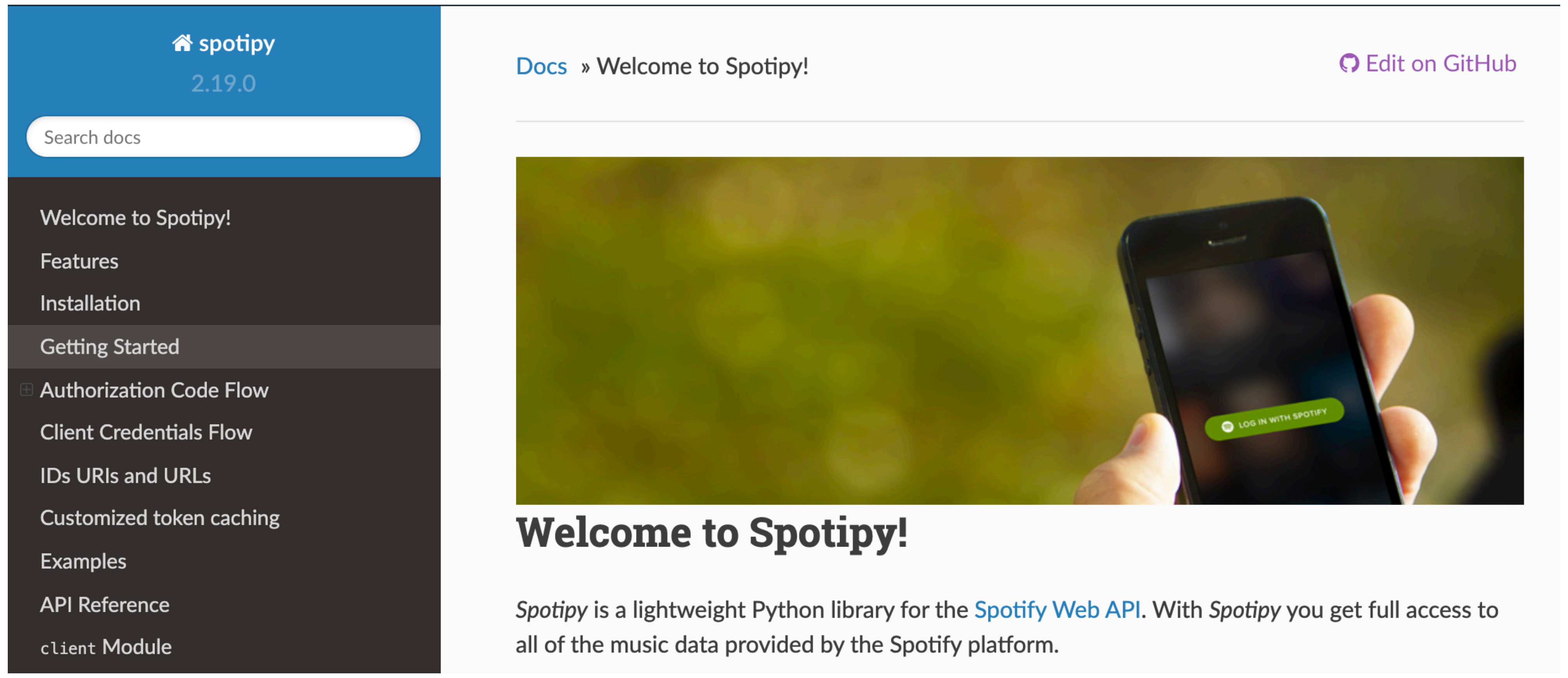
Recommended Frequencies
How?

Use readily available audio features

Spotify API

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

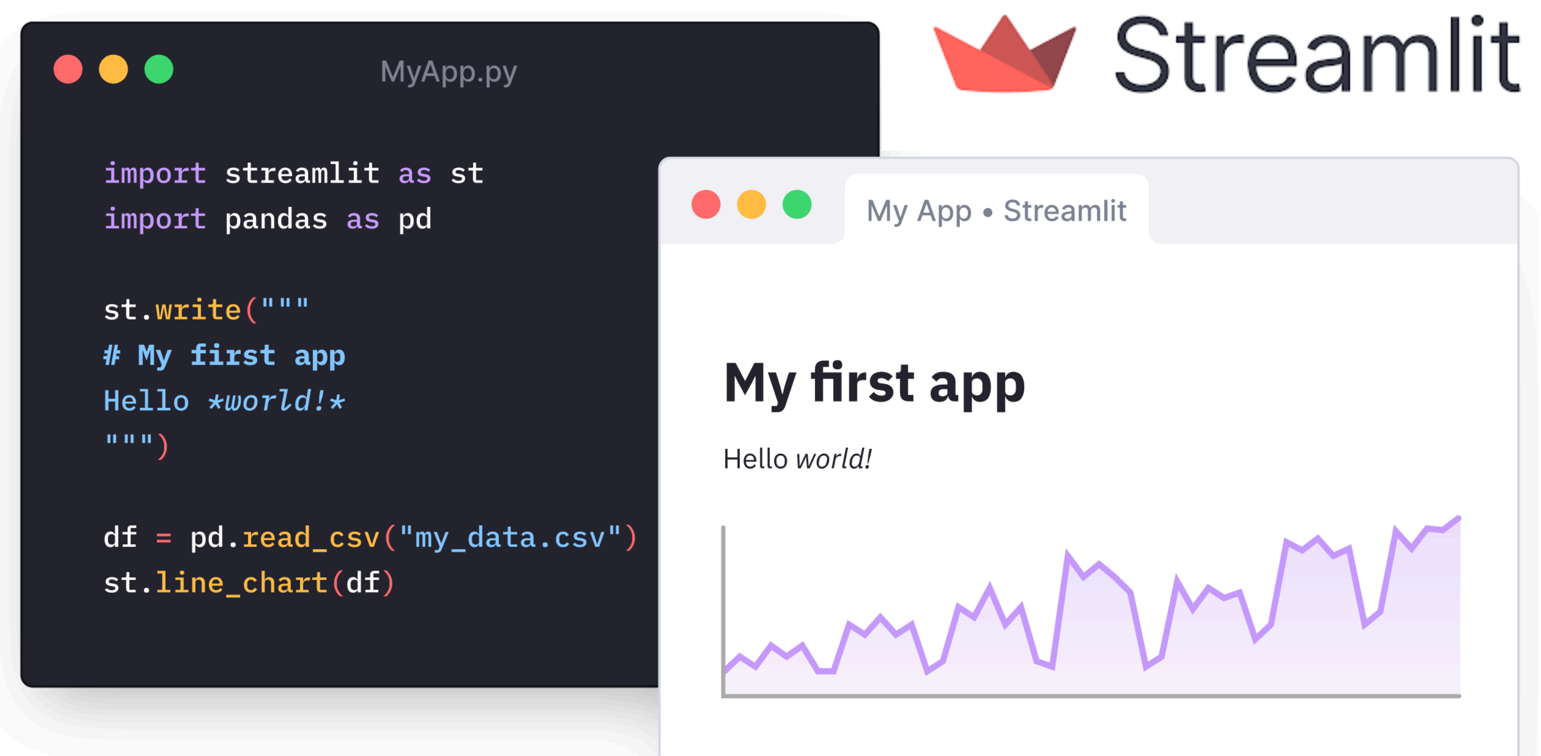




Build a dashboard for interacting with results

Streamlit

- "The fastest way to build and share data apps"



Data, or should I say…

Spotify API
Audio Features

Body application/json

audio_features array of objects required

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.

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

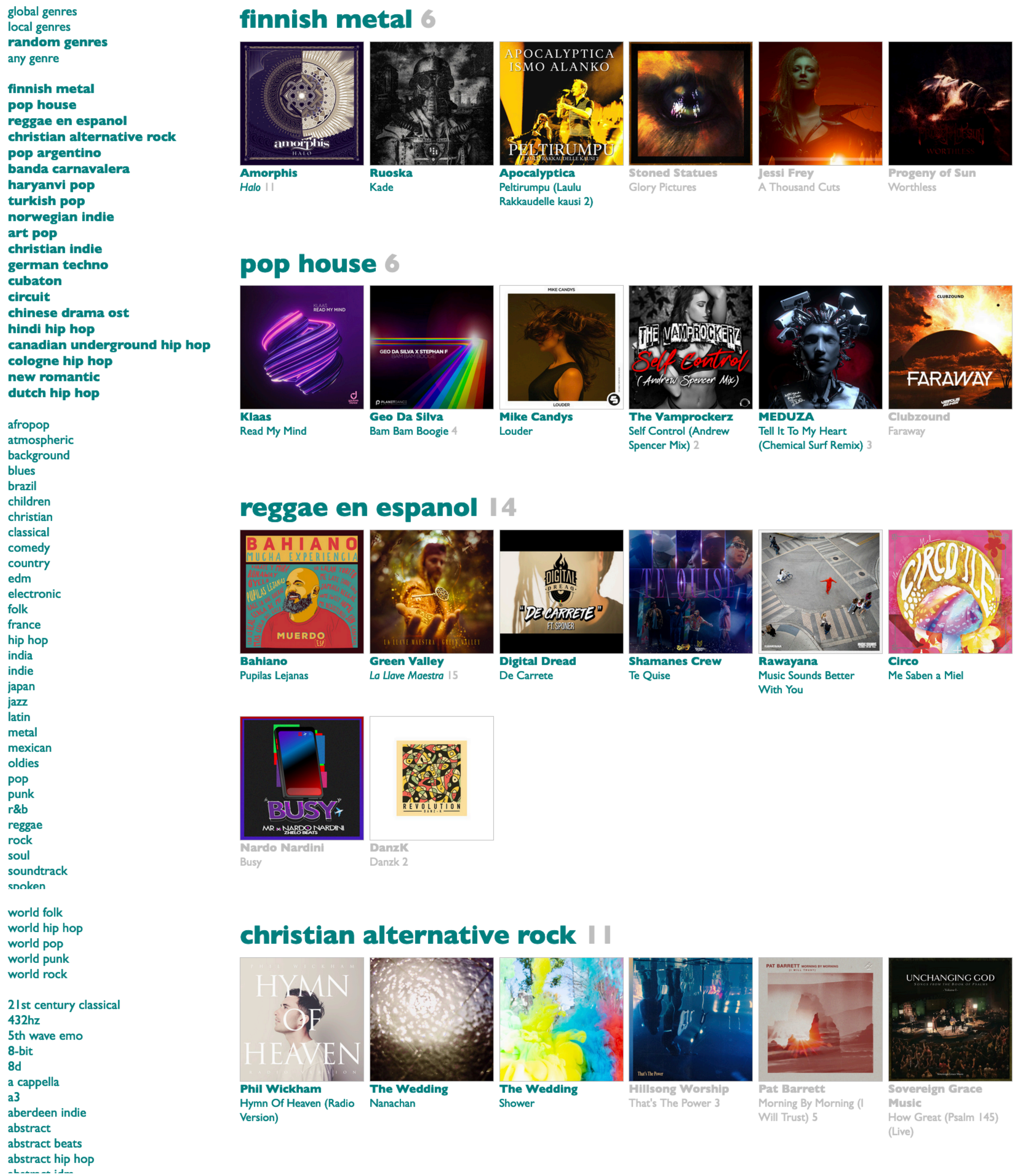
release_date string — required

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)!



https://everynoise.com/new_releases_by_genre

Features


Verified Artist
Machine ~~Gun Kelly~~ Learning
18,242,348 monthly listeners

Look at this graph…

… every time it makes me laugh

Quantifying Song Attributes

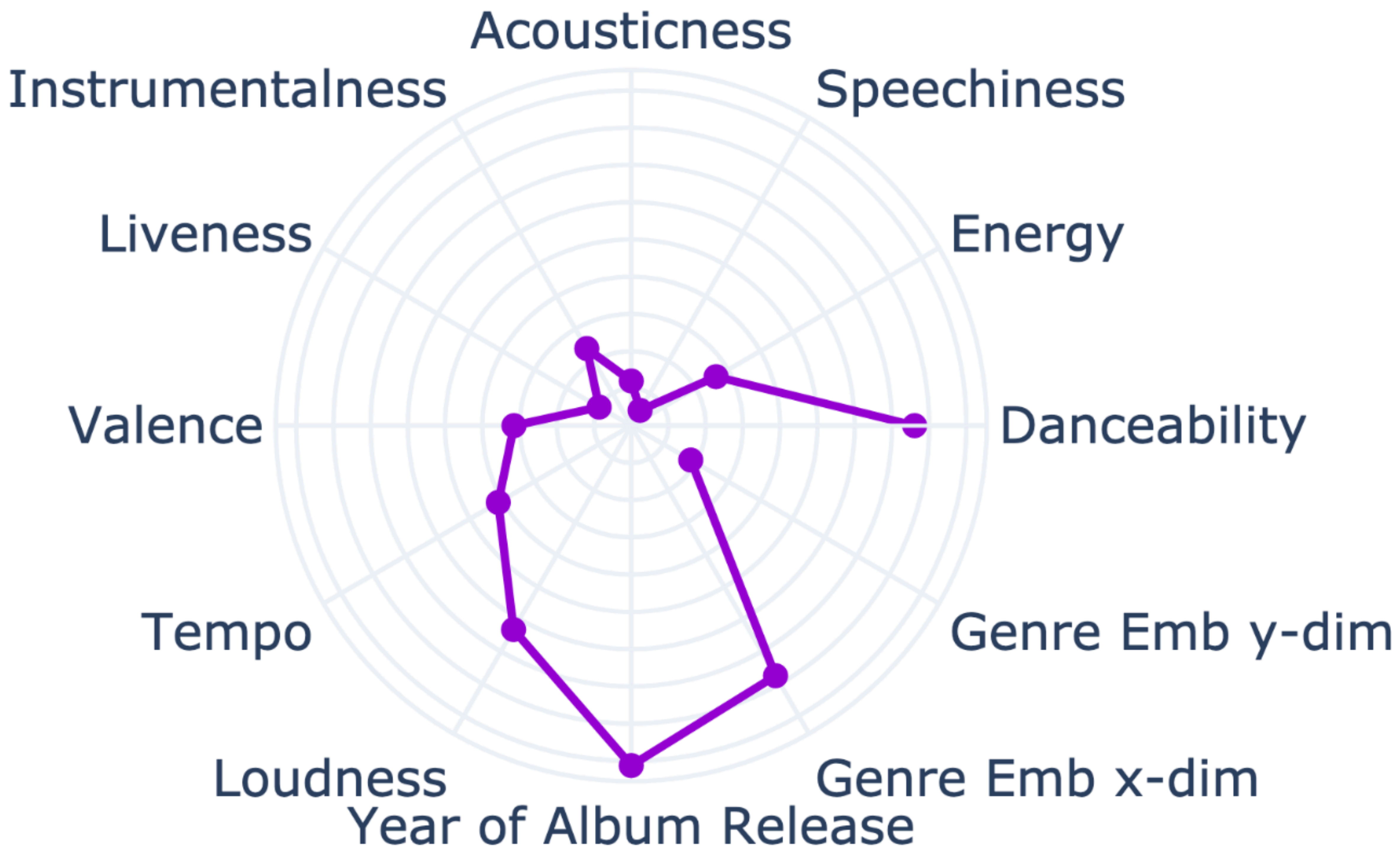
Feature Vector $\boldsymbol{s} \in \mathbb{R}^d$ *with d = 12*

- 9 audio features
- 1 year of album release
- 2 coordinates of genre embedding

All features are scaled to fall into interval [0, 1]

Genre embeddings are obtained from everynoise.com

Feature vector for song "Cheer Up, My Brother" by HNNY

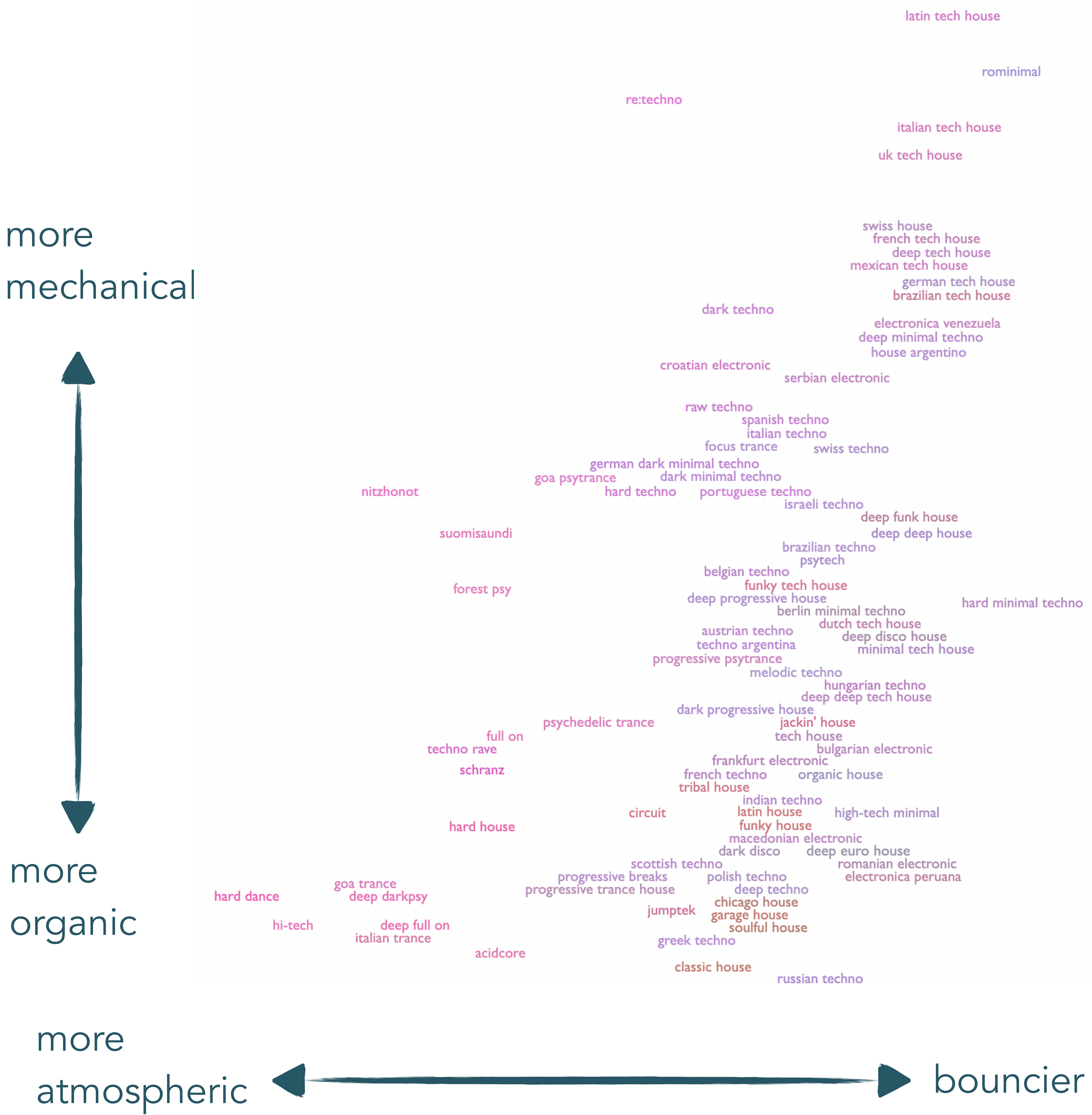


Quantifying Genre
Every Noise at Once

- everynoise.com provides an "algorithmically-generated […] scatter-plot of the musical genre-space" of Spotify
- Embeddings equal (x, y) coordinates of genre in plot, which can be obtained from the HTML source

```
▸<div id="item2627" preview_url="https://p.scdn.co/mp3-preview/8f54913108882baf589270d12840b087ae33adf0" class="genre scanme" scan="true" style="color: #d382c9; top: 0px; left: 1427px; font-size: 101%" onclick="playx("5K7Dmv4712ml7tbzvljdTA", "latin tech house", this);" title="e.g. Hector Couto "Salimo"">…
</div>
```

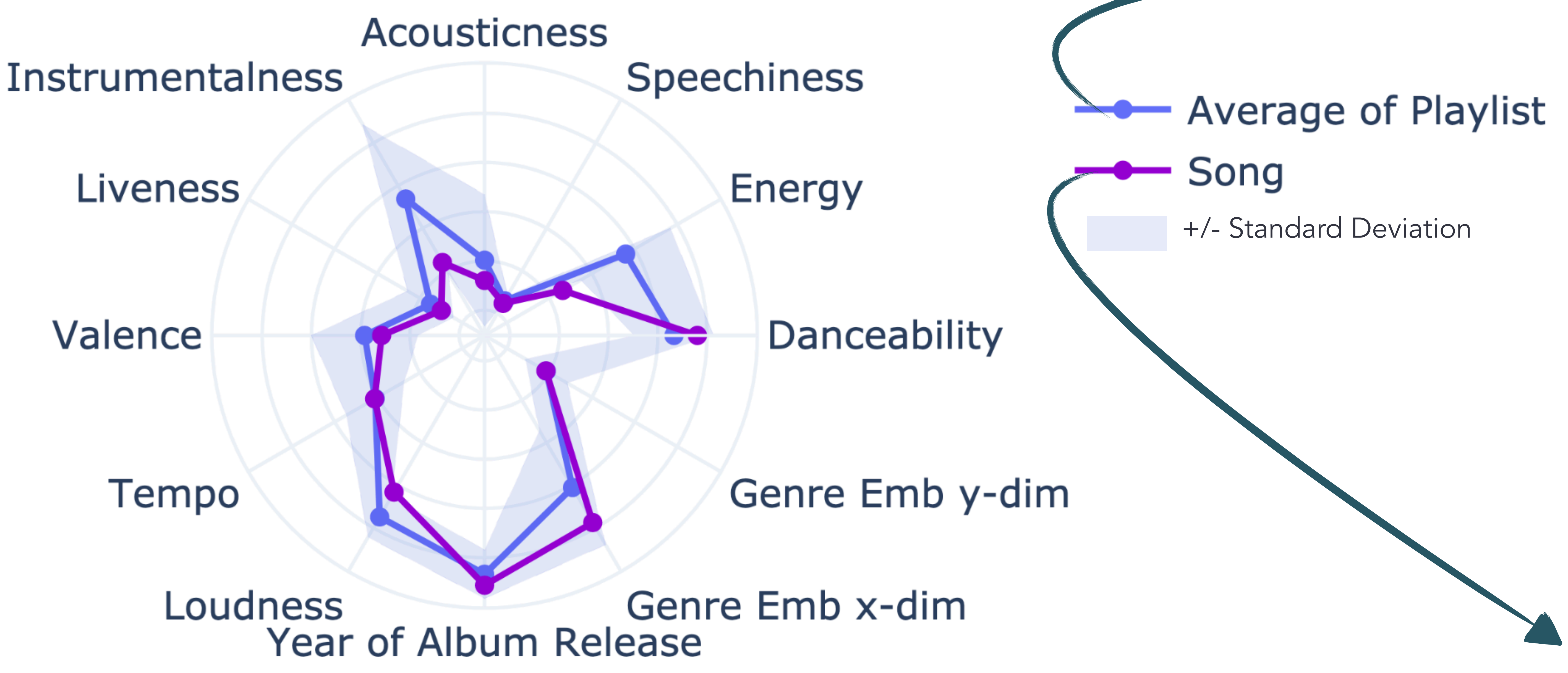
- Song's genre embedding equals $(\bar{x}, \bar{y})$, i.e. centroid of all associated genres
- Similar genres are supposed to be close in this embedding space

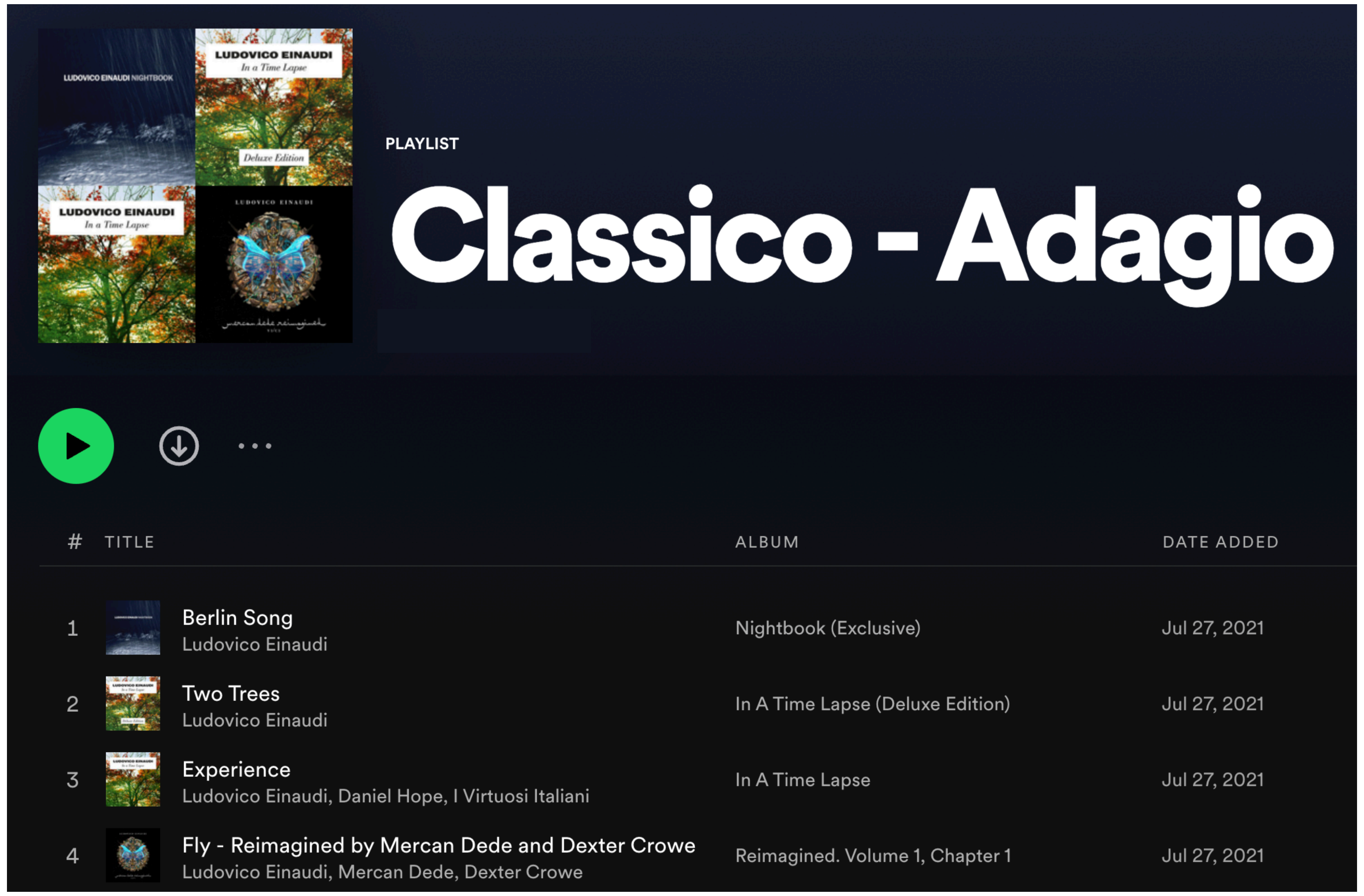


Methodology, a.k.a

Song Similarity

Baseline: Euclidean Distance





Top 1 match

Observation: Euclidean distance between song features does not capture similarity very well!

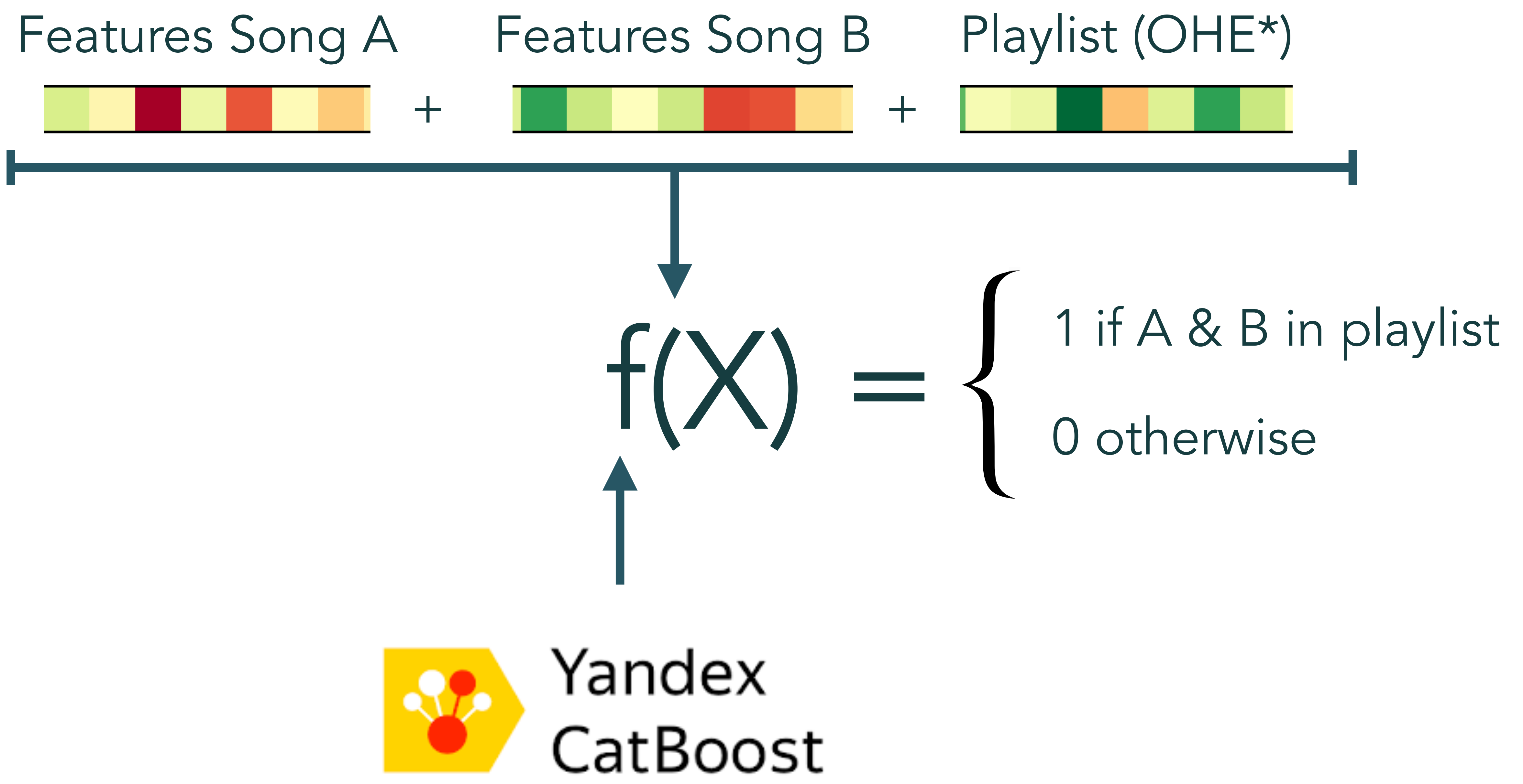
Song Similarity

Catboost

- Simple distance measure for feature vectors fails to capture subtleties in music similarity
- Similarity of songs is also conditional on playlist (to some degree)

Solution

- Machine Learning Model → **Catboost**
- Trained by creating positive and negative song pairs
  - Positive: songs in the same playlist
  - Negative: songs in **very** different playlists



*One-hot-encoded


YOU BROKE
ME FIRST
Verified Artist
Dash ~~Berlin~~ board
Dash Berlin
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

---

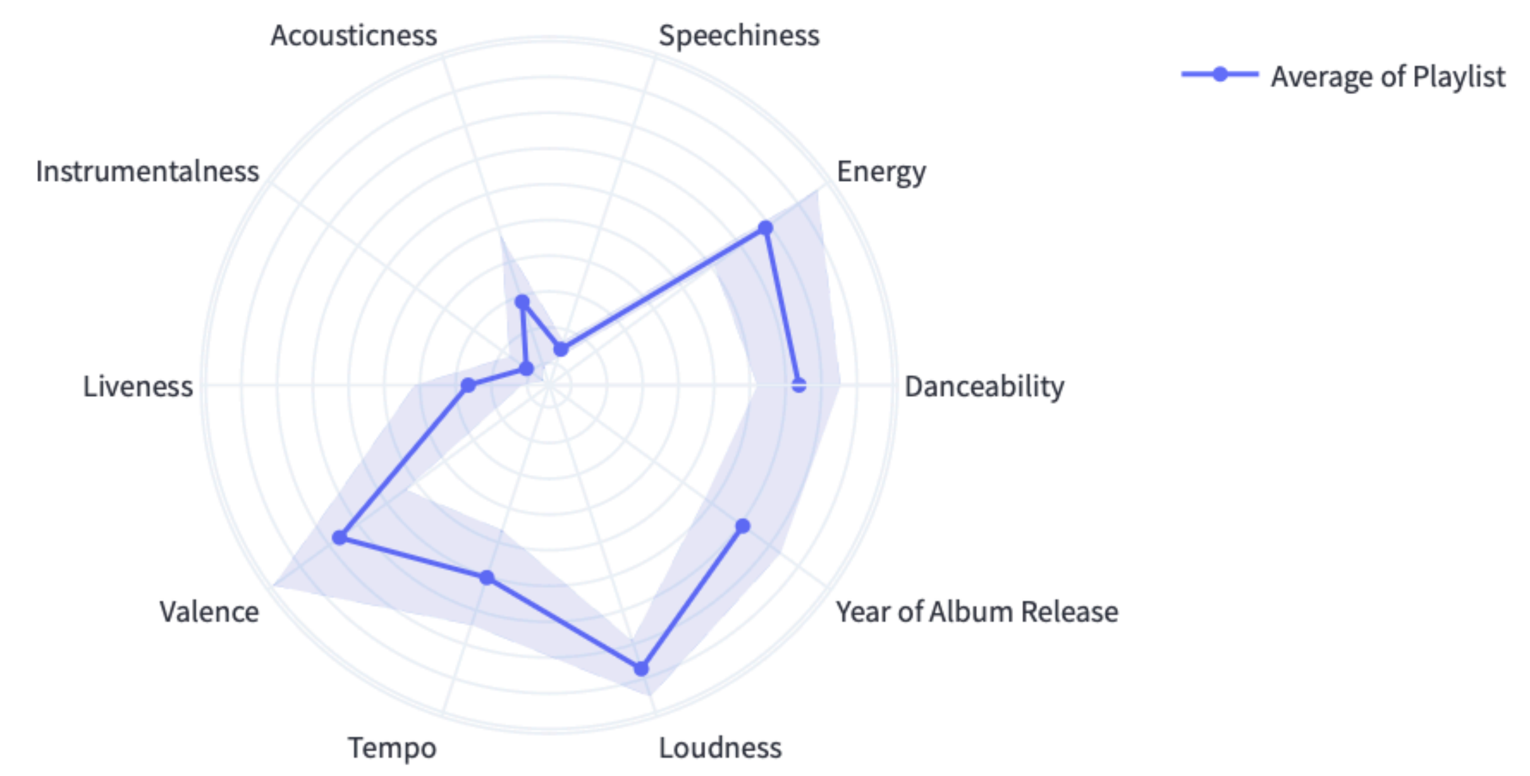
1. Choose a playlist

80's

Some songs in playlist «80's»

	SongName	Artist	ID
0	Wouldn't It Be Good	Nik Kershaw	00FDHurakzVEiPutdUxXXq
1	Sledgehammer	Peter Gabriel	029NqmlySn1kOY305AAhxT
2	Always on My Mind	Pet Shop Boys	07ABETRdek3ACMpRPvQuaT
3	There Must Be An Angel P	Luciano Pavarotti	0AeMfVr7exf7lf2RwcpPMc
4	200度	Sally Yeh	0CYelmjEps63DAuqLV9b6J
5	What About Me	Moving Pictures	0MHeOVBIRkg9mD29VMTkET
6	Stella Stai	Umberto Tozzi	0NUyAEi7WInhF0SJGVavUG
7	What A Feeling	Irene Cara	0aAR5HogGoT68EWFbyRFqx
8	Tainted Love	Soft Cell	0cGG2EouYCEEC3xfa0tDFV
9	Ti Amo	Umberto Tozzi	0gAbf0NL9no1Urk1Wj8Uui

Song attributes for playlist «80's»



2. Find similar songs

Similarity Settings

Most similar songs to playlist «80's»

Result Page #

1

	SongName	Artist	ID	Similarity
0	Glory Days	Bruce Springsteen	2Y90nL1ohB4sgYELDs7uNx	98.3%
1	If You Love Somebody Set Them Free	Sting	5Xhqe9xu6bKRSqLj1mS1SB	97.8%
2	Walking On Sunshine	Katrina & The Waves	05wIrZSwuaVWhcv5FfqeH0	97.0%
3	Conga	Gloria Estefan	4aMT5LHe8A2uIc11H8Cx2m	96.4%
4	Hungry Heart	Bruce Springsteen	1KsI8NEeAna8ZIdojI3FiT	96.3%
5	West End Girls - 2001 Remaster	Pet Shop Boys	2yzPBlE5UXK2sqvnNM9QQ0	96.2%
6	Brandy (You're a Fine Girl) - Rerecorded	Looking Glass	4l4f4tI1JNGiXXynCoMe3j	95.8%
7	Englishman In New York	Sting	4KFM3A5QF2IMcc6nHsu3Wp	95.7%
8	Stars	Simply Red	75CgD6l7K4qMzZrn4CbZqz	95.6%
9	Holding Out for a Hero - From "Footloose" Soundtrack	Bonnie Tyler	5Hyr47BBGpvOfcykSCcaw9	95.5%

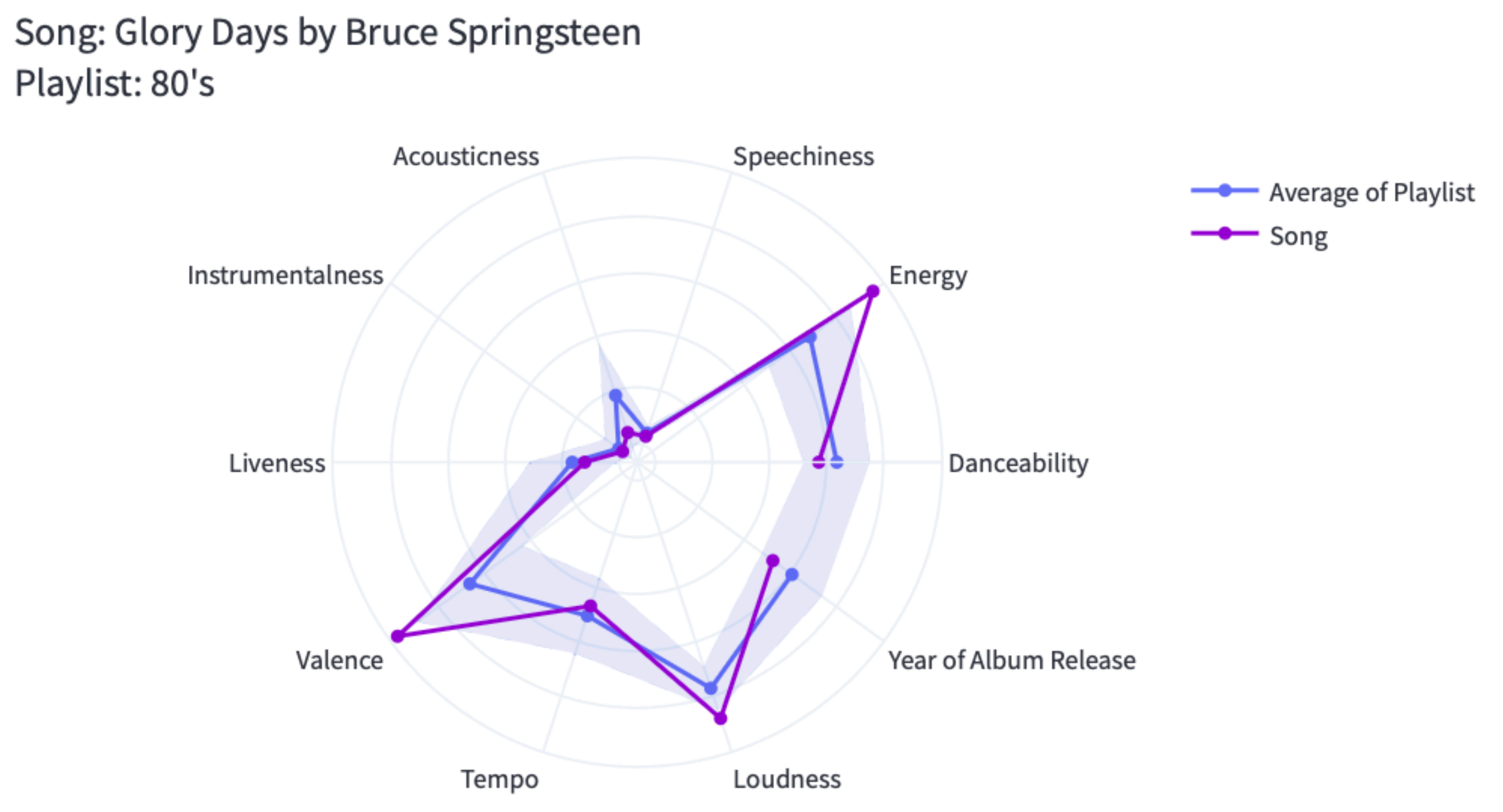
Visualise similarity of proposed song

Search for song by

- ID
- Name

ID of song to visualise

2Y90nL1ohB4sgYELDs7uNx



Listen to proposed song

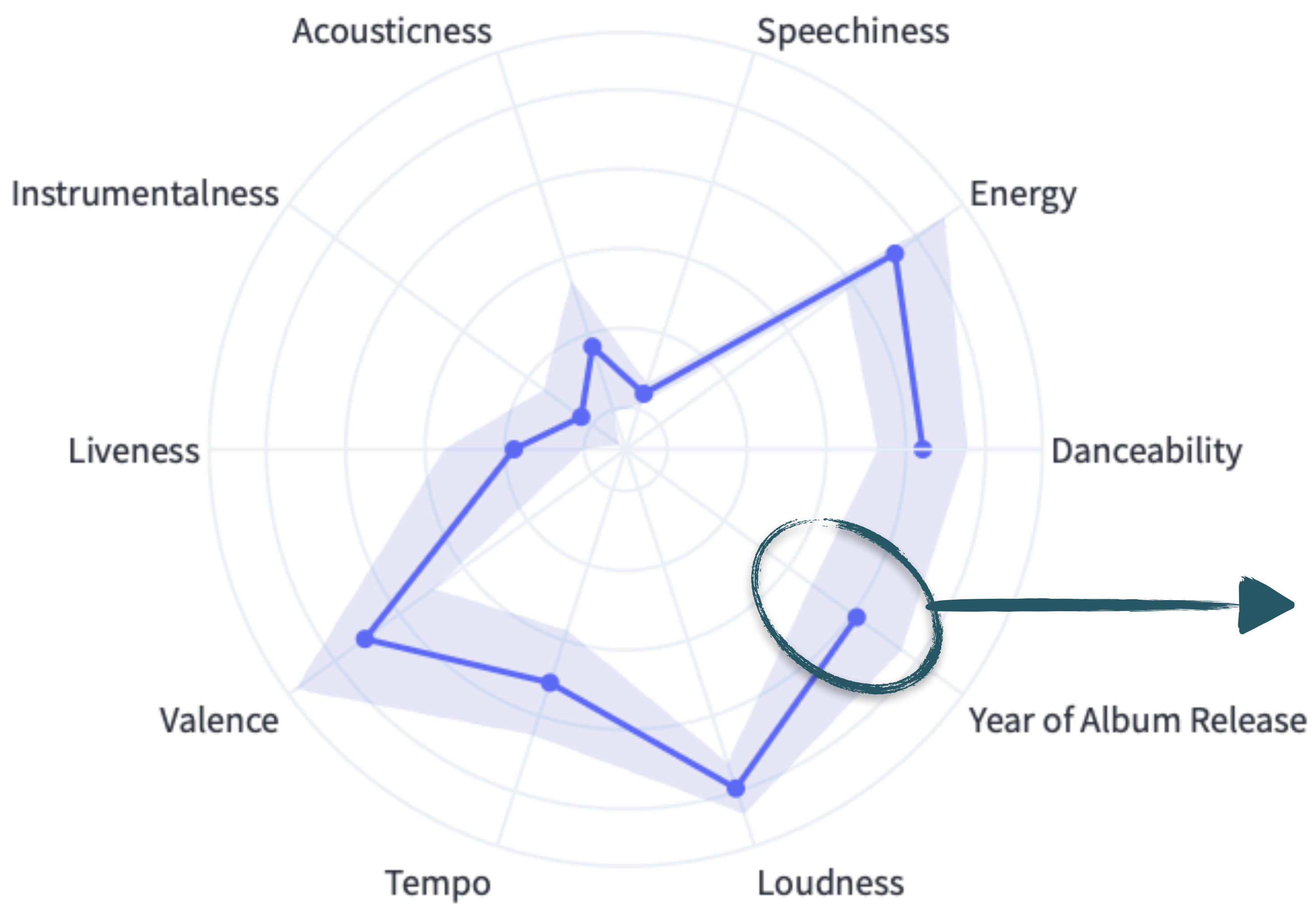
0:00 0:29

Let’s deep dive into some results

«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



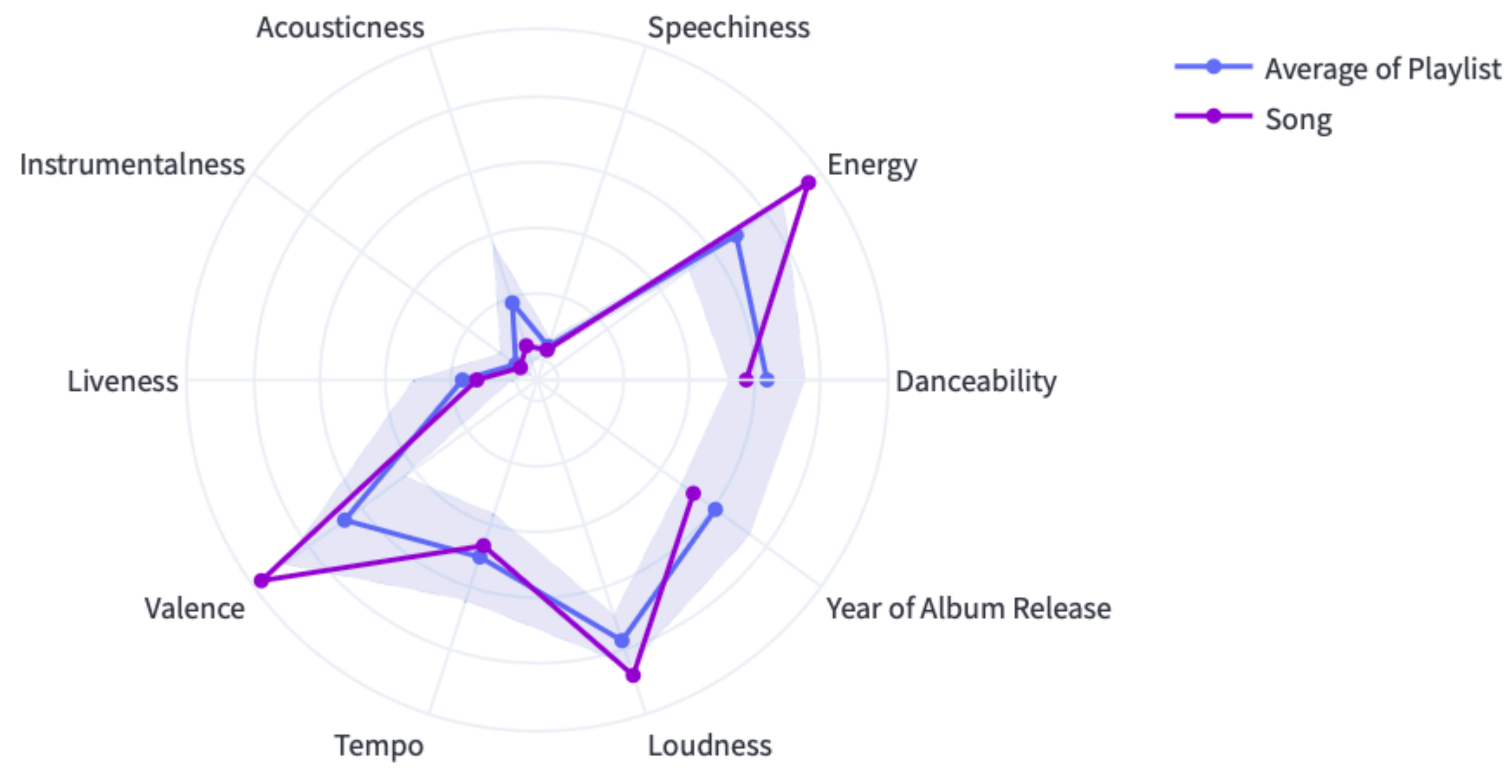
Some albums are remastered

→ album release not in the 80's

Top recommendations

🤔	Glory Days	Bruce Springsteen
🤔	If You Love Somebody, Set Them Free	Sting
👍	Walking On Sunshine	Katrina & The Waves
👌	Conga	Gloria Estefan
🤔	Hungry Heart	Bruce Springsteen
👌	West End Girls	Pet Shop Boys
🤔	Brandy (You're a Fine Girl)	Looking Glass
🤔	Englishman in New York	Sting
👍	Stars	Simply Red
👌	Holding Out for a Hero	Bonnie Tyler

Song: Glory Days by Bruce Springsteen
Playlist: 80's



Song

Takeaway(s)

The Chainsmokers

- Catboost model better picks up on subtleties of song similarity
- Highly depends on creating informative positive and negative song pairs
- Model works well for homogeneous playlists (e.g. same style, era, etc.) much less for say "best of library" playlists

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 that capture certain mood

The End