

BUILDING A BETTER PLAYLIST

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PROBLEM STATEMENT

- 🎵 Create better alternatives to Spotify's premade playlists
- 🎵 Mounting frustration over suboptimal playlists
- 🎵 Classify songs of a given genre into four moods
- 🎵 Generate playlists in Spotify based on mood

01

**AQUIRE/CLEAN
DATA**

02

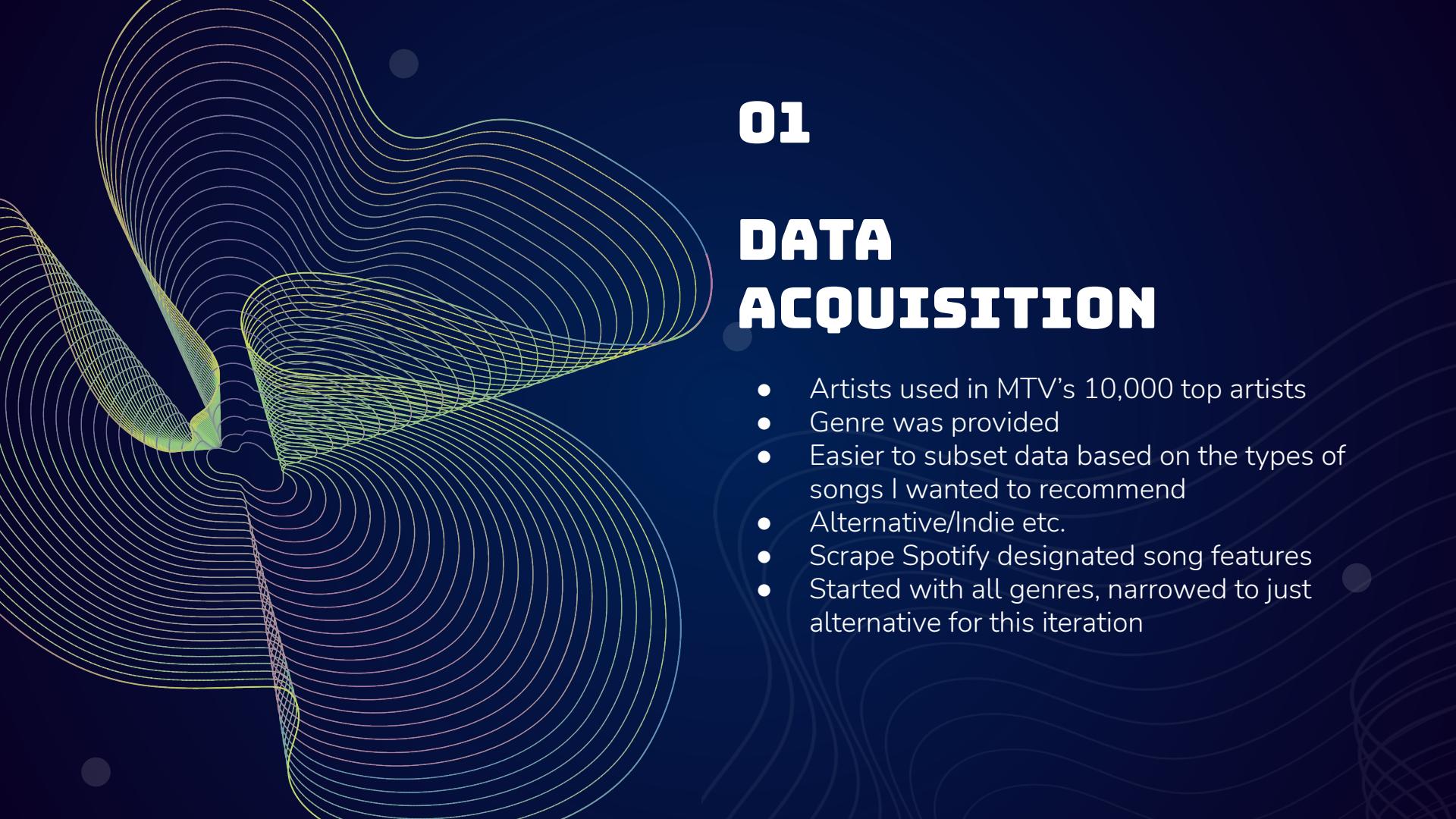
**DETERMINE
BEST MODEL**

03

**INTERPRET
RESULTS**

04

**MAKE SONG
RECOMMENDATIONS**

The background features a dark blue gradient with a complex pattern of thin, light-colored wavy lines and small white dots. A prominent yellow-green wavy line forms a large loop on the left side. Several small white dots are scattered across the slide.

01

DATA ACQUISITION

- Artists used in MTV's 10,000 top artists
- Genre was provided
- Easier to subset data based on the types of songs I wanted to recommend
- Alternative/Indie etc.
- Scrape Spotify designated song features
- Started with all genres, narrowed to just alternative for this iteration

GENRES USED

ALTERNATIVE



INDIE ROCK



ALT ROCK



FOLK/ROCK



WHY THESE?

1. THEY'RE MY PERSONAL FAVORITE GENRES
2. TREATING ALL GENRES THE SAME WAY DOESN'T MAKE SENSE

02.A

DATA CLEANING/EDA

- Was able to bypass values that didn't exist in Spotify with try/except statements
- Some nulls, dropped them (mostly artists that did not have their discographies in Spotify)
- Only had to drop ~100 songs

02.B

DATA CLEANING/EDA

- Visualize feature distributions
- Drop outliers
- Ultimately focus on valence, danceability, energy, tempo - other features added noise

03 MODELING



DECIDE ON MODEL



FEATURE SELECTION



FIT MODEL



MAKE INTERPRETATIONS



03 MODEL SELECTION



KERAS ✕

- Could use existing classifications
- Easier to interpret
- Dataset was too small ~700 rows
- Any errors would be exponentiated



KMEANS ✓

- Specify number of clusters (moods)
- Interpretation more difficult
- Ultimately more accurate

FEATURE SELECTION



VALENCE



ENERGY



DANCEABILITY



TEMPO (BPM)



POPULARITY



LOUDNESS (DB)



LIVENESS



ACOUSTICNESS



SPEECHINESS



INSTRUMENTAL
NESS

MODEL RESULTS

24.3%

Silhouette Score using
Four Clusters

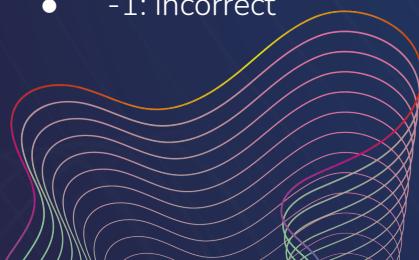
67,100

Number of songs classified

WHAT DOES THAT MEAN?

SCORE

- Score falls between -1 and 1
- Closer to 1: nicely separated
- 0: overlap
- -1: incorrect

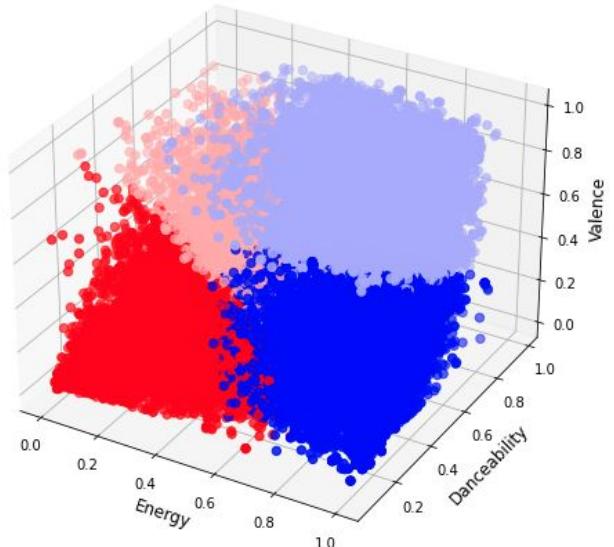


CLUSTERS

- Four clusters to classify songs into four moods
- Happy, sad, energetic, calm



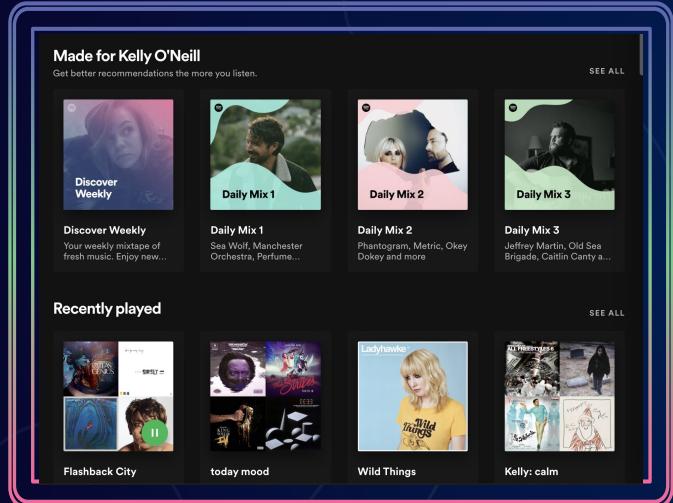
3D Scatter Plot of Songs Clustered



MODEL INTERPRETATION

- 🎵 Score was satisfactory
- 🎵 Labels provided by model were 0, 1, 2, 3
- 🎵 Separated songs into four separate dataframes
- 🎵 Analyzed median values of top four features
- 🎵 Determined moods:
 - 0 = sad
 - 1 = calm
 - 2 = energetic
 - 3 = happy

PLAYLIST CREATION



- Python function takes user input for name, mood, and playlist title
- Generates song ids
- Creates empty playlist in user's account and fills with song ids
- Currently only available on my account due to app permissions

NEXT STEPS

- Add additional clusters to provide more accurate and granular mood determinations AND
- Use separate model for each genre category (Rock, rap, pop, etc)
- Use additional genres
- Flask app for playlist maker
- Ability to create playlists for other users

SOURCES

[MTV artist dataset](#)

[Spotify documentation](#)

[Spotipy documentation](#)

[Clustering algorithm research](#)

[Silhouette score analysis for num_clusters](#)

[3D Scatterplot](#)

[Additional reading on KMeans](#)

THANK YOU!

Any questions?

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