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# Decoding Popularity

A Data-Driven Exploration of  
Spotify Hits

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# Outline

- Introduction
- Data Sources & API Documentation
- Business Problem
- Breakdown of Analysis
- Key Visualizations and Key Findings
- Recommendations



# Spotify

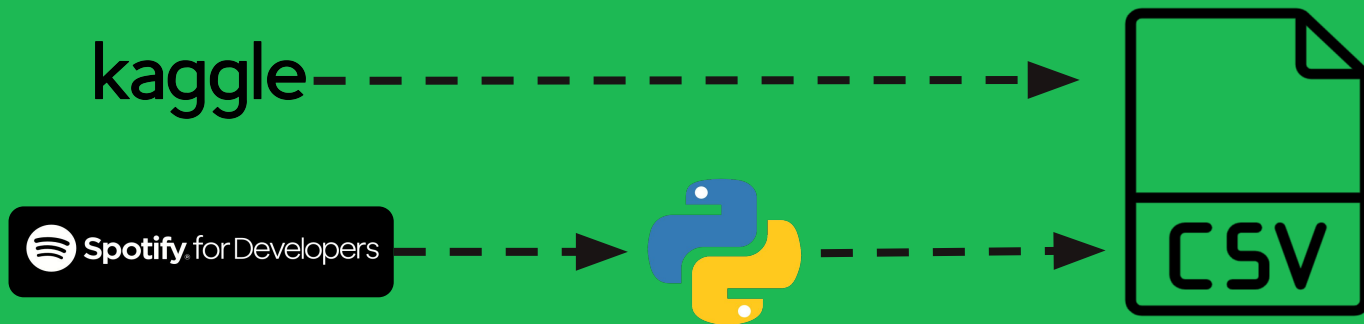
What is it?

- Spotify is the largest music streaming service in the world.
- It has revolutionized the modern listening experience with Machine Learning applications such as NLP & Reinforcement Learning



# Data Sources

- Kaggle
- Spotify API



# Dataset & Variables of Interest

## Summary

- ~20,000 rows of unique tracks
- Random sample of the Spotify ecosystem

## Track Popularity

- Measured from 0 - 100
- Live metric that is calculated by Spotify
- Generally, songs currently being played a lot will be more popular

## Audio Features

- Measured from 0 - 1
- Tracks are made up multiple features with unique values
- (ex. Danceability, Energy, Valence, Acousticness)



# Business Problem Statement:

How can Track Popularity be utilized to create value for artists and Spotify stakeholders?



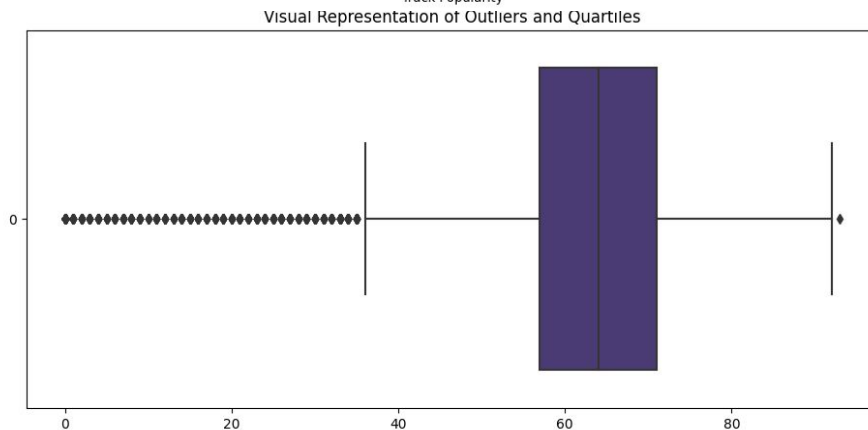
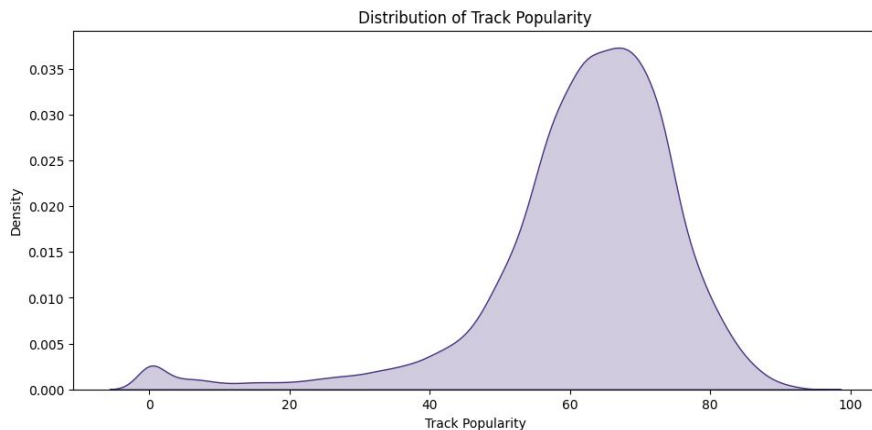
# Key Findings

Visualizations and Analysis



# Track Popularity Distribution

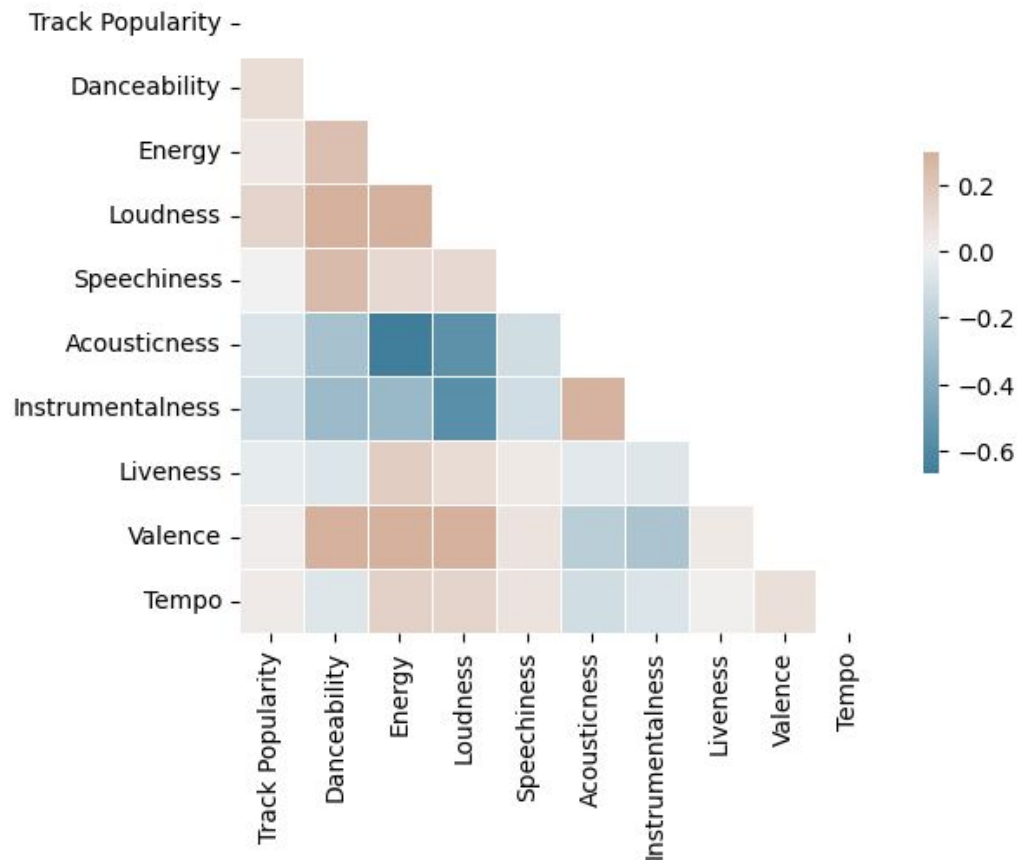
- Track Popularity is not normally distributed
- Outliers are likely not true artists, so it doesn't make sense to include them



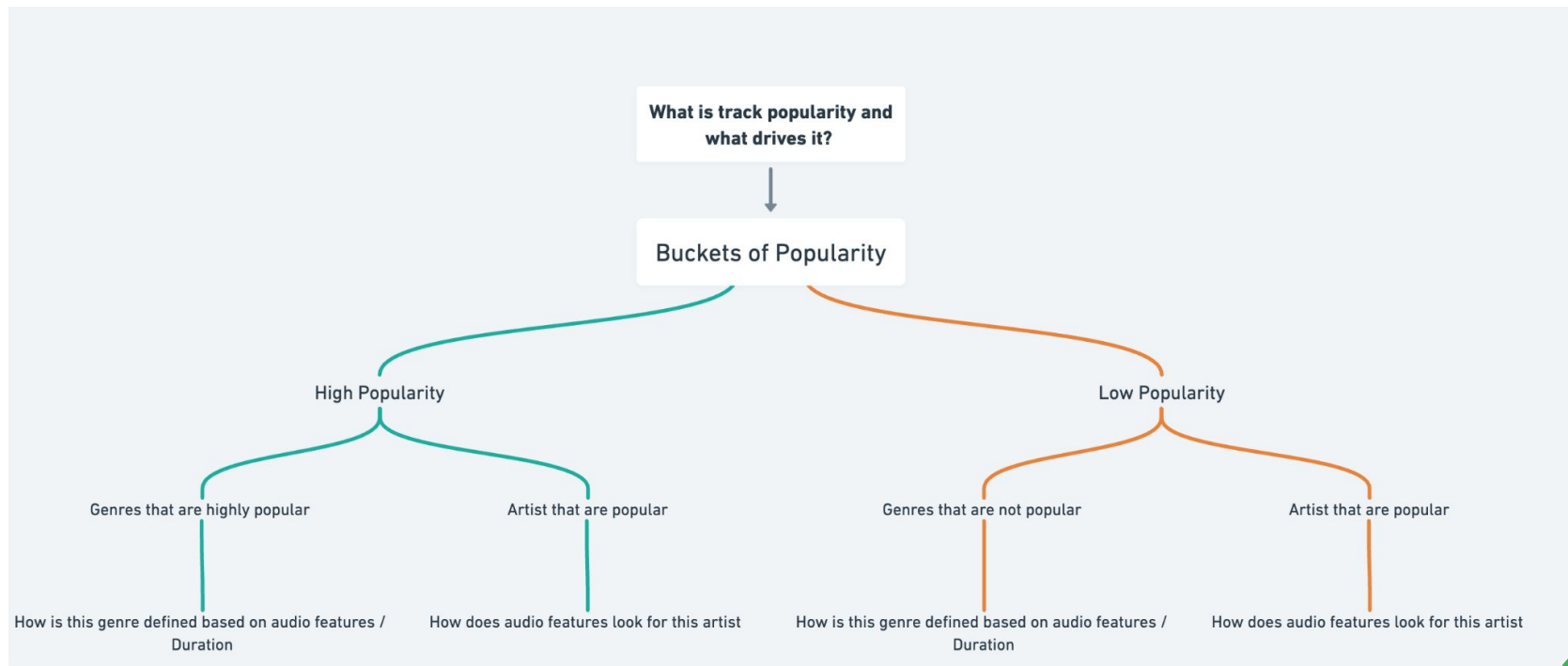


# Do Individual Features Drive Track Popularity?

- Goal is to identify a specific driver of Track Popularity
- Heatmap shows us that this is actually not the case

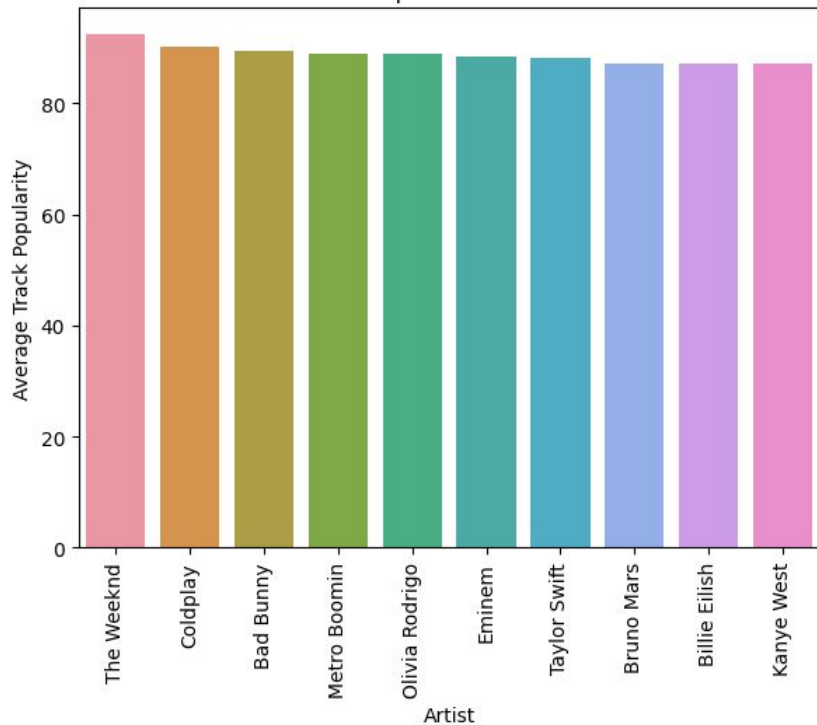


# Rethinking our Analysis

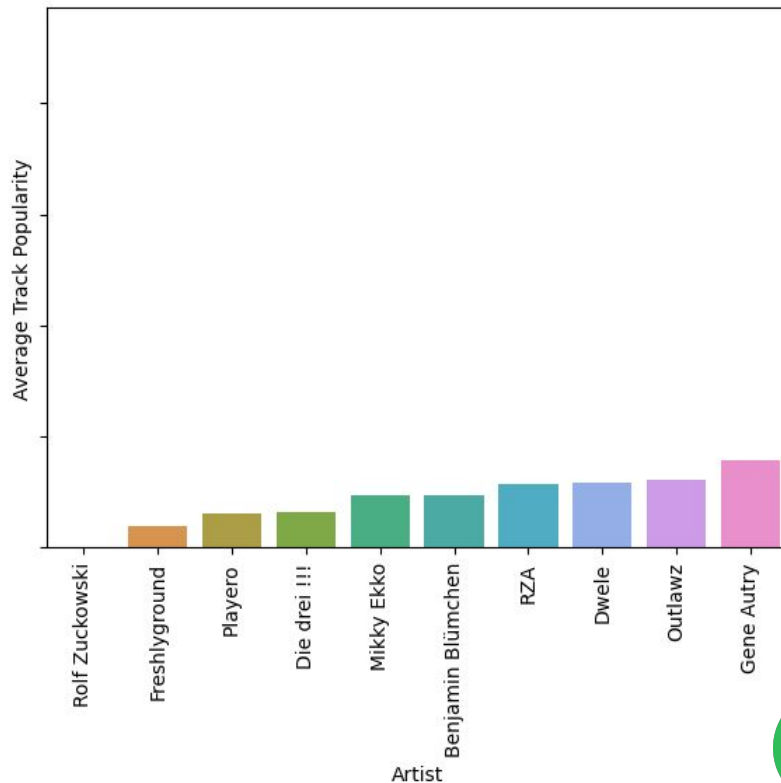


# What's Popular Now? (Trending Artists)

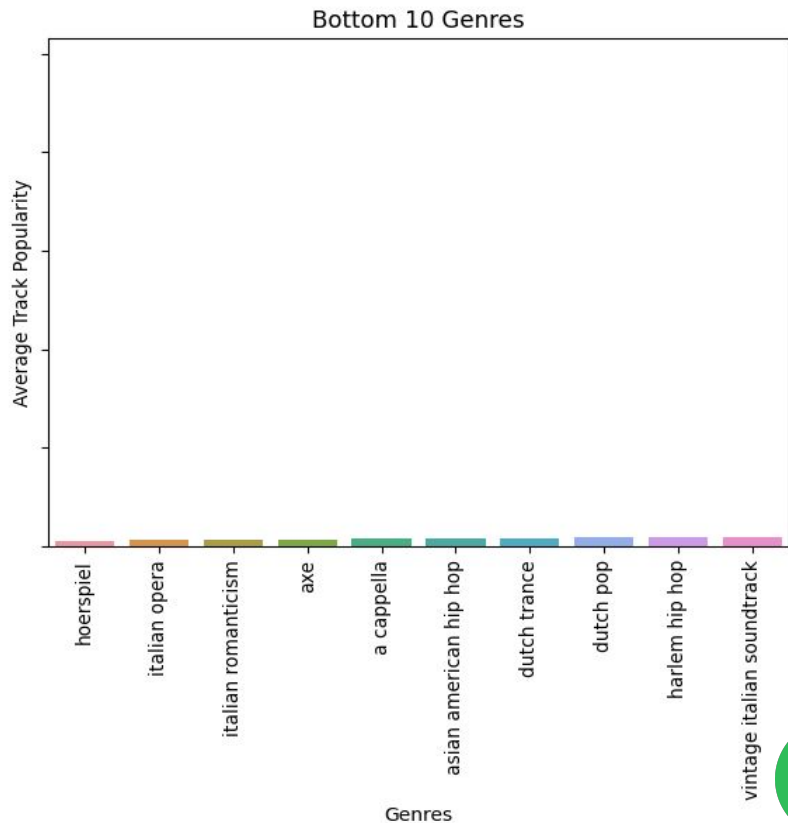
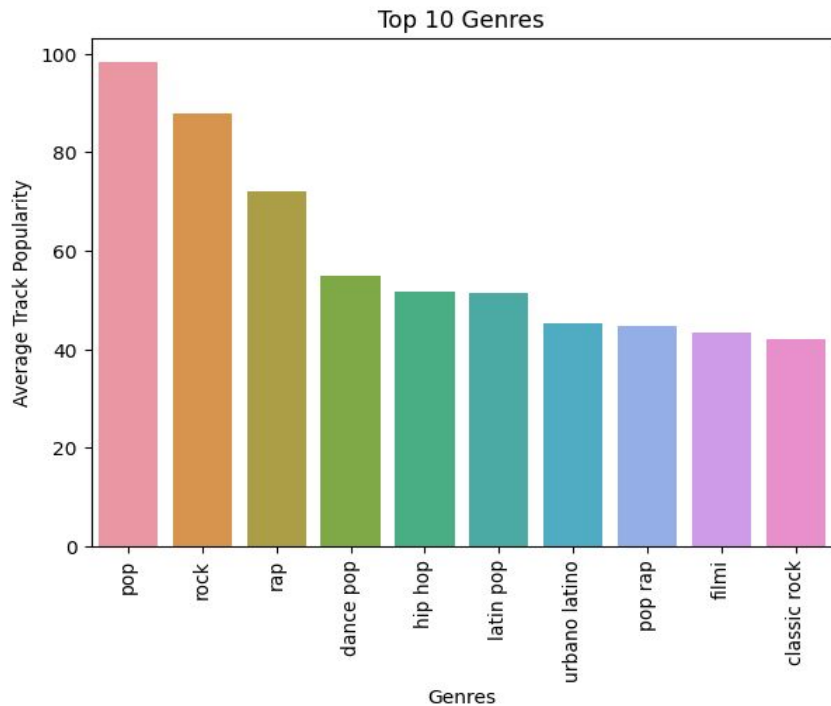
Top 10 Artists



Bottom 10 Artists



# What's Popular Now? (Trending Genres)



# Artist Archetypes

- Consistency among top artists in audio feature makeup
- Lack of consistency among unpopular artists

## Bottom Artists



## Top Artists



# Genre Archetypes

- Consistency among top genres in audio feature makeup
- Lack of consistency among unpopular genres

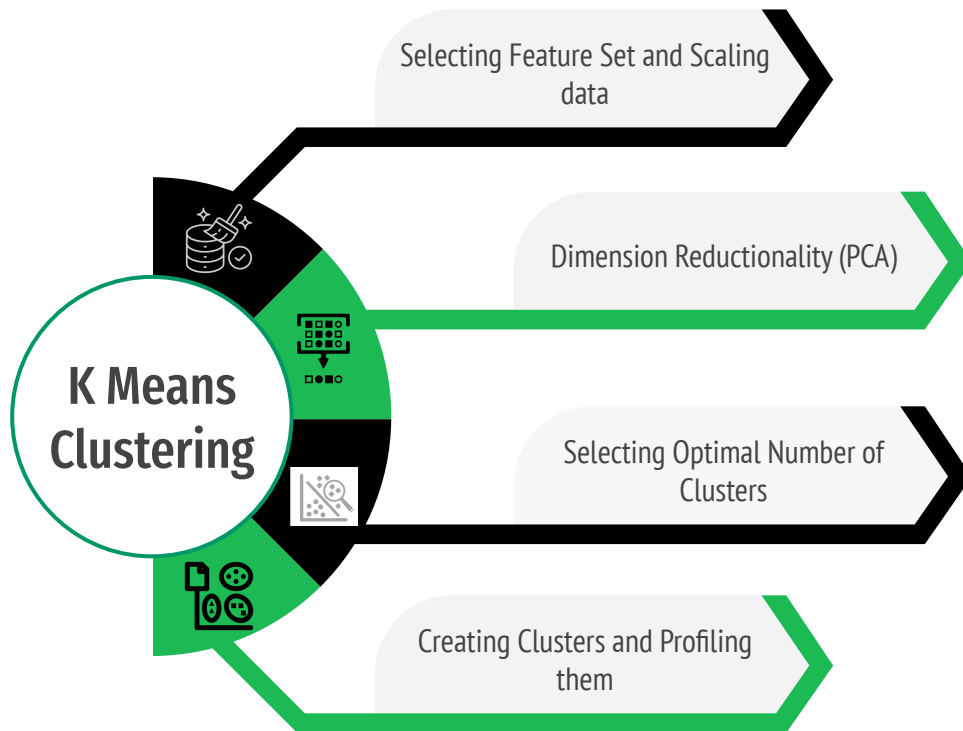
## Bottom Genres



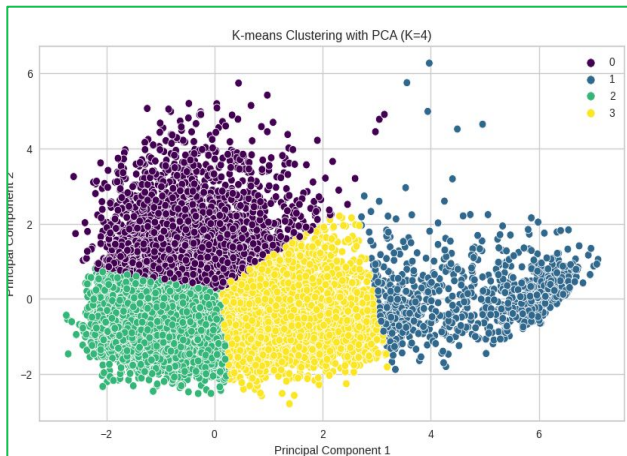
## Top Genres



# Clustering



# Clustering



Feature	Metric	Cluster 0	Cluster 1	Cluster 2	Cluster 3
Track Popularity	Mean	60	57	66	63
Danceability		0.55	0.32	0.72	0.56
Energy		0.78	0.16	0.71	0.46
Acousticness		0.13	0.87	0.18	0.51
Instrumentalness		0.03	0.63	0.01	0.05
Liveness		0.36	0.13	0.14	0.14
Valence		0.49	0.15	0.66	0.39





# Recommendations

- For Spotify
  - Utilize clusters with highest feature to pursue users on platforms that correspond with that feature
  - Utilize cluster with highest track popularity for top-funnel marketing and on audiences with little known information
  - Utilize clusters to create new playlists
- For Upcoming Artists
  - Utilize audio feature radar charts and produce tracks within those parameters for higher growth



# Appendix

- Notebook & Data Dictionary:

[https://github.com/jbblancojr/spotify/blob/main/A01 Decoding the Secret to Popularity Spotify.ipynb](https://github.com/jbblancojr/spotify/blob/main/A01%20Decoding%20the%20Secret%20to%20Popularity%20Spotify.ipynb)



# Elbow Plot for Clustering

