Increasing Audio Streaming Engagement via Music Recommendation Systems

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Introduction

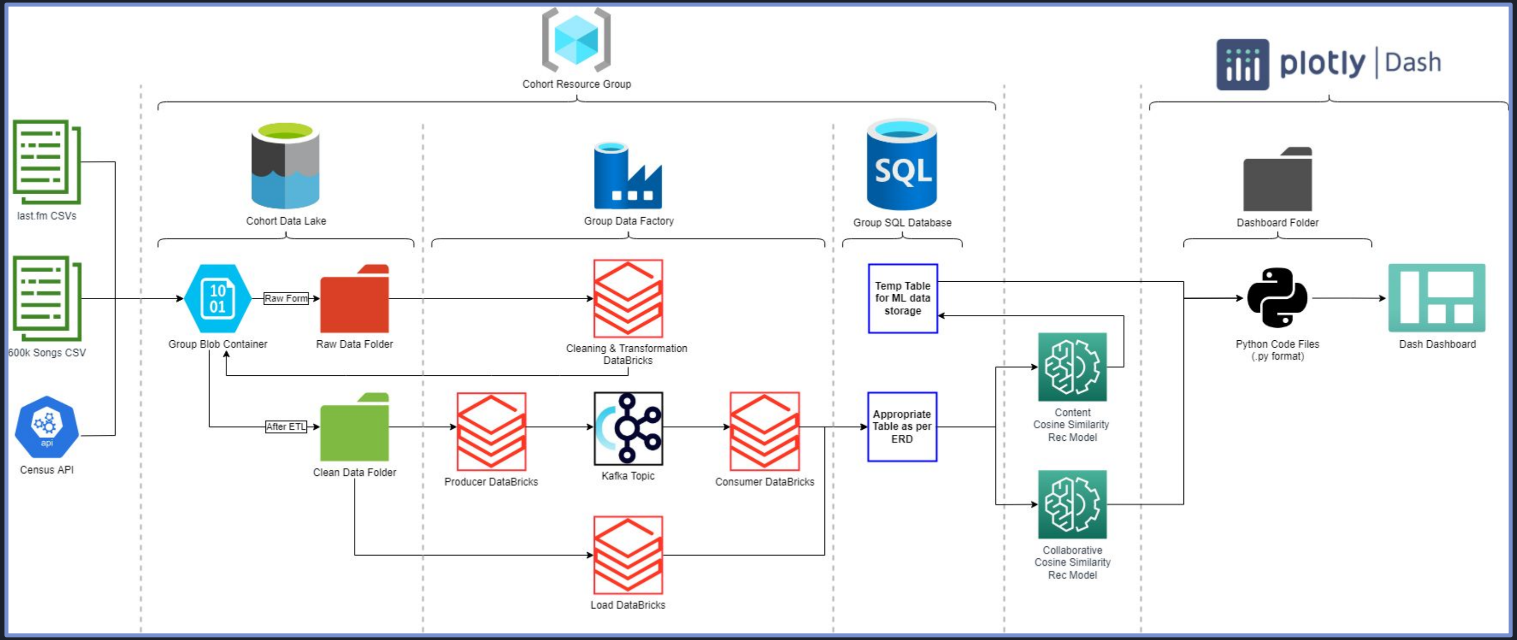
Why song recommenders?

Exploratory questions:

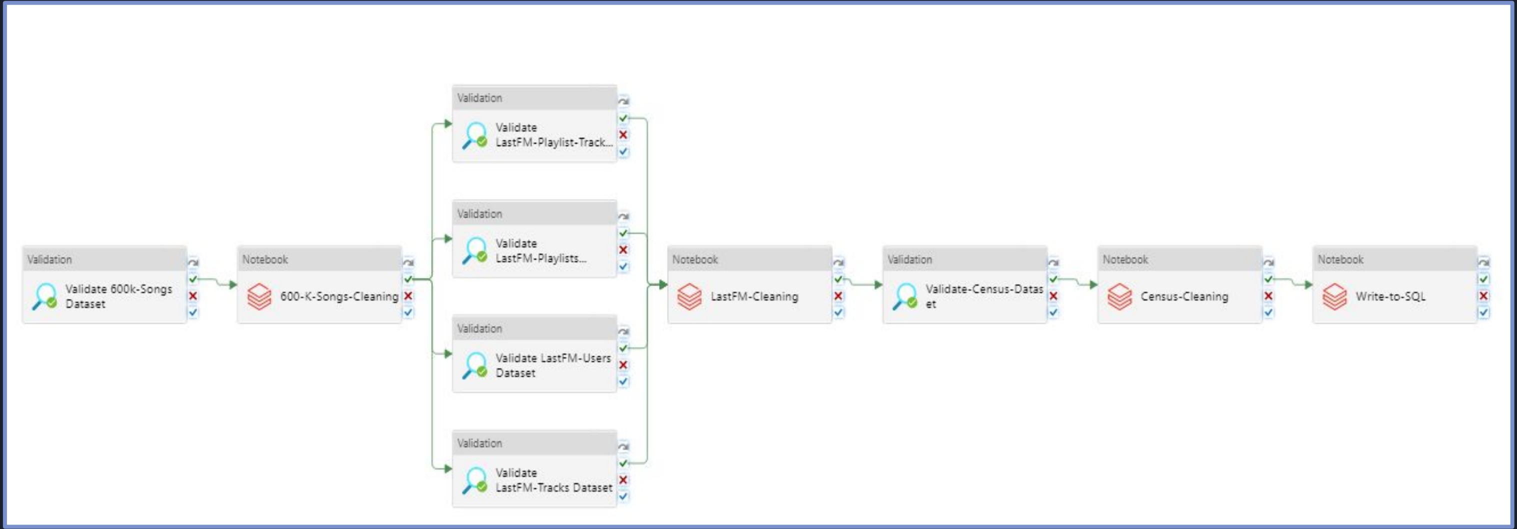
- Who are the people who use audio streaming services?
- How might we build a database that allows us to make recommendations based on music?
- How would songs trend over time in this database?
- What trends or patterns are there in the user metrics of our application?
- How does our database compare to actual music streaming services?
- Are recommendation models important to user retention on a music platform?

Source: https://www.npr.org/sections/allsongs/2013/07/10/200788243/the-good-listener-when-you-make-someone-a-mix-what-do-they-owe-you

Data Platform

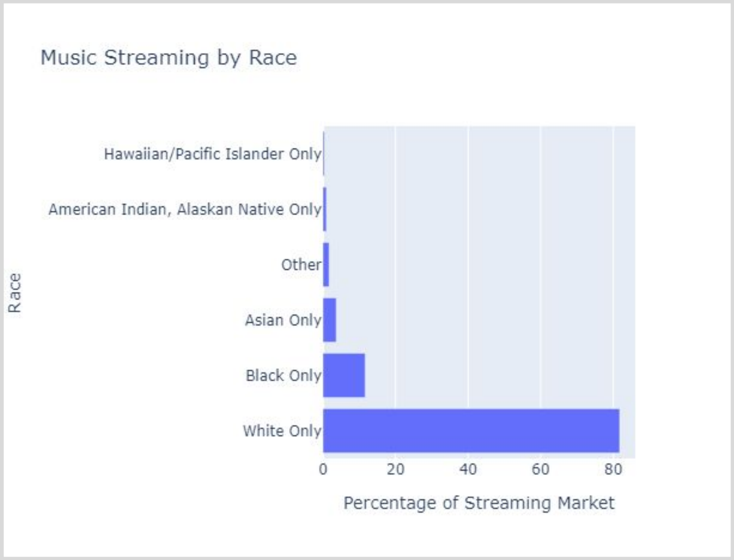


ETL Pipeline



Audio Streaming Market

Age:	23-30 years old
Location:	Major cities within highly populated states
Income Level:	Middle and Upper Middle Class
Race:	White
Sex:	Males and females evenly

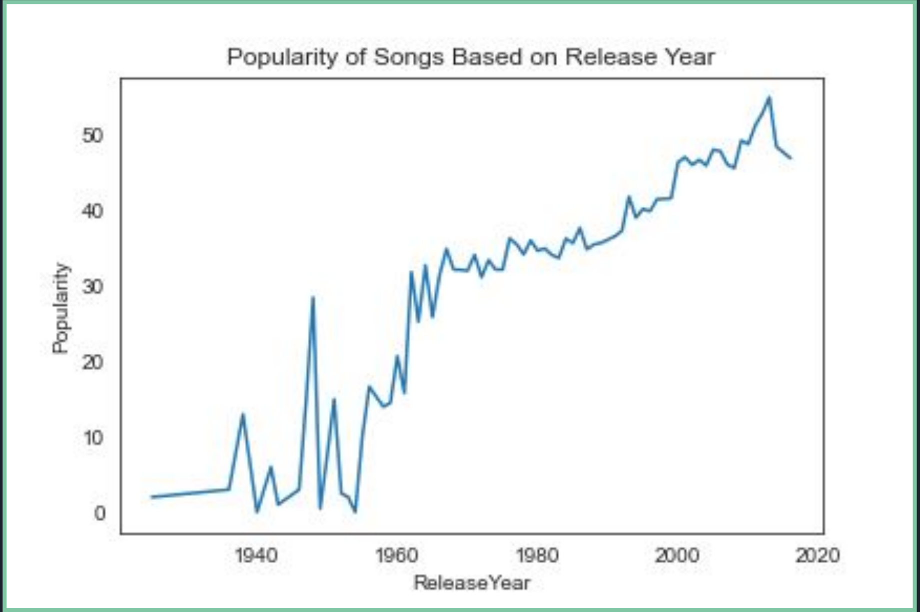


Trends of Songs in our Library

Popularity calculated based on the number total number of track plays and how recent those plays were

General increases with release year

Spike in popularity for songs released around 1950



What trends or patterns are there in the user metrics of music applications?

8000+ Tracks

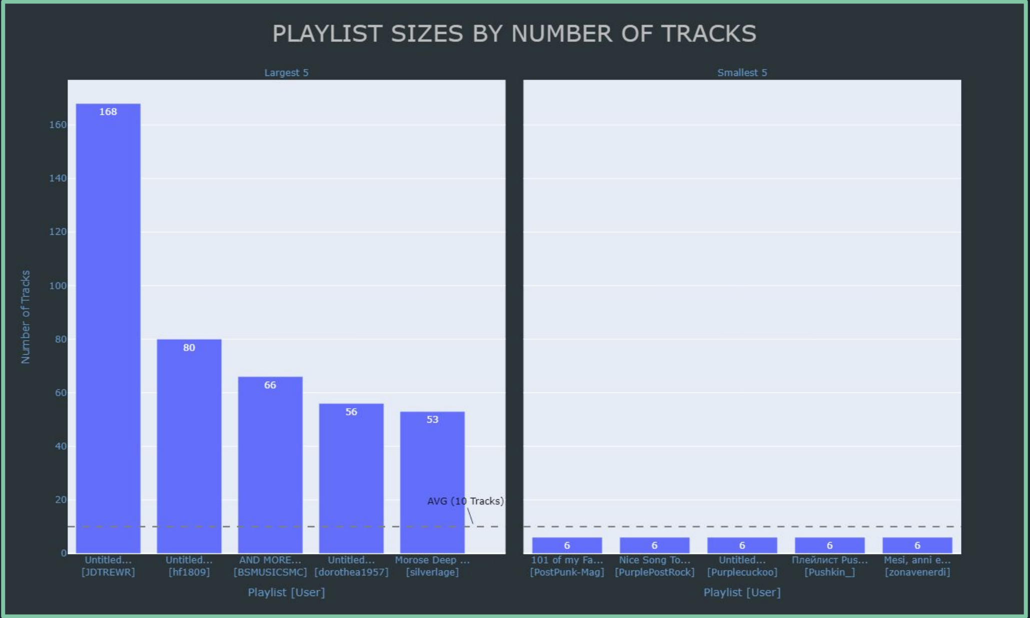
3000+ Artists

1-67 Tracks to an Artist

1400+ Users

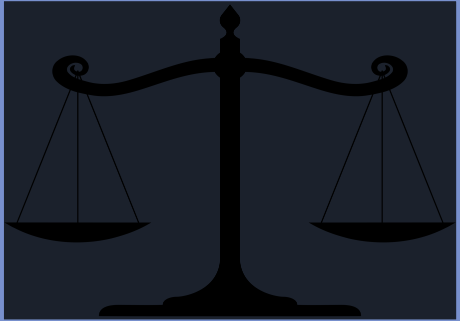
2600+ Playlists

1-73 Playlists to a User



How does our database compare to actual music streaming services?

In the year 2022, Spotify has "82 million songs" and "11 million artists" (Ruby, 2022).



Without proprietary information, there is no way to ensure that our database is a representative sample.

This means that despite using songs and tracks from Spotify, we cannot make substantiated claims about their platform off of our data.

We can, however, make a realistic recommender using that data that can give us insight into how they work and can be properly scaled should new data be introduced.

Importance of Recommenders in User Retention

Maximize user engagement	“Consumers will get themselves more engaged in a music streaming service when personalized music recommendations are made to them.” (Culture Next 2022)
Easy music discoverability	53% said they’ve sought more content from more diverse creators and podcasts in the past year (Culture Next 2021)
Increased customer satisfaction	“69% of American Gen Zs feel ‘more centered and generally happier’ when listening to their favorite music on a daily basis” (Culture Next 2022)

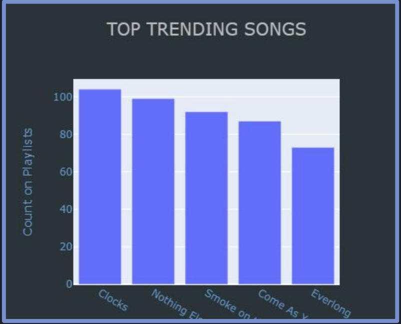
Source: https://happinesson.com/how-to-be-happy-by-listening-to-music/

Types of Recommenders

Non-personalized

Trending songs, playlists, artists

Does not require streaming platform to know anything specific about the user



Personalized

Need to know listening history of the user but more personalized

Content based

What are the attributes of the user’s songs?
What songs have similar attributes?

Collaborative based

When users listen to a song, the model searches for playlists that have that song. The songs that appear most often in playlists with the user’s song are returned as recommendations

Content Based Recommender

An unsupervised cosine similarity model

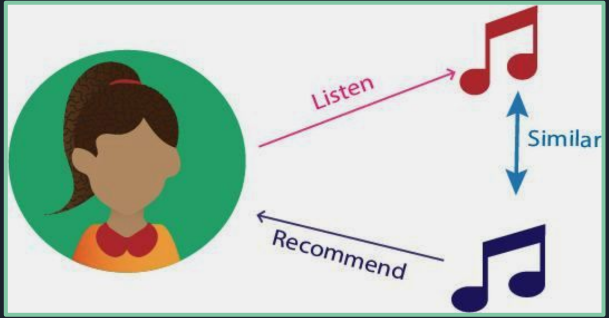
Create a vector for each song within our database

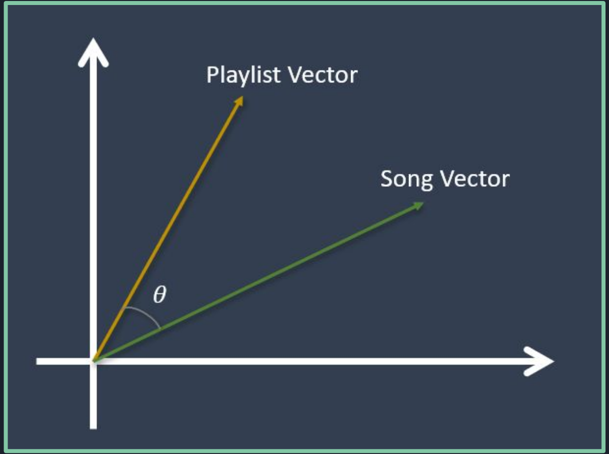
- Create dummy variables for categorical columns
- Scale numerical columns to a range between 0-1
- Further scale our features based on what attributes were more important

Create a vector for a selected playlist

Calculate the cosine similarity

Recommend the songs with the greatest cosine similarity





Collaborative Recommender

An unsupervised cosine distance model

Pivot table with the index being the TrackID, and the columns being PlaylistID

- 1 if TrackID is in PlaylistID
- 0 if not

Convert to a sparse matrix (bottom right)

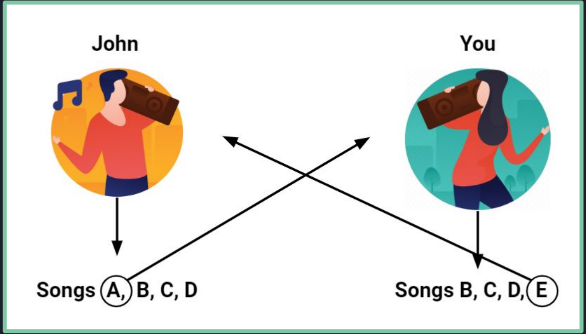
Calculate the cosine distance (-1 to 1)

Convert to pairwise distance (0 to 1)

- 0 is most similar

Returns a distance matrix

When user searches a song, the songs closest to 0 are returned



Source: https://www.univ.ai/post/spotify-recommendations

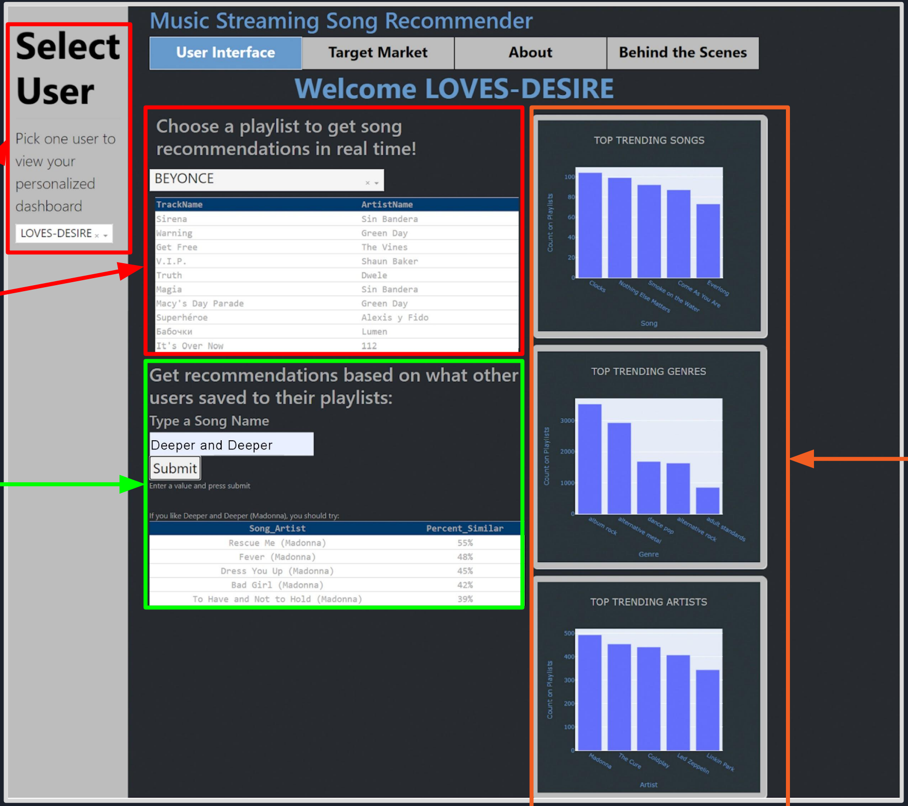
Sparse Matrix sample

```
(0, 2643)     1.0
(1, 438)      1.0
(1, 2034)     1.0
```

Dashboard

Content Recommender

Collaborative Recommender



Non Personalized Recommender

Datasets

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Learn more about our project

Github

Thank you for your time!

Questions?

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