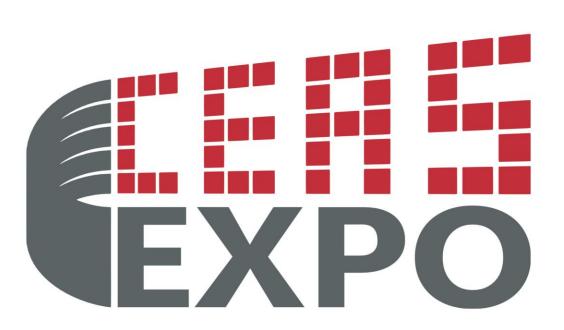
# Spotify Stats - Discover your sound



User Opens App i

genre caches



Generate Playlists

**User Relation Classifier** 

Jser Relatio

Classifier

Most Similar

Least Similai

[Feature 1]

Diversity

———————————— Calculate Genre Distribution

**User Relation Classfier** 

Genre Mappings

recommendation quality, and runtime performance.

Cosine Similarity, Correlation Distance, etc.,

Clustering & Similarity Techniques

**Distance Metrics**:

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We tested multiple approaches to measuring user similarity, evaluating each by accuracy, subjective

Objective metrics (e.g., Silhouette Score, Elbow Method), subjective testing (perceived recommendation quality),

This comprehensive analysis guided the selection of a method that balances interoperability, performance, cost, and

K-Means, Fuzzy C-Means, DBSCAN, Spectral Clustering, Gaussian Mixture Models (GMM), etc...

# Abstract

Spotify Stats is a web application that will transform users' Spotify listening data into meaningful insights and personalized music recommendations. Through an engaging and innovative interface, users will explore two main features: a comprehensive genre distribution and an intelligent music recommendation system via a user comparison social aspect. The application will leverage Spotify's API and intelligent data analysis to analyze listening patterns and suggest new music that aligns with users' tastes. By combining music genre analysis with future recommendations in a visually distinctive package, Spotify Stats will offer music enthusiasts a unique platform for understanding their listening habits and discovering new artists.

## **Project Overview**

By connecting to a user's Spotify account, our application provides both insight and discovery through two core features:

#### **Data Visualization**

Data visualizations are presented in a way to best articulate the insights discovered through our genre comparisons and intelligent data analysis used. We used a combination of polar area, spider, and cartesian planes to show insights along with direct playlist recommendations.

#### Playlist Generation

We analyze listening history across all users to identify patterns and similarities. By training a model that calculates user similarities, we can pinpoint the most and least similar listeners.

Using this similarity data, we generate playlists from:

- The most similar users, to discover new music of familiar taste
- The least similar users, to encourage exploration and discovery

The result is a **private**, **personalized**, yet **social** discovery experience, helping users find new music to love, and music they may never have heard before.

# **Key Design Considerations**

#### . User-Centered Experience

- We prioritized recommendations that feel right over those that are mathematically perfect
- Preprocessing and caching ensure a smooth, responsive experience without heavy real-time computation

#### Performance & Cost Efficiency

- o To reduce computation, we rely on lightweight classifiers, retraining only when deemed necessary
- AWS services were chosen for affordability, modularity, and scalability

#### 3. Compliance and Security

- User data privacy and API usage guidelines were strictly followed, especially when interacting with Spotify's platform
- System design considered minimal data retention and secure handling of user tokens and metadata

# **User Similarity & Recommendation Pipeline**

#### Real Users or Playlists

o ensure the system was enjoyable and accurate from launch, we needed meaningful user data from the start.

his allowed us to train and validate the recommendation engine before live users were onboarded, providing a

since we couldn't rely on real-time adoption alone, we developed a strategy to simulate and collect real user data

Parse Track Meta Data

top\_tracks

enre distributions

classification

Artificial Users based on Spotify charts over past s.

Artificial Users by Forum Submission

Artificial Users By Genre Distribution

Artificial Users By Genre Distribution

Save user

\_\_\_\_\_\_

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**Backend Processing** 

The pipeline begins by gathering listening data from the Spotify API, and transforming it into structured insights about the users preferences.[Feature One]

This information is placed into user profiles, which are securely stored in AWS DynamoDB to support scalable access and comparison.

The data is then abstracted into high-dimensional genre vectors and passed through a similarity modeling system, where user affinities are inferred, clustered, and used to drive tailored music discovery and recommendation experiences.[Feature Two]

#### **Artificial Training Data and Bootstrapping**

To support early development and improve model robustness, we built a bootstrapping system that generates artificial user profiles based on historical Spotify chart data and custom genre patterns.

These synthetic users allow us to validate the system's behavior before deployment and ensure that recommendations remain high-quality—even when real user data is limited.

## Technologies Used

#### AWS

o DynamoDB: Amazon's NoSQL storage service that allows us to efficiently store and receive data without constantly accessing user's Spotify data.

#### Python

- o Flask: A lightweight web framework that handles HTTP requests, routing, and session management.
- Spotipy: A Python library that provides easy access to the Spotify Web API for authentication and music data retrieval.
- o Boto3: The AWS SDK for Python that enables programmatic interaction with AWS services, particularly DynamoDB for this project.

#### Render

Render for hosting the Python flask app



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# Our project initially planned to use Spotify's 13 track-level audio attributes

(e.g., danceability, energy, tempo) to train a machine learning model that

could generate new playlists by requesting songs with similar characteristics.

### However, midway through development, Spotify deprecated key parts 2. of their API, limiting access to the very data we relied on. This change,

intended to protect their data from being used in external models, broke

#### This forced a major architectural shift:

- Adopted user-based similarity and genre-driven clustering
- Reduced API dependency with local processing and caching

#### A Blessing in Disguise

core parts of our approach.

This led us to create a more social, user-centered experience. System built around shared tastes rather than raw audio features, resulting in a more unique, gratifying, and personal platform