EXPLORE

Explainable Song Recommendations With Dynamic Mood control

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Objective

EXPLORE addresses the gap in current music recommendations paradigms by providing users with high-quality **interpretable recommendations** as well as accessibility to **control** them as per their **mood**

Approach

Data

We are using the MLHD dataset consisting of track listening event history of **1k** users and **900k tracks** amounting to **2.5 GB**. For new users, we use the Spotfiy API to extract their public playlists.

Recommendation Algorithm

Employing **collaborative filtering**, we are able to find the sweet spot of recommendation performance and interpretability. Given the sheer number of songs, we chose user-user collaborative filtering to simplify computations. For visibility into our recommendations, we show the **closest neighbour profiles** to help users better understand our recommendation

Additionally, since we use the Music Listening History Dataset we use **inference to create user-song ratings**. The rating is based on the following: Song Frequency, Song Popularity, Recency Bias and User-Platform affinity.

Integration

Our product starts its lifecycle from pinging the Spotify API and ends with creating visualization in Tableau

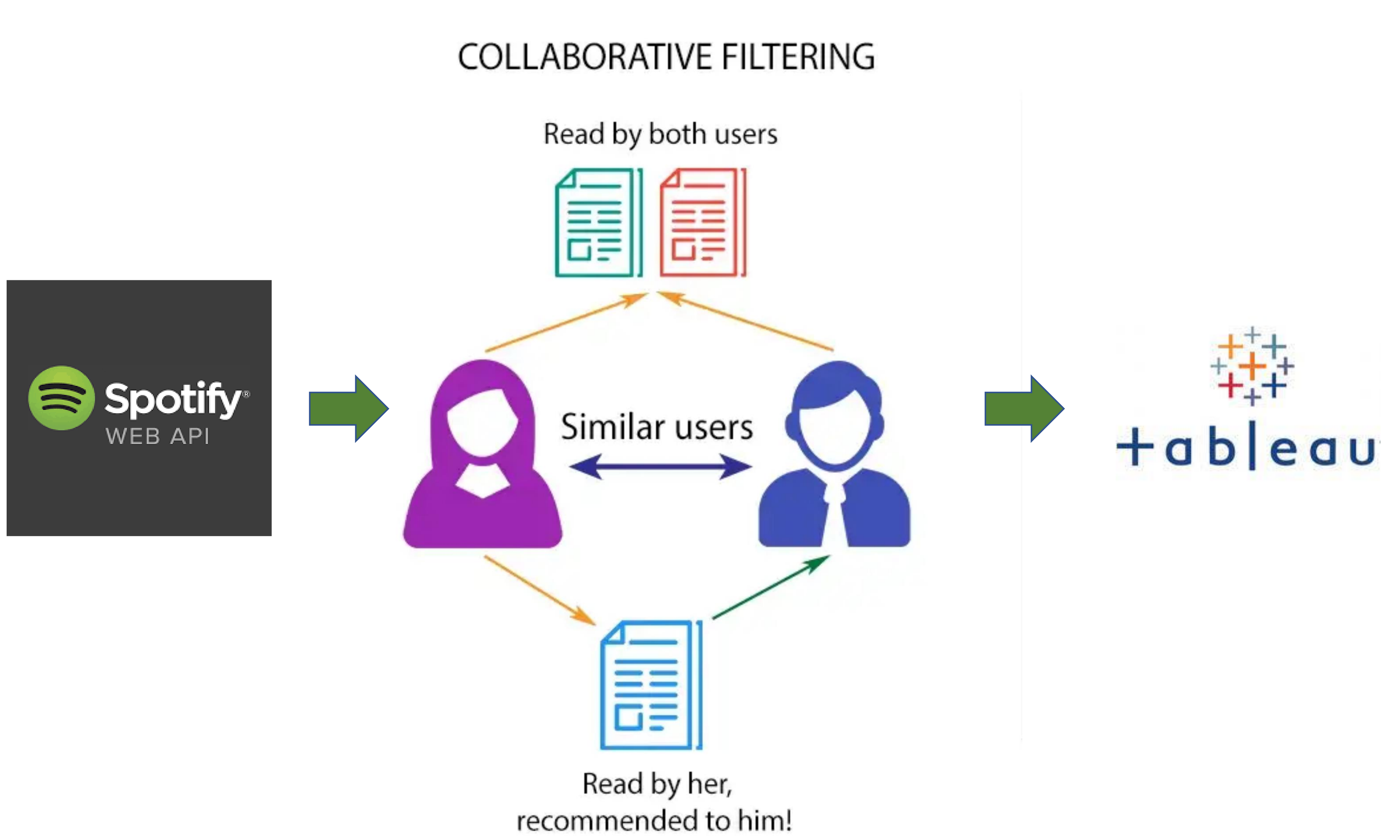

Fig 1: Project Workflow

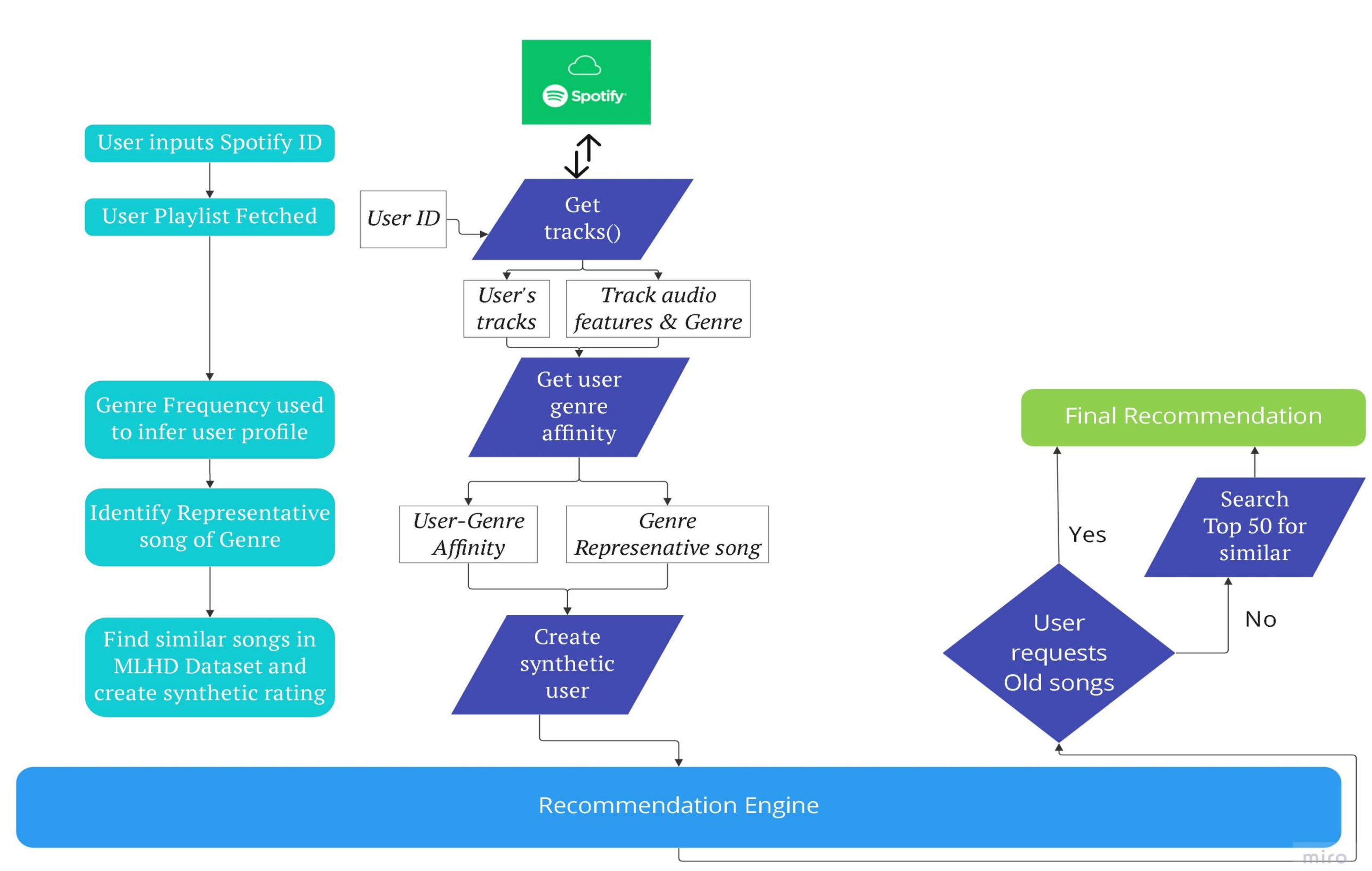

Fig 2: Data Workflow: Using User's Spotify ID to generate personalized recommendations

Product Visualization

Tableau Dashboard takes Spotify User ID as an input and generates the following:

- Your Personalized Playlist: **Recommended Playlist**
- Your Personalized List Looks like: **Characteristics of Suggestions**
- Mood Controls: **Toggles for Mood Control**

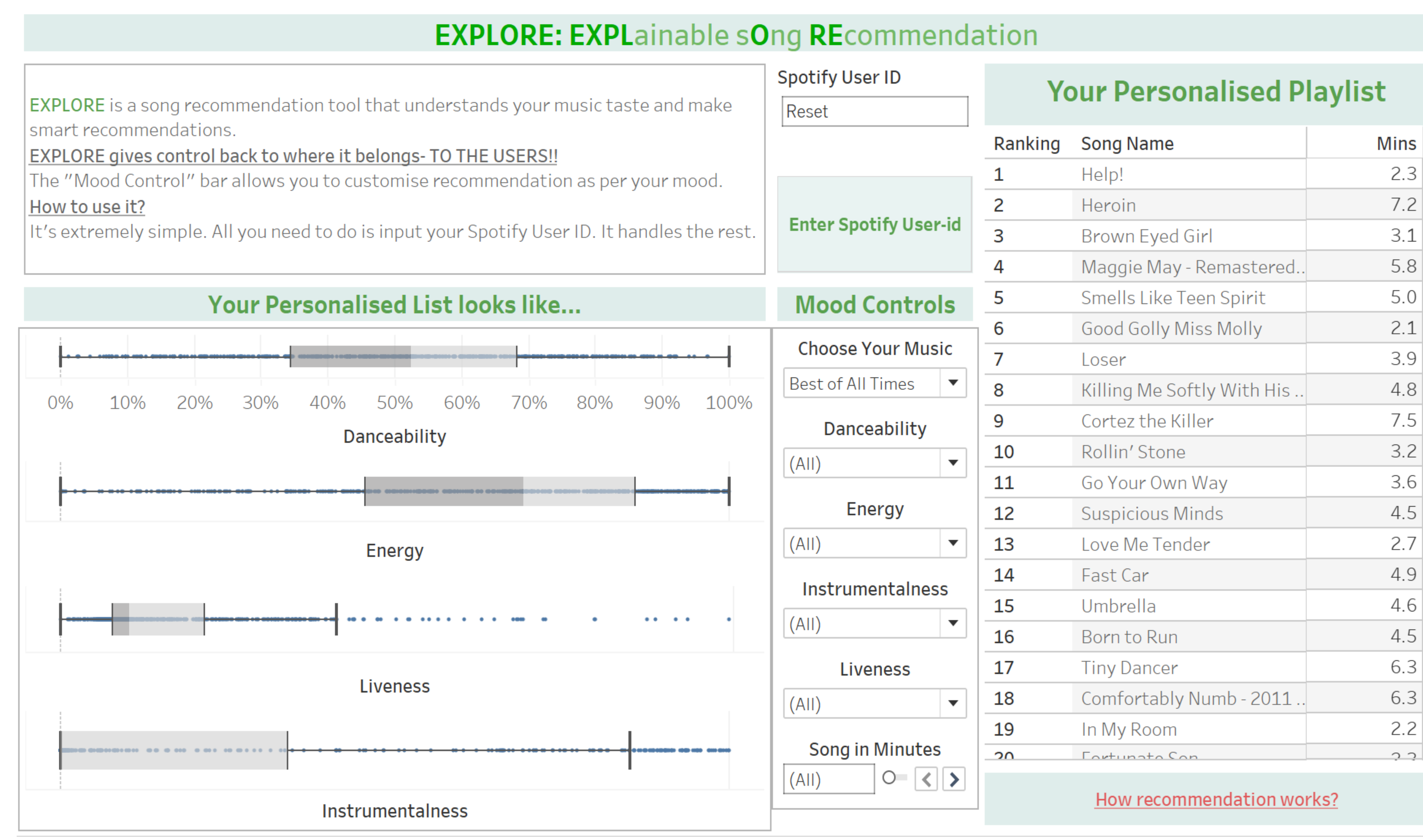

Fig 3: EXPLORE UI: Personalized recommendations with playlist attribute visualization and mood controls

The User Neighbour Network Graph **projects neighbors spatially based on similarity**. Clicking on a neighbor node, the user gets immediate access to compare their music taste to that of the neighbor

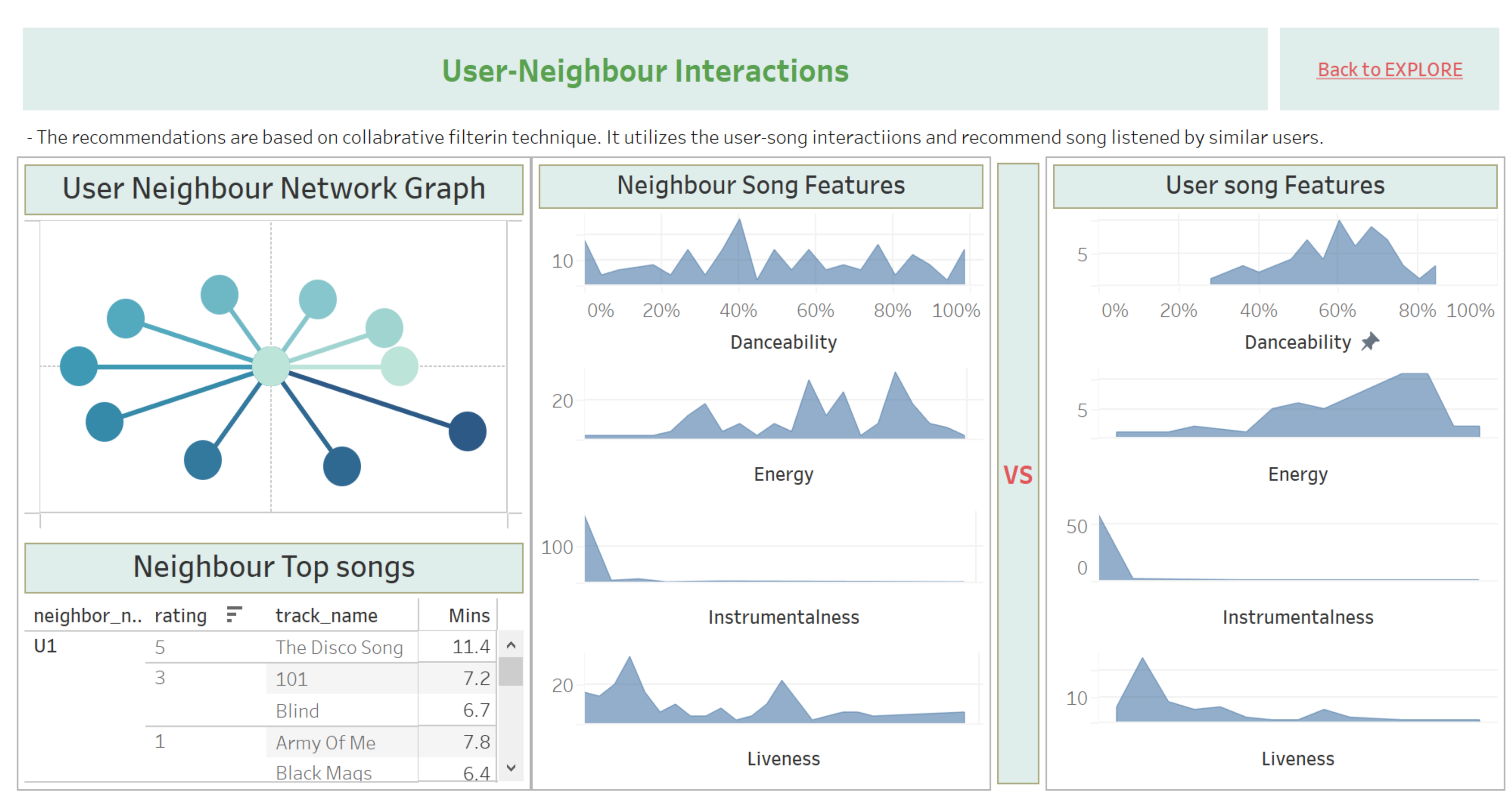

Fig 4: User Neighbour Interactions: Visualizing closest neighbors of a user and comparing their music taste

Evaluation

- **Metrics: 1. Deviation** (MSE and RMSE – RMSE ranges from 1 to 4, 1 being the ideal value) **2. Ranking Based** (MAP@ k and NDCG)
- **Train, Test Split (80%, 20%):** Stratified vs Random Sampling
- **Results:**

1. Deviation Measures:

Train Test Split	Mean Squared Error (Test)	Root Mean squared Error (Test)
Stratified	2.407	1.551
Random Sampling	2.538	1.593

2. Ranking Measures: Stratified sampling for ranking metrics

Train Test Split	MAP@K (K = 3)	Mean NDCG
Stratified	0.773	0.873

Our recommendation does a fine job in not only predicting ratings but also in fetching the most relevant songs emphasized by MAP@k and mean NDCG score.