Song Recommender

The Recommendation system can show similar songs to a song. It can also recommend songs acoording to user liked songs.

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Technologies Used

- **Frontend:** React.js
- **Backend:** Django
- **Database:** SQLite3
- **Contanerisation:** Docker
- **Data Processing and ML:** Pandas, Numpy, Scikit-learn(sklearn)
- **Dataset:** Kaggle (spotify-600k-tracks)

Feature Engineering

The idea is to represents songs into linear vectors according to there audio features such as danceability, energy, loudness, speechiness, acousticness etc. and other categorical features such as genres, release year, key (major note of track [0: C, 1: C#/Db, 2: D, …]), etc.

For the Genres

1.Word Embeddings (Word2Vec)

We use Word2Vec to create meaningful numerical representations (vectors) for genres. This helps us understand the relationships between different types of music.

2.TF-IDF Weighting

We apply TF-IDF (Term Frequency-Inverse Document Frequency) to the genre vectors. This step makes rare and important genres more influential in our track representations.

3. Weighted Average

By calculating a weighted average of genre vectors for each track (tf-idf is used as weights), we create a unique representation for every song based on its genres.

For Categorical and Numerical Variable

Categorical Variable Encoding

Era Flags Era flags are created by dividing songs into decades (e.g., 40s, 50s) to capture historical trends and associations with different time periods.

One-Hot Encoding We use one-hot encoding for categorical variables like “key,” “time_signature,” and “era_flags”. This encoding transforms these categorical variables into binary vectors, with each category represented as a binary column.

Numerical Variable Encoding

Bucketing For numerical variables such as artists' followers, track popularity, and artist popularity, we employ bucketing. This technique groups numerical values into ranges (0-5, 6-10) and converts them into categorical features. This helps manage dimensionality and making them suitable for categorical analysis.

PCA Dimensionality Reduction: Used to simplify numerical variables, making them easier to work with for cosine similarity calculations. This step helps improve the efficiency and scalability of the recommendation system.

Similarity Calculation

Cosine Similarity

Cosine similarity is a mathematical concept used in various fields, including natural language processing and recommendation systems, to determine the similarity between two vectors. In the context of song recommendation systems, cosine similarity can be a powerful approach.

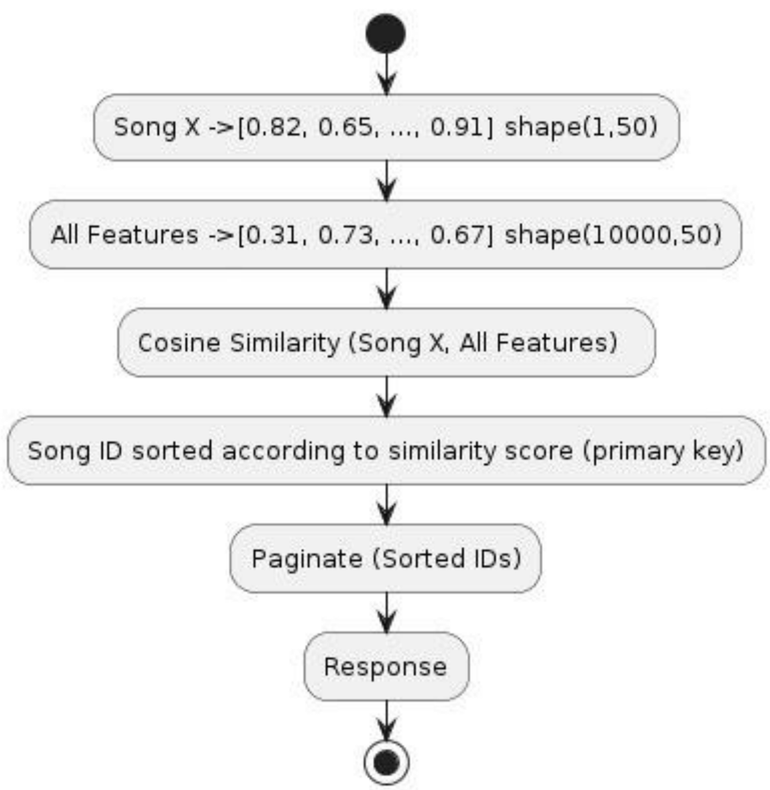
How Does It Work?

1. **Vector Representation**: Each song is represented as a vector in a multidimensional space, with each dimension corresponding to a feature such as genre, tempo, mood, or instrument usage.

2. **Cosine Calculation**: When a user interacts with a song (e.g., listens to it, adds it to a playlist), their preferences are captured as a vector. To recommend similar songs, the cosine similarity between the user's vector and other song vectors is calculated.
3. **Similarity Measurement**: Cosine similarity measures the cosine of the angle between two vectors. A higher cosine value indicates a smaller angle and thus greater similarity between the songs.

Cosine similarity, with its simplicity and effectiveness, plays a vital role in enhancing user experience and engagement in music streaming platforms.

Similar Songs



Like/Unlike Songs