Lab Oriented Project

On

Harmonizing Tunes

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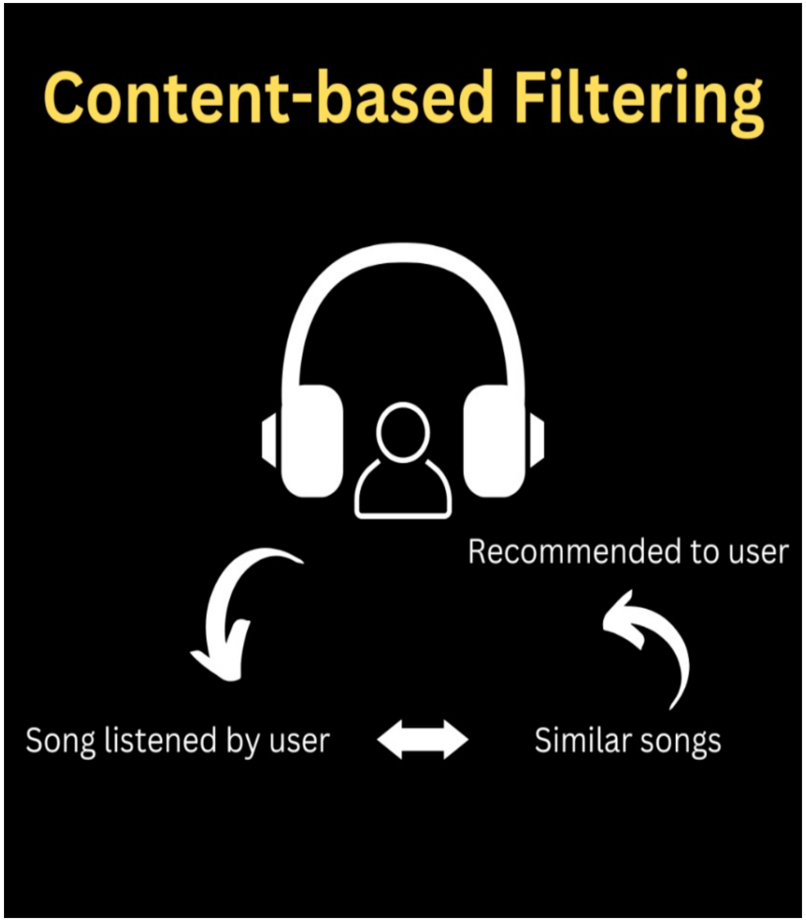
Introduction

In a world where music plays an indispensable role in our daily lives, finding the perfect tune can often feel like solving a complex puzzle. We are thrilled to present our cutting-edge initiative, which aims to solve this musical mystery. Our goal is to develop a **content-based song recommendation system** that will revolutionize the way you discover music.



Introduction

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With our system, you'll no longer need to rely on generic playlists or struggle to find the right song for your mood. Instead, we'll provide you with personalized song recommendations that seamlessly harmonize with a reference track of your choice. Additionally, we'll help you explore and understand the genres that resonate with your unique musical preferences. This project is designed with you, the music enthusiast, in mind, to enhance your music discovery journey and make it a truly delightful experience.

Data Overview

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Within our dataset, we have a total of 24 features, with a significant focus on 12 key audio features which includes speechiness, danceability , loudness, etc.

About Dataset

1. `id` : A unique identifier for each track.
2. `name` : The name of the track.
3. `album` : The name of the album to which the track belongs.
4. `album_id` : An identifier for the album.
5. `artists` : The name of the artist(s) who performed the track.
6. `artist_ids` : Identifier(s) for the artist(s).
7. `track_number` : The position of the track within the album.
8. `disc_number` : The disc number (if it's a multi-disc album).
9. `explicit` : A boolean indicating whether the track contains explicit content.
10. `danceability` : A measure of how suitable the track is for dancing.
11. `energy` : Represents the energy of the track.
12. `key` : The key of the track.
13. `loudness` : Loudness of the track in decibels (dB).
14. `mode` : Whether the track is in major mode (1) or minor mode (0).
15. `speechiness` : A measure of the presence of spoken words or speech in the track.
16. `acousticness` : Represents the amount of acoustic sound in the track.
17. `instrumentalness` : A measure of how instrumental the track is.
18. `liveness` : A measure of the presence of a live audience in the track.
19. `valence` : Indicates the positivity of the track.
20. `tempo` : The tempo of the track in beats per minute (BPM).
21. `duration_ms` : The duration of the track in milliseconds.
22. `time_signature` : The time signature of the track.
23. `year` : The year in which the track was released.
24. `release_date` : The release date of the track.

Methodology - Data Collection and Preprocessing

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Data Source: We gathered our dataset from a robust repository of music data on Kaggle. This dataset is a treasure trove, containing audio features for over 1.2 million songs, spanning various genres and musical attributes, from which we have taken the originals songs from 2015-present.

Data Cleaning: To maintain data quality and consistency, we meticulously cleaned the dataset. This involved identifying and addressing issues like missing values, duplicates, and outlier data points. By rectifying these issues, we guarantee that our recommendations are based on high-quality data.

Methodology- Feature Extraction

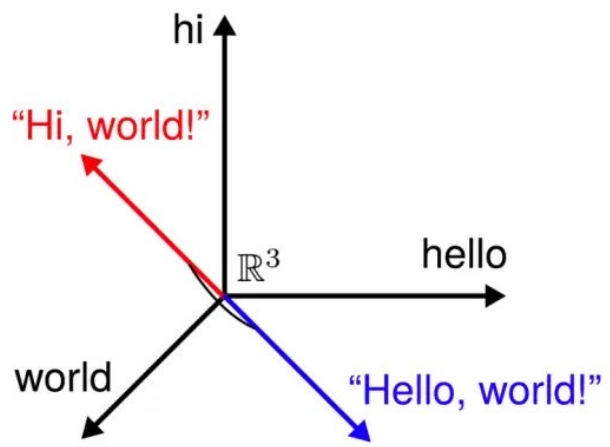
Feature Extraction: One of the critical tasks in this phase is the extraction of audio features from the raw dataset. These features include danceability, energy, key, loudness, and more. These attributes are vital for understanding the unique characteristics of each song and serve as the building blocks of our recommendation system.

explicit	danceability	energy	key	loudness	mode	speechiness	acousticness	instrumentalness	liveness	valence	tempo
False	0.470	0.978	7	-5.399	1	0.0727	0.0261	0.000011	0.356	0.503	117.906
True	0.599	0.957	11	-5.764	1	0.1880	0.0129	0.000071	0.155	0.489	103.680
False	0.315	0.970	7	-5.424	1	0.4830	0.0234	0.000002	0.122	0.370	149.749

Methodology – Recommendation Model

Cosine Similarity: The cosine similarity function is the engine behind our ability to measure how alike songs are in terms of their audio features. It calculates the cosine of the angle between two vectors, providing a numerical measure of feature similarity. When two songs have a higher cosine similarity value, it indicates that they share more common audio attributes.

The cosine function is the mathematical tool that allows us to uncover the stylistic and thematic connections between songs, ensuring that our recommendations are finely tuned to the user's specific preferences.



Cosine Similarity

Methodology – Recommendation Model

User Input: Our system is designed with the user in mind. We've created a user-friendly web interface that empowers users to provide a reference song. This reference song becomes the foundation for generating song recommendations, allowing users to shape the recommendation process based on their preferences.

Song Ranking: Songs in our dataset are ranked based on their cosine similarity with the attribute vector of the user-provided reference song. Those songs with the highest cosine similarity values are considered the most similar and are recommended to the user.

The recommendation model is where the magic happens. It enables our system to connect the dots between songs, quantify their similarity, and provide users with tailored song recommendations that align with their musical tastes.

Methodology- Creating Music Genres with deep learning

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The Five Common Genres:

1. Rock
2. Pop
3. Hip-Hop
4. Rap
5. Electronic

CNN (Convolutional Neural Networks) - Our core technology for breaking down music into its fundamental elements. It is proficient in identifying intricate patterns like rhythms and melodies.

By harnessing CNN, we've successfully crafted these five common music genres, each with its own unique traits.

Methodology-Evaluation

Evaluation Metrics: We employ a set of industry-standard evaluation metrics, including Mean Average Precision (MAP) , classification report and others. These metrics provide quantitative measures of how effectively our recommendations align with user preferences and expectations.

We aim to provide the highest quality of song recommendations to our users, and this phase is where we fine-tune the system for peak performance.

Methodology-Deployment

User Interface: A user-friendly web interface has been thoughtfully designed to make it easy for users to provide their reference track. The interface is intuitive and user-centric, enhancing the overall user experience and making it effortless to interact with the system.

Heroku Deployment: We chose the Heroku platform for hosting and deploying the recommendation system. Heroku's scalability and accessibility make it an ideal choice for ensuring that the system is readily available to a broad user base. It adeptly handles increased user traffic and demand, guaranteeing a seamless user experience.

Flask: It has played a central role in developing the user interface, handling user interactions, and guiding users through the recommendation process.

Tools & Technologies - Data Source

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Kaggle: Kaggle is the source of the music data used in our project. Our dataset, containing audio features for over 1.2 million songs, is obtained from Kaggle's music data repository.

This dataset serves as the cornerstone of our recommendation system, offering a diverse and extensive collection of songs with a wide variety of audio attributes for analysis and recommendation.

Kaggle's contribution to our project's data source ensures that our recommendation system is built on a solid foundation of data, enabling it to provide high-quality, diverse, and relevant song recommendations to users.

Tools & Technologies - Data Collection and Preprocessing

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Python: We use Python to perform various tasks, including data collection, data preprocessing, and model development.
Pandas: Pandas, a Python library, plays a pivotal role in data preprocessing. It enables us to efficiently load, manipulate, and clean our large dataset of audio features.

Jupyter Notebook: It is employed for creating, executing, and documenting data preprocessing workflows. This helps maintain transparency and allows for collaborative data analysis.

Dataspell: It ensures that text-based attributes, such as song titles, artist names, and album titles, are free from spelling errors and inconsistencies. Clean and accurate textual data contributes to more effective recommendations.

Tools & Technologies – Feature Engineering and Recommendation Model

Scikit-Learn: We leverage its capabilities to calculate TF-IDF (Term Frequency-Inverse Document Frequency) values, compute cosine similarity, and develop the recommendation model. Scikit-Learn offers a wide range of algorithms and functionalities, ensuring our recommendation system is technically robust and capable of generating high-quality song recommendations. It's the engine that powers our system's ability to quantify the importance of audio features and suggest similar songs.

NumPy: NumPy accelerates numerical operations and optimizes system performance, especially when dealing with large matrices and arrays. It's the technology that makes the complex math behind our recommendation model efficient.

Tools and Technologies: Music Genre with CNN

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CNNs are a class of deep learning neural networks designed for image and signal processing tasks. In our context, they play a pivotal role in analyzing the patterns within music tracks to classify them into specific genres. CNNs are well-suited for this task due to their ability to capture hierarchical and spatial relationships in data, making them effective in identifying musical patterns.

Leveraging CNNs, our system can automatically categorize songs into various genres based on their audio attributes, allowing us to provide users with genre-specific song recommendations. This technology forms the backbone of our music genre classification, enabling our recommendation system to align users with their preferred musical styles.

Tools & Technologies - Web Development and Deployment

Flask: It has played a central role in developing the user interface, handling user interactions, and guiding users through the recommendation process. With Flask, we've created an intuitive and user-centric web interface that empowers users to provide a reference song effortlessly.

Streamlit: Streamlit is another powerful web application framework we've utilized. It has helped us present data-driven insights and recommendations in an interactive and user-friendly manner.
These web development tools are the key to making our recommendation system accessible to users.

References

Kaggle Music Data Repository:
https://www.kaggle.com/datasets/rodolfofigueroa/spotify-12m-songs/data
This dataset serves as the foundation of our project, providing audio features for over 1.2 million songs, enabling the analysis and recommendation of songs.

Scikit-Learn Documentation: https://scikit-learn.org/
The official documentation of Scikit-Learn, a key machine learning library, provided valuable guidance for feature engineering and recommendation model development.

Python Documentation: https://python.org/doc/
The Python documentation served as a reference for Python programming, Pandas, and NumPy, which played central roles in our data preprocessing and analysis.

References

Heroku: https://devcenter.heroku.com/categories/reference
Heroku's platform documentation and resources were consulted for the deployment of our recommendation system. Heroku provided the hosting infrastructure for making our system accessible to users.

Flask: https://flask.palletsprojects.com/en/3.0.x/
Flask's official documentation and tutorials were instrumental in the development of the user interface for our system.

Conclusion

Enhancing the Music Experience: Our project is driven by the quest to enhance the music listening experience. We've harnessed the power of data, technology, and machine learning to provide music enthusiasts with personalized song recommendations that align with their unique musical tastes.

Data-Driven Excellence: The project's foundation lies in the robust dataset sourced from Kaggle, containing audio features for over 1.2 million songs. This wealth of data enriches our recommendation process and ensures diversity and quality in suggestions.

User-Centric Design: We've designed a user-friendly web interface that empowers users to provide a reference song, putting them in control of the recommendation process and enhancing their overall experience.

Rigorous Evaluation: The project is underpinned by rigorous evaluation and fine-tuning. We've used industry-standard evaluation metrics and hyperparameter tuning to ensure that our recommendations are accurate, relevant, and of the highest quality.

Thank You