Context Aware Music Recommendation System

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ABSTRACT

Music recommendation systems play a pivotal role in the digital music industry, significantly enhancing user experience by personalizing music selections. However, the majority of existing systems predominantly focus on leveraging user preferences and song metadata, neglecting the critical influence of contextual information on music choice. Our project, "Context-Aware Music Recommendation System," seeks to bridge this gap by incorporating a variety of contextual factors, such as the user's emotional state, physical environment, and temporal variables, into the recommendation process. This report presents the initial progress of our project, including a comprehensive review of related work, the development and preprocessing of our datasets, and a preliminary methodology for context incorporation. We discuss the challenges encountered in integrating contextual data and outline our proposed solutions and future work directions. Our findings suggest that contextual information significantly enhances recommendation relevance, setting a foundation for further exploration in the pursuit of a more nuanced and user-centered approach to music recommendation.

KEYWORDS

Recommendation Systems, Collaborative Filtering, Factorization Machines

1 INTRODUCTION

Music recommendation systems are crucial in the digital age, where the abundance of available content can overwhelm users. These systems aim to personalize the user experience by suggesting songs, artists, or playlists that align with individual tastes and preferences. The evolution of recommendation systems has led to the development of various approaches, each with its strengths and limitations.

1.1 Collaborative Filtering

Collaborative Filtering (CF) is one of the most widely used techniques in recommendation systems. It makes predictions about a user's interests by collecting preferences from many users. The underlying assumption is that if users agreed in the past, they would agree in the future. Despite its popularity, CF suffers from cold start and sparsity issues, limiting its effectiveness when new users or items have insufficient interaction data.

1.2 Content-Based Filtering

Content-Based Filtering approaches recommend items by comparing the content of the items and a user profile. In the context of music, this could involve analyzing the audio features of tracks, such as tempo, genre, and harmony, or lyrical content to predict user preferences. While addressing some of the CF limitations, content-based methods can lead to a lack of diversity in recommendations, as they rely solely on item attributes.

1.3 Hybrid Methods

Hybrid methods combine collaborative and content-based filtering to leverage the strengths of both. By integrating diverse data sources, hybrid systems can provide more accurate and personalized recommendations, mitigating the limitations of individual approaches. These methods have shown significant promise in improving recommendation quality and user satisfaction.

1.4 Context Aware and 3D Algorithms

The advent of **deep learning** and **context-aware algorithms** has introduced a new dimension to recommendation systems. These advanced techniques consider not only the historical preferences of users and the characteristics of music tracks but also the contextual information surrounding each listening session. In our exploration, we are particularly interested in the potential of **Factorization Machines** for their ability to model interactions among users, items, and contextual factors efficiently.

This paper is organized as follows: Section 2 reviews related work in the field of music recommendation systems, highlighting the evolution from traditional methods to advanced, context-aware approaches. Section 3 presents an exploratory data analysis (EDA) of the datasets employed in our study. Section 4 details the methodology, with a focus on our considerations for employing Factorization Machines. Section 5 describes the experiments conducted, followed by Section 6, which presents the results. Section 7 discusses the implications of our findings, and Section 8 concludes the paper with reflections on our research and future directions.

2 RELATED WORK

Recent advancements in music recommendation systems have significantly emphasized the integration of contextual information and the application of innovative machine learning techniques to enhance personalization and accuracy. A growing body of research explores a variety of contextual data sources, such as playlist names, user behaviors, and audio-lyric features, to better understand user preferences in specific situations. Studies by Pichl et al. [6] and Baxter et al. [2] highlight the importance of contextual clues from playlist names and song attributes in achieving more accurate user preference predictions than traditional collaborative filtering methods. Similarly, Zamani et al. [8] and another study by Pichl et al. [5] emphasize the significance of situational context integration, indicating that multi-context-aware systems can considerably enhance recommendation relevance and accuracy.

Furthermore, the effectiveness of machine learning algorithms in extracting deep features from music content and user interaction data is widely recognized. Chang et al. [3] demonstrate the potential of combining audio and lyric features with reinforcement learning for dynamic recommendations that adapt over time. Moreover, Yong Zheng and David Wang [9] propose a multi-criteria ranking framework that utilizes user criteria, such as click-through rates and ratings, showcasing that sophisticated data analysis techniques can yield high-quality recommendations.

Nonetheless, the scalability and generalizability of these approaches remain subjects of debate. Adomavicius and Tuzhilin [1] provide a comprehensive framework for context-aware recommendations, acknowledging the necessity for broader experimentation and more concrete implementations across different domains. The dependency on specific types of contextual information also raises concerns regarding the depth of personalization and the systems' ability to capture accurate situational contexts. Elbir and Aydin [4] discuss how the success of a recommendation system based on Convolutional Neural Networks hinges on the noise within the training data, underscoring the need for models that account for a broader range of contextual factors.

In addition to exploring these approaches, our research leans towards the application of Factorization Machines (FMs), introduced by Rendle [7], for their capability to model interactions among users, items, and contextual factors efficiently, even with sparse data. Adomavicius et al. [1] suggest that 3D algorithms such as Context-Aware Recommender Systems (CARS) can be simplified to a 2D recommendation algorithm with a contextual filtering step, illustrating the potential for polynomial regression models and FMs to achieve contextual modeling in music recommendations.

This body of work forms the foundation for our exploration of context-aware music recommendation systems, acknowledging the ongoing debates and suggesting a direction towards innovative solutions that balance technological sophistication with practical applicability.

3 EXPLORATORY DATA ANALYSIS

3.1 Dataset Overview

We use the #nowplaying-RS [?] dataset for this project. It consists of both context and content based features along with timestamps of listening events. This dataset is structured across three distinct tables, each providing valuable insights into user behavior and preferences. These datasets comprise various aspects of music streaming sessions from Spotify, including sentiment scores derived from Twitter hashtags, track features, and user interaction data. The three data tables are as follows:

- **User Track Hashtags With Timestamps**: It contains basic information about each listening event such as user_id, track_id, hashtag and created_at.
- **Content Features**: It encompasses a comprehensive set of features, incorporating both song characteristics (such as valence, loudness, tempo, etc.) and user-related information, including location, language.
- **Sentiment values**: It contains the sentiment features of all hashtags collected from four different sentiment dictionaries: AFINN, Opinion Lexicon, Sentistrength Lexicon and vader.

3.2 Data Preprocessing

3.2.1 Data Loading and Cleaning. The datasets were loaded and inspected for dimensions and missing values. Preprocessing steps included:

- Converting data types for numeric columns that were mistakenly encoded as objects.
- Detecting and handling missing values by either filling with averages or removing rows with null values.
- Dropping unnecessary columns that did not contribute valuable information for the analysis or modeling processes.

3.2.2 Sentiment Analysis Dataset. The sentiment analysis dataset contained various sentiment scores associated with specific hashtags. The following preprocessing steps were applied:

- Renaming columns for clarity.
- Dropping columns with redundant or no valuable information.
- Filling missing values with column averages where applicable.

3.2.3 Dataset Size Reduction. The dataset comprises over 9 million Listening Events (LEs), which was reduced to 2.5 million to accommodate computational resource constraints. This reduction involved:

- Excluding LEs for songs listened to less than 50 times.
- Filtering out data not associated with UK or US time zones.
- Removing entries without a vader sentiment score.

3.3 Feature Overview

The analysis utilizes features such as sentiment_score, instrumentalness, danceability, energy, loudness, tempo, acousticness, valence, mode, and key to understand music preferences and listening behaviors.

3.4 Exploratory Data Visualization

Visualizations were created to explore the distribution of sentiment scores and track features. Key insights include:

- A wide range of sentiment scores, indicating diverse emotional contexts associated with music listening experiences.

- The distribution of track features such as danceability, energy, and acousticness, highlighting the variability in musical content.

3.4.1 Correlation Matrix. Pearson's correlation coefficient was used to estimate correlations among musical features, revealing:

- A positive correlation between energy and loudness, suggesting that tracks with high energy typically exhibit higher loudness levels.
- A negative correlation between energy and acousticness, indicating that songs with higher energy are generally less acoustic.

Notably, the 'mode' and 'key' features, being categorical, do not imply any correlation through this analysis.

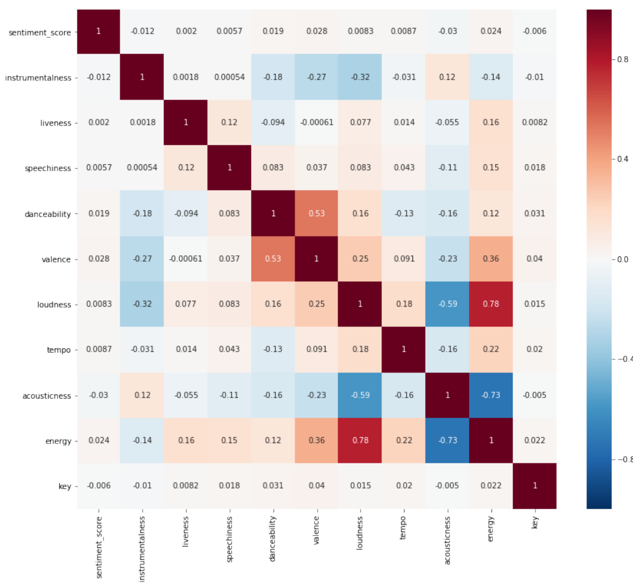

Figure 1: Estimating correlations among the musical features by visualizing correlation matrix after computing Pearson's correlation coefficient

3.4.2 Context-Based Recommendations Insight. Visualization of the danceability feature against mood (sadness and happiness) demonstrates:

- Sad songs (low valence) tend to have lower danceability values, whereas happy songs (high valence) show the opposite trend. This aligns with intuitive expectations regarding the emotional content of music and its impact on danceability.
- Extremes in acousticness are more often associated with sad songs, while the loudness feature inversely correlates with sadness, suggesting quieter songs are more likely to evoke sadness.
- Tempo analysis further supports that slower-paced songs are more often perceived as sad compared to their faster counterparts.

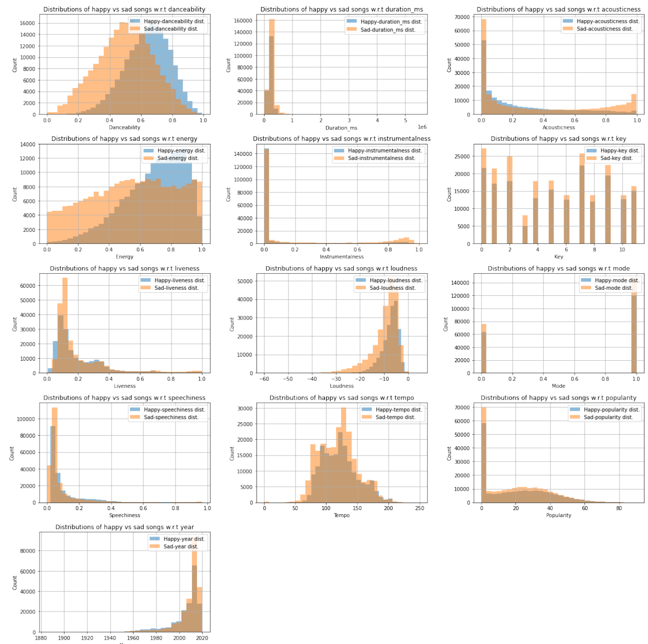

Figure 2: Plots throwing light on context (in this case, mood - happy or sad) based recommendation

3.5 Initial Data Insights

From the exploratory data analysis, several initial insights were gathered:

- The significant impact of sentiment scores on music recommendation, emphasizing the need for context-aware recommendation systems.
- The potential for deep learning models to capture complex patterns in music preference and listening behavior.

The exploratory data analysis provided foundational insights into the datasets, guiding the subsequent modeling efforts. By understanding the data's characteristics, the team can better tailor the recommendation system to incorporate user sentiment and track features effectively.

4 METHODOLOGY

In this project, a multi-faceted approach will be adopted to enhance the accuracy of song recommendations for users. The following methods will be explored and implemented:

1. *Collaborative Filtering*: Collaborative filtering techniques will be employed to analyze user preferences and behaviors, leveraging similarities between users to generate personalized song recommendations.

2. *Linear Regression*: Linear regression models will be utilized to establish relationships between various song features and user preferences. This approach will involve identifying significant features and predicting user preferences based on regression analysis.

3. *Graph-Based Models*: Graph-based models will be investigated to represent the relationships between users, songs, and their attributes. Graph algorithms will be applied to uncover patterns and

connections within the data, leading to more accurate recommendations.

In contrast to existing methods, our approach aims to offer a more comprehensive understanding of the user's circumstances, thereby refining the recommendations. By integrating principles from Factorization Machines to handle sparse data and facilitate efficient interaction among features (users, items, context), this method holds the potential to significantly enhance recommendation relevance, particularly by factoring in user mood as a contextual element.

Further details on the implementation and integration of these methods will be determined as the project progresses. The selection of specific algorithms, data preprocessing techniques, and evaluation metrics will be based on empirical analysis and experimentation. Additionally, the incorporation of additional methods or refinements to existing approaches may be considered based on interim findings and feedback.

5 EXPERIMENTS

The experiments will involve performing hyperparameter tuning on various machine learning models to optimize their performance. By systematically tuning the hyperparameters of various models and evaluating their performance, we aim to identify the most effective model configuration for the task of music recommendation. This iterative process allows us to fine-tune the models and optimize their performance, ultimately leading to more accurate and reliable recommendations for users.

6 RESULTS

Comparing the performance of the tuned models using appropriate evaluation metrics, such as accuracy, precision, recall, F1-score, etc., to determine which model performs best. Descriptive perforamnce graphs will also be provided.

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