Adaptive Melodies: A User-Shift Preference Music Recommendation System

DISCLAIMER

The adaptive melodies project prioritizes building an effective recommendation system that solves music recommendation bias in user adaptability, therefore it doesn't dwell on overseeing the ethical side of user privacy. Kindly know that this project is one of two, with the other (which is not included in this project) focusing on user privacy concerns using a decentralized recommendation system. My reason for not adding it is due to the given timeframe for the submission of the project and since it deals with a lot of research work, I have not gotten enough idea to implement this yet. However, after the success of this project, the decentralized recommendation system will be looked into.

INTRODUCTION

Recommendation systems have emerged as crucial tools for navigating content, which guides users through an overwhelming array of choices in several domains such as entertainment, e-commerce, news and social media. By fitting selections based on user preferences, these systems aim to enhance user engagement, boost content consumption and optimize the overall user experience. Although these systems may be robust, they face an inherent challenge: the dynamic nature of human preference.

For this reason, "user-shift preference", which is a phenomenon where users change their tastes and preferences over time, poses a significant challenge to the efficiency of recommendation systems. Some of these shifts include evolving personal circumstances, exposure, or a changing stage of life (from a teenager to an adult). In a situation when a recommendation system fails to account for these shifts, the system begins to experience looming risks thereby presenting users with outdated or irrelevant suggestions.

Recognizing and addressing the problem of use-shift preference is not just a matter of building sophisticated algorithms - it is fundamental to the core purpose of the recommendation system. Therefore this challenge proves imperative, and the continuous growth in the technology ecosystem creates a necessity to ensure that recommendation systems remain dynamic, responsive, secured and in tune with the fluidity of human preference.

PROJECT DESCRIPTION

In building music recommendations, recognizing user's preferences are dynamic. Over time, listeners evolve, explore new genres, and shift away from previously adored tracks. A system that can adapt to these ever-changing preferences can greatly enhance user satisfaction and engagement

Problem to be solved: The key issue that this project addresses is the inherent dynamism in users' musical preferences. To challenge this proposed problem, the solution is divided into two folds;

1. Detecting the shift in preferences in real-time or near-real-time.
2. Modifying the recommendation engine to adapt to these detected shifts promptly.

Existing Solutions: Several approaches have been taken to solve this problem:

1. Collaborative Filtering: A traditional method that uses recommended items other users have liked. However, its effectiveness diminishes when users deviate from their previous patterns.

2. Content-based Filtering: This recommends items by comparing the content of the items and a user profile, which contains descriptors that are inherent to the item (e.g., a song's genre, or artist). It's limited by the descriptors used and may not capture evolving nuances of user preference.

3. Hybrid Methods: Combines collaborative and content-based filtering to provide recommendations. It is more effective but lacks the adaptiveness needed for rapidly shifting preferences.

4. Time-Decay Models: With recent interactions given more weight, ensuring the model leans on recent preferences. While this approach can capture shifts, the decay parameters need careful tuning, and it might still miss sudden changes in taste.

PROPOSED METHOD

My objective is to experimentally evaluate the effectiveness of Graph Neural Networks (GNNs), in comparison with a baseline model of the Time-Decay Collaborative Filtering (TDCF) in addressing user-shift preference in music recommendation.

The DS/ML pipeline includes all the following;

1. Data collection: Obtaining any of Spotify API, Last.fm and Million Song datasets are the three likely suitable datasets to use for this project

2. Data preprocessing: This involves cleaning and splitting the dataset

3. Feature Engineering: Extraction of temporal features like interaction frequency, seasonal patterns, etc.

4. Model development & training (both models): This includes building the model pipeline for both the time decay collaborative filter (TDCF) and the graph neural networks (GNNs)

5. Model Evaluation: Usage of necessary evaluation metrics like mean average precision (MAP), among others

6. Model deployment: After identifying the superior model, this process involves integrating the model into the recommendation system infrastructure

PROPOSED SPLIT

Project contributor: Samuel Oyeneye

PROPOSED TIMELINE

The table below provides a summary overview of the milestones for the completion of this project with time durations;

S/N	PROJECT MILESTONES	TIME DURATION
1.	Data sourcing	2 weeks
2.	Data cleaning	1 week
3.	Data splitting	1 week
4.	Feature engineering	2 weeks
5.	TDCF: Model development/training	2 weeks
6.	GNNs: Model development/training	2 weeks
7.	Model evaluation	1 week
8.	Parameter optimization/insight generation	2 weeks
9.	Model deployment: frontend & backend	2 weeks
10.	Iteration/testing	2 weeks
	TOTAL	**17 WEEKS (~4 MONTHS)**

CONCLUSION

As the digital music landscape continues to evolve, the user-shift preference recommendation system offers a dynamic, adaptive solution that aligns with listeners' changing tastes. Therefore, by utilizing both Time Decay Collaborative Filtering and GNNs, the system promises more relevant, adaptive music suggestions. As the potential to make user shift preferences continues to grow, future extensions could delve into integrating and leveraging real-time feedback loops to further enhance recommendation accuracy and user satisfaction. For now, the timeframe for this project seems feasible but there may be some setbacks along the way, but my aim is to complete the project within the stipulated timeframe (if possible).

REFERENCES

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