P7: Recommendation System

Team Members:

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Roles of Team Members:

1. Chinmay Janwalkar: Project Coordinator, Data Acquisition
2. Isha Kaushik: Literature Review, Model Development
3. Nihar Nayak: Data Preprocessing, Baseline Implementation
4. Prashant Gaurav: Advanced Techniques Integration, Model Evaluation
5. Priyanka Ojha: EDA, Report Preparation, Presentation

Problem Description:

This project aims to build an advanced recommendation system using state-of-the-art collaborative filtering techniques inspired by methodologies developed in the Netflix Prize competition, subsequent research papers, and Netflix's insights into navigating feedback loops in recommender systems. Personalized content delivery is a crucial component of platforms like Netflix, Amazon, and Spotify, and the effectiveness of these platforms hinges on algorithms that can provide highly accurate and relevant recommendations.

Traditional recommendation systems often face challenges such as data sparsity, user cold-start issues, and the dynamic nature of user preferences. A notable challenge, as outlined in the Netflix research paper, is the feedback loop inherent in recommendation systems. When users interact with recommendations, they influence future algorithmic outputs. This feedback loop can lead to issues like popularity bias, where highly recommended items gain even more visibility, overshadowing niche but potentially relevant content.

Our project addresses these challenges by exploring advanced collaborative filtering methods that can capture user-item interactions more effectively and efficiently while incorporating strategies to manage the feedback loop in dynamic environments. We will focus on matrix factorization-based approaches, which offer a robust way to reduce the dimensionality of the user-item interaction space, providing better scalability and accuracy. Additionally, by integrating contextual and temporal factors, we aim to build a dynamic recommendation system that can adapt to changing user preferences over time. Incorporating social and contextual information will further enhance the recommendations by considering user-item interactions and the relationships and dependencies among users.

The project aims to provide a comprehensive solution by comparing traditional methods with advanced models, refining the recommendation system's performance, and optimizing it to meet the evolving demands of real-world applications. We will also explore the system's ability to self-correct and evolve, examining how incorporating user feedback in real-time can further optimize recommendations.

Preliminary Plan (Milestones):

1.) **Milestone 1: Problem Understanding and Literature Review**
Conduct an in-depth literature review to understand traditional and advanced collaborative filtering methods. Identify key research gaps and formulate the project's objectives.

2.) **Milestone 2: Data Preparation and Exploration**
Acquire and preprocess the required datasets, perform exploratory data analysis (EDA) to identify trends, and prepare the data for model development. Preprocess the data, handling missing values, normalizing features, and converting data into a user-item interaction matrix.

3.) **Milestone 3: Model Development and Baseline Implementation**
Develop baseline models using traditional collaborative filtering techniques to establish reference metrics and understand the basic data patterns.

4.) **Milestone 4: Advanced Techniques**
Implement advanced models like matrix factorization and hybrid approaches, integrating contextual and temporal factors to improve recommendation accuracy. Address the feedback loop challenge, where user interactions influence future recommendations, by implementing techniques to balance feedback and novelty, reducing popularity bias and improving recommendation diversity.

5.) **Milestone 5: Model Evaluation and Optimization**
Evaluate model performance using metrics such as RMSE and precision/recall. Optimize models through hyperparameter tuning and feature engineering.

6.) **Milestone 6: Final Evaluation and Report Preparation**
Compare all models to see which performs best and how they adapt to changing user preferences. Consolidate results, prepare the final report and presentation, and provide recommendations for future work based on findings and challenges encountered.

References:

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