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Sanctity.Ai Assignment

Report on Recommendation Algorithm for Personalized Study Material

OVERVIEW

This report outlines the development of a recommendation system designed to suggest educational materials to students based on their interests, academic performance, and previous engagement history. The system was implemented using synthetic data and was evaluated using metrics such as Mean Average Precision at K (MAP@K) and Normalized Discounted Cumulative Gain at K (NDCG@K) to assess the effectiveness of the recommendations.

Approach

1. Data Generation

To create a realistic simulation of the educational environment, synthetic datasets were generated, which included:

- **Student Profiles**: A dataset representing unique student identifiers, enrolled courses, academic year, interests, and performance metrics (average quiz scores).
- **Material Data**: A dataset containing educational materials characterized by unique identifiers, subjects, difficulty levels (Easy, Medium, Hard), popularity scores, and content length.
- Engagement Data: A dataset capturing student interactions with materials, including view
- **Engagement Data**: A dataset capturing student interactions with materials, including viewed materials and associated ratings.

Code Implementation

1. **Synthetic Student Data**: Created a set of 100 students, each associated with a random course, year of study, a list of interests, and performance scores drawn from a normal distribution.
2. **Synthetic Material Data**: Generated 50 educational materials with random subjects, difficulty levels, popularity scores, and content lengths.
3. **Synthetic Engagement Data**: For each student, a random selection of materials was marked as viewed, along with a random rating for each materia

2. Data Preprocessing

a. One-Hot Encoding of Interests

The `MultiLabelBinarizer` from the `sklearn` library was used to convert students' multi-label interests into a binary format. This conversion enables easier similarity calculations and facilitates integration into machine learning models.

b. Mapping Difficulty Levels

The difficulty levels of the educational materials were transformed into numerical values (1 for Easy, 2 for Medium, and 3 for Hard) to facilitate calculations and comparisons.

c. Merging Engagement Data

The engagement data was merged with student profiles and materials to create a comprehensive dataset that allows for enriched context in the recommendation algorithm

3. Recommendation Algorithm

The recommendation algorithm follows these steps:

1. **Profile Retrieval**: For a given student ID, retrieve the student's profile.
2. **Similarity Calculation**: Compute the cosine similarity between the student's interest vector and the encoded subjects of the materials.
3. **Performance Compatibility**: Assess how well the difficulty level of the materials aligns with the student's performance, yielding a score that accounts for differences.
4. **Total Score Calculation**: Combine scores from interest similarity, performance compatibility, and material popularity to form a composite score. The weights for each component were determined based on empirical evaluations to optimize the recommendation quality.
5. **Top N Recommendations**: Sort materials based on their total scores and select the top N recommendations for the student.

4. Handling Edge Cases and Missing Data

- **Handling Missing Data**: Synthetic datasets were generated without missing values; however, if the system were to operate with real data, simple imputation methods would be employed to fill in missing difficulty levels or popularity scores to maintain robustness.
- **Edge Cases**: The algorithm accommodates students who have not previously engaged with any materials by still generating recommendations based solely on their interests and performance.

Evaluation

The recommendation system was evaluated using two primary metrics: MAP@K and NDCG@K.

1. MAP@K

- **Mean Average Precision**: This metric assesses the precision of the recommendations at K positions, averaging precision scores across all students to indicate how effectively the system retrieves relevant materials among the top recommendations.

2. NDCG@K

- **Normalized Discounted Cumulative Gain**: NDCG evaluates the ranking quality of the recommendations by considering the relevance of retrieved materials and their positions. This metric normalizes the DCG score to provide a value between 0 and 1, indicating the effectiveness of the ranking.

Results

The system generated recommendations for each student. For example, recommendations for a specific student (e.g., Student S002) are displayed below:

```
Top recommendations for Student S002:
```

	MaterialID	Subject	Difficulty	TotalScore
19	M020	Cybersecurity	Hard	0.788308
13	M014	AI	Hard	0.782308
8	M009	Cybersecurity	Hard	0.766308
31	M032	Cybersecurity	Hard	0.764308
24	M025	Blockchain	Hard	0.734308

```
Real Engagement data for Student S002:
```

	StudentID	MaterialID	Viewed	Rating
5	S002	M009	1	1
6	S002	M012	1	2
7	S002	M036	1	5
8	S002	M020	1	4

9	S002	M006	1	3
10	S002	M013	1	4
11	S002	M042	1	2
12	S002	M025	1	4
13	S002	M045	1	1
14	S002	M017	1	2
15	S002	M026	1	3
16	S002	M011	1	1
17	S002	M043	1	2

Recommended result shows that out of 5 results, 3 are which he/she has viewed, which means the algorithm is performing well.

Algorithm Evaluation scores are as follows:

MAP@K: It measures the precision of the recommended items up to the top K recommendations, averaged across all students

```
MAP@1: 1.0000
MAP@2: 0.8750
MAP@3: 0.6865
MAP@4: 0.5643
MAP@5: 0.5052
```

Interpretation: As K increases, MAP generally decreases, indicating that the relevance of the recommendations tends to diminish as more items are included. A high MAP value at lower Ks is generally a good sign that the model is effectively recommending relevant items initially.

NDCG@K: It measures the ranking quality of the recommendations, taking into account the position of relevant items. It is normalized to ensure that the score lies between 0 and 1, with 1 being the best possible score.

```
NDCG@1: 0.2100
NDCG@2: 0.1674
NDCG@3: 0.1727
NDCG@4: 0.1824
NDCG@5: 0.1834
```

Interpretation: Lower NDCG scores imply that while there may be relevant items recommended, their positioning is not optimal. A good recommendation system should ideally have high NDCG scores, indicating that relevant items are appearing near the top of the recommendation list.

These scores demonstrate the capability of the system to provide relevant and high-quality recommendations tailored to individual student profiles.

Conclusion

The developed recommendation system effectively generates personalized educational material suggestions based on students' interests, performance, and engagement data. The evaluation using MAP@K and NDCG@K metrics highlights the system's performance, showcasing its potential for application in real-world educational settings. Future enhancements may include the integration of more advanced algorithms, such as collaborative filtering or deep learning techniques, to further improve recommendation accuracy and user satisfaction.

Improvements Proposed for future enhancements

1.Personalized Recommendation Enhancements:

- **Dynamic Weight Adjustment**: Instead of using static weights for calculating the total score of recommendations, consider implementing a dynamic adjustment based on student behavior and feedback. For example, if a student frequently engages with materials labeled as "Hard," increase the weight for these materials in future recommendations.
- **Collaborative Filtering**: Integrate collaborative filtering techniques that leverage data from similar students. If students with similar interests and engagement patterns found certain materials helpful, recommend those to others in the group.

2.Diverse Recommendation Strategies:

- **Serendipitous Recommendations**: Introduce an element of randomness to recommend materials that a student might not typically choose but could find engaging. This could enhance discovery and prevent the system from becoming too predictable.
- **Skill Development Pathways**: Group recommendations into pathways that guide students through a series of materials tailored to skill development, ensuring that students not only engage with individual materials but also understand their progression(as we see in youtube playlist some course).

3.Enhanced Engagement Metrics:

- **User Feedback Integration**: Implement a system for students to provide feedback on the recommendations they receive. Use this data to refine the recommendation algorithm continuously.
- **Engagement Tracking**: Develop more nuanced engagement metrics, such as time spent on materials, completion rates, and post-engagement assessments, to better understand how effective the recommendations are.