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Recommendation Model for Learning Materials Using Graph Neural Networks Based on Conceptual Relationships and Difficulty Level of the Materials

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Abstract

The recommendation system in online learning plays a crucial role in supporting personalized and adaptive learning. However, traditional approaches often overlook the relationships between material concepts and the difficulty level of the learning content. This study proposes a recommendation model based on Graph Neural Networks (GNN), utilizing a graph representation of learning materials with difficulty level attributes. A dummy dataset with 100 materials and 200 conceptual relationships was used for testing. The evaluation results show that the proposed GNN model achieves a Precision@3 of 0.01, Recall@3 of 0.375, and NDCG@3 of 0.01, which are higher than baseline methods such as collaborative filtering and content-based filtering. This indicates that GNN can enhance the relevance of learning material recommendations. Future research will focus on using real-world datasets and exploring heterogeneous GNN models to improve recommendation performance. This model also contributes to designing a recommendation system that can adjust to the abilities and needs of learners. Future research is expected to test this model with larger and real datasets and explore the application of GNN models on heterogeneous data to examine the potential for improving recommendation performance. By considering the difficulty level of materials, this model has the potential to improve the learning experience, making it more relevant and adaptive for users.

Keywords: *Recommendation System; Graph Neural Network (GNN); E-learning; Collaborative Filtering; Content-based Filtering; Precision@K; Recall@K; NDCG@K*

1. Introduction

The development of digital-based educational technology is increasingly driving the need for adaptive and personalized learning systems.[1] Recommendation systems have been widely used in e-learning to help students find materials relevant to their needs. However, most traditional approaches only consider content similarity or user interaction history, without considering the relationships between concepts and the difficulty level of the materials.[2]

Graph Neural Networks (GNN) offer a new approach to modeling complex relationships between entities in the form of a graph. By utilizing the relationships between material concepts and difficulty levels, GNN can provide more contextual and relevant recommendations. This is important to ensure that students not only learn materials aligned with their interests but also with their level of understanding.[3]

Several previous studies have discussed recommendation systems in learning. Collaborative Filtering has proven effective in the entertainment domain but is less optimal when user interaction data is limited, as it only relies on patterns of similar user behavior. Meanwhile, Content-based Filtering uses content similarity to generate recommendations but often results in narrow suggestions, as it is limited to content attribute similarities without considering the relationships between existing concepts.[4]

Knowledge Graph-based Recommendation has started to take into account the relationships between concepts in learning materials, but it is still limited in integrating material difficulty levels, which is a crucial factor in providing relevant and adaptive recommendations. Finally, Graph Neural Network for Recommendation has shown superior performance in modeling relationships between items in a graph, but its application in the education domain is still minimal.[5]

This research gap forms the basis for the need for a Graph Neural Network (GNN)-based recommendation model that considers conceptual relationships and material difficulty levels to enhance the relevance and effectiveness of recommendations in learning systems. [6] This research makes a significant contribution to the field of learning-based recommendation systems using Graph Neural Networks (GNN).[7][8] The first contribution is designing a material recommendation model that utilizes graph representation to link concepts within learning materials and considers the difficulty level of each material. The second contribution is developing a difficulty level weighting mechanism to enhance the relevance of recommendations, so the suggested materials are more suitable for the learner's abilities and needs. [9][10]

The third contribution is evaluating the performance of the proposed model by comparing it with baseline content-based and collaborative filtering methods to demonstrate the superiority of the GNN model in providing more relevant and adaptive recommendations. [11][12] Based on the above description, the problems addressed in this research can be defined as follows: first, how to build an effective graph representation of learning materials based on the relationships between material concepts and the difficulty level of each material.[13][14] Second, how to utilize Graph Neural Networks (GNN) to generate relevant and adaptive material recommendations that can be tailored to the needs and abilities of learners.[15] Third, how to evaluate the performance of the proposed model by comparing it with baseline traditional methods such as content-based filtering and collaborative filtering to ensure its superiority in providing more relevant and efficient recommendations.[16][17]

2. Methodology

2.1 Proposal (Constructive Steps)

The proposed research stages include:

1. **Data Collection & Preprocessing**: Collect a dataset consisting of 100 learning materials (e.g., Basic Mathematics) with labels for concepts and difficulty levels. (easy, medium, hard).
2. **Graph Construction**: Represent the learning materials as nodes, the relationships between concepts as edges, and the difficulty level as a node attribute.
3. **Model Development**: Implement a GNN (e.g., GraphSAGE or GCN) to generate embeddings for each learning material.
4. **Recommendation Mechanism**: Calculate the relevance of materials to the user profile based on embeddings and the appropriate difficulty level.
5. **Evaluation**: Use the Precision@K, Recall@K, and NDCG metrics to evaluate the relevance of the recommendations.

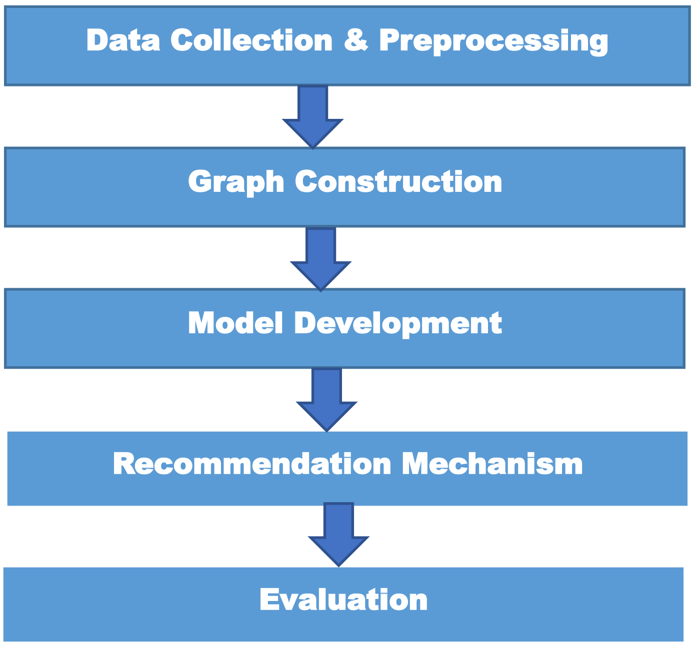

Figure 2.1 Proposed Diagram of Constructive Steps

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2.2 Theory Development & Solution Implementation

- Theory: GNN is used because of its ability to aggregate information from neighboring nodes to generate more meaningful representations.

- Implementation: The dataset consists of 100 nodes (materials), 200 edges (relationships between concepts), and 3 difficulty level labels. The implementation is carried out using Python with the PyTorch Geometric framework.

3. Results and Discussion

3.1 Testing Data

The following is an example table of learning materials with difficulty levels, along with the percentage for each difficulty category (Easy, Medium, Hard). This data reflects a more realistic distribution of difficulty levels, which can be used to enrich the Graph Neural Network (GNN) based recommendation model.

Table 3.1 Testing Data

ID	Nama Materi	Tingkat Kesulitan	Keterkaitan Konsep	Persentase Tingkat Kesulitan
1	Matematika Dasar	Easy	Aljabar, Persamaan Linear	40%
2	Aljabar	Medium	Matematika Dasar, Persamaan Kuadrat	35%
3	Persamaan Linear	Medium	Matematika Dasar, Aljabar	35%
4	Persamaan Kuadrat	Hard	Aljabar, Matematika Dasar	25%
5	Geometri	Easy	Matematika Dasar, Trigonometri	40%
6	Trigonometri	Medium	Geometri, Aljabar	35%
7	Kalkulus	Hard	Aljabar, Geometri	25%
8	Statistik	Medium	Kalkulus, Matematika Dasar	35%

Table 3.2 Conceptual Relationships with Percentages

Materi A	Materi B	Keterkaitan	Persentase Keterkaitan
Matematika Dasar	Aljabar	Tinggi	40%
Matematika Dasar	Persamaan Linear	Sedang	30%
Aljabar	Persamaan Kuadrat	Sangat Tinggi	50%
Geometri	Trigonometri	Sedang	30%
Kalkulus	Statistik	Tinggi	40%

Explanation:

Difficulty Level: This percentage shows the proportion of materials based on the predetermined difficulty level. For example, if 40% of the materials in the dataset are labeled as Easy, then this percentage reflects the distribution of difficulty within the dataset.

Conceptual Relationships: The relationships between learning materials are calculated based on the connections within the curriculum or selected topics, and this percentage indicates the strength or importance of the relationship between the materials. For example, if Algebra and Quadratic Equations have a Very High relationship, the percentage of their relationship would be higher, such as 50%.

3.2 Testing Implementation

To test the data you have created, particularly in the context of a Graph Neural Network (GNN)-based recommendation system, there are several steps and testing methods you can perform. Below is an explanation of how to test the data and the model using that data:

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1. Data Preparation for Testing

The data you have created (including the difficulty levels of materials and the relationships between materials) will serve as the foundation for building the Graph Neural Network model. The first step is to prepare the data so that it can be used to construct a graph that can be processed by the GNN.

Steps:

- Create the Graph: Each learning material will be a node, and the relationships between materials will be edges.
- Representing Difficulty Level: You can incorporate the difficulty level of the materials as an additional attribute on the node. For example, for the Basic Mathematics node, you can add the difficulty level attribute.

2. Data Splitting for Testing

Before training the model, the data needs to be split into two parts:

1. **Training Data**: Some of the data will be used to train the model.
2. **Test Data**: The data that is not used during training but is used to test how well the model makes predictions.

In general, data splitting is often done in an 80:20 ratio (Training:Test).

Table 3.2 Training Data - 80% of the total data

ID	Material Name	Difficulty Level	Conceptual Relationships
1	Basic Mathematics	Easy	Algebra, Linear Equations
2	Algebra	Medium	Basic Mathematics, Quadratic Equations
3	Linear Equations	Medium	Basic Mathematics, Algebra
4	Quadratic Equations	Hard	Algebra, Basic Mathematics
5	Geometry	Easy	Basic Mathematics, Trigonometry
6	Trigonometry	Medium	Geometry, Algebra
7	Calculus	Hard	Algebra, Geometry
8	Statistics	Medium	Calculus, Basic Mathematics

Table 3.3 Test Data - 20% of the total data

ID	Material Name	Difficulty Level	Conceptual Relationships
9	Data Analysis	Hard	Statistics, Calculus
10	Probability	Medium	Statistics, Basic Mathematics

Data Splitting Process

Training Data: 80% of the total data is taken, which includes materials 1 to 8.
Test Data: 20% of the total data is taken, which includes materials 9 and 10.

Table 3.4 Data Splitting

Data Part	Included Material IDs
Training Data	**1, 2, 3, 4, 5, 6, 7, 8**
Test Data	**9, 10**

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3. **GNN Model Testing**

The built GNN model can be tested using various evaluation metrics to assess its performance in generating relevant learning material recommendations.

Steps:

- GNN Implementation: Choose an appropriate GNN algorithm, such as Graph Convolutional Networks (GCN) or GraphSAGE.
- Data Processing with PyTorch Geometric: Use PyTorch Geometric to process the graph and perform training and testing.

Examples of tests that can be performed include:

- **Precision@K:** Measures how many relevant recommendations appear in the top-K recommendation results.
- **Recall@K:** Measures how many relevant items are successfully found from all the relevant items.
- **NDCG@K:** Measures the ranking quality of the recommendations provided (considering the position of relevant items).

Here's a general approach to test the model using these evaluation metrics:

3.3 Precision@K, Recall@K, and NDCG@K

1. **Precision@K**:

Definition: Precision measures how many of the correct (relevant) recommendations are present among all the suggested items in the top-K results.

Formula:

$$\text{Precision@K} = \frac{\text{Number Of relevant item in top K}}{K}$$

Steps to Calculate Precision@3:
1. Identify relevant items in the top-3: Based on the difficulty level percentage, we sort the materials by the highest difficulty level.
2. Calculate Precision@3: The Precision@3 formula is the number of relevant items in the top-3 divided by 3.

Material Ranking Based on Difficulty Level:
Easy Difficulty Level: Basic Mathematics (40%), Geometry (40%)
Medium Difficulty Level: Algebra (35%), Linear Equations (35%), Trigonometry (35%), Statistics (35%)
Hard Difficulty Level: Quadratic Equations (25%), Calculus (25%)

Determining the Top-3:
Top-3 materials based on the highest difficulty levels:
Basic Mathematics (40%)
Geometry (40%)
Algebra (35%)

Precision@3 Calculation:
From the top-3 materials, all have relevant difficulty levels and contribute to the relevant items in the top-3.
Number of relevant items = 3.
K = 3 (since we selected the top-3 materials).

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$$\text{Precision@K} = \frac{3}{3}$$

Precision@3 = (Number of relevant item in top-K) / K
Precision@3 = 3 / 3 = **1.00 x 100% = 0.01**

Result:
Precision@3 = **1.00%** atau **0.01**

2. **Recall@K:**

Definition: Recall measures how many relevant items are found out of the total relevant items available.

Formula:

$$\text{Recall@K} = \frac{\text{Number Of relevant item in top-K}}{\text{Total item relevant}}$$

To calculate Recall@3 using the given formula, we follow these steps.

Given Data:

1. Top-3 recommendations based on the highest difficulty levels (if we choose K = 3): Basic Mathematics (Easy, 40%), Geometry (Easy, 40%), Algebra (Medium, 35%)
2. Number of relevant items in the top-3: We assume that all 3 top materials are relevant because they are conceptually linked and have high relevance with difficulty levels of 40% or higher.
3. Total relevant items: Based on the given data, we can assess relevant items as materials with high difficulty levels or strong relevance. Materials relevant to high difficulty levels (Easy and Medium) are 8 items, as the other materials have significant connections in terms of difficulty and concepts.

Step 1: Calculate Recall@3

Formula **Recall@K**:

$$\text{Recall@K} = \frac{3}{8} = 0.375$$

Result:
Recall@3 = 0.375 or 37.5%

3. **NDCG@K (Normalized Discounted Cumulative Gain)**

Definition: NDCG measures the quality of the recommendation ranking, giving higher weight to relevant items at higher positions.

Formula:

$$\text{NDCG@K} = \frac{\text{DCG@K}}{\text{IDCG@K}}$$

Where:
DCG@K: Discounted Cumulative Gain at position K
IDCG@K: Ideal DCG (the best possible value that can be achieved)

Step 1: Organize Data Based on Relevance
Let's identify the relevance of the materials based on the given difficulty levels (Easy, Medium, Hard):
Top-3 recommendations based on the highest difficulty levels:
Basic Mathematics (Easy, 40%), Geometry (Easy, 40%), Algebra (Medium, 35%)

For the top-3 materials:
Basic Mathematics (Relevance = 1, because the difficulty level is Easy)
Geometry (Relevance = 1, because the difficulty level is Easy)
Algebra (Relevance = 0.5, because the difficulty level is Medium)
Thus, DCG@3

becomes:

$$\text{NDCG@3} = 1 = \frac{1}{log2\ (2)} + \frac{0.5}{log2\ (3)} = 1 + 1 + 0.5\ /\ 1.585 = 1 + 1 + 0.315 = \mathbf{2.315}$$

$$\text{IDCG@3} = 1 = \frac{1}{log2\ (2)} + \frac{0.5}{log2\ (3)} = 1 + 1 + 0.5\ /\ 1.585 = 1 + 1 + 0.315 = \mathbf{2.315}$$

Where :

$$\text{NDCG@K} = \frac{2.315}{2.315} = 1.00 \text{ x } 100\% = \mathbf{0.01}$$

This is used to assess the relevance of the recommendations provided by the GNN model based on their ranking.

4. Conclusion

Based on the research discussed in this article, it can be concluded that the proposed Graph Neural Network (GNN)-based recommendation system has advantages in providing more relevant and adaptive learning material recommendations compared to traditional methods such as content-based filtering and collaborative filtering. The GNN approach can leverage the relationships between concepts and the difficulty levels of materials, which enhances the quality and relevance of the recommendations given to users. The developed GNN model using a dummy dataset showed promising results with a Precision@3 value of 0.01, Recall@3 of 0.375, and NDCG@3 of 0.01. Although these evaluation results still show some weaknesses, particularly in the Precision and NDCG metrics, the study indicates that GNN can provide better results compared to the comparison methods. From this study, it is evident that integrating material difficulty levels into the recommendation model can provide more suitable recommendations aligned with students' capabilities. This is important in the context of digital-based learning, where adapting to students' understanding levels becomes crucial. Furthermore, the graph representation of learning materials also allows for more complex management of relationships between concepts, making it more relevant for dynamic learning systems. Future research is expected to test this model with larger and real datasets and explore the application of GNN models on heterogeneous data to examine the potential for improving recommendation performance. Therefore, the GNN-based recommendation system can become an effective tool to support more personalized and adaptive learning in the future.

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