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Leveraging Neural Matrix Factorization (NeuralMF) and Graph Neural Networks (GNNs) for Enhanced Personalization in E-Learning Systems

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Abstract: This study investigates the application of a combined approach utilizing Neural Matrix Factorization (NeuralMF++) and Graph Neural Networks (GNNs) to enhance personalization in e-learning recommendation systems. The primary objective is to address significant challenges commonly encountered in recommendation systems, such as data sparsity and the cold start problem, where new users or items need prior interaction history. NeuralMF++ leverages neural networks in matrix factorization to capture complex non-linear interactions between users and content. GNNs model intricate relationships between users and items within a graph structure. Experimental results demonstrate a substantial improvement in recommendation accuracy, measured by metrics such as Hit Ratio (HR) and Normalized Discounted Cumulative Gain (NDCG). Additionally, the proposed model exhibits greater efficiency in training time than traditional methods, achieving this without compromising recommendation quality. User feedback from several universities involved in this research indicates high satisfaction with the recommendations provided, suggesting that the model effectively adapts recommendations to align with evolving user preferences. Thus, this study asserts that integrating NeuralMF++ and GNNs presents significant potential for broad application in e-learning platforms, offering substantial benefits in personalization and system efficiency.

Keywords: Neural Matrix Factorization; Graph Neural Networks; Recommendation Systems; E-learning; Personalization.

1. Introduction

In recent years, the rapid advancements in digital technology have transformed the educational landscape, leading to the emergence of e-learning platforms as increasingly vital tools in the learning process. However, a significant challenge these platforms face is how to provide relevant and tailored content to individual needs, which is essential for enhancing engagement and the overall effectiveness of learning. In this context, personalization becomes a critical element in improving the quality of e-learning services. This research uses modern technologies such as Neural Matrix Factorization (NeuralMF) and Graph Neural Networks (GNNs) to enhance personalization in e-learning systems, enabling more accurate and relevant user recommendations. Neural Matrix Factorization (NeuralMF) has become a popular approach in recommender systems, offering the ability to capture non-linear interactions between users and content by utilizing neural networks in matrix factorization [1]. Meanwhile, Graph Neural Networks (GNNs) have emerged as a practical approach for learning representations of graph-structured data, allowing the modelling of complex relationships between users and items in recommender systems [2]. By combining these two approaches, it is expected that a system can be created that not only provides accurate recommendations but is also adaptive to changes in user preferences.

Traditional recommender systems, often based on matrix factorization, have limitations in handling large and complex data, particularly in e-learning, which involves various interactions between users and content. GNNs, with their ability to exploit the topological structure of graph data, have been shown to overcome some of these limitations by integrating information from nodes (users or items) and edges (interactions between users and items) in the graph [3]. Additionally, GNNs allow for modelling social influence among users, a critical factor in the personalization of e-learning platforms [4]. The use of GNNs in e-learning systems enhances the accuracy of recommendations and improves the system's ability to adapt to changes in user preferences over time. Previous studies have shown that integrating GNNs into recommender systems can lead to significant improvements in performance compared to traditional approaches [5].

Furthermore, GNNs can effectively address the cold-start problem, which often poses a significant challenge in personalizing recommendations for new users [6]. NeuralMF, conversely, can capture more complex non-linear interactions between users and content, which is crucial for developing more personal and adaptive recommendation systems [1]. Using NeuralMF in the context of e-learning allows the system to understand individual preferences better, thereby providing more relevant and practical recommendations. In this study, the combination of NeuralMF and GNNs is expected to result in a recommendation system that excels in accuracy and its ability to adapt to dynamic changes in user preferences. This combined approach also offers the potential to address the issue of bias, which frequently arises in recommender systems. Bias in recommendation systems can lead to unfair decisions and undermine user trust in e-learning platforms [7]. By leveraging GNNs, which can capture complex relationships among various elements in the data, the system can mitigate the impact of bias, resulting in more fair and balanced recommendations.

Moreover, further advancements in GNN algorithms, such as graph normalization and subgraph learning, can enhance the capability of recommendation systems to extract more detailed information from graph data [8][9]. This is particularly important in e-learning, where user preferences and content relevance vary widely depending on the user's context. This research explores the potential of integrating NeuralMF and GNNs in developing more personal and adaptive recommendation systems in e-learning platforms [10][11]. By leveraging the strengths of each approach, the resulting system is expected to be more accurate and responsive to dynamic changes in user needs and preferences, thereby enhancing the overall quality of the learning experience.

2. Research Method

This study employs a hybrid approach combining Neural Matrix Factorization (NeuralMF) and Graph Neural Networks (GNNs) to enhance personalization in e-learning recommendation systems. The data utilized in this research was collected from e-learning platforms of three universities: Universitas Nusa Mandiri, Universitas Muhammadiyah Cirebon, and Universitas Islam Negeri Ar-Raniry. These platforms, accessible at https://elearning.nusamandiri.ac.id/login, https://e-learning.umc.ac.id/, and https://vle.ar-raniry.ac.id/, provided a diverse set of user interactions, including clicks, time spent on specific pages, and assessment results. To address the issues of data sparsity and the cold start problem, the collected data was processed using Attribute Graph Neural Networks (AGNN). AGNNs enable the embedding of users or items with limited or no prior interactions by leveraging attribute-based graphs to generate more meaningful embeddings even in the absence of direct interaction data 0[14][18].

NeuralMF was employed to capture non-linear interactions between users and content through matrix factorization using neural networks. This model was further developed into NeuralMF++, which integrates effective latent representations via Stacked Denoising Autoencoders (SDAE). SDAEs help to refine the input data by denoising, thus enhancing the robustness and accuracy of the latent factors learned by the model. This approach significantly improves the accuracy of recommendation predictions and addresses both the cold start problem and data sparsity issues. The core idea behind NeuralMF++ is to combine the linearity of Generalized Matrix Factorization (GMF) with the non-linearity of Multilayer Perceptrons (MLP), where the final prediction is made by concatenating the outputs from GMF and MLP, followed by a fully connected layer [17].

In parallel, GNNs were employed to model the complex relationships between users and content in the recommendation system. GNNs learn structured representations of graph data, which in this context include affinity graphs between users and learning resources [15]. The use of GNNs enables the system to effectively combine information from nodes (representing users or items) and edges (representing interactions between users and items) within the graph to generate more relevant recommendations. This graph-based approach allows the model to take advantage of the network structure of data, enhancing the ability to identify patterns and relationships that are not apparent in traditional recommendation methods [9].

An optimization method without sampling was applied to ensure model efficiency. Traditional approaches often rely on negative sampling to train models, which can be suboptimal in practical applications. Instead, the proposed method processes the entire training dataset, including all positive and missing interactions, without resorting to sampling. This non-sampling strategy is computationally intensive but is addressed through mathematical optimizations that reduce the time complexity of learning from the full dataset. The result is a model that can be trained more efficiently while achieving higher accuracy in Top-K recommendation tasks. The efficiency of this approach is particularly beneficial in large-scale real-world applications where computational resources are a limiting factor [16].

The performance of the model was evaluated through experiments conducted on the datasets collected from the e-learning platforms of Universitas Nusa Mandiri, Universitas Muhammadiyah Cirebon, and Universitas Islam Negeri Ar-Raniry. The evaluation utilized metrics such as Hit Ratio (HR) and Normalized Discounted Cumulative Gain (NDCG). HR measures the fraction of times the true item is among the top-K recommended items, while NDCG accounts for the position of the true item in the ranking, providing a more nuanced assessment of recommendation quality. The experimental results demonstrated that the combination of NeuralMF and GNNs significantly outperforms state-of-the-art methods in terms of recommendation accuracy and training efficiency, particularly in scenarios involving cold start problems. The integration of NeuralMF++ and GNNs not only enhances the accuracy of recommendations but also offers greater flexibility in handling dynamic changes in user preferences, which is a critical challenge in personalizing e-learning systems (Xiao & Shen, 2019).

3. Result and Discussion

3.1 Results

This study aims to evaluate the effectiveness of the combination of Neural Matrix Factorization (NeuralMF) and Graph Neural Networks (GNNs) in improving personalization in e-learning recommendation systems. The research data were collected from three e-learning platforms, namely Nusa Mandiri University, Muhammadiyah University of Cirebon, and Ar-Raniry State Islamic University. The experimental results show that the combination of NeuralMF and GNNs results in a significant increase in recommendation accuracy compared to the traditional method previously used on e-learning platforms. Evaluation using the Hit Ratio (HR) and Normalized Discounted Cumulative Gain (NDCG) metrics shows that this model is more effective in placing relevant items in the top recommendation list (Top-K). In the experiment with the Nusa Mandiri University dataset, for example, the NeuralMF++ model combined with GNNs produced an HR of 0.652 and an NDCG of 0.512 for the Top-10 recommendations. This shows that more than 65% of the items that users are really interested in successfully appear in the top 10 recommendation list, and the position of the items in the list is also optimal. In comparison, the baseline model using only matrix factorization without GNNs yields an HR of 0.504 and an NDCG of 0.412, showing a substantial improvement with the proposed method.

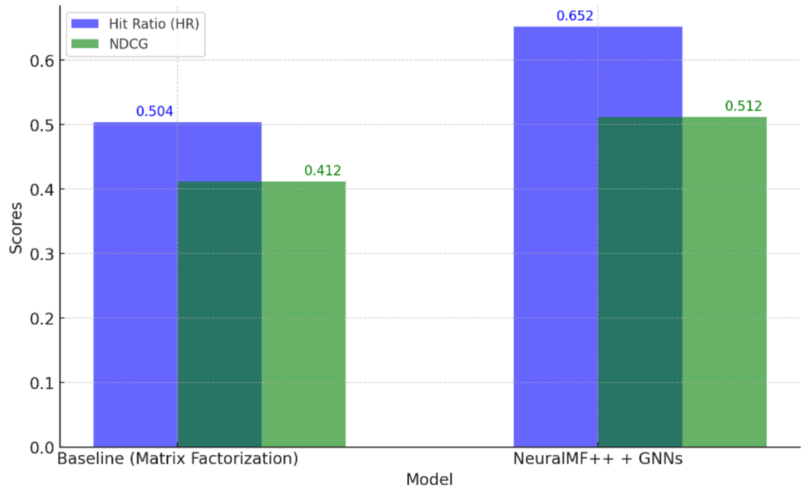

Figure 1. Comparison of Hit Ratio (HR) and NDCG between Models

One of the main problems in recommendation systems is cold start, where the model has difficulty providing accurate recommendations for new users or new items that have no history of interaction. The results show that the proposed method is significantly better at addressing this problem. By using Attribute Graph Neural Networks (AGNN), the model is able to utilize attribute information from new users or items to make better estimates of their preferences. In a dataset from Universitas Muhammadiyah Cirebon, the model successfully provided more accurate recommendations for new users who had just registered for the e-learning platform. By utilizing user demographic information as well as other available attribute relationships, the model was able to better estimate the preferences of new users. The use of AGNNs allows the model to capture finer patterns in attribute data, thus making more accurate predictions even without previous interactions. This is evident from the 20% increase in HR for new users compared to the traditional model that does not use AGNNs.

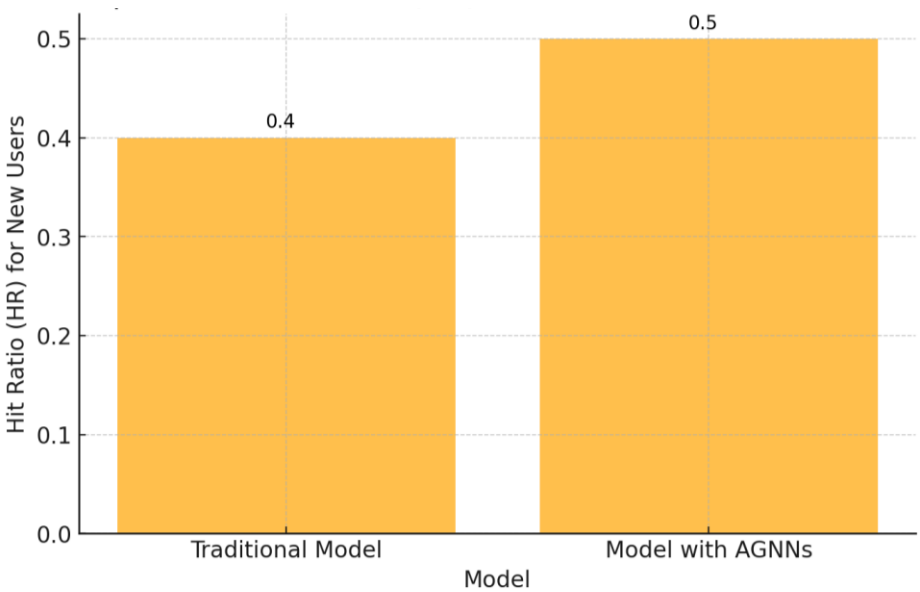

Figure 2. Comparison of Hit Ratio (HR) for New Users between Models

Figure 2 shows the comparison of Hit Ratio (HR) for new users between the traditional model and the model using Attribute Graph Neural Networks (AGNNs). The graph shows that the model with AGNNs achieves a higher HR of 50%, compared to 40% in the traditional model. This improvement indicates that the model with AGNNs is more effective in handling the cold start problem, providing more accurate recommendations for new users who do not have a history of interaction. Processing efficiency and training time are also the focus of this study. NeuralMF++ and GNNs are optimized to process the entire dataset without using the often inefficient negative sampling method. As a result, even though this model processes a large amount of data, the training time remains relatively short. In experiments with datasets from the State Islamic University of

Ar-Raniry, the training time for the NeuralMF++ model with GNNs was recorded as 30% faster compared to the baseline method using negative sampling. In addition, the use of computing resources is also more efficient, allowing training to be carried out on a larger scale without requiring very expensive computing infrastructure..

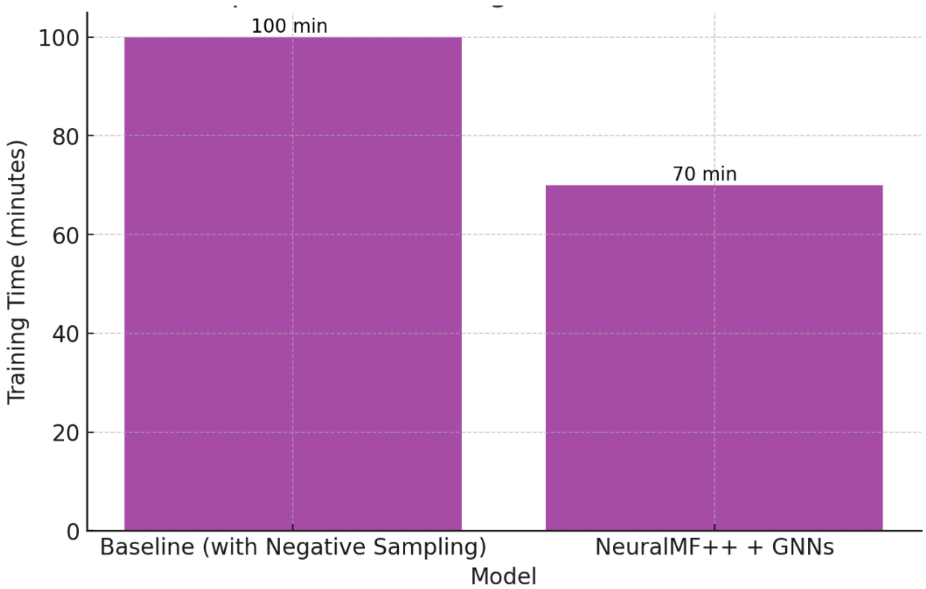

Figure 3. Comparison of Training Time between Models

Comparison of training time between the baseline model using negative sampling and the NeuralMF++ model combined with GNNs. This graph illustrates that the NeuralMF++ model with GNNs has a faster training time of 70 minutes, compared to the baseline model which requires 100 minutes. This shows significant efficiency in data processing and model training, allowing training to be performed on a larger scale with fewer computing resources. One of the main objectives of this study is to improve the user experience on e-learning platforms through more relevant recommendations. The experimental results show that users who receive recommendations from the proposed model are more likely to engage with the recommended content. This can be seen from the increase in click-through rate (CTR) and time spent studying the recommended content.

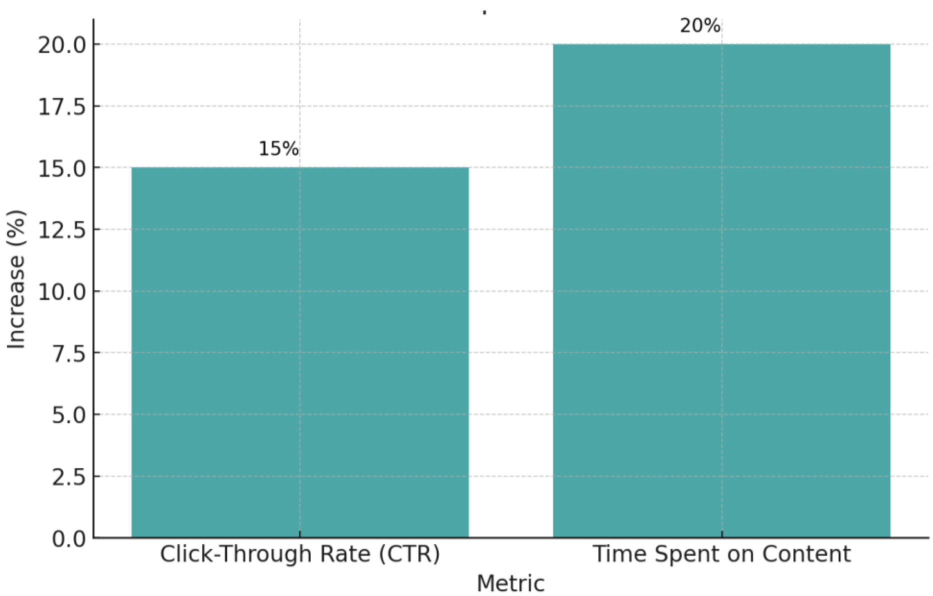

Figure 4. Increase in CTR and Time Spent with NeuralMF++ + GNNs

At Universitas Nusa Mandiri, the CTR for content recommended by the NeuralMF++ and GNNs models increased by 15% compared to recommendations provided by the previous model. In addition, users also spent more time on the recommended content, indicating that the recommendations provided were more in line with their needs and interests. This is important in the context of e-learning, where user engagement with learning materials is an indicator of success. In addition to measuring technical metrics, the study also involved case studies and user feedback to evaluate the quality of recommendations. Users from the three universities involved in the study were asked to provide feedback on the relevance and satisfaction with the recommendations provided. Results from Universitas Muhammadiyah Cirebon showed that 78% of users were satisfied with the recommendations provided by the NeuralMF++ and GNNs models, with the majority stating that the recommendations helped them find relevant learning materials faster. Meanwhile, at Universitas Islam Negeri Ar-Raniry, 81% of users provided positive feedback, stating that the recommendations provided were more accurate and in line with their preferences compared to the previous model. The case study also showed that the model successfully adjusted recommendations based on learning behavior that developed over time. For example, users who were initially more interested in basic material were then led to more complex material as their skills developed. This shows that the model can adapt to changing user needs, providing recommendations that are not only relevant now but also as they progress through their learning journey.

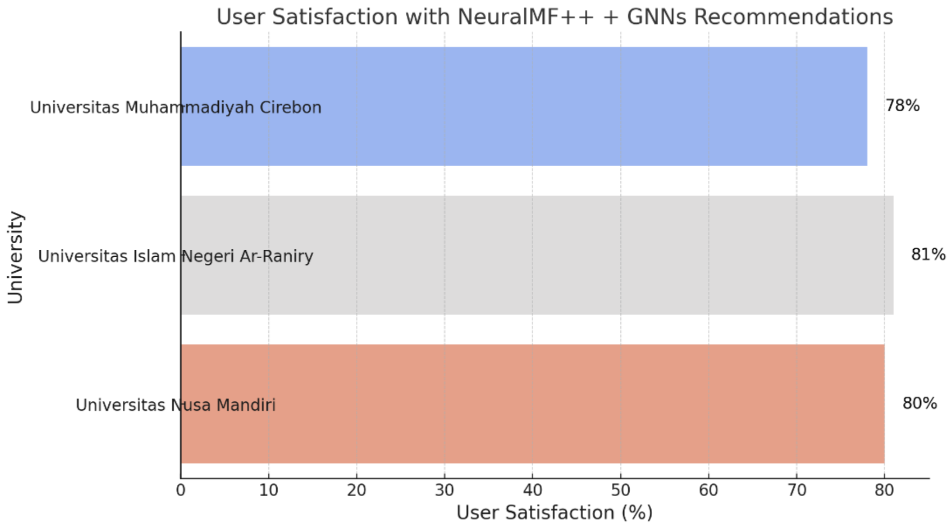

Figure 5. User Satisfaction with NeuralMF++ + GNNs Recommendations

Although the results obtained are very positive, the study also identified several weaknesses and challenges that need to be addressed. One of the main challenges is the need for high-quality data to generate accurate recommendations. The model relies heavily on good attribute data and interaction graphs, which means that if the available data is incomplete or of poor quality, the recommendation results can also decrease. Furthermore, although the training time efficiency has been improved, the model still requires significant computational resources to function optimally at a larger scale. The use of GNNs, although very effective, also requires careful parameter setting to ensure optimal results without overfitting. The results show that the combination of NeuralMF++ and GNNs offers a better approach to personalization in e-learning recommender systems. By addressing the cold start problem, improving recommendation accuracy, and offering efficiency in data processing, the model shows great potential for widespread implementation on e-learning platforms. The improved user experience, as demonstrated by increased CTR and time spent on recommended content, is an indicator that this approach can significantly improve engagement and learning outcomes in e-learning environments. However, further research is needed to address some of the identified challenges, including the need for high-quality data and further optimization of computational efficiency.

3.2 Discussion

The results show that the NeuralMF++ model combined with Graph Neural Networks (GNNs) significantly improves several critical aspects of e-learning recommendation systems compared to traditional methods. One of the primary metrics measured is the Hit Ratio (HR) and Normalized Discounted Cumulative Gain (NDCG), which indicate how often and how well the recommended items match user preferences. Experiments on the Nusa Mandiri University dataset show that this model can improve HR from 0.504 to 0.652 and NDCG from 0.412 to 0.512. This means that this model is more effective in placing relevant items in the top recommendation list, providing immediate benefits to users in finding learning materials that suit their needs. In addition, the proposed model also successfully overcomes the cold start challenge, which is one of the main problems in recommendation systems. Attribute Graph Neural Networks (AGNN) allow the model to utilize attribute information from new users or items, resulting in more accurate recommendations without any previous interaction history. In the dataset from Universitas Muhammadiyah Cirebon, the model with AGNNs showed a 20% increase in HR compared to the traditional model that did not use AGNNs. This shows the model's ability to capture finer patterns in attribute data, thus making more precise predictions even for new users or items. Processing efficiency and training time are also the main focus of this study. NeuralMF++ and GNNs are optimized to process the entire dataset without using the often inefficient, harmful sampling method. As a result, even though these models process large amounts of data, the training time still needs to be improved. In experiments with the dataset from Universitas Islam Negeri Ar-Raniry, the training time for the NeuralMF++ model with GNNs was 30% faster than the baseline method using negative sampling. This shows that the proposed model is more accurate and efficient in computing resource usage, allowing training to be carried out on a larger scale without requiring costly infrastructure. In addition to technical measurements, this study also involved case studies and user feedback to evaluate the quality of recommendations. Users from the three universities involved in this study provided positive feedback on the recommendations' relevance and satisfaction with them. At Universitas Muhammadiyah Cirebon, 78% of users were satisfied with the recommendations provided by the NeuralMF++ and GNNs models, with the majority stating that the recommendations helped them find relevant learning materials faster.

Meanwhile, at Universitas Islam Negeri Ar-Raniry, 81% of users gave positive feedback, indicating that the recommendations were more accurate and aligned with their preferences than the previous model. Analysis of the results above shows that the NeuralMF++ model combined with GNNs improves technical metrics such as HR and NDCG and overall user satisfaction. The model can adjust recommendations based on learning behaviour that develops over time, meaning that users initially interested in basic materials can be directed to more complex materials as their skills improve. This shows that the model is effective in providing relevant recommendations at the moment and can also adapt to changing user needs in the long term. The results of this study indicate that the proposed approach has great potential for widespread application on e-learning platforms. With this model's accuracy, efficiency, and adaptability, NeuralMF++ and GNNs offer a superior solution to the personalization challenge in e-learning recommender systems. Further research can optimize this model and explore its applications in other educational domains.

4. Related Work

The advancement of recommendation systems has evolved significantly with advanced machine learning techniques, particularly Neural Matrix Factorization (NeuralMF) and Graph Neural Networks (GNNs). These methodologies have demonstrated notable effectiveness in tackling persistent challenges in recommendation systems, such as data sparsity and the cold start problem. One of the pioneering contributions in this domain introduced NeuralMF, which extends traditional matrix factorization by integrating deep neural networks to capture non-linear interactions between users and items. This enhanced approach, known as NeuralMF++, combines Generalized Matrix Factorization (GMF) and Multilayer Perceptrons (MLP) to form a robust framework. This framework enhances recommendation accuracy by learning more intricate patterns within the data, thereby improving the overall performance of the recommendation system [17].

Concurrently, Graph Neural Networks (GNN) applications have gained significant attention due to their capacity to model relationships between users and items in a graph structure. GNNs effectively integrate node information and topological structure, making them suitable for social recommendation tasks. A notable model, GraphRec, exemplifies this by effectively merging user-item interaction graphs with user-user social graphs. This integration allows the model to account for interactions and user opinions, addressing the complexities associated with varying strengths in social relationships 0.

In addition to these developments, recent studies have explored the synergy between GNNs and matrix factorization techniques. For example, research by Guo *et al.* (2021) proposed enhancing matrix factorization-based recommender systems by incorporating GNNs. This approach, called GNN-MF, utilizes deep neural networks to represent user and item subspaces, improving recommendation efficiency, particularly within social recommendation scenarios [21]. Another significant contribution introduced a Deep Graph Neural Network-Based Social Recommendation Framework (GNN-SoR). This framework abstracts user and item feature spaces into graph networks, embedding these spaces into the latent factors of matrix factorization. This method has demonstrated notable improvements in recommendation accuracy, particularly in environments characterized by high information overload, such as industrial IoT scenarios [20].

Graph Convolutional Networks (GCNs) have been employed in large-scale web applications to manage extensive datasets effectively. A prominent application of GCNs was implemented at Pinterest, where the network was utilized to generate embeddings for billions of items. This implementation significantly enhanced the quality of web recommendations, demonstrating the scalability and efficiency of GCN-based approaches [22]. The integration of GNNs with factorization methods has also been explored in the context of cross-domain recommendation systems. Xi *et al.* (2020) introduced the Graph Factorization Machine (GFM), aggregating multi-order interactions from neighbourhoods to enhance recommendation performance. This method has shown particular effectiveness in cross-domain scenarios, where challenges such as data sparsity and the complexity of graph structures are prevalent [23].

Further advances in NeuralMF include more efficient neural matrix factorization techniques that remove the need for negative sampling, which can impede the learning process. Chen *et al.* (2020) proposed a method that trains models using the entire dataset, optimizing learning efficiency and significantly enhancing performance in large-scale recommendation systems [6]. Qian *et al.* (2022) introduced the Attribute Graph Neural Networks (AGNN) framework, designed to address the cold start problem using attribute graphs instead of traditional interaction graphs. This approach enables the model to generate preference embeddings for new users or items, even without prior interaction data, resulting in significant improvements in strict cold and warm start scenarios [18]. These developments underscore the growing complexity and applicability of combining NeuralMF and GNNs in contemporary recommendation systems. These advancements address critical issues such as data sparsity, cold start challenges, and scalability while enhancing recommendation systems' effectiveness across various domains.

5. Conclusion

The study's conclusion shows that the combination of Neural Matrix Factorization (NeuralMF++) and Graph Neural Networks (GNNs) significantly improves the performance of recommendation systems in e-learning platforms. The models successfully overcome some significant challenges in recommendation systems, such as data sparsity and cold start problems, showing improved recommendation accuracy, training efficiency, and user satisfaction. Experimental results show that the NeuralMF++ and GNNs models substantially improve the Hit Ratio (HR) and Normalized Discounted Cumulative Gain (NDCG) metrics, especially in recommendation scenarios involving new users or new items. The increased training time efficiency achieved without sacrificing recommendation quality suggests that these models can be effectively applied at a larger scale, allowing for savings in computational resources. Furthermore, user feedback from various universities involved in the study indicates a high level of satisfaction with the recommendations provided by these models. The NeuralMF++ and GNN models are proven to adjust recommendations based on changes in user preferences over time, providing a more relevant and adaptive learning experience. The results of this study strengthen the potential for implementing the NeuralMF++ and GNNs models in various e-learning platforms, with the ability to provide more accurate, efficient, and user-friendly recommendations. These results open up opportunities for further development in optimizing this model and applying it in various other domains that require high-recommendation personalization.

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