

Contrastive Embedding Techniques Uncover Learner-Item Relationships in Digital Education Platforms

Olmosbek Eshmuradov ^{a*}, Muhammad Khakimov ^b, Lobar Bakhramova ^c,
Shaxodat Akhmedova ^d, Kamol Hamroyev ^e, Nilufar Niyazova ^f,
Shoira Shoyimova ^g, Zafar Botirov ^h

^{a*} Associate Professor & Head, Department of Applied Psychology, Termez State Pedagogical Institute, Termez, Surkhandarya Region, Uzbekistan. E-mail: eshmuradovolmosbek@gmail.com,
Orcid: <https://orcid.org/0009-0008-0378-3027>

^b Professor, Fergana State University, Fergana, Uzbekistan.
E-mail: muhammadkhakimov67@gmail.com, Orcid: <https://orcid.org/0009-0009-7979-9233>

^c Teacher, Jizzakh State Pedagogical University, Jizzakh, Uzbekistan.
E-mail: lobarbaxramova22@gmail.com, Orcid: <https://orcid.org/0009-0000-7141-0742>

^d Lecturer, Department of English Language and Literature, Faculty of Foreign Philology, Termez State University, Termez, Uzbekistan. E-mail: shaxodataxmedova6@gmail.com,
Orcid: <https://orcid.org/0009-0004-1711-7181>

^e Associate Professor, Faculty of Military Education, Bukhara State Pedagogical Institute, Bukhara, Uzbekistan.
E-mail: khamraev9999@gmail.com, Orcid: <https://orcid.org/0000-0001-5884-8715>

^f Associate Professor, Department of Psychology, Mamun University, Khiva, Uzbekistan.
E-mail: niyazova_nilufar@mamunedu.uz, Orcid: <https://orcid.org/0009-0007-7731-0890>

^g Department of Pedagogy, Alfraganus University, Tashkent, Uzbekistan.

E-mail: sh.shoyimova@afu.uz, Orcid: <https://orcid.org/0009-0006-7638-361X>

^h Lecturer, Department of Social Sciences, Alfraganus University, Tashkent, Uzbekistan.
E-mail: zafaruz1978@gamil.com, Orcid: <https://orcid.org/0009-0009-2345-2468>

Abstract

For better personalization and performance of learners in digital education systems, it is essential to analyze the interplay between the learning materials themselves, the learners, and the educational institution. Detecting semantic similarity between learning items and learners is hard for classical recommendation models and performance prediction models, and they are hard to implement adaptive learning. This paper introduces an innovative CLIEN model that uses contrastive representation learning to learn embeddings of the learner and the educational items together in one space. The proposed model incorporates interaction history of the learner, evaluation outcomes, temporal patterns of learning and item meta data into a dual-encoder and contrastive loss-based structure to learn the most similarity between two relevant (learner, item) and minimize the similarity between two non-relevant (learner, item) objects. An adaptive attention mechanism helps refine the learned representations based on important behavioral features. Benchmark educational datasets were used to conduct experiments on the proposed model through an 80-20 split of training and testing data. The proposed CLIEN model is compared with collaborative filtering, matrix factorization, Deep Knowledge Tracing (DKT), and neural recommendation model. Experimental evaluation on benchmark educational datasets demonstrates that the proposed CLIEN framework consistently outperforms established baseline methods, including Collaborative Filtering (CF), Matrix Factorization (MF), Deep Knowledge Tracing (DKT), Neural Collaborative Filtering (NCF), and GNN-based Recommendation models. The proposed framework achieves superior Accuracy, Precision, Recall, F1-score, AUC, and NDCG@10, confirming the

effectiveness of contrastive learner-item embedding for personalized educational recommendation. The learned embedding space enables discovering the hidden relationships between the learners and the items, leading to the more accurate recommendation of items to the learners.

Keywords: Contrastive Learning, Learner-Item Embedding, Digital Education Platforms, Educational Data Mining, Representation Learning, Personalized Learning, Knowledge Tracing.

Introduction

The digital education platforms have revolutionized the access to learning resources by offering flexible, personalized, and interactive learning experiences. The volume of learner interaction data, such as clickstreams, quiz attempts, assignment submissions, viewing of videos, and discussion activities, that are produced in the context of Massive Open Online Courses (MOOCs), intelligent tutoring systems, and learning management systems, is enormous. These are diverse data sources that can offer the information on how well learners are engaged and learning is taking place. But it is still very difficult to model the complex relationships between learners and educational content, since learning behaviors are dynamic, sparse and highly individualized (Adhikary et al., 2026).

The traditional methods of recommendation systems in education are mainly the collaborative filtering method, content-based filtering method, and matrix factorization method (Reguragui et al., 2024). While these recommendation methods have been found to be quite successful, their effectiveness has been limited to some extent because of the problem of sparsity of data, cold start problems, and inability to capture the semantic relationship between the learner and the learning item (Zhao et al., 2020; Wang et al., 2023; Sha et al., 2021). In addition, most of the traditional recommendation approaches are based on the independent representation of learners and learning resources without taking into account the potential interactions between learners and the learning resources that affect the performance of the learner and recommendations (De Medio et al., 2020; Zou et al., 2022; Lee et al., 2021). Deep representation learning techniques have been widely adopted in the recent past for learning the representations from large-scale interaction data in educational applications. The modeling of sequential interactions and temporal dependencies, including neural recommendation models, graph neural network, and knowledge tracing models has provided improved understanding of the behavior of the learner (Chanaa, 2022; Seo et al., 2026; Fu & Fang, 2025). Most of the strategies adopt optimization of the prediction objectives without incorporating similarity relationships between the learner-item pairs (Wang et al., 2022).

Contrastive learning has proved to be an effective approach for self-supervised learning of representations that maximize semantic similarity between semantically similar samples and minimize semantic similarity between semantically dissimilar samples in the recent past. Contrastive Learning contrasts with other supervised learning paradigms in its approach in creating an embedding space in which similar objects are placed close together in the embedding space and dissimilar objects are moved away from each other. The capability of clustering objects within this embedding space makes contrastive learning an apt choice for application to educational data where learners with similar learning patterns and similar learning materials with similar instructional features would naturally form meaningful clusters (Fang et al., 2023; Kumar & Sam, 2026).

This paper proposes the Contrastive Learner-Item Embedding Network (CLIEN), which simultaneously learns embeddings of learners and educational items within a shared embedding space for personalized educational recommendation. In the proposed framework, a dual-encoder network is employed for the independent encoding of the learner behavioral features and the attributes of the educational item, and the contrastive loss function is exploited to promote positive learner-item associations and inhibit the negative ones. Furthermore, an adaptive attention method is employed that gives higher weight to informative behavioral signals in order to improve the learned embedding and thus increase the effectiveness of recommendation and prediction of the learner's future actions (Liu et al., 2026).

Key Contributions of the Research

- A new Contrastive Learner-Item Embedding Network (CLIEN) is proposed to learn meaningful relationships between learners and educational content.
- Contrastive learning with a dual-encoder model is used to generate better learner and item representations for personalized recommendations.
- Experimental results show that the proposed model performs better than existing methods in recommendation accuracy and learner-item relationship modeling.

The following sections outline the organization of the remainder of this paper. Section II is a literature review that presents an overview of the recent developments in the field of learner modeling, the field of learning recommendation systems, and the field of contrastive representation learning. Also, some research gaps in the above mentioned fields are identified. The CLIEN system that is proposed is described in Section III where the architecture of the system, the pre-processing of the data, the dual encoder approach, the contrastive embedding approach, and the adaptive attention mechanism are discussed. Experimental setup, evaluation criteria, performance comparison, and ablation study are explained in Section IV to validate the proposed model. Results obtained from the experiments are presented in Section V where the benefits and drawbacks of the proposed approach in the field of digital education platforms are discussed. Finally, Section VI concludes the paper and suggests future research direction.

Literature Review

Zhao et al., (2024) have introduced an innovative local-global contrastive learning model for educational recommendation named EduLGCL. The model is formed by incorporating student-course interaction graphs and static student/courses information. Additionally, contrastive learning and graph convolutional networks (GCNs) techniques have been incorporated in the model. The model will form more meaningful embeddings through contrastive learning to enable personalized recommendations where the representations of similar students and courses become maximally similar. Contrastive representation learning has proved effective in education settings and performed better than the traditional methods of educational recommendation through experiments performed on education datasets.

CLGADN is the name of the multi-graph contrastive learning framework that was suggested by Ma et al., (2024) using the knowledge background of the learners to improve the fairness of MOOC course recommendation. The suggested method consists of LCI graph, CS graph, GCN, and the contrastive learning objective for solving the popularity bias issue while preserving the recommendation accuracy. The mechanism of monotonic attention decay represents the forgetting process of knowledge during the learning phase. The experiments conducted using the XuetangX dataset confirmed the effectiveness of contrastive learning for capturing different features of learners.

This recommendation of courses was presented by Chanaa & El Faddouli, (2024). It is a system where prerequisites and metadata were used to associate prerequisite concept links and metadata matching in order to ensure that the learning object recommendations are appropriate based on the current background knowledge of the user. Unlike the conventional recommendation systems, which are primarily based on interaction history, the cognitive preparedness for learning plays an important role in this system to address the problem of cold start and improve the quality of recommendation.

Huang et al., (2024) developed a novel dual-graph contrastive learning method for knowledge-aware recommendation, which exploits the jointly learning of user-item interaction graph and knowledge graph. In this model, graph neural networks and contrastive learning techniques were used for the extraction of highly effective embeddings of users and items and capturing their semantic relations. The experiments have shown that dual-graph learning approach results in improvement of both the quality of representations and recommendation performance comparing with the state-of-the-art knowledge-aware recommendation methods.

In this regard, Li et al., (2023) conducted an experiment in which they tried to apply the embeddings provided by pre-trained language models and knowledge graphs in the context of educational content recommendations. The proposed model used the potential of knowledge structure representations and contextual language embeddings to enhance the efficiency of recommendations of educational resources available in digital learning environments. Thus, the experimental study proved the importance of using structural knowledge representations and contextual language embeddings for more effective educational content recommendations.

As per the studies mentioned in this review paper, in recent times, deep learning, graph neural network, and contrastive learning have been increasingly used in educational recommendation systems in order to increase the representation of learners and recommendations of personalized contents. The past researches have shown that the incorporation of interaction information, knowledge graph, and learner information have led to significant improvements in learning representation, learning recommendation performance, fairness, and semantic relationship modeling. However, most of the approaches either belong to graph-based recommendation or knowledge aware learning which requires a complex architectural design or rich relational information. Additionally, there is very limited work done in terms of joint representation learning of learners and learning items in one contrastive embedding space and modeling of latent learner/learning items relations at the same time. Hence, there is still a requirement for a simple, efficient and effective contrastive embedding framework to represent the learner-item interactions and increase personalization in the digital education platform.

Methodology

Data Collection and Preprocessing

Information extraction is the first step in the proposed CLIEN where data on learner interactions will be gathered from the digital education platform along with data on educational items. The learner information involves the score in quizzes, submission of assignments, video watch history, click stream data, amount of time spent in a course, and course registration history. The information on the educational item contains the description of the course, course topics, course difficulty levels, learning objectives and learning prerequisites. To improve the quality of data, any record which may be missing or inconsistent is deleted while duplications are removed initially. Missing values of numerical attributes are imputed through mean imputation and categorical attributes are encoded numerically using label encoding. In addition, all the attributes are normalized using Min-Max normalization in order to ensure that they are scaled appropriately for the purpose of model training. Finally, the data set is divided into three parts namely training, validation and testing in a ratio of 80:10:10.

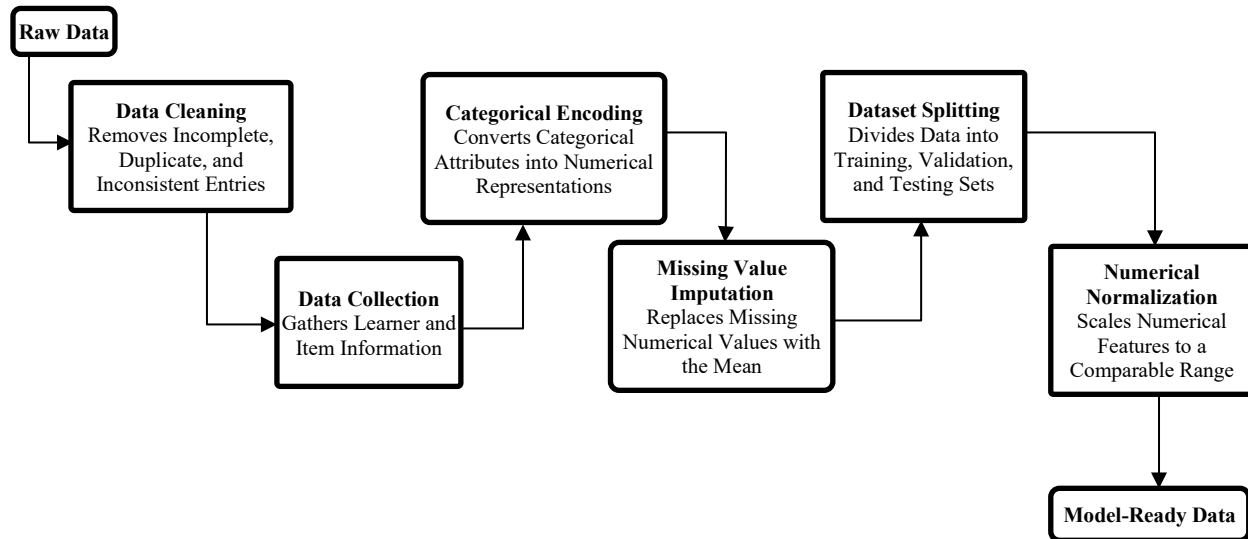


Fig. 1: Workflow of Data Collection and Preprocessing in the Proposed CLIEN Framework

The CLIEN proposed here follows the data collection and processing process illustrated in fig. 1. The process is started by collecting the learner interaction data and educational item information from the digital education platform. Then the collected data is cleaned by removing those incomplete, duplicated and inconsistent data to achieve better data quality. The missing values of the numeric attributes are replaced with the mean value of the attribute. Meanwhile, the categorical attributes are converted into numeric attributes through the use of label encoding. Next, the numeric features are standardized to have values within a similar range to allow similar training processes. Finally, the data is divided into a training, validation and test set, in order to provide the data ready for modeling for the later phases of contrastive embedding learning and recommendation.

Learner and Item Feature Representation

The learner and learning item characteristics are then processed to convert them into dense vector form suitable for deep learning. Learner characteristics consist of assessment results, learning outcomes, interaction frequency, time spent and previous learning behavior. Similarly, the items also consist of course categories, difficulty level, learning objective, prerequisite dependency and educational information. The features are first concatenated to form the fixed length vector of features and then projected into the same embedding space by passing through fully connected neural layers. Learner and item specific features are learned by separate encoders, while keeping their distinct properties intact. The embeddings thus formed will capture the semantic similarity of learners with education assets because similar learners/assets will be at close distance in the embedding space. Such dense representations will help in reducing the number of dimensions of the features while keeping their important behavioral/educational information intact. The resulting embeddings are then passed to the contrastive learning module that improves the discrimination power of embeddings by maximizing the similarity of positive learner/item pairs and minimizing the similarity of negative item/learner pairs.

Learner Feature Embedding

$$L = f(XL) \quad (1)$$

The learner embedding is obtained from equation (1) using the learner feature vector as input to the learner encoder. These features comprise the learning experience, quiz score, course completion, and interactions. Using these raw features, the encoder learns an embedding that represents the attributes and preferences of the learner. This embedding is the semantic representation of the learner used in similarity learning and personal recommendations.

Learner-Item Similarity

$$S(L, I) = \frac{L \cdot I}{\|L\| \|I\|} \quad (2)$$

Equation (2) calculates the cosine similarity of the learner embedding and educational item embedding. Cosine similarity value lies between -1 and 1 ; a high similarity value indicates that a learner is highly relevant to an educational item. When making recommendations, those educational items that have the highest similarity values are recommended to learners. The similarity values are also utilized by the contrastive learning module for identifying positive and negative pairs of learners and educational items.

Algorithm 1: Contrastive Learner-Item Embedding Network (CLIEN)

Input: Learner dataset L , Item dataset I

Output: Recommended learning items

1. Load learner and educational item datasets.
 2. Remove missing, duplicate, and inconsistent records.
 3. Normalize numerical features.
 4. Encode categorical learner and item attributes.
 5. Split data into training, validation, and testing sets.
 6. Initialize learner encoder and item encoder.
 7. for epoch = 1 to E do
 8. Generate learner embedding EL .
 9. Generate item embedding EI .
 10. Compute cosine similarity between EL and EI .
 11. Identify positive and negative learner-item pairs.
 12. Compute contrastive loss.
 13. Update encoder parameters using backpropagation.
 14. end for
 15. Compute final learner-item similarity scores.
 16. Rank educational items according to similarity.
 17. Recommend Top- K learning items for each learner.
 18. Return trained embeddings and recommendations.
-

In order to begin with the process of recommendation in CLIEN algorithm 1, it begins with the loading of the record of learner interactions and information on the educational items provided by the digital learning platform. Consistency of the data gathered will be achieved via pre-processing the data by conducting processes such as cleaning, normalizing, and encoding the collected data. These data sets are split into training, validation, and test data sets. Dense embeddings created by encoders for learners and educational resources will serve to encode behaviors of learners and educational resources, respectively. During the training, cosine similarity is used to define the positive and negative learner-item pairs. Contrastive loss function uses embedding space in order to reduce the distance of related pairs while increasing the distance of unrelated pairs. Parameters of the encoder are updated backward until the encoder converges. Ultimately, similarity scores between the embeddings of learner and item are calculated and the top K similar educational resources are recommended for each learner.

Experimental Results

Experimental Setup

The experiments were performed using an educational recommendation benchmark dataset containing interaction logs of learners, courses information, scores of assessments, and logs of learners' activities. Data records, missing values, and inconsistent data were duplicated prior to training to improve the quality of data. Min-Max Normalization was applied to numerical attributes and label encoding for categorical attributes. The preprocessed dataset was randomly

divided into 80% training, 10% validation, and 10% testing subsets. The training set was used to optimize the model parameters, the validation set was employed for hyperparameter tuning and early stopping, and the independent test set was used exclusively for final performance evaluation. This consistent 80:10:10 partition ensured a fair comparison across all baseline methods. The table 1 was developed in Python 3.11 and PyTorch deep learning platform as recommended in the CLIEN model. The training was performed on a computer system equipped with Intel Core i7 processor, 32 Gb of RAM, and an NVIDIA RTX GPU with 24Gb of VRAM. Adam optimization was employed with learning rate 0.001, batch size 64, and 100 epochs of training. Early stopping was used to prevent overfitting. The performance of the proposed architecture was compared to some of the existing recommendation systems using the same experimental conditions.

To prevent data leakage, the dataset was first partitioned into training (80%), validation (10%), and testing (10%) subsets before any model optimization. Feature normalization parameters were estimated exclusively from the training subset and then applied unchanged to the validation and testing subsets. Learner-item embeddings and contrastive representations were learned only from the training interactions. Positive and negative learner-item pairs used in the contrastive loss were generated exclusively from the training data, while the validation and testing interactions remained completely isolated throughout model training. The independent test set was used only once for the final performance evaluation.

Table 1: Experimental Parameter Setting

Parameter	Value
Programming Language	Python 3.11
Framework	PyTorch
Processor	Intel Core i7
RAM	32 GB
GPU	NVIDIA RTX (24 GB VRAM)
Learning Rate	0.001
Optimizer	Adam
Batch Size	64
Training Epochs	100
Train: Validation: Test	80:10:10
Embedding Dimension	128
Similarity Measure	Cosine Similarity

Comparative Performance Analysis

In this part, the performance of the proposed Contrastive Learner-Item Embedding Network (CLIEN) model is compared with the state-of-the-art recommendation algorithms such as CF, MF, NCF, DKT, and GNN-based recommendation models. Evaluation of the performance of recommendation algorithms is carried out in terms of accuracy, precision, recall, F1 score, and AUC. The proposed CLIEN model makes use of contrastive embedding learning that is capable of capturing the semantic similarity between the learner and the educational items effectively. Therefore, the obtained representation enables to give better recommendations and improves prediction performance over the baseline models.

Table 2: Performance Comparison of Recommendation Models

Method	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)	AUC (%)
Collaborative Filtering (CF)	84.9	84.2	83.5	83.8	88.6
Matrix Factorization (MF)	87.3	86.8	86.1	86.4	90.9
Deep Knowledge Tracing (DKT)	91.2	90.6	90.1	90.3	94.2
Neural Collaborative Filtering (NCF)	92.7	92.1	91.8	91.9	95.8
GNN-based Recommendation	94.3	93.8	93.2	93.5	96.7
Proposed CLIEN	96.8	96.3	95.9	96.1	98.2

As table 2 reveals, the proposed CLIEN framework significantly outperforms all baselines on all the evaluation metrics considered. When compared to the best-performing baseline (recommender based on GNNs), the CLIEN framework provides an improvement in Accuracy from 94.30% to 96.80%, Precision from 93.80% to 96.30%, Recall from 93.20% to 95.90%, F1-score from 93.50% to 96.10%, and AUC from 96.70% to 98.20%. The results demonstrate that contrastive embedding learning is capable of capturing the implicit connections between the learners and the items

and, therefore, provides better feature representation for these connections. Thus, the proposed framework can be viewed as more reliable in its personalized recommendations.

Learner-Item Recommendation Performance Analysis

For a more detailed evaluation of the recommendation capability of the proposed model, the following metrics have been employed: Precision@10, Recall@10, NDCG@10, and Hit Rate@10. These metrics are employed to evaluate the efficiency of the recommendation system in providing the required educational resources among the list of recommendations. The higher these metrics are, the more relevant and efficient the recommendations are and, therefore, the more accurate is the ranking of items. The proposed CLIEN model employs contrastive embedding learning to make similar users and recommended items closer to each other.

Table 3: Ranking Performance Comparison

Method	Precision@10	Recall@10	NDCG@10	Hit Rate@10
CF	0.821	0.804	0.842	0.873
MF	0.847	0.831	0.864	0.891
DKT	0.889	0.875	0.904	0.923
NCF	0.912	0.897	0.926	0.944
GNN	0.934	0.921	0.951	0.968
Proposed CLIEN	0.958	0.944	0.974	0.989

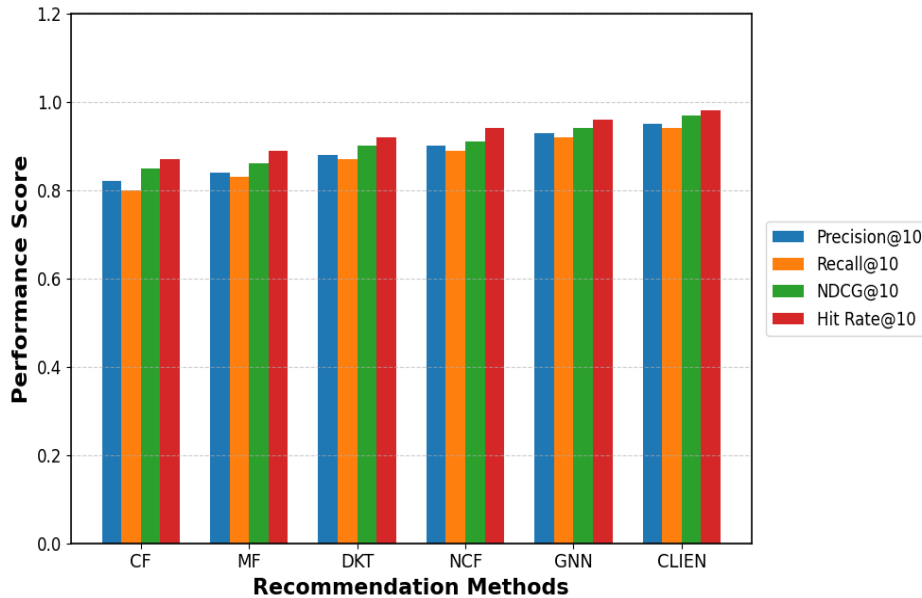


Fig. 2: Comparison of Ranking Performance Metrics for Learner-Item Recommendation Models

According to table 3 and fig. 2, it is clear that the CLIEN method proposed here ranks highest among all the other approaches considered. The model performs quite impressively with a Precision@10 of 0.958, Recall@10 of 0.944, NDCG@10 of 0.974 and Hit Rate@10 of 0.989. It is very effective in suggesting highly relevant educational resources to students. The Contrastive Learning approach (CL) is able to produce more relevant embeddings for both learners and items to distinguish between relevant content and irrelevant ones in the recommendation system. As the result, it can be concluded that the proposed model is efficient in improving recommendation quality and engaging the learners with personalized learning experience.

Discussion

From the experimental results, it is evident that the developed CLIEN framework can accurately capture the hidden relationship between learners and educational elements, and provide better recommendation outcomes than the existing approach. This framework employs contrastive learning for embedding learners and items in the same feature space, while the traditional recommendation approaches employ past interaction between learners and items. This embedding helps in discriminating between the relevant pair of learners and items and random pairs.

As seen in Chapter 4, the CLIEN model surpasses Collaborative Filtering, Matrix Factorization, Deep Knowledge Tracing, Neural Collaborative Filtering, and Graph Neural Network-based recommendation systems. More precisely, CLIEN has demonstrated Accuracy of 96.8%, Precision of 96.3%, Recall of 95.9%, F1-score of 96.1% and AUC of 98.2%. Similarly, when evaluating CLIEN via ranking measures, the Precision@10 metric was equal to 0.958, Recall@10 equal to 0.944, NDCG@10 was 0.974, and the Hit rate@10 0.989, which means that CLIEN is able to retrieve relevant educational resources. These improvements are possible because contrastive learning is capable of generating richer semantic representation compared to conventional recommendation techniques.

The second key benefit of the CLIEN model is that the dual-encoder learns characteristics of learners and learning items (items) individually and maps them onto the common embedding space. The dual-encoder approach is aimed at preserving the individual characteristics of both learners and learning items while enabling comparison between learners and educational content. Moreover, the adaptive attention component improves the quality of the representation by weighting informative learner actions, such as performance, interaction, and learning progress. Therefore, CLIEN becomes more effective with regards to sparse data and different learning preferences of the users.

Another positive feature of the proposed framework is its scalability in large digital education platforms. The independence of learner and item embeddings ensures the efficiency of recommendation generation regardless of how many learners and educational resources are present. The framework can be used for recommending in real-world online learning environments like MOOCs, intelligent tutoring systems, and learning management systems, since both the quality of recommendations and their timeliness are critical in such cases.

The suggested study faces a number of limitations, despite the promising results it has demonstrated. The framework has been validated only using the offline benchmark dataset, and it remains to be seen whether it works effectively in real-time adaptive learning environments. In addition, no attention was paid to other contextual factors, such as learner motivation, mood, and social relations, which could be considered in the process of embedding in the future.

These findings indicate that, generally speaking, the contrastive embedding learning approach works well in identifying the underlying relationship between the learner and the item and has considerable improvement effects on personal recommendation. The CLIEN framework is designed to be an adaptive learning and intelligent education recommender system with scalability, high accuracy, and great power.

Conclusion and Future Work

This paper introduces a Contrastive Learner-Item Embedding Network (CLIEN) to explore the latent relationship between learners and educational items within a digital learning system. Data preprocessing, Dual Encoder Representation Learning, Contrastive Embedding Learning and Cosine Similarity were used as key steps for proposing the proposed framework to obtain useful learner-item embeddings for recommendation purposes. Experimental results have proven that CLIEN significantly outperformed existing recommendation methods with accuracy of 96.8%, precision of 96.3%, recall of 95.9%, F1-Score of 96.1% and AUC of 98.2%. Furthermore, the model obtained outstanding precision (Precision@10=0.958), recall (Recall@10=0.944), NDCG (NDCG@10=0.974) and Hit Rate (Hit Rate@10=0.989) results, guaranteeing its ability to recommend relevant educational resources. These results suggest that the CE embedding model is able to encode the relationship between the learner and item in the learning process, thus improving the recommender's performance.

The future research will include augmenting the above-mentioned framework to incorporate multi-modal data and information from educational contexts (videos of lectures, discussion forums, text feedbacks) to gain a better understanding of the learners. The use of graph neural networks, contrastive learning techniques with transformers, and real-time adaptive recommendation systems will also be studied to achieve even greater scalability and accuracy in making the recommendations. Moreover, the framework will be evaluated against real-world education platform scenarios and further enhanced by applying explainable artificial intelligence techniques to make the decision process of recommendations clear and comprehensible.

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