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Evaluation of the Quality of Online Education Based on a Learning Interactive Network

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Abstract
Contemporary education models are undergoing significant transformation, driven by the goals of ubiquity, intelligence, and personalization. This transformation is particularly evident in online education, exemplified by massive open online courses (MOOCs), which are increasingly becoming mainstream. The quality of online learning is now heavily influenced by interactivity, recognized as pivotal in supporting effective learning outcomes through enhanced help and feedback mechanisms. This study establishes an interaction network model for online learning, utilizing recurrent neural networks (RNNs) to embed learner and learning resource nodes into a Euclidean space. The primary aim is to evaluate the quality of interactions and determine whether they align with expected learning outcomes. The research methodology involves the development of an interaction network model and the application of RNNs for embedding nodes. Key metrics are proposed to assess interaction quality, integrating assessment feedback to enhance learning outcomes. Experimental validation on real-world datasets demonstrated the efficacy of the approach. The findings indicate that the proposed model significantly improves interaction quality in online learning environments. Recommendations include the adoption of similar interaction network models in educational platforms to optimize learning experiences. The implications of this study underscore the importance of robust interaction metrics in designing effective online learning environments. This study contributes to advancing the understanding and methodologies for modeling interactions in online education, emphasizing the critical role of interaction quality in achieving desirable learning outcomes.

Keywords: Online education, recurrent neural networks, MOOCs, interactive evaluation
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Introduction

With the advent of the internet era, online learning has progressively become the prevailing mode of education. Massive open online courses (MOOCs) represent a typical form of online learning, offering the convenience of two-way interaction, rich teaching resources, and diverse teaching interactions. Online learning platforms, such as MOOCs, host numerous interactive behaviors, such as watching course videos, taking tests, and participating in forum discussions.

Numerous pedagogical studies assert that interaction is pivotal for the integration of teaching and learning (Keegan, 1993). Knowledge establishment and formation during the learning process rely on interaction development (Downes, 2012), with effective teaching interaction enhancing learning outcomes. Ullah *et al.*, (2007) proposed that interaction, when applied to online courses, can enrich learners' learning experiences (Parker & Parker, 2013) and facilitate the creation of new meanings. Su et al. argued that meaningful learning interactions in online learning can foster learners' knowledge construction (Rossi *et al.*, 2012).

Globally, online learning has experienced exponential growth. According to Class Central's 2020 report, more than 180 million learners are enrolled in MOOCs, reflecting a significant rise in online education adoption worldwide. Countries such as the United States, the United Kingdom, and China are leading in this educational transformation, leveraging online platforms to provide accessible, flexible, and diverse learning opportunities. This global trend is driven by the increasing demand for continuous learning, professional development, and the need to bridge educational gaps.

In Africa, the landscape of online learning is evolving rapidly. The African Union's Agenda 2063 underscores the importance of leveraging technology to enhance education across the continent. Online learning platforms are vital tools for addressing educational challenges in Africa, such as inadequate infrastructure, teacher shortages, and the need for quality education. Countries such as Kenya, Nigeria, and South Africa are making significant strides in integrating online learning into their education systems. However, challenges such as limited internet access, high data costs, and lack of digital skills still hinder widespread adoption.

In Tanzania, online learning is gradually gaining traction, especially in the wake of the COVID-19 pandemic, which has necessitated a shift to remote learning. The Tanzanian government, through initiatives such as the Tanzania Education and Training Policy (ETP) 2014, is committed to improving access to quality education by integrating ICT in teaching and learning. Despite these efforts, Tanzanian students face challenges such as limited internet connectivity, insufficient digital infrastructure, and low levels of digital literacy.

Since the 1980s, with the gradual evolution of educational paradigms, there has been a shift in considering learning quality not only based solely on learning outcomes but also on the learning process itself (Poulsen & Hewson, 2013). Attention is now directed not only toward evaluating learning outcomes but also toward evaluating learning methods and processes. Evaluation not only provides valuable information on learning outcomes but also significantly impacts the learning process (Yang *et al.*, 2006). Despite the global and regional advancements in online learning, the quality of interaction in these platforms remains a critical issue, particularly in Tanzania. Effective interaction is essential for enhancing learning outcomes, yet there is a lack of efficient methods for evaluating the quality of these interactions. Traditional educational research methods often involve broad and complex evaluation metrics that are difficult to automate, leading to challenges in assessing and improving interaction quality.

Among the studies evaluating online learning, specific attention has been given to evaluating the quality of interaction. Presently, the primary research model for evaluating the interactive quality of online learning still adheres to traditional pedagogical research methods. This involves proposing evaluation rubrics for interactive quality from various perspectives, followed by experimental verification through questionnaire-based methods. However, such methods face challenges including difficulties in achieving automated evaluation, wide definitions of evaluation indicators, complex evaluation criteria, and low reliability and validity of evaluation indicators.

Moreover, from a learning perspective, Siemens proposes that learning is a network phenomenon centered around interaction, where network formation relies on interaction development (Siemens, 2012). In recent years, researchers have conducted extensive applied research, including on teaching resource recommendation and behavior prediction through network data mining and machine learning technologies based on learning interaction networks (Shrestha *et al.*, 2019; Cai et al., 2018; Feng *et al.*, 2019). However, relatively few studies have investigated interactive quality evaluation methods.

This paper aims to bridge this gap by combining the current status and trends of education big data, education interaction, and interactive evaluation both domestically and abroad. It draws on recent research results and experiences in education big data management and dynamic embedding, as well as domestic and foreign expertise in data mining, neural networks, and network representation learning. With practical applications as a backdrop, this paper endeavors to conduct innovative theoretical and practical work, focusing on evaluating the quality of online learning interactions. The proposed method aims to effectively evaluate the quality of online learning interactions and provide solutions to existing challenges. Specifically, the paper focuses on the interaction between the main entities of the online learning platform learners and learning resources. The method involves establishing a clear dynamic learning interaction network, representing learning methods as low-dimensional representations within the learning interaction network entities, and ultimately proposing evaluation methods.

Literature Review

Interaction Quality Evaluation

Moore initially proposed three types of interactions in online teaching: learner-content interaction, learner-instructor interaction, and learner-learner interaction (Moore et al. 2016). In research on the evaluation of online learning interaction quality, various evaluation metrics are proposed based on these three interactions. Laurillard (2002) argued that instructors in higher education must be more specialized in teaching methods and possess research-oriented professionalism. To improve teaching and enhance student learning outcomes, Laurillard (200) provides a solid theoretical foundation for the design and use of learning technologies in teaching. However, its evaluation focuses on assessing the advantages and disadvantages of interactive learning environments for learners, and analyses of teaching interaction behaviors are lacking. Roblyer *et al.,* (2003) evaluate interaction levels across dimensions such as social interaction, instructional interaction, resource interaction, and information quality, and propose indicators for designing and assessing online course interaction quality based on theoretical and research findings. However, their measurement design is broad and subjective to teachers and students, which may not ensure sufficient objectivity and high reliability. Chen *et al.,* (2021) build on existing educational research, proposed a system of 47 indicators for evaluating online learning interaction quality across five dimensions: media interaction design, learner-resource interaction design, community interaction design, teacher involvement, and student engagement. However, the credibility and evaluation effectiveness of this theoretical research still require practical verification. In contrast to the above works, this paper focuses on learner-content interaction, aiming to propose computable interaction quality evaluation metrics based on interaction networks.

Network Representation Learning

In recent years, with the development of machine learning techniques, network embedding technologies have garnered widespread attention, making feature learning for nodes in networks a burgeoning research task. A key issue in the analysis and research of networks is how to reasonably represent feature information within the network. Inspired by word2vec, the DeepWalk algorithm Perozzi, *et al.,* (2014) first introduced deep learning techniques into the field of network representation learning by leveraging information from random walk sequences in network structures. The Node2vec algorithm (Grover & Leskovec, 2016), by altering the way random walk sequences are generated, further extends the DeepWalk algorithm. The Struc2vec algorithm is based on the Node2vec algorithm, effectively models nodes with structural similarities even at long distances (Figueirodo, *et al.*, 2017). These algorithms are all representation methods based on the SkipGram language model.

The Hin2vec algorithm is a framework for heterogeneous information network representation learning (Fu, *et al.*, 2017). Unlike the above methods, the core of Hin2vec is a neural network model that not only learns representations of nodes in the network but also representations of relationships (meta-paths). Representation learning provides powerful tools for modeling and inference in networks. However, over time, these single static network embeddings alone are insufficient for representing the dynamic changes in networks.

In recent years, researchers Dai *et al.,* (2017) and Kumar *et al.*, (2019) build on existing work, have established dynamic network models and used representation learning techniques to capture changes in network node characteristics for applications such as recommendations and user behavior prediction. This paper employs representation learning techniques in dynamic learning interaction networks to evaluate interaction quality.

Materials and Methods

Interactive Network Construction

Many real-world scenarios can be abstracted into graph structures, such as social networks, transportation networks, and relationship networks between users and e-commerce sites regarding goods. Network representation learning, also known as network embedding, involves projecting network nodes into low-dimensional continuous spaces while preserving the network structure and inherent characteristics. This results in low-dimensional embeddings of learning entities, which are used to represent the evolving properties of learners and learning resources. Given that learners frequently interact with learning resources, and that a single learner may interact with various learning resources over time, these interactions form a network between learners and learning resources that evolves dynamically.

Establishing a dynamic interaction network between learners and learning resources forms the foundation of this paper. The dynamic evolution of learners and learning resources can be modeled by representing learning methods. Each learner and learning resource can be embedded in a Euclidean space. Over time, learners interact with different learning resources, and the characteristics of learners and learning resources influence each other and develop in tandem. These attribute characteristics further impact the interaction between learners and learning resources in the future. This paper primarily evaluates the quality of interaction between learners and learning resources in the learning process. Therefore, interactive data between learners and learning resources serve as the research basis, and learners' interactions during the learning process are quantitatively evaluated.

Taking a MOOC platform as an example, students' learning activities encompass interactive behaviors such as video viewing, page navigation, and participation in tests. These interactions are recorded as clickstream logs, where each clickstream is a collection of records. Each interaction record typically includes learner ID, learning resource ID, interaction time, and an interaction feature vector containing information such as document viewing and video watching. Given the interactions between learners and different learning resources during the learning process, the model of the learning interaction network is depicted in Figure 1.

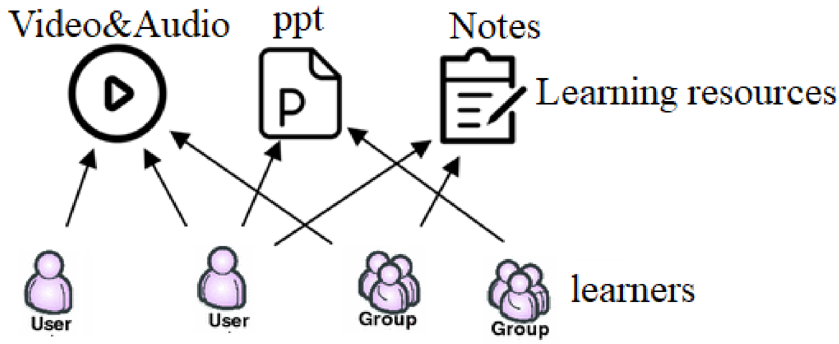

Figure 1: Learning interactive network

The learning interaction network comprises two types of nodes: learners and learning resources. The edge between these nodes represents the interaction between a learner and a learning resource. Since interactions can occur multiple times and may have different characteristics, each edge is annotated with information such as interaction time and interaction characteristics. The following is the definition of the learning interaction network:

Definition 1 (Learning Interaction Network): The learning interaction network is denoted as $G = (u, i, e_{ui}(t, f))$, where:

- $u \in U$ represents the learner node,
- $i \in I$ represents the learning resource node,
- e_{ui} represents the edge formed during the interaction between the learner node and the learning resource node,
- t denotes the interaction time,
- f denotes the interaction characteristics.

Based on the definition of the learning interaction network, the embedding representation of the nodes in the network is described as follows:

Let $u(t) \in \mathbb{R}^n$, $\forall u \in U$ denote the embedding representation of the learner at time t, and $i(t) \in \mathbb{R}^n$, $\forall i \in I$ represent the embedding representation of the learning resource at time t, for $\forall t \in [0, T]$.

The interactive activity feature vector of learner $u \in U$ and learning resource $i \in I$ at time $t \in R + (0 < t1 < t2 \leq T)$ is denoted by f. Here, $\boldsymbol{u}(\boldsymbol{t})$ and $\boldsymbol{i}(\boldsymbol{t})$ represent the embedding representation of learner u and learning resource i at time t, respectively. Additionally, $\boldsymbol{u}(\boldsymbol{t}-)$ and $\boldsymbol{i}(\boldsymbol{t}-)$represent the embedded representation of learner u and learning resource i before time t, respectively.

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Interactive network embedding

Embedded model

This paper initially learns the embedding representations of learners and learning resources using the recurrent neural network (RNN) model. Subsequently, it employs two neural networks to update the embeddings of learners and learning resources at each interaction, embedding each entity into Euclidean space. Finally, this paper proposes an evaluation method for the quality of learning interactions by analyzing changes in learners' embedded attributes.

Figure 2 illustrates the online learning entity embedding model based on representation learning proposed in this paper. The model utilizes two RNNs to update the embeddings: the learner RNN and the learning resource RNN. The learner RNN, which is shared by all the learners, updates the learner embedding, while the learning resource RNN, which is shared by all the learning resources, updates the curriculum resource embedding. The embedding of the learner and the learning resource is represented by the hidden state of the RNN.

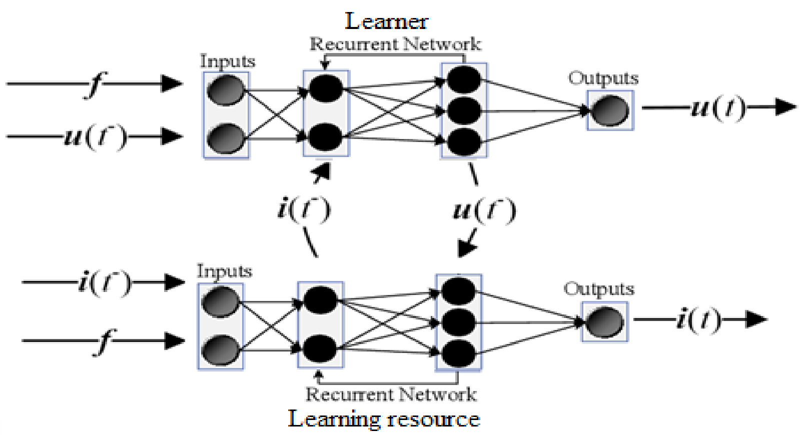

Figure 2: Online learning entity embedding model based on representation learning

In this article, the recurrent neural networks (RNNs) utilized are mutually recursive, and the embedding result is initialized to 0. When a learner interacts with a learning resource, the learner RNN updates the learner embedding $u(t)$using the embedded learning resource $\boldsymbol{i(t-)}$ from the learning resource before time $\boldsymbol{t}$ as input. This approach ensures that learner embedding using learning resources can effectively reflect the current state of learning resources, leading to more meaningful learner embeddings and simplified training. Similarly, the embedding of learning resources uses the learning dynamic embedding $\boldsymbol{u(t^-)}$ of the learner before time $\boldsymbol{t}$ to update the learning resource embedding $\boldsymbol{u(t)}$.This mutual recursive dependency in embeddings ensures that the embeddings are well-aligned and captures the evolving interactions between learners and learning resources over time.

Learner And Learning Resource Embedding

The learner's embedding is obtained by equation (1):

$$\boldsymbol{u(t) = \sigma(W_1^u u(t^-) + W_2^u i(t^-) + W_3^u f + W_4^u \Delta u)} \quad (1)$$

Among the matrices $\boldsymbol{W_1^u}$,… , $\boldsymbol{W_4^u}$ are the parameters of the learner's RNN, which are obtained by training. $\Delta\boldsymbol{u}$ represents the time difference from the learner's last interaction with any learning resource to the current interaction, f represents the interaction feature vector, $\boldsymbol{\sigma}$ is the nonlinear incentive sigmoid function, $\boldsymbol{u}(\boldsymbol{t}^-)$ represents the embedding representation of the learner before time t, and $\boldsymbol{i}(\boldsymbol{t}^-)$ represents the embedding representation of the learning resource before time $\boldsymbol{t}$. The learner embedding $\boldsymbol{u}(\boldsymbol{t})$ is finally updated.

The embedding of learning resources is obtained by equation (2):

$$\boldsymbol{i}(\boldsymbol{t}) = \boldsymbol{\sigma}\left(\boldsymbol{W_1^i}\boldsymbol{i}(\boldsymbol{t}^-) + \boldsymbol{W_2^i}\boldsymbol{u}(\boldsymbol{t}^-) + \boldsymbol{W_3^i}\boldsymbol{f} + \boldsymbol{W_4^i}\Delta\boldsymbol{i}\right) \tag{2}$$

The matrices $\boldsymbol{W_1^i}$,…, and $\boldsymbol{W_4^i}$ are the parameters of the learning resource RNN, obtained through training. $\Delta\boldsymbol{i}$ represents the time difference between the last interaction of the learning resource with the learner and the current interaction. $\boldsymbol{i}(\boldsymbol{t}^-)$ represents the time difference of the learning resource before time $\boldsymbol{t}$, while $\boldsymbol{u}(\boldsymbol{t}^-)$ represents the embedding representation of the learner before time $\boldsymbol{t}$. Finally, the learning resource embedding $\boldsymbol{i}(\boldsymbol{t})$ is updated.

Although the updates in equations (1) and (2) involve only learners and learning resource pairs that directly participate in specific interactive activities, the influence of specific learners or learning resources can propagate throughout the entire binary interactive network. It is evident that a learner's embedding will affect the embedding of learning resources with which it directly interacts, and the updated learning resource embedding will affect different learners who will engage in interactive activities in the future. This propagation effect extends across the entire network.

Parameter Learning

The parameters of the recurrent neural network can be learned using the gradient descent method.

The loss function for learning the learner's embedding at time $\boldsymbol{t}$ is as follows:

$$\boldsymbol{L_t} = \boldsymbol{L}\left(\boldsymbol{u}(\boldsymbol{t}), \boldsymbol{u}(\boldsymbol{t}^-)\right) \tag{3}$$

where $\boldsymbol{L}$ is a differentiable loss function, such as the mean square error (MSE) loss function; $\boldsymbol{u}(\boldsymbol{t})$ is the output of the learner's embedding at time $\boldsymbol{t}$, and $\boldsymbol{u}(\boldsymbol{t}^-)$is the input of the learner's embedding at time $\boldsymbol{t}$. The backpropagation through time (BPTT) algorithm is used to calculate the gradient.

Interactive Quality Evaluation

Based on the embedding representation results of learners and learning resources in Section 4, this paper proposes a widely applicable and computable interactive quality evaluation index from the perspective of learners' learning effects. As interactive activities between learners and learning resources become more frequent, the embedding results influence each other, resulting in closer distances between the embedding vectors obtained in Euclidean space. Based on this, the paper proposes an evaluation index to measure the interactive quality of the learner, as shown in equation (4):

$$D(p) = \sum_{q\in(0,Q)} \|u(p) - i(q)\|_2 \tag{4}$$

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where p represents a single learner, q represents learning resources, and Q is the number of learning resources. The smaller the value of $D(p)$ is, the better the interactive learning quality of the student, while the larger the value is, the worse the interactive learning quality of the student.

To validate the correctness of the indicator, based on the assumption that interaction quality is related to the learning effect, this article utilizes this indicator to predict the state of the learner. When the learner's learning state is poor (indicating a potential dropout), the user's label is assigned as 1; when the learning status is good, the user's label is assigned as 0. The student's interactive evaluation index $D(p)$ is then sorted in descending order, and the prediction accuracy (precision) can be calculated by considering the presence of labels in the top $N\%$ of learners.

Results and Discussion

Experimental Data Set

The experimental analysis in this article is conducted on two public datasets from Xuetang Online. Xuetang Online, launched in October 2013, has become one of the largest MOOC platforms in China. When learners engage with a course on the platform, the system records multiple types of interactive activities, including watching videos, answering questions, completing assignments, and more.

This article utilizes two datasets. The first dataset is sourced from the international knowledge discovery and data mining competition KDDCUP2015, referred to as KDD15. The second dataset is obtained from the MOOCDATA platform, and this article refers to it as XTdata. The datasets include information about learners and learning resources, interaction features, interaction occurrence times, etc., etc. Table 1 presents the statistical information of the two datasets.

Table 1: Statistics of datasets

	KDD15	XTdata
Learner	7050	6373
Learning resources	98	27
Number of interactive activities	411800	397085
Dropout	4067	4986

Experimental Setup

In this experiment, PyTorch is utilized to implement recurrent neural networks (RNNs), and the Adam optimizer is used to optimize the model. The learning rate is set to 0.001. The rectified linear unit (ReLU) is used as the activation function. The embedding dimension of the model is set to 128, and the model is trained for 50 epochs.

All the interactive features are normalized before being input into the model. The first 60% of the dataset is used as the training set to train the model, while 20% of the data is set aside as the validation set to evaluate the model. The remaining 20% of the data serve as the test set to assess the generalization ability of the model. Finally, the model training results with the best performances are selected. For comparison purposes, this article selects three static network representation methods DeepWalk, Struc2vec, and Hin2vec to embed the learner and learning resource pairs.

Experimental Results

This paper conducted experiments on two datasets and calculated the interactive quality evaluation index $D(p)$ of all learners as defined by equation (4). The distribution of $D(p)$ is illustrated in Figure 3 and Figure 4.

In these figures, the abscissa represents the value range of $D(p)$, while the ordinate indicates the number of learners within each value range of $D(p)$. Figure 3 and Figure 4 show that the interaction quality varies among different learners. Notably, compared with the XTdata dataset, the value range of $D(p)$ on the KDD15 dataset is larger, indicating a more pronounced difference in the interactive quality of learners.

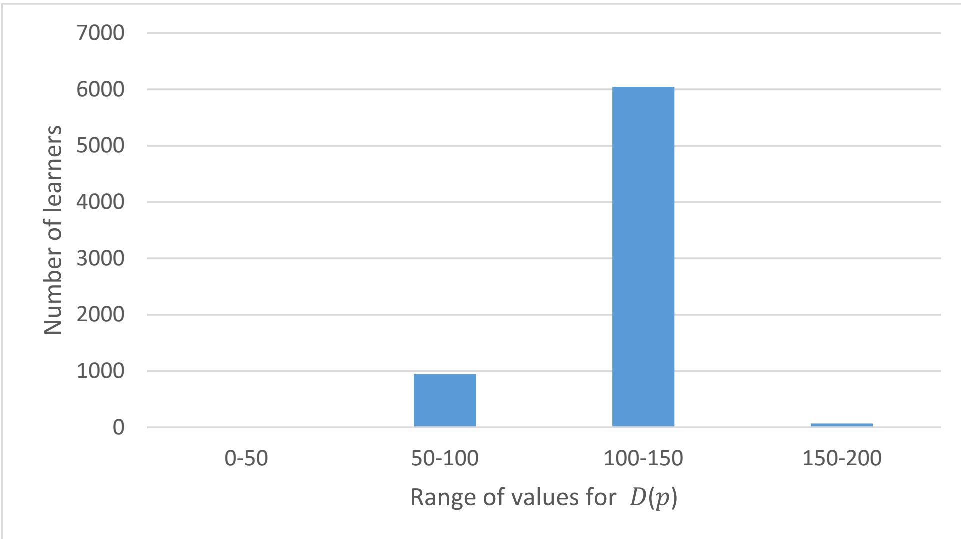

Figure 3: Statistical distribution of $D(p)$ on the KDD 15 dataset

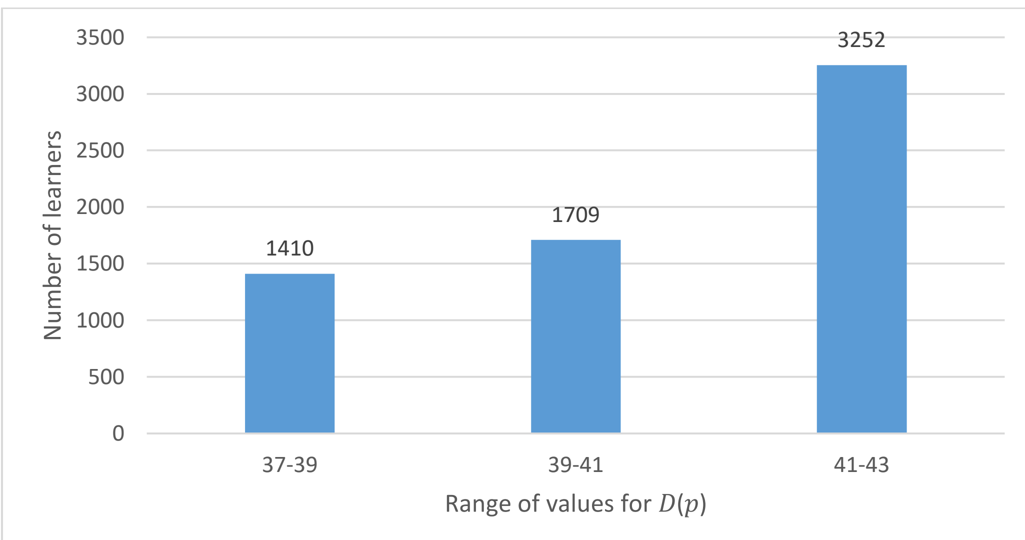

Figure 4: Statistical distribution of $D(p)$ on the XTdata dataset

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In the training stage of the embedding representation model, the experiment compared the performance of the training model at all epochs and selected the training results with the highest accuracy. The training results for the two datasets are illustrated in Figure 5 and Figure 6.
In these figures, the abscissa represents the number of training epochs, while the ordinate represents the accuracy of the learner's state prediction.

From a subjective standpoint, the variations observed in the predictive accuracy of the model (Figures 5 and 6) across different epochs highlight the importance of optimizing the number of training epochs to balance model accuracy and overfitting. Specifically, while the KDD15 dataset achieved peak accuracy at the 40th epoch, the XTdata dataset reached optimal performance at the 36th epoch. This difference could be influenced by the intrinsic characteristics of each dataset, such as the complexity of interactions and the nature of the learning resources involved.

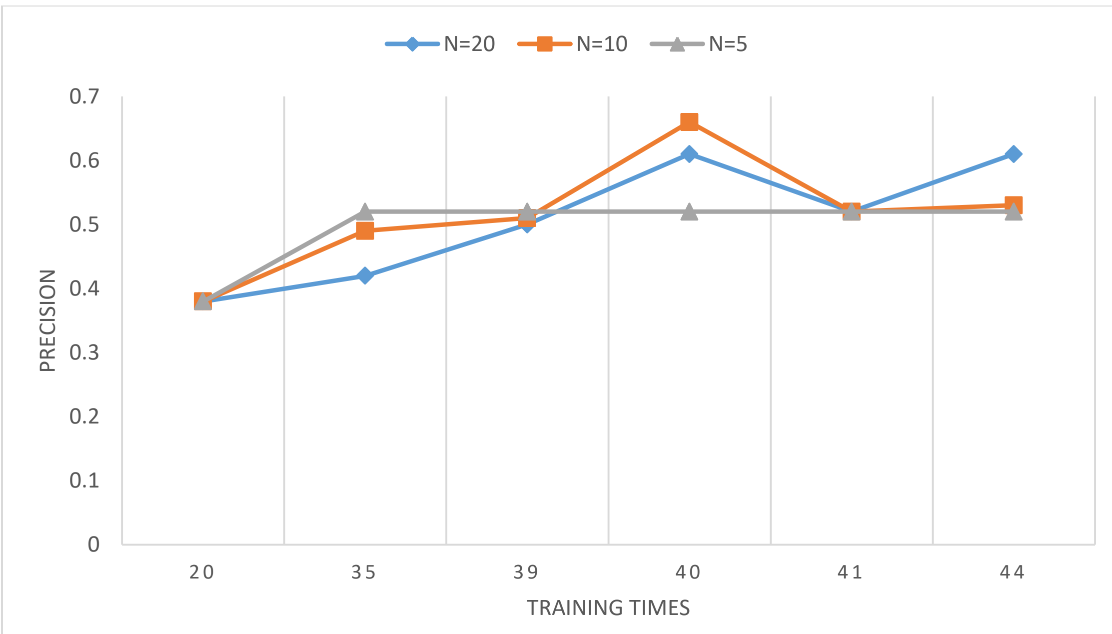

Figure 5: Comparison of model precision on the KDD 15 dataset

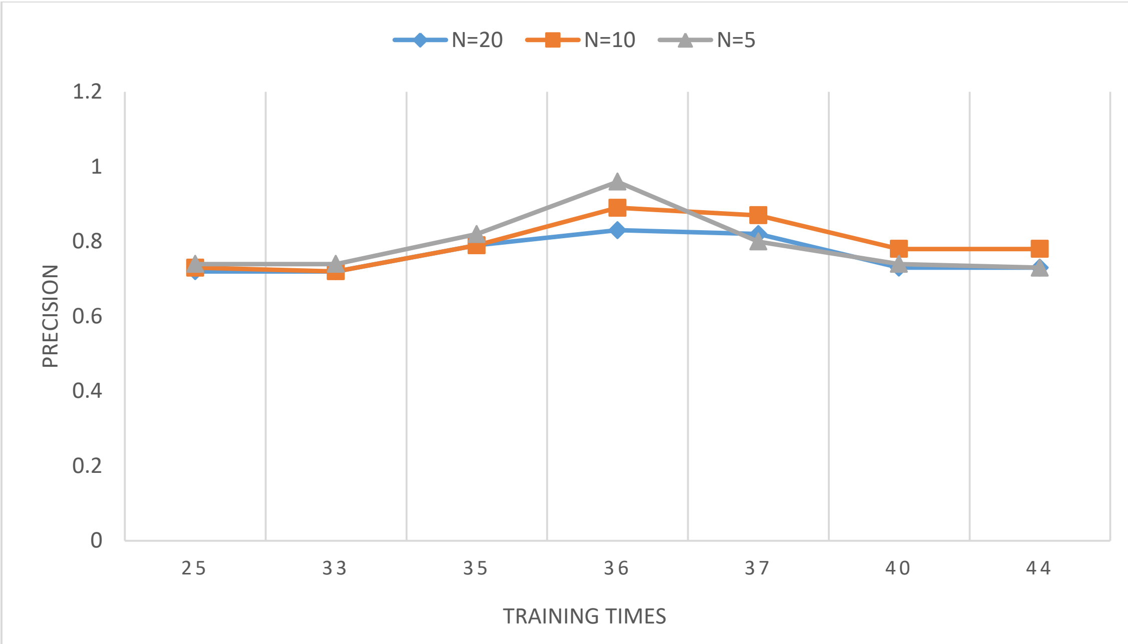

Figure 6: Comparison of model precision on the XTdata dataset

Figure 5 shows that when the KDD15 dataset is trained up to the 40th epoch, the model achieves its highest accuracy when *N* is set to 5, 10, and 20, respectively. Similarly, from Figure 6, when the XTdata dataset is trained up to the 36th epoch, the model's accuracy is also highest when *N* is set to 5, 10, and 20, respectively. As the number of training epochs increases, the model's accuracy gradually improves. However, excessive training may lead to overfitting, resulting in reduced model accuracy. Notably, the number of training epochs with the highest accuracy varies for different datasets. Finally, this paper compares the dynamic network representation method RNNs with other static network representation methods, and the results are summarized in Table 2 and Table 3.

Table 2: Learner state prediction results on the KDD 15 dataset

Method	N=5	N=10	N=20
Deepwalk	0.30683	0.32102	0.41022
Struc2vec	0.13352	0.01776	0.20227
Hin2vec	0.51989	0.53759	0.55106
RNNs	0.55397	0.62269	0.62670

Table 3: Learner state prediction results on the XTdata dataset

Method	N=5	N=10	N=20
Deepwalk	0.79937	0.80377	0.80534
Struc2vec	0.79310	0.80534	0.80847
Hin2vec	0.75548	0.76766	0.75510
RNNs	0.95298	0.87912	0.83987

Comparing the dynamic network representation method (RNNs) with static methods (Deepwalk, Struc2vec, Hin2vec), the superior performance of RNNs across both datasets (Tables 2 and 3) illustrates the efficacy of dynamic modeling in capturing temporal interaction patterns. This finding aligns with the hypothesis that learning is a dynamic process in which the quality of interactions evolves over time, making static methods less effective in predicting learner states. Two experimental datasets were examined, and the average number of interactions of learners in different learning states is listed in Table 4.

Notably, the influence between the learner node and the learning resource node in the XTdata dataset is more pronounced, resulting in better experimental accuracy compared to the KDD15 dataset. However, compared with that of static network representation methods, the accuracy of the evaluation model proposed in this article significantly improved on both datasets, demonstrating superior performance.

Additionally, the greater average number of interactions among learners in the XTdata dataset (Table 4) suggests a more engaged learning environment, which likely contributes to the improved predictive accuracy observed. This insight emphasizes the role of frequent and meaningful interactions in enhancing learning outcomes, supporting the notion that fostering a highly interactive learning environment can lead to better educational results.

Table 4: Statistics of the average number of learner interactions

	KDD15	XTdata
Label 0	96	161
Label 1	30	35

In the context of the integration of education and the internet, evaluating the quality of learning interaction and utilizing the generated learning interaction data to enhance learners' performance and learning outcomes will be inevitable trends in the future development of education. In the future, researchers will increasingly apply neural networks and representation learning techniques in computer technology to conduct more in-depth mining and analysis of learners' interactive data. This will enable interventions in online teaching, representing a deeper and more advanced technical application direction.

However, it is essential to consider the limitations of this study, such as the potential biases introduced by the specific datasets used and the generalizability of the findings to other educational contexts. Future research should aim to validate these results across a broader range of datasets and explore the impact of different types of interactions on learning outcomes in more detail. Overall, the findings of this study underscore the importance of dynamic interaction evaluation in online learning environments and provide valuable insights into optimizing learning processes for improved educational outcomes.

Conclusion

This study established a clear online learning dynamic interactive network model and utilized recurrent neural networks (RNNs) to embed learners and learning resource nodes into a Euclidean space. The primary contribution lies in the development of an evaluation index for interactive quality, which assesses whether the learning outcomes of learners meet expectations based on these embeddings. Key findings indicate that the proposed model significantly enhances our ability to assess and improve interactive quality in online learning environments. However, this research has highlighted two critical challenges that merit further attention: first, the limitations of current data from online teaching platforms in fully capturing learner background information and behavior; second, the need for stronger theoretical foundations to support the design and validation of interactive quality evaluation indicators.

Moving forward, future research efforts will prioritize addressing these challenges. This includes exploring innovative data collection methods to better capture learner nuances and behaviors, as well as integrating more robust pedagogical theories to refine interactive quality evaluation metrics.

The implications of this study extend beyond its immediate findings. By advancing our understanding of interactive quality assessment in online learning, this research contributes to the broader body of scientific knowledge in educational technology and pedagogy. It provides a framework for educators and platform developers to enhance learning experiences through more informed design and assessment practices.

Furthermore, the insights gained from this study have practical implications for educational institutions and policymakers, as they offer guidance for optimizing online learning environments to better meet the needs of diverse learners. This includes strategies for improving engagement and personalized learning experiences and ultimately enhancing educational outcomes on a scalable basis.

In conclusion, this study not only advances methodologies for evaluating interactive quality in online learning but also underscores the importance of ongoing research in refining these methodologies to ensure their efficacy and applicability in diverse educational settings.

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