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Research Article

Intelligent Analysis on the Rationalization of Children's Physical Education Curriculum Based on Recurrent Neural Networks

Kexian Hao , Kunpeng Zhao, and Hanqing Cao

Xi'an Traffic Engineering Institute, Shaan Xi, Xi'an 710300, China

Correspondence should be addressed to Kexian Hao; haokexian@xjy.edu.cn

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In the future, the majority of PE (physical education) students in regular schools will become preschool teachers. As a result, these students' sports habits and feelings will have a direct impact on future preschool education and the training of preschool children's sports habits. As a result, PE curriculum in preschool normal schools must adapt to the future development of preschool education. This article develops a scientific, reasonable, and valuable children's PE curriculum by constructing the basic framework of modern children's PE curriculum. As a result, this research proposes two RNN-based models: one is a personalized recommendation model for children's PE curriculum—LSAPR (long short-attention point-of-interest recommendation) model, and the other is a recommendation model for children's PE curriculum sequence LSTM-RNNSR (long- and short-term memory-RNN sequence recommendation). The two models proposed in this paper have produced good off-line experimental results in various datasets, as well as a real-time personalized point-of-interest recommendation effect in practice.

1. Introduction

Children's sports have gradually become the focus of education practitioners, parents, and society in China, thanks to the Sunshine Sports Project's multilevel and all-around development [1]. The development of preschool education is directly influenced by the quality of preschool education. As a result, reforming the PE curriculum in preschool normal schools and improving students' attitudes toward physical activity are critical for exporting qualified preschool teachers, cultivating talents in line with social development, and improving preschool education quality.

At present, the research on curriculum teaching reform in general higher vocational colleges has changed from the traditional focus on technology, and teaching methods and means to all-round and multilevel research on teaching reform, such as teaching material construction, teacher team construction, teaching idea renewal, teaching mode, teaching organization form, teaching content, and teaching environment. [2] For example, some scholars have performed research on the reform of professional teaching in PE colleges; some scholars have performed research on fitness value development and other related aspects from their own point of view [3, 4]. Literature [5] writes that it is necessary to cater to students' main needs, create problem situations, stimulate students' interest in inquiry, and experience the happiness brought by success, thus breaking the competitive sports teaching mode that ignores students' psychological experience, changing the traditional organization mode, and closely combining school sports with social sports activity groups. Literature [6] found that the current mode of PE (physical education) courses in universities is mostly "three-stage," that is, the first-year basic PE class, the second-year optional courses, and the third-year and above elective courses. Literature [7, 8] makes a survey of the most popular sports among students in five universities, including table tennis, football, basketball, badminton aerobics, volleyball, and swimming. The results show that among the most popular sports in the universities surveyed, football actually ranks last, and the situation is not optimistic.

Preschool normal education in China has developed rapidly as the education system reform has progressed, and the educational concept and talent training mode of preschool normal education have changed dramatically, and the educational mode is becoming increasingly diversified [9]. However, there are still many issues to be resolved in terms of teaching mode and content in actual teaching. This study uses RNN (recurrent neural network) to assist and educate preschool teachers, develop more effective and sustainable preschool PE curriculum ideas, establish successful curriculum models, and provide high-quality educational services for young children.

At present, in the establishment of a teaching system, the school has established the PE teaching target system, which focuses on lifelong PE, supplemented by healthy PE and sports skills learning. However, it seldom involves the direction of sports culture shaping and sports appreciation, and the teaching evaluation methods are different. Therefore, this article applies the RNN model to the analysis of rationalization of preschool PE curriculum.

2. Related Work

DL (deep learning) usually uses the artificial neural network to learn the high-level data representation. By learning the depth model of a large amount of data, high-level data representations can be extracted from lower levels. For example, literature [10] proposed a method of processing a song as a group of 599 consecutive frames and trained CNN (convolutional neural network) [11, 12] to learn its sentences to solve the cold start problem in recommendation. Literature [13] proposed that the CNN (convolutional neural network) integrates product description into probability matrix decomposition. Compared with the topic model, it can capture context information of text. Because the size of convolution kernel is fixed during CNN training, the CNN with different convolution kernel sizes may be needed to improve the performance. A more common way to model text sequences is to use the RNN model.

Up to now, only a few recommendation methods based on the neural network have been proposed for POI (point-of-interest) recommendation, and the main network structure of these methods is the RNN structure and its variants. Literature [14–16] point out that both short-term preferences and long-term preferences of users cannot be ignored, but the traditional RNN structure is not designed to distinguish these two preferences at the same time. The popularization of literature [17] has brought some successful practices of model-based methods, which are based on MF (matrix factorization) technology. Literature [18] combines social influence with CF (collaborative filtering) model based on users and uses the Bayesian model to model geographical location context. Literature [19] shows how inner product linearly combines with potential features and limits the expressive ability of MF. Literature [20] proposed a latent model based on tensor, which considered the influence of users' latent behavior patterns on the recommendation results. The pattern was determined by context time and category information. Literature [21] uses the RNN to predict the click of online advertisements. At every moment, they train the RNN with the latest click of users and the previous state of the network and use the classification loss measure (cross-entropy loss) to predict the next click of users. Literature [22] proposes a context-adaptive method for constructing session-aware recommenders, which can deal with long-term (e.g., seasonal) and short-term changes of user preferences in the news field. In their work, the author put forward a semantic structural model of time depth, which combines the characteristics of users and projects with the characteristics of users' time into a joint model, in which the static characteristics are modeled by several feedforward neural networks and the time characteristics are modeled by a group of RNN.

3. Research Method

3.1. Curriculum Structure of Preschool PE. The definition of children's PE can be divided into different levels from a social standpoint. In a broad sense, it refers to children as the subject of sports activities, and in a more specific sense, it refers to the public's perception of kindergarten PE. Children's PE should follow the rules of children's growth and development, improve health, systematically teach children sports, health care, and a healthy lifestyle, cultivate children's interests and hobbies in sports, form the habit of exercising, and promote the all-round development of children's physical and mental personalities, according to this article. Curriculum development is a difficult and time-consuming task that encompasses not only the dominant curriculum idea, curriculum setting principles, and curriculum structure, but also the implementation and evaluation of curriculum. As a preschool teacher training institution, it is critical to establish clear training objectives, training modes, and principles for preschool teachers in today's society, as well as to train and adjust teachers' skills on a timely basis.

With the deepening of the educational system reform, the preschool normal education in China is developing rapidly. The educational concept and talent training mode of preschool normal education have been greatly improved, and the educational mode is becoming more and more diversified. However, in actual teaching, there are still \many problems to be solved in teaching mode and teaching content. In preschool normal PE, the ratio of male to female is seriously out of balance. If the teaching content of PE cannot be arranged reasonably. The teaching evaluation of PE is single, the evaluation method lacks scientificity, and the PE in preschool normal schools still focuses on physical quality assessment items, paying attention to the results and ignoring the differences of students' individual basis. This teaching mode lacks motivation and unfairness, which is not conducive to the development of quality education.

The theoretical basis of curriculum includes policy basis and academic basis. As a course, there must be a clear educational outline, including the requirements and indicators of educational tasks and objectives, educational principles, educational environment, and educational contents and methods. The basic framework of the course is shown in Figure 1.

There is explicit and implicit curriculum content in the curriculum. Explicit content in kindergartens refers to daily sports activities, whereas implicit content refers to material and spiritual content such as environmental creation, work

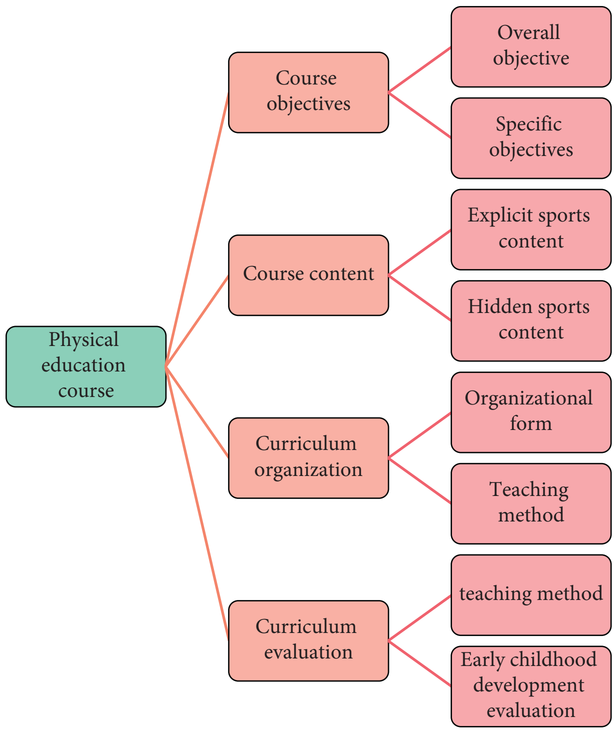

FIGURE 1: Basic framework of modern preschool PE curriculum.

and rest time, teacher-student relationships, good atmosphere, and home cooperation, among other things. The terms teaching methods and "teaching means" are used interchangeably. Individualized, group, and collective teaching methods are commonly used in preschool PE. Appropriate teaching methods and means should be used to improve children's interest in learning, taking into account the teaching objectives, children's abilities, and teaching resources.

3.2. Personalized POI Recommendation Model with AM. The formation of children's motor skills is the complementary connection of vision, hearing, vestibule, and other organs. Preschool teachers should use correct and graceful motor demonstration, and concise and neat oral instructions, and protect children in the teaching of difficult movements. It is difficult for children to fully understand and master what they have learned. Therefore, teachers require children to practice the actions they have learned repeatedly and attach importance to their active experience, independence, and innovation.

Among the means of curriculum evaluation, one is measurement-based evaluation, which aims at obtaining empirical data through strict measurement. The other kind of evaluation is based on speculation and logical inference, through rigorous analysis and demonstration at a higher theoretical level. Reveal the significance of the course and explain the value of the course. The evaluation of modern curriculum generally pays attention to the effective combination of the two.

In this chapter, an LSAPR (long short-attention point-of-interest recommendation) model is proposed, which uses all historical POISS of users to capture users' real long-term preferences and weights different times of the current POI sign-in sequence with AM (attention mechanism) [23].

RNN is a kind of artificial neural network modeled by sequence information. The structure of RNN is shown in Figure 2.

Specifically, given the sequence $x = (x_1, x_2, \ldots, x_T)$, the RNN updates the circular hidden state h_t by the following formula:

$$h_t = \begin{cases} 0, & t = 0, \\ \sigma(h_{t-1}, x_t), & t \neq 0, \end{cases} \tag{1}$$

where σ is a nonlinear function, such as tanh and sigmoid function.

Specifically, the hidden state update of the RNN in formula (1) is usually realized by the following formula:

$$h_t = g(Wx_t + Uh_{t-1}), \tag{2}$$

where g is a nonlinear function and W, U is a weight matrix.

An LSA algorithm using all user login sequences is proposed, which can dig out the user's long-term preferences from all the user's historical POISS (POI sign-in sequences) and pay attention to the short-term preferences in the current POISS. See the following formula for the specific forward propagation process:

$$\begin{aligned} \alpha_i &= Z_0 \sigma\left(Z_1 h_i^m + Z_2 h_t^m + Z_3 \overline{h}_t = b_\alpha\right), \\ h_{LSA}^m &= \sum_{i=1}^{t} \alpha_i h_i^m. \end{aligned} \tag{3}$$

Here, α_i represents the weight of the i th moment in the current POISS; h_{LSA}^m is the attention representation of the current POISS obtained by the AM; h_i^m indicates that the hidden state of the first moment in the current POISS represents the overall representation of the current POISS; h_t^m represents the user's long-term preference; and Z_*, b_α is the weight matrix and the deviation vector, respectively.

This article introduces the LSA mentioned above into the decoder of CAPR (context-aware point-of-interest recommendation), which can mine users' long-term preferences from all historical POISSs of users. Figure 3 is a schematic diagram of the network structure of LSAPR.

In this article, the general GRU structure is extended, the context information is integrated into the gating structure, and a CAGRU (context-aware gated recurrent unit) is proposed. Based on the natural geographical location attribute, time point attribute, and category information of POI, this expansion can make GRU structure more suitable for POI recommendation tasks.

It can be seen from Figure 3 that the LSAPR model first inputs the user's historical POISS into the CAGRU encoder to encode the whole sequence and at the same time uses the CAGRU. The encoder obtains the hidden state of each moment of the current sequence of the user. Then, input

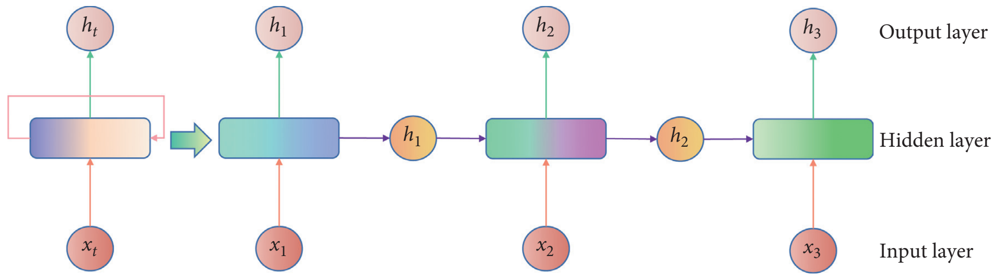

FIGURE 2: RNN structure diagram.

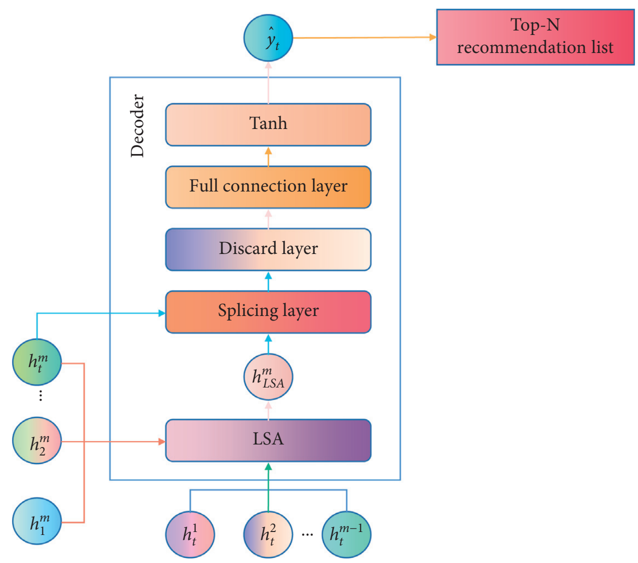

FIGURE 3: Schematic diagram of the LSAPR model structure.

these data into LSA to obtain the attention expression of the current POISS, which is given as

$$h^m_{LSA} = LSA\left(\left\{h^1_t, h^2_t, \ldots, h^{m-1}_t\right\}, \left\{h^m_1, h^m_2, \ldots, h^m_t\right\}\right). \tag{4}$$

It is necessary to train the data of each user separately during the LSAPR model training process in order to obtain personalized recommendation results for that user. Each user's POISS is sorted by starting time and then divided using the subsequence division method described in CAPR model training. To speed up the calculation of the attention score, the entire representation of the sequence before it is stored in memory for each POISS.

3.3. Sequence Recommendation Model Based on RNN. The learning evaluation system for PE courses in ordinary schools, as an important part of PE, lags behind in terms of reform and does not fully reflect its inherent function of guiding and encouraging people to grow up healthy and harmoniously. The goal of improving and perfecting the PE teaching content, teaching mode, and evaluation system is to meet the needs of society and comply with relevant requirements and norms, with the ultimate goal of "cultivating students' lifelong sports habits" and the specific goal of "enhancing students' physique, improving students' enthusiasm for participating in sports activities, and promoting students' physical and mental health development."

Today, with the increasingly severe social competition, the training objectives of school education are becoming more and more clear. How to make these technical applied talents who are fighting in the front line of society have good physical qualities and put them into the construction of society will become the development focus and development trend of school PE.

In this article, a new recommendation model LSTM-RNNSR (long- and short-term memory-RNN sequence recommendation) is proposed. The model consists of RNN attention module and item-item relationship module, which is integrated with the matrix decomposition model and optimized by Bayesian personalized sorting.

LSTM (long- and short-term memory) introduces gating mechanisms such as forgetting gate and input gate [24], which better solves the problem of gradient disappearance or explosion, so the LSTM-based model is widely used for text modeling, especially for long text modeling.

There are three gates in the LSTM unit to protect and control the state flow. For each time step t, given the input x_t and the current cell state c_t, the hidden state h_t can be updated with the previous cell state c_{t-1} and the hidden state h_{t-1}, and the update formula is as follows:

$$\begin{bmatrix} i_t \\ f_t \\ o_t \end{bmatrix} = \begin{bmatrix} \sigma \\ \sigma \\ \sigma \end{bmatrix} \left(W\left[h_{t-1}; x_t\right] + b\right),$$
$$\widehat{c}_t = \tan h\left(W\left[h_{t-1}; x_t\right] + b_c\right),$$
$$c_t = f_t \otimes \widehat{c}_{t-1} + i_t \otimes \widehat{c}_t,$$
$$h_t = o_t \otimes \tan h\left(c_t\right). \tag{5}$$

Here, i_t, f_t, o_t are the input gate, the forgetting gate, and the output gate, respectively, and the value range is $[0,1]$, σ is the sigmoid function, and $\otimes$ represents the element multiplication. The hidden state h_t represents the output information of the LSTM unit at time step t.

Because closely related project pairs may appear in L, T at the same time, different from previous studies, this article applies inner product between input item embedding and output item embedding to capture the item relationship between L, T:

$$\sum_{e_i \in S_{u,l}} e_i^T \cdot Q, \tag{6}$$

where $Q \in R^{d\times N}$ is the output item embedding, and the sum of inner product results captures the cumulative item-item relationship scores from each item in L to all other items.

Because the training data come from implicit feedback from users, this article optimizes the proposed model through Bayesian personalized sorting:

$$\arg\min \sum_{\left(u,L_u,i,k\right)\in D} -\log\, \sigma\left(\widehat{r}_{u,i} - \widehat{r}_{u,k}\right) + \Omega. \tag{7}$$

Here, L_u represents the continuous term of a user u in $|L|$, k represents the negative term of random sampling, and Ω is the regularization term to prevent overfitting. By minimizing the objective function, the partial derivatives of all parameters can be calculated by back propagation and gradient descent. At the same time, the Adam optimizer is used to automatically adjust the learning rate in the process of model learning.

Therefore, the PE teaching in preschool normal schools should constantly update the teaching content, so that students can lay a good foundation of knowledge. In teaching practice, it is necessary to provide students with opportunities for in-depth preschool education activities and practice, so that they have stronger social adaptability and at the same time can also integrate theory with practice and continuously improve their theoretical level in practice. In addition, the PE curriculum in preschool normal schools should reflect the characteristics of the school, add special courses in combination with the nature, characteristics, conditions, and personnel training objectives of the school, and provide more choices of courses to meet the diversified needs of students' future development.

4. Results Analysis and Discussion

4.1. Theoretical Results and Analysis. Following visits to and consultations with several schools, eight of the ten schools surveyed have developed their own PE curriculum in accordance with the National General Universities PE Teaching Guidelines, and some preschool normal schools have developed their own curriculum in accordance with their own operating conditions and actual teaching situation. Figure 4 depicts the statistical results of the selected public curriculum questionnaire in PE class.

The curriculum of the old syllabus finally determined by the questionnaire is basketball, gymnastics, track and field, volleyball, and so on. The final curriculum of the new syllabus is basketball, badminton, table tennis, yoga, physical training, sports theory, theoretical investigation, swimming, sports dance, gymnastics, track and field, and soft volleyball. The statistical results of the questionnaire selected for the test index of students' physical quality in preschool schools are shown in Figure 5.

The final test methods of students' physical fitness determined by the questionnaire are 30-meter run, shot put in place, shot put back, bench push, squat, and standing long jump.

Teachers must devise sports games and thoroughly explain the rules to children in accordance with the syllabus's requirements. Teachers only need to explain and emphasize the scope of the children's activities and the game rules when playing games. Teachers must re-explain the content of their lessons and determine the most effective teaching techniques. Recognize the parts that are difficult for children to master on a technical level. Children have already gained active experience and a new understanding of the teaching content as a result of this process. Teachers should also pay close attention to the standardization and details of the experience process, and set higher expectations for the children. Observe the children's experiences as bystanders and make a note of the characteristics of a few of the observations. For example, if a teacher needs to get closer to the students, he can squat and pass on the content of the lesson to the students.

4.2. Analysis of Personalized POI Recommendation Model of Preschool PE Curriculum. In order to accurately evaluate the performance of each model in POI recommendation tasks, this article adopts two evaluation indexes, Recall@K (recall rate) and MRR @ k (mean recall rank), which are widely used in recommendation systems. k represents the length of the recommendation list. In order to accurately evaluate the influence of different list lengths on recommendation results, this article selects the values of each evaluation index when the lengths of the report list are 2, 6, and 10.

In order to determine the appropriate hidden state dimension of the CAGRU structure in the model, this article uses the training set and the verification set to select the hidden state dimension parameters of the two models under the same other parameters. Take the experiment of CAPR model on Foursquare dataset as an example, and the results are shown in Figures 6 and 7.

It can be seen that with the increase in the hidden state dimension, the performance of the model gradually gets better, but under the condition that the number of

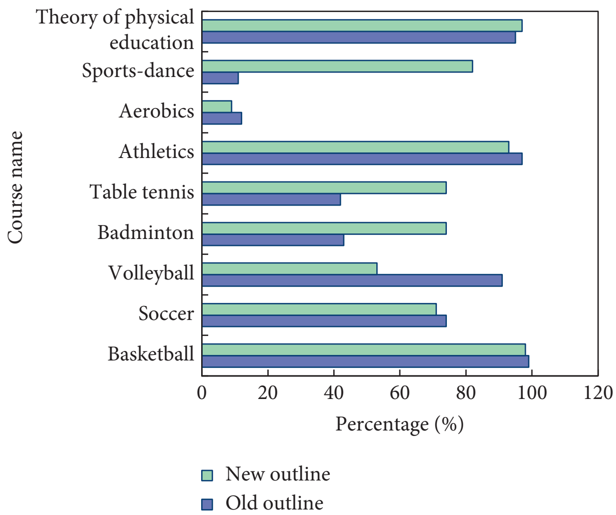

Figure 4: Questionnaire statistical results.

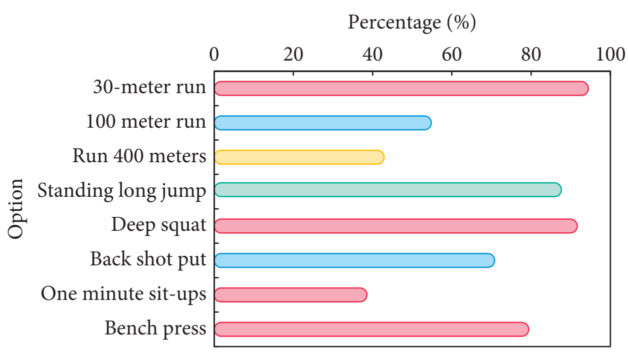

Figure 5: Test index selected questionnaire statistical results.

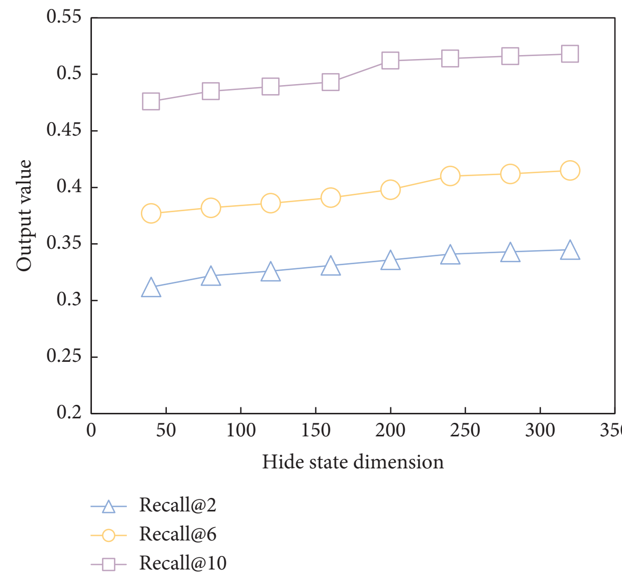

Figure 6: Hiding the experimental results of state dimension parameter selection (Recall@K).

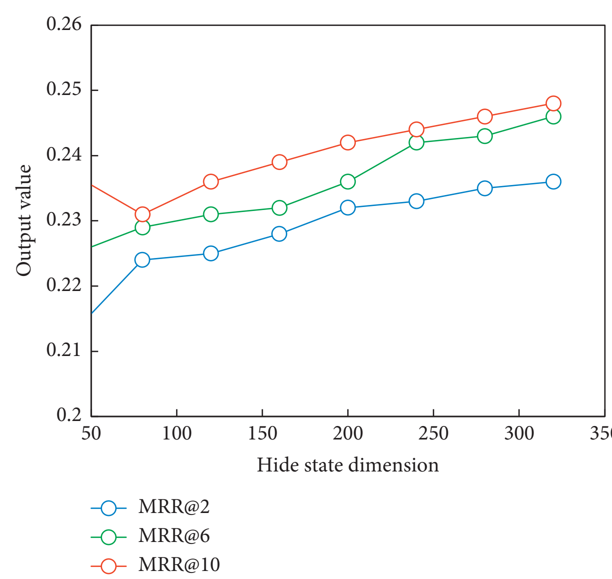

Figure 7: Hiding the experimental results of state dimension parameter selection (MRR@K).

dimensions increases unchanged every time, the improvement speed of the model performance gradually slows down or even stops improving.

The increase in the hidden state dimension will not only bring greater computational complexity, resulting in higher training overhead, but also make the model structure very complicated, which is prone to overfitting problems when the existing data are insufficient. According to the above analysis, in order to balance the model performance and training cost, this article sets the hidden state dimension of the model to 240 dimensions.

When the learning rate of the optimization algorithm is too high, the model loss will drop rapidly at the beginning, but then it will fluctuate greatly, in which case it will not converge. When the learning rate of the optimization algorithm is small, the loss of the model decreases very slowly, and it will take many iterations to achieve the desired effect.

The comparison model mentioned above and CAPR and LSAPR models proposed in this article are trained and tested on two datasets, respectively. Figure 8 shows the statistics of experimental results of different models on two datasets, all of which are obtained by averaging multiple experiments.

The majority of the indexes of the two models on two real datasets exceed the currently popular POI recommendation model or sequence-aware recommendation model, according to the analysis of the experimental results in Figure 8. In general, as the length of the recommendation list grows longer, the model's performance on two evaluation indexes improves. Take the model's performance on a 10-item recommendation list as an example for analysis. In general, the CAPR and LSAPR models proposed in this article outperform the comparison model in each of the two datasets' indexes. The experimental results show that the CAPR and LSAPR models can more effectively capture users' long- and short-term preferences, and they can perform well in POI recommendation tasks regardless of whether the users are cold start or personalized recommendations.

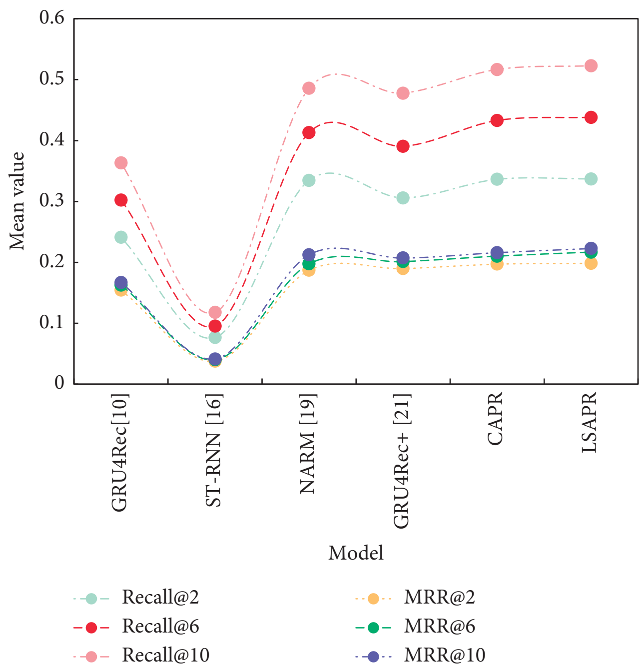

Figure 8: Foursquare comparative experiment results.

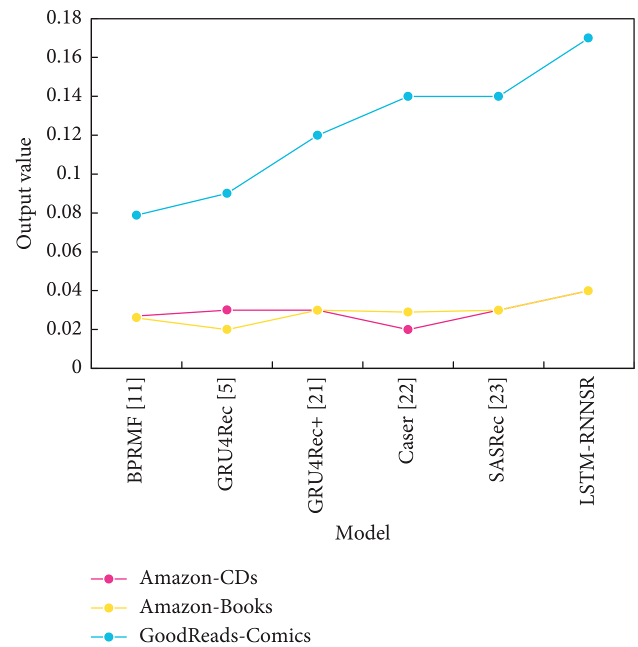

Figure 9: R@8 comparison of different recommendation algorithms.

4.3. Analysis of the Recommendation Model of Preschool PE Curriculum Sequence. In order to verify the recommendation performance of the model proposed in this article, the experiment will compare and analyze the LSTM-RNNSR model in this article with the commonly used recommendation models in three real datasets with different fields and sparsity.

In this article, Recall@k and NDCG@k are used to evaluate the recommendation accuracy of each model. For each user, Recall@k(R@k) represents the percentage of the first k recommended items that appear in the scoring items, and NDCG@k(N@k) is the normalized cumulative loss gain of the first k recommended items, taking into account the position of the correct recommended items.

In this article, six groups of algorithms are tested on Amazon-CDs, Amazon-Books, and GoodReads-Comics datasets, and the difference between the score prediction results of R@8 and N@8 is analyzed. The comparison results of the LSTM-RNNSR model with five comparison algorithms of R@8 and N@8 are given in Figures 9 and 10 respectively.

It can be seen from the table that the recommended performance of the LSTM-RNNSR model on Amazon-CDs, Amazon-Books, and GoodReads-Comics datasets exceeds all comparison methods.

The model LSTM-RNNSR in this article achieves better recommendation performance than SASRec. The main reasons are that SAREC only uses part of the user's historical interactive data, which may lead to the inability to fully learn users' long-term interests, and that SAREC does not explicitly consider the relationship between projects.

Based on BPRMF, this model uses the RNN and AM to capture users' short-term interest preferences and at the same time considers the relationship between users' historical interaction items and prediction items, thus making the model LSTM-RNNSR obtain better recommendation performance.

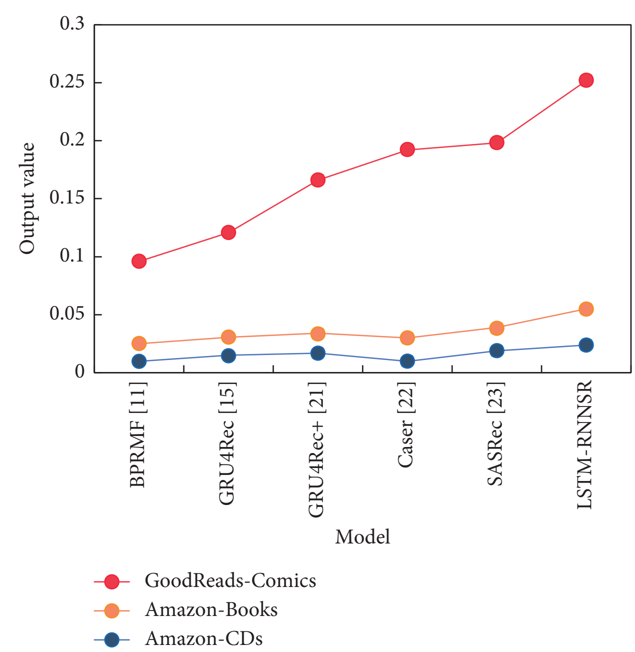

Figure 10: N@8 comparison of different recommendation algorithms.

The effects of different values of item embedded dimension d on the model on Amazon-CDs dataset are shown in Figure 11.

It can be seen from Figure 11 that when the embedded dimension of the project is too small, the model recommendation performance is not good at this time, because the dimension of the project is too small to model the potential characteristics of the project. With the increase in the item embedding dimension d, the model performance gradually improves and becomes stable.

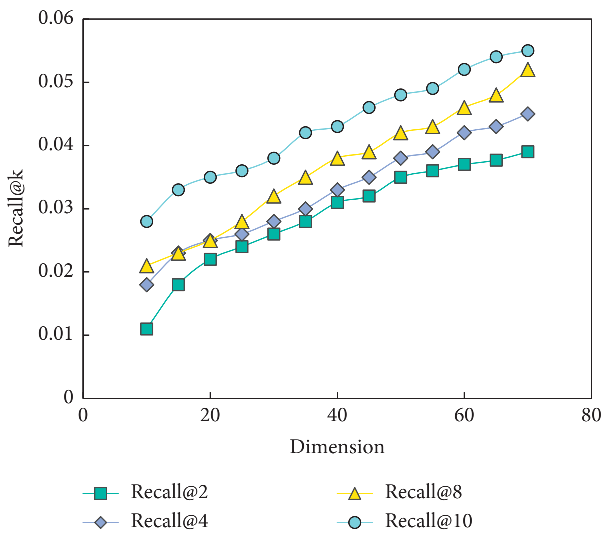

Figure 11: Change in embedded dimension.

5. Conclusion

The teaching status of preschool normal schools can be changed, and the teaching quality and effect can be improved, so that the PE curriculum in preschool normal schools can truly adapt to the future development of students, laying the foundation for cultivating more talents needed by society and improving the quality of preschool education. Based on the improved structure GRU of the RNN and the sequence nature of POI sign-in data, this article designs and implements two POI recommendation models: LSAPR and LSTM-RNNSR. To achieve the goal of personalization, the model uses all of the users' POISSs, as well as the long-term and short-term AM LSAs to more accurately capture the long-term and short-term preferences of users reflected in POISSs. The experimental results of the method proposed in this article on three real datasets with different categories and sparsity show that it outperforms the currently used sequence recommendation methods.

Because of the scarcity of data, the performance of the POI recommendation model may be severely limited. We hope to continue exploring the impact of data sparsity on model performance in the next step and to propose solutions to the problem of data sparsity.

Data Availability

The data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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