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iJET International Journal of Emerging Technologies in Learning

iJET | eISSN: 1863-0383 | Vol. 18 No. 17 (2023) | OPEN ACCESS

https://doi.org/10.3991/ijet.v18i17.43491

PAPER

Intelligent Content Distribution System: A Machine Learning–Based Teaching Content Customization Method

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ABSTRACT

With the rapid development of information technology and the increasing diversity in the education field, personalized teaching has become the key to educational innovation. However, existing methods of customizing and distributing teaching contents often fail to effectively cope with complex teaching environments and resource constraints. To solve this problem, this study proposed a novel intelligent content distribution system, i.e., a teaching content customization method based on machine learning. First, an inverse optimization model of teaching content customization targeted at content combinations was constructed, which minimized the adjustment of configuration parameters and customized resource constraints. This model generated more reasonable and effective teaching content configuration plans by comprehensively considering content diversity, students' needs, and resource constraints. Second, to further improve the efficiency and effect of content distribution, an intelligent content distribution algorithm based on a hierarchical reinforcement learning network was developed, which allowed the system to automatically learn and adjust content distribution strategies based on students' needs and preferences, and optimized the teaching content configuration while meeting resource constraints. The method proposed in this study not only significantly improved the teaching effect, but also provided strong technical support for the rational allocation of educational resources, thereby bringing profound impacts to modern education. This study is of great significance for intelligent content distribution and personalized teaching in the education field.

KEYWORDS

personalized teaching, machine learning, teaching content customization, intelligent content distribution

1 INTRODUCTION

In the 21st century, the rapid development of information technology and the increasing popularity of the Internet have been changing people's way of life and learning profoundly. As an important field for cultivating talents and disseminating knowledge, education is at the forefront of this transformation [1, 2]. Traditional

He, Q., Wang, K. (2023). Intelligent Content Distribution System: A Machine Learning–Based Teaching Content Customization Method. *International Journal of Emerging Technologies in Learning (iJET)*, 18(17), pp. 98–112. https://doi.org/10.3991/ijet.v18i17.43491

Article submitted 2023-06-05. Revision uploaded 2023-07-20. Final acceptance 2023-07-25.

teaching methods, such as classroom teaching, are limited by geographical location, time, and physical space, which greatly reduce the efficiency of acquiring and utilizing learning resources. At the same time, the education field has been facing the problem of increasing differences in students. In this diversified world, the learning needs, interests, and abilities of each student are unique. Therefore, the traditional "one-size-fits-all" teaching method no longer meets the needs of modern education [3–6]. Personalized teaching, which provides customized teaching content and methods based on the characteristics and needs of each student, has gradually become an important direction for educational innovation [7–13].

To achieve personalized teaching, many machine learning–based methods have emerged in the field of educational technology in recent years [14–16]. By collecting and analyzing a large amount of learning data, including learning process, grades and feedback of students, machine learning algorithms gain insight into their learning needs and preferences to some extent [17–20], which enables the education system to provide students with more precise and personalized teaching content. In addition, based on students' learning progress and feedback, intelligent teaching systems dynamically adjust teaching strategies to continuously optimize teaching [21, 22].

However, existing methods of customizing and distributing teaching content still face many challenges in practical application. First, many methods fail to fully consider the configuration of teaching content combinations and its complex relationship with students' needs, resulting in distributed content not optimally meeting their needs [23–25]. Second, existing teaching content distribution methods are often complex and require a large amount of computing resources, which is not feasible in large-scale educational scenarios. More importantly, existing methods often fail to take into account the limitations of educational resources, which is a serious drawback in educational environments with limited resources.

To solve the above problems, this study proposed a novel intelligent content distribution system, i.e., a teaching content customization method based on machine learning. The method focused on constructing an inverse optimization model of teaching content customization targeted at content combinations, which minimized the adjustment of configuration parameters and customized resource constraints. This model generated more reasonable and effective teaching content configuration plans by considering content diversity, students' needs, and resource constraints. To further improve the efficiency and effect of content distribution, an intelligent content distribution algorithm based on a hierarchical reinforcement learning network was developed, which allowed the system to automatically learn and adjust content distribution strategies in order to better adapt to students' needs and preferences. At the same time, the algorithm optimized the teaching content configuration while meeting resource constraints. Use of this method not only significantly improved the teaching effect but also provided strong technical support for the rational allocation of educational resources, thereby bringing profound impacts to modern education.

2 INVERSE OPTIMIZATION MODEL OF TEACHING CONTENT CUSTOMIZATION

2.1 Combining content

Optimization of both teaching content combination plans and customized teaching resource allocation is related to two indexes: configuration parameters and customized resource constraints. The inverse optimization model can be used to minimize the adjustment of both indexes, which guides the intelligent content distribution system to reasonably change the parameter configuration of teaching content combinations and to reasonably adjust customized resources, thereby realizing targeted optimization of content combination plans and customized teaching resource allocation to achieve the given teaching objectives.

After customizing the actual teaching contents, the intelligent content distribution system predicts whether the distributed teaching content meets the condition of utility maximization. If this condition can be met, the teaching content configuration plans are submitted and distributed immediately to enter the system's subsequent process. However, the process of customizing teaching content is cumbersome and prone to errors. The intelligent content distribution system does not have a clear understanding of whether the attributes of teaching content match the teaching objectives of courses and the learning needs of students, and cannot choose specific teaching content to create clear plans of customizing teaching content. For teaching content combinations, the selected attribute parameter level does not correspond to the optimal parameter level of teaching effect. A more ideal teaching effect can be achieved by changing the configuration parameters corresponding to certain teaching content. On the other hand, teachers and students have a certain tolerance for the combination quality of teaching content combination plans, allowing for certain combination deviations, that is, allowing for appropriate adjustments to the configuration parameters corresponding to the current teaching content. Therefore, this study constructed an inverse optimization model of teaching content customization, with the configuration parameters corresponding to the teaching content as parameters, which changed the configuration parameters to the minimum to seek the optimal solution of the teaching content combination plans.

Let v_{ku} be the configuration parameters, n_j be the customized resource constraints, z^* and t^* be the optimal solutions of the original model and its dual model for multi-type teaching content customization. The following equation provided the dual model expression for the multi-type teaching content customization:

$$\begin{cases} MIN \quad x = \sum_{j=1}^{j} n_j t_j \\ s.t. \quad H^{-1}T \le i_u \quad u = 1,2,...,B \\ \qquad t_j \ge 0 \quad j = 1,2,...,J \end{cases} \tag{1}$$

The following equations provide the expressions of corresponding complementary optimality conditions:

$$t^*(H \cdot z^* - n) = 0 \tag{2}$$

$$(i - t^* \cdot H)z^* = 0 \tag{3}$$

The above two equations were used as constraint conditions to construct the inverse optimization model of parameters v_{ku}. Assume $\bar{h}_{j.}$ was obtained after $h_{j.}$ was inversely optimized, and $\bar{h}_{j.} = h_{j.} + \lambda_{j.} - \zeta_{j}$. Let $\lambda_{j.}$ and $\zeta_{j.}$ be the increment and decrement of $h_{j.}$, and let $\lambda_{j.} \ge 0$, $\zeta_{j.} \ge 0$, and $\lambda_j * \zeta_{j.} = 0$. The following equation provided the expression of the corresponding inverse optimization model:

$$\begin{cases} MIN & \left\| \bar{H} - H \right\| \\ s.t. & \bar{h}_{j.}\bar{z} - n_j = 0 \quad j \in U \\ & \bar{h}_{j.}\bar{z} - n_j \le 0 \quad j \in \bar{U} \end{cases} \tag{4}$$

Considering $|\lambda_{j.} - \zeta_{j.}| \le |\lambda_{j.} + \zeta_{j.}|$, the inverse optimization model shown in the following equation was constructed under the L_1 norm:

$$\begin{cases} MIN & \left\| \lambda + \zeta \right\| \\ s.t. & \left(h_{j.} + \lambda_{j.} - \xi_{j.}\right)\bar{z} = n_j \qquad j \in U \\ & \left(h_{j.} + \lambda_{j.} - \xi_{j.}\right)\bar{z} \le n_j \qquad j \in \bar{U} \\ & \lambda_{j.}, \zeta_{j.} \ge 0, j = 1,2,\ldots,J \end{cases} \tag{5}$$

abs-norm $\left|H\right|_{sna} = \sum_{j=1}^{J}\sum_{k=1}^{B}\left|\lambda_{ju} + \zeta_{ju}\right|$ of the matrix H was defined, which further obtained:

$$\begin{cases} MIN & \sum_{j=1}^{J}\sum_{u=1}^{B}\left|\lambda_{ju} + \zeta_{ju}\right| \\ s.t. & \left(h_{j.} - \zeta_{j.}\right)\bar{z} \le n_j \qquad j \in U \\ & -\left(h_{j.} + \lambda_{j.}\right)\bar{z} \le -n_j \quad j \in U \\ & \left(h_{j.} - \zeta_{j.}\right)\bar{z} \le n_j \qquad j \in \bar{U} \\ & \zeta_{j.} \ge 0 \quad j \in U \cup \bar{U} \\ & \lambda_{j.} \ge 0 \quad j \in \bar{U} \end{cases} \tag{6}$$

The *D-W* decomposition algorithm was used for calculation, which obtained $\bar{h}_{j.}$, because the above equation was a general linear programming model. Let $\bar{v}_{ku}$ be the adjusted configuration parameters; then it was inferred from $h_{ju} = \sum_{k=1}^{L} e_{ju} * v_{ku}$ as follows:

$$\bar{h}_{ju} = \sum_{k=1}^{L} e_{ju} \cdot \bar{v}_{ku} \tag{7}$$

$\bar{v}_{ku}$ was solved by combining the above two equations. According to the above derivation process, the process of seeking the optimal teaching content combination plan was the process, where v_{ku} changed to $\bar{v}_{ku}$, i.e., the inverse optimization process of adjusting configuration parameters. The process inversely optimized based on the teaching objectives of courses and the learning needs of students, aiming to maximize the total efficiency of the teaching effect.

2.2 Allocating teaching resources

Under the constraints of rigid teaching resources, the number of teaching content combination plans provided by an intelligent content distribution system is limited. The teaching objectives of courses and the learning needs of students should meet the limitations of customized resources; otherwise, the operability of teaching content customization does not exist. However, in the process of teaching resource allocation, the intelligent content distribution system does not have a clear understanding of the system's resource constraints. The customization plans of teaching resource allocation, which are planned and solved using existing teaching resources, may not meet the teaching and learning needs of teachers or students, which affects the effective achievement of teaching quality and greatly limits the customization ability of the intelligent content distribution system. Therefore, this study established an inverse optimization model of customizing teaching contents, with customized resource constraints n_j as parameters, which turned the determined teaching goal point into the optimal solution of the constructed model.

Similarly, the inverse optimization model of customized resource constraints n_j was constructed, with the complementary optimality conditions shown in Equations 2 and 3 in the previous section as constraints. Let $\bar{n}_j$ be the inversely optimized n_j; $U = \{j \mid t_j^* > 0\}$ and $\bar{U} = \{j \mid t_j^* > 0\}$ according to the constraint conditions; $Y = \{y_1, y_2, ..., y_j\}$ be the additional costs caused by changing certain teaching resources; $\bar{n}_j = n_j + \sigma_j - \alpha_j$, and $j = 1, 2, ..., J$, where, σ_j is the increment of n_j with $\sigma_j > 0$, α_j is the decrement of n_j with $\alpha_j > 0$, and $\sigma_j * \alpha_j = 0$. The inverse optimization model shown in the following equation was constructed under the L_1 norm:

$$\begin{cases} MIN & Y\left\|\bar{n}-n\right\| \\ s.t. & h_{j.}\bar{z}-\bar{n}_j = 0 \quad j \in U \\ & h_{j.}\bar{z}-\bar{n}_j \le 0 \quad j \in \bar{U} \end{cases} \tag{8}$$

Considering $\left|\sigma_j - \alpha_j\right| \le \left|\sigma_j + \alpha_j\right|$, the above equation was modified as follows:

$$\begin{cases} MIN & Y\left\|\sigma+\alpha\right\| \\ s.t. & h_{j.}\bar{z}-\sigma_j+\alpha_j = n_j \qquad j \in U \\ & h_{j.}\bar{z}-\sigma_j+\alpha_j \le n_j \qquad j \in \bar{U} \\ & h_j, \alpha_j \ge 0, j = 1,2,\ldots,J \end{cases} \tag{9}$$

The following was further obtained:

$$\begin{cases} MIN & \sum_{j=1}^{J} y_j \left\|\sigma_j+\alpha_j\right\| \\ s.t. & h_{j.}\bar{z}-\sigma_j \le n_j \quad j \in U \\ & -\left(h_{j.}\bar{z}+\alpha_j\right) \le -n_j \quad n \in U \\ & h_{j.}\bar{z}-\sigma_j \le n_j \quad j \in \bar{U} \\ & \sigma_j \ge 0 \qquad j \in U \cup \bar{U} \\ & \alpha_j \ge 0 \qquad j \in \bar{U} \end{cases} \tag{10}$$

2.3 Customization

The inverse optimization method of linear programming was used for highly flexible teaching resource allocation targeted at actual teaching scenarios. By establishing an inverse optimization model with v_{ku} and n_j as decision variables, the teaching content combination plans and customized teaching resources targeted at teaching objectives of actual courses and students' learning needs were flexibly adjusted at the same time. The expression of the corresponding inverse optimization model was given in the following equation:

$$\begin{cases} MIN & \left\|\bar{H}-H\right\|+Y\left\|\bar{n}-n\right\| \\ s.t. & \bar{h}_{j.}\bar{z}=\bar{n}_j \quad j\in U \\ & \bar{h}_{j.}\bar{z}\le\bar{n}_j \quad j\in\bar{U} \end{cases} \tag{11}$$

Considering $|\lambda j_{.}-\zeta_{j.}|\le|\lambda j_{.}+\zeta_{j.}|$ and $|\alpha_j-\alpha_j|\le|\alpha_j+\alpha_j|$, the above equation was modified as follows:

$$\begin{cases} MIN & \sum_{j=1}^{J}\sum_{u=1}^{B}\left|\lambda_{ju}+\zeta_{ju}\right|+\sum_{j=1}^{J}y_j\left|\sigma_j+\sigma_j\right| \\ s.t. & \left(h_{j.}-\zeta_{j.}\right)\bar{z}-\sigma_j\le n_j \quad n\in U \\ & -\left(h_{j.}+\lambda_{j.}\right)\bar{z}-\alpha_j\le -n_j \quad j\in U \\ & \left(h_{j.}-\zeta_{j.}\right)\bar{z}-\sigma_j\le n_j \quad j\in\bar{U} \\ & \zeta_{j.},\sigma_j\ge 0 \quad j\in U\cup\bar{U} \\ & \lambda_{j.},\alpha_j\ge 0 \quad j\in U \end{cases} \tag{12}$$

According to Equation 7 and the above equation, new $\bar{n}_j$ and $\bar{v}_{ku}$ were solved, which obtained new teaching content combination plans and customized teaching resource allocation plans.

3 INTELLIGENT CONTENT DISTRIBUTION BASED ON A HIERARCHICAL REINFORCEMENT LEARNING NETWORK

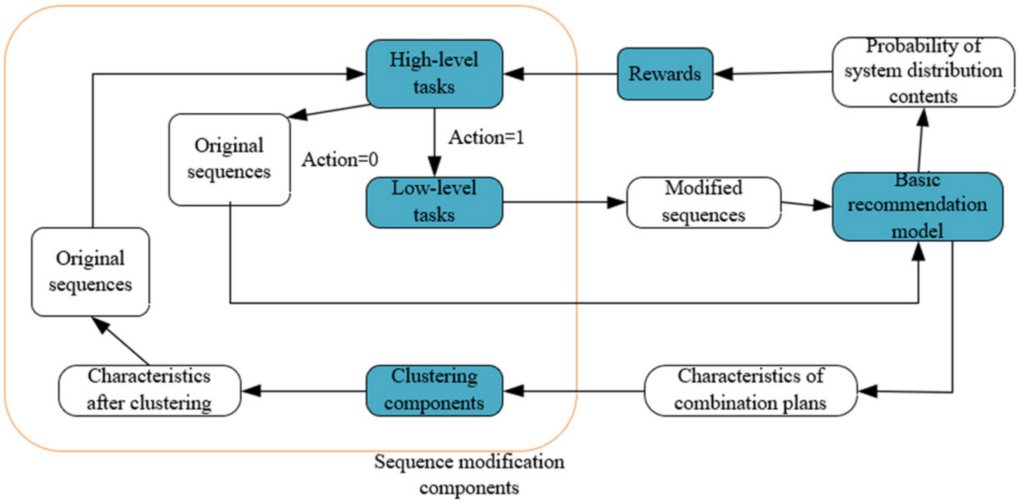

Fig. 1. Basic architecture of intelligent content distribution system

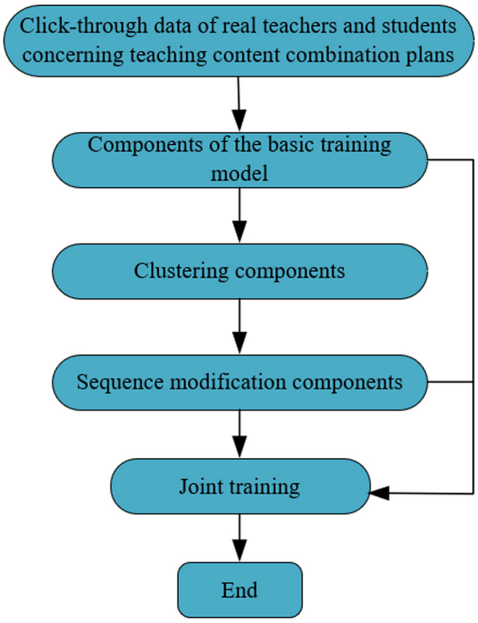

Fig. 2. Workflow diagram of the system

This section introduces an intelligent content distribution algorithm based on a hierarchical reinforcement learning network. According to existing click-through data of real teachers and students concerning teaching content combination plans, the intelligent content distribution system based on deep reinforcement learning was studied. The click-through data have two negative characteristics: (1) Teachers or students may mistakenly click some plans that are not suitable for them. During the content distribution process of the system, these data become noises in the sequence, which affects the final distribution results. (2) The system has a relatively large amount of teaching resources, and each teaching resource is combined very few times on average, resulting in sparse data of teaching resource allocation. Figure 1 shows the basic architecture of the intelligent content distribution system.

Teachers or students may mistakenly click plans not suitable for themselves in practice. These mistakenly clicked data exist as noise, which may mislead the content distribution algorithm and reduce the accuracy of distribution results. The sequence modification model in a hierarchical reinforcement learning network was designed to solve this problem. By using the hierarchical reinforcement learning method, the model effectively filtered out this noise, thereby improving the accuracy of distribution results. This study integrated the basic distribution model and the sequence modification model with the clustering model, which formed a complete hierarchical reinforcement learning network. This integrated architecture fully utilized the advantages of different models while solving the problems, such as noise and data sparsity, thereby distributing the contents more efficiently and accurately. Figure 2 shows the system's workflow.

3.1 Algorithm framework

Components of the basic distribution model. In the teaching content distribution system, it is important to understand the similarities between different teaching resources. In the click sequence, not every clicked item has the same importance.

As the basic distribution model, the neural attentive item similarity (NAIS) algorithm was used to model the click sequence. Each item was represented as an eigenvector in the algorithm, and the inner product of these vectors was used to model the similarity between items, thereby effectively handling this problem, which helped recommend new resources to users, which were similar to the teaching resources that they had been interested in. The NAIS algorithm learned the different importance of each item in the sequence using the attention mechanism and made more accurate recommendations.

In this study, the teaching content combination preferences should be represented based on the click sequence of teachers or students concerning teaching resources. Therefore, the teaching content combination plans clicked by each user were represented by a real-valued low-dimensional eigenvector. Let o_y^i be the eigenvector, $o_1^i,\ldots,o_y^i$ be the click sequence, o_u be the characteristic representation of the target teaching resources n^u, and w_i be the click records. The probability of system distribution contents was calculated using the following equation:

$$O = \delta(w_i^Y o_u) \tag{13}$$

Characteristics of the sequence w_i were represented in this study based on the attention mechanism, and the attention factors were introduced to represent user preferences for the element O_y^i in w_i.

Sequence modification components. Based on hierarchical reinforcement learning technology, this study filtered out noise records from click sequences of teachers or students concerning teaching resources. The technology used hierarchical Markov decision processes (HMDP) to process the click sequences. HMDP decomposed a complex task into multiple relatively simple subtasks, making the problem solving more structured and efficient. By decomposing a problem into high- and low-level tasks, the hierarchical reinforcement learning provided a structured decision-making method, which helped deal with problems more accurately and efficiently. High-level tasks first evaluated the entire click sequence to determine whether modifications were needed. If it was determined that they were needed, low-level tasks were entered. The low-level tasks analyzed each record in the sequence to determine whether the record should be deleted as noise. Hierarchical reinforcement learning learned and optimized strategies by delaying rewards, meaning that the system continuously improved its noise-filtering performance, with more data being input over time.

This study further elaborated on the key definitions used in the sequence modification components of intelligent content distribution system.

Environment: In this system, environment is a set, including teaching resource datasets and the pre-trained basic distribution model. The environment provides a series of possible states and actions for the intelligent agent, which interacts with the environment based on these states and actions. The environment reflects the actual situations of teaching resources and the pre-training situations of the basic distribution model.

States: In high-level tasks, states may include characteristics of the entire click sequence, such as sequence length, resource types included in the sequence, and so on. The state information is used to determine whether the entire click sequence needs to be modified. In low-level tasks, states are typically the characteristics of each specific record in the click sequence, such as resource ID, click time, and other information that may be related to the record. The state information is used to determine whether specific records in the sequence should be deleted.

Actions and decisions: In high-level tasks, an action may be a binary decision, that is, whether or not the entire click sequence needs to be modified. In low-level tasks, actions usually involve specific operations, such as retaining or deleting specific records. High- and low-level task actions are defined as Boolean values $s^g \in \{0,1\}$ and $S_y^m \in \{0,1\}$, which represent whether low-level tasks are entered and click records are modified, and whether each sequence element is deleted, respectively.

A decision is the process of selecting an action based on the current state. In this system, the model uses probability to determine which action should be performed. Based on feedback from the environment and states, the system learns how to make better decisions.

Let $Q_y^m \in E^{(fm1\times fm2)}$, $Q_2^m \in E^{(f21\times 1)}$ and $n^m \in E^{(fm2)}$ be the parameters to be learned by the model, i.e. $\Phi^M = \{Q_1^m, Q_2^m, n^m\}$, f_1^2 be the number of dimensions of the hidden layer, G_y^m be the eigenvector of the input state, and δ be the sigmoid function. For high-level tasks, the parameters only needed to be changed to $\Phi g = \{Q_1^m, Q_2^m, n^g\}$. The model performed the following low-level actions based on strategies:

$$G_y^m = R\text{elu}(Q_1^m a_1^m + n^m) \tag{14}$$

$$\tau\left(a_y^m, s_y^m\right) = O\left(s_y^m \middle| a_y^m, \Phi^m\right) = s_y^m \delta\left(Q_2^m G_y^m\right) + \left(1 - s_y^m\right)\left(1 - \delta\left(Q_2^m G_y^m\right)\right) \tag{15}$$

Rewards are scalar feedback, indicating whether the actions performed by the intelligent agent are reasonable. For example, if the intelligent agent successfully deletes a noise record, it may receive positive rewards. On the contrary, if the intelligent agent mistakenly deletes a valuable record, it may receive negative rewards. Let $o(R^i, v_u)$ be the abbreviation for $o = (t = 1 \mid R^i, v_u)$, and $\hat{R}^i$ be the modified sequence. This study used the sequence accuracy difference before and after modification to represent the rewards of low-level tasks:

$$\begin{cases} E\left(s_y^m, a_y^m\right) = \log o\left(\hat{R}^i, v_u\right) - \log o\left(R^i, v_u\right), ud \quad y = y_i \\ 0, \quad \text{else} \end{cases} \tag{16}$$

Internal rewards were defined for the system in this study, which aimed to guide the system to consider the correlation between teaching objectives of courses and learning needs of students when making decisions. Specifically, when the system distributed teaching contents, internal rewards evaluated and adjusted the decisions based on the degree to which the contents matched the teaching objectives and students' needs. By using internal rewards, the system was more inclined to choose teaching content highly related to teaching objectives of courses and learning needs of students. In this way, content distribution was more in line with practical needs and improved the teaching effect.

The average cosine similarity difference values between sequence elements and target teaching content combination plans before and after sequence modification were defined as the internal rewards H. Let Φ be Φ^g or Φ^M, π be the sequence of sampling operations and transition states, $O_\Phi(\pi; \Phi)$ be the corresponding sampling probability, and $E(\pi)$ be the rewards for sampling sequence π. The calculation equation was given as follows:

$$\Phi^* = \arg\max_\Phi \sum_\pi O_\Phi(\pi;\Phi) E(\pi) \tag{17}$$

The sampling sequence was $\{a_1^m, s_1^m, a_2^m, \ldots, a_y^m, s_y^m, a_{y+1}^m, \ldots\}$ in low-level tasks or $\{a^g, s^g\}$ in high-level tasks. Let $E(s_y^j, a_y^j) + H(s_y^j, a_y^j)$ be the rewards for each action state pair in the sequence π^y; then $E(s_y^j, a_y^j) + H(s_y^j, a_y^j)$were numerically equal to the final rewards $E(s_{yi}^j, a_{yi}^j) + H(s_{yi}^j, a_{yi}^j)$. The parameter gradient of low-level policy functions was further calculated based on trajectory J:

$$\nabla_\varphi = \frac{1}{j}\sum_{j=1}^{j} \nabla_\varphi \log \tau_\varphi \left(a_y^j, s_y^j\right)\left(E\left(a_y^j, s_y^j\right) + H\left(a_y^j, s_y^j\right)\right) \tag{18}$$

The gradient calculation equation for the high-level policy functions was as follows:

$$\nabla_\varphi = \frac{1}{j}\sum_{j=1}^{j} \nabla_\varphi \log \tau_\varphi \left(a_y^j, s_y^j\right) E\left(a_y^j, s_y^j\right) \tag{19}$$

To utilize the click historical records processed by sequence modification components, this study improved and optimized the basic distribution model to obtain more accurate teaching content distribution results. This process was based on the understanding that the original click historical records may contain noise and inaccurate information. Therefore, the data processed by the sequence modification components better reflected the real needs and preferences of teachers or students.

4 EXPERIMENTAL RESULTS AND ANALYSIS

Table 1. Comparative experimental results of sample set A

	HR@5	HR@10	NDCG@5	NDCG@10
Collaborative filtering algorithm	0.4947	0.4993	0.2527	0.2026
Content-based filtering algorithm	0.2946	0.3738	0.1526	0.2378
Matrix decomposition algorithm	0.2628	0.2926	0.1307	0.1679
Association rule learning	0.4036	0.5637	0.3926	0.3738
K-nearest neighbor algorithm	0.6947	0.7028	0.4377	0.5026
Method proposed in this study	0.8746	0.9648	0.5027	0.6627

Table 1 shows the comparative experimental results of six different algorithms (i.e., collaborative filtering algorithm, content-based filtering algorithm, matrix decomposition algorithm, association rule learning, K-nearest neighbor algorithm, and the method proposed in this study) on sample set A, and the evaluation indexes include HR@5, HR@10, NDCG@5 and NDCG@10. It can be seen from the table that the method proposed in this study performs well in all evaluation indexes, because the method integrates multiple components (i.e., the basic distribution model, the sequence modification model, and the clustering model) through the hierarchical reinforcement learning network, which has advantages in filtering noise, processing data sparsity, and customizing teaching contents according to user preferences.

Table 2. Comparative experimental results of sample set B

	HR@5	HR@10	NDCG@5	NDCG@10
Collaborative filtering algorithm	0.4267	0.5993	0.1527	0.1026
Content-based filtering algorithm	0.4946	0.5738	0.2526	0.3378
Matrix decomposition algorithm	0.3628	0.4926	0.2307	0.2679
Association rule learning	0.4036	0.5637	0.2926	0.3336
K-nearest neighbor algorithm	0.2947	0.3028	0.1377	0.1026
Method proposed in this study	0.4746	0.7648	0.3027	0.4627

Table 2 shows the comparative experimental results of the six algorithms on sample set B using the same evaluation indexes of HR@5, HR@10, NDCG@5, and NDCG@10. It can be seen from the table that the method proposed in this study still performs well on sample set B, especially in generating long recommendation lists and sorting quality. The conclusion shows that the method based on hierarchical reinforcement learning proposed in this study maintains high performance on different sample sets, which proves its robustness and adaptability. At the same time, significant differences exist in the performance of different algorithms on different sample sets, which emphasizes the importance of selecting algorithms that are suitable for specific data and tasks.

Table 3. Comparison of the model's performance before and after HMDP introduction

<table>
<tr><th colspan="2"></th><th>HR@5</th><th>HR@10</th><th>NDCG@5</th><th>NDCG@10</th></tr>
<tr><td rowspan="2">Before HMDP introduction</td><td>Average values</td><td>0.2834</td><td>0.3946</td><td>0.1072</td><td>0.2197</td></tr>
<tr><td>Standard deviations</td><td>0.2028</td><td>0.2028</td><td>0.1962</td><td>0.1176</td></tr>
<tr><td rowspan="2">After HMDP introduction</td><td>Average values</td><td>0.7826</td><td>0.9647</td><td>0.5024</td><td>0.5156</td></tr>
<tr><td>Standard deviations</td><td>0.0309</td><td>0.0135</td><td>0.0516</td><td>0.0414</td></tr>
</table>

Table 3 shows comparison of the model's performance before and after HMDP is introduced. The evaluation indexes are the same as those in the above two tables. It can be seen from the table that introduction of HMDP significantly improves the model's performance in teaching content recommendation tasks. Average values in all evaluation indexes significantly increase, indicating an improvement in the correlation and sorting quality of recommendations. In addition, significant reduction of standard deviations shows that the model's stability has been improved.

Table 4. Recommendation results of the basic recommendation model, the sequence modification model, and joint training

	HR@5	HR@10	NDCG@5	NDCG@10
Basic recommendation model	0.2247	0.2913	0.1467	0.1926
Sequence modification model	0.7945	0.8748	0.5501	0.5398
Joint training	0.8618	0.9126	0.5347	0.6279

Table 4 shows the recommendation results of the basic recommendation model, the sequence modification model, and joint training. Evaluation indexes include HR@5, HR@10, NDCG@5 and NDCG@10. It can be seen from the table that the sequence modification model has a significant improvement compared with the basic recommendation model, with an increase in correlation in the top five items of the recommendation list. Joint training further improves HR@5, indicating that the joint training of the sequence modification model and the basic distribution model further improves the correlation of the top five recommended items. In the top ten items on the recommendation list, the values of HR@10 also significantly increase after sequence modification and joint training, indicating an improvement in the correlation of recommendations. The significant increase of NDCG@5 in the sequence modification model indicates an improvement in the sorting quality of the top five recommended items. NDCG@5 in joint training slightly decreases, because the model sacrifices sorting quality slightly in the process of optimizing other objectives. NDCG@10 significantly improves in the sequence modification model, and it further increases after joint training, indicating that the sorting quality of the top ten recommended items continues to improve throughout the entire process.

Table 5. Comparison of experimental results with different numbers of sample categories

Categories	HR@5	HR@10	NDCG@5	NDCG@10
10,000	0.3241	0.4582	0.2987	0.2982
5,000	0.6245	0.7662	0.4521	0.5198
2,000	0.8512	0.9235	0.4125	0.6294
1,000	0.8124	0.8452	0.5624	0.5289

Table 5 shows the experimental results with different numbers of sample categories (i.e., 10,000, 5,000, 2,000, and 1,000). Evaluation indexes include HR@5, HR@10, NDCG@5, and NDCG@10. When the number of sample categories decreases from 10,000 to 2,000, HR@5 significantly increases, indicating that reduction of categories improves the correlation of the top five recommended items. However, when the number of categories further decreases to 1,000, HR@5 slightly decreases, because too few categories lead to overfitting of the model or insufficient information being captured. Similar to HR@5, HR@10 significantly increases when the number of categories decreases from 10,000 to 2,000 but slightly decreases when the number of categories decreases to 1,000. When the numbers of categories are 5,000 and 1,000, NDCG@5 is relatively high, indicating that the sorting quality of the top five recommended items is better in these situations. However, when the number of categories is 2,000, NDCG@5 decreases, because the relationship between the number of categories and data distribution is complex. NDCG@10 is the highest when the number of categories is 2,000, indicating that the sorting quality of the top ten recommended items is the best with this number of categories.

5 CONCLUSION

This research studied a machine learning–based teaching content customization method, aiming to effectively distribute teaching content most relevant to teaching objectives of courses and learning needs of student through an intelligent content distribution system. Combined with the click historical records of teachers or students concerning teaching resources, the system adjusted the basic distribution model to obtain more accurate distribution results using sequence modification components.

In the comparative experiments of sample sets A and B, the method proposed in this study was superior to other common recommendation algorithms in HR@5, HR@10, NDCG@5 and NDCG@10, indicating its advantages in correlation and sorting quality. The comparison results of the model's performance before and after HMDP introduction showed that the introduction significantly improved the model's performance, reduced the standard deviations of the results, and enhanced the model's stability. The recommendation results of the basic recommendation model, the sequence modification model, and joint training showed that joint training significantly improved the model's performance. The experimental results with different numbers of sample categories showed that selecting the appropriate number of sample categories was crucial for the model's performance. In this case, when the number of sample categories was 2,000, the optimal level was achieved for most indexes.

The machine learning–based teaching content customization method proposed in this study demonstrated high performance and reliability in experiments. Combined with sequence modification components and an internal reward mechanism, the method effectively distributed content highly related to teaching objectives and students' needs, using the NAIS algorithm as the basic distribution model. In addition, the model's performance was further optimized through joint training and reasonable selection of the number of sample categories. Overall, this study provided an effective solution to improve the precision and correlation of teaching content distribution.

6 ACKNOWLEDGMENTS

This paper was supported by the Hunan Provincial Education Science 14th Five Year Plan Project, Reform and Practice of the Training Model for Excellent and Innovative Talents in Computer Science in Local Universities under the Background of New Engineering (Grant No.: XJK23CGD068); Hunan Province General Higher Education Teaching Reform Research Project, Reform and Practice of the "134" Excellent Innovative Talent Training Model for Computer Majors under the Background of New Engineering (Grant No.: HNJG-2022-0999); and The Ministry of Education's Industry School Cooperation Collaborative Education Project, Construction of Information Technology Innovation and Entrepreneurship Education Base (Grant No.: 220501363203108).

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